A model of risk-sensitive route-choice behaviour and the potential benefit of route guidance

J. Illenberger, G. Flötteröd, 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 travellers. We set up a simple two-routes scenario where travellers are repeatedly faced with risky route-choice decisions. The risk-averseness of the travellers is implicitly controlled through a generic utility function. We vary both the travellers' sensitivity towards risk and the equipment fraction with route guidance devices and show that the benefits of guided travellers increase with their sensitivity towards risk.**

I. Introduction

In recent years, much research has been conducted in the field of advanced traveller information systems (ATIS) [1]. Empirical insights have been gained from emerging applications of ATIS as well as from in-laboratory experiments [2], where the later have proven to be useful approaches to derive detailed behavioural models. Studies agree that the benefit of ATIS is the greatest in the case of non-recurrent congestion [3]. In such situations, congestion is usually caused by unpredictable external shocks (accidents, extreme weather conditions, 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 (for instance [8]) and none address the specific question on how ATIS can support users' decisions by reducing the costs of uncertainty only.

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

The remainder of this article is organised as follows. Section II discusses related work on decision-making under uncertainty and different levels of travel time reliability. In Sec. 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 Sec. IV, and the results of the simulation studies are presented in Sec. V. The paper is closed with a discussion in Sec. VI and a summary of the results in Sec. VII.

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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 behaviour. They also show that ATIS has the potential to help travellers 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 work. 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 travellers' behaviour, 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 the latter 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 is 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 intensively than the disutility caused by travel time of the same amount.

Existing behavioural models that account for travel time variability, both in terms of departure time choice as well as route choice, can be roughly grouped into three approaches: (i) the "safety-margin" approach, (ii) the "mean-variance" approach and (iii) models that make explicit use of a concave or convex utility function to represent risk-averse or risk-loving behaviour.

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

Another approach (corresponding to (ii)) is to capture 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 behaviour in that travellers would depart earlier or travel longer in order 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 it is the case in [15]. Ettema and Timmermans conclude that the provision of information leads to a significant reduction of scheduling costs, amounting up to one Euro per trip, whereas the quality of information and the misperception of the quality have only a minor effect.

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

The simulation study presented here continues the research by 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 being a random variable which 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 non-decreasing and strictly concave utility function, which means that the marginal utility of the utility is diminishing as z increases. The expected utility is $\langle U(z)\rangle = pU(z_1) + (1-p)U(z_2)$.

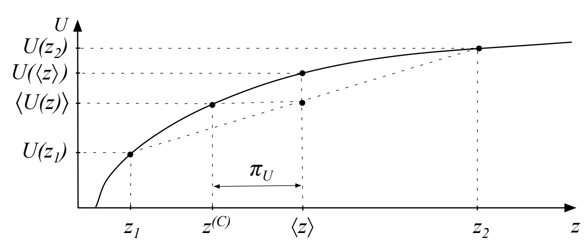

Figure 1. Expected utility theory with log utility function.

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

$$\begin{aligned}\langle U(z)\rangle &= pU(z_1) + (1-p)U(z_2)\\ &\le U(pz_1 + (1-p)\,z_2) = U(\langle z\rangle)\,. \quad (1)\end{aligned}$$

This represents the utility-decreasing aspect of risk-bearing. One can think of a player facing two lotteries. The risky lottery pays z_1 or z_2 with probabilities p and $1-p$ respectively, while 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 is what is captured in the inequality $\langle U(z)\rangle \le U(\langle z\rangle)$.

Consider now a third lottery which 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., $U\left(z^{(C)}\right) = \langle U(z)\rangle$. $z_U^{(C)}$ is known as the outcome of the certainty equivalent lottery, i.e., the sure-thing lottery which 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 lottery. The difference $\pi_U = \langle z\rangle - z_U^{(C)}$ is known as the risk-premium, i.e., the maximum amount of outcome a player is willing to forgo in order 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 define

- *Risk-Aversion* if $z_U^{(C)} < \langle z\rangle$, i.e., $U(z)$ is concave,
- *Risk-Neutrality* if $z_U^{(C)} = \langle z\rangle$, i.e., $U(z)$ is linear, and
- *Risk-Proclivity* if $z_U^{(C)} > \langle z\rangle$, i.e., $U(z)$ is convex.

The above concept dates back to the 18th century and has been mainly promoted by Daniel Bernoulli [21]. The ideas of Bernoulli have been intensively 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. Specifically, consider the random variable to be the uncertain travel time of a route. For the purpose of our studies, we model risk-aversion as shown in Fig. 2. The utility for travel is linear in time. The traveller has a desired arrival time or, equivalently, a maximum travel time budget. If she arrives late (exceeds her travel time budget), she incurs an extra penalty.

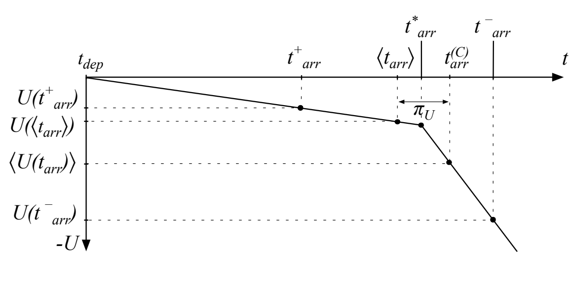

Figure 2. Utility function of a risk-averse traveller.

The following example clarifies the workings of this specification. Consider a driver travelling along a route with 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 in time. However, since 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 traveller is willing to "pay" in order to eliminate the risk. If the certain route is at $t_{arr,U}^{(C)}$, the traveller is indifferent between the two routes.

In the context of ATIS, the certainty equivalent $t_{arr,U}^{(C)}$ allows to capture the users' willingness-to-pay for such services. Consider a traffic management centre (TMC) that provides real-time traffic information to drivers, and the situation as described above 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. The MATSim framework

For the studies in this paper, we use the MATSim framework [24], [25], a fully agent-based transport simulation. The key aspects of MATSim can be summarised as follows: MATSim distinguishes between a physical and a mental layer. The physical layer comprises the simulation of the traffic flow, implemented as a queueing model with physical queues and spillback [26]. The mental layer handles the reasoning and decision making process, such as the choice of a route to travel. Decisions made in the mental layer are based on the feedback of the physical layer, 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 below. In the following sections, we first describe the simulation scenario and then discuss the details of the the behavioural 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:

- The safe route has a fixed capacity of 7200 vehicles per hour and a free-flow travel time of 435 seconds.
- 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 that reduces the capacity by a factor of 0.3. The free-flow travel time of the risky route is 327 seconds, which is less than the travel time of the safe route.

In the following, iterations where an incident occurs are referred as "bad days" or "bad states of nature", while iterations without incidents are referred 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 two options: travelling along the safe or the risky route. Both options are a priori known to the agent. In the following, the two options will be refereed as the "safe" and "risky" plan. Departure times are prescribed such that every second two agents enter the system, starting at 05:50. This means that without the capacity reduction of the risky route no congestion occurs even if all users take the same route.

C. Behavioural Model

The simulation of the mental layer comprises two steps: (i) updating the evaluation of the plan executed in the previous run of the physical layer and (ii) selection of a plan to be executed in the next run of the physical layer. We describe here only those aspects of the behavioural model that are relevant for the understanding of the presented study, more details can be found in [28], [29].

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

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

The utility for travelling is assumed to be linear in time:

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

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

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

where t_{arr}^{*} is the desired arrival time, t_{arr} 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 to risk, whereas $\beta_{late} = 0$ represents risk-neutral users. Risk-loving agents could be represented by choosing $\beta_{late} > 0$, but this 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 the experienced utility in iteration k, $\bar{U}_k$ its smoothed counterpart, and $0 < \alpha < 1$ the learning rate of the agents. The larger α, the more the agents update their utility perception in reaction to the most recent iteration.

Based upon 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 one that has been executed in the previous run of the physical layer) to the alternative plan:

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

where p_i is the selection probability of the currently selected plan, p_j the selection probability of the alternative plan, κ a non-negative parameter controlling explorative behaviour, γ a parameter controlling 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 plan respectively.

The above formula comprises two aspects: If κ is set to zero, Eq. 6 results in a logit model (stochastic user equilibrium, e.g., [31]) $p_i/p_j = \exp\left(2\gamma\left(U_i - U_j\right)\right)$. The non-negative 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 behavioural model. Increasing κ leads to less influence of the logit model, i.e., more explorative behaviour. Sufficiently high values for κ result in an equal distribution of the selection probabilities such that the risky and the safe plan 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 exists that an agent gets stuck with one plan only. If, for instance, the risky plans 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 plan 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 select the risky plan again, 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. One 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 it takes to process all vehicles currently on the route. The value of t_q is estimated based on standard queueing theory for a congested route with $t_q = \frac{n}{f}$ where n is the number of vehicles on the route (determined by counting in- 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 already on the route. This travel time estimate is consistent with workings of the deployed queueing simulation.

Travellers 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 travellers.

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}, denoting the penalty for being late, controls the risk-aversion of the agents. The values are varied form 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 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 would go beyond the scope of this paper. All remaining parameters are 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 behaviour, 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 distribute approximately equally 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 travellers use the safe route. As a consequence, the travel time on the risky route on bad days as well as the average travel time over good and bad days decreases. On the one hand, decreasing β_{late} pushes the system towards the safe route, but 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. Figure 3a 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, also the unguided agents benefit, which reduces the equipment gain to approximately 25 s at $f = 0.7$. This effect is due to the fact that on bad days the guided vehicles avoid the bottleneck, thus making it faster for the unguided vehicles. The utility (Fig. 3c) behaves qualitatively similar to Fig. 3a since travel time values are just multiplied with the marginal utility of travelling and there is no penalty for being late.

The picture for $\beta_{late} = -100$ €/h is similar to the one 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 (Fig. 3a). To 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 dynamics behind this are quite complicated:

- Initially, at a low equipment fraction, the risky route is used just up to capacity on bad days, since any increase of travel time over the safe route is heavily punished for the risk-averse users. This also means that the risky route is under-utilised 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 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 slower with increasing equipment fraction in the risk-averse system compared to 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 travellers, 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 (Fig. 3c). In the risk-averse system (Fig. 3d), the utility gain is much more pronounced (note the different scaling in Fig. 3c and 3d). 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 means that risk-sensitive users are willing to pay more for route guidance compared to risk-neutral users even if the effective travel time savings are of the same magnitude.

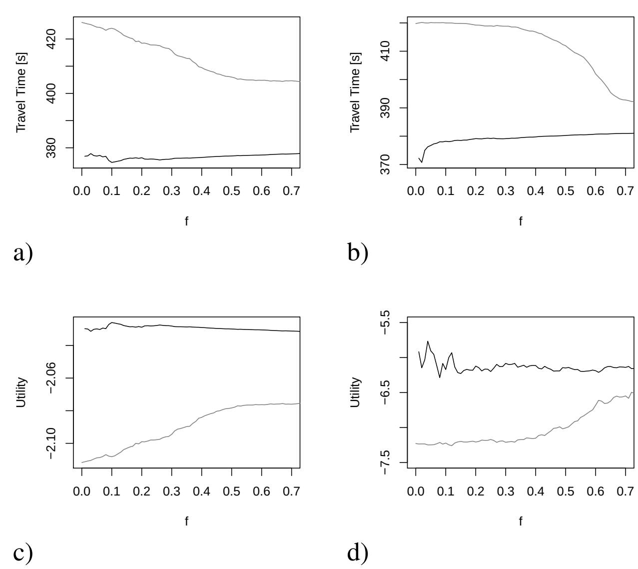

Figure 3. Travel time and utility for guided (black) and unguided (grey) agents. a) and c) $\beta_{late} = 0$ €/h, b) and d) $\beta_{late} = -100$ €/h.

VI. Discussion

The results of this simulation study show that risk-sensitive users exhibit a higher willingness-to-pay for route guidance compared to risk-neutral users. This may appear trivial since the utility is a function of β_{late}. However, it demonstrates that there is a substantial difference if one uses the objective travel time savings as an evaluation criteria or the individual utility-gain. Moreover, it shows the potential of the agent-based approach since it allows to distinguish between certain user groups, such as guided and unguided users, and allows 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 since they all use different approaches to monetarise the value-of-reliability or the risk-aversion of travellers. 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 saving in the extreme case of $\beta_{late} = -100$ €/h. In the literature, one finds 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 [33], or, as estimated by Small, Noland and Polak [15], [17], values that are on average about three times the cost of travel. If one uses $\beta_{late} = -18$ €/h ($\beta_{late} = 3 \cdot \beta_{trav} = 3 \cdot (-6\,€/\mathrm{h}) = -18$ €/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 (approx. 34 \$/h). These values are in the same magnitude as those estimates for the value-of-reliability 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 traveller who wants to catch an airplane.

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

VII. Summary

This paper presents simulation studies where travellers are repeatedly faced with risky route-choice decisions. The sensitivity of drivers towards 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 the paper, the following conclusions can be drawn:

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

The model shows that the inclusion of risk-aversion increases the willingness to pay for guidance compared to 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 end-user by not only reducing travel time but also by reducing variability.

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

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