J. Indian Inst. Sci., Nov.–Dec. 2006, **86**, 681–693

Development of generalized cost model for private car trip makers under traffic information

DEBASIS BASU[1] AND BHARGAB MAITRA[2]*
Department of Civil Engineering, Indian Institute of Technology Kharagpur, Kharagpur 721 302, India.
email: [1]basudebasis2k@gmail.com and [2]bhargab@civil.iitkgp.ernet.in; Phone: 91-3222-283 458
Mobile: 0-9434040738.

Received on July 18, 2006; Revised on December 22, 2006.

Abstract

To formulate rational improvement proposal under traffic information, it is necessary to develop a generalized cost (GC) model of trip makers' route selection process under the effect of traffic information. The paper demonstrates a methodology for developing GC models for private car trip makers, when travel time is projected as instantaneous traffic information along with its variation level on a roadside variable message sign (VMS) board as a measure of influencing trip makers' route choice behavior. As an empirical study, two competitive traffic corridors in Kolkata Metro City, India, are considered. A stated preference (choice based) experiment is carried out and both multinomial logit (MNL) and random parameter logit (RPL) techniques are employed for the estimation of coefficients of the relevant attributes. Considering a priori constrained T-distribution of random parameters, two different RPL models are explored: one without accounting heterogeneity and the other with accounting heterogeneity around the mean of random parameter(s).

Keywords: Generalized cost (GC), instantaneous traffic information, stated choice, multinomial logit, random parameter logit, constrained T-distribution, and heterogeneity.

1. Introduction

The growing road traffic congestion in urban areas is a major concern for most of the developed and developing countries. Traffic congestion is the outcome of the interaction between demand and supply sides of a transportation system in the interface of control. Therefore, mitigation of congestion can be achieved through augmentation of supply, improvement of control strategies and application of suitable demand management strategies. In developing countries, expansion and improvement of roads are generally restricted by increasingly tight fiscal and physical constraints. Also, it is well known that augmentation of supply alone cannot be effective for mitigation of congestion in a sustainable manner. Therefore, there is a greater emphasis on formulating efficient control and demand management measures. Such measures are generally not capital intensive and have greater importance for developing countries where availability of financial resources is a major constraint. As a part of demand management, both spatially and temporarily, there has been a trend of applying traffic information using various types of advanced traveler information system (ATIS). Roadside variable message sign (VMS) board is a form of ATIS that influ-

*Author for correspondence.

ences route choice decision of trip makers. In fact, as mentioned by Emmerink *et al.* [1], there has been a great potential for the development of VMS systems in providing traffic information to drivers.

Research on the applicability and suitability of VMS system has grown in many facets in the last decade. One of the facets of research for a successful application of VMS system is on the content and its format to be displayed [2, 3]. Though there have been a lot of works on the content of information and its format, yet it is found from the established literature that most of the research has focused on content including a single item like travel time or delay. There have been very few studies on understanding the trip makers' behavior, when more than one item is presented to trip makers as traffic information.

In the present work, an attempt has been made to study the impact of adding travel time variation information from the previous time interval to the present along with the instantaneous travel time on route choice behavior of trip makers. Though this additional piece of information is not making the traffic information a predictive one, it is expected to have an impact on route choice behavior of trip makers as they will evaluate the present travel time information in the light of this variation information. The school of thought to include instantaneous travel times for alternative routes and also the variation in instantaneous travel times from the previous interval to the present as traffic information is essentially to improve the quality/reliability of instantaneous traffic information. In the wake of understanding the effectiveness of such type of traffic information and estimating users' likely benefits, it is invariably required to know how trip makers value travel time and its variation and to develop generalized cost (GC) models.

Two competitive traffic corridors in the Kolkata Metro City, India, are considered as a case study where at the junction of two corridors, traffic information is considered to be displayed on a roadside VMS board. No other traffic information systems are considered to exist along either of these corridors to act as en-route traffic information provider. For valuing purpose, a stated choice (SC) method is adopted to elicit preferences by generating hypothetical profiles using various levels of stated instantaneous travel time, stated levels of variation of that travel time and travel cost attributes. Instantaneous travel time is presented in quantitative format (in minute) and its variation level is presented in qualitative format (such as Very High/High/Moderate/Low). During stated choice experimentation, the respondents are also informed about the quantitative basis used for defining the variation levels. In the course of coefficient estimation of relevant attributes, both the multinomial logit (MNL) and random parameter logit (RPL) techniques are explored. The study also takes a measure to observe the presence of any heterogeneity effect on the coefficients estimate and its subsequent effect on the valuation.

2. Methodology

2.1. *Approach*

In discrete choice models valuing of an attribute is relatively straightforward as given by the ratio of partial derivatives of the utility function with respect to that attribute and travel cost (i.e. marginal rate of substitution between the attribute and travel cost at constant utility). It is important to appreciate that the justification for this approach rests on a substantial body of microeconomic theory that addresses the issue of how individuals allocate time and its variation amongst alternatives.

To develop the utility model, it is necessary to collect preferences of trip makers either in the form of revealed preference (RP) or stated preference (SP) data. RP and/or SP data has been used in diverse fields for estimating willingness-to-pay (WTP) indicators [4–10]. With a richer disaggregation of travel time, RP data is usually inappropriate. It is best described as ‘dirty’ from the point of view of statistical estimation of the individual preferences on choice. Some attribute levels may not be observed in RP data and the predictor variables (attributes of alternatives, and contextual effects) may exhibit high or extreme levels of multicollinearity consequent to market forces, technology and sampling considerations [11]. On the other hand, SP data is rich and effective in estimating marginal WTP values [12]. In SP experiment, a systematic combination of levels of each attribute can be done to reveal new opportunities (i.e. new travel scenarios) relative to the existing circumstances of time-cost on offer [11]. Therefore, in the present work, SP data is used for the development of utility model. However, SP experiments have many features that can influence the resulting value of time and its variations. In particular it is thought that the estimates are sensitive to the design of the SP experiment [11], especially, (1) the number of alternatives in a choice set, (2) the number of choice sets (treatments) evaluated, and (3) the range and levels of attributes being traded. Though SP data may be collected in the form of rating, ranking and choice, stated choice SC experiments provide a framework for studying the relative marginal disutility of variations in attributes and their potential correlations [13].

Generally, SP and/or RP data is analyzed using traditional MNL models due to simplicity in estimation. However, the MNL models impose some restrictions such as independence of irrelevant alternatives (IIA). It is seen that valuing of attributes is likely to be underestimated in MNL model because an element of the unobserved influences on travel choices is ‘forced’ into the parameter estimates of the observed effects when the strict independently and identically distributed (IID) condition of standard MNL model is imposed on the utility function. Theory suggests that this impact on the time attributes more than the cost attribute because many of the unobserved attributes are more correlated with travel time than travel cost [14, 15]. From the econometric perspective, it can be said that the mean of a random parameter is likely to be larger than that of MNL because the random parameter logit model decomposes the unobserved component of utility and normalizes (through scale parameter) the parameter estimates on the basis of part of the unobserved component. Therefore, modifications to the MNL model to reduce the influence of these restrictions lead to RPL or random coefficient logit (RCL) models.

2.2. *Theoretical basis and econometric models*

In econometric models based on random utility theory [16, 17], the utility of each element consists of an observed (deterministic) component denoted by V and a random (disturbance) component denoted by ε,

$$U = V + \varepsilon. \tag{1}$$

The deterministic part V is again a function of the observed attributes (z) of the choice as faced by the individual, the observed socioeconomic attributes of the individual (S) and a vector of coefficients (β), then

$$V = V(z, S, \beta). \tag{2}$$

A probabilistic statement can be made (due to the presence of random component) as, when an individual 'n' is facing a choice set, C_n, consisting of J_n choices, the choice probability of alternative i is equal to the probability that the utility of alternative 'i', U_{in}, is greater than or equal to the utilities of all other alternatives in the choice set, i.e.

$$P_n(i) = \Pr(U_{in} \geq U_{jn}, \text{ for all } j \in C_n); \tag{3}$$

$$P_n(i) = \Pr(V_{in} + \varepsilon_{in} \geq V_{jn} + \varepsilon_{jn}, \text{ for all } j \in C_n, \ \forall j \neq i). \tag{4}$$

Assuming IID (Gumbel distribution) for ε, the probability that an individual chooses i can be given by the MNL model [17, 18],

$$P_{in} = \frac{e^{V_{in}}}{\sum_{j \in C_n} e^{V_{in}}}. \tag{5}$$

This model can be estimated by maximum likelihood technique, and is useful for modeling choice behavior. However, several limitations apply to this model. The most severe of these is the IIA property which states that a change in the attributes of one alternative changes the probabilities of the other alternatives in proportion. This substitution pattern may not be realistic in all settings. Secondly, the coefficients of all attributes are assumed to be the same for all the respondents in a choice experiment, whereas in reality there may be substantial variability in how different individuals respond to attributes. Actually there is a need to introduce a conventional form of heterogeneity of preferences to understand the interactions between alternative attributes and individual socioeconomic characteristics such as gender, age, income level, trip purpose [19–21]. In this case, the parameter of each attribute is required to be a function of the individuals' observed socioeconomic characteristics as mentioned which allows us to detect the systematic variations in tastes. However, on many occasions individual information is not available, or tastes may vary with characteristics that are difficult to measure or cannot be observed. In such cases, (2) can be generalized to consider heterogeneity specifying random parameters for each individual. Thus, the utility of alternative i for an individual n would be

$$u_{in} = \beta_n x_{in} + \varepsilon_{in} = \bar{\beta} x_{in} + \hat{\beta}_n x_{in} + \varepsilon_{in}. \tag{6}$$

Thus, each individual's coefficient vector β_n is the sum of the population mean $\bar{\beta}$ and individual deviation $\hat{\beta}_n$ from the average value for the population. $\hat{\beta}_n x_{in}$ is the error component that induces heteroskedasticity in the unobserved portion of the utility. This implies an important implication of RPL specification where we do not have to assume the IIA property holds. In eqn (6), x_{in} are observed variables that relate to the alternative and individual, and β_n is a vector of coefficients of these variables for individual n. Let the coefficients vary over individuals in the population with density $f(\beta_n|\theta)$, where θ represent the mean and covariance of β_n in the population and if the error term ε_{in} follows the IID type I extreme value distribution, then the RPL model is called mixed logit (ML) random parameter model [22] because then the choice probability is the mixture of logits with f as mixing distribution [23].

In this case, the individual knows the value of her/his own β_n and ε_{in}s for all i and chooses alternative i if and only if $U_{in} \geq U_{jn}$ for all $J \in C_n$, $\forall$ $j \neq i$. On the other hand, the modeler/researcher observes x_{in}s but not β_n or the ε_{in}s. If the modeler observed β_n, then the choice probability would be standard logit, since the ε_{in}s are IID type I extreme value distribution. Then the probability, conditional on β_n is

$$L_{in}(\beta_n) = \frac{\exp(\beta_n x_{in})}{\sum_{i=1}^{J} \exp(\beta_n x_{in})}. \tag{7}$$

However, the modeler does not know β_n, and therefore cannot condition. Therefore, the unconditional choice probability is the integral of $L_n\beta_n$ over all possible variables of β_n [22].

$$P_{in} = \int \left(\frac{\exp(\beta_n x_{in})}{\sum_{i=1}^{J} \exp(\beta_n x_{in})} \right) f(\beta_n \mid \theta) \mathrm{d}\beta_n. \tag{8}$$

In general, the integral cannot be evaluated analytically, and one has to rely on a simulation method for the probabilities. Here, a simulated maximum likelihood estimator is used. This type of random parameter model is less restrictive than standard conditional logit models. However, the less-restrictive models should be applied cautiously. Apart from being rather difficult to estimate, literature shows that the results can be rather sensitive to the distributional assumptions and the number of draws applied in the simulation [24].

2.3. *Selection of distribution*

In RPL model, it is necessary to make an assumption regarding the distribution of each of the random coefficients. The choice of distribution is often limited by difficulty of model estimation and availability of econometric software. The alternative distributions available are normal, log-normal, uniform and triangular. The log-normal form is often used if the mean of random parameter needs to be a specific (non-negative) sign. The disadvantage of lognormal is that it has a long upper tail. A uniform distribution with a (0, 1) bound is sensible when dummy variables are to be estimated. For the triangular distribution, the density function looks like a tent: a peak in the centre and dropping off linearly on both sides of the center. The disadvantage with normal, uniform and triangular distributions is that they give the wrong sign to some shares due to spread or standard deviation of the distributions. This can be avoided by imposing a constraint on the distributions so that the mean is equal to spread [24]. In the present work, constrained triangular distribution is assumed for random parameters in RPL models. Constrained triangular distribution is a generalization of the uniform distribution with a peak in the density function and two endpoints fixed at zero and 2* mean. Although it has several advantages over the other distributions, its application in WTP calculation has not been explored adequately. In the present work, the application of constrained triangular distribution is explored while developing RPL models.

3. Empirical study

3.1. *Study area*

Two distinct competitive traffic corridors are selected in Kolkata. For the study corridors, origin and destination are selected based on catchment area concept, rather than zoning concept. The origin of both traffic corridors is Park Circus and the destination is Esplanade/Dalhousie area. One traffic corridor (called as Flyover corridor, FO) starts at Park Circus and then goes via the newly constructed Flyover to Rabindra Sadan and then via Red Road to Esplanade/Dalhousie area. This corridor is almost a free flow corridor and the length is 5 km. The alternative traffic corridor (called as Park Street corridor, PS) goes via Park Street, and the length of this corridor is 3.4 km. The PS corridor becomes highly congested during the peak periods. From the reconnaissance survey, it is observed that both the traffic corridors carry only private cars and taxis. Also, it is found that large amount of traffic enters at the Park Circus junction in the morning peak hours from different locations of the Kolkata city to go to Esplanade/Dalhousie area.

3.2. *Survey instrument*

The three attributes considered for the SP study are travel time, its variation level and travel cost. Depending on the possible variation in instantaneous travel time from one time interval to the next, four levels of variation are defined in a qualitative manner as follows:

Low: If the change in instantaneous travel time from the previous time interval to the present is within 20% of the instantaneous travel time.

Medium: If the change in instantaneous travel time from the previous time interval to the present is within 20–30% of the instantaneous travel time.

High: If the change in instantaneous travel time from the previous time interval to the present is within 30–40% of the instantaneous travel time.

Very High: If the change in instantaneous travel time from the previous time interval to the present is within 40–50% of the instantaneous travel time.

Based on preliminary site investigations and discussions with regional traffic experts, local traffic police and private car trip makers, the levels of the attributes (Table I) are selected for two corridors. Travel cost of private cars is calculated considering 80% petrol vehicles and 20% diesel vehicles.

Table I
Attributes and their levels

Corridor	Attribute	Levels
Flyover	Travel time (min)	5, 10, 15
	Level of variation	Low, medium
	Travel cost (Rs)*	15, 25, 35, 45, 55
Park Street	Travel time (min)	10, 15, 20, 25, 30, 35, 40
	Level of variation	Medium, high, very high
	Travel cost (Rs)*	5, 15, 25, 35, 45

*1 USD ~ 45 INR (Indian rupees).

Alternative corridors	Travel time (min)	Level of variation	Travel cost (Rs)	Please state your choice by √
Via Flyover	5	Low	45	
Via Park Street	35	High	15	

FIG. 1. A sample SP choice set.

It is a common practice to develop alternatives using either full factorial or fractional factorial design. However, it is neither necessary nor practically possible to include all these combinations in SP experiments. Therefore, some of the choice sets are eliminated using fractional factorial orthogonal technique without loss of much of statistical properties of full factorial design. Fractional factorial/orthogonal main effects only design [25] and reduces the number of combinations effectively by eliminating some of the higher-order combinations. Fractional factorial orthogonal design is used to produce the alternatives. A sum of 80 alternatives is generated for each of the two corridors for different trip makers. Subject to preservation of orthogonality, the levels of attributes for both SP alternatives (corridors) are ‘swapped’ to ensure that neither Flyover corridor nor Park Street corridor dominates each other [11]. This way 80 competitive choice sets are generated for each of the two types of trip makers. Each questionnaire consists of five choice sets (i.e. observations) which are randomly picked. This way 16 (i.e. 80/5 = 16) different questionnaires are developed. The questionnaire consists of two parts. The first, which is common to all 16 questionnaires, is to collect respondents’ socioeconomic status, present travel behavior and trip characteristics, whereas the second is to collect the stated choice responses. In the introduction to the choice experiment, the purpose of application of pre-trip instantaneous traffic information system is briefly explained. The respondents are also briefed about the attributes and the quantitative basis used for defining variation levels. A sample of SP choice set for private car trip makers is presented in Fig. 1.

3.3. *Database development*

A choice-based stated preference survey was carried out in Kolkata in the month of May–June, 2005. A paper–pencil-based survey was carried out as face-to-face interview of private car trip makers. As many as ten enumerators were selected and trained in multiple sessions to administer the survey work. For wide distribution of sample, various strategic places were identified and survey was carried out in each of those places. Respondents were requested to reveal their present route choice behavior between Park-street and Flyover corridors with their perceived travel time and travel cost from Park Circus to Esplanade/ Dalhousie area along with their socioeconomic characteristics. Besides this, they were also requested to state their route choice under different stated traffic information scenarios. For each respondent, the process was repeated five times. During data collection process, more than 1100 private car trip makers’ questionnaires were collected. However, for various reasons like inconsistency in the responses, incomplete responses, only 955 questionnaires

Table II
Descriptive statistics

Gender	Male	87%
	Female	13%
Age	< 20 years	2%
	20 to 35 years	40%
	36 to 55 years	52%
	> 55 years	6%
Education	Up to 10th Standard	10%
	Up to 12th Standard	26%
	Graduate/Master level	64%
Monthly family income	< Rs 20,000	64%
	> Rs 20,000	36%
Household size	<3	13%
	3 to 5	74%
	>5	13%
Trip purpose	Revenue-generating	29%
	Non-revenue-generating	71%

were finally selected for private car trip makers. Some descriptive statistics of the database of private car trip makers are presented in Table II.

3.4. *Model development*

To develop utility models, a total of 4643 refined observations are selected for representing choice behavior for private car trip makers. The analysis is carried out separately under heads of two different trip purposes: One, the revenue-generating trips (i.e. consisting of almost regular kind of work, office, business trips; a total of 1341 out of 4643 observations) and other one, the non-revenue-generating trips (i.e. consisting of social, recreational and other trips; a total of 3302 out of 4643 observations). Linear utility models are developed for both trip purposes considering instantaneous travel time and its variation in quantitative format (i.e. in minutes) as attributes of the models. The travel time variation is expressed in minutes by taking the mid-value of the defined variation level and multiplying it with the corresponding instantaneous travel time. Flyover corridor is considered as an alternative-specific intercept for all the logit models. For rational valuing of attributes, the less-restrictive RPL technique is explored along with the MNL technique. Two different RPL modeling techniques are explored: one without accounting heterogeneity (i.e. effect of socio-demographic parameters) and the other with accounting heterogeneity around the mean of random parameter(s). In the course of heterogeneity study, private car trip makers are grouped under two heads: the low income group, whose family income per month is less than or equal to Rs 20,000/-, and the high income group, whose family income per month is more than Rs 20,000 (1 USD ~ 45 INR). In the process of RPL model development, travel cost attribute is considered as not randomly distributed because of three reasons: (1) it simplifies the estimation of value of time and its variation, i.e. valuing is simple division of the coefficient of an attribute by the coefficient of cost, (2) the distribution of the marginal value for travel time/its variation is simply the distribution of that attribute, and (3) the travel cost attribute is restricted to non-positive value for all individuals. The alternative specific intercept is also kept as non-random. On the other hand, other attributes, i.e. travel time and its variation are assumed as randomly distributed following the constrained T-distribution.

3.5. *Results and discussion*

It may be observed from Table III that the signs of parameter estimates are as expected and in agreement with the actual scenario of the study corridors. The coefficient estimates of all attributes are negative representing the attributes as disutility. It is evident from *t*-stat (more than 1.96) of the coefficients of attributes that the coefficient estimates are statistically (more than 95% confidence level) significantly different from zero. The overall goodness of fit is considered using pseudo R^2 (ρ^2). In a process of RPL model development, a series of heterogeneity studies are carried out based on socio-demographic variables and it is found that family income per month decomposes heterogeneity around the mean of random parameter(s). A slight improvement in ρ^2 value of the standard RPL model is also noticed when heterogeneity study (based on income group) is carried out, implying that trip makers from two income groups perceive the chosen attributes of the model differently and distinctly. For revenue-generating trips, heterogeneity is found significant around the mean of the variation in travel time, whereas for non-revenue-generating trips around the mean of the travel time. The interpretation of model coefficients in Table III are not straightforward except for significance and goodness-of-fit. So, the marginal rates of substitution between attributes and cost are calculated.

Table IV shows the value of travel time and its variation for revenue- and non-revenue-generating trips, respectively. It is observed that higher-order values are estimated when RPL techniques are employed. The reason can be attributed to the travel time with its variation level stated as traffic information together does not suffice to convey the full information a rational trip maker seeks for choice decision. Several unobserved parameters like traffic congestion level, possible longer delay, queuing of traffic, on-road incident, etc. a trip maker may consider and correlate with travel time and its variation for opting for a corridor, which is not included in the SP questionnaire. So, travel time and its variation represent those unobserved parameters in a proxy way during coefficient estimates using RPL technique and because of that a higher-order value in travel time and its variation are noticed when RPL technique is employed. In this way, the less-restrictive RPL technique overcomes the difficulties associated with underestimation of values emanating from MNL technique. Table IV shows that for revenue-generating trips the value of travel time variation is quite higher than that of travel time, whereas for non-revenue-generating trips (from Table IV) values of travel time and their variation are nearly equal.

3.6. *Development of generalized cost model*

Though the valuing of attributes gives an idea about how different categories of trip makers value travel time and its variation stated as traffic information, yet a subsequent development of generalized cost model is necessary for rational estimation of user benefits resulting from such traffic information system. The GC model requires values of travel time and their variation as inputs. It is found that RPL technique overcomes the difficulties associ-

Table III
Coefficient estimates from MNL and RPL techniques for revenue- and non-revenue generating trips

Attributes	Revenue-generating trips			Non-revenue-generating trips		
	MNL model	RPL models		MNL model	RPL models	
	Coefficient (t-stat)	Standard RPL coefficient (t-stat)	RPL with heterogeneity study coefficient (t-stat)	Coefficient (t-stat)	Standard RPL coefficient (t-stat)	RPL with heterogeneity study coefficient (t-stat)
		Random parameters (Constrained T-distribution)			Random parameters (Constrained T-distribution)	
Travel time (TT)	–0.12455 (–6.61)	–0.19370 (–5.11)	–0.17978 (–4.79)	–0.16083 (–15.04)	–0.21297 (–10.90)	–0.20394 (–8.84)
Variation in TT	–0.19723 (–4.32)	–0.28762 (–3.40)	–0.29057 (–2.84)	–0.13904 (–5.66)	–0.21544 (–6.53)	–0.21359 (–5.11)
		Non-random parameters			Non-random parameters	
Travel cost (TC)	–0.11638 (–8.10)	–0.14043 (–6.52)	–0.14319 (–5.71)	–0.16910 (–19.16)	–0.20281 (–14.70)	–0.20127 (–14.196)
Asc. to FO@	0.24740 (1.10)*	–0.26320 (–0.87)*	–0.37946 (–1.195)*	0.60535 (4.544)	0.41368 (2.36)	0.42633 (2.40)
		Standard deviation or spread of random parameter			Standard deviation or spread of random parameter	
Travel time (TT)		0.19370 (5.11)	0.17978 (4.79)		0.21297 (10.90)	0.20394 (8.84)
Variation in TT		0.28762 (3.40)	0.29057 (2.84)		0.21544 (6.53)	0.21359 (5.11)
			Income heterogeneity			Income heterogeneity
Travel Time (TT)			–			–0.01255 (–1.53)**
Variation in TT			–0.15518 (–4.17)			–
No. of observations	1341	1341	1341	3302	3302	3302
Log likelihood function	–505.88	–506.01	–495.09	–1398.994	–1422.567	–1421.988
ρ^2	0.22622	0.22622	0.24272	0.26765	0.25531	0.25561

@Stands for Flyover corridor.
*Insignificant almost at 95% confidence level.
**Significant almost at 90% confidence level (t = 1.69).

Table IV
Value of travel time and its variation for revenue- and non-revenue generating trips

Attribute	MNL model	Standard RPL	RPL models – Heterogeneity around mean: Low-income group	RPL models – Heterogeneity around mean: High-income group
Revenue-generating trips				
Travel time (TT) (Rs/min)	1.07	1.38	1.26	1.26
Variation of TT (Rs/min)	1.69	2.05	2.03	3.11
Non-revenue-generating trips				
Travel time (TT) (Rs/min)	0.95	1.05	1.01	1.07
Variation of TT (Rs/min)	0.82	1.06	1.06	1.06

1 US \$ ~ 45 Indian rupees (INR) and 1INR=100 Paise.

ated with the underestimation of values emanating from the MNL technique. Moreover, the effects of socio-demographic variables on valuing are also captured in RPL models accounting heterogeneity. Therefore, values obtained from RPL models accounting heterogeneity are accepted for proposing GC models. Two sets of GC models are developed to represent revenue- and non-revenue-generating trips, respectively. In each set, GC models are developed separately for high- and low-income group trip makers.

A. Revenue-generating trips

Low-income group

$$GC = 1.26 \times TT + 2.03 \times TT \times \text{travel time variation level} + \text{travel cost}$$

High-income group

$$GC = 1.26 \times TT + 3.11 \times TT \times \text{travel time variation level} + \text{travel cost}$$

B. Non-revenue-generating trips

Low-income group

$$GC = 1.01 \times TT + 1.06 \times TT \times \text{travel time variation level} + \text{travel cost}$$

High-income group

$$GC = 1.07 \times TT + 1.06 \times TT \times \text{travel time variation level} + \text{travel cost.}$$

4. Conclusion

Valuing of transport planning attributes and subsequent development of GC model are critical and essential analysis part for transport project appraisal and pricing, especially when a new transport project is undertaken which the trip makers have never experienced. The present work makes an attempt to understand the impact of instantaneous travel time information along with its variation level information through valuation. In the wake of evaluating the impact of such traffic information through valuation, the paper demonstrates a methodology utilizing a stated preference (choice based) database collected under different combinations of stated traffic information scenarios. As a case study, two competitive traffic corridors are considered in Kolkata and the route choice behavior of private car trip makers is investigated for valuing purpose. For rational valuing of travel time and its variation, the reasonability and applicability of the less-restrictive RPL technique is explored along with the MNL technique. Both the travel time and its variation are considered as randomly distributed following constrained t-distribution for the development of RPL models. The study takes care of relevant socio-demographic variables to decompose the heterogeneity effect around the mean of random parameters in RPL models. Family income per month is found to decompose the heterogeneity effect around the mean of travel time and/or its variation. It is found from t-stats of all the logit models that trip makers pay due attention to the travel time variation as a part of the choice process. The negative signs of travel time variation coefficient signify trip-makers' disutility towards higher-order variation of instantaneous travel time information. From the valuation of attributes, it is understood that trip makers perceive both travel time and its variation attributes distinctly and differently. Though for non-revenue-generating trips, values of travel time and their variation are almost equal, for revenue-generating trips, higher values are observed for variation in travel time. The findings from the present work may encourage further investigation on the effectiveness of providing instantaneous travel time and its variation as traffic information for management of traffic congestion on alternative corridors both temporally and spatially.

References

1. R. H. M. Emmerink, P. Nijkamp, P. Rietveld, and J. N. Van Ommeren, Variable message signs and road traffic information: An integrated empirical analysis of drivers' route choice behaviour, *Transp. Res. A*, **30**, 135–153 (1996).
2. J. Catchpole, A. Hancock, and P. Cairney, *Driver comprehension of formats for presenting traffic information on dynamic signs*, Res. Rep. ARR 269, ARRB Transport Research, Vermont South, Victory, Australia (1995).
3. K.-H. Lai, and W.-G. Wong, SP approach toward driver comprehension of message formats on VMS, *J. Transp. Engng,* ASCE, **126**, 221–227 (2000).
4. W. L. Adamowicz, J. Louviere, and M. Williams, Combining stated and revealed preference methods for valuing environmental amenities, *J. Environ. Econ. Mgmt*, **26**, 271–292 (1994).
5. J. J. Bates, Stated preference techniques for the analysis of transportation behaviour, *Proc. World Conf. on Transportation Research*, Hamburg, W. Germany, 1982, pp. 252–265 (1982).
6. E. P. Kroes, and R. J. Sheldon, Stated preference methods: An introduction, *J. Transp. Econ. Policy*, **22**, 11–25 (1988).
7. J. J. Louviere, Conjoint analysis modeling of stated preferences: A review of theory, methods, recent developments and external validity, *J. Transp. Econ. Policy,* **22**, 93–119 (1988).
8. D. A. Hensher, Stated preference analysis of travel choices—the state of practice, *Transportation,* **21**, 107–133 (1994).
9. P. E. Jose Holguin-Veras, Revealed preference analysis of commercial vehicle choice process, *J. Transp. Engng,* ASCE, **128**, 236–346 (2002).
10. C. V. Phanikumar, D. Basu, and B. Maitra, Modeling generalized cost of travel for rural bus users: A case study, *J. Public Transp.*, **7**, 59–72 (2004).
11. D. A. Hensher, Measurement of the valuation of travel time savings, *J. Transp. Econ. Policy*, **35**, 71–98 (2001).
12. D. A. Hensher, and C. Sullivan, Willingness to pay for road curviness and road type, *Transp. Res.*, *D*, **8**, 139–155 (2003).

13. J. J. Louviere, D. A. Hensher, and J. D. Swait, *Stated choice methods: Analysis and application*, Cambridge University Press (2000).

14. S. R. Jara-Diaz, Time and income in travel choice: Towards a microeconomic activity-based theoretical framework, in *Theoretical foundations of travel choice modeling* (T. Garling, T. Laitila and K. Westin, eds), Pergamon Press, Ch. 3, pp. 51–74 (1998).

15. S. R. Jara-Diaz, Allocation and valuation of travel time savings, in *Transport modelling. Handbooks in transport* (D. A. Hensher and K. J. Button, eds), Pergamon Press, Ch. 19 (2000).

16. L. L. Thurstone, A law of comparative judgment, *Psychol. Rev.*, **4**, 273–286 (1927).

17. D. McFadden, Conditional logit analysis of qualitative choice behavior, in *Frontiers in econometrics* (P. Zarembka, ed.), Academic Press, pp. 105–142 (1974).

18. M. E. Ben-Akiva, and S. R. Lerman, *Discrete choice analysis: Theory and applications to travel demand*, The MIT Press (1985).

19. R. A. Pollak, and T. J. Wales, *Demand specification and estimation*, Oxford University Press (1992).

20. D. Revelt, and K. Train, Mixed logit with repeated choices: Households' choices of appliance efficiency level, *Rev. Econ. Stat.*, **80**, 647–657 (1998).

21. J. De D. Ortuzar, and L. G. Willumsen, *Modelling transport*, 3rd edn, Wiley (2001).

22. K. Train, *Discrete choice methods with simulation*, Cambridge University Press (2003).

23. D. A. Hensher, J. M. Rose, and W. H. Greene, *Applied choice analysis: A primer*, Cambridge University Press (2005).

24. D. A. Hensher, and W. H. Greene, *The mixed logit model: The state of practice and warnings for the unwary*, Working Paper, School of Business, University of Sidney (2001).

25. P. E. Green, A. M. Krieger, and Y. Jerry Wind, *Thirty years of conjoint analysis: Reflections and prospects*, *Interfaces*, **31**, (Suppl.) Part 2 of 2, May–June, S56–S73 (2001).