EXPERIMENTAL ANALYSIS APPROACH TO ESTIMATION OF DYNAMIC ROUTE CHOICE MODEL CONSIDERING TRAVEL TIME PREDICTION

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1. INTRODUCTION

The society in which we live today is highly informational, and the car we drive is no exception. Accordingly the effects and advantages of providing motorists with information have been extensively discussed. In urban areas, there has been an increase in user demand brought on by concentrations of socioeconomic activity, and delays of improvement or new construction of roads caused by an increase in the value of real property and by land use limitations; thus, traffic conditions on road networks must be seriously considered. Providing information is apt to be regarded as a short-term scheme to relieve the conditions on urban road networks. In the long run, the level of service of road networks available is advanced by providing information.

Delivering motorists information about alternative routes' traffic conditions in assisting their route choices and guiding them to utilize existing road networks efficiently is regarded as one possible and effective strategy for traffic management. Further evaluation of the content of the delivered information is required, however, in catching up with the advancement in hardware. But some people have doubts about the effect of providing travelers information. Arnott et al.(1), for example, examined the relation between the quality of information (information on road capacity) and travel cost, and pointed out that providing low quality information induces higher costs than providing no information. Therefore, we should clarify the relation between information delivered and travel behaviour in order to evaluate the effects of providing information.

When we consider delivering information as a means of traffic control, the primary targets are commuters and motorists on business in congested urban areas. These motorists repeatedly take specific routes almost everyday and experience day-to-day varying traffic conditions on the routes. Under such circumstances, the questions become, according to accumulation of driving experience and information acquisition, how is a motorist's knowledge attained, and can the 'perfect information' hypothesis of user-equilibrium assignment be achieved. In addition, we need a model which dynamically expresses motorist route choice in order to estimate motorist response to certain given information, and evaluate the effects of information on traffic conditions. These objects require time-series observations of motorists behaviour.

In this study we propose an experimental approach that repeatedly asks participants their responses for hypothetical route choice in a laboratory. Since we need panel data in order to collect time-series data in investigating the dynamics of travel behaviour. In this study, we aim to examine the relation between travel experiences and dynamic route choice, especially the mechanism of travel time prediction. In the future, in order to evaluate the effects of providing travelers with traffic information, we are going to build up the dynamic route choice models based on random utility theory using the knowledge obtained in this study.

The rest of this paper is organized as follows. The basic concept of the dynamic route choice model using through random utility theory is discussed in Section 2. The outlines of the laboratory-like experiments conducted are roughly explained in Section 3. Some features of experimental results are presented and we attempt to classify participants according to the index in clarifying the characteristics of route choice in Section 4. In Section 5, considering the results in the preceding section, Predicted Travel Time Models that correspond to the deterministic utility function in random utility model are estimated. The last section discusses future extensions.

2. THE ROUTE CHOICE MODEL

2.1. Concept of the Route Choice Model

Construction of a route choice model which includes a travelers' behaviour rule is attempted. The model is based on the same concept as the random utility model. Horowitz mentions that random utility models provide the only currently available methods for developing empirically implementable testable travel demand models that are consistent with an explicit theory of choice (2). Random utility models assume that the individual selects the alternative with the greatest utility among the available alternatives. In this study, according to this assumption, the route choice model assumes that the traveler predicts each available route's utility based on personal driving experiences and provided information, and chooses the route which is likely to provide the greatest utility.

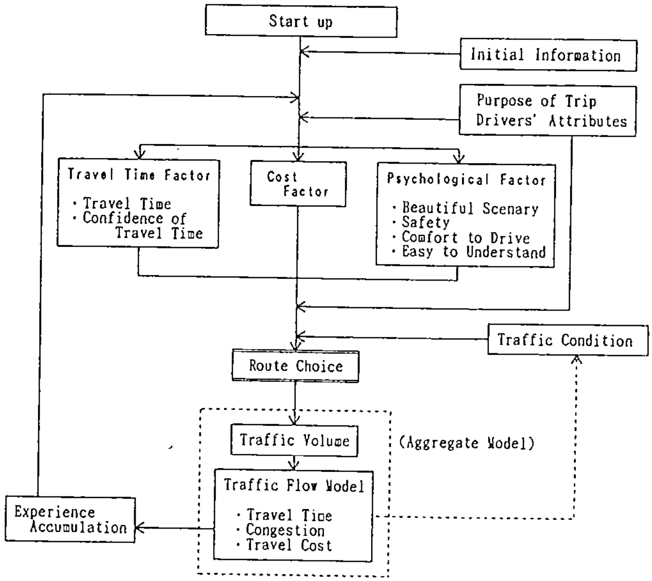

Fig. 1 Basic Concept of Route Choice Model

The explanatory factors of route choice are assumed to be as follows.

1. Travel time factors (e.g. travel time, confidence of travel time)
2. Cost factors
3. Psychological factors (e.g. beautiful scenery, safety, comfort to drive, easy to understand)

The outline of the comprehensive route choice model which includes these factors is shown in Figure 1. As travel time factors and cost factors are quantitative, the route choice model can easily take them as explanatory variables. But since psychological factors have not been analyzed enough to be understood, they are not adequate as explanatory variables for the route choice model at present.

In this study we choose the travel time as the explanatory variables for the route choice model for two reasons. The first reason pertains to the objects of the route choice model. The route choice model is going to be used for examining the effects of delivering information as a means of traffic control. The primary targets of such traffic control are commuters and motorists on business in congested urban areas. They make much of travel time and hope to arrive at their destination without delay caused by traffic congestion. Second, the traffic assignment model, one of the existing static travel demand models, takes travel time as an explanatory variable. Therefore, a route choice model that includes travel time as its explanatory variable is constructed.

2.2. The Application of Laboratory-like Experiments

In this study we assume that every motorist makes a route choice decision in predicting his travel time based on previous driving experiences and provided information. We intend to grasp the relation between travel time prediction and driving experiences and provided information by estimating a travel time prediction model whose explanatory variables include experiences and information. Estimating this model corresponds to identifying the utility function of the random utility model.

In this study we propose an experimental approach that repeatedly ask participants their responses for hypothetical route choices in a laboratory. Observations acquired by such experimental approach are regarded as stated preference data. Panel data is necessary to investigate the dynamics of a motorist's route choice and to estimate the parameters of a Predicted Travel Time Model. It is difficult to acquire repeated travel behaviour's revealed preference data, because of the inaccuracy of the data, expense, and term of study, etc. Therefore, the parameters of the model are estimated using SP data.

But there is still the question of whether the acquired SP data describe travelers' actual behaviours. We are going to examine whether the model constructed using SP data has external validity in the future.

In discussing laboratory choice experiments and SP data, Horowitz states that it is unrealistic to expect that models based on laboratory choice experiments are directly transferable to the real world except for special cases. Rather, the main value of laboratory-based models is likely to be in providing information on functional specifications and coefficient ratios (2). Therefore, we would like to construct a prototype of route choice model based on laboratory route choice experiments, and improve the model through repeated simulations and experiments.

3. AN EXPERIMENTAL APPROACH TO ANALYZING ROUTE CHOICE

3.1. Premises of the Experiments

In designing the experiments, the following premises are assumed:

1. Dozens of participants are simultaneously and repeatedly asked for a hypothetical route choice. Each participant predicts the travel times for all of the alternative routes and then chooses a route for him/herself.
2. Each iteration of the experiment corresponds to one day's morning peak period.
3. Departure time is fixed and choice dimension involves only routes. There are two

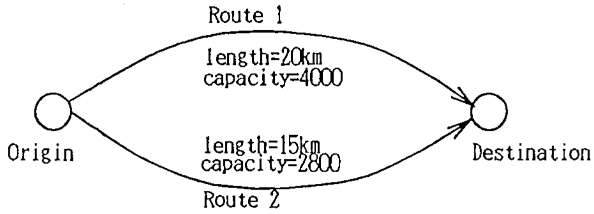

Fig. 2 Hypothetical Routes in the Experiments

Table 1. Designs of Experiments

	Designs of the Experiments	
	Experiment A	Experiment B
Number of Participants	56	82
Number of Iterations	21	21
Purpose of Trips	commute to work	
Time Period	1 hour in the morning peak(e.g. 8:00-9:00)	
No. of OD Pair	1 pair with 1 direction	
No. of Routes	2 routes in parallel	
OD Traffic Volume	5600(veh/h)	
Characteristics of Routes	Route 1	Route 2
Length	20km	15km
Capacity	$C=4000$(台/h)	$C=2800$(台/h)
Travel Time Function	$t=t_0\{1+a(V/C)^2\}$ $a=1.00,\ t_0=20$(min)	$t=t_0\{1+a(V/C)^2\}$ $a=1.00,\ t_0=15$(min)
Factor of Route Choice	each participant's predicted travel time	
Information Provided	1. characteristics of Routes, e.g. length, No. of lanes, free-flow travel time 2. actual travel time on the route chosen for the last iteration	
Questions	1. predicted travel time on the both routes for the next iteration 2. choice of the route for the next iteration	

alternative routes that connect one O–D pair (see Figure 2.).
4. Participants predict the (n+1)–th iteration's travel time based on preceding iterations' travel experiences. Travel experience can be defined as the route chosen by each participant, actual travel time on the chosen route and the travel time prediction error (the difference between the predicted and actual travel time).
5. The distribution of departure times is not considered. A conventional performance function (e.g. a BPR function) is used to represent the relationship between the route flow and travel time.

3.2. Experiment Designs

Laboratory route choice experiment designs are shown in Table 1. As there is no space for a full and detailed explanation about the experiments, see reference (4) for further necessary information about the route choice experiments. In conducting the experiments, for each iteration a questionnaire sheet is distributed to each participant and then recalled. Each iteration of the experiment consists of the following steps: 1) the experimenter presents the last (n–th) iteration's results (the route chosen by each participant and the actual travel time on the chosen route), 2) each participant predicts and writes the travel time for each route for this ((n+1)–th) iteration, and 3) each participant chooses a route for this iteration. The experimenter informs participants of the characteristics of the routes at the beginning of the experiment.

In this study two types of experiments, Experiment A and Experiment B, are conducted. These two experiments differ only in the way to the actual travel time is determined. In Experiment A, the actual travel times are calculated endogenously by aggregating the route choices of the participants, whereas, in Experiment B, the actual travel times are exogenously determined beforehand. In Experiment B, total traffic volume is fixed at V_0 and traffic volume on each route oscillates periodically around the equilibrium flow($V_0/2$) relative to the sine–curve. Actual travel time on each route is calculated by substituting link travel time function with traffic volume as shown in Table 1.

Experiment B was conducted three times at different places and times. Experiment B's data were acquired by combining these three independent samples into one sample. The validity of pooling data in Experiment B has been examined through variance analysis. The travel time prediction error TPE is adopted as a dependent variable that reflects the time–dependent participant's character. The experimental case and participant attributes (car license ownership and driving frequency) are adopted as explanatory variables. As a result of variance analysis, the validity of pooling data was proved. Thère is no space for an extended description of the variance analysis results. If further explanation is needed, see reference (4).

Participants attributes (sex, age, car license ownership, driving experience / frequency / objectives, car ownership) were obtained through a questionnaire for further analysis. Another participant questionnaire for participants focusing on actual route choice and on outside factors which influenced their route choice was also conducted after the route choice experiment to roughly examine the relation between route choice in the laboratory and that in the real world.

4. A PRELIMINARY EXAMINATION OF EXPERIMENTAL RESULTS

4.1. An Analysis of the Route Choice Rate

At the outset, let us analyze the experimental results from the point of view of the route choice rate. Figure 3 plots Experiment A's route choice rate for route 1 and route 2 against experimental iteration. The route choice rate corresponds to traffic conditions, namely, traffic volume on each route. From the 9th to the 14th iteration, traffic conditions on each route vary infinitesimally around the equilibrium state and reach a relatively stable state. From the 15th to the last iteration, traffic conditions on each route continue to oscillate. Traffic volume on route 1 is larger while traffic volume on route 2 is smaller than volume in the

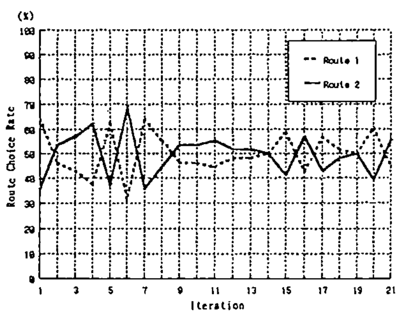

Fig. 3 Route Choice Rate Versus Iteration (Experiment A)

equilibrium state. We cannot judge by this experimental result whether the oscillation of traffic conditions on each route will converge or not.

Figure 4 plots two types of route choice rates for route 1, an actual and a given rate, against experimental iteration. The actual route choice rate is calculated by aggregating the participant's route choice. As we have mentioned before, a given route choice rate is determined in advance. In Experiment B, traffic volume continues to oscillate from beginning to end unaffected by the participant's route choice. Travel times provided for the participants are determined exogenously. Therefore, route choice rate continues to vary and appears not to reach a relatively stable state according to the oscillation of traffic condition on each route.

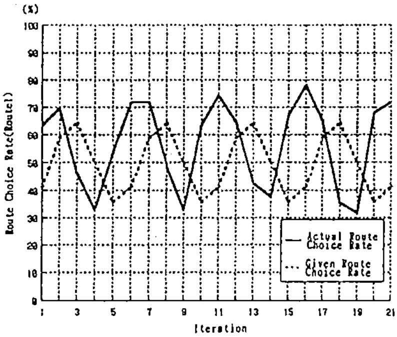

Fig. 4 Route Choice Rate Versus Iteration (Experiment B)

4.2. Classification of Participants

A number of route switches and rational route choices are used for the indexes that describe the characteristics of participant route choice in this study. The term "rational route choice" can be defined as choosing the route whose travel time predicted by each participant is smaller than (or equal to) that for another route. The results of both experiments are presented in Table 2 and Table 3. These tables indicate the relation between the route switching rate and number of rational choices.

In both experiments, many participants chose their route rationally. About 39% of participants in Experiment A and 56% of participants in Experiment B chose their

Table 2 Relation between the Number of Route Switches and Number of Rational Route Choices

		Number of Route Switches			Total
Experiment A		0～3	4～7	8～	
Number of Rational Route Choices	～17	4 (7.1)	0 (0.0)	0 (0.0)	4 (7.1)
	18	3 (5.4)	2 (3.6)	2 (3.6)	7 (12.6)
	19	2 (3.6)	4 (7.1)	1 (1.8)	7 (12.6)
	20	6 (10.7)	7 (12.6)	3 (5.4)	16 (28.6)
	21	6 (10.7)	8 (14.2)	8 (14.2)	22 (39.1)
Total		21 (37.5)	21 (37.5)	14 (25.0)	56(100.0)

Table 3 Relation between the Number of Route Switches and Number of Rational Route Choices

		Number of Route Switches			Total
Experiment B		0～5	6～9	10～	
Number of Rational Route Choices	～17	9 (11.0)	5 (6.1)	0 (0.0)	14 (17.1)
	18	0 (0.0)	0 (0.0)	1 (1.2)	1 (1.2)
	19	0 (0.0)	4 (4.9)	3 (3.6)	7 (8.5)
	20	2 (2.4)	7 (8.5)	5 (6.2)	14 (17.1)
	21	9 (11.0)	24 (29.3)	13 (15.8)	46 (56.1)
Total		20 (24.4)	40 (48.8)	22 (26.8)	82(100.0)

route rationally from the beginning to the end of the experiments. In Experiment A, approximately 93% of participants chose their route rationally more than 18 times while 83% did in Experiment B. It follows from what has been said that many participants considered the instruction given at the beginning of the experiments in which each participant was informed that choosing a route according to his or her predicted travel time means choosing route rationally. As there is little difference in the number of rational route choices of each participant, the number of route switches NRS is used for the index that describes participant route choice.

Considering the mean value and standard deviation of the number of route switches NRS, we may classify the participants into three groups.

Table 4 Effects of the NRS and the Participant Attributes on Prediction Error

Experiment A		DF	Sum of Squares	F-Value	PR>F
Model		93	8350.69	2.42	0.0001
Error		860	31968.27		
Source					
Iteration	①	17	3872.96	6.13	0.0001
Number of Route Switching	②	2	1170.79	15.75	0.0001
Frequency of Driving	③	2	29.74	0.40	0.6705
	①×②	34	1530.33	1.21	0.1917
	①×③	34	1336.66	1.06	0.3805
	②×③	4	343.32	2.31	0.0564

Table 5 Effects of the NRS and the Participant Attributes on Prediction Error

Experiment B		DF	Sum of Squares	F-Value	PR>F
Model		93	5605.00	1.69	0.0001
Error		1238	44214.81		
Source					
Iteration	①	17	2312.73	3.81	0.0001
Number of Route Switching	②	2	819.07	11.47	0.0001
Frequency of Driving	③	2	329.87	4.62	0.0100
	①×②	34	1059.36	0.87	0.6790
	①×③	34	1032.54	0.85	0.7137
	②×③	4	86.66	0.61	0.6579

<u>Experiment A</u>

Group S1: participant whose NRS is greater than or equal to 0 and less than 4
Group S2: participant whose NRS is greater than or equal to 4 and less than 8
Group S3: participant whose NRS is greater than or equal to 8

<u>Experiment B</u>

Group S1: participant whose NRS is greater than or equal to 0 and less than 6
Group S2: participant whose NRS is greater than or equal to 6 and less than 10
Group S3: participant whose NRS is greater than or equal to 10

The significant difference among these three groups in travel time prediction is examined using variance analysis. Table 4 and Table 5 indicate the variance analysis results. Travel time prediction error TPE is adopted as a dependent variable. Explanatory variables consist of experimental iteration, the participant group classified by the number of route switches and the group divided according to participant attributes (driving frequency). In accordance with the data form the additional analysis of participant attributes, participants are classified into three groups:

Group F1: participant who drives everyday
Group F2: participant who drives less than five days a week
Group F3: participant who seldom drives or doesn't own car license

In both experiments, we confirm that experimental iteration and the number of route switches affect travel time prediction significantly. Therefore, three Predicted Travel Time Models are estimated using the samples mentioned above segmented by the number of route switches. Also, a Predicted Travel Time Model where the dummy variable includes the participant group classified by the number of route switches is

Table 6 Relation between the NRS and the Feature of Everyday Route Choices

Experiment A	Number of Route Switches			Total
Feature of Everyday Route Choice	0 ~ 3	4 ~ 7	8 ~	
Knowing alternative routes and using alternative routes.	12 (21.4)	10 (17.9)	8 (14.3)	30 (53.6)
Knowing alternative routes but not using alternative routes.	8 (14.3)	8 (14.3)	3 (5.4)	19 (34.0)
Not knowing alternative routes and not using alternative routes.	0 (0.0)	2 (3.5)	1 (1.8)	3 (5.3)
No Answer	1 (1.8)	1 (1.8)	2 (3.5)	4 (7.1)
Total	21 (37.5)	21 (37.5)	16 (25.0)	56(100.0)

Table 7 Relation between the NRS and the Feature of Everyday Route Choices

Experiment B	Number of Route Switches			Total
Feature of Everyday Route Choice	0 ~ 5	6 ~ 9	10~	
Knowing alternative routes and using alternative routes.	7 (8.5)	18 (22.0)	8 (9.7)	33 (40.2)
Knowing alternative routes but not using alternative routes.	11 (13.5)	20 (24.4)	13 (15.9)	44 (53.8)
Not knowing alternative routes and not using alternative routes.	2 (2.4)	2 (2.4)	1 (1.2)	5 (6.0)
No Answer	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)
Total	20 (24.4)	40 (48.8)	22 (26.8)	82(100.0)

estimated. In Experiment B, driving frequency affects travel time prediction significantly at a confidence level of 99%. This is not true for in Experiment A. In this study, considering the number of route switches, we are going to estimate Predicted Travel Time Models in analyzing the interrelation between participant route choice and travel time prediction mechanisms.

4.3. The Relation between Respondents in Experiments and Actual Route Choice

As mentioned previously, a questionnaire for participants on route choice in the real world was conducted and used in roughly analyzing the relation between participant responses during experiments and actual route choice. Table 6 and 7 indicate the findings of the investigation. Excluding those who did not respond, about 94% of participants knew alternative routes available for commuting in Experiment A, while 94% of participants knew of alternative routes in Experiment B.

There are many participants who belong to Group S3 in Experiment A who switch their route according to day–to–day traffic condition. We guess that the route choices of participants who belong to groups other than Group S3 in Experiment A are uncharacteristic. From a microscopic point of view, we cannot say for certain whether each participant's route choices in the experiments correspond to actual route choices on one–to–one basis. We regard a one–to–one correspondence as the observation of a participant who switches his/her route frequently in experiment and in the real world. But considering the NRS possibilities, we believe that the findings acquired through these experiments can explain the diversity of actual route choice behaviour in part.

5. PREDICTED TRAVEL TIME MODELS

5.1. Travel Time Prediction Mechanisms

In this study, the assumption that a participant chooses a route according to his

Table 8 Definition of Variables

No. of Iteration		at n-th iteration Chosen Route
n	Predicted Travel Time	$\hat{t}_s^{\,n}$
n	Prediction Error	$\hat{t}_s^{\,n} - t_s^{\,n}\ (= x_s^{\,n})$
n	Actual Travel Time	$t_s^{\,n}$
n+1	Corrective Value	$\hat{t}_s^{\,n+1} - t_s^{\,n} (= y_s^{\,n+1})$
n+1	Predicted Travel Time	$\hat{t}_s^{\,n+1}$

travel time prediction is made. It is assumed that each participant predicts travel time for both routes based on previous travel experiences. Since each traveler repeatedly chooses his/her route, it seems reasonable to suppose that the travel time prediction mechanism is affected by previous travel experiences. Therefore we may say that this travel time prediction assumption is valid.

Conforming to these assumptions mentioned above, Predicted Travel Time Models are estimated. It is possible to treat the previous predicted travel time PT and travel time prediction error TPE, as well as the actual travel time for the chosen route, as explanatory variables representing travel experience. There is a possibility that both the predicted travel time TP and travel time correction value TC will be selected as dependent variables. In order to select the variables for Predicted Travel Time Models, the correlations between variables representing travel experiences and dependent variables have been examined. Here, there is space only for explaining the results. If further explanation is desired, see the reference (4). In both experiments, for the chosen route (regardless of route number), correlations between the TC and the previous iteration's TPE are evident. For the route not chosen, there seems to be no relation between the PT and previous travel experiences, in spite of the fact that the PT seems to correlate with the previous iteration's PT. Also, the correlation coefficient between the unchosen route's PT and chosen route's PT is low. Therefore, this study focuses on the chosen route and the Predicted Travel Time Models in which the previous iteration's TPE is used as the explanatory variable and the TC is selected as the dependent variable for estimations.

Though the experiments conducted in this study are very simplistic, the diversity of the participants' route choice is observed and the variety of each participant's standard of route choice is taken into account. This study selects the number of route switches as the factor for explaining the characteristics of route choice. Thus, the models are estimated considering the NRS. The Predicted Travel Time Models estimated are as follows:

Model 1 : model estimated using all data
Model 2 : model where dummy variable includes the participant group classified by the number of route switches
Model 3 : model estimated using the sample segmented by the number of route switches

Explanatory and dependent variables of the Predicted Travel Time Models are shown in Table 8. The model equations are

Model 1 : $y^{n+1}=\alpha_1+\beta_1 x_0^n \gamma_1 x_1^n+\delta_1 x_2^n+\varepsilon_1$ (n=3,4,....20) (1)

Model 2 : $y^{n+1}=\alpha_2+\beta_2 x_0^n \gamma_2 x_1^n+\delta_2 x_2^n+\eta_2 d_1+\theta_2 d_2+\varepsilon_2$ (n=3,4,....20) (2)

Model 3 : the same as that of Model 1
Model 3–1 : model estimated using the Group S1 sample
Model 3–2 : model estimated using the Group S2 sample
Model 3–3 : model estimated using the Group S3 sample

where $y^{n+1} = \hat{t}_s^{n+1} - t_s^n$,
$x_k^n = \hat{t}_s^{n-k} - t_s^{n-k}$ (k=0,1,2)
d_1 = 1, if participant belongs to Group S1
0, otherwise
d_2 = 1, if participant belongs to Group S2
0, otherwise
ε : random error term.

Each model includes the latest three travel experiences on a chosen route as the explanatory variables. It assumes that travel time prediction errors TPE are accumulated as travel experiences and affect the travel time correction value TC. The predicted travel time PT is obtained by adding the TC to the preceding iteration's AT.

Parameters of the models mentioned above are estimated by using the least squares method. When the model is estimated using panel data, because of each participant's time–series responses, an autocorrelation between the random error terms exists. Therefore the Parks method, which assumes a first–order autoregressive model in the random error, is used to estimate parameters. As there is no space for further explanation, see references 4, and 5.

5.2. Estimating Models Considering the Number of Route Switches

Table 9 indicates the parameters of each model estimated by using the Parks method. Absolute value β is the largest of the parameters which correspond to the travel experiences of each model, while absolute value of γ is larger than that of δ in

Table 9 Parameters Estimates of Predicted Travel Time

	No. of Samples	Parameter estimates (t-statistics)						MSE
		α	β	γ	δ	η_2	θ_2	
Experiment A								
Model 1	954	0.453 (24.7)	0.511 (161)	0.073 (24.5)	0.034 (11.1)	–	–	0.3402
Model 2	954	1.939 (41.2)	0.534 (232)	0.087 (37.6)	0.047 (20.4)	-2.132 (-17.7)	-1.508 (-59.7)	0.3390
Model 3-1	612	-0.044 (-6.13)	0.371 (162)	0.087 (46.3)	0.116 (70.9)	–	–	1.0101
Model 3-2	162	0.825 (24.9)	0.784 (205)	0.135 (30.4)	0.013 (5.51)	–	–	0.8611
Model 3-3	180	1.364 (15.6)	0.374 (26.2)	0.016* (1.13)	0.041 (3.16)	–	–	1.0034
Experiment B								
Model 1	1332	0.984 (1.9E7)	0.455 (1.4E8)	0.101 (2.9E7)	-0.022 (-9.9E6)	–	–	1.5781
Model 2	1332	1.486 (158)	0.465 (1.8E8)	0.110 (3.5E7)	-0.015 (-5.5E6)	-0.852 (-27.2)	-0.529 (-24.2)	3.0573
Model 3-1	252	0.538 (7.42)	0.513 (29.6)	0.086 (4.90)	-0.018* (-1.04)	–	–	1.0030
Model 3-2	684	0.780 (38.0)	0.388 (145)	0.113 (45.0)	-0.026 (-10.6)	–	–	0.4707
Model 3-3	396	1.879 (33.5)	0.558 (127)	0.111 (26.1)	-0.003* (-0.83)	–	–	0.8196

* : insiginificant at 99% confidence level

Table 10 Correlation Coefficients between Actual and Estimated Value of Dependent Variable

Case	Experiment A						
Variables	y^{n+1}	N	Mean	SD	Min	Max	COR*1
	Actual	954	0.111	6.294	-36.0	92.0	
Model 1	Estimated	954	-0.063	3.386	-13.8	30.3	0.555
Model 2	Estimated	954	0.061	3.499	-14.9	32.2	0.563
Model 3	Estimated	954	0.115	3.748	-20.6	47.7	0.604
Variables	$\tilde{t}^{n+1}$						
	Actual	954	30.77	5.946	1.0	120.0	
Model 1	Estimated	954	30.60	3.359	12.0	58.5	0.481
Model 2	Estimated	954	30.72	3.439	11.2	60.2	0.492
Model 3	Estimated	954	30.78	3.728	6.58	75.7	0.543
Case	Experiment B						
Variables	y^{n+1}	N	Mean	SD	Min	Max	COR*1
	Actual	1332	0.056	4.472	-20.0	20.0	
Model 1	Estimated	1332	0.069	2.820	- 9.6	8.2	0.607
Model 2	Estimated	1332	0.092	2.860	- 9.5	8.1	0.612
Model 3	Estimated	1332	0.077	2.887	-11.2	8.1	0.622
Variables	$\tilde{t}^{n+1}$						
	Actual	1332	29.91	4.502	10.0	45.0	
Model 1	Estimated	1332	29.93	3.593	19.3	39.2	0.635
Model 2	Estimated	1332	29.95	3.539	19.0	39.2	0.636
Model 3	Estimated	1332	29.93	3.561	18.2	39.4	0.645

*1 : Pearson Correlation Coefficients

the majority of the models. In other words, the most recent travel experience affects travel time prediction on the chosen route more strongly than earlier experience. The effect of travel experiences on travel time prediction is exponentially reduced as time passes.

The constant term α can be regarded as the safety margin for the driver considering the safety risks (4). We compare the α of model 3 for three participant groups. According to the comparison, we obtain the results that the safety margin estimated by participants in Group S1 is the smallest and the largest value of safety margin belongs to Group S3. Namely, the greater the number of route switches is, the larger the safety margin is. Therefore we presume that there is an interrelation between the NRS and travel time prediction, and that the driver who switches his route frequently can be regarded as a driver concerned with travel time risk avoidance.

Next we analyze the parameters in Model 3 that explain the degree of the effect of travel experience. The absolute values of these parameters of Group S2 in Experiment A and of Group S3 in Experiment B are larger than those of the other groups. Therefore, most participants who are highly affected by travel experience in predicting travel time belong to Group S2 in Experiment A. In Experiment B, Group S3 has the most participants whose travel time prediction is affected most strongly by personal travel experience. Judging from the above, we believe that the participant who does not frequently switch his/her route tends to predict travel time without much concern for personal travel experiences.

In order to test the internal validity of each model, correlations between actual and estimated TCs and PTs, respectively, are examined. These correlation coefficients are shown in Table 10. Comparing maximum values, minimum values and standard deviations in each case, ranges of actual TC and PT are wider than that of the predicted TC and PT. Thus, the models estimated in this study appears unable to account for a value largely different from the mean value.

In both experiments, the correlation coefficients of Model 3 between estimated and actual dependent variables are the highest. The correlation coefficients of Model 1 are the lowest. In other words, the models where the explanatory variable includes participant groups classified by the number of route switches as the dummy variable appear to be more valid internally. Therefore, there exists an interrelation between the mechanism of travel time prediction and participant route choice behaviour represented by the number of route switches.

6. CONCLUSIONS

The problems brought to view here are limited but we think that the initial steps for resolving these problems through an experimental approach have been successfully taken. Moreover, while the model's estimated results cannot be generalized, we are able to obtain useful information. For example,

1. From a microscopic point of view, we cannot say for certain whether each participant's route choice behaviour corresponds to their behaviour in the real world. But considering the variety of number of route switches of each participant, the results of the experiments may represent the diversity of actual route choice behaviours.
2. The most recent ravel experiences affect travel time predictions more strongly than earlier ones, and, the effect of travel experiences on travel prediction decreases as time passes.
3. There exists an interrelation between the mechanism of travel time prediction and participant route choice behaviour depicted in the number of route switches.

In future studies, the following issues are treated:

1. We are going to estimate the Predicted Travel Time Model in which explanatory variables include participant attributes in order to improve internal validity.
2. The possibility of transferring the Predicted Travel Time Model must be examined. For this, we will carry out the experiments in which the participants' characteristics will be further generalized and compared with this study's results.
3. We will select the outside factors that enable us to explain the characteristics of traveler route choice behaviours.
4. In the future, we will simulate the travel behaviour of motorists based on the knowledge acquired through this study and future studies in order to examine the validity of delivering information to motorists as a means of traffic management.

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