A MODAL CHOICE MODEL WITH STATED DEPENDENCE EFFECTS AND ITS ESTIMATION USING STATED PREFERENCE DATA

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1. INTRODUCTION

In establishing transport policy and planning which aims to reduce the excess demand of car traffic in an urban area, it is necessary to predict the effects of such policy and planning on the change in modal choice as accurate as possible. For this end, since mid '70's disaggregate modal choice models have been used, and a number of methods for developing those models have been established (Domencich and McFadden, 1975; Hensher and Johnson, 1981; Ben-Akiva and Lerman, 1985). Most of those models are static; they are based on the implicit assumptions that the resistance to change in modal choice from one mode to another is negligible and there are no differences in evaluating the transport services among individuals who use different modes. Thus, models are usually estimated by using cross-sectional data set of one point in time.

However, in a short-run prediction of changes of modal choice behavior, especially for daily repeated travels such as work trips, it is well considered that such models are not appropriate because in real situations the resistance to change is not negligible and the evaluation of transport services are different among the travellers who use different modes due to habits (Goodwin, 1977; Clarke et al, 1982; Kawakami and Hirobata, 1984). Therefore, it is desirable to develop a dynamic modal choice model.

The dynamics of behavior due to habit are discussed in economic literature (e.g., Pollack, 1976; Mannering and Winston, 1985). In addition, econometric theory of dynamic models of discrete choice has been worked out fairly extensively (e.g., Heckman, 1981), and also in transportation field the dynamic aspects of choices have been studied (e.g., Tardiff, 1980; Johnson and Hensher, 1982; Daganzo and Sheffi, 1982; Hensher and Plastrier, 1985). However, empirical examinations have not been made so much as static choice models.

In estimating the parameters of disaggregate behavioral models, traditionally, so-called revealed preference data have been used. However, when we estimate the dynamic disaggregate model we need panel data which are usually difficult to be obtained in actual planning situations. By contrast, stated preference data which potentially possess the dynamic nature of behavior are easily to be collected. Stated preference data obtained from a questionnaire survey on purely hypothetical choice situations, however, seem to have problems. A major problem is that there may be inconsistency between stated preference and actual behavior. Therefore, it is necessary to obtain stated preference data which are as close to actual behavior as possible.

In these contexts, the authors tried to develop a disaggregate modal switching model of car-traveler, and examined the model formulation and the method of estimation using stated preference data (Hirobata and Kawakami, 1990). The models formulated in the prior work are based on the hypotheses that there exists differences in evaluation mechanism among travelers who use different modes. They can incorporate the resistance to change which is dependent on the transport service level before the change, and can also allow the existence of heterogeneity in the random term of utility due to unobserved and omitted variables. However, the assumption on structure of the random term of those models are restrictive; they employ the value of serial correlation in the random term of 0 or 1. Since the value of serial correlation lies in the range between 0 and 1, it is not exactly adequate to apply such models in the real world. Therefore, in the present paper, an extension of the model developed in prior work is tried.

The contents of the paper are as follows: Firstly, we formulate a new disaggregate modal switching model based on the random utility theory within the dynamic framework, and show that it is the generalized version of the models developed in the prior work. Secondly, we present a method of generating stated preference data for model estimation based on an originally designed questionnaire survey. Thirdly, we estimate the parameters of the models by using data obtained in Nagoya, Japan, and examine those statistical properties and applicabilities to real situations.

2. MODEL FORMULATION

2.1 Hypotheses

We set the following hypotheses on modal choice behavior:

H-1: There are differences in the structure of the subjective evaluation of transport service among travelers who use different modes (e.g., car users have different subjective evaluations of transit service from transit users);

H-2: While a traveller basically tries to select a mode which maximizes his utility, in changing a mode in response to a change of transport service, there exists resistance to change. The magnitude of the resistance to change may be dependent on the level of service before the change of transport service.

The first hypothesis means that utility functions of modes are different among travelers who use different modes before the change in transport service. The second hypothesis is employed since there may exist some transport service attributes for which travellers require some additional improvements rather than those absolute improvements in their modal switching and the extent of those additional improvements depend on attribute levels before the transport service change.

In order to incorporate the first hypothesis, we focus on modal switching behavior by current mode, and formulate a modal switching model, based on the random utility modeling framework. The second hypothesis is explicitly considered in formulating the model by distinguishing the resistance to change from the utility.

2.2 Derivation of a modal switching model

We suppose a population of travelers (e.g., commuters) who are using a certain mode B (e.g., car) and can use a certain alternative mode A (e.g., transit), and formulate a model which predicts the modal switching probability of a traveler.

At first, we assume that the difference of utility between mode A and mode B, U_{tn}, for traveler n using mode B at point t can be expressed as follows:

$$U_{tn} = V_{tn} + \varepsilon_{tn} , \tag{1}$$

where V_{tn} is a deterministic component which is a function of the observed attributes of the traveller and the two modes at time point t, and ϵ_{tn} is a random component which account for the effects of unobserved attributes at time point t. The randomness of ϵ_{tn} leads to probabilistic nature of the travel behavior.

In addition, we assume the structure of ϵ_{tn} as

$$\varepsilon_{tn} = \mu_n + \upsilon_{tn} \tag{2}$$

where μ_n is the random component which varies among travellers but does not vary temporally, and υ_{tn} is the purely random component which varies both among travellers and temporally. It should be noted that this assumption does lead to the generation of the serial correlation among the random components of the utility in different points in time.

We suppose two points in time, t and t + 1, where due to the change in levels of transport service attributes the difference of utility between mode A and B changes from U_{tn} to $U_{t+1,n}$. Then, it follows from hypothesis H-2 that after the change of transport service traveler n switches his using mode from B to A if and only if $U_{t+1,n}$ exceeds the value of the resistance to change, $C_{t+1,n}$.

$$C_{t+1,n} = C_0 + R_{tn} , \tag{3}$$

where C_0 is the component of the resistance to change which is constant for all travelers, and R_{tn} is the component which is dependent on the transport service level for traveler n at the time point t (before the change of transport service).

Then, the probability, P_n, that traveler n switches his using mode from B to A at the time point t+1 (after the change of transport service) can be expressed as

$$\begin{aligned} P_n &= Prob[\ U_{t+1,n} > C_{t+1,n}] \\ &= Prob[\ V_{t+1,n} + \varepsilon_{t+1,n} > C_{t+1,n}] \quad . \end{aligned} \tag{4}$$

Accordingly, by assuming a specific probability distribution on $\epsilon_{t+1,n}$, we can derive a model which predicts the value of P_n as a function of $V_{t+1,n}$ and $C_{t+1,n}$, as usually done in random utility modelling. There seems to be no problem. However, in our case, it is not so easy to formulate an estimable form of model, as described below.

It should be noted that the following equation does not hold for all travelers who use mode B at the time point t.

$$U_{tn} < C_{tn} \tag{5.a}$$

or

$$\varepsilon_{tn} < C_{tn} - V_{tn} \tag{5.b}$$

That is, since the traveler for whom equation (5) does not hold is no longer a mode B user at the time point t, there exists an upper limit in the range of the value of ϵ_{tn}. Consequently, it must be assumed that the probability distribution of ϵ_{tn} is a truncated distribution. The distribution of $\epsilon_{t+1,n}$ which is correlated with ϵ_{tn} is affected by this limit. The expectation $U_{t+1,n}$ does not coincide with $V_{t+1,n}$, and the magnitudes of the variance in utility at the time point t+1 differ among travelers. Therefore, the assumption of the random term with zero mean and constant variance, which is commonly employed in the derivation of the disaggregate model is no longer adequate for formulating the modal switching model, although to derive a complicated model is possible (Kitamura, 1987; Kitamura and Bovy, 1987).

In order to overcome the difficulty, we consider the joint probability distribution of the random term ϵ_{tn} and $\epsilon_{t+1,n}$ which is not truncated, instead of that of ϵ_{tn} and $\epsilon_{t+1,n}$. This means that we consider the joint distribution of random component over a population which includes the travelers who were mode B users at past (the point t-1) but are not mode B users at present (the time point t).

Let the joint density function of ϵ^*_{tn} and ϵ^*_{t+1},n to be a two-dimensional normal distribution with zero means, constant variances s and correlation coefficient ρ: $N_2(0,0,\sigma^2,\sigma^2,\rho)$. The value of ρ lies between 0 and 1, because random components in different points in time share the time-invarying term μ_n.

Then, the probability Pn that traveler n who uses mode B at the time point t switches j is mode from B to A at the time point t+1 is given by the conditional probability as follows:

$$\begin{aligned} P_n &= Prob[\ U^*_{t+1,n} > C_{t+1,n} \mid U^*_{tn} < C_{tn}\ ] \\ &= \frac{Prob[\ (\ U^*_{t+1,n} > C_{t+1,n}\ )\ and\ (\ U^*_{tn} < C_{tn}\ ]}{Prob\ [\ U^*_{tn} < C_{tn}\ ]} \\ &= \frac{Prob[\ (V_{t+1,n}+\varepsilon^*_{t+1,n} > C_{t+1,n})\ and\ (V_{tn}+\varepsilon^*_{tn} < C_{tn}]}{Prob[\ V_{tn}+\varepsilon^*_{tn} < C_{tn}\ ]} \end{aligned} \tag{6}$$

When we denote the joint density function as $f(\epsilon^*_{tn}, \epsilon^*_{t+1,n})$ and the marginal density function of ϵ^*tn as $f(\epsilon tn)$, equation (6) is expressed by the following equation.

$$P_n = \frac{\int_{-\infty}^{C_{tn}-V_{tn}} \int_{C_{t+1,n}-V_{t+1,n}}^{\infty} f(\varepsilon^*_t, \varepsilon^*_{t+1})\, d\varepsilon^*_t d\varepsilon^*_{t+1}}{\int_{-\infty}^{C_{tn}-Vtn} f(\varepsilon^*_t)\, d\varepsilon^*_t}$$

$$= \frac{\int_{C_{t+1,n}-V_{t+1,n}}^{\infty} f(\varepsilon^*_{t+1} d\varepsilon^*_{t+1} - \int_{-\infty}^{C_{tn}-V_{tn}} \int_{C_{t+1,n}-V_{t+1,n}}^{\infty} f(\varepsilon^*_t, \varepsilon^*_t}{\int_{-\infty}^{C_{tn}-V_{tn}} f(\varepsilon^*_t)\, d\varepsilon^*_t}$$

$$= \frac{[1-\Phi(\frac{C_{t+1,n}-V_{t+1,n}}{\sigma})] - L(\frac{C_{tn}-V_{tn}}{\sigma}, \frac{C_{t+1,n}-V_{t+1,n}}{\sigma}, \rho)}{\Phi(\frac{C_{tn}-V_{tn}}{\sigma})} \tag{7}$$

normal distribution N(0,1) and $L(a,b,\rho)$ expresses the equation:

$$L(a,b,\rho) = \int_a^{\infty}\int_b^{\infty} \phi(u_1, u_2)\, du_1 du_2 \tag{8}$$

where $\phi(*)$ is the density function of two-dimensional standard normal distribution $N_2(0,0,1,1,\rho)$.

Thus, even in the case where the distribution of the random term is truncated, the modal switching model can be formulated as a relatively simple form. However, since the calculation of L(*) is still not so easy because of its non-linearity with respect to p, it is difficult to estimate the parameters of the model by using eqn (7). Accordingly, we try to approximate L(*) as a linear function of p.

In the extreme cases, the values of L(*) in eqn (7) are easily obtained from the property of two-dimensional normal distribution as (Johnson and Kotz,1970; Johnson and Kotz,1972)

$$L(a,b,\rho) = 1 - \Phi(a) \qquad \text{if } \rho = 1 \text{ and } a > b$$

$$L(a,b,\rho) = \{1 - \Phi(a)\}*\{1 - \Phi(b)\} \qquad \text{if } \rho = 0 \tag{9}$$

where "a" and "b" in eqn (9) are as follows:

$$a = (C_{tn} - Vtn) / \sigma$$

$$b = (C_{t+1,n} - V_{t+1,n}) / \sigma.$$

We approximate L(*) as a linear function of p so that the values for extreme cases are forced to coincide with their true values. This approximated function are as follows:

$$L(a,b,\rho) = \{1 - \Phi(a)\}*[\Phi(b)*\rho + \{1 - \Phi(b)\}] \tag{10}$$

Then, eqn (7) is expressed as

$$P_n = \frac{\Phi(a)*\{\Phi(b)*(\rho-1) + 1\} - \rho*\Phi(b)}{\Phi(a)} \tag{11}$$

In addition, by approximating Φ(*) as

$$\Phi(x) = \frac{1}{1 + \exp(-\lambda x)} \tag{12}$$

we can finally obtain the following equation.

$$P_n = \frac{\exp[\lambda(\frac{V_{t+1,n} - C_0}{\sigma})] - \rho*\exp[\lambda(\frac{V_{tn} - C_0 + (R_{tn} - R_{t+1,n})}{\sigma})]}{\exp[\lambda(\frac{R_{tn}}{\sigma})] + \exp[\lambda(\frac{V_{t+1,n} - C_0}{\sigma})]} \tag{13}$$

2.4 The restrictive models

As mentioned earlier, the authors have formulated four modal switching models by making different assumptions on the nature of the resistance to change, C_{tn}, and the random component utility, ϵ_{tn}. These models are as follows:

MODEL-1:

$$P_n = \frac{1}{1 + \exp[\frac{\lambda (C_0 - V_{t+1,n})}{\sigma}]} \tag{14}$$

This model is not distinct from the binary logit model which is well known as a representative model of random utility models, excepting that the resistance to change is considered. Therefore, eqn (14) can be derived by assuming that the random component of utility ϵ_{tn} in eqn (1) is composed of the random components of two modes and those components are independently and identically distributed with Type I extreme value distribution.

MODEL-2:

$$P_n = \frac{1}{1 + \exp[\lambda (\frac{C_0 + R_{tn} - V_{t+1,n}}{\sigma})]} \tag{15}$$

This model takes the form of the binary logit model, as is MODEL-1. However, the probability that traveler n switches his using mode is influenced not only by the attribute levels after the transport service change but also by the attribute levels before the transport service change.

MODEL-3:

$$P_n = \frac{\exp[\lambda (\frac{V_{t+1,n} - C_0}{\sigma})] - \exp[\lambda (\frac{V_{tn} - C_0}{\sigma})]}{1 + \exp[\lambda (\frac{V_{t+1,n} - C_0}{\sigma})]} \tag{16}$$

This model is derived assuming that the value of random component for traveler n, ϵ_{tn}, is kept constant irrespective of the transport service change. That is, we assume that the value of $\epsilon_{t+1,n}$ is equal to the value of ϵ_{tn}. This implies that the term ϵ_{tn} is a traveler specific effect and the value of that does not change temporally.

MODEL-4:

$$P_n = \frac{\exp[\lambda(\frac{V_{t+1,n}-C_0}{\sigma})] - \exp[\lambda(\frac{V_{tn}-C_0}{\sigma})]}{\exp[\lambda(\frac{R_{tn}}{\sigma})] + \exp[\lambda(\frac{V_{t+1,n}-C_0}{\sigma})]} \tag{17}$$

This model is derived by assuming that ϵtn is distributed with a truncated normal distribution whose upper limit depends on the attribute levels before the transport service change.

For distinguishing with these four models, we call the model formulated in this paper MODEL-5.

2.5 Relationship among the five models

For summarizing the relationships among five alternative modal switching models, following the work of Tardiff(1980), we again define a utility function as eqn (18), which combines the utility and the resistance to change.

$$U_{tn} = V_{tn} - C_0 - R_{t-1,n} + \mu_n + \nu_{tn} \quad , \tag{18}$$

It should be noted that the term $R_{t-1,n}$ is not considered in Tardiff's utility function. By making different assumptions on the terms of eqn (18), we can get five alternative models. The restrictive assumptions of these models are summarized in Table 1.

Table 1.

The restrictive assumptions	Model				
	Model-1	Model-2	Model-3	Model-4	Model-5
$\mu_n = 0$	○	○	–	–	–
$\upsilon_{tn} = 0$	–	–	○	○	–
$R_{t-1,n} = 0$	○	–	○	–	–

"○" indicates to set the corresponding restrictive assumption and "–" indicates not to set it. All the models are assumed to include C_0 .

As can be seen from this table, the models formulated in our prior work are restrictive in those assumptions; MODEL-1 and MODEL-3 do not include the effects of 'before' transport service levels on the resistance to change, while MODEL-2 and MODEL-4 include those effects, and MODEL-1 and MODEL-2 assume no serial correlation in random components, while MODEL-3 and MODEL-4 assume complete dependence of random components. On the contrary, there is no restrictive assumption on MODEL-5. Of course, these four models can be derived directly from eqn (13). That is, MODEL-5 is a generalized version of the four models.

3. ESTIMATION METHOD

3.1 Stated preference data

In order to calibrate the disaggregate modal switching models, we need a data set which contains the information on each traveler concerning to the using and alternatively available modes and their attribute levels of both before and after the change of transport service. That is, we need a data set which is not cross-sectional but time-serial for each traveler.

For this purpose, the so-called panel data seems to be appropriate, because it contains both cross-sectional and time-serial characteristics. However, it is difficult to obtain a panel data set in actual planning context, and usually there are some problem in revealed preference data due to the narrowness of the value ranges of attribute levels and the internal correlations among attributes.

By contrast, there have been the modelling approaches which use stated preference data which are obtained by questionnaire survey. The methods based on these approaches have several advantages. For example, they can overcome the above-mentioned problems in revealed preference approaches, because we can control the choice situations. Moreover, it is easily collected in comparison with panel data, and it can also capture the dynamic nature of travel behavior. Therefore, the stated preference data set seems to be appropriate for the calibration of the disaggregate modal switching models.

However, there are the following problems in the usual stated preference data obtained through the questions on purely hypothetical situations:

1) there is a problem of accuracy in respondents' perception of the hypothetical situations,

2) there may be some gaps between stated preference and actual behavior, and

3) the numbers of attributes and attribute-levels which can be considered simultaneously are limited in usual stated preference survey.

Therefore, it is important to reduce the above-mentioned problems when we use stated preference data. In this study, we adopt a questionnaire format which can capture the stated preference of each traveler that is closely related to his real situation, in order to reduce the first and third problems. However, since the second problem can not be avoided so long as we use stated preference data, the validity of the calibrated models based on the stated preference data should be tested by applying them to the real situations, and if the fitness of the models are poor the models need to be adjusted using the data on real situations.

3.2 Contents of the questionnaire survey

The data set for calibrating the disaggregate modal switching models should satisfy the following requirements:

1) it contains each traveler's using and alternatively available modes and those attribute levels both before and after the transport service change,

2) it is easily collected,

3) it precisely reflects the preference structure of each traveler,

4) it can capture the effects of almost all the relevant attributes simultaneously; it can take general advantages of disaggregate models, and

5) it can easily capture the effect of each attribute separately.

By considering these requirements comprehensively, we adopt a method in which we carry out the survey on present travel behavior and the survey on future mode-use intention simultaneously and convert these data into calibration data set.

The contents of the survey are as follows:

1) traveler's socio-economic characteristics (income, age, etc.),

2) travel characteristics (destination, time of day, etc.),

3) using mode and its attribute levels,

4) alternatively available modes and its attribute levels,

5) intention about the mode use (a question of whether he switches his using mode when attribute levels of using mode are worsened or when those alternatively available mode are improved), and

6) the critical levels of transport service attributes for switching his mode (only if he has intention of modal switching).

From the question 5), we can see whether or not a traveler is a "choice" or a "captive" in mode use. The question 6) ask about the critical level for mode switching by each attribute of mode, with keeping the levels of other attributes to be unchanged. From the responses to question 6) and the answers to questions 3) and 4), we can generate a data set for model calibrations by using a method described in the next subsection.

3.3 Method for making a calibration data set

Information on using and alternatively available modes and their attribute levels before the transport service change is directly obtained from the questions 3) and 4), but that of those after the change of transport service is not obtained from these questions. So, we generate the data set for calibrating the models by using the following method.

This method uses the answers to question 3), 4) and 6). Firstly, for each traveler the transport service condition after only one transport service attribute is changed is set, based on the answers to question 3) and 4). That is, by changing the present level of only one transport service attribute, the condition after the transport service change is generated.

Next, the changed level of one transport service attribute and the critical level of that attribute for modal switching which is obtained from question 6) are compared, and if the former is better than the latter then the traveler is judged to switch his mode under the changed condition, because if he switches his mode under the condition which he answered to question 6) he does switch his mode under the better condition.

This operation is repeated for all travellers and for all transport service attributes incorporated in the models, and the data set for model calibration is made out.

In changing a transport service attribute, we give a value γ_{kn} to transport service attribute k of traveler n. For example, when we consider the case where the transport service level of alternatively available mode is improved, we judge that traveler n will change his using mode if the following inequality holds:

$$\gamma_{kn} * S_{Akn} < Q_{Akn} \qquad (19)$$

where S_{Akn} is a present level of k-th attribute of alternatively available mode A for traveler n and Q_{Akn} is a critical level of that attribute for his modal switching to mode A. In this case, γ_{kn} takes a value between 0 and 1, and it is given by generating a uniformly distributed random variable. Therefore, the value of the product of γ_{kn} and S_{Akn} corresponds to the level of k-th attribute after the transport service change. It should be noted here that the attribute levels of transport service are usually defined in a way that the larger those values the worse those service levels, as in travel time and travel cost. Thus, if the inequality (19) holds, traveler n will switch his mode under the condition in which the level of only one attribute k is changed to $\gamma_{kn}*S_{Akn}$ and the levels of other attributes ($S_{Ak'n}$, $k' \neq k$, $k'=1,...,K$; S_{Bkn}, $k=1,...,K$, where S_{Bkn} is level of k-th attribute of using mode B and K is the number of transport service attributes) are kept at the present levels, and otherwise, he will not switch his mode under that condition.

4. EMPIRICAL EXAMINATION

4.1 Data

We estimate the parameters of the disaggregate modal switching models and examine the validity of the model, based on the questionnaire survey for car users. The survey was carried out in the suburbs of Nagoya by hand-on and mail-back method. The respondents of the survey were drawn from the car-users driving to the CBD of Nagoya during the morning peak hours. The percent of the effective answers was 24.5% and the sample size was 2451.

4.2 Estimation results

In estimating the disaggregate modal switching models, the linear utility functions are assumed. The forms of the models in the estimation are expressed as follows:

MODEL-1:

$$P_n = \frac{1}{1 + \exp(\beta_0 + \Sigma\beta_k X_{knt})} \qquad (20)$$

MODEL-2:

$$P_n = \frac{1}{1 + \exp(\beta_0 + \Sigma\beta_k X_{knt} - \Sigma\alpha_k X_{kn,t-1})} \qquad (21)$$

MODEL-3:

$$P_n = \frac{\exp(-\Sigma\beta_k X_{knt} - \beta_0) - \exp(-\Sigma\beta_k X_{kn,t-1} - \beta_0)}{1 + \exp(-\Sigma\beta_k X_{knt} - \beta_0)} \qquad (22)$$

MODEL-4:

$$P_n = \frac{\exp(-\Sigma\beta_k X_{knt} - \beta_0) - \exp(-\Sigma\beta_k X_{kn,t-1} - \beta_0)}{\exp(-\Sigma\alpha_k X_{kn,t-1}) + \exp(-\Sigma\beta_k X_{knt} - \beta_0)} \tag{23}$$

MODEL-5:

$$P_n = \frac{\exp(-\Sigma\beta_k X_{knt} - \beta_0) - \rho*\exp(-\Sigma\beta_k X_{kn,t-1} - \beta_0)}{\exp(-\Sigma\alpha_k X_{kn,t-1}) + \exp(-\Sigma\beta_k X_{knt} - \beta_0)} \tag{24}$$

where X_{knt} is a difference of k-th explanatory variable of traveler n (trânsport attribute levels and user's socio-economic characteristics) between car and transit after the change of transport service, and $X_{kn,t-1}$ is that of before the change of transport service.

The effect of C_0 is included into the constant term β_0 of the utility functions and parameters λ and σ are included into each parameter of utility functions, β_0, β_k, α_k .

In the survey, 17 transport attributes were included, and it is possible to incorporate the effects of many transport service attributes into the disaggregate mode switching models. In this paper, we present the estimation results which seem to be fairly reasonable.

Table 2 shoes the results of the five models estimated by using the maximum likelihood method based on the intention data. Many of the income coefficients are not statistically significant. Thus some aggregation of this variable would be necessary if we apply these models to the prediction of modal switching behavior. However, we do not matter the issue here, since the main interest of this study is in the examination of the relative performance of the five models.

When we compare the five models based on the likelihood ratio indices and the percent of correct estimation, we can see that the goodness of fit of MODEL-2, MODEL-3, MODEL-4, and MODEL-5 are fairly high and there are little differences among these models (i.e., the goodness of fit of MODEL-5 is not so good as compared with the other three models) but that of MODEL-1 is lower than those of the other four models.

The t-values of parameters of attributes before the transport service change (i.e., the α's) in MODEL-2, MODEL-4 and MODEL-5 are all significant. The signs of these parameters should be interpreted together with the signs of those in eqn (21), (23), and (24). Given the way the variables are defined (the value of car minus the value of transit), the negative coefficients indicate that the travelers whose service levels of transit were only a little worse than those of car before the change of transport service are less likely to change their mode than those whose service levels of transit were considerably worse than car, even though levels after the change of transport service are identical. This result is consistent with our expectation about these coefficients.

In addition, the t-values of 'after' coefficients (i.e., the β's) in MODEL-2, MODEL-3, MODEL-4, and MODEL-5 in which the effects of transport service levels before the change are considered in the model formulation are larger than those of MODEL-1 in which those effects are not considered.

The value of serial correlation ρ which is only estimable for MODEL-5 is 0.78, and it implies that there is considerable serial correlation between the random terms at different points in time. However, it should be noted that this result is based on the stated preference data.

As a result, it was found that the estimated models which explicitly consider the effect of state dependence are statistically valid and it is very important either to incorporate the effects of transport service levels before the change of transport service or to consider them in the model formulation when we predict the modal switching behavior in response to change of transport service. Among such models, MODEL-5 developed in the present study has not so very good statistical properties compared with other models. However, since it can estimate the effect of the serial correlation among random terms of utility separately from other effects so as to be best fit to the data, it seems to be good model in forecasting the modal switching behavior.

Table 2. Estimation results of the modal parameters based on SP data

		MODEL-1	MODEL-2	MODEL-3	MODEL-4	MODEL-5
CONSTANT		-0.413E+00(5.39)	-0.248E+00(0.66)	-0.104E+02(6.83)	-0.400E+01(3.96)	-0.222E+01(2.44)
income (1x10⁴ yen per year)	~200 ~300 ~400 ~600	0.413E+00(1.28) 0.217E+00(0.79) 0.181E-01(0.07) -0.423E+00(1.64)	0.371E+00(1.01) 0.247E+00(0.79) 0.588E-01(0.20) -0.429E+00(1.46)	0.107E+07(0.56) 0.147E+01(0.97) 0.240E+01(1.63) -0.986E+00(0.59)	0.647E+00(0.85) 0.745E+00(1.24) 0.731E+00(1.21) -0.528E+00(0.68)	0.555E+00(1.07) 0.470E+00(1.08) 0.329E+00(0.76) -0.458E+00(1.10)
travel time difference (car-transit)	A* B*	-0.623E+02(2.43)	-0.599E-01(10.05) -0.490E-01(7.69)	-0.206E-01(11.09)	-0.307E-01(6.80) -0.212E-01(2.50)	-0.366E-01(5.50) -0.291E-01(3.39)
waiting time** (car-transit)	A B	-0.545e-01(4.75)	-0.409E+00(9.59) -0.336E+00(7.99)	-0.243E+00(10.41)	-0.322E+00(8.62) -0.193E+00(3.88)	-0.333E+00(7.59) -0.238E+00(4.63)
walking time** (car-transit)	A B	-0.408E-01(4.66)	-0.183E+00(9.08) -0.148E+00(7.24)	-0.823E-01(8.21)	-0.120E+00(6.70) -0.704E-01(3.01)	-0.136E+00(6.04) -0.916E-01(3.49)
departure time headway** (car-transit)	A B	-0.618E-01(6.64)				
serial correlation in the random term: ρ	total					
log-likelihood		-639	-532	-548	-539	-527
$\rho_c 2$-value		0.108	0.256	0.226	0.249	0.264
percent of correct estimations***	total	66.2%	75.7%	74.9%	75.9%	75.6%
	non-switcher	78.3%	84.2%	83.2%	82.5%	82.8%
	switcher	49.3%	64.1%	63.4%	66.8%	65.7%
sample size: 1034						

(E+01 – 10+01; figures in parentheses are t values)
*:"A" refers to "after" and "B" refers to "before".
**:the value of car is set to zero.
***:this statistic is not rigorous, but it can be used in model comparison

4.3 Applications of the intention model to actual situations

The disaggregate modal switching models which were estimated using the stated preference data (intention data) were applied to the prediction of the actual modal choice behavior in order to examine the external validity of them. In this examination, we used the work-trip data which were obtained before and after the opening of a railway line in the suburb of Nagoya, Japan.

Table 3 shows the results of applications. From these results, it is found that while the percent of correct estimation is not so low as compared with those of original intention models the predicted average modal switching probabilities of the models are very high as compared with share of switchers in actual data. Many factors can be considered as the causes of these over-predictions; one of which is that in spite of the efforts taken in this study there may still exist some gaps between the stated preference and the real behavior. Another of which is that there may exist transferability problems. Although these problems are to some extent removed by applying the scale factor method, further examinations of these problems are left to future work.

5. CONCLUDING REMARKS

In this study, based on new hypotheses which differ from those employed in usual random utility modeling, a new disaggregate modal switching model was developed. The model not only incorporates the resistance to change in modal switching behavior due to habit, but also permits the any value of serial correlation among the random components of utility at different points in time. The model was shown to be the generalized version of the models formulated in our prior work. It seems to be useful in the sense that it is the empirically estimable form of model and can estimate the value of the serial correlation separately from pure state dependence effects.

The empirical examination showed that the statistical goodness of fit of the model formulated in the present study is not so very high as compared with those models formulated in our prior work. However, since the value of the serial correlation is fairly large and statistically significant, it seems to be a good model for forecasting the modal switching behavior after the change of transport service.

In addition, while all the estimated models based on the stated preference data tend to over-estimate the actual modal switching behavior due to the change in transport service, this over-estimation can be adjusted if we use revealed preference data. Since the usefulness of the estimation method based on stated preference data will be increased in travel demand modeling, we argue that further studies along these lines should be carried out.

Finally, although the present study is carried out in Japan contexts, the model and the estimation method developed in the present study could be applied also to the analysis in Philippines contexts.

Table 3. Applications of the intention-based (SP) models to the actual situation data

		MODEL-1	MODEL-2	MODEL-3	MODEL-4	MODEL-5
percent of correct estimations	total	67.1%	67.1%	62.4%	61.7%	63.1%
	switcher	78.8%	67.4%	61.4%	60.6%	62.9%
	non-switcher	64.7%	64.7%	70.6%	70.6%	64.7%
average switching probability	total	0.426	0.404	0.381	0.381	0.383
	switcher	0.511	0.636	0.630	0.647	0.637
	non-switcher	0.414	0.374	0.349	0.347	0.350
sample size:149 (switcher:17)						

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