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The Impact of Travel Time Information on Travellers' Learning under Uncertainty

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Abstract

In this work, route-choice simulations and laboratory experiments were conducted in order to evaluate the effect of feedback mechanism on decision-making under uncertainty, with and without provided information about travel times. We discuss the prediction of travellers' response to uncertainty in two route-choice situations. In the first situation travellers are faced with a route-choice problem in which travel times are uncertain but some information (which may be static or dynamic) about travel times of each (or some) route is provided. The second situation takes place in a more uncertain environment in which information about routes is not provided, and the travellers' only source of information is their own experience. Experimental results are in conflict with the paradigm about traveller information systems: providing travellers with information will not necessarily lead them to make better decisions. There are situations when propensity to choose a more efficient route might be decreased (instead of increased) when travel time information about the routes is provided. As a consequence of information, the propensity of travellers to maximize utility is not always increased. It was found out that providing travellers with static information about expected travel times increases the non-homogeneity of travellers and reduces the maximization rate. These findings are described and explained. This better understanding of route-choice behaviour may improve traffic predictions based on route-choice modelling. The design of better cost-effective ATIS may benefit from such an insight.

Keywords

Route-Choice, Information, Uncertainty, Learning, Utility Maximization, International Conference on Travel Behaviour Research, IATBR

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1. Introduction

Advanced Traveller Information Systems (ATIS) are a major component of *Intelligent Transportation Systems* (ITS). ATIS aims are to provide travellers with real-time travel information in order to help them proceed to their destinations efficiently and safely. On-going development of ATIS technologies includes on-board navigation systems, pre-trip route planning systems, traffic information broadcasting and electronic route-guidance systems. Successful application of ATIS may assist travellers in making more efficient travel choices. Two of the critical aspects involved in the design of ATIS which should not be overlooked are information acquisition and cognitive processing. Information acquisition and cognitive processing have a major impact on the travellers' abilities to predict network conditions as well as making rational route-choice decisions.

In route-choice process there exists a relation between the network performances which occurred in past time periods and travellers' current route choices. Route attributes, such as travel time, are usually not constant, and are not likely to be known to travellers before current travel occurs. Therefore, route-choices in the current period are based on information concerning network performances in previous time periods. There are many studies that have been focusing on modelling travellers' learning and the day-to-day dynamics of network flow, among them: **Horowitz** (**1984**), **Friesz** *et al.* (**1984**), **Smith** (**1984**), **Cascatta** (**1989**), **Cascatta** & **Canterella** (**1991**) and **van Berkum** & **van der Mede** (**1998**).

The common route-choice models are based on the assumption of utility maximization. Each individual tries to maximize the utility U_j of choosing route j. Many experiments in behavioural studies often find the predictions of utility maximization to be violated (for example, **Kahneman** & **Tversky**, **1979**). Humans' rationality was found to be restricted by cognitive limitations (**Simon**, **1957**). **Hogarth** (**1987**) states that there are four consequences of limited human information-processing capacity that affect judgment: (1) humans have a selective perception of information, (2) the nature of human processing is generally sequential, (3) humans have a limited capacity to process information: they typically use heuristics or simple rules, and (4) humans have limited memory. These limitations suggest that the amount of information provided to decision-makers may not be as important as the method of presentation or the stage in the choice process that it is presented (**Adler**, **1993**). **Mahmassani** (**1996**) has suggested that the behaviour of repetitive travellers is guided by simple heuristic strategies and by a limited set of mental choice rules. **Chang** & **Mahmassani** (**1988**) conducted simulation experiments to analyze how individuals adjust their departure time choice in response to previous experience. They conclude that the most recent information, essentially the previous trip's travel time, is the key factor to the current decisions. **Iida** *et al.* (**1992**) also conducted a laboratory experiment to analyze route-choice behaviour and dynamic adjustment over time. Their empirical estimates suggested that more recent travel experience is more important than less recent travel experience.

Several studies of the route-choice process by repetitive travellers have been made based on behavioural decision theory, among them: **Horowitz** (**1984**), **Mahmassani** & **Chang** (**1985**, **1987**), **Chang** & **Mahmassani** (**1988**), **Mahmassani** (**1990**), **Iida** *et al.* (**1992**); **Supernak** (**1992**), **Lottan** & **Koutsopoulos (1993)**; **Emmerink** *et al.* (**1998**); **Nakayame** *et al.* (**1999**); **Polak** & **Oladeinde** (**2000**); **Fujii** & **Kitamura** (**2000**) and **Avineri** & **Prashker** (**2003**). The above studies represent a great variety of approaches to model information acquisition and learning process. They vary tremendously in their complexity and data requirements. **Bonsall** (**2000**) found that it would be naive to imagine that one and only approach will be suitable to all circumstances.

Analysis of choice behaviour in iterative tasks with immediate feedback reveals robust deviations from utility maximization. The most obvious class of such failures is the *Payoff Variability Effect*: High payoff variability seems to move choice behaviour toward random choice (See **Myers** *et al.*, **1965**; **Busemeyer** & **Townsend**, **1993**; **Erev** *et al*., **1999**). Evidence of the *Payoff Variability Effect* in route-choice situations was found in recent studies. **Avineri** & **Prashker** (**2003**) have showed, that the higher the variance in travel times is, the lower is the travellers' sensitivity to travel time differences. Particularly, it was found out that in some cases, increasing travel time variability of a less attractive route can enlarges its perceived attractiveness. This affects the choice proportion of specific route, and produces results which completely differ from those predicted by models based on the utility maximization assumption. The *Payoff Variability Effect* is predicted by learning models.

Many researchers have studied the effect of provided information on route-choice. In some of these studies it was found that learning speed is accelerated by the provision of information. **Polak** & **Oladeinde** (**2000**) have conducted lab experiments, in which separate groups of subjects were provided with different level of information accuracy. They found that even bad information accelerate the speed of travellers' learning.

In this work we would like to discuss the effect of providing travel-time information on the learning process under uncertainty.

There are many different methods in which travellers can acquire information. Travellers' perceptions of the routes' attributes may be formed through actual experience, through ATIS technologies, or through a combination of different methods. Traveller information systems, such as broadcasts of traffic conditions, *Variable Message Signs* (VMS), or cellular information systems can provide the traveller with information which is more comprehensive and more accurate than the information acquired only by their own experience.

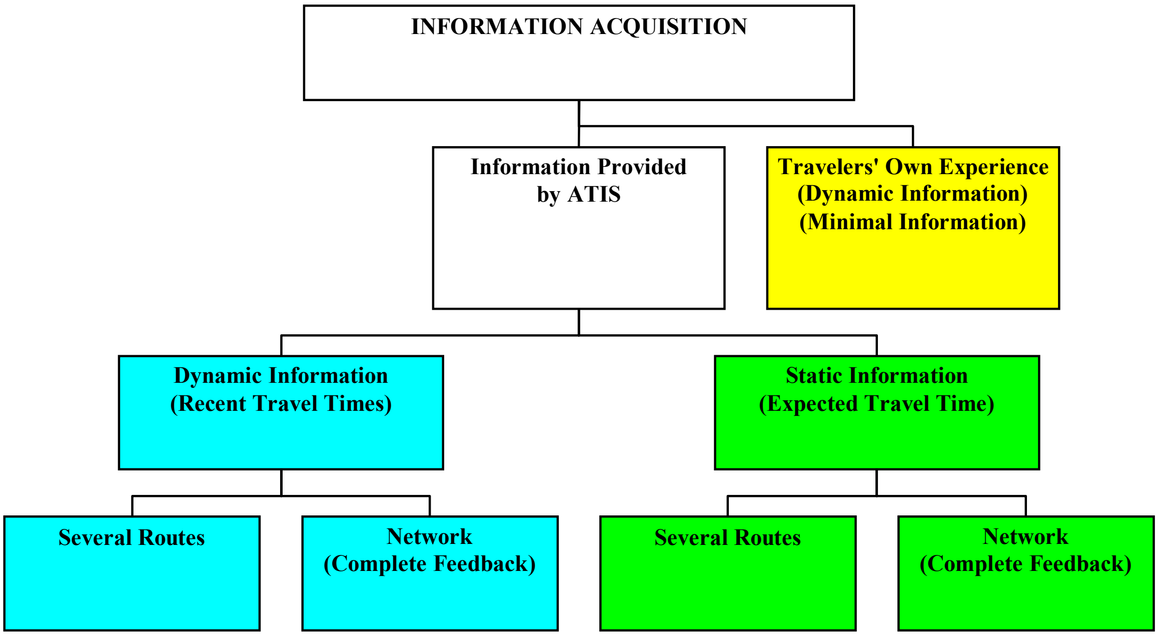
Information acquired using ATIS may be represented in a dynamic or a static manner. For example providing average (expected) travel time of each the routes, without updating this information, is an example to static information. Information may be presented in a dynamic form, such as recent travel time which occurred the available routes. Dynamic information may be based on real-time information gathered and processed by the ATIS. There may be different reasons for providing information in a static form. It may be provided due to ATIS limited capabilities of collecting and calculating recent data, or due to ATIS design specifications. ATIS designers may consider not to update travel information too often, in order to achieve better system stability and reliability in the mind of the travellers.

2. Models of Information Acquisition Process: Learning as a Sequential Sampling Process

Five basic different models of information acquisition process are discussed in this section: (1) Travellers are provided with *dynamic information* about past network performance, about *all* of the routes. (2) Information is being acquired by travellers only through their *own experience*. (3) Travellers acquire information by their *own experience*, and are provided as well with *dynamic information* based on past performance of *some* of the routes. (4) Travellers acquire information based on their *own experience*, and are provided as well with *static information* about network performance, about *all* of the routes. (5) Travellers acquire information by their *own experience*, and are provided as well with *static information* about network performance about *some* of the routes.

A classification of information acquisition models is provided in **Figure 1**.

Figure 1 A Classification of Information Acquisition Models



2.1 Model 1: Travellers are provided with dynamic information about all of the routes

In route-choice decision-making process there exists a relation between the perception of route attributes, which is based on network performances in past time periods, and the travellers' current route-choice decisions. We may describe travellers' route-choice behaviour as an iterative process, in which, at each iteration, the traveller uses historical frequencies of different travel times and form a belief about the routes' expected travel times. Based on his/her belief, the traveller chooses a route, which is supposed to minimize the expected (or random) travel time.

Horowitz (1984) described a simple learning model. In this model, in order to treat route-choice decisions over time, one assumes that in each period t these decisions are based on weighted average of measured travel utilities in previous time periods. This learning model is formulated as follows:

$$\hat{U}_j(t) = \sum_{r=1}^{t-1} w_{r,j}(t-1)\, U_j(t) + \varepsilon_{jt} \qquad ; i = 1,\ldots,m \tag{1}$$

where $\hat{U}_j(t)$ is the utility of route j as perceived by the traveller at time period t; $U_j(t)$ is the measured utility of travel of route j in time period t; ε_{jt} is a random variable whose probability distribution is independent of t; and $w_r(t\text{-}1)$ is a non-negative weight. For each route j, for each time period t, the weights satisfy

$$\sum_{r=1}^{t-1} w_{r,j}(t-1) = 1 \qquad\qquad \forall t = 1,\ldots,T \tag{2}$$

The left term in **eq. 2**, $\sum_{r=1}^{t-1} w_{r,j}(t-1)$, represents the composite effect of past measured route performances on current perceived utility. The weights $w_{r,j}(t-1)$ describe the relative influences of recent and distant past route performances on current utility perception (**Horowitz**, **1984**).

The probability of choosing route j in time period t may be predicted using the Multinomial Logit model:

$$p_j(t) = \frac{e^{\mu \sum_{r=1}^{t-1} w_{r,j}(t-1) U_j(t)}}{\sum_{k=1}^{m} e^{\mu \sum_{r=1}^{t-1} w_{r,k}(t-1) U_k(t)}} \tag{3}$$

where $U_j(t)$ is the measured utility of travel on route j in time period t. The parameters of this model are μ and the time period weights $w_{r,k}(t-1)$; $\mu>0$ is a free parameter that determines the "*extremeness*" of the choice probabilities and the sum is over m, the number of alternative routes in the choice set.

In many studies, the rate of learning is determined (or estimated) using an exponential weighted moving average approach (for example, **Ben-Akiva** *et al.*, **1991**; **Koutsopoulos** & **Xu**, **1993**; **Axhausen** *et al.*, **1995**; **van Berkum** & **van der Mede**, **1998**; **Emmerink** *et al.*, **1998**). This approach requires (at least) another parameter which would determine the learning rate measure. For simplicity, we assumed that all the weights till current time period t are equal:

$$w_{1,j}(t-1) = w_{2,j}(t-1) = \ldots = w_{t-1,j}(t-1) = 1/t \qquad \forall j;\ \forall t=1,\ldots,T \tag{4}$$

where T is the number of time periods.

The models described by **Horowitz** (**1984**) are typical *Stochastic Fictitious Play* (SFP) learning models, described and discussed by **Brown** (**1951**), **Robinson** (**1951**), **Fudenberg** & **Levine** (**1998)** and **Cheung** & **Friedman** (**1998**).

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2.2 Model 2: Information acquired by travellers only through their own experience

Model 2 describes a situation where travellers acquire information only through their own experience. Model 2 is similar to model 1, but instead of averaging *all* of the past travel times of a specific route, *only travel times experienced by the traveller are averaged*. This may reduce the amount of information provided by $(1 - {}^{1}\!/_{m})$, where m is the number of the routes in the choice set. This learning model is formulated as follows:

$$\hat{U}_j(t) = \begin{cases} \sum_{r=1}^{t-1} w_{r,j}(t-1)U_j(t) + \varepsilon_{jt} & ; i = 1,...,m \qquad if\ t \in t_j \\ \hat{U}_j(t-1) & if\ t \notin t_j \end{cases} \tag{5}$$

where t_j is the set of past time periods in which route *j* was chosen; $\hat{U}_j(t)$ is the utility of route *j* as perceived by the traveller at time period *t*; $U_j(t)$ is the measured utility of travel of route *j* if it was chosen in time period *t*; ε_{jt} is a random variable whose probability distribution is independent of *t*; and $w_{r,j}(t-1)$ is a non-negative weight. For each route *j*, for each time period *t*, the weights satisfy the following equation:

$$\sum_{\substack{r=1;\\ r \in t_j}}^{t-1} w_{r,j}(t-1) = 1 \qquad \forall t \in t_j \tag{6}$$

The left term in **eq. 6**, $\sum_{r=1}^{t-1} w_{r,j}(t-1)$, represents the composite effect of past measured route performances on current perceived utility. The weights $w_{r,k}(t-1)$ describe the relative influences of recent and distant past performances on current utility perception (**Horowitz**, **1984**). Notice that the value of the weight $w_{r,j}(t-1)$ has no meaning when route *j* is not chosen at travel time period *r*.

The probability of choosing route *j* in time period *t* may be predicted using a Logit model:

$$p_j(t) = \frac{e^{\mu \sum_{r=1}^{t-1} w_{r,j}(t-1) U_j(t)}}{\sum_{k=1}^{m} e^{\mu \sum_{r=1}^{t-1} w_{r,k}(t-1) U_k(t)}} \tag{7}$$

where $U_j(t)$ is the measured utility of travel at route *j* in time period *t*.

The parameters of this model are μ and the time period weights $w_{r,k}(t-1)$. For simplicity, we assumed that all the weights of measured travel times of route *j*, till the last experienced travel time, are equal.

2.3 Model 3: Travellers are provided with dynamic information about some of the routes

This model is a combination of the last two models. Routes which explicit information is provided, the perceived utility at time t, $\hat{U}_j(t)$, is calculated based on model 1 assumptions (**eq. 1**). For routes in which information is acquired by the travellers only through their own experience, the perceived utility at time t, $\hat{U}_j(t)$, is calculated based on model 2 assumptions (**eq. 5**).

The probability of choosing route j in time period t may be predicted using the MNL model, as described in **eq. 8**.

$$p_j(t) = \frac{e^{\mu \hat{u}_j(t)}}{\sum_{k=1}^{m} e^{\mu \hat{u}_k(t)}} \tag{8}$$

2.4 Model 4: Travellers are provided with static information about all of the routes

This model can be summarized by the following assumptions:

L1: Initial propensities: The traveller has an initial propensity to choose each route. The initial propensity to select route j (at travel period 1) is given by $q_j(1)$:

$$q_j(1) = \begin{cases} 1 \text{ if } L_j = \min_j(L_j) \\ 0 \text{ if } L_j > \min_j(L_j) \end{cases} \tag{9}$$

where L_j is the expected travel time of route j, provided to the traveller before he/she has experienced traveling. Thus, on the *first* travel time period, where traveller *only* source of information is the static information provided, he/she will tend to choose the route with the minimal expected travel time.

In the particular case, where there is more than one route provided with a minimal travel time, $q_j(1)=1/N$, where N is the number of routes in which given travel times are minimal.

L2: Average updating: The propensity to choose route j in travel period $t+1$ is a weighted average of the initial propensity ($q_j(1)$) and the average travel time obtained from choosing j at the first t rounds ($U_j(t)$). The weight of the initial propensity is a function of a "*strength of initial propensities*" parameter $N(1)$. The weight of the average past travel times is a function of the number of times route j has actually been chosen in the past ($C_j(t)$). Specifically,

$$q_j(t+1) = q_j(1)\frac{N(1)}{C_j(t)+N(1)} + U_j(t)\frac{C_j(t)}{C_j(t)+N(1)} \tag{10}$$

In the above equation, the average of the obtained travel times in route j, $U_j(t)$, is not weighted, i.e., all the weights of measured travel times, till the last experienced travel time, are equal.

L3: Exponential Response Rule: The probability $p_j(t)$ of choosing route j in travel period t is given by:

$$p_j(t) = \frac{e^{\mu q_j(t)}}{\sum_{k=1}^{m} e^{\mu q_k(t)}} \tag{11}$$

2.5 Model 5: Travellers are provided with static information about some of the routes

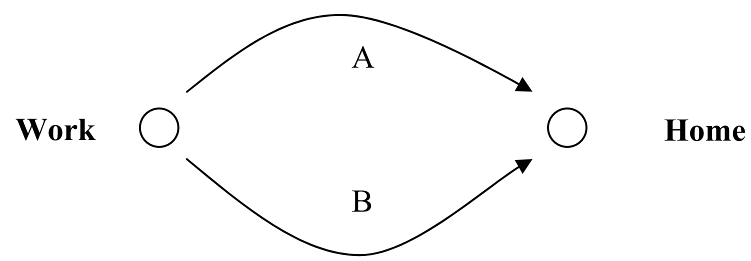
This model is a combination of model 2 and model 4. Routes for which explicit static information is provided, the perceived utility at time t, $\hat{U}_j(t)$, is calculated based on model 4 assumptions (**eqs. 9-11**). Routes for which information is acquired by the travellers only through their own experience, the perceived utility at time t, $\hat{U}_j(t)$, is calculated based on model 2 assumptions (**eqs. 5-7**).
An exponential response rule is assumed, as in the former models.

In the next section, some numeric examples are given in order to evaluate the information acquisition process under uncertainty. Simulation was used in order to analyze these examples.

3. Route-Choice with Dynamic Information: Simulated Examples

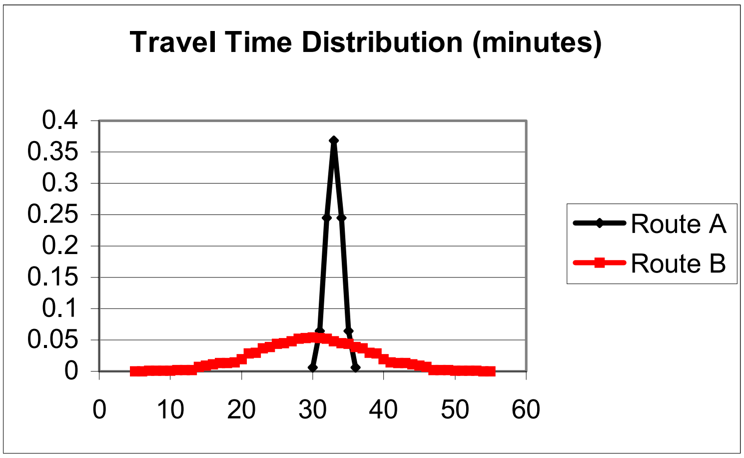
In order to study the impact of travel time dynamic information on travellers' information acquisition and learning process, different situations involving dynamic information are discussed. Monte-Carlo simulation, based on the models described in section 2, was used in order to analyze several situations. Four examples of simplified route-choice decision tasks were studied; all of them were based on the following binary route-choice situation (**Figure 2**):

Figure 2 The binary route-choice problem



In all of the examples, one choice (route A) yielded an average travel time of *33* minutes and the other (route B) yielded an average travel time of *30* minutes. Routes A and B travel times were normally distributed travel times with standard deviations of *1* minute and *7.5* minutes respectively. Travel time distributions for both routes are described in **Figure 3**. All values in this work were drawn from the normal distributions and assumed to be positive and discrete (i.e., integer travel times, in minutes).

Figure 3 Route A and route B travel time distributions



The following route-choice situations were simulated:

Example 1

There are two alternative routes, A and B, to get from a traveller's work to his/her home. The traveller does not have any information about the travel time on either of the routes. The traveller has to choose one of the routes (A or B) in order to get from work to home. After a choice is being made, the traveller is informed about the duration of the trip he/she has made (in minutes). Then he/she chooses again, until 400 daily trips are accomplished.

Example 2

There are two alternative routes, A and B, to get from a traveller's work to his/her home. The traveller does not have any information about the travel time on either of the routes. The traveller has to choose one of the routes (A or B) in order to get from work to home. After a choice is being made, the traveller is informed about the duration of the trip he/she has made (in minutes), as well as how long it could have taken if the second route was chosen. Then he/she chooses again, until 400 daily trips are accomplished.

Example 3

There are two alternative routes, A and B, to get from a traveller's work to his/her home. The traveller does not have any information about the travel time on either of the routes. The traveller has to choose *one of the routes (A or B) in order to get from work to home. After a choice is being made, the traveller is informed about the duration of the trip he/she has made (in minutes). The traveller is informed as well on route's A recent measured travel time, even if it wasn't chosen by him/her. Then he/she chooses again, until 400 daily trips are accomplished.*

Example 4

There are two alternative routes, A and B, to get from a traveller's work to his/her home. The traveller does not have any information about the travel time on either of the routes. The traveller has to choose one of the routes (A or B) in order to get from work to home. After a choice is being made, the traveller is informed about the duration of the trip he/she has made (in minutes). The traveller is informed as well on route's B recent measured travel time, even if it wasn't chosen by him/her. Then he/she chooses again, until 400 daily trips are accomplished.

Obviously, Example 1 is framed in the context of model 2 (information acquired by travellers only through their own experience). Example 2 is framed in the context of model 1 (travellers are provided with dynamic information about past network performance, for all of the routes). Examples 3 and 4 are framed in the context of model 3 (travellers acquire information by their own experience, and are provided as well with dynamic information about past performance of one of the routes).

Figure 4 presents the prediction of the discussed information acquisition models, for each of the four examples. The results present the proportion of route A choices in 5 blocks of 20 trials each. In all the examples, μ value was *1.2*.

In the simulated results of all the four examples, travellers "learn" to prefer route B, which has lower expected travel time. At the end of the simulation process, the predicted preference of route B is higher than the predicted final preference for route A ($P_A < P_B$, or $0 < P_A < 0.5$).

The models used capture the effect of learning rate on preferences behaviour: the fast learning to prefer route B occurs when dynamic information is provided on both routes (Example 2, $P_A = 0.02$ after *400* trials), and the slow learning to prefer route B occurs when information is acquired by travellers only through their own experience (Example 1, $P_A = 0.21$ after *400* trials).

One may wonder why the learning process is so slow. The proportion of route A choices, using model 3 (experience-based information), is not approaching zero, even after *400* time periods. The explanation for that is that people's perception of the travel time distribution, as modeled in the simulation of the information acquisition process, is biased. Typically, people use sample data to infer population characteristics. Since sample expectation and sample variance are biased estimates of population expectation and population variance, to the extent that people use sample data in their perception of population distribution, their perception is different from the true values.

Figure 4 Proportion of route A choices, presented in blocks of 20 time periods each.

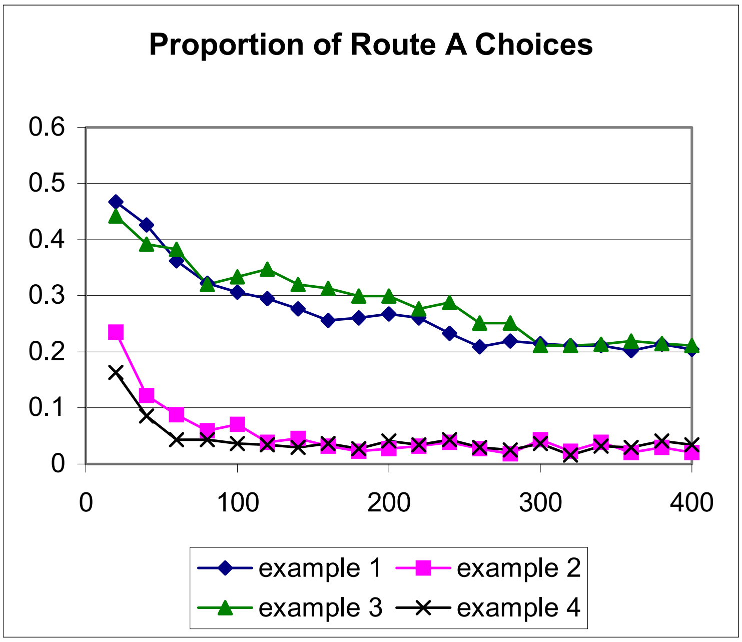
The four examples described on section 3:

Example 1: Information acquired only by experience

Example 2: Dynamic information provided for both routes

Example 3: Information acquired by experience, as well as dynamic information about route A

Example 4: Information acquired by experience, as well as dynamic information about route B



Travellers' learning in route choice situations may be considered as a *sequential decision problem*. At each stage, the traveller takes an action and observes a stochastic outcome (travel time). The traveller's stage utility depends on his/her action, the observed outcome and on previous outcomes. We may assume the traveller is Bayesian and is endowed with a subjective belief over the distribution of travel times. The traveller's initial belief is typically inaccurate. Therefore, his/her subjectively optimal strategy is initially suboptimal. As time passes, information about the true dynamics is accumulated and, depending on the compatibility of the belief with respect to the truth, the traveller may eventually learn to optimize.

In many examples a subjective agent may never learn to optimize. In other examples agents always learn and there are cases where agents may or may not learn, depending on the specific realized sequence of outcomes. **Lehrer** & **Smorodinsky** (**2000**) presented conditions that determine whether a Bayesian agent will eventually learn to optimize.

Providing dynamic information only for route B, as in Example 4, may be sufficient, and even slightly better than providing information about both routes. It can be seen from **Figure 4** that the learning process is somewhat faster when dynamic information is provided only for route B, instead of both of the routes.

Providing dynamic information only for route A, as in Example 3, results in a learning process which is faster than in the situation where information is acquired by travellers only through their own experience (Example 1). This tendency changes after about *100* trials, and the learning process becomes faster for the case where dynamic information is not provided.

One may wonder why providing information about route A (as in examples 3 and 4) results in a larger propensity to choose it, compared with the situation where there is lack of information about route A (as in examples 1 and 2). This may be explained by the hypothesis the learning can be represented as a *sequential sampling process*. In such a process, learning modifies the sampling rate of the alternatives (by changing behaviour) which in turn changes the outcomes. By shifting sampling from inferior to more superior alternatives, the process improves the choice. However, reducing a sampling rate reduces the ability to accurately measure the alternative, which could be disadvantageous for high variance returns (**March**, **1996**). Having some good results of a choice leads to a high propensity to choose this choice again and again. Thus, it might reduce the sampling rates of alternatives which may be good ones. Small sample learning with respect to risky alternatives is quite likely to be misguided. Route B, which is usually fairly good but occasionally very poor, is likely to be interpreted as worse than it really is.

Based on the assumption of *sequential sampling process*, risk "preference" can be interpreted as a learned response. The greater is the variability of one of the alternatives, the more profound is the effect. In this simple binary route-choice problem, the more risky choice (route B) is likely to be more rewarding, which translates into a propensity to choose it. The joint probability of choosing the route A and being rewarded for it becomes smaller and smaller. But in the domain of losses (as in travel times), sampling is more self-correcting. Many choices of route A result in a smaller loss than most choices of the route B, which reduces the learning process rate to prefer route B (i.e., reduces the utility maximization rate). This result is that learners tend to oscillate between the two alternatives, which bring the overall behaviour closer to risk neutral, i.e. choices are close to the predictions based on the assumption of utility maximization.
Another aspect of representing learning as sequential sampling process is the travellers' sensitivity to travel time variability: The higher the variance in travel times, the lower is travellers' sensitivity to travel time differences. Specifically, it was found in route-choice laboratory experiment (**Avineri** & **Prashker**, **2003**) that in some cases, increasing travel time variability of a less attractive route (such as route A) could increase its perceived attractiveness.

The representation of learning as sequential sampling process may be relevant to the designer of cost-effective ATIS. This better understanding of travellers' behaviour may help in ATIS design, such as in which routes to assign VMS. Providing dynamic information about routes with high-variance travel times influences significantly the propensities to choose routes, even when travellers have much experience. On the other hand, providing dynamic information about routes with low-variance travel time may slow down the learning process of experienced travellers.

It appears that the learning effects described in this section will be generated by any learning process in which information about the alternative routes can only be gained from choosing them and in which choice depends on experience with alternatives.

The above discussion and results follow some of the principals of limited human information-processing capacity. However, one of the principals that were not considered in the simulation experiments is the limited memory of humans. Travellers have a real difficulty processing dozens and hundreds of past travel times. Also, travellers are not necessarily utility maximizers, neither rational learners. In the next section, route-choice decision-making under uncertainty is examined in laboratory experiments.

4. Route-Choice with Static Information: A Laboratory Experiment

The main limitation of the models discussed in the previous section is that their assumptions do not have much psychological bases. People's rationality is restricted by their cognitive limitations (**Simon**, **1957**). In order to make "good" choices, people must come to know the environment in which they live. However, time constraints (e.g., the need for a speedy decision), memory limitations[1] (e.g., the limit on sample size imposed by working-memory capacity), or simply the unavailability of more information, often force people to use sample data (statistics) to infer population characteristics (**Kareev** *et al.*, **2002**). Usually, travellers are faced with large-scale route-choice decision problems, with many alternative routes to be evaluated, and to make their decisions in an uncertain environment and under time constraints. This directly implies that travellers' perception of travel time characteristics are wrong. Even if travellers do behave according to the concept of utility maximization, they can not remember all the travel times experienced in the past, nor to compute travel time frequencies.

Experiments in behavioural studies often find the predictions of utility maximization to be violated. A principal contribution in this area is the fundamental work of **Tversky** & **Kahneman** (**1974**, **1979** & **1981**). They have provided extensive empirical, laboratory-based, evidence of instances in which human decision making deviated from Bayesian logic, and concluded that biases, errors and misconceptions typify much of human decision making in the

[1] For example, t was found that humans are able to process only about *7±2* items of information effectively at any one time (**Miller**, **1956**).

presence of risk. **Kahneman** & **Tversky** (**1979**) showed that changing the ways in which options are framed could generate predictable and dramatic shifts in preference. Their experiments capture a pattern of risk attitudes which differ from utility maximization: risk aversion when lotteries are framed as gains, and risk seeking when lotteries are framed as losses.

Moreover, a traveller does not necessarily minimize travel time when choosing a route, but rather adopts some other simple rules (for discussion and examples, see **Lottan** & **Koutsopoulos**, **1993**; **Mahmassani**, **1996**; **Gärling**, **1998**; **Nakayama** *et al.*, **1999**).

Route-choice experiments were conducted to evaluate the effect of the feedback mechanism on decision-making under uncertainty, in two scenarios: (1) static travel time information is provided on each of the routes; (2) Information acquired by travellers only through their own experience.

The basic task in both scenarios was a choice between two alternative routes from work to home. In the first scenario, route A yielded an average travel time of *33* minutes and route B yielded an average travel time of *30* minutes. These average travel times were chosen since the average travel time per trip from work to home in Israel was *29.1* minutes in 1996 (**Central Bureau of Statistics**, **2001**). Routes A and B travel times were normally distributed with standard deviations of *1* minute and *7.5* minutes respectively. At the first scenario, subjects received no prior information about the experiment's travel time distributions. At the second scenario, subjects were provided with the average travel times on both routes, at the beginning of the experiment (static information). Travel time distributions for both scenarios are described in **Figure 3**.

4.1 Participants

The experiment subjects were *46* Israeli men and women, holding a driving license for *12* years on average. The first scenario's data was taken from **Avineri** & **Prashker** (**2003**).

4.2 Apparatus

The experiment was programmed and ran on *Windows 98/ME* environment. This system was installed on *Pentium 3* computers with Super VGA 17'' screens.

4.3 Procedure

The subjects were introduced to a simple network problem shown in **Figure 5**. Each subject was seated (alone) in front of a computer screen. No calculation aids such as calculators were allowed. On each trial, each participant was asked to choose one of the two alternative routes to travel home from work, by clicking on one of the two routes represented by "*radio buttons*". Following a choice, the travel time (in minutes) simulated from the distributions defined earlier was displayed. The participants had to wait (a delay function was used) and view the assigned travel time for at least *2.5* seconds before they were allowed to make a route choice for the next trial. In order not to "help" the participant to have precise information of the history of travel times, only the last travel time was presented. The experiment interface is displayed in **Figure 6**.

Figure 5 Experiment instructions

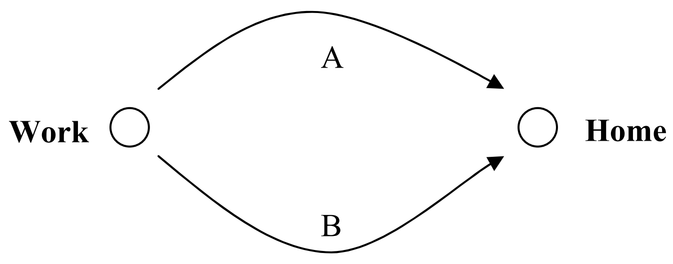
(Translated from Hebrew)

You are about to participate in a route-choice decision making experiment.

There are two alternative routes, A and B, to get from your work to your home.

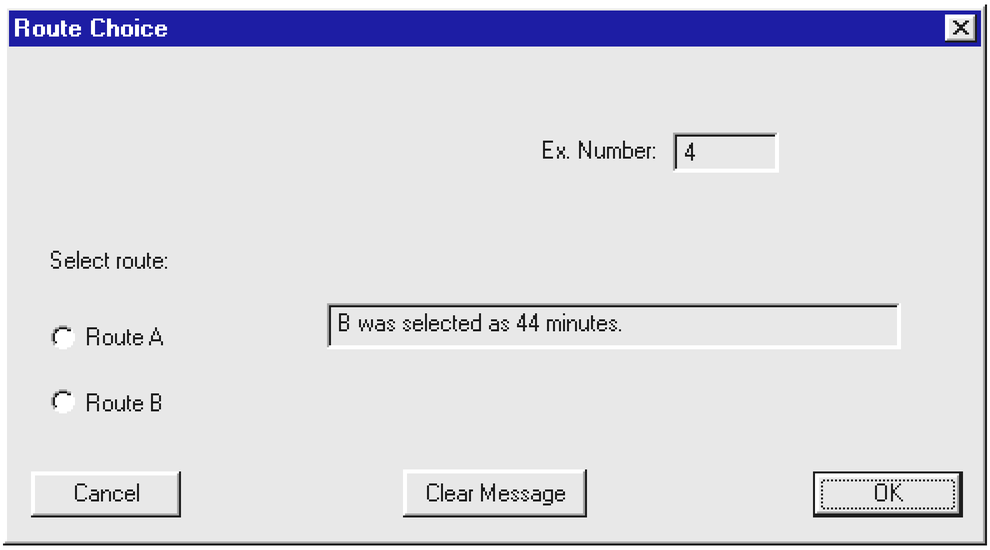
Scenario 1:
"*You have no information about the travel time, the distance or the travel speed on either of the routes.*"

Scenario 2:
"Route's *A average travel time is 33 minutes; Route's B average travel time is 30 minutes.*"



During the experiment, you will be asked to perform 100 daily trips. Every time you will be asked to choose one of the routes (A or B) in order to get from work to home. After a choice is made, you'll be informed how long your trip was (in minutes).

Figure 6 Screen display in scenarios 1 & 2

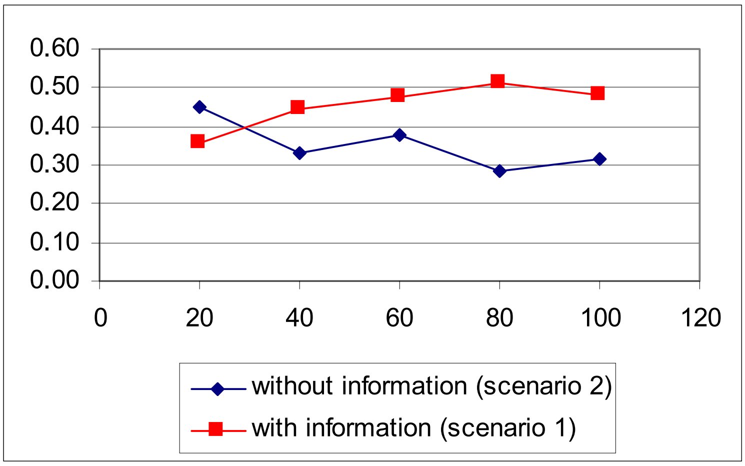


5. Experimental Results

Figure 7 presents the experimental results, described as the proportion of route A choices (P_A) at both scenarios. For simplicity, the results are arranged in 5 blocks of 20 trials each.

As predicted by the learning models, subjects that were not provided with information about travel times, tended to choose route B more than route A (on average *35%* of the choices in scenario 1 were route A choices). In the last 20 time periods of scenario 1 the proportion of route A choices was *32%*. **Figure 7** shows this learning effect.

Figure 7 Proportion of route A choices, presented in blocks of 20 time periods each, for both scenarios (with and without information)



Many models studied by **Avineri** & **Prashker** (**2003**) capture this learning effect. These models include the *Reinforcement Learning Model* (**Erev** *et al*., **1999**), SFP model (**Brown**, **1951**; **Robinson**, **1951**; **Cheung** & **Friedman**, **1998**; **Fudenberg** & **Levine**, **1998**; also discussed by **Horowitz**, **1984**), and the *Cumulative Prospect Theory Learning Model* (CPTL), a dynamic generalization of the static *Cumulative Prospect Theory* Model (**Kahneman** & **Tversky**, **1979**; **Tversky** & **Kahneman**, **1992**), introduced by **Avineri** & **Prashker** (**2003**). Model 2 in **Figure 3**, where information is acquired by travellers only by their own experience, fit well these experimental results.

Assuming risk-natural behaviour, travellers were supposed to choose route B when provided with the travel time information. However, it looks like providing this information made many of the travellers to be risk-prone.

It can be seen from **Figure 7** that the proportion of route A choices in scenario 2, where subjects were provided with static information about the routes travel times, are higher than the proportion of A choices in scenario 1.

At the first trials, subjects provided with static information about travel time, tended to follow this information. It is difficult to explain why these subjects tended to choose route A (the longer one) more than subjects in the group that was not provided with static information (on average *46%* of the choices in scenario 2 were route A choices, versus *35%* of the choices in scenario 1). Furthermore, in the last 20 trips this difference comes to *16%* (frequencies of *0.48* versus *0.32*, respectively). These results do not the static information model introduced in section 2.4, regardless of the parameters values.

Looking at **Figure 7**, one may conclude that the learning rate with static information provided does not converge to the utility maximization based prediction ($P_A<0.5$), and wonder if there is an evidence to learning process involved in this situation: after gathering much information (last block of 20 trials), the proportion of both routes is about the same, $P_A \approx P_B \approx 0.5$. To better understand what have happened during the route choice process we need to investigate the behaviour of individuals during this process, rather than looking at the aggregated results.

Depending on their route choice behaviour, subjects may be roughly classified into five classes:

(1) *Highly Risk-Averse travellers*: those who would like to decrease the risk by (almost) always choosing route A ($0.95 \le P_A \le 1$ at the last 20 travel periods).

(2) *Risk-Averse travellers*: those who would like to decrease the risk by usually choosing route A ($0.65 \le P_A \le 0.85$ at the last 20 travel periods).

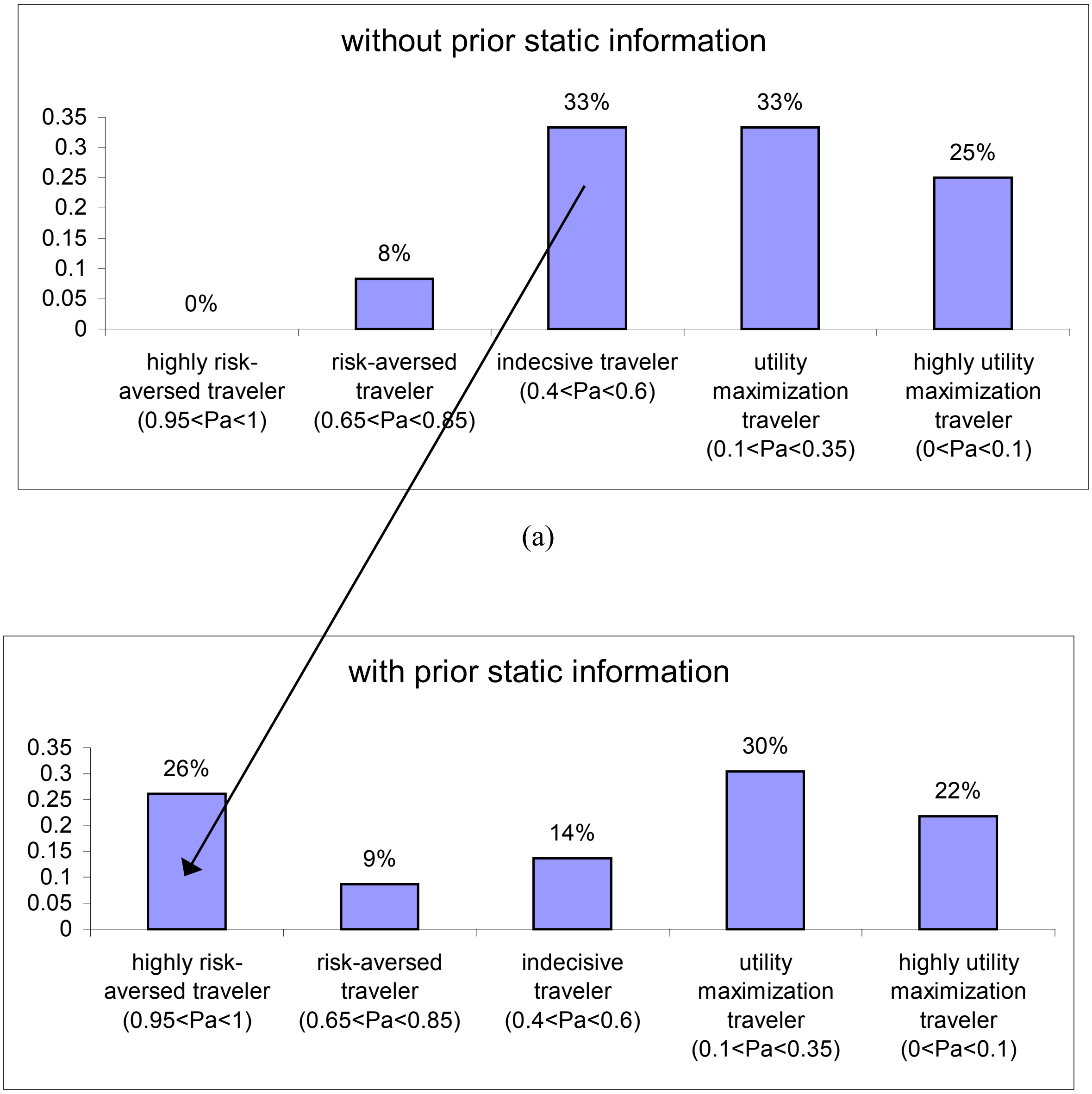
(3) *Indecisive travellers*: those who are neutral between alternatives, choosing route A in about the same proportion as route B ($0.4 \le P_A \le 0.6$ at the last 20 travel periods)

(4) *Utility-Maximization travellers*: those who would like to increase their utility by usually choosing route B ($0.1 \le P_A \le 0.35$ at the last 20 travel periods).

(5) *Highly Utility-Maximization travellers*: those who would like to increase their utility by (almost) always choosing route B ($0 \le P_A \le 0.05$ at the last 20 travel periods).

The distribution of travellers by the above definitions of behaviour types is presented in **Figure 8**. The graphs represent the proportion of route A choices (P_A) in the last block of 20 time periods ($81 \le t \le 100$), with and without providing static information.

Figure 8 Distribution of traveller types, by the proportion of route A choices in the last block. (a) Scenario 1: Without prior static information; (b) Scenario 2: Prior Static information provided



(a)

(b)

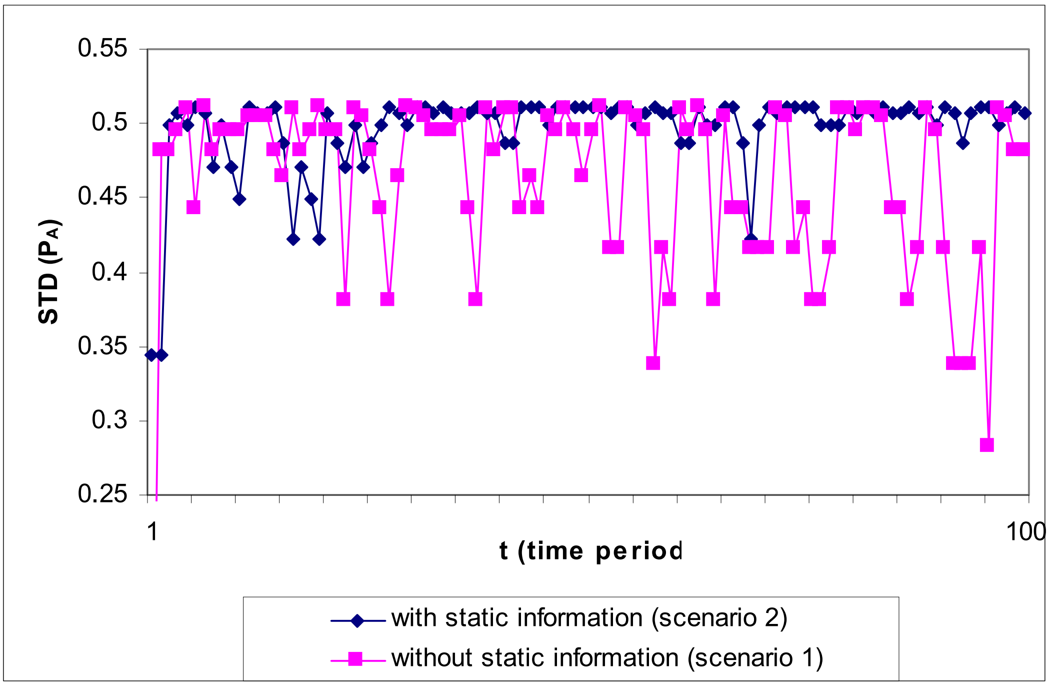
It can be seen, that when static information was not provided (see **Figure 8a**), about *33%* of the subjects may be considered as indecisive travellers. When static information was provided for both routes (see **Figure 8b**), the proportion of indecisive travellers was dropped to only *9%*. Thus, the static information provided did not reduce their learning rate. On the contrary: learning rate of the travellers is *higher*, but their behaviour became *less homogenous*. Thus, we distinguish the *learning* process from the *utility maximization* process.

Furthermore, the proportion of highly risk-averse travellers is *26%* in the scenario where static information was provided. No subjects are classified as highly risk-averse travellers in the scenario where subjects were not provided with static information.

We may explain the empirical results by a *Classification Effect*: providing static information to a traveller assist him/her to adopt a certain behaviour pattern such as risk aversion or utility maximization, thus the proportion of indecisive travellers is reduced.

Another way to represent the non-homogeneity in travellers' behaviour is displayed in **Figure 9**. Each point of this graph represents the standard deviation of P_A (the proportion of route A choices) between subjects, at time period t. It can be seen, that when static information was not provided (scenario 1), the standard deviation of P_A was *lower* than in the case where static information was provided (scenario 2). Thus, the behaviour of subjects provided with static information is less homogenous. An explanation of the large non-homogeneity in individual behaviour of choices in scenario 2 may be explained by the classification effect which occurs during the choice process when information is provided.

Figure 9 Standard deviation of P_A, for both scenarios (with and without information)



6. Summary and Conclusions

In this work we have conducted simulation experiments and laboratory experiments to evaluate the effect of providing information about route-choice decision-making under uncertainty.

Common route-choice models usually ignore the travellers' perception of uncertainty. The common paradigm about providing travel times information to travellers is that it will lead them to make better route-choice decisions, i.e. increase their utilities. We argue against this general statement, and bring forward some criticism about it. The results of the simulation experiments show that, in some situations, providing additional dynamic information does not have a significant effect on route-choice. In other situations, observed in the simulation as well as in the laboratory experiments, the propensity to choose the more efficient route is *de-*

creased (instead of *increased*) when static/dynamic information about travel times was provided.

We conclude that the availability of information about travel times is not sufficient to lead route-choice behaviour toward maximization. In some cases it may even affect choice to be less efficient. One of the interesting findings of the laboratory experiments described here concerns with the *Payoff Variability Effect*: high payoff variability seems to move choice behaviour toward random choice. *The Payoff Variability Effect*, which was observed in a scenario where information was not provided, is replaced by the *Classification Effect*: when static information about the expected travel-times is provided, individuals become faster learners, but not necessarily better utility maximizers.

The better understanding of travellers' sensitivity to uncertainty when information is provided may help transportation systems planners and designers in several aspects:

First, it may improve predictions of travellers' response to ATIS. Since travel time variability and travellers' perception of travel time characteristics under different types of information provided have a great influence on route-choice behaviour, development and application of descriptive models of behaviour is an issue of great importance

Secondly, the design of better cost-effective ATIS may benefit as well. For example, it was found in the simulation experiment, that in some cases, additional dynamic information provided to travellers does not have a significant effect (and may even make the choices somewhat worse). Awareness of such effects, ATIS designers may make better decisions, such as where to locate VMS's and where not to locate them, and to predict the expected benefit of an ATIS.

Finally, an individual, who is faced with a routine route-choice problem, may also benefit from this better understanding of the information acquisition process. In order to reduce the modal bias, which causes the *Payoff Variability Effect*, he/she may better try a two-stage information acquisition process. At the first stage, a "*sample*" of each of the alternative routes should be collected. Only when having a certain size of samples, the traveller may start the second stage, which may be a typical *Stochastic Fictitious Play*. Such an information acquisition process will make the travellers' learning rate much faster, and may be considered as a component of a future in-car individual ATIS.

Much more empirical and methodological research should be done in order to support the findings of this work and to formulate a general route-choice model, based on the assumptions discussed here. Although a full-pledged route-choice model is not achievable, we may benefit from a descriptive model which will capture better the information acquisition and learning process.

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