EXPERIMENTAL ANALYSIS OF ROUTE-CHOICE BEHAVIOUR USING TREND INFORMATION WITH JAM LENGTH

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ABSTRACT

Recently, the traffic congestion situation in the city is getting worse. The traffic manager has been providing traffic information for alleviating the traffic congestion. However, traffic information used broadly assumes that the current traffic situation does not change. This sometimes makes hunting phenomena that parallel routes are congested in turn, which means temporary oscillation of over-concentration on route is occurred by traffic information. To alleviate this over-concentration, many researchers have researched a study of advanced traffic information. Among these studies, we found trend information as a kind of advanced traffic information and we analysed influences of provision of trend information with jam length information. We made computer-based in-laboratory route choice experiment to collect this data. And we estimated travel time forecast model and route choice model with using the experimental results. Consequently, trend information variables were insignificant except longer and decreasing dummy variables which meant a situation where jam length of a route was longer than one of the other route but traffic condition was improved. In other words, it could be said that trend information of longer jam length route influenced driver's route-choice behaviour.

Keywords: trend information, jam length information, route-choice behaviour

INSTRUCTION

Today, traffic information can be easily obtained by variable message signs (VMS), such as navigation systems and smart phones, for expressways and main arteries. However, traffic conditions change from moment to moment, and, thus, there is a high possibility that the traffic condition provided to travellers may differ from the one they experience. Therefore, it is important to predict the traffic situation in the near future from the viewpoint of better traffic management and service for travellers. It is, however, not easy to predict the future accurately because traffic situations change every second, and various incidents, such as accidents, repair work or natural disasters, may occur and change the traffic situation drastically. Therefore, a different approach should be considered to improve the overall quality of traffic information.

Most of the traffic information systems currently used provide descriptive information about traffic conditions to travellers. This type of information represents the current traffic situation. Neither temporal changes in traffic conditions nor the responses of travellers to the information provided are considered in the descriptive type of information. For example, travel time gives travellers the estimated time for a vehicle to traverse a route in the current traffic situation. In most cases, the descriptive travel time does not coincide with the actual travel time each traveller experiences. Commonly, descriptive information is determined to summate a travel time of each link section at the same time step by using detectors between link sections on a expressway.

Another predominant type of traffic information is traffic jam information, which reports the length, location and cause of the jam to the travellers. Most jam information is regarded as descriptive information. Similar to the travel time information, jam information gives travellers the current traffic situation. The provision of travel time information requires the estimation of the time for a vehicle to traverse a route, but the jam information only reports the current situation of the traffic jam. According to driver interviews, many experienced drivers tend to prefer jam information to travel time information. Generally, jam information is calculated by obtained data using detectors. If the average speed is 20km and less between detectors, the traffic condition of the link section is regarded as a congestion condition. Jam length is estimated to find how many link sections are congested continuously.

Traffic is concentrated in routes with shorter travel time according to traffic information, especially if descriptive information is provided to travellers. Oguchi et al. (2003) found that hunting phenomena may occur when descriptive information about traffic jams is provided continually on a parallel route section of an intercity expressway. Hunting phenomena are temporal oscillations in traffic concentration among two or more routes in response to (descriptive) traffic information. The hunting phenomena might be caused by the difference between descriptive information and the traffic conditions each traveller actually experiences. Most travellers hope to obtain a type of predicted traffic information to make the information provided more useful by reducing the difference between the provided information and the actual traffic conditions.

Recent progress in sensing and information and communication technology (ICT) in the field of traffic and transportation engineering has enabled real-time observation of traffic conditions. In addition to real-time observations, the accumulated data on traffic conditions can and should be utilised for better management and control of traffic in the network. One of the approaches that can be applied is to obtain a short-term forecast representing the increasing or decreasing trend of the traffic jam utilising the accumulated and real-time data on the traffic conditions. The short-term forecast on the increasing or decreasing trend of the traffic jam could be provided to travellers as additional information with the descriptive traffic jam information, thereby improving the overall quality of traffic information. The information on the short-term forecast on the increasing or decreasing trend of the traffic jam is referred to as 'trend information' hereinafter. The provision of trend information is expected to enhance rational decision-making of travellers in terms of route choice. Actually, the trend information with travel time information is provided at metropolitan expressway only in Japan. If traffic condition deteriorates, the upper arrow trend information with travel time information is provided and vice versa. Trend information is estimated to compare current travel time with travel time of one previous time step in this expressway (Warita et al., 2006).

The goal of this study is to analyse the influence of providing trend information on the driver's route-choice behaviour. The study is performed using in-laboratory SP route-choice experiments. The accuracy of both jam and trend information are explicitly considered as factors influencing the respondent's route choices.

Literature review

It is generally accepted that providing traffic information changes route-choice behaviour. Advanced traveller information services (ATIS) has been studied by many researchers since the early 1990s (Chorus *et al.*, 2006). The effect of providing travel time information on network dynamics has also been studied (Ben-Akiva *et al.*, 1991). Understanding travellers' behaviour when traffic information is provided is one of the most important aspects of successful ATIS design.

Bonsall (1992) focussed on the accuracy of information and concluded that a driver's compliance with the provided information depends on their knowledge of the network and the accuracy of information they receive. Liu and Mahmassani (1998) analysed the influence of pre-trip and en-route information on driver route choices using in-laboratory experiments and found that the reliability of real-time information and supplied schedule delays significantly influenced route-switching behaviour. Bogers *et al*. (2005) developed a route-choice model based on data obtained by an interactive travel simulator and found that travellers could choose the best route when the most accurate information was provided and that habit and inertia, as well as en-route information, significantly influence route-choice behaviour. As Oguchi *et al*. (2003) and Avineri and Prashker (2006) mentioned, however, providing static information does not always increase the propensity of travellers to minimise travel time because it might lead to a concentration of traffic on the route with the predicted minimum travel time.

Uno *et al*. (2002) proposed providing "trend information", which indicates the current trend of travel time and showed that trend information relaxed traffic congestion along a specific route

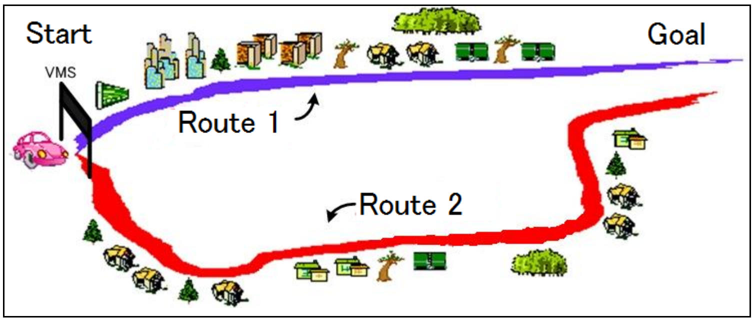

Figure 1 - 1 OD 2 route simple network

and could also improve reliability of the network through a simple network simulation based on hypothetical route-choice behaviour. To analyse the effect of trend information on route-choice behaviour more practically, a questionnaire-type survey was conducted for actual users of an intercity expressway (Uno *et al*., 2004). Additionally, Ahn *et al*. (2006) conducted PC-based experiments of route-choice behaviour with the provision of trend information. Tanaka *et al*. (2008) estimated the parameters of a mixed logit model to statistically analyse the influence of trend information upon the decision-making of respondents, considering the accuracy of the information. They concluded that the influence of information upon the decision-making process of respondents may depend upon the accuracy of both travel time information and trend information, and there must be heterogeneity in sensitivity toward the travel time information among the respondents. Although the research work performed by Uno et al. and this study are both aimed at the influence of trend information on route-choice behaviour, this study primarily focusses on the information related to traffic jam, which is regarded as essential and predominant traffic information.

In-laboratory route-choice experiment

Outline of the experiment

The goal of this study is to analyse the influence of trend information with jam length on the driver's route-choice behaviour. Because it is difficult to obtain real behaviour data when trend information is provided, the in-laboratory route-choice experiment is supposed to perform. Using the experimental results, it can be verified whether trend information influences driver's route-choice behaviour statistically. Although jam length is longer than the other route, the reason why the route is selected can be explained that trend information influence their behaviour.

The design of the in-laboratory experiment to study route-choice behaviour is explained in this section. Respondents of the experiment are required to select their route repeatedly considering traffic information including jam and trend information, as well as their (hypothetical) travel experiences during the experiment. For the sake of convenience, it is assumed that the respondents are travelling to work or school. Using the experimental results, the effects of providing the trend information on route-choice behaviour is analysed. This study adopts the simplest network composed of 1 OD and 2 routes, where each respondent can choose his/her route freely. Because this study intends to collect data about

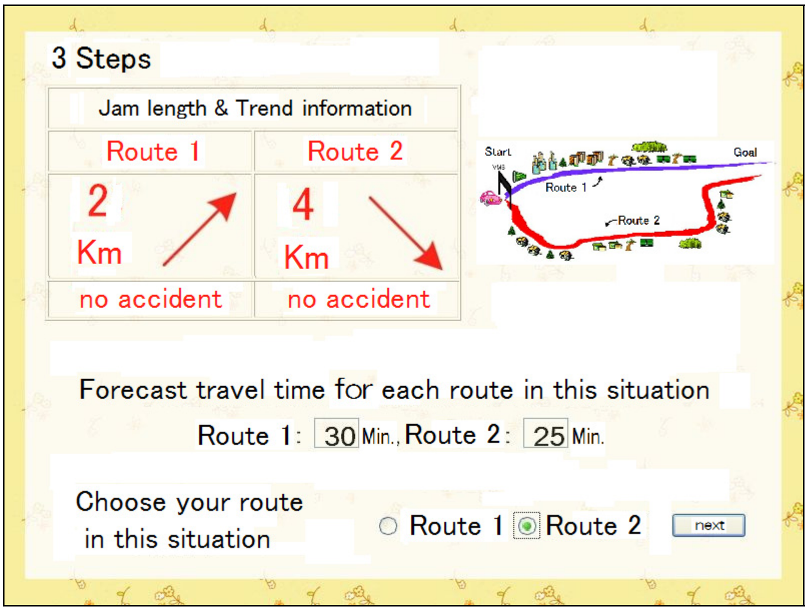

Figure 2 - Experiment screen

the stated preferences of the respondents on route choice by the computer-based in-laboratory experiment, the network is simplified to allow the respondents to clearly understand the traffic condition on each route. As shown in Figure 1, there is a network to be used in this experiment. Route 1 is 15 km from origin to destination and we assume that traffic congestion is often occurred in this route. On the contrary, Route 2 is 20 km and looks like a detour route for Route 1 and it is assumed that traffic condition of Route 2 is stable relatively. OD flows in the experiment don't use data collected on a real network, but these are generated by following a statistical distribution.

Design of the computer-based in-laboratory experiment

Experimental procedure

It is assumed that each experimental case is composed of three phases, characterised by the amount of information provided, and each phase consists of twenty iterations to collect the stated preference data from respondents. In other words, each respondent is required to supply his/her preference on route choice sixty times in total. The in-laboratory experiment consists of three phases:

Phase1: No information is given.
Phase2: Only jam information is given.
Phase3: Both jam and trend information is given, as shown in Figure 2.

The procedure of the in-laboratory experiment is outlined below.

Step 1: The experimenter explains the objectives and outlines of the experiment, including the studied network and the definition of information, to the respondents. The experimenter also reminds the respondents not to discuss anything related to their replies to the question with the other respondents.

Step 2: The respondents predict the travel time of each route, considering their travel experience and/or provided information, and choose their route based on the predicted travel time. In Phase 1, each respondent predicts his/her travel time considering only his/her own travel experience because no traffic information is given to the respondent.

Step 3: The actual travel time of the route chosen by the respondent is provided as his/her travel result.

Step 4: To clearly differentiate between the travel results to be accumulated as the experience of the respondent and the information just provided, the respondent is required to input his/her chosen route and its actual travel time into the system to confirm his/her travel result.

The respondent is required to repeat steps 2 to 4 until reaching the predetermined number of iterations (60 times).

Step 5: After the route-choice experiment, the respondent is required to enter his/her personal attributes in the questionnaire. The items in the questionnaire are gender, age, occupation, retention of driving license, frequency of vehicle usage, private car ownership and impression of this experiment.

To evaluate the effect of the accuracy of traffic information on route-choice behaviour, this study introduces the hypothesis that the effect of information provided upon route-choice behaviour may differ according to the accuracy of the traffic information. To analyse the influence of jam and trend information provided for the above hypothesis, this study assumes three different scenarios in terms of accuracy of information, as follows:

Case HH: Highly accurate traffic information and highly accurate trend information are provided.

Case LH: Less accurate traffic information and highly accurate trend information are provided.

Case LL: Less accurate traffic information and less accurate trend information are provided.

This study pays special attention to case LH, which will highlight the potential of the trend information. In the actual environment, jam information can be regarded as a type of descriptive information. Accordingly, it is difficult to expect that the accuracy of jam information is high, and the trend information is expected to have the potential to mitigate the drawbacks of such descriptive information.

Setting of the traffic information

In the experiment, traffic jam information and trend information are determined according to the procedure below.

1) The actual travel time corresponding to the travel result is calculated using an assumed exponential distribution for travel time because it is difficult to expect the actual travel time of a route on real network accurately. By adjusting the average and the standard deviation parameter of the distribution, characteristic of each route is divided.
2) The estimated travel time corresponding to the travel time information is calculated by adding an error following a normal distribution to the actual travel time mentioned above.

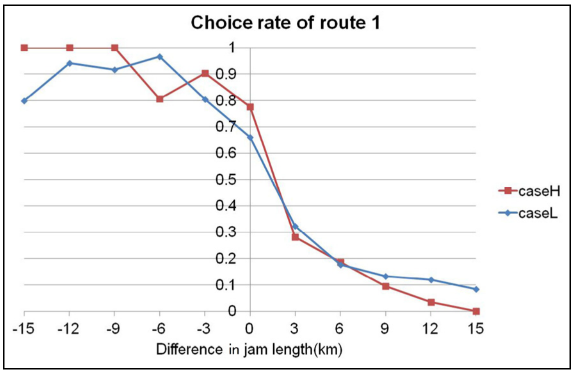

Figure 3 - Choice rate of route 1 during phase 2

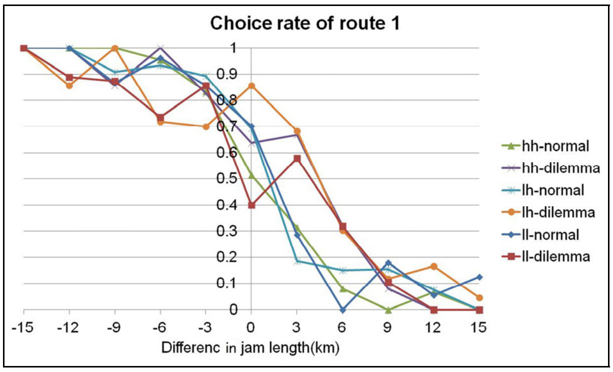

Figure 4 - Choice rate of route 1 during phase 3

3) The jam length used for provided information is converted from the estimated travel time mentioned above using an assumed relation between travel time and jam length. The accuracy of jam information can be controlled by adjusting the standard deviation of the normal distribution above.
4) The short-term trend of the traffic condition is determined according to the difference between the actual travel time from 1) and the estimated travel time from 2).
5) The short-term trend is classified into three categories: increasing trend, stable and decreasing trend. The increasing and decreasing trends correspond to the situation where the traffic condition might be worse or better, respectively, in the short-term. The stable trend corresponds to the situation where the difference of travel time is 1 minute and less or the difference of jam length is 1 km and less in the experiment. The accuracy of the trend information can be controlled by utilising a uniform random number.

Basic analysis of the experiment

A total of 60 respondents participated in the in-laboratory route-choice experiment. Considering the scenarios defined by the accuracy of information provided, 20 respondents were assigned to each scenario.

The goals of the study are to determine if trend information affects route-choice behaviour and if trend information can help to alleviate the over-concentration of traffic from descriptive information. Figures 3 and 4 show the choice rate of route 1 vs. the difference in jam length. Figure 3 shows the choice rate of route 1 in phase 2 and figure 4 shows the results for phase 3. Figure 3 suggests that route 1 is preferred (because the choice rate is over 0.5) in instances where the difference in jam length is 1 - 2 kilometres. Because route 1 is an unstable route through the city, but travel time is faster than the other route, respondents prefer route 1 in spite of the 1 - 2 km jam delay. However, the results in figure 4 show a different tendency. Especially in the dilemma case, the choice rate of route 1 between -3 and 3 kilometres increases inversely. The dilemma case is when drivers experience a dilemma when choosing their route because trend information is added to traffic information. For example, drivers are confused about their route choice when a route has a longer jam length based on jam information but the congestion situation is alleviated based on trend information and the other route is vice versa. If drivers choose a longer jam length route in the dilemma case, this choice means that drivers believe the trend information that shows the traffic situation will improve. Table 1 shows a definition of the dilemma case in terms of jam and trend information. Table 2 shows a number and a rate when respondents choose the longer jam length route in the dilemma case. Generally, in the dilemma case, when the difference in jam length is short, the effect of trend information is stronger. It is shown that approximately 10% of the respondents are influenced by trend information when the difference in jam length is short.

Table 1 - Dilemma case

	Jam length		Trend arrow	
	Route 1	Route 2	Route 1	Route 2
Dilemma 1	Longer	Shorter	↘	↗
Dilemma 2	Shorter	Longer	↗	↘

Table 2 - Choice rate of trend information in the dilemma case

	HH case	LH case	LL case
number/sample	7/113	16/136	11/95
rate	6.2%	11.8%	11.6%

Travel Time Forecast Model

Model overview

In this section, a model is developed to forecast the travel time of each route. Respondents in this experiment do not know the distribution of actual travel time for each route. However, the experiment has been conducted 60 times; thus, the distribution of the actual travel time can be estimated. Some individual heterogeneity in route choice may exist and can be evaluated among the 20 respondents for each repeated experiment. In the experiment, the respondents are asked to predict the travel time for each route before the trip, but they only know the actual travel time of the chosen route. Therefore, the knowledge gained by each step is asymmetric among the chosen and not chosen routes. Accordingly, two travel time forecast models were constructed, one for the chosen route and one for the not chosen route. The travel time forecast models, however, have similar constructions, and the results of the not chosen route model were confirmed to be similar to the results of the chosen route model. The travel time forecast models for the chosen route are explained in the following.

A multiple regression model is applied to estimate travel time in the forecast models. The dependent variable is the travel time of the route which was chosen at the previous step, and the independent variables are the experiences of the last step. The multiple regression model can be described as follows:

$$y_{it} = \alpha + X'_{it}\beta + u_{it} \quad i = 1,2,\ldots,N; \ t = 1,2,\ldots,T \qquad \text{Eq. 1}$$

Equation 1 shows a regression model equation with panel data, where i represents an individual, t represents the step and u_{it} is the error term for step t of individual i. Because 60 route choices are observed repeatedly from each respondent, the correlation among individual respondents must be considered as well as each step. To consider individual and time correlations, the error term is composed of three terms, expressed as Equation 2, where μ_i are errors from individual effects, λ_t are errors from time effects and ν_{it} is white noise.

$$u_{it} = \mu_i + \lambda_t + \nu_{it} \qquad \text{Eq. 2}$$

This type of model is generally called a random effect model. The Lagrange multiplier test is used to test the validity of the random effect model. The Hausman test is also performed to determine if random effects exist in the model.

Explanatory variables, i.e., actual travel time in the last step, forecast error in the last step, average experienced travel time, jam length information, accident information, alternative specific constant for route 1, and dummy variables about trend information, are constant. In the experiment, trend information is provided but it is not a quantitative value. Therefore, dummy variables are used to express the traffic situation and the trend situation in the model. Table 3 explains the dummy variables used for trend information in the model.

Table 3 - Trend information dummy variables

Dummy variables	Explanations	Examples
Shorter but increasing (S+I)	Jam length of route 1 is shorter and Arrow of route 1 is up; arrow of route 2 is down	3 km↗・4 km↘
Longer and increasing (L+I)	Jam length of route 1 is longer and Arrow of route 1 is up; arrow of route 2 is down	4 km↗・3 km↘
Shorter and decreasing (S+D)	Jam length of route 1 is shorter and Arrow of route 1 is down; arrow of route 2 is up	3 km↘・4 km↗
Longer but decreasing (L+D)	Jam length of route 1 is longer and Arrow of route 1 is down; arrow of route 2 is up	4 km↘・3 km↗

To distinguish the difference among effects when the different accuracy of traffic information is provided, the experiment consists of several cases. The parameters of the estimated variables may be different for the travel time forecast model if the effects of forecasting the travel time are different among cases. Accordingly, a statistical test is needed to estimate weather the difference of parameters among the cases exists or not. The Chow test is adopted to examine an identity of parameters among the cases.

Estimated results for phase 2

Table 4 - Estimated results for phase 2

	Case H		Case L	
Explanatory Variables	parameter	t value	parameter	t value
Constant	20.203	4.456	18.635	5.203
Actual travel time in the last step	0.125*	1.917*	0.023*	0.462*
Forecast error in the last step	-0.015*	-0.233*	0.036*	0.904*
Average experienced travel time	0.101*	0.612*	0.366	2.789
Jam length information	2.193	16.948	1.894	20.717
Accident information	8.872	7.456	9.453	9.149
ASC for route 1	-3.841	-2.737	-2.635	-2.870
Sample	680		680	
R^2	0.712		0.662	
LM test	105.82(0.000)		205.92(0.000)	
Hausman test	11.52(0.174)		76.07(0.000)	
Var ν	86.670		N/A	
Var μ	57.441		N/A	
Var λ	5.537		N/A	

(*insignificant at the 5% significance level)
(Right-hand values of the LM test and the Hausman test are p values)

Table 5 - Results of Chow test in phase 2

F-value	F_α-value
3.01	1.91

The travel time forecast model for phase 2 is estimated separately using the accuracy of information. The results are shown in Table 4. From the table, 'constant', 'jam length information', 'accident information' and 'alternative-specific constant (ASC) for route 1' can explain the travel time forecast at the 5% significance level. Comparing the difference in information accuracy, 'average experienced travel time' is added as a significant variable in the low accuracy case (L). Because traffic information is less accurate in case L, respondents need to refer to other information. This can also be justified by the value of parameter estimates. The estimate for 'jam length information' is larger in the high accuracy case (H) than in the low accuracy case (L). The influence of 'accident information' is smaller in the high accuracy case. This may be because 'jam length information' is sufficiently accurate and the respondents do not need to rely as much on 'accident information'. Additionally, the parameter estimates suggest that the respondents forecast that the 1-kilometre jam may take approximately 2 minutes, and 9 minutes are added when accident information is provided.

The R squared values are 0.712 and 0.662 for case H and L, respectively. Generally, these values are adequate to explain the model. Because the null hypothesis (H_0) of the LM test was rejected, the fixed effects model or random effects model should be used. Because the H_0 of the Hausman test was not rejected in case H, the random effects model should be used in case H. Variance of the individual effect is approximately 57 and the existence of individual

Table 6 - Estimated results for phase 3

	Case HH		Case LH		Case LL	
Expl. Variables	parameter	t value	parameter	t value	parameter	t value
Constant	13.490	3.468	26.614	6.418	31.297	6.244
Actual travel time in the last step	0.195	3.329	0.015*	0.244*	0.023*	0.340*
Forecast error in the last step	0.205	3.046	-0.021*	-0.377*	-0.047*	-0.885*
Average experienced travel time	0.036*	0.304*	0.259	2.069	-0.158*	-0.957*
Jam length information	2.192	17.799	1.811	12.687	1.995	15.261
Accident information	3.832	3.914	7.002	5.672	2.185*	1.671*
ASC for route 1	-3.992	-4.199	-2.618	-2.358	-4.855	-4.215
Trend info.(S+I)	7.130	5.863	4.153	2.379	4.115	2.612
Trend info(L+I)	3.403	2.022	5.604	2.591	4.132	2.470
Trend info.(S+D)	-1.234*	-1.000*	-4.281	-2.235	-2.559*	-1.603*
Trend info.(L+D)	-2.712	-2.053	-6.492	-3.357	-6.180	-3.666
Sample	323		340		340	
R^2	0.778		0.770		0.675	
LM test	27.68(0.000)		91.92(0.000)		44.77(0.000)	
Hausman test	20.35(0.061)		122.105(0.000)		14.58(0.265)	
Var ν	50.938		N/A		81.082	
Var μ	49.357		N/A		28.566	
Var λ	2.957		N/A		8.123	

(*insignificant at the 5% significant level)
(Right-hand values of the LM test and the Hausman test are p values)

Table 7 - Results of Chow test in phase 3

HH=LH		HH=LL		LH=LL	
F-value	F_α-value	*F*-value	F_α-value	*F*-value	F_α-value
4.29	1.74	3.82	1.74	3.94	1.74

heterogeneity when accurate jam length information is provided (case H) is confirmed.

Table 5 shows the results of the Chow test at the 5% significance level. H_0, i.e., the parameters of jam length between case H and case L are same, was rejected at the 5% significance level. Thus, the effect on jam length between case H and case L is different, and recognition of the difference between cases for respondents is formed by means of forecasting travel time repeatedly.

Estimated results for phase 3

Table 6 summarises the estimation results for phase 3. As the results show, 'constant', 'jam length information', 'accident information' and 'alternative specific constants for route 1' influence the travel time forecast of all cases at the 5% significance level. 'Actual travel time in the last step' and 'forecast error in the last step' are significant only in case HH, 'average experienced travel time' is only significant in case LH, and 'accident information' is not significant in case LL. Comparing the estimates for 'constant', the estimate increases when the accuracy of information is low. This means that the travel time forecast in the lower information accuracy case is less sensitive to other information. Parameters for 'jam length information' are similar to the estimation result for phase 2 in all cases. To discuss the influence of trend information, four cases are considered: 'the jam length of the selected route is shorter but is increasing (S+I)', 'the jam length of the selected route is longer and is increasing (L+I)', 'the jam length of the selected route is shorter and is decreasing (S+D)', and 'the jam length of the selected route is longer but is decreasing (L+D)'. Apparently, the dilemma exists in the first and fourth cases. Looking at table 5, 'trend information dummy for S+D' is not significant for case HH and case LL. Looking at the estimates for 'S+I', the value decreases when the accuracy of information gets lower. The influence of 'currently shorter jam length but increasing information' may decrease when information accuracy is lower. However, this tendency does not hold for another dilemma case, 'L+D'. In this case, the absolute values of parameter estimates are larger when information accuracy is low. Therefore, the effect of 'currently longer jam length but decreasing information' is larger when information accuracy is low. Drivers are thought to feel traffic congestion when even 1 - 2 kilometres of jam information is provided. However, when the jam length is only 1 - 2 kilometres, drivers may not perceive congestion when travel time information alone is provided. Thus the effect of 'L+D' is larger when information accuracy is low.

The H_0 of the LM test was rejected in all cases. The H_0 of the Hausman test was not rejected in case HH or case LL. Therefore, the random effect models are suitable for cases HH and LL, and the fixed effect model is suitable for case LH. Variances of the individual effects are 49.3 and 28.5 for cases HH and LL, respectively. These values are similar to the results for phase 2. The R squared values are 0.78, 0.77 and 0.68, and the models explain the travel time forecast behaviour well.

Table 7 shows the results of the Chow test at the 5% significance level. All the H_0, i.e., the parameters of jam length between each case pair are the same, were rejected at the 5% significance level. Thus the effects of jam length among all cases are different, similar to phase 2.

Route-choice model

Model overview

In the basic analysis, the trend information was found to influence route-choice behaviour because the gradient of choice rate of route 1 changed inversely in the dilemma cases. In this section, a route-choice model is estimated to evaluate the effects of providing trend information statistically. As described in the section estimating the travel time forecast model, choice behaviour is obtained repeatedly. The data thus obtained are regarded as panel data. Commonly, the logit model is used to estimate a discrete choice model. However, to use logit, the data must be independent because error terms in logit must follow independently identically distributed (IID) Gumbel distributions. For the panel data, however, choices from the same respondents are often correlated. This study adopts the mixed logit model (Train 2003). Equation 3 describes the utility function of the mixed logit model as follows:

$$U_{int} = \boldsymbol{\beta} X_{int} + \varepsilon_{int} \qquad \text{Eq. 3}$$

where:
U_{int} = Utility of an alternative i for a respondent n at the t-th iteration,
$\boldsymbol{\beta}$ = Parameter vector to be estimated,
X_{int} = Explanatory variables of alternative *i* for a respondent *n* at the *t*-th iteration, and
ε_{int} = Error term following IID Gumbel distribution.

If $\boldsymbol{\beta}$ is a random parameter and its probability density function is identified, the model calculates an integral of probability density function as follows:

$$L_{in}(\boldsymbol{\beta}) = \prod_{t=1}^{T} \left[\frac{e^{\boldsymbol{\beta}' X_{int}}}{\sum_{J} e^{\boldsymbol{\beta}' X_{jnt}}} \right] \qquad \text{Eq. 4}$$

$$P_{in} = \int L_{in}(\boldsymbol{\beta}) f(\boldsymbol{\beta} | \boldsymbol{\Omega}) d\boldsymbol{\beta} \qquad \text{Eq. 5}$$

where:
$L_{in}(\boldsymbol{\beta})$ = Probability of an alternative i for a respondent n, with a given vector $\boldsymbol{\beta}$,
P_{in} = Choice probability of an alternative i for a respondent n, and
$f(\boldsymbol{\beta} | \boldsymbol{\Omega})$ = Probability density function of $\boldsymbol{\beta}$ with covariance matrix $\boldsymbol{\Omega}$.

Maximum likelihood estimation is performed to determine the parameters. Because the P_{in} in Equation 5 is not in a closed form, an approximate choice probability is calculated in the mixed logit model using the Monte Carlo simulation method, shown in Equation 6 as follows:

$$SP_{in} = \frac{1}{R} \sum_{r=1}^{R} L_{in}(\boldsymbol{\beta}^{r}) \qquad \text{Eq. 6}$$

where:
R = The total number of random numbers,
$\boldsymbol{\beta}^{r}$ = The value of $\boldsymbol{\beta}$ obtained by the r^{th} draw of a random sampling, and
SP_{in} = The approximate choice probability of alternative i for respondent n

To distinguish a difference among the influences of route-choice behaviour, such as the

Table 8 - Estimated results for phase 2

Cases			Case H		Case L	
Explanatory variables			param.	t-val.	param.	t-val.
Random Parameters	ASV for route 1	Avg.	1.602	3.659	1.116	4.050
		S.D.	1.027	2.954	1.193	5.396
	Jam length	Avg.	-0.626	-6.451	-0.484	-7.867
		S.D.	0.088*	0.795*	0.327	6.475
	Accident information	Avg.	-4.870	-3.206	-2.256	-4.652
		S.D.	3.761	3.034	2.322	5.001
Non random	Gender		-0.183*	-0.200*	0.018*	0.030*
	Age		-1.378*	-1.907*	-0.629*	-1.492*
Samples			400		800	
ρ^2			0.618		0.461	

(*insignificant at the 5% significance level)

Table 9 - Validation results of the identities of parameters between case H and case L

	Score	*P*-value (5%)
F test	0.072*	1.151*
T test	-26.351	1.962

(*insignificant at the 5% significance level)

travel time forecast model, when the accuracy of the traffic information is different, a statistical test is needed to estimate whether a difference in parameters among cases exists. The random parameters are assumed to follow a normal distribution; therefore, the average and standard deviation of each parameter are estimated in the random parameter variables in the mixed logit model. Then, the T test and F test are used to validate the identities of the parameters in all cases.

Estimated results for phase 2

Table 8 shows the estimation results of the route-choice model for phase 2. ‘Alternative specific constant (ASC) for route 1’, ‘jam length’ and ‘accident information’ are included as random parameter variables in this model. Gender and age are also included as non-random parameter variables. Both the average and the standard deviation for ‘ASC for route 1’ are significant at the 5% significance level, suggesting individual heterogeneity in route preference. The average of ‘jam length’ is significant in case H, and both its average and standard deviation are significant in case L. This result suggests that ‘jam length’ information for case H is adequately accurate and everyone can rely on it. For ‘accident information’, the average and standard deviation are statistically significant for both cases. The impact of ‘accident information’ may differ among drivers. In this model, gender and age are not statistically significant. Additionally, the adjusted rho squared values are 0.618 and 0.461, and the model fitness is good.

The parameters of jam length for case H are different than those for case L. Accordingly, the T test and the F test were performed to validate the identity of the parameters between

Table 10 - Estimated results for phase 3

Cases			Case HH		Case LH		Case LL	
Explanatory variables			param.	t-val.	param.	t-val.	param.	t-val.
Random Parameters	ASC for route 1	Avg.	0.698	2.203	0.731	2.529	0.776	2.477
		S.D.	0.626	2.046	0.491*	1.859*	0.817	2.848
	Jam length	Avg.	-0.455	-7.217	-0.350	-6.331	-0.397	-5.274
		S.D.	0.177*	0.220*	0.106	2.359	0.228	4.446
	Accident info.	Avg.	-1.312	-2.810	-0.759	-2.876	-1.007	-3.011
		S.D.	1.141	2.104	0.213*	0.323*	0.164*	0.203*
	S+I	Avg.	-0.452*	-0.528*	-0.499*	-0.505*	-2.894	-3.215
		S.D.	0.256*	0.138*	2.023	1.995	1.816*	1.131*
	L+D	Avg.	2.431	3.559	1.394	2.946	-0.031*	-0.057*
		S.D.	1.183*	0.999*	0.277*	0.277*	0.192*	0.137*
Non-random	L+I		-3.271	-2.511	-0.736*	-0.870*	-0.644*	-0.746*
	S+D		10.16*	0.055*	10.91*	0.069*	0.610*	0.505*
	Gender		0.694*	1.034*	-0.002*	-0.003*	-0.782*	-0.966*
	Age		-0.891*	-1.813*	-0.358*	-0.910*	0.420*	0.581*
Samples			400		400		400	
ρ^2			0.492		0.359		0.446	

(*insignificant at the 5% significance level)

Table 11 - Validation results of identities of parameters among cases

	HH=LH		HH=LL		LH=LL	
	Score	*P*-v. (5%)	Score	*P*-v. (5%)	Score	*P*-v. (5%)
F test	2.788	1.182	0.603*	1.182*	0.216*	1.179*
T test	9.987	1.964	-4.574	1.963	6.271	1.963

(*insignificant at the 5% significance level)

case H and case L. Table 9 shows the results of the tests. H_0 of the F test was not rejected at the 5% significance level, which means that the variance of the parameter is the same. H_0 of the T test was rejected, however, implying that the parameters of jam length in case H and case L are different. In other words, the effects of route-choice behaviour are different when the accuracy of traffic information is different.

Estimated results for phase 3

Table 10 shows the estimation results of the route-choice model for phase 3. Dummy variables of trend information are added from phase 2. The random parameter variables are set as ‘ASC for route 1’, ‘jam length’, ‘accident information’ and dummy variables of the trend information for the dilemma case at phase 3 (S+I and L+D). The non-random parameter variables are ‘gender’, ‘age’ and dummy variables of trend information in the no-dilemma case. As a result, averages of ‘ASC for route 1’, ‘jam length’ and ‘accident information’ are found to be significant at the 5% significance level in all cases, similar to phase 2. The estimates of standard deviation show that the values of ‘jam length’ for case HH and 'accident information' for cases LH and LL are not significant. Heterogeneity among individuals for 'jam length' information is small when the information is accurately provided, but it may be large when its accuracy is low. The results for trend information show that most of the dummy variables are insignificant. This may be because respondents are confused when jam length information and trend information are both provided. When jam length information is provided, drivers generally tend to regard the congestion of the traffic and hope that the traffic situation will improve. Thus, decreasing trend information may influence route-choice behaviour on a longer jam length route but increasing trend information does not help because drivers do not want to be in a jam situation. Consequently, the 'L+D' dummy variable is significant in cases HH and LH. The adjusted rho squared values for all cases are high enough and the models fit well to the data.

A T test and an F test were performed to validate the identity of the jam length parameter. Table 11 shows the results of the tests. In the results, H_0 of the F test was not rejected at the 5% significance level, except when HH=LH, i.e., the variance of the parameter between case HH and case LH is not the same. Because the H_0 of the T test for all case pairs was rejected, the parameters of jam length in all cases are different. In other words, the effects of route-choice behaviour are different when the accuracy of traffic information is different.

Conclusions

In this study, computer-based in-laboratory route-choice experiments were implemented with added trend and jam length information. As the repeated data were obtained, they were regarded as panel data. A travel time forecast model and a route-choice model were developed to evaluate the effects of providing the trend information.

In the travel time forecast model, trend information variables were significant, and it was found that the time was considered by respondents when trend information was provided in all cases. Consequently, in the dilemma case, by providing trend information, it was possible to disperse over-concentrated traffic on a route.

To include individual heterogeneity, the expected travel time model used a random effects model and a fixed effects model. As a result, all cases included individual heterogeneity.

In the route-choice model, the obtained data were treated as panel data, similar to the treatment in the travel time forecast model. The mixed logit model was used to include individual differences. Because the trend information variables are not quantitative, dummy variables were used. Moreover, the trend information dummy variables for the dilemma case were estimated as random parameters. Jam length and accident information were significant at the 5% significance level, however, most of the trend information dummy variables were insignificant except the 'L+D' dummy variable. It was found that if decreasing trend information was provided on a longer jam length route for the dilemma case, it was possible to disperse over-concentration on a shorter jam length route.

In this study, result data in the experiment was estimated using a statistical method. It seemed that trend information was reliable to respondents when traffic condition was dilemma condition. It means that longer jam length route is selected and hunting phenomena may be alleviated when trend information is provided on a real network. However, trend information may confuse driver's route-choice behaviour among 3 routes and over on a real network. And traffic flows on a real network cannot be understood when trend information with jam length information is provided in this study. Therefore, the dynamic changes in a traffic network, when trend information and jam length information is provided, must be analysed. It may be possible to analyse this situation utilising a traffic simulation model.

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