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A Model of Risk-Sensitive Route-Choice Behavior and the Potential Benefit of Route Guidance

J. Illenberger, G. Flötteröd, and K. Nagel

***Abstract*—In this paper, we present a simulation-based investigation of the potential benefit of route-guidance information in the context of risk-sensitive travelers. We set up a simple two-route scenario where travelers are repeatedly faced with risky route-choice decisions. The risk averseness of the travelers is implicitly controlled through a generic utility function. We vary both the travelers' sensitivity toward risk and the equipment fraction with route-guidance devices and show that the benefits of guided travelers increase with their sensitivity toward risk.**

I. Introduction

In recent years, much research has been conducted in advanced traveler information systems (ATIS) [1]. Empirical insights have been gained from emerging applications of ATIS and from in-laboratory experiments [2], where the experiments have proven to be useful approaches to derive detailed behavioral models. Studies agree that the benefit of ATIS is the greatest in the case of nonrecurrent congestion [3]. In such situations, congestion is usually caused by unpredictable external shocks (e.g., accidents, extreme weather conditions, and large events). The literature also agrees that uncertainty in travel time is a crucial aspect of the users' decision-making processes [4] and that the accuracy of information provision has an impact on the users' acceptance [5]. Moreover, it has been shown that, as a system becomes less reliable, the application of ATIS becomes more beneficial [6].

Simulation-based frameworks have been developed to evaluate the use of ATIS and to support local authorities in the implementation of such technologies. However, those studies usually evaluate the benefit of ATIS in terms of average travel times [7]. Only few simulation studies address the evaluation of uncertainty (e.g., [8]), and none addresses the specific question on how ATIS can support users' decisions by reducing the costs of uncertainty only.

In this paper, we present simulation studies where we investigate the potential benefit of route guidance in a system with risk-averse travelers. The benefit of route guidance is measured in terms of the individual utility of simulated travelers, and we show that, as the system is made more risk averse, the users' utility increases.

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The remainder of this paper is organized as follows. Section II discusses related work on decision making under uncertainty and different levels of travel-time reliability. In Section III, the concepts of risk aversion from psychology and economy are introduced and translated into transport terms. The simulation model used for the experimental studies is described in Section IV, and the results of the simulation studies are presented in Section V. This paper is closed with a discussion in Section VI and a summary of the results in Section VII.

II. Related Work

Abdel-Aty *et al.* [9] show, through stated preference surveys, that travel-time variability plays a significant role in explaining route-choice behavior. They also show that ATIS has the potential to help travelers, even if routes that differ from habitual ones are recommended. In driving-simulation experiments, Katsikopoulos *et al.* [10], [11] face participants with the decision whether to stay on a route with a certain travel time or to divert to an alternative route that could take a range of travel times. The experimental setup is similar to the simulation scenario presented in this paper. Katsikopoulos *et al.* observe that the participants are risk averse even when the average travel time on the alternative route is shorter than the certain travel time of the initial route. Furthermore, they show that the degree of travel-time variability has an effect on the travelers' behavior, and they also discuss the potential of ATIS to support driver decisions by reducing uncertainty.

Lam and Small [12] use loop detector data to estimate the value of time (VOT) and value of reliability (VOR), where VOR is quantified by the difference between the 90th percentile and the median of the travel-time distribution. They show that unreliability is perceived as significant additional cost. The same loop detector data are used by Liu *et al.* [13] to estimate a mixed-logit route-choice model. Apart from VOT and VOR, they also estimate a "degree of risk aversion" of 1.73, which means that the disutility of a certain amount of travel-time unreliability is perceived 1.73 times more intensive than the disutility caused by travel time of the same amount.

Existing behavioral models that account for travel-time variability, both in terms of departure time choice and route choice, can roughly be grouped into the following three approaches: 1) the "safety-margin" approach; 2) the "mean-variance" approach; and 3) models that make explicit use of a concave or convex utility function to represent risk-averse or risk-loving behavior.

Travel-time variability can be modeled as an additional cost term in a utility function. This idea, which corresponds to approach 1, is embodied in the concept of a "safety margin" that travelers generate by departing earlier than they would do without travel-time variability [14].

Another approach (which corresponds to approach 2) captures the disutility of variability by cost terms for early or late arrival, which is the approach of Small [15]. His model already captures risk-averse behavior in that travelers would depart earlier or travel longer to avoid the risk of being late.

The model has been extended by Noland and Small [16], [17] and later by Ettema and Timmermans [18] to a model based on expected travel times, rather than travel times assumed to be known to the user, as in the case in [15]. Ettema and Timmermans conclude that the provision of information leads to a significant reduction of scheduling costs, amounting to up to one Euro per trip, whereas the quality of

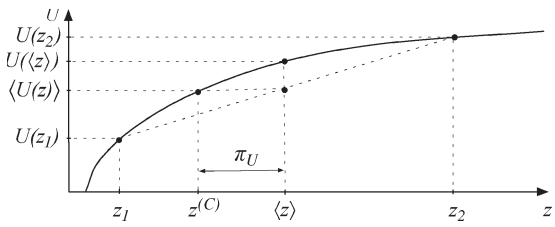

Fig. 1. Expected utility theory with the log utility function.

information and the misperception of the quality have only a minor effect.

De Palma and Picard [19] make use of a utility function to model route choice under uncertainty. Their approach would correspond to approach 3. More recently, Marchal and de Palma [8] have implemented those models into a microscopic simulation framework to evaluate the costs of uncertainty. To the knowledge of the authors, this paper has been the only study that followed such a simulation-based approach.

The simulation study presented here continues the research of Marchal and de Palma in that it explicitly addresses the evaluation of ATIS in an environment with uncertainty.

III. Concepts of Risk Aversion

A. Risk Aversion in Psychology and Economy

Consider z as a random variable that can take the two discrete values z_1 and z_2. Let p be the probability that z_1 occurs and $(1-p)$ the probability that z_2 occurs. The expected outcome is $\langle z \rangle = pz_1 + (1-p)z_2$. Let $U(z)$ be a nondecreasing and strictly concave utility function, which means that the marginal utility of the utility is diminishing as z increases. The expected utility is $\langle U(z) \rangle = pU(z_1) + (1-p)U(z_2)$.

For a concave utility function, Jensen's inequality [20] implies that the expected utility is not larger than the utility of the expected outcome, i.e.,

$$\langle U(z) \rangle = pU(z_1) + (1-p)U(z_2) \leq U\left(pz_1 + (1-p)z_2\right) = U\left(\langle z \rangle\right). \quad (1)$$

This expression represents the utility-decreasing aspect of risk bearing. We can think of a player who faces two lotteries. The risky lottery pays z_1 or z_2 with probabilities p and $1-p$, respectively, whereas the safe lottery pays $\langle z \rangle$ for sure. Although the expected outcome in both lotteries is the same, a risk-averse player would prefer $\langle z \rangle$ with certainty over an uncertain outcome z, even if the expectation is the same. This case is what is captured in the inequality $\langle U(z) \rangle \leq U(\langle z \rangle)$.

Consider now a third lottery that yields in the outcome $z^{(C)}$ with certainty. As depicted in Fig. 1, the utility of this allocation is equal to the expected utility of the random lottery, i.e., $U(z^{(C)}) = \langle U(z) \rangle$. $z_U^{(C)}$ is known as the outcome of the certainty equivalent lottery, i.e., the sure-thing lottery that yields in the same utility as the random lottery, where the subscript U indicates that the certainty equivalent is dependent on the utility function $U(z)$. Although the certain outcome $z_U^{(C)}$ is less than the expected outcome $\langle z \rangle$ of the random lottery, a player would be indifferent between the random and the certainty-equivalent lotteries. The difference $\pi_U = \langle z \rangle - z_U^{(C)}$ is known as the risk premium, i.e., the maximum amount of outcome that a player is willing to forgo to avoid an allocation with risk.

More generally, let $U(z)$ be a utility function, z a random variable, $\langle z \rangle$ the expectation of z, and $z_U^{(C)}$ the certainty equivalent. We have

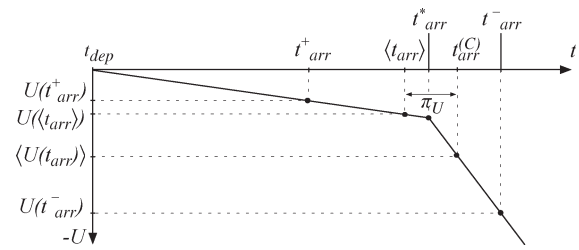

Fig. 2. Utility function of a risk-averse traveler.

the following three definitions.

- *Risk aversion*: $z_U^{(C)} < \langle z \rangle$, i.e., $U(z)$ is concave.
- *Risk neutrality*: $z_U^{(C)} = \langle z \rangle$, i.e., $U(z)$ is linear.
- *Risk proclivity*: $z_U^{(C)} > \langle z \rangle$, i.e., $U(z)$ is convex.

The aforementioned concepts date back to the 18th century and have mainly been promoted by Bernoulli [21]. The ideas of Bernoulli have intensively been seized by psychologists and economists since the 20th century and led to the expected utility hypothesis [22] and later in prospect theory [23].

B. Risk Aversion in Transport

The concept of risk aversion also has applications in transport. In particular, consider the random variable as the uncertain travel time of a route. For our studies, we model risk aversion, as shown in Fig. 2. The utility for travel is linear in time. The traveler has a desired arrival time or, equivalently, a maximum travel-time budget. If the traveler arrives late (exceeds the travel-time budget), he/she incurs an extra penalty.

The following example clarifies the workings of this specification. Consider a driver who travels along a route with an uncertain travel time. The driver always departs at t_{dep} and arrives on good days at t_{arr}^{+} and on bad days at t_{arr}^{-}, where $t_{arr}^{+} < t_{arr}^{*} < t_{arr}^{-}$, where t_{arr}^{*} is the desired arrival time. We assume that the expected arrival time is $\langle t_{arr} \rangle < t_{arr}^{*}$; thus, on average, the driver can expect to arrive on time. However, because arriving late on bad days causes an extra penalty, the expected utility $\langle U(t_{arr}) \rangle$ is smaller than the utility of the expected arrival time $U(\langle t_{arr} \rangle)$. The driver will select an alternative route, as long as the alternative route has a guaranteed travel time $t_{arr}^{alt} \leq t_{arr,U}^{(C)}$, where $t_{arr,U}^{(C)}$ (certainty equivalent) is the guaranteed travel time on the original route that induces $\langle U(t_{arr}) \rangle$. The absolute difference $\pi_U = \langle t_{arr} \rangle - t_{arr,U}^{(C)}$ is the additional amount of travel time that a risk-averse traveler is willing to "pay" to eliminate the risk. If the certain route is at $t_{arr,U}^{(C)}$, the traveler is indifferent between the two routes.

In the context of ATIS, the certainty equivalent $t_{arr,U}^{(C)}$ allows us to capture the user's willingness to pay for such services. Consider a traffic management center (TMC) that provides real-time traffic information to drivers and the aforementioned situation, together with a second route that always operates at $t_{arr,U}^{(C)}$. If the TMC can guarantee a certain travel time for the uncertain route, then it can charge a monetary equivalent of the difference between the users' certainty equivalent and the guaranteed travel time.

IV. Simulation Model

A. MATSim Framework

For the studies in this paper, we use the MATSim framework [24], [25], which is a fully agent-based transport simulation. The key aspects of MATSim can be summarized as follows. MATSim distinguishes between a physical and a mental layer. The physical layer comprises the simulation of the traffic flow, implemented as a queuing model

with physical queues and spillback [26]. The mental layer handles the reasoning and decision-making processes, such as the choice of a route to travel. Decisions made in the mental layer are based on the feedback of the physical layer, which are usually travel times. MATSim iterates between both layers until the system reaches a stationary state in the sense of Cascetta [27], which is similar to a stochastic user equilibrium [28]; more details are given as follows. In the following sections, we first describe the simulation scenario and then discuss the details of the behavioral model.

B. Simulation Scenario

Consider a simple road network with one origin and one destination connected by two different routes. One route is denoted as the "safe" route, and the other as the "risky" route, where the following conditions hold.

- The safe route has a fixed capacity of 7200 vehicles per hour and a free-flow travel time of 435 s.
- The risky route has a default capacity of 7200 vehicles per hour; however, an incident is simulated in each iteration (i.e., in each execution of the physical layer) with probability 0.5, which reduces the capacity by a factor of 0.3. The free-flow travel time of the risky route is 327 s, which is less than the travel time of the safe route.

In the following discussion, iterations where an incident occurs are referred to as "bad days" or "bad states of nature," whereas iterations without incidents are referred to as "good days" or "good states of nature." At the beginning of each iteration, the state of nature is unknown to the agents.

The population consists of 1000 agents. Each agent has the following two options: 1) traveling along the safe or 2) traveling along the risky route. Both options are *a priori* known to the agent. In the following sections, the two options will be referred to as the "safe" and "risky" plans. Departure times are prescribed such that, every second, two agents enter the system, starting at 05:50. This condition means that, without the capacity reduction of the risky route, no congestion occurs, even if all users take the same route.

C. Behavioral Model

The simulation of the mental layer comprises the following two steps: 1) updating the evaluation of the plan executed in the previous run of the physical layer and 2) the selection of a plan to be executed in the next run of the physical layer. We describe here only the aspects of the behavioral model that are relevant for the understanding of this, and more details can be found in [28] and [29].

To evaluate a plan, the model uses a utility function that is related to the Vickrey bottleneck model [30]. The utility is composed of the (negative) utility for traveling U_{trav} and an extra penalty for being late U_{late}, i.e.,

$$U = U_{trav} + U_{late}. \tag{2}$$

The utility for traveling is assumed to be linear in time, i.e.,

$$U_{trav}(t_{trav}) = \beta_{trav} t_{trav} \tag{3}$$

where β_{trav} denotes the marginal utility for travel [€/h] and t_{trav} the time spent traveling (in seconds). The extra penalty for being late is (see Fig. 2) given as

$$U_{late} = \begin{cases} \beta_{late}\left(t_{arr} - t^*_{arr}\right), & \text{if } t_{arr} > t^*_{arr} \\ 0, & \text{else} \end{cases} \tag{4}$$

where t^*_{arr} is the desired arrival time, t_{arr} is the experienced arrival time, and β_{late} is the marginal utility for being late, which controls the risk aversion of agents. Values less than zero make agents averse risk, whereas $\beta_{late} = 0$ represents risk-neutral users. Risk-loving agents could be represented by choosing $\beta_{late} > 0$, but this case is not considered here.

The updating rule for a plan's utility is

$$\bar{U}_k = \alpha U_k + (1-\alpha)\bar{U}_{k-1} \tag{5}$$

where k denotes the iteration index, U_k is the experienced utility in iteration k, $\bar{U}_k$ is its smoothed counterpart, and $0 < \alpha < 1$ is the learning rate of the agents. The larger α is, the more the agents update their utility perception in reaction to the most recent iteration.

Based on the evaluation, each agent selects one plan to be executed in the next run of the physical layer. The selection rule specifies the probability of a plan transition from the currently selected plan (the plan that has been executed in the previous run of the physical layer) to the alternative plan. We have

$$\frac{p_i}{p_j} = \frac{\kappa + e^{\gamma(\bar{U}_i - \bar{U}_j)}}{\kappa + e^{\gamma(\bar{U}_j - \bar{U}_i)}} \tag{6}$$

where p_i is the selection probability of the currently selected plan, p_j is the selection probability of the alternative plan, κ is a nonnegative parameter that controls explorative behavior, γ is a parameter that controls the rationality of the agent's decision, and $\bar{U}_i$ and $\bar{U}_j$ are the utilities for the currently selected and the alternative plans, respectively.

The aforementioned formula comprises two aspects. If κ is set to zero, (6) results in a logit model (stochastic user equilibrium, e.g., [31]) $p_i/p_j = \exp(2\gamma(U_i - U_j))$. The nonnegative γ coefficient controls the randomness in the model: The larger it gets, the more likely is the alternative of higher utility to be chosen. The parameter κ introduces an explorative component to the behavioral model. Increasing κ leads to less influence of the logit model, i.e., more explorative behavior. Sufficiently high values for κ result in an equal distribution of the selection probabilities such that the risky and the safe plans are selected with equal probabilities.

It is required that agents are forced from time to time to select the alternative plan and to "renew" the plan's utility. Otherwise, the danger that an agent gets stuck with only one plan exists. If, for instance, the risky plan is executed once on a bad day, it receives a low utility. In the next iteration, the safe plan is executed and gains a better score. If the utility difference between the risky and safe plans is sufficiently high, there is a low probability that the logit model will ever select the risky plan again. If the agent is forced to again select the risky plan, which is controlled by κ, then there exists a substantial probability that the risky plan is eventually executed on a good day and gains a better utility. Consequently, the probability of a plan transition increases.

D. Guidance

A certain fraction f of agents is equipped with an in-vehicle device. We can regard this device as a personal digital assistant (PDA), which is supplied with link travel-time information from a TMC and generates route recommendations. If an agent is equipped with such a device, it will request the fastest route at departure. The route recommendations are based on estimated expected travel times. The estimated expected travel time of a route at any point in time is given by $\max[t_0, t_q]$, where t_0 denotes the free-flow travel time and t_q the time that it takes to process all vehicles that are currently on the route. The value of t_q is estimated based on the standard queuing theory for a congested route, with $t_q = n/f$, where n is the number of vehicles on

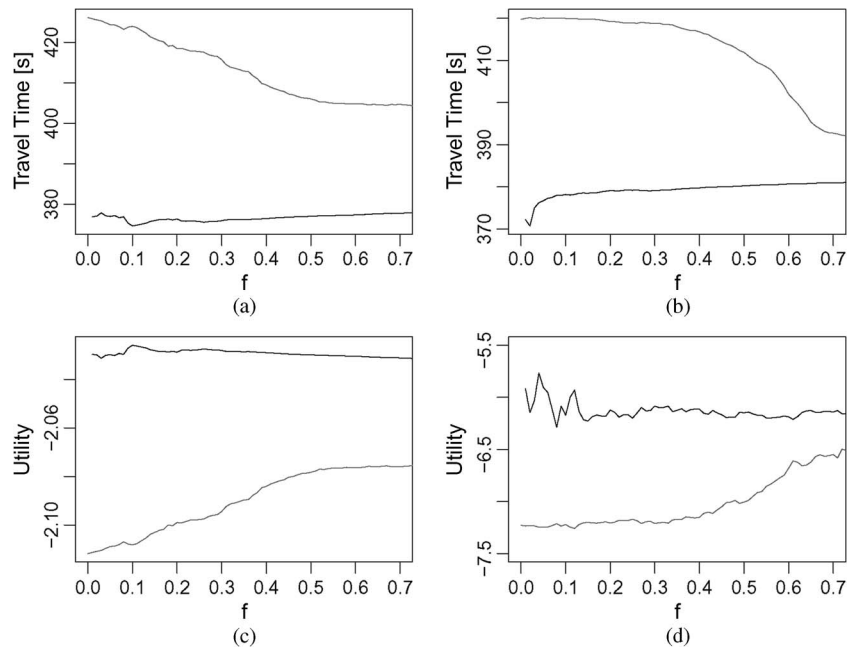

Fig. 3. Travel time and utility for guided (black) and unguided (gray) agents. (a) and (c) $\beta_{late} = 0$ €/h. (b) and (d) $\beta_{late} = -100$ €/h.

the route (determined by counting incoming and outgoing vehicles), and f is the downstream flow capacity. That is, the travel time of a route is either the free-flow travel time, as long as the load is below its capacity, or the estimated time required to process the vehicles that are already on the route. This travel-time estimate is consistent with workings of the deployed queuing simulation.

Travelers equipped with an in-vehicle device are denoted as "guided" agents and always comply with the guidance. This specification implicitly accounts for guidance compliance in that f constitutes the fraction of equipped *and* compliant travelers.

V. Simulation Results

A. Parameter Setup

In the following simulation studies, the effects of the parameters β_{late} and f are investigated. The parameter β_{late}, which denotes the penalty for being late, controls the risk aversion of the agents. The values are varied from 0 €/h (risk neutral) to -100 €/h (risk averse). The parameter f represents the effective fraction of compliant agents equipped with guidance devices and is varied from 0 (no equipped agents) to 0.7 (70% of agents are equipped and compliant). Simulation results with $f > 0.7$ are not shown here, because the simulation exhibits heavy fluctuations with high equipment fractions; a discussion of these conditions would go beyond the scope of this paper. All remaining parameters are given as the following fixed values.

- *Plan evaluation*. The marginal utility for travel β_{trav} is set to -6 €/h, and the desired arrival time t^*_{arr} is uniformly set to 6:00 for all agents. The learning rate α is set to 0.2, i.e., slow learning.
- *Plan selection*. The parameter γ, which controls the agent's objective rationality, is set to 5, and κ, which controls the explorative behavior, is set to 2.

Simulation runs are conducted with 1000 iterations, which ensures that the system reaches a steady state.

B. Results

In the base case with $\beta_{late} = 0$ €/h and $f = 0$, the users approximately equally distribute over both routes (500:500). As the users are made more risk averse, i.e., as β_{late} is made increasingly negative, more agents switch to the safe route. With $\beta_{late} = -100$ €/h, roughly 600 travelers use the safe route. As a consequence, the travel time on the risky route on bad days and the average travel time over good and bad days decreases. On one hand, decreasing β_{late} pushes the system toward the safe route. On the other hand, the decreasing travel time on the risky route partially counteracts this effect.

To investigate the effects of the guidance, the fraction f of equipped users is varied from 0 to 0.7. Fig. 3(a) shows the travel time of both the unguided and guided agents in the risk-neutral system ($\beta_{late} = 0$ €/h). At low equipment fractions, the travel-time savings of the guided over the unguided agents are about 40 s. With increasing equipment fractions, the unguided agents also benefit, which reduces the equipment gain to approximately 25 s at $f = 0.7$. This effect occurs because, on bad days, the guided vehicles avoid the bottleneck, thus making it faster for the unguided vehicles. The utility [see Fig. 3(c)] behaves qualitatively similar to Fig. 3(a), because travel-time values are just multiplied with the marginal utility of traveling, and there is no penalty for being late.

The picture for $\beta_{late} = -100$ €/h is similar to the case with $\beta_{late} = 0$. However, by the increased absolute value of β_{late}, the utility reactions are more pronounced. At low equipment fractions, the travel-time savings are comparable with the risk-neutral system [see Fig. 3(a)]. On the contrary, at high equipment fractions, unguided users benefit even more than in the risk-neutral system, and the equipment gain is reduced to only 10 s. The following dynamics behind this case are quite complicated.

- Initially, at a low equipment fraction, the risky route is used just up to capacity on bad days, because any increase of travel time over the safe route is heavily punished for the risk-averse users. This case also means that the risky route is underutilized on good days.
- As the equipment fraction increases, the guided users have a tendency, on bad days, to equilibrate the risky route with the safe route. This case means that the risky route becomes more reliable. If the risky route becomes more reliable, it becomes more attractive for the unguided users, and thus, there is a shift back to the risky route. Overall, the load of unguided users on

the risky route decreases more slowly with increasing equipment fraction in the risk-averse system compared with the risk-neutral system, which, in turn, exhibits a more pronounced travel-time gain for the unguided users.

The utility gain of guided over unguided travelers, which corresponds to the willingness to pay for guidance, is initially about 0.08 € and decreases to 0.04 € with increasing equipment fraction in the risk-neutral system [see Fig. 3(c)]. In the risk-averse system [Fig. 3(d)], the utility gain is much more pronounced [note the different scaling in Fig. 3(c) and (d)]. Starting at 1.2 €, the utility gain decreases to approximately 0.3 € per user, although the travel-time savings are lower than in the risk-neutral system. This condition means that risk-sensitive users are willing to pay more for route guidance compared with risk-neutral users, even if the effective travel-time savings are of the same magnitude.

VI. Discussion

The results of this simulation study show that risk-sensitive users exhibit higher willingness to pay for route guidance compared with risk-neutral users. This condition may appear trivial, because the utility is a function of β_{late}. However, it demonstrates that there is a substantial difference if we use the objective travel-time savings as evaluation criteria or the individual utility gain. Moreover, it shows the potential of the agent-based approach, because it allows us to distinguish between certain user groups, such as guided and unguided users, and to identify the individual utility gain or loss of each group. Furthermore, the microsimulation-based approach lends itself to the evaluation of complex real-world scenarios that would be intractable for a formal mathematical analysis.

The identified willingness to pay is hard to compare with existing empirical studies, because they all use different approaches for monetarizing VOR or the risk aversion of travelers. However, what this study shows is that there is a significant cost of uncertainty. In the presented scenario, risk-averse users are willing to pay about 1.2 € for roughly 40-s travel-time savings in the extreme case of $\beta_{late} = -100$ €/h. In the literature, we find different values for β_{late}: varying from 18 \$/h in the Vickrey bottleneck scenario [30], [32] to 15 €/h to 21 €/h in studies from Amelsfort and Bliemer [15], [17], or, as estimated by Small, *et al.* [15], [17], values that are, on the average, about three times the cost of travel. If we use $\beta_{late} = -18$ €/h ($\beta_{late} = 3 \cdot \beta_{trav} = 3 \cdot (-6$ €/h$) = -18$ €/h), the simulation results show a willingness to pay of approximately 0.30 € for travel-time savings of 45 s, i.e., a willingness to pay of 24 €/h (approximately 34 \$/h). These values are in the same magnitude as the estimates for VOR by Lam and Small (from 12 \$/h to 29 \$/h) [12] and Liu *et al.* (21 \$/h) [13]. We have found no study that evaluates the value of β_{late} by trip purpose, e.g., for a business traveler who wants to catch an airplane.

There are further aspects that should be addressed for a real-world scenario, such as heterogeneous risk-taking behavior, a more realistic route-guidance device, individual preferred arrival times, larger route-choice sets, as well as departure time choice. The last aspect is rather important, because we may argue that changes in departure time choice more frequently occur than changes in route choice.

VII. Conclusion

This paper has presented simulation studies where travelers are repeatedly faced with risky route-choice decisions. The sensitivity of drivers toward risk and the effective equipment rate with route-guidance devices are varied to investigate the potential benefit of such devices in a system with uncertainty. For the synthetic scenario of this paper, the following conclusions can be drawn.

- In a system with risk-neutral travelers ($\beta_{late} = 0$ €/h), the average disutility of travel for a guided traveler is about 4% less compared with an unguided traveler. This condition results in a willingness to pay of about 0.08 €.
- In a risk-averse system ($\beta_{late} = -100$ €/h), the average disutility of travel for a guided traveler is about 19% less compared with an unguided traveler. This condition results in a willingness to pay of about 1.2 €, i.e., a factor of 15 larger.
- Deploying guidance reduces the variance of travel time on the risky route, which also results in less uncertainty for the unguided users.

The model shows that the inclusion of risk aversion increases the willingness to pay for guidance compared with risk-neutral agents, even if the travel-time savings are of the same magnitude. This evaluation is crucial for the design of ATIS. It demonstrates the benefit for the user by not only reducing travel time but by reducing variability as well.

In that context, note that, in the simulation-based approach, the willingness to pay (economic benefit) directly comes from the individual agents. This condition makes it possible to differentiate the willingness to pay by attributes such as trip purpose or income. For a private-sector ATIS provider, this condition will help test certain market strategies and identify potential user groups, such as people with tight schedules, where ATIS will really make a difference. For a public-sector ATIS provider, this condition will help target parts of the system that yield high overall economic benefits. Finally, the deployed microsimulation-based approach quite naturally carries over to more complex scenarios, circumventing the difficulties of capturing such scenarios with closed-from mathematical equations.

References

[1] C. Chorus, E. Molin, and B. van Wee, "Use and effects of advanced traveler information services (ATIS): A review of the literature," *Transp. Rev.*, vol. 26, no. 2, pp. 127–149, Mar. 2006.

[2] C. Chorus, E. Molin, T. Arentze, S. Hoogendoorn, H. Timmermans, and B. van Wee, "Observing the making of travel choices under uncertainty and information: Validation of a travel simulator," presented at the Transp. Res. Board Annu. Meeting, Washington, DC, 2006.

[3] D. Levinson, "The value of advanced traveler information systems for route choice," *Transp. Res. Part C*, vol. 11, no. 1, pp. 75–87, Feb. 2003.

[4] E. Avineri and J. N. Prashker, "Sensitivity of travel time variability: Travelers' learning perspective," *Transp. Res. Part C*, vol. 13, no. 2, pp. 157–183, Apr. 2005.

[5] M. Yang, Y. Liu, and Z. You, "The reliability of travel time forecasting," *IEEE Trans. Intell. Transp. Syst.*, vol. 11, no. 1, pp. 162–171, Mar. 2010.

[6] B. Bartin and K. Ozbay, "Determining the optimal configuration of highway routes for real-time traffic information: A case study," *IEEE Trans. Intell. Transp. Syst.*, vol. 11, no. 1, pp. 225–231, Mar. 2010.

[7] R. Balakrishna, H. N. Koutsopoulos, M. Ben-Akiva, B. M. F. Ruiz, and M. Mehta, "Simulation-based evaluation of advanced traveler information systems," *Transp. Res. Rec.*, vol. 1910, pp. 90–98, 2005.

[8] F. Marchal and A. de Palma, "Measurement of uncertainty costs with dynamic traffic simulations," *Transp. Res. Rec.*, vol. 2085, pp. 67–75, 2008.

[9] M. A. Abdel-Aty, R. Kitamura, and P. P. Jovanis, "Using stated preference data for studying the effect of advanced traffic information on drivers' route choice," *Transp. Res. Part C*, vol. 5, no. 1, pp. 39–50, Feb. 1997.

[10] K. V. Katsikopoulos, Y. Duse-Anthony, D. L. Fisher, and S. A. Duffy, "The framing of drivers' route choices when travel time information is provided under varying degrees of cognitive load," *Hum. Factors*, vol. 42, no. 3, pp. 470–481, 2000.

[11] K. V. Katsikopoulos, Y. Duse-Anthony, D. L. Fisher, and S. A. Duffy, "Risk attitude reversals in drivers' route choice when range of travel time information is provided," *Hum. Factors*, vol. 44, no. 3, pp. 466–473, 2002.

[12] T. C. Lam and K. A. Small, "The value of time and reliability: Measurement from a value pricing experiment," *Transp. Res. Part E*, vol. 37, no. 2/3, pp. 231–251, Apr.–Jul. 2001.

[13] H. X. Liu, W. Recker, and A. Chen, "Uncovering the contribution of travel time reliability to dynamic route choice using real-time loop data," *Transp. Res. Part A*, vol. 38, no. 6, pp. 435–453, Jul. 2004.
[14] T. E. Knight, "An approach to the evaluation of changes in travel time unreliability: A 'safety margin' hypothesis," *Transportation*, vol. 3, no. 4, pp. 393–408, Dec. 1974.
[15] K. A. Small, "The scheduling of consumer activities: Work trips," *Amer. Econ. Rev.*, vol. 72, no. 3, pp. 467–479, Jun. 1982.
[16] R. B. Noland and K. A. Small, "Travel-time uncertainty, departure time choice, and the costs of morning commutes," *Transp. Res. Rec.*, vol. 1493, pp. 150–158, 1995.
[17] R. B. Noland and J. W. Polak, "Travel time variability: A review of theoretical and empirical issues," *Transp. Rev.*, vol. 22, no. 1, pp. 39–54, 2002.
[18] D. Ettema and H. Timmermans, "Costs of travel time uncertainty and benefits of travel time information: Conceptual model and numerical examples," *Transp. Res. Part C*, vol. 14, no. 5, pp. 335–350, Oct. 2006.
[19] A. de Palma and N. Picard, "Route-choice decision under travel time uncertainty," *Transp. Res. Part A*, vol. 39, no. 4, pp. 295–324, May 2005.
[20] J. L. W. V. Jensen, "Sur les fonctions convexes et les inégalités entre les valeurs moyennes," *Acta Math.*, vol. 30, no. 1, pp. 175–193, Dec. 1906.
[21] D. Bernoulli, "Exposition of a new theory on the measurement of risk," *Econometrica*, vol. 22, no. 1, pp. 23–36, Jan. 1954.
[22] J. von Neumann and O. Morgenstern, *Theory of Games and Economic Behavior*. Princeton, NJ: Princeton Univ. Press, 1944.
[23] D. Kahneman and A. Tversky, "Prospect theory: An analysis of decision under risk," *Econometrica*, vol. 47, no. 2, pp. 263–291, Mar. 1979.
[24] Jul. 2009. [Online]. Available: www.matsim.org
[25] M. Balmer, K. W. Axhausen, and K. Nagel, "A demand generation framework for large-scale micro simulations," presented at the Transp. Res. Board 85th Annu. Meeting, Washington, DC, 2006.
[26] N. Cetin, A. Burri, and K. Nagel, "A large-scale agent-based traffic microsimulation based on queue model," presented at the Transp. Res. Board Annu. Meeting, Washington, DC, 2003, Paper 03-4272.
[27] E. Cascetta, "A stochastic process approach to the analysis of temporal dynamics in transportation networks," *Transp. Res. Part B*, vol. 23, no. 1, pp. 1–17, 1989.
[28] K. Nagel and G. Flötteröd, "Agent-based traffic assignment: Going from trips to behavioral travelers," in *Proc. 12th Int. Conf. Travel Behav. Res.*, Jaipur, India, Dec. 2009.
[29] B. Raney and K. Nagel, "An improved framework for large-scale multiagent simulations of travel behavior," in *Towards Better Performing European Transportation Systems*, P. Rietveld, B. Jourquin, and K. Westin, Eds. Evanston, IL: Routledge, 2006, pp. 305–347.
[30] W. S. Vickrey, "Congestion theory and transport investment," *Amer. Econ. Rev.*, vol. 59, no. 2, pp. 251–260, May 1969.
[31] Y. Sheffi, *Urban Transportation Networks: Equilibrium Analysis With Mathematical Programming Methods*. Englewood Cliffs, NJ: Prentice-Hall, 1985.
[32] R. Arnott, A. de Palma, and R. Lindsey, "A structural model of peak-period congestion: A traffic bottleneck with elastic demand," *Amer. Econ. Rev.*, vol. 83, no. 1, pp. 161–179, Mar. 1993.
[33] D. H. van Amelsfort and M. C. Bliemer, "Valuation of uncertainty in travel time and arrival time: Some findings from a choice experiment," in *Proc. 45th Congr. Eur. Regional Sci. Assoc.*, 2005, pp. 1–24.