SP-RP JOINT MODE CHOICE MODELING AND POLICY SIMULATION: A CASE STUDY OF JAKARTA

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ABSTRACT

A study was conducted to determine how demand for a new bus rapid transit (BRT) is likely to vary as a function of attributes that distinguish this new travel mode from other existing conventional alternatives. This paper presents the result of a mode choice model developed using data from a stated preference (SP) opinion survey in Jakarta, Indonesia. In particular, by using both SP and revealed preference (RP) data, this study explored a joint mixed logit discrete choice modeling approach to evaluate travelers' choice behaviour. A total of six travel modes were set for this study including drive alone, shared ride, motorcycle, transit, non-motorized, and future BRT. A variety of explanatory variables were used including cost, time, and distance of travel, and socioeconomic attributes of the household and the individual. Then, the joint SP-RP mixed logit model was used for simulation analysis of some transportation policies scenarios currently under review in Jakarta, such as BRT and area pricing as part of transportation control measures. The model established in this study presents a great potential in capturing the key variables that are significant for modeling mode choice in a large metropolitan area of the developing world.

KEY WORDS

Mode Choice Modeling, Stated Preference, Revealed Preference, Policy Simulation, Jakarta.

INTRODUCTION

Japan International Cooperation Agency (JICA) conducted "The Study on Integrated Transportation Master Plan (SITRAMP)" in the Jakarta Metropolitan Area from November 2001 to March 2004 (National Development Planning Agency 2004). The overall objective was to identify possible policy measures and solutions to develop sustainable transportation system in the Jakarta Metropolitan Area with a focus on encouraging public transport usage and improving mobility of people. As such, detailed transportation surveys such as Household Travel Survey (HTS) and analyses were undertaken to prepare a comprehensive long-term transportation plan.

A Stated Preference opinion survey on transport system (SP survey) was also conducted in Jakarta to obtain the information regarding travelers' preference among existing and future transportation modes under different conditions and policies such as costs and service levels. Utilizing the SP data, the main purpose of this study is to determine how demand for a new

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bus rapid transit (BRT) is likely to vary as a function of attributes that distinguish this new travel mode from other existing conventional alternatives in the region. In particular, the study adopts a mixed logit discrete choice model to predict the mode choice using both revealed preference (RP) and SP data. The analysis takes a further step into simulation and evaluation of transportation management policies.

STATED PREFERENCE DATA

SP refers to a wide array of possible ways of asking consumers about preferences, choices, ways of using options, frequencies of use, and so forth, while RP is associated only with actual choices (Louviere and Street 2000). The results of the SP survey actually contain both RP and SP data that can be used to establish discrete mode choice models for future forecasting. Three types of surveys were conducted with different target groups of respondents:

In Jakarta, an SP survey was conducted in the central business district (CBD), targeting at the residents who live along the planned BRT network corridors and commute to the CBD. In the survey, transit users and car/motorcycle users were interviewed with regard to their preference of BRT to the existing mode under different conditions. In particular, the survey focused on the to-work, to-school, and shopping trips with zones along the planned BRT corridors as the origin and with zones in the CBD as the destination. Information of sampled residents who make such trips was taken from the large-scale HTS database, and the survey was conducted by re-interviewing the persons who actually made trips from home to CBD.

The SP survey in CBD first asked information on the socioeconomic details of the respondents and their households. Then, as the current travel behaviour constitutes the RP data, the survey asked the respondents about details of to-work/school trips to the CBD that they made including the details such as mode(s) used, travel cost, and time. For the SP part, since there was no BRT in operation yet when the survey was conducted, detailed explanation and images of the planned BRT such as Figure 1 were presented to the respondents. Then, the survey asked respondents about their potential responses to different fare levels of the planned BRT. A total of 13 fare levels were prepared to ask the respondents whether they would be willing to shift from their current mode to BRT to make the same travel. With regard to the trips that fulfill the above OD-zone criteria, effort was made to collect the samples so that the purpose and mode compositions would comply with those of the HTS database. In this way, the entire OD-zone pairs would be applied for mode choice modeling and policy simulation without using weights to the RP alternatives.

Figure 1: Proposed BRT System (BAPPENAS and JICA 2004)

MIXED LOGIT MODEL

Random utility based discrete choice models have found their ways in many disciplines including transportation, marketing, and other fields. Multinomial logit (MNL) model is the most popular form of discrete choice model in practical applications (Mohammadian and Doherty 2005). It is based on several simplifying assumptions such as independent and identical Gumbel distribution (IID) of random components of the utilities and the absence of heteroscedasticity and autocorrelation in the model. As such, the MNL model belongs to a class of models that possesses the so-called independence of irrelevant alternatives (IIA) property, which is both one of the strengths of the MNL model and its major weakness (Meyer and Miller 2001).

Recent research works contribute to the development of closed form models which relax some of the above-mentioned simplifying assumptions to provide a more realistic representation of choice probabilities. Mixed logit (ML) model is an example of these alternative structures (Bhat 2002). In ML models, heterogeneity can be accounted for by letting certain parameters of the utility function differ across individuals. It has been shown that this formulation can significantly improve both the explanatory power of models and the precision of parameter estimates (Bhat 2000). There are a growing number of empirical studies implementing ML method.

JOINT SP-RP MODEL

Both RP and SP data have their strengths and weaknesses, namely that RP data are cognitively congruent with actual behaviour while SP surveys can be collected in a tightly controlled choice environment and can provide richer information on preferences (Walker and Ben-Akiva 2002). The strengths of both data sources could be exploited and weaknesses ameliorated by pooling both data sources as a joint SP-RP model (Louviere, et al. 2000). This “data enrichment” process should provide more robust parameter estimates and should increase confidence and accuracy in predictions (Verhoef and Franses 2002).

Techniques of joint SP-RP models have been commonly used in different disciplines such as marketing, transportation, and environment for quite some time. In the context of activity-based modeling, Shiftan, et al. (2003) developed an SP-RP combined mode choice model as the lowest-level model for the primary tour within an activity-based modeling system. The model relies on various RP and SP data sources for the city of Tel-Aviv.

MODEL ESTIMATION

DATA PREPARATION

The SP dataset comprises 797 effective samples. Excluding data records presenting modes with few samples such as railways and focusing only on to-work and to-school trips for the purpose of this study, a dataset containing 761 samples was established for mode choice analysis. Major characteristics of the respondents were found to be:

- Workers constitute more than 80% of the total, and the remaining are students;
- Males comprise about two thirds of the total respondents;

- About 33% and 40% of the total respondents have automobile and motorcycle driver's licenses, respectively, whereas 40% have neither license; and
- Approximately 40% of the households own automobiles and 60% own motorcycles.

ALTERNATIVE SETTING

For this study, three major motorized modes were included as existing modes: automobile (car), motorcycle (MC), and transit (TR). Furthermore, car trips were divided into two modes: drive alone (DA) and shared ride (SR). As for non-motorized mode of transport (NM), it tends to be omitted from the mode choice models of all but a few metropolitan areas; however, such an omission is problematic, not only because these trips are an important component of personal mobility, but because cross-elasticities are quite high between non-motorized trips and automobile or transit trips, depending on cost, time, and so on (Harvey and Deakin 1993). Although the share of NM in the SP survey was only 1.8%, it was included in the model as a major mode. As such, there are a total of five existing modes that have been set for this study: DA, SR, MC, TR, and NM. Shares of these representative modes in the dataset are 20.8%, 7.7%, 31.4%, 38.5%, and 1.7% respectively. For the SP part of the model, BRT (BR) is added to these five existing modes. It is assumed that modes of TR, BR, and NM are available to all individuals, while availability of car (DA and SR) and MC modes is limited to vehicle owner households.

EXPLANATORY VARIABLES

The variables tested for modeling are attributes related to the travel as well as socioeconomic attributes of the household and the individual, and are listed as below:

- Travel related variables: travel cost, travel time, and travel distance;
- Household related variables: household income and vehicle ownership (i.e., number of automobiles and motorcycles in the household); and
- Individual related variable: employment status (e.g., full-time, part-time, and student), school type, personal income, gender, age, vehicle availability, and work/school location.

In addition, some composite variables such as travel time multiplied by the household income were also tested as explanatory variables.

MODELING RESULTS

A joint SP-RP model was estimated in which one subset is labelled as the RP choice set and the other is labelled as the SP choice set, and both subsets were placed on the same tier in the ML model. In the joint SP-RP model, effort was made to have common coefficients in both RP and SP utility functions for the same alternative. This means that the marginal rates of substitution among some of the variables are the same in the SP and RP models.

For the ML modeling, 1,000 repetitions are used to estimate the unconditional probability by simulation. This improves the accuracy of the simulation of individual log-likelihood functions and reduces simulation variance of the maximum simulated log-likelihood estimator. Random parameters for this ML model are estimated as normally distributed parameters in order to allow parameters to get both negative and positive values. Both observed attributes associated with the mode alternative, individual, and household (explanatory variables) and the unobserved attributes (alternative specific constants) were tested by introducing random parameters.

Results of the estimated joint SP-RP ML model are shown in Table 1. The adjusted ρ^2 is 0.472, presenting a good model fit with statistically significant parameters. Furthermore, estimated results of the variable representing the travel cost and the constant specific to non-motorized transport (NM) are statistically significant in the model at 80% confidence level or better. The *t*-statistics for the standard deviations of the random parameters indicate that these are likely to be statistically different from zero, confirming that parameters indeed vary across individuals.

Table 1: ML Model: Joint Estimation of SP and RP Mode Choices

Variable	Alternative	SP Coeff.	SP *(t-stat)*	RP Coeff.	RP *(t-stat)*
Continuous Vaiables:					
Travel cost (thousand Rp.)	[DA, SR, MC,	-0.126	*(-3.64)*	-0.126	*(-3.64)*
standard deviation	TR, BR]	0.396	*(5.20)*	0.396	*(5.20)*
Travel time(hr) * hhd income(mil. Rp./mo.)	[TR]	-0.035	*(-1.84)*	-0.035	*(-1.84)*
Log of travel (line) distance (km)	[NM]	-2.436	*(-2.66)*	-2.436	*(-2.66)*
Dummy Variables:					
High-income household (> 4 mil. Rp./mo.)	[SR, BR]	0.429	*(3.21)*	0.429	*(3.21)*
Motorcycle-owning household	[TR, NM]	-0.506	*(-3.99)*	-0.506	*(-3.99)*
Male adult (age >= 17)	[MC, BR]	0.565	*(4.64)*	0.565	*(4.64)*
	[NM]	2.313	*(2.19)*	2.313	*(2.19)*
Having motorcycle driver's license	[TR, NM]	-0.656	*(-4.68)*	-0.656	*(-4.68)*
Work/school location within the 3-in-1 area	[DA]	-0.364	*(-1.60)*	-0.364	*(-1.60)*
Alternative-Specific Constants:					
Car (drive alone)	[DA]	-	-	-	-
Car (shared ride)	[SR]	-2.162	*(-8.48)*	-1.516	*(-6.39)*
Motorcycle	[MC]	-2.217	*(-8.33)*	-1.556	*(-5.95)*
Transit	[TR]	-2.351	*(-9.76)*	-1.677	*(-7.06)*
BRT	[BR]	-2.607	*(-10.60)*	-	-
Non-motorized transport	[NM]	-7.961	*(-1.76)*	-8.838	*(-1.55)*
standard deviation		2.833	*(1.16)*	3.776	*(1.24)*
Summary Statisics:	2930 observations, $L(0)$ = -6393, $L(\beta)$ = -3370, ρ^2 = 0.472				

All variables associated with the travel are included in the model as continuous variables. Travel cost was included in all the utility functions except for NM. It became clear that travel time variable alone was no statistically significant in the model. However, travel time multiplied by household income was included in the utility function of the TR mode. This implies that decision makers, especially in higher-income household, perceive travel time as an important factor when selecting public transit mode. It also implies that travel time does not affect the choice of the private modes as much as it affects transit mode. This suggests that automobile users are less likely to shift to the public mode whether there is serious congestion or not on the way to work/school. As for travel distance, its logarithm value is significant in NM mode, implying that the longer travel distance reduces the utility of walking/biking all the way to work/school.

Variables related to the household and individual are all included in the model as dummy variables. There are two household-related variables involved in the model. One is a high-income household dummy, which is positively significant in SR and BR. In Jakarta, many people in the high-income household do not actually drive by themselves but hire chauffeurs. Such trips with chauffeurs are considered as shared automobile rides of which utility is increased by this dummy variable. BRT is also regarded as a prospective alternative means of transport by people in the high-income household. As for the dummy variable indicating whether the household owns a motorcycle, it proves to be significant in the model, but is not directly included in the utility of MC mode. It is rather included in the utilities of TR and NM modes with a negative parameter, implying that having a motorcycle relatively increases the utilities of selecting the private modes in general.

Similar tendencies can be found in one of the variables related to the individual, that is, a dummy of whether the individual has a motorcycle driver's license. It reduces the utility to walk/bike or to use transit and relatively increases the utility to select a private mode of transportation. Being a male adult considerably increases the utility to walk/bike. It also increases the utility to use motorcycle, which seems to be reasonable in the case of Jakarta. Male adults also have higher utility to use BRT.

Jakarta is famous for its unique transportation control measure (TCM) that has long been implemented in the CBD. It is called a "3-in-1" regulation, in which only high-occupancy vehicles with three or more occupants are allowed to use the main corridor roads in the CBD of Jakarta during morning and evening peak periods. The variable which indicates whether work/school is located on these roads regulated by the 3-in-1 is included with a negative parameter in the utility of DA mode, reducing the probability of driving alone to work/school because of the 3-in-1 regulation.

SIMULATION OF MODE CHOICE

CURRENT POLICIES UNDER REVIEW

Since December, 2003, the 3-in-1 regulation has been modified in terms of two major points. First, the corridor roads for the 3-in-1 have been extended, and it has been effective in the evening (4:00 – 7:00 p.m.) in addition to the morning period (7:00 – 10:00 a.m.). Second, while number of passengers in each vehicle was monitored only at the time of entering the designated road before December 2003, vehicles now must always have three or more occupants to pass through any section of the designated roads covered by the regulation.

Along with the new 3-in-1 regulation, the city of Jakarta initiated the first BRT operation on the same corridor in January 2004. Furthermore, the government of Jakarta has been trying to accelerate and move up the implementation schedule of the eight BRT corridors proposed by SITRAMP, though it was originally a phased plan and the entire BRT network would be completed in 2020. Their goal now is to complete the BRT network by 2010.

Moreover, SITRAMP has proposed an area pricing scheme as an effective TCM to replace the existing 3-in-1 regulation, and the government of Jakarta is currently following the schedule and considering implementation of the area pricing in 2007. Target area for this scheme has not been finalized yet, but it includes the existing 3-in-1 corridor and covers more spatially most of the CBD which the current vehicular trips are generated from and attracted to. It is an intention that the proposed pricing area should be served by improved public transit including BRT in 2007. The objective is to reduce the current vehicular traffic in the CBD as much as possible so that the current level of congestion will not deteriorate in the future. It is also envisaged that the area for pricing will be expanded towards 2020.

While this area pricing scheme may be effective for congestion reduction in the CBD, provision of alternative means of transportation for the “pushed-out” users by the area pricing is of great importance to obtain public acceptance. Hence, it is necessary to consider simultaneously the area pricing scheme and the BRT development which may serve as an alternative for assumed pushed-out vehicle users. As such, in this study these two major policies are simulated in the mode choice model.

ASSUMPTIONS

The assumptions employed for the simulation are as follows:

- The operation hours of area pricing include at least those of the current 3-in-1 regulation, that is, morning and evening peak hours. Since all the samples in the dataset are either to-work or to-school trips with CBD zones as the destination, all the trips are affected by the area pricing scheme;
- A variety of fare levels were tested for the BRT, ranging from Rp. (Indonesian Rupee) 2,000 to Rp. 8,000 per ride with an interval of Rp. 1,000. The BRT service frequency is every three minutes in all the cases;
- Six cases of levy rate were tested for area pricing, namely, Rp. 0 (i.e., no area pricing), Rp. 4,000, Rp. 8,000, Rp. 12,000, Rp. 16,000, and Rp. 20,000 per trip;
- All vehicles passing/driving in the target area are to be charged under this area pricing scheme, and it is different from the cordon pricing scheme in which only vehicles entering the area are to be charged; and
- Analyses are made as if changes took place now. Most of the transportation-related costs such as transit fares, expressway tolls, parking prices, and fuel cost have been raised since the time that the SP survey was conducted (August 2003). Though the rates of increase vary depending on the items, an average increase rate of 10% was assumed in the simulation.

As of July 2005, the new BRT is operated with a fare of Rp. 2,500, while the existing air-conditioned express bus costs Rp. 3,500 per trip. The initial taxi fare is Rp. 4,000. Prices of this range may not be so painful for high-income people but may be significant enough to low/middle-income class people. Meanwhile, the highest area pricing assumed, Rp. 20,000, is something that high-income car users can still afford, but it is not negligible even for them.

SIMULATION RESULTS

For each individual, the model simulates the mode choice decision to go to work/school in the CBD. As such, shares of the six representative modes, that is, drive alone, shared ride, motorcycle, transit, BRT, and non-motorized are simulated under each combination of the BRT fare and the area pricing levy rates that are shown in Table 2. "No BRT" and "no area pricing" cases are also included in the table. Furthermore, changes of the mode shares of BRT and car (drive alone and shared ride) are graphically depicted in Figure 2. Major changes of the mode shares can be summarized as below.

Table 2: Predicted Percentages of Mode Shares Using Joint SP-RP ML Model

Mode	No Area Pricing					Area Pricing: Rp. 4,000 per Entry				
	No BRT	With BRT: Fare Level (Rp.)				No BRT	With BRT: Fare Level (Rp.)			
		2,000	4,000	6,000	8,000		2,000	4,000	6,000	8,000
Car (drive alone)	15.8	13.3	13.4	13.2	12.9	14.7	11.9	12.4	12.5	12.3
Car (shared ride)	6.1	4.4	4.6	4.7	4.6	5.4	3.6	3.8	3.8	3.8
Motorcycle	24.5	16.8	17.3	17.5	17.5	24.8	17.1	17.7	17.8	17.8
Transit	52.8	22.2	23.8	25.7	27.2	54.2	22.5	24.8	27.2	29.0
BRT	-	42.9	40.3	38.4	37.3	-	44.5	40.8	38.1	36.4
Non-motorized	0.8	0.4	0.5	0.6	0.6	0.9	0.4	0.6	0.6	0.7
Total	100	100	100	100	100	100	100	100	100	100

Mode	Area Pricing: Rp. 12,000 per Entry					Area Pricing: Rp. 20,000 per Entry				
	No BRT	With BRT: Fare Level (Rp.)				No BRT	With BRT: Fare Level (Rp.)			
		2,000	4,000	6,000	8,000		2,000	4,000	6,000	8,000
Car (drive alone)	11.0	8.9	9.2	9.4	9.5	9.2	8.0	8.1	8.2	8.3
Car (shared ride)	4.0	3.1	3.2	3.2	3.1	3.6	3.0	3.0	3.1	3.1
Motorcycle	25.1	17.3	17.9	18.1	18.1	25.2	17.3	18.0	18.2	18.2
Transit	58.9	23.4	26.6	30.0	32.6	61.0	23.6	27.1	30.7	33.6
BRT	-	46.8	42.5	38.6	35.8	-	47.5	43.2	39.2	36.1
Non-motorized	1.0	0.5	0.6	0.7	0.8	1.1	0.5	0.6	0.7	0.8
Total	100	100	100	100	100	100	100	100	100	100

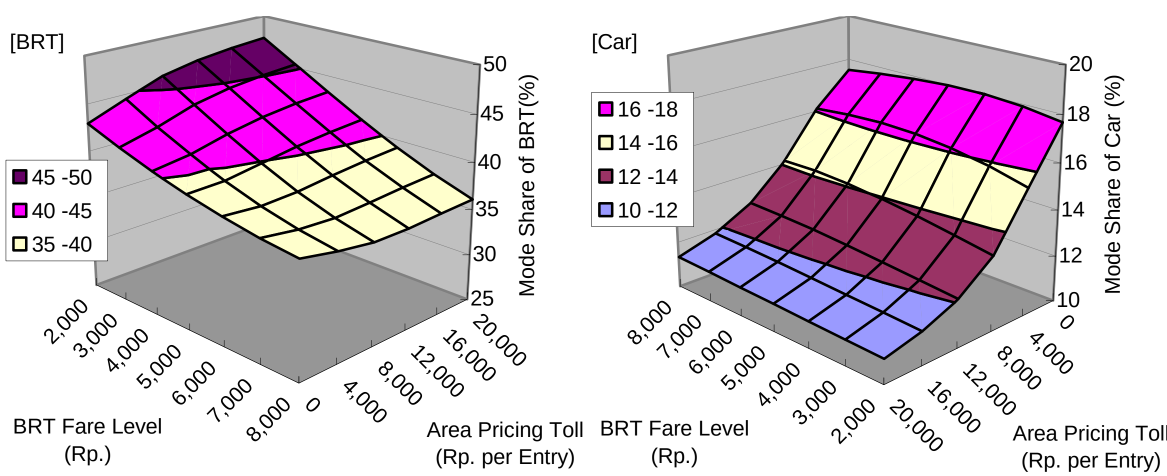

Figure 2: Simulated Changes of Mode Shares

When BRT is introduced, it is expected to play an important role with the largest mode share in place of transit. Figures show that the majority of the prospective BRT passengers will come from the current transit users, that is, within the public modes. A significant portion of the current motorcycle users are also expected to shift to BRT, implying that motorcycle users are rather flexible in mode choice. Some of the current car users (both drive alone and shared ride) are expected to shift to BRT as well; however, such portions are relatively small.

As the BRT fare rises, the share of BRT naturally decreases significantly. All the other transport modes will get their shares increased accordingly. This is especially remarkable for transit which is a mode previously used by many BRT passengers. Shares of car users will also increase, but only marginally. All these mode share changes caused by the BRT fare increase are more striking under the area pricing scheme, especially with a higher levy rate.

If the area pricing scheme is applied to the CBD, the share of car users are expected to drop as the levy rate increases. This impact is greater for car users who drive alone rather than those who share the ride. This is because the impact could be alleviated by sharing the cost, or because the impact is relatively small for higher-income car users who tend to hire chauffeurs, forming "ridesharing." It seems that the area pricing with a higher levy rate makes car users shift to BRT the most. Increase in shares of other modes is smaller. All these influences of the area pricing levy rates are more noticeable under the lower-fare cases of BRT. It implies that, as BRT becomes more affordable in terms of cost, it is expected to better serve as an alternative mode for cars under the area pricing scheme.

CONCLUSIONS

This study developed a ML model to simulate the mode choice using the RP and SP data obtained in Jakarta, Indonesia. The model is part of a larger scale activity-based micro-simulation modeling system for a developing country. The model captured the key variables that are significant in explaining mode choice behaviour in the Jakarta Metropolitan Area and analyzed some of the policy scenarios that are currently under review through the simulation.

Interpretation of the effects of each explanatory variable in the model led to several interesting insights. A wide variety of different types of variables contributed significantly to the model, including basic travel characteristics (cost, time, and distance), household characteristics (income and vehicle ownership), and individual characteristics (gender/age, vehicle availability, driver's license, and work/school location). Thus, it appears that only the characteristics associated with the trip may not suffice to fully explain mode choice; rather, several household and individual factors play an important role. Moreover, as demonstrated in this paper, the choice model that has incorporated such factors enables better analysis of policy scenarios through the simulation.

Although the dataset consists of only from-home trips to the CBD, mode choice in this first segment of the individual's travel tour is important because these trips constrain the modes of the subsequent segments such as returning home trips and work-based sub-tours. Furthermore, according to the results of the SP survey, more than 80% of shopping tours are made by the same mode that are selected to go to work/school, whether it is on weekdays or weekends. As such, one extension of the study will be to develop a model that determines modes of the subsequent trips in a tour, focusing on the mode transition.

Although a variety of variables proved to be significant in this study, activity patterns were not included as explanatory variables in the mode choice, because the SP survey data lacked such information. Using the abundant RP data available from the HTS, a full-scale mode choice model that includes activity-related variables as input and returns full information to the upper-level choice of the modeling system is being developed. Such model will present a comprehensive mode choice model that is applicable to the activity-based micro-simulation modeling system. The prototype mode choice model presented in this study is a powerful tool for policy analysis and still useful in predicting travelers' mode shift caused by new policies such as BRT and area pricing.

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