Policy sensitive mode choice analysis of Port-Said City, Egypt

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Abstract
This paper aimed at developing advanced Logit discrete choice models with several individual and mode attributes affecting the prediction of individual choice. The models have been applied to Port-Said (PS) city and have been used to investigate innovative transport systems such as Bus Rapid Transit (BRT) as a hypothetical mode situation beside the regular modes of transport (car and taxi). The methodology provides data collection of PS transportation mode system and develops Multinomial Logit Model (MNL), Nested Logit Model (NL), and Mixed Logit Model (MXL) using Visual-tm Software. The survey was formed by the Stated Preference (SP) technique conducted for individuals from all PS zones and the predictable travel mode choice behavior was analyzed. The findings showed that in PS, income is the most important attribute affecting the mode choice behavior model. The high values and positive signs of income parameters indicate that the higher income earners are more likely to use private car than taxi or bus. Contrary to most cases in developed countries, out-of-vehicle time that represents the accessibility shows higher impacts than the in-vehicle time as a result of poor access facilities in developing countries.

1. Introduction

In the recent years, urban policymakers are faced with growing and complex problems of congestion. Therefore they have begun to ask for more sophisticated decision-making tools, including models to forecast travel demand and its effect under various circumstances. Discrete choice models have played an important role in transportation modeling for the last few years.
They are specifically used to provide a detailed representation of the complex aspects of transportation demand, based on strong theoretical justifications. The art of finding the appropriate model for a particular application requires from the analyst both a close familiarity with the reality under interest and a strong understanding of the methodological and theoretical background of the model. The choice of transport mode is one of the most important classic models in transport planning because of the key role played by public transport in policy making [15].

This research rests on a scientific literature about travel choice behavior modeling, with particular reference to random utility models and stated preference methods [2,21]. In particular, it is based on urban transport demand modeling background.

Most literature has been stated the different factors affecting the reliability of mode choice process in developed countries especially for rural areas [2,1]. However in Egypt as a developing country, El-Esawey and Ghareib [9] studied the mode choice behavior in Greater Cairo Region (GCR). The study concentrated on sensitivity of cost changes when applying a new policy. It predicted the potential modal shifts in GCR under four hypothetical policy scenarios; increasing bus fare, increasing metro fare, increasing shared taxi fare and increasing individual income level. The results showed that “Age” appeared in all models with a positive sign indicating an increased utility with an age increase. This means that, in Egypt, an older person usually has more responsibilities. Gender also had a positive sign in all models indicating that the utility perceived by a male is higher than that received by a female when they both use the same mode of travel.

Li et al. [16] investigated another issue of mode choice reliability in terms of willingness to pay. This review focused on car, rail and bus, each by their single mode and revealed the importance of reliability in travelers’ decision making.

This paper introduces Port-Said (PS) city mode choice behavior modeling. Its transport system is characterized as a “weak” public transport system with many problems including:

1. High percentage of personal mode such as car and taxi with no existence of large public transport such as Bus Rapid Transit (BRT) or Car Sharing systems.
2. The interference with the car traffic has a negative impact on frequency and comfort.
3. Lack of adequate/sufficient access facilities such as parking and footpaths to different service centers.

The first objective of this paper was to develop a hypothetical mode choice situation models. The models use innovative transport systems such as BRT as a hypothetical mode in addition to the regular modes of transport (private car and taxi). Private car and taxi represent more than 50% of the current PS transport system. For model development, the advanced discrete choice models including Multinomial Logit Model (MNL), Nested Logit Model (NL), Mixed Logit Model (MXL) will be employed using Visual-tm Logit calibration software. The second objective of this paper was to study the sensitivity of transport speed and time for several levels of income on the accessibility concept caused from new BRT policy.

This paper consists of five sections. In the next section, a background of discrete choice models is presented. Section 2 describes the study area and the data collection methodology. Section 3 explains the supposed BRT policy logit calibration and the derived model analysis. The impact of BRT policy is estimated in the fourth section. Conclusions and recommendations for future work are drawn in the fifth section.

2. Discrete choice models background

A variety of discrete choice models are widely used for transportation applications appreciation to their ability to reflect key determinants of individuals’ choice behaviors while facilitating model estimation and/or providing a defensible behavioral basis such as random-utility maximization [20]. Discrete choice models are used for modeling choice experiment data. The research in this area began in the 1970s. Since then both the multinomial Logit and Probit models have been widely used in transportation, economics, marketing and many other areas to study both revealed and stated preference data.

Recently, the research in this field has paid special attention to the error term of the models in an effort to solve some of the problems of the discrete choice models and to make them more flexible. However, over the past ten years, gains in computing power as well as improvements in estimation techniques have led to the increased use of advanced nesting structures, and more recently, models based on mixture distributions such as Mixed Logit (MXL), but all depend on random utility maximization theory. These gains in estimation capability have also spurred new developments, for example in the form of advanced mixture models.

The random utility theory assumes a utility maximization principle if an individual chooses one alternative over another, and then the utility from the chosen alternative is greater than that from the unselected alternative. The obvious objective in discrete choice modeling is to analyze the individual’s choice in relation to the characteristics (attributes) of the product (e.g., choice of a transportation mode in relation to its price, quality, comfort etc.) by using logit calibration software.

The logit modeling is the mathematical relationship that defines the probability of deciding which alternative to take based on attributes describing the features of the alternative, the choice model coefficients and the particular logit model form. The logit model describes a family of equations. When using a logit model the user needs to define which member of the family is being used. The most common forms are the multinomial logit, the nested logit, the cross nested logit, the mixed logit, and the latent class logit models.

Models of choice behavior require three key factors to be taken into account:

1. Objects of choice and sets of alternatives available to decision makers, known as choice set generation.
2. The observed attributes of decision makers on the same household and a rule for combining them.
3. A model of individual choice and behavior, and the distribution of behavior patterns in the population.

Many previous studies examined several commonly used discrete choice models including conditional logit, multinomial logit, and nested logit. The current study will look slightly at
more advanced discrete choice models such as mixed nested logit and mixed logit. Although these models are less common, they do open up a lot of interesting avenues of research [24].

2.1. Basic concepts

In this section, basic concepts of discrete choice models describing decision makers’ choices among a set of alternatives are presented. Utility is assumed to be composed of a deterministic component $V_{nj}$ and a random component, $e_{nj}$. The deterministic component can be measured, as this component is related to the alternatives in the choice set. The random section cannot be measured (unobserved). The most appropriate way to model this component is to assign a distribution to the random element and estimate the probabilities of choice. Therefore, in random utility models the utility expression is outlined as in the following equation:

$$ U_{nj} = V_{nj} + e_{nj} \tag{1} $$

where:
- $U_{nj}$: The overall utility for alternative $j$ to individual $n$
- $V_{nj}$: The measured or observable utility for alternative $j$ to individual $n$
- $e_{nj}$: The unobservable utility or the error term for alternative $j$ to individual $n$.

As the random component cannot be modeled, the probability that individual $n$ will choose alternative $i$ can be expressed as in the following equation:

$$ P_{ni} = \text{Prob}(U_{ni} > U_{nj} \text{ for all } j \neq i) \tag{2} $$

Therefore, the probability that the respondent will choose alternative $i$ is the probability that the utility of that alternative is greater than any of the other alternatives in the choice set.

A brief summary about Multinomial Logit Model (MNL), Nested Logit Model (NL), and Mixed Logit Model (MXL) will be illustrated in the following subsections.

2.2. Multinomial Logit (MNL) Model

The Multinomial logit (MNL), for the past several years, has been an effective tool for analyzing individual travel behavior and appraising transport schemes [17]. However, the assumptions underlying this model resulted in the so-called IIA (Independent of Irrelevant Alternatives) property. Although this property can be very beneficial in certain applications such as reduction in data and estimation costs if the IIA reflects reality [23], it places severe limitations on the ability of the MNL model to produce expected or intuitive results under many applications.

The weakness in the MNL model was demonstrated in Hess et al. [13]. They showed that there is no correlation across choice alternatives due to unobserved attributes that could lead to a misleading forecast of demand. There are no common unobserved factors affecting the utilities of the various alternatives, making the MNL unsuitable for several applications. For example, the MNL is unsuitable for predicting mode shares when a decision-maker assigns a higher utility to all public transport including train and bus modes because of the same opportunity to using a car. The multinomial equation to choose the alternative (car) is as follows:

$$ P_{car} = \frac{e^{U_{car}}}{\logsum (e^{U_{car}} + e^{U_{train}} + e^{U_{bus}} + e^{U_{walk}})} \tag{3} $$

where:
- $U_{car}$: Car utility
- $P_{car}$: Probability of choosing car and the probability of other alternatives is calculated by the same way.

The MNL model has these advantages:

- It is easy and has a closed function form.
- One of the main advantages of the IIA property is the ability to deal with a large set of alternatives to estimate a model on a sub-set of these alternatives.
- Another advantage of the IIA property in that if one was only interested in a respondent’s choice between two alternatives, even if the choice set contains multiple alternatives, providing the IIA property holds, the MNL can make estimates on this sub-set.

The direct and cross elasticity formulae for the other models such as the Nested Logit (NL) model are functions of the structural parameters. All these structural parameters, which are used to measure the degree of correlation among the alternatives in the same nest [23], are illustrated in the following subtitle.

2.3. Nested Logit (NL) Model

Given the restrictive nature of the NL model due to the IIA assumption, approaches such as the nested multinomial logit model have been developed [6]. These models use generalized extreme value (GEV) models to model the unobserved proportion of the utility function as NL. GEV models allow for correlations over alternatives.

A nested logit model can be used when a set of alternatives faced by the decision maker can be partitioned into subsets or a nest, providing the IIA property holds. This sub-section provides an overview of the nested approach (more detailed overview of this model can be found at Train [23] or Hensher et al. [12]).

NL seeks to group alternatives together into mutually exclusive subsets called Nests. These alternatives believed to be similar in unobserved factors. They have the correlation that allows alternatives within the same nest to be better substitutes for each other than for those outside the nest. Thus the unconditional probability of an alternative becomes:

$$ P_{ni} = P_{nm} \times P_{nim} \tag{4} $$

where $P_{nim}$ is the probability of individual $n$ choosing alternative $i$ ($i = 1, 2, \ldots, J$) in nest $m$ ($m = 1, 2, \ldots, M$), $P_{nim}$ is expressed as:

$$ P_{nim} = \frac{\delta_{im} \exp(V_{ni}/\mu_{im})}{\sum_{j=1}^{J} \delta_{jm} \exp(V_{nj}/\mu_{jm})} \tag{5} $$

where:
- $\mu_{im}$ is an indicator variable which equals 1 if alternative $i$ is assigned to nest $m$ and 0 otherwise. $\delta_{im}$ is called the structural or sensitivity parameter for nest $m$ and discrete choice theory suggests that this parameter should lie between 0 and 1 [23]. The log of the denominator is called the logsum or the
maximum expected utility and represents the composite benefit that individual \( n \) receives from the entire choice process in nest \( m \),

\[
L_{mn} = \log \sum_{j=1}^{J} \delta_{jm} \exp(V_{nj}/\mu_{nm})
\]  

Although, nested logit models capture some level of correlation in the unobserved factors of the utility, several researchers [25] argue that the inability to allow cross correlation across nests may still not be practical or realistic in many applications. For example if you have three alternatives (Car, Bus and Park and Ride (P&R)), the P&R alternative consists of journeys made partly by Car and partly by Bus. Clearly the P&R mode could have both Car and Bus unobserved factors, so putting say Car and P&R together in a nest may overstate the share of the Car mode when the P&R modes becomes unavailable. This is because Car becomes a better substitute for the P&R mode than the Bus. Similar conclusions can be drawn when the Bus and the P&R are assigned to the same nest.

The Cross Nested Logit (CNL) model on the other hand allows the P&R alternative to be in both nests with a set of parameters called the allocation parameters describing its degree of membership in each nest.

2.4. Mixed Multinomial Logit (MXL) Model

All the models discussed belong to the family of GEV form (Generalized Extreme Value) models. The probabilities of GEV models have closed form, and many of the members relax the IIA assumption and thus account for correlation in the unobserved utility components although this flexibility usually brings with it the need to estimate larger sets of parameters, which may lead to problems in estimation and identification [5].

Additionally, under these models, all sampled individuals are assumed to have identical choice process (homogeneous). That is they give the same weight or importance to each attribute in the utility equation. This assumption is clearly not reasonable in reality as you would expect different people to place different emphasis (weights) on the various attributes under consideration. For example, a poor person may think that travel cost is very important, but a millionaire probably would not care much about cost especially in urban areas.

It therefore seems desirable to allow different individuals to have different weights (\( \beta, \alpha \)). However, it is not computationally possible to estimate different sets of weights for different individuals. Instead it is assumed that these weights follow a certain probability distribution [18,4]. So, if it was able to estimate just the key parameters (mean and standard deviation), then it can effectively draw different weights (coefficients) for different individuals using the chosen probability distribution.

This assumption leads to mixed logit or more generally mixed GEV models.

Mixed logit or mixed multinomial logit (MXL) models are derived by allowing the weights (\( \beta, \alpha \)) to follow some joint probability distribution (density) function \( f(\beta; \theta) \) where \( \theta \) is a set of parameters describing the distribution \( f \).

For example, if \( f \) was the normal distribution, then \( \theta \) might be the mean vector and covariance matrix. So with known \( \theta \) it can generate different coefficients for each individual using the probability distribution \( f \) and then use following equation to compute the probabilities for each individual. For example if \( \beta_n \) is the generated coefficient for individual \( n \), then from this equation, the conditional probability of the individual choosing alternative \( i \), becomes:

\[
P_{ni} = \frac{e^{\beta_n x_{ni}}}{\sum_{j=1}^{J} e^{\beta_n x_{nj}}}
\]  

But of course it does not know \( \beta_n \). However, it can assume, its distribution in the population: That is \( f(\beta_n; \theta) \) and so using Bayes theorem [22], it can be just weight each possible value of \( \beta_n \) by its probability, and then average (integrate) over all possible values:

\[
P_{ni} = \int \frac{e^{\beta_n x_{ni}}}{\sum_{j=1}^{J} e^{\beta_n x_{nj}}} f(\beta_n; \theta) d\beta_n
\]  

Integrating previous equation for all possible values for \( \beta_n \) is not computationally efficient, especially with larger numbers of random coefficients. If \( D \) is the number of random attributes in the probability equations, then computing the choice probabilities will require the evaluation of \( D \)-dimensional integrals.

Integrals with more than 3 dimensions cannot be evaluated analytically with sufficient speed and precision for finding the probabilities [23,13]. Integrals of this nature are approximated through simulation [23,4,3].

Based on the detailed theoretical and practical background presented in the previous subsections, the next sections are devoted to develop MNL, NL, and MXL mode choice models for Port-Said city considering new hypothetical scenarios (i.e. BRT) and calibrate them using Visual-Tm software.

3. Characteristics of the study area

The study area, Port-Said city, plays a leading role in Egyptian trade because of the presence of Suez Canal and East of Port-Said Port. In particular, Port-Said urban network is not wide enough and its service capacity is limited by constraints to serve private modes. Therefore, it needs a car sharing mode to reduce congestion and, concurrently, reduce travel time and cost.

Port-Said city (PS) has an area of 1,351.14 km². According to administrative divisions of the city; the economies of its urban populations are trade and services business. It consists of seven zones as shown in Fig. 1: El-Sharq, El-Arab, El-Dawahy, El-Manakh, El-Zohor, Port Fouad, and the South area.

The total population is 630,000 in all zones excluding south zone. South zone was excluded from the urban study area because it is out of inter-transportation network service [26].

Fig. 2 illustrates existing PS modal split. The existing transport system in PS can be characterized as follows:

- Shortage in the public transport capacity.
- Priorities to individual transport over public transport.
- No integration between the various components of the public transport system.

The available public transport modes are operated randomly in terms of routes, stations, headways, etc.

Moreover, in spite of covering the whole urban area, the road public transport suffers from the interference with the
car traffic, with a negative impact on frequency and comfort, which can be ascribed to the insufficient development of the bus way network. Other problem is the lack of suitable parking areas for private vehicles, especially within the Central Business District (CBD), and the need for new parking facilities.

The next part presents the data collection process using a stated preference questionnaire (SP) adding a hypothetical BRT public service to PS transportation network.

3.1. Questionnaire structure

A SP questionnaire is a set of options refer to the individual’s preference. The options are descriptions of hypothetical travel scenarios. It is where one would measure what individuals say. The questions of SP questionnaire need many steps to be prepared such as definition of variables and levels of factors to form the utility function. Generally, SP technique is used to:

- Estimate the demand for new transport services (new polices) or new attributes to existing services; and
- Examine how the choice made by individuals differs by individual attributes such as income, age, etc.

The survey contains SP exercises (choice games) submitted to the sample of respondents. The decision-maker (respondent) has to choose from the alternatives. The choice scenarios can be constructed by combining attribute levels with each other, as shown in Fig. 3. The figure contains an example of SP paper questionnaire suitable for developing communities.

The survey was for all sets of urban communities and zones (about 100 respondents). The questionnaire contained a SP experiment regarding the choice among three different transport alternatives: Private Car, Taxi and Bus Rapid Transit (BRT). The scenarios of survey are shown in Table 1. As shown in the table, each value of attributes is different for each scenario. This process is called factorial design [8]. These were used in asking sample people of the study. After collecting survey sheets, the choice of such question was recorded. SP outputs are modal split comparisons as shown in Fig. 4.

For scenarios 1, 3, 8, 10, 11, and 12, it seems that the individual preferred to use private car than other Public Transport (PT) modes. The person imagined to have a car even he/she does not have one. He/she chooses the car for more comfort and safe. For scenarios 7 and 9, the mode preference skewed to other two PT modes because of high cost and walking time of the car. This makes these scenarios to be equally distributed modal split.

After collecting data, the logit model calibration was estimated to analyze the expected choice behavior, as explained in the next paragraphs.

4. Logit model calibration

A model calibration was for the specific case of Port-Said using the above choice set contained three alternatives. The main variables identified to affect mode choice behavior include the one-way trip travel time (TIME), the travel cost (COST), the waiting time (WTT), the walking time (WKT), and interchange (INT) which is the number of modes need to be changed in one traveling direction (0 or 1 interchange). These variables are used to form the utility function in addition to individual income (INC), as a social variable. INC seems effective in utility function for developing countries, as in the
Table 1  Stated preference survey scenarios.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Alt.</th>
<th>IVT (MIN)</th>
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<th>Waiting time</th>
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previous studies. The calibration of the logit model was implemented by VISUAL-tm software.

4.1. VISUAL-TM software

It is an integrated transport modeling workbench for transport planners. It has been under development at Peter Davidson Consultancy since the company’s inception in 1988. Visual-tm was launched in May 2004. It includes all the tools needed for building multi-modal transport models, which can be used by the transport planners for forecasting, planning and monitoring [7].

4.2. Logit calibration outputs

The outputs will be illustrated in Table 2. The sample includes 100 individuals which reply on 12 questions with two (the best and the worst) choices that gives 100 * 12 * 2 = 2400 observations. These were the inputs of the model. After entering all data, the three types of calibration were chosen. The outputs shown in the table have many calibration borders:

Coefficient: It is a numeric value which shows how each attribute influences the choice of one alternative over another. A positive coefficient means that utility increases with increasing the associated attributes and hence makes that alternative more attractive. Negative coefficient of an attribute (e.g., in-vehicle time) makes the associated alternative unattractive as it increases.

t-statistic: This defines the significance of the coefficient and hence the significance of the associated attribute in the choice process. The bigger the t-ratio the better the coefficient.

The Number of Estimated Parameters: This indicates the number of coefficients estimated in the model.

Number of Observations: This indicates the number of observations used to fit the model.

Null log-likelihood LL(0): The log-likelihood without any coefficients. This is the total variation in the data and is similar to the total sums of squares given in linear regression.

Model log-likelihood LL(model): The log-likelihood after having fitted the coefficients. The higher this value the better the model. The outputs are illustrated as follows:

For MNL model, all the parameters of the model were significant at the 5% level and had the expected signs. The sample showed a positive preference toward income and had negative preferences toward time, cost, waiting time, and walking time. The mode constants also have the expected signs, indicating that all things being equal people will prefer car to taxi or bus. The implied Value of Time (VOT) is 0.60 LE (6 cent) per minute. Waiting and walking times are valued at 0.1 LE and 0.2 LE per minutes respectively. The model was statistically significant.

For NL model, the model result suggests that Taxi and BRT are credible substitute of each other as the structural parameter (0.55) for the PT nest is less than 1. This result is expected as majority of the population are preferred to use taxis in case of unavailability of BRT. In terms of model fits, the NL reported a log-likelihood of – 1971 which is significantly better than that of the MNL model. The two mode constants were shown not to be significant. Also the implied Value of Time (VOT) is 0.70 LE (7 cent) per minute, which is higher than MNL. The reported waiting and walking times are valued at 0.1 LE and 0.3 LE per minutes respectively.

For MXL Model, it was investigated among the existence of taste heterogeneity among the respondents. The model allowed the time coefficients to vary across the respondents but fixed the cost coefficient. This provides the means of estimation the distribution of VOT.

The results reveal that means and standard deviations of all the time attributes (IVT, WTT, and WKT) are all significant at 95% confidence level. This means there are significant variations to the weight or importance people attach to the time attributes in the choice process. The MXL model produced a mean VOT of 0.5 LE (5 cent) per minute with a standard deviation of 0.1 LE. The Value of Waiting Time (VOWT) is 0.1 LE per minute with a standard deviation of 0.004 LE. The results also show that higher income earners are more likely to use car than taxi or bus.

The principal aim of the study was the calibration of a demand model to forecast the modal split of the urban transport demand, allowing for the possibility of using innovative transport systems like BRT. The model was applied to analyze the potential demand for Car, Taxi and BRT in Port-Said, under a future scenario characterized by several policy actions for limiting private transport use.

5. Accessibility in transport planning

This section will be devoted to the estimation of transport speed and time (mode choice attributes) sensitivity for several levels of income on the accessibility concept caused from new
BRT policy. The worked example is PS public transport system.

One of the important concepts of travel demand modeling is accessibility [10]. The previous international research on accessibility in developing countries concentrated on the interaction between accessibility and rural development [11]. Now, accessibility of urban areas has more attention to check mobility of road infrastructure resulting from new strategies.

The advantages of including the concept of accessibility in transport and land-use planning are twofold. Firstly, it allows recognition of the interrelation of transport and land-use. Thus, it enables account to be taken of the restriction effect of travel on participation in activities. Also it allows travel to be treated as a derived demand. People travel in order to reach activities rather than desiring travel for its own sake.

Secondly, it enables account to be taken of variations in types of people, in terms of, for example, their abilities to use different methods of travel, their needs or desires to participate in different activities, and the constraints on their time [19].

Travel process has many attributes forms the Accessibility-Benefit function. This function seems as the utility function of the mode in discrete choice models. It is very useful in case of examining new strategy effect. Odoki [19] had formulated the travel cost influence travel cost change equations for developing countries. By using these equations, the Speed Sensitivity of BRT strategy and Time Budget Sensitivity will be calculated.

### Table 2 Summary of the discrete choice logit models for testing new BRT policy.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Multinomial (MNL)</th>
<th>Nested logit (NL)</th>
<th>Mixed logit (MXL)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient</td>
<td>t stat</td>
<td>Coefficient</td>
</tr>
<tr>
<td>IVT(Min)</td>
<td>-0.0257</td>
<td>8</td>
<td>-0.0218</td>
</tr>
<tr>
<td>Value of time (LE/Min)</td>
<td>0.6</td>
<td>6</td>
<td>0.5</td>
</tr>
<tr>
<td>Cost(Pia)</td>
<td>-0.044</td>
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<td>-0.0354</td>
</tr>
<tr>
<td>Wait(Min)</td>
<td>-0.01</td>
<td>2</td>
<td>-0.005</td>
</tr>
<tr>
<td>Value of walk time(LE/Min)</td>
<td>0.1</td>
<td>1</td>
<td>0.1</td>
</tr>
<tr>
<td>Walk(Min)</td>
<td>-0.01</td>
<td>2</td>
<td>-0.01</td>
</tr>
<tr>
<td>Value of wait time(LE/Min)</td>
<td>0.2</td>
<td>2</td>
<td>0.3</td>
</tr>
<tr>
<td>Income(LE)</td>
<td>0.91</td>
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<td>1.16</td>
</tr>
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<td>Taxi Constant</td>
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<td>-0.06</td>
</tr>
<tr>
<td>Relative to IVT</td>
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<td>5</td>
<td>2.7</td>
</tr>
<tr>
<td>Bus Constant</td>
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<td>2</td>
<td>0.14</td>
</tr>
<tr>
<td>Relative to IVT</td>
<td>8.0</td>
<td>2</td>
<td>-6.6</td>
</tr>
<tr>
<td>Car Nest Logsum Coef</td>
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<td></td>
</tr>
<tr>
<td>PT Nest Logsum Coef</td>
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<tr>
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<td>No of Observations</td>
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<td></td>
<td>2400</td>
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<td>Null log likelihood</td>
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<td>-1972</td>
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<td>Model log likelihood</td>
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<td></td>
<td>-1974</td>
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<tr>
<td>BIC Statistic</td>
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<td></td>
<td>4018</td>
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</table>

5.1. Analytical comparisons of hypothetical strategies at Port-Said

The analytical comparison of different strategies is based on the Benefit Measure (BM) of accessibility. The elasticity concept of model variables of the accessibility frame work provides an integrated approach for evaluating alternatives for enhancing accessibility in developing countries. The frame-work considers all components of accessibility. These strategies include the provision of transportation infrastructure and services. An accessibility enhancing strategy is considered to influence one or more of benefit function parameters. For example, many transportation infrastructures affect monitory travel cost (m), travel speed (v), and the distance away from the origin (x).

The elasticity of BM with respect to changes in parameters can be compared against one another. It is convenient to translate BM into a common policy-sensitive unit. Monetary unit is often the most convenient unit for these comparisons. Some analytical sensitivity of accessibility-enhancing strategies of study area will be illustrated in the following paragraphs.

5.2. Speed sensitivity of hypothetical strategies

The monetary travel cost changes by hypothetical strategies lead to changes in accessibility-benefits derived by individual in household that effected travel speed (v). This cost influences...
their travel behavior and represents through $\Delta m$ in monetary term of accessibility-benefit. The worked example is public transport modes substitution by BRT. This will make change in $v$ and $m$, assuming that all other variables remain constant, when the initial travel speed $v_1$ is changed to $v_2$.

Applicable example is to obtain the accessibility-benefits that could occur to a household head under these conditions:

- He uses a bus to his work located 3 km from home;
- The total daily time budget available for this; daily activity is 5 h;
- The average daily income is 100 L.E.; and
- The average travel speed is 30 km/h.

That situation is to use BRT that increases the average travel speed to and from the work place. The total benefits that the individual obtained can be quantified using this equation [14]:

$$\Delta m = 2 \tau \log_e \left( \frac{\tau - \left( \frac{v_2 - v_1}{v_1} \right)}{\tau - \left( \frac{v_2 - v_1}{v_1} \right) + 1} \right) - \frac{1}{\left( v_1 + \Delta v \right)}$$

where:
- $\Delta m$: the reduction of monitory travel cost
- $zI$: income level
- $v_1$: the current speed before policy application
- $\gamma$: time utility component
- $\tau$: daily time budget
- $x$: the distance away from the origin
- $\Delta v$: the change in speed.

The values of accessibility-benefit act as the speed sensitivity. It causes from reduction in monitory travel cost ($\Delta m$) for individuals under the same activity. It calculates with different income levels and velocities. After application into the equation, the speed sensitivity is shown in Fig. 5.

The chart illustrates the positive relationship between the increase in average speed and the reduction in monetary travel cost per km. The hypothetical worked example illustrates the effect of changing the average travel speed from $v_1 = 30$ km/h by bus to $v_2 = 90$ km/h for an individual has attributes that $x = 3$ km, $\tau = 5$ h, $\gamma = 1.0$, and value of time (depend on income level) $zI = 0.3, 0.5, 1.33, 1.5$ [10]. When applying BRT policy by marked on the chart on $\Delta v = 60$ km/h, and with $zI = 1.33$, the change in monetary travel cost ($\Delta m$) is equal to 0.177 L.E./KM. assuming that he/she works five days a week then the total annual distance would be 2130 km. so, the total annual benefits is 377 L.E. that is obtained from the following formula;

$$\Delta m = \Delta m \times \text{the total annual distance}$$

So, the hypothetical strategy could benefit a number of individuals in the area of study when summing the annual benefits of each individual by considering groups in term of their temporal constraints, transport mode, income, household, and other socio-economic characteristics.

5.3. Time budget sensitivity

For new transportation strategy, temporal reduction aims at increasing of the time budget available to an individual for participating in activities. This strategy could benefit a number of individuals in terms of the accessibility-benefit ($\Delta m$) derived from the following equation:

$$\Delta m = \frac{zI}{2x} \tau \log_e \left( \frac{\tau_1 + \Delta \tau - 2x/v}{\tau_1 - 2x/v} \right)$$

For example, if an individual has to go to work place which locates 0.5 km from home, the budget for working is 5 h, and the daily income is 30 L.E. the objective is to derive the accessibility-benefit ($\Delta m$) from increasing him/her daily time budget from 5 to 7 h. The following model parameters is assumed for the new change; $x = 0.5$ km, $\tau = 5$ h, $v = 4$ km/h, $zI = 0.5$, $\Delta \tau = 2$ h, and $\gamma = 1.0$. The values of $\Delta m$ can be derived from Fig. 6 which illustrates the marginal effectiveness of different magnitudes of time budget increase relative to the initial time budget $\tau_1$.

The change in monetary travel cost ($\Delta m$) is equal to 0.467 L.E/km. assuming that he/she works five days a week then the total annual kilometreage would be 13,150 km. so, the total annual benefits is 6049 L.e that is obtained from the following formula;

$$\Delta m = \Delta m \times \text{the total annual kilometreage}$$

For studying of hypothetical strategies, it is recommended that aggregation of individual’s gender and activities types be considered. It is logical considered that for activities in developing

![Figure 5 Effect of increase of speed on the reduction of disutility ($\Delta m$).](image)
countries, the minimum value of utility $\gamma$ is unity = 1 for a man, because the individual, if he is a man, spends a large proportion of his time at but for a women $\gamma = 1.5$ because she spends a small portion of her total time at work place and she willing to spend more time on the work in order to increase her earning.

6. Conclusions

In the framework of this paper, mode choice models are developed using Visual-tm Software for Port Said (PS) city with the aim of determining the mode choice as a result of implementing new policy. The stated preference technique is used for collecting the individual response to the new policies. The study team applied the logit calibration of advanced discrete choice models (i.e. Multinomial Logit Model (MNL), Nested Logit Model (NL), and Mixed Logit Model (MXL)). A Bus Rapid Transit (BRT) mode is proposed as a new regular public transport mode of transport in PS. Different attributes such as income, waiting time, walking time, and cost are analyzed for each model.

The main findings of this research were as follows:

(1) Income is the most important attribute affecting the mode choice behavior model. The higher income earners are more likely to use car than taxi or bus. This is reflected by the high values and positive signs of income parameters.

(2) Contrary to most cases in developed countries, out-of-vehicle time which represents the accessibility shows higher impacts than the in-vehicle time as a result of poor access facilities in developing countries.

(3) A positive raise in speed and time budget with the reduction in monetary travel cost caused by applying new policy.

The scope of this paper was limited to the above outputs; however more case studies as well as other types of models (e.g. Probit, and Fuzzy logic) have to be investigated with the aim of capturing the mode choice variations in developing countries and forming their individual characteristics. This will support the government, public transportation agencies, and private carriers in making accurate decisions for the future implemented strategies.

References

Policy sensitive mode choice analysis of Port-Said City, Egypt


