Is ATIS Useful for Route Choice?-An Interpretation based on a Bayesian Model

Liao, Chun-Hsiung
Associate Professor, Institute of Telecommunications Management and Department of Department of Transportation & Communication Management Science, National Cheng Kung University
Email: chliao@mail.ncku.edu.tw

Chen, Chun-Wei
PhD. Student, Department of Transportation and Communication Management Science, National Cheng Kung University.
Email: pipillpipi@gmail.com

Abstract

The study applies the concept of a Bayesian game to the route choice problem when network travelers are maximizing the degree of satisfaction by choosing routes and modes. The advanced traveler information system (ATIS) now offers travelers a number of benefits, such as reduced travel time and uncertainty and improved traffic safety. The reliability of travel time provided by ATIS has an effect on travelers' choice of route. But, the market for ATIS devices is relatively small, and its users may or may not follow the information and instructions provided by the system. Hence, there is some information heterogeneity among travelers, which arises from the imperfect information with regard to other travelers' preferences and types. A Bayesian Model is used in this work to analyze the impact of this heterogeneity on travelers' route choices. We find that the ATIS information would be more complete and perfect if the type of traveler is indeed heterogeneous. In addition, it provides different information if travelers are similar in real life. Finally, achieving a strategic equilibrium of travelers is the optimal solution with the shortest travel time, and the equilibrium traffic performance is thus the most efficient.

Keywords: Route choice, Bayesian model, Information set generation, Traveler heterogeneity,

Introduction

For several decades, the analysis of daily route choice using game theory has received a growing amount of interest. Route choice has also been investigated with revealed and stated-preference survey techniques concentrating on the real routes taken by individuals. The core aspects of route choice that have not been investigated fully include how to scheme routes and how to calculate route scheming sequences for optimal traffic efficiency. Innovative tracking technologies and survey techniques are now making it easier to address these types of questions. The principle of route choice is that network travelers choose their route and mode to maximize their satisfaction. The main purpose of this paper is to investigate how the asymmetric information and beliefs of travelers in the network influence network reliability and the preference for mode of transport?

In this paper, we introduce the basic concepts of game theory and possible ways of applying it to route choice. Some well-known examples of such approaches include Administrative Information Technology Services (AITS), Advanced Traffic Management Systems (ATMS), Vehicle Routing Problems (VRP), Network Assignment and the Route Choice Model. The route choice problem is solved in a bottom up fashion, and it is helpful to construct an efficient traffic system through individual-foundation problem solving. An important factor which has been introduced into related work over the past few years is traffic information and its effect on travelers' route choice.

There are several reasons why studying models of decision making in the presence of both strategic interactions and heterogeneity of information appears to be important. First, travelers' attitudes towards congestion are not homogeneous, and actual differences exist in travelers' preference with regard to travel time and reliability (Liu et al. 2004; Small et al. 2002). Second, information heterogeneity could lead to an explicit contradistinction between the effects of internal uncertainty (uncertainty of travelers about the route decisions and beliefs of other travelers in the network) and external uncertainty (travelers' uncertainty about the evolution of the exogenous variables) in the solution to the model.

The approach presented in this work is based on the of Advanced Traveler Information System (ATIS), which provides real-time travel information, like link travel times. However, the response of network travelers to information is still a controversial issue, and it is not clear whether more information is beneficial. Travelers confronted with too much information may become oversaturated in the sense that decision processing becomes too difficult, and so they may instead use a simple heuristic to solve the problem. Travelers may also over-react to information, causing them to take extra precautions. ATIS can reduce precarious actions only if behavioral effects are correctly taken into consideration. Within a one-shot game, each player chooses their action only once and all players’ decisions are made simultaneously to maximize self-utility. However, the traffic flow varies by day-to-day, and travelers’ learning, beliefs and behavior all adjust in a dynamic process. Therefore, a Bayesian game approach should be utilized to find out the Wardrop equilibrium wherein no traveler can unilaterally reduce their travel cost by modifying their current routing pattern for system period in this study (Wardrop 1952). Therefore, we propose the first research question: is more information provided by ATIS more beneficial for travelers?

In traffic flow theory, network planners can construct models describing relationships between traffic systems and the environment, designers can evaluate traffic systems in anticipation of real flows and the performance, and operators can check if there is something wrong with the system afterwards. Improving the performance of a transport network is thus an important practical problem for designers and planners involved in network design. The above issues can be regarded as supply-side, but in order to find the general equilibrium we also need to comprehend the demand-side. Greater understanding of route choice and the factors that influence the network traveler would thus be more beneficial in the area of traffic assignment.

The main objectives of the route choice model are improving network reliability and optimizing the performance of network traffic. The main uncertainties in a traveler's route choice situation are network configuration and travel time. In classical network simulation and network assignment models, the values used for travel time (cost) are deterministic and objective; and further, all the travelers are not only assumed to have perfect information about network conditions, but also regarded as homogeneous. However, in reality, different travelers may have different channels of information and different types of utility, and so travelers' route choice behavior is still not well understood. In past articles there was little less discussion on uncertainty or asymmetrical information sets, but this is what tends to exist in the real world. Therefore, in this work we construct a route choice model using a Bayesian approach with heterogeneity in information and the model presented in this paper is essentially non-cooperative. The second research question is then: what information should be provided by the ATIS and ATMS systems, and how should it be provided?

The main purpose of this study is to understand how to improve network reliability and optimize the preference of network traffic given asymmetric information and beliefs among network travelers. The main uncertainties in a travelers' route choice are network disturbances like accidents or diversions, and interactions with other travelers. In this paper, with the assumption of limited road space, heterogeneous types of traveler are considered, with different values for time, experience and knowledge about the set of route choices and the state of the traffic system. In addition, we attempt to answer the two research questions set out, above. The remainder of this paper is organized as follows. Section 2 briefly discusses the related literature about route choice and game theory. Section 3 describes the Bayesian game-theoretic model that we employ and presents applications and the solution algorithm in the route choice model, while Section 4 discusses the results and provides the conclusions. Finally, directions for further research are presented in the last section.

Literature review

Research indicates that individuals choose their routes based on factors such as the distribution of locations within their activity space and social space outside the home (Horton & Reynolds 1971). As the individual is familiar with those locations, they will most likely choose to travel through the space between them. Golledge and Stimson (1997) developed the concept of what is commonly known as a 'knowledge base'. This is usually constructed as attitude and cognition of the territory. The decision process of route choice is based on existing knowledge and experience, which then develops the individual's evaluation of choice alternatives. Travelers' cognitive abilities and personal characteristics also influence the patterns of learning new routes and regulating information process (Adler 2001; Arentze and Timmermans 2003; Golledge et al. 1992; Wilkniss et al. 1997).

Abdel-Aty et al. (1997) shows that both expected travel time and variation in travel time influence route choice, so the attitudes of travelers toward several travel characteristics, such as distance and traffic safety and the related socioeconomic factors, has a significant influences on route choice. The traffic information set is also found to have a significant effect on route choice. Information might be used by travelers to reduce the degree of travel time uncertainty, and it also enables them to choose routes adaptively from their expectations about what will happen based on the past. For the reinforcement of route learning, individuals explore their surrounding environment and learn from their experiences. Risk-taking behavior and departure times are thus studied in the literature to understand the willingness to modify the choice of lane and route, and this is commonly examined using stated-preference (SP) data. In terms of travel time and route choice, gender and age are shown to have an impact on the willingness to take risks. In addition, travelers are more likely to switch routes when they know in advance that their original route would lead to round-trip delays (Polydoropoulou et al. 1996; Liu and Mahmassani 1998).

ATIS has been adapted widely by researchers and subscribers as a promising technology that assists travelers and improves traffic performance in the course of transportation management. In order to evaluate the benefits of ATIS, the traffic information/advice travelers access must be fully understood by the travelers. The number of traffic signals on the regular and suggested routes affects the individual's willingness to switch from the former to the latter. In addition, travelers prefer to use travel time instead of distance measures when making their decisions (Abdel-Aty and Abdalla 2006). Previous studies also take account of the characteristic of information quality with regard to various route choice behaviors. Finally, the market penetration of ATIS, defined as the proportion of vehicles (travelers) equipped with the system, has been widely cited as an important and even endogenous factor that can be used to determine the actual advantages of implementing ATIS (Yang 1998; Lo and Szeto 2002; Yin 2003).

Although ATIS is intended to provide more accurate real-time information for travelers in order to decrease uncertainty with regard to travel time, it is doubtful whether travelers would ever completely trust these computerized navigation systems. Therefore, compliance is another important factor in traveler's behavior that has investigated by a number of studies. Travelers' compliance with ATIS is still influenced by beliefs such as quality of information, reliability of the system, traffic conditions, traveler characteristics and prior experience. In recognition of this, a few authors have investigated ATIS compliance behaviors by addressing how different factors affect travelers' performance and limit compliance with ATIS advice (Srinivasan and Mahmassani 2000; Chen et al. 1999; Boehm-Davis and Fox 1998; Bonsall and Parry 1991). Oh et al. (2001) examined the compliance rate as an endogenous variable and then developed a framework based on this to parametrically evaluate networks under user equilibrium route guidance (UERG) and system optimal route guidance (SORG), assuming that the unguided traffic is in stochastic user equilibrium.

A game is a description of strategic interaction which places constraints on the actions that the players can take and their interests, but does not specify the actions that the players do take. A solution is a systematic description of the outcomes that may emerge in a family of games. Game theory suggests reasonable solutions for classes of games and examines their properties. In all game theory models the basic entity is a player, and this may be interpreted as an individual or as a group of individuals. Once a game includes a set of players, we can divide game models into two types. The first type includes those where the set of possible actions of individual players is fundamental and selfish, and these are referred to as "non-cooperative''. The second type includes those in which the set of possible actions of group players is fundamental, and these are referred to as "cooperative''. In the case of a route choice model, an individual's choice of route can be regarded as a route choice which involves perception and cognition of traffic information, including the weather, traffic reports and previous experience (Ben-Elia et al. 2008). An individual's choice will then be affected by what has been seen in a parallel environment and what has been formulated in their mind—that is, the information set that they have.

In some studies based on the characteristics of human and traffic, non-cooperative game theory has been widely applied to the issue of route choice. Non-cooperative game theory mainly deals with how rational individuals interact with one another in an effort to achieve their primary goal — to minimize expected trip costs (Fudenberg and Tirole 1991; Rasmusen 2001). Bell (2000) describes a zero-sum game between two network travelers, who choose a driving path through a road network and selfish entity which chooses the costs of using the network links. The goal of the travelers is to minimize the trip cost, while the selfish entity aims to increase the cost to others. And he proposes that the expected trip cost for risk-averse (pessimistic) trip-makers offers a suitable measure of network reliability for network design.

Bell and Cassir (2002) extended this methodology to a case which involves multiple travelers, and includes traveler equilibrium across the network. The selfish entity is here replaced with multiple demons, which seek to cause trouble for each origin-destination pair. The formulation contains a series of pairs of programming problems, solved for each origin-destination. The results show that a deterministic traveler equilibrium traffic assignment is shown to be equivalent to the mixed-strategy Nash equilibrium of an n-player, non-cooperative game. An n to m player, non-cooperative game is usually formulated, where n network travelers seek their best routes and m origin–destination (OD)-specific demons penalize the network travelers by causing links to fail. The mixed-strategy Nash equilibrium of this game is shown to describe a risk-averse (pessimistic) traveler equilibrium traffic assignment. A similar concept is employed by Bell (2004) for a freight vehicle routing problem. A two-player, zero-sum game is defined between a dispatcher, who seeks the lowest cost vehicle route, and a demon, which has the power to cause a road link to fail. The solution is interpreted as the risk-averse expectation of a worst-case scenario.

Van Vugt et al. (1995) set up a two-player strategic-form game, where each player chooses either a car or public transport. The finite strategic game can be described as in Table 1, where there is no importance given to the exact values, only to the relationship between them. The left and right numbers in each cell are the payoffs for players 1 and 2, respectively. The table shows that using a car is the best strategy for any of the players only if the other player uses public transport, that is, when there is no congestion. If both players choose public transport, their payoffs are high, because increased ridership enables service improvements. Still, the only Nash equilibrium is when both travelers choose the car, and the conclusion is that the selfish way in which travelers make their choices is bad for everyone. This is the typical prisoners' dilemma.

Table 1. A game by Van Vugt et al. (1995)

Player 2

		Public transport	Car
Player 1	Public transport	(4, 4)	(-4, 8)
	Car	(8, -4)	(0, 0)

On a limited road space assumption, the relationship between travelers is one of competing with each other. Many games discuss short term cases of the famous prisoners' dilemma, in which all players would be better off if they did not act selfishly, but individual travelers would then be able to improve their situation by acting selfishly.

Stark et al. (2007) has found that the question of optimally distributed entity-flows in capacity-restricted networks is a certain kind of social dilemma. Using the folk theorem of game theory, he suggests that individuals in an iterated setting of a day-to-day route choice game with identical conditions spontaneously establish cooperation in order to increase their returns. Through experiments, they confirm the folk theory, and the results suggest that the coordination process towards persistent cooperation may be the bigger problem compared to the evolution of cooperativeness.

Pedersen (2003) tests the hypothesis that improved safety increases the number of travelers who behave aggressively. He sets a game between two travelers, where each of them chooses their level of care when driving. Two types of travelers are defined: one of which is represented by a dove, and the other one by a hawk. In a situation where two doves meet, the game is solved as a Cournot game with Nash equilibrium, assuming that the travelers act simultaneously. An encounter between a hawk and a dove is solved as a Stackelberg game, where the hawk is the leader. When two hawks meet, the author suggests that they both try wrongly to behave as leaders, resulting in a state of no-equilibrium. This game is shown in Table 2 below.

Table 2. Hawk-Dove game1

	Doves	Hawks
Doves	(3,3)	(1,4)
Hawks	(4,1)	(0,0)

A number of studies discuss the differences between the time interval, the different travelers, the time value and the function form of payoffs to each player. For example, the time spent on working, tourism and business trips has different values for dissimilar purposes. Further research on this issue should also consider the differences among network travelers. Perhaps by considering the road network superintendent's decision-making, network equilibrium will be found to be influenced by supply-side or network itinerary. For example, in Braess's Paradox (Braess 1968), a road network was built where n travelers wish to travel from origin (O) to destination (D), and this is shown in Fig. 1. One path (O–R–D) consists of an edge with a fixed cost (time) 1 and the cost of the other edge varies with the number of travelers (m/n, where m is the number of travelers). The equilibrium will be at m=n/2 and each traveler's cost is 1+1/2. Assuming that the network designer built a super highway, a new road (R to L) with no congestion at all (cost is 0), then the previous solution is no longer an equilibrium. This is because the traveler who has previously used the link from O to L with a cost of 1 cost between two nodes, will have the incentive to change to the new link (O-R-L) that has only has a cost of 1/2+0=1/2. Similarly, the link (R-D) will be dominated by the link (R-L-D) (cost of R-L-D is 1/2+0 = 1/2 < cost of R-D = 1). Once every one of the network system users switches to the path O-R-L-D, the route is congested everywhere, and the cost will be 2. Hence, everyone will be worse off.

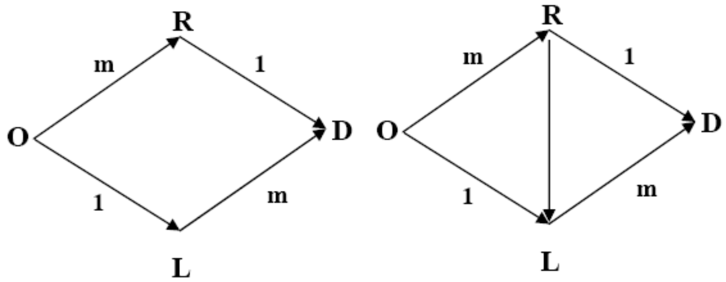

Fig 1. Braess's Paradox

Methodology

According to the network assignment concept, the Nash equilibrium of game theory or the Wardrop equilibrium are commonly used to as the goal in related studies. This notion captures the steady state of the player in a strategic game in which each player holds the correct expectation about the other players' behavior and acts rationally. None of players attempt to change their strategy, and thus the equilibrium is reached.

Concept of Bayesian game

In most papers, the Nash equilibrium and Wardrop equilibrium are the same. In this paper, we will describe a Bayesian game which is a strategic game with imperfect information. We set up a model in which there are N travelers and each traveler *i* has an available activities set A_i and a finite set Ω of natural states and other opponents *j*. The adaption of signal function, t_i, represents the information observed by the traveler about the current state. Let T_i be the set of all possible values of t_i, and refer to the set of types for traveler *i*. We assume each traveler *i* has a positive prior belief about every member of T_i with regard to knowing the current state, $p_i\left(\tau_i^{-i}\left(t_i\right)\right) > 0$ for all $t_i \in T_i$. As a strategic game, each traveler will choose the best route out of all available ones, based on their beliefs and information to maximize utility. A Nash equilibrium of a Bayesian game $\left(N,\ \Omega,\ \left(A_i\right),\ \left(T_i\right),\ \left(\tau_i\right),\ \left(p_i\right),\ \left(\geq\right)\right)$ is the Nash equilibrium of strategic game G^*, in which for each $i \in N$ and each possible signal $t_i \in T_i$ there is a traveler, whom we refer to as (*i*, t_i) (type t_i of traveler *i*). The set of routes of each traveler (*i*, t_i) is A_i; thus the set of route profiles in G^* is $\times_{t_i \in T_i} A_j$. The preference of each traveler (*i*, t_i) is defined as follows. The posterior belief of a traveler, together with a route profile a^* in G^*, generate a lottery $L_i\left(a^*,\ t_i\right)$ over $A\times\Omega$: the probability assigned by $L_i\left(a^*,\ t_i\right)$ to $\left(\left(a^*\left(j,\ \tau_i\left(\omega\right)\right)\right)_{i\in N},\ \omega\right)$ is the posterior belief of traveler *i* that the state is ω when they observe the signal $t_i\left(a^*\left(j,\ \tau_i\left(\omega\right)\right)\right)$ as the route of the other travelers. Traveler (*i*, *t_i*) in G^* prefers the route profile a^* to the route profile b^* if only if traveler *i* in the Bayesian game prefers the lottery $L_i\left(a^*,\ t_i\right)$ to the lottery $L_i\left(b^*,\ t_i\right)$. To summarize, we present the definition of the Nash equilibrium of the Bayesian game used in this work, as follows.

The set of travelers is the set of all couples (*i*, t_i) for $i\in N$ and $t_i\in T_i$. The set of routes of each traveler (*i*, t_i) is A_i. The preference ranking $\succ^*_{(i,\ t_i)}$ of each player (*i*, t_i) is defined by $a^*\succ^*_{(i,\ t_i)} b^*$ if and only if $L_i\left(a^*,\ t_i\right)\succ^*_{(i,\ t_i)} L_i\left(b^*,\ t_i\right)$, where $L_i\left(a^*,\ t_i\right)$ is the lottery over $A\times\Omega$ that assigns probability $p_i\left(\omega\right)\big/p_i\left(\tau_i^{-1}\left(t_i\right)\right)$ to $\left(\left(a^*\left(j,\ \tau_i\left(\omega\right)\right)\right)_{i\in N},\ \omega\right)$ if $\omega\in\tau_i^{-1}\left(t_i\right)$, and zero otherwise. In other words, in the Nash equilibrium of the Bayesian game, each traveler chooses the best route available to them given the signal that they observe, beliefs about the state and the other travelers' route choices that they infer from this signal.

More information, more advantages?

Advanced Traveler Information Systems are used to provide travelers with the greatest amount of accurate information as possible, enabling individuals to choose the best route. But more information may be worse than less in some situations. We will use a simple example to explain how this is possible. Consider an extensive form game has been transformed into the strategic form, as the following Fig. 2 and Table 3.

In this example, $N=\left\{1,2\right\}$, $\Omega=\left\{\omega_1,\omega_2\right\}$, the set of actions of traveler 1 is {*T, B*}, the set of actions of traveler 2 is {*L, M, R*}. Traveler 1's signal function is defined by $\tau_1\left(\omega_1\right)=\tau_1\left(\omega_2\right)=t_1^{'}$, traveler 2's signal function is defined by $\tau_2\left(\omega_1\right)=\tau_2\left(\omega_2\right)=t_2^{'}$,

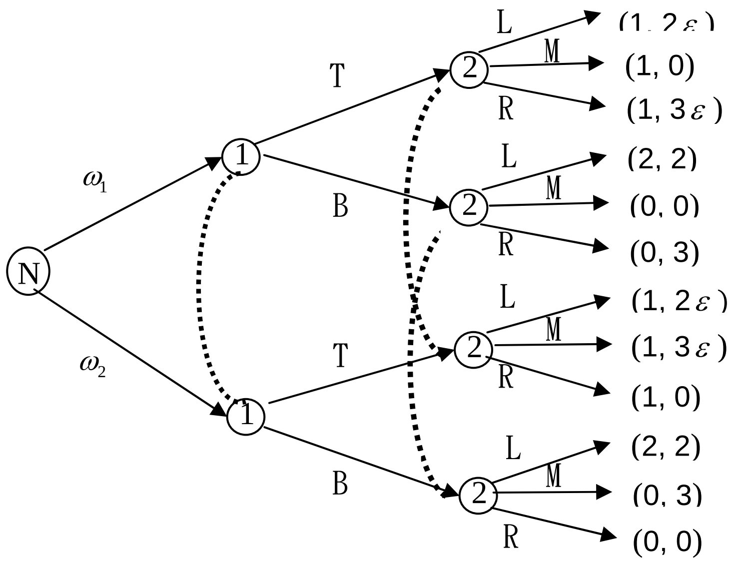

Fig. 2 An extensive form game of the simple example.

Table 3. The payoffs in the Bayesian game

		Traveler 2 (State ω_1)				Traveler 2 (State ω_2)		
		L	*M*	*R*		*L*	*M*	*R*
Traveler 1	*T*	1, 2ε	1, 0	1, 3ε	*T*	1, 2ε	1, 3ε	1, 0
	B	2, 2	0, 0	0, 3	*B*	2, 2	0, 3	0, 0

are represented by the expected value of the payoffs matrix, shown in Table 3. In the base case, neither of them have any information about which state they are.

Table 4. The expected payoffs in the base case

		traveler 2		
		L	M	R
traveler 1	T	(1, 2ε)	(1, 3ε/2)	(1, 3ε/2)
	B	(2, 2)	(0, 3/2)	(0, 3/2)

The unique Nash equilibrium of the game is at (*B*, *L*), where the expected payoffs at the equilibrium are (2, 2). Then, consider a variant of the game named Case 2 in which traveler 2 is informed of the state by using ATIS. The signal function of traveler 2 becomes $\tau_2(\omega_1) = t_2^{'} \neq \tau_2(\omega_2) = t_2^{''}$; therefore the unique Nash equilibrium of the game switches to (*T*, (*R*, *M*)), where the expected payoffs at the equilibrium are (1, 3ε). As 3ε (where $0 < \varepsilon < 1/2$) is less than 2, this shows that traveler 2 is worse off when using ATIS than when less informed.

Table 5. The expected payoff of traveler 1 in Case 2.

		(L, L)	(L, M)	(L, R)	(M, L)	(M, M)	(M, R)	(R, L)	(R, M)	(R, R)
traveler 1's expected payoff	T	1	1	1	1	1	1	1	1*	1
	B	2	1	1	1	1	1	1	1	1

This game has a unique Nash equilibrium (T, (R, M)), which means that traveler 2 chooses R in state 1 and M in state 2, while traveler 1 chooses T. Traveler 2's payoff in the unique Nash equilibrium in which he knows the state is 3ε in both states, and thus they are worse off when they know the state. In Case 3, traveler 1 knows the state, but traveler 2 does not. Therefore, traveler 2 needs to consider the expected payoffs. In the ω_1 state, traveler 1 chooses B if traveler 2 chooses L, but in the ω_2 state, play 1 chooses B if player 2 chooses L. Thus, the expected payoff for traveler 2 is equal 0.5*2+0.5*2=2. The strategic form is as follows:

Table 6. The expected payoff of traveler 2 in Case 2.

(T, T)	(T, B)	(B, T)	(B, B)

traveler2's expected payoff	L	2ε	$\varepsilon+1$	$\varepsilon+1$	2*
	M	$3\varepsilon/2$	3/2	$3\varepsilon/2$	3/2
	R	$3\varepsilon/2$	$3\varepsilon/2$	3/2	3/2

This game has a unique Nash equilibrium of ((B, B), L), which means that traveler 1 chooses B in both states and traveler 2 chooses L. The payoffs are 2 for both travelers. Finally, in Case 4, in which both travelers know the state, the unique Nash equilibrium when the state is ω_1 is (T, R), and the unique Nash equilibrium when the state is ω_2 is (T, M). In both situations, the payoff (1, 3ε) is worse off than the base case in which neither travels know the state. The results show that when both players know the state or traveler 2 has more information then both travelers will be worse off.

In addition to the situation in which travelers are uncertain about each other's preferences, the Bayesian game may describe the situation in which they are uncertain about each other's knowledge. Consider, for example, a Bayesian game in which the set of travelers is $N=\{1,2\}$, the set of states is , $\Omega=\{\omega_1,\omega_2,\omega_3\}$, the prior belief of each traveler assigns a probability of 1/3 to each state, the signal functions are defined by $\tau_1(\omega_1)=\tau_1(\omega_2)=t_1^{'}, \tau_1(\omega_3)=t_1^{''}$ and $\tau_2(\omega_1)=t_2^{'}, \tau_2(\omega_2)=\tau_2(\omega_3)=t_2^{''}$, then traveler 1's best response satisfies $(b,\omega_j)\succ_1(c,\omega_j)$ for *j* = 1, 2 and $(c,\omega_3)\succ_1(b,\omega_3)$ for route profiles *b* and *c*, while traveler 2 is indifferent between all pairs (a,ω). In state ω_1 in such a game, traveler 2 knows that traveler 1 prefers *b* to *c*, while in state ω_2 they do not know whether traveler 1 prefers *b* to *c* or *c* to *b*. Since in state ω_1 traveler 1 does not know whether the state is ω_1 or ω_2, they do not know whether traveler 2 knows whether traveler 1 prefers *b* to *c* or *c* to *b*.

Notice that traveler 2's preferences are the same in all three states, and traveler 1's preferences are the same in states 1 and 2. In particular, in state ω_1, each traveler knows the other traveler's preference and traveler 2 knows that traveler 1 knows their preference. But traveler 1 does not know that traveler 2 knows their preference. The imperfection in traveler 1's knowledge of traveler 2's information significantly affects the equilibrium of the game. If the information was perfect in state ω_1, then the Nash equilibrium would simply be (*b*, *a*). However, the Bayesian game has both Nash equilibriums, (*b, a*) and (*c, a*). If the outcome is the latter, traveler 1 may be worse off. In general senses, the more information you have, the more advantages or benefits you acquire in the route choice game. However, the results show the existence of uncertainties in a traveler's route choice situation once the the interactions between travelers' responses and beliefs are considered simultaneously. As a result of incomplete information with regard to the opponent's preference or type, a traveler acquiring more information still faces conscious randomization on the part of the opponent, and this may adversely affect their payoffs under certain situations.

Bayesian model with application to Braess's Paradox

We set a simple model involving two rational travelers in the traffic network shown in Fig. 1. Let $N=\{1,2\}$ and assume that each traveler has two possible natures $\theta_i=\{C,I\}$, $i=1,\ 2.$.

A type *C* traveler is conservative and prefers their habitual route, so here we set up traveler 1's route of habit as U_1 and traveler 2's route of habit as U_2. A type *I* traveler will choose route *H* for both travelers. The set of actions of traveler 1 is $A_1 = \{H, U_1\}$, and the set of actions of traveler 2 is $A_2 = \{H, U_2\}$ (*H*:O-R-L-D; U_1:O-R-D; U_2:O-L-D). The set of states is $\Omega = \{(H,H),(H,U),(U,H),(U,U)\}$. We assume that the traveler types are independently portrayed as type *C* occurring with probability $p \in (0,1)$. So the prior belief of each traveler assigns a probability *p* that the opponent is conservative. Traveler i has the following travel cost, c_i:

$$c_i\left(a_i, a_{-i}; \theta_i\right) = \begin{cases} 1/2+1+(-\varepsilon) & \text{if } a_1 = H,\ a_{-1} = U_{-i} \quad \text{and } \theta_i = I \\ 1/2+1 & \text{if } a_1 = U_i,\ a_{-1} = U_{-i} \quad \text{and } \theta_i = I \\ 1+1+(-\varepsilon) & \text{if } a_1 = H,\ a_{-1} = H \quad \text{and } \theta_i = I \\ 1+1 & \text{if } a_1 = U_i,\ a_{-1} = H \quad \text{and } \theta_i = I \\ 1/2+1+(-\varepsilon) & \text{if } a_1 = U_i,\ a_{-1} = U_{-i} \text{ and } \theta_i = C \\ 1/2+1 & \text{if } a_1 = H,\ a_{-1} = U_{-i} \quad \text{and } \theta_i = C \\ 1+1+(-\varepsilon) & \text{if } a_1 = H,\ a_{-1} = H \quad \text{and } \theta_i = C \\ 1+1 & \text{if } a_1 = U_i,\ a_{-1} = H \quad \text{and } \theta_i = C \end{cases}$$

A strategy is a mapping $a_i(\theta_i):\{C, I\} \to \{U_i, H\}$. We assume that the *I* type of traveler always prefers *H* to U_i, regardless of the choices of the opponent. The total cost is time cost and the willing-to-pay for amusement$(-\varepsilon)$. The *C* type of traveler always prefers to go with another traveler. The strategic objective of travelers is to minimize the total cost. Obviously, if it was common knowledge that both travelers were type *I* then the game would be a typical Braess's Paradox, and each traveler would have a dominant strategy of choosing *H*. In this case, the outcome of the payoff would be (((1+1+$(-\varepsilon)$), (1+1+$(-\varepsilon)$)), which is worse than 1/2+1 for both travelers (where 0<ε<1/2). Alternatively, if it was common knowledge that both travelers were type *C,* then the pure Nash equilibrium is (*H,H*).

In the Bayesian model, the information is incomplete, that is the travelers do not know what type their opponent is. However, they know their own type, so the possible outcome would be reduced to $\left(a_i(I), a_{-i}(\theta_{-i})\right) = (H, U_{-i})$ and (H,H) or $\left(a_i(C), a_{-i}(\theta_{-i})\right)$ $= (U_i, U_{-i})$ and (U_i, H) for *i* = 1, 2. If traveler 2 complies with the strategic logic, then the $a_2(C) = U_2$ with probability *p* and $a_2(I) = H$ with probability (1-*p*). Thus traveler 1's expected cost, E[c_1] is:

$$\mathrm{E}\left[c_1\left(a_1 : \theta_1 = C\right)\right] = \begin{cases} p\cdot[1/2+1+(-\varepsilon)] + (1-p)\cdot[1+1] & \text{if } a_1 = U_1 \\ p\cdot[1/2+1] + (1-p)\cdot[1+1+(-\varepsilon)] & \text{if } a_1 = H \end{cases}$$

$$\mathrm{E}\left[c_1\left(a_1 : \theta_1 = I\right)\right] = \begin{cases} p\cdot[1/2+1] + (1-p)\cdot[1+1] & \text{if } a_1 = U_1 \\ p\cdot[1/2+1+(-\varepsilon)] + (1-p)\cdot[1+1+(-\varepsilon)] & \text{if } a_1 = H \end{cases}$$

The strategy $a_1(I) = H$ is the best response, because type *I* has a dominant strategy to choose route *H* to minimize the expected cost. Alternatively, $a_1(C) = U_1$ is the best response for type *C* when

$p \cdot [1/2 + 1 + (-\varepsilon)] + (1-p) \cdot [1+1] \leq p \cdot [1/2 + 1] + (1-p) \cdot [1 + 1 + (-\varepsilon)]$

which is true only if $P \geq 1/2$. The calculation of traveler 2 is a symmetric solution, so we have the result that the profile $a_i(C) = U_i$ and $a_i(I) = H$ for $P \geq 1/2$ is a Bayesian Nash equilibrium.

Further, we consider the possibility that $a_i(C) = H$ for both travelers could be the optimal strategy. If traveler 2 always uses the strategy $a_2(\theta_2) = H$ regardless of whether traveler 2 is type *C* or *I*, traveler 1 has the following expected cost

$$\mathrm{E}\left[c_1\left(a_1 : \theta_1 = C\right)\right] = \begin{cases} [1+1] & \text{if } a_1 = U_1 \\ [1+1+(-\varepsilon)] & \text{if } a_1 = H \end{cases}$$

$$\mathrm{E}\left[c_1\left(a_1 : \theta_1 = I\right)\right] = \begin{cases} [1+1] & \text{if } a_1 = U_1 \\ [1+1+(-\varepsilon)] & \text{if } a_1 = H \end{cases}$$

This means that traveler 1's optimal strategy is $a_1(\theta_1) = H$, and the same is true for the traveler 2. Finally, the Bayesian Nash equilibrium for both travelers is $a_i(C) = H$ and $a_i(I) = H,\ i = 1,\ 2.$ Moreover, if $P \geq 1/2$ there is a best equilibrium with $a_i(C) = U_i$ and $a_i(I) = H.$ In the equilibrium, the highway building policy and whole network system could be efficient, which happens with the likelihood $p \cdot (1-p).$ The maximum likelihood will be caused in $P = 1/2$, and it is most worthwhile to implement its policies when the p is closer to 0.5. In other words, the equilibrium status requires that one traveler is conservative and expects their opponent to be of a different type. This observation confirms the previous studies on travelers' attitudes towards congestion are not homogeneous, and actual differences exist in travelers' preferences with regard to travel time and reliability (Liu et al. 2004; Small et al. 2002). The implication of this result is that the ATIS or ATMS (Advanced Traffic Management Systems) should provide an information mechanism to divide the different type of travelers if there are indeed appropriate proportions of different types of traveler in real life. Otherwise, it constructs the optimal traffic scenario in which there are heterogeneities in traveler types and beliefs through a process of calibration.

Discussion and Conclusions

The Bayesian model presented in this work could provide an alternative explanation for the the uncertain benefits of ATIS. The goal of all such technological innovations is to provide complete and perfect information to all travelers to enable them to make optimal route choices and hence optimize the performance of network traffic. But the model has shown that travelers who are provided with more information via ATIS may in fact be worse off, and the information system may be a distortion of the day-by-day route choice. In this study, the key concepts of the Bayesian model are the travelers beliefs in the established process, and the the heterogeneity between travelers in the traffic network.

This paper presents a Bayesian game-theoretic model and offers an explanation as to why an ATIS may actually provide worse outcomes with regard to network efficiency. The model considers the uncertain information for travelers in route choices. The travelers' decision-making process is influenced by imperfect, incomplete and heterogeneous information, interactions and beliefs. As illustrated in this paper, the travelers adopting ATIS, advanced traveler assistance systems (ADAS) or other information and communication technologies (ICTs) to collect more information were not necessarily better off than those who did not.

With regard to the first research question, in a general sense, the more information you have, the more benefits you acquire in the route choice game. But the results show that the existence of uncertainties in a traveler's route choice situation once the interactions between travelers' responses and beliefs are considered simultaneously. This is because \the availability of these technologies is not common knowledge among all travelers in the traffic network. If the travelers have used ICT technologies, the context of it made the beliefs in the adjustment process were too complex to generate the common knowledge about the interpretation of the providing signals. Mahmassani and Chen (1993) conclude that there is no clear measure of the effect of this information on the travelers independent of the traveler choice behavior, prevailing traffic conditions, and network interactions. There are some ways to generate the common knowledge for all travelers in a network system to guarantee complete and perfect information. One way is to popularize the ATIS system using technologies such as GPS or Telematics and to provide more real-time traffic information. Another way is that all travelers should comply completely with the information from ATIS or other devices, although this is likely to be impossible in practice.

A traveler's beliefs are shaped by past experiences and their guesses as to the actions of others. To achieve the optimal equilibrium in a Bayesian game, the beliefs of each traveler must become more accurate. There are at least two approaches for this, On is the greater use of technologies accessing the ATIS system, and the other is the improvement of the traffic system, including the method of providing traffic information, usage of the system and design techniques for urban traffic management planning. As all the information becomes more complete and perfect, the strategic game converged on the optimal equilibrium outcome, and the travelers' traffic preferences were also more efficient. In addition to the main principles mentioned above, traffic information is full of time-inconsistencies, and this can be averted through providing more real-time traffic information, increasing the adoption of the ATIS system in technologies like GPS or Telematics[1] or the prestige and public reliance for authorities of traffic.

With regard to the second research question, we find that the equilibrium state requires that one traveler is conservative and expects their opponent to be of a different type. This observation confirms the previous studies which found that travelers' attitudes towards congestion are not homogeneous, and that real differences exist in their preferences with regard to travel time and reliability (Liu et al. 2004; Small et al. 2002). The implication of this is that the ATIS or ATMS should provide an information mechanism to divide the different types of traveler if there are indeed appropriate proportions of different travelers in real life. In

[1]The integrated use of telecommunications and informatics, also known as ICT. More specifically it is the science of sending, receiving and storing information via telecommunication devices.

addition, an optimal traffic scenario can be constructed in which there are differences in traveler type and beliefs through a process of calibration. The policy implication is that ATIS should provide a variety of information for users to alter their beliefs, and thus enable the optimal equilibrium to be achieved through an incentive mechanism.

In reality, however, different travelers may have different channels of information and different types of utility. Therefore, there is much scope to explore traveler's route choice behavior further. With regard to the trend of ICT, ATIS technologies are mobile and mean that the game of route choice can be conducted with continuity. Technologies like GPS, Telematics, and Vehicle Information System via Mobile Communication are all ways of providing updated information to travelers to alter their choices of route. But the innovative science and technologies necessarily accomplish their objective which should be cooperated with other term. For example, all the travelers in the system have the same common knowledge base (Golledge and Stimson 1997) in the long-run. In the short-run, since travelers' beliefs about the probabilities of various outcomes are the key to decision-making under uncertainty, it is important to analyze how a rational agent should respond to new information about the likelihood of various outcomes. This issue should be considered using the Bayesian learning game in future work.

References

Adler, J. L. (2001). Investigating the learning effects of route guidance and traffic advisories on route choice behavior. Transportation Research C, 9, 1–14.

Arentze, T. and H. Timmermans (2003). Modeling learning and adaptation processes in activity-travel choice. Transportation, 30, 37–62.

Bell, M. G. H. (2000). A game theory approach to measuring the performance reliability of transport networks. Transportation Research Part B, 34, 6, 533–546.

Bell, M. G. H. and C. Cassir (2002). Risk-averse traveler equilibrium traffic assignment: an application of game theory. Transportation Research Part B, 36, 8, 671–681.

Ben-Elia, E., I. Erev and Y. Shiftan (2008). The combined effect of information and experience on travelers' route-choice behavior. Transportation, 35, 165–177.

Boehm-Davis, D. A. and J. E. Fox (1998). Effects of age and congestion information accuracy of advanced traveler information systems on user trust and compliance. Transportation Research Record, 1621, 43–49.

Bonsall, P. W. and T. Parry (1991). Using an interactive route-choice simulator to investigate travelers' compliance with route guidance information. Transportation Research Record, 1306, 59–68.

Braess, D (1968). Über ein Paradoxon der Verkehrsplanung. Unternehmensforschung, 12, 258–268.

Fudenberg D and J. Tirole (1991). Game theory. Cambridge, MA: MIT Press..

Golledge, R. G. and R. J. Stimson (1997). Decision making and choice behavior models. In Spatial behavior: A geographic perspective, pp. 31–70. Guilford Press, New York.

Hans, U. S., D. Helbing, M. Schonhof and J. A. Holyst (2007). Alternating cooperation strategies in a Route Choice Game:Theory, experiments, and effects of a learning scenario. http://www.sg.ethz.ch/

Horton, F. E. and D. R. Reynolds (1971). Effects of urban spatial structure on individual behavior. Economic Geography, 47, 36–48.

Mahmassani H. and P. Chen (1993). An investigation of the reliability of realtime information for route choice decisions in a congested traffic network system. Transports, 20, 2, 157–178.

Liu, Y. and H. Mahmassani (1998). Dynamic aspects of departure time and route decision behavior under advanced traveler information systems (ATIS): Modeling framework and experimental results. Transportation Research Record, 1645,. 111–119.

Liu, H. X., W. Recker and A. Chen (2004). Uncovering the contribution of travel time reliability to dynamic route choice using real-time loop data. Transportation Research Part A: Policy and Practice, 38, 435-453.

Lo, H. K. and W. Y. Szeto (2002). A methodology for Sustained Traveler Information's Server. Transportation Research Part B, 36, 113-30.

Oh, J. S., R. Jayakrishnan, A. Chen and H. Yang (2001). A parametric framework for route guidance in advanced traveler information systems with endogenously determined driver compliance. Transportation Research Record 1771, 18–27.

Osborne, M. J., and A. Rubinstein (1994). A Course in Game Theory. MIT Press, Cambridge.

Rasmusen E. (2001). Games and information: an introduction to game theory (3rd ed), Oxford, Blackwell.

Small, K. A., C. Winston and J. Ya (2002). Uncovering the distribution of motorists' preferences. Working paper 01-02-10, Department of Economics, University of California, Irvine.

Srinivasan, K. and H. S. Mahmassani (2000). Modeling inertia and compliance mechanisms in route choice behavior under real-time information. Transportation Research Record: Journal of the Transportation Research Board , 1725, 45-53.

Sun, L. J. and Z.Y. Gao (2007). An equilibrium model for urban transit assignment based on game theory. European Journal of Operational Research, 181, 1, 305–314.

Pedersen, P. A. (2003). Moral hazard in traffic games. Journal of Transport Economics and Policy, 37, 1, 47–68.

Polydoropoulou, A., M. Ben-Akiva, A. Khattak and G. Lauprete (1996). Modeling revealed and stated en-route travel response to advanced traveler information systems. Transportation Research Record, 1537, 38–45.

Van Vugt, M., R. M. Meertens, and P. A. M. Van Lange (1995). Car versus public transportation? The role of social value orientations in a real-life social dilemma. Journal of Applied Social Psychology, 25, 258–278.

Wardrop, J. G. (1952). Some theoretical aspects of road traffic research, Proceedings, Institute of Civil Engineers, Vol.1, 325-378.

Wilkniss, S. M., M. G. Jones, D. L. Karol, P. E. Gold and C. A. Manning (1997). Age-related differences in an ecologically based study of route learning. Psychology and Aging, 12, 372–375.

Yang, H. (1998). Multiple equilibrium behavior and advanced traveler information systems with endogenous market penetration. Transportation Research B, 32, 205–218.

Yin Y. and H. Yang (2003). Simultaneous determination of the equilibrium market penetration and compliance rate of advanced traveler information systems. Transportation Research Part A: Policy and Practice, 37, 165-181