Integration of Information Provision in Large-Scale Traffic Simulations

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1 Introduction

A potential benefit of Advanced Traveler Information Systems (ATIS) is the reduction of unexpected traffic delays. Non-recurrent congestion occurs haphazardly at any moment of the day. It may be a consequence of external changes in the demand for travel (special events, holidays, emergency evacuations, etc.) or in the capacities of the infrastructure (impact of weather conditions, accidents, road repairs, etc.). Several empirical studies such as [4, 6] point out that up to one third of the congestion in metropolitan areas is non-recurrent but figures can vary. The boundary between recurrent and non-recurrent congestion is somewhat blurred because they influence each other mutually. Indeed, if some incidents are well-known to occur frequently at about the same location and under given traffic conditions (e.g. delivery trucks blocking a lane), users may anticipate the corresponding delays and select another itinerary from the start, thereby causing congestion elsewhere on a regular basis. Conversely, non-recurrent congestion can also be induced by recurrent congestion. For instance, the probability of an accident on a road might increase with its traffic load.

ATIS are designed to alleviate non-recurrent congestion by providing users with information about travel conditions. The design and the evaluation of the implementation of these technologies has been made with traffic simulation models and with laboratory experiments in order to predict *ex ante* their ability to reduce congestion costs. Therefore, these models need to integrate consistently information provision and the behavioral perception of non-recurrent congestion. Most of the existing models that address these issues are focused on the evaluation of a set of ITS technologies such as Variable Message Signs (VMS). They often include an advanced microscopic traffic simulator and a behavioral model that describes users' reaction to information provision. The usual methodology is the following (see e.g. [2]):

- Start from a base case scenario given by a planning model.
- Generate time-dependent O-D flows (i.e. dynamic O-D matrix).
- Run the microscopic traffic simulation with a set of given incidents (e.g. road closures, accidents) without ATIS.
- Enable a set of given ATIS (e.g. VMS) and run the simulation again.
- Compare the performances with and without ATIS.

Consequently, the efficiency of the ATIS is evaluated for a particular time-dependent travel demand. It can be quite different from the long-term efficiency of the system because users will adapt their behavior and will depart at different hours, thus changing the demand patterns. The adaptation of drivers to ATIS depends on their compliance, which in turn depends on the validity of the provided information. The fixed point problem of consistent information provision has been addressed by [1]. We focus only on the adaptation to the occurrences of incidents. For instance, if users adapt to the most likely incidents by reducing the usage of unreliable itineraries, they increase the road usage of other routes. Obviously, incidents at a given location have then consequences on the upstream part of the network.

For these reasons, we propose to study the situation where users can react to the occurrences of incidents from one day to the next. We argue that models that aim for long-term evaluation of ATIS should comply with a minimum of three specifications: (1) the ability to simulate large-scale networks, (2) behavioral foundations and (3) explicit description of supply and demand in a time-dependent context. The first requirement stems from the fact that adjustments are global: drivers adapt their route and their departure time depending on the reliability of the different routes. Pre-trip decisions are made upstream well in advance and influence the traffic patterns at the metropolitan scale. Microscopic models often include sophisticated behavioral models. Unfortunately, they cannot cope with large-scale networks because of computational performances. In most cases, their application is limited to local subsystems such as corridors, major motorways intersections, etc. Similarly, most microscopic models have a fine-grained temporal scale for traffic dynamics but do not include the demand counterpart: within-day re-planning (i.e. route diversion) and departure time shift. Analytical models such as [5] can be adapted to take into account non-recurrent congestion by integrating probabilistic travel delays and risk aversion. However, their application is still limited to the traffic assignment on small networks with exogenous input flows. For these reasons, mesoscopic traffic models offer a good compromise to meet the requirements above.

2 Method

METROPOLIS [3] is a modular mesoscopic traffic model that features within-day as well as day-to-day dynamics. The traffic assignment module uses an event-based approach and simple congestion laws. Users are assumed to minimize a generalized cost which takes into account queuing costs as well as schedule delay costs. Users react to congestion by departing at a time that is compatible with their own schedule constraints and their willingness to incur congestion delays. METROPOLIS is based on the concept of user information which can be of three types:

- *historical* or *pre-trip* information is the users' perception of the traffic congestion from previous days,
- *instantaneous* information is acquired en-route and plays a role in the route choice: users perform direction choice at each intersection and can be diverted from their original paths due to changes in the information structure,
- *external* information consists of any information provided to the users exogenously by any devices or technology (ATIS, variable messages signs, radio broadcasts, etc.).

The day-to-day dynamics is modeled by a learning process which updates constantly the historical information based on the experienced traffic conditions using a Bayesian mechanism. We resort to simple heuristic laws. The historical information available to users on day $\omega + 1$ is the output of the learning process on day ω, that is, the accumulated knowledge of the ω previous days (i.e. a Markov process of order 1). For a given O-D pair, the expected travel time $E(\tau)$ when departing at time t_d on day $\omega + 1$ is computed as follows:

$$E^{\omega+1}\left(\tau\left(t_d\right)\right) = (1-\lambda)\, E^{\omega}\left(\tau\left(t_d\right)\right) + \lambda \tau^{\omega}\left(t_d\right)$$

Note that this process is considerably different from MSA (Moving Successive Average) since it does not converge necessarily. A typical value used in practice is $\lambda = 0.1$.

External information (ATIS) is not considered in this study but random incidents are generated every day. The introduction of incidents in an event-based model is straightforward. At the beginning of each day, a random number R is drawn for each link where a potential incident can happen. If $R < p$ then an incident happens on that link. The probability of occurrence p is the same for a selected subset of important links of the network (e.g. main arterials with more than two lanes) and $p = 0$ for the rest of the network. The incidents are characterized by a capacity drop of 50% that lasts for the whole morning peak. Simulations are run for a long period so that users can adapt to the stochastic travel conditions.

We assume that drivers are mostly risk averse and that the variability of travel conditions corresponds to a loss of utility. The Constant Absolute Risk Aversion (CARA) utility function is used: the utility of a journey with travel time τ is given by:

$$U_\theta\left(\tau\right) = \frac{1 - e^{\theta\tau}}{\theta}$$

where θ denotes the index of absolute risk aversion. The limit case $\theta \to 0$ corresponds to the risk neutral individual. The time compensation, denoted by χ, is defined as the amount of time that users are willing to spend in order to reduce the utility loss caused by uncertainty. That is, the travelers are indifferent between the stochastic system and a risk-free system with an average travel time $\langle\tau\rangle + \chi$:

$$U_\theta\left(\langle\tau\rangle + \chi\right) = E\left\{U_\theta\left(t\right)\right\}$$

3 Results

The first experiments are performed on a real-world example for the Paris area. The coded network consists of about $17,000$ links and more than $3,000,000$ individual trips are simulated for each morning period. Both commuting trips and non-commuting trips are simulated to take off-peak congestion into account. The incidents are introduced on the major roads of the area (i.e. roads with at least three lanes). Simulations are run for different probabilities of occurrence p ranking from 0 to 1. In each case, 50 iterations (days) are performed. The corresponding global indicators are reported in Tab. 1. The impacts are significant since each traveler uses on average at least one road section belonging to the major roads. Obviously, drivers arrive later than expected when the level of incidents increases. Note that the indicators show that the case $p = 0.5$ is slightly worse than the risk-free case $p = 1$, even if the average capacity of the overall system is higher.

Table 1: Impacts of non-recurrent congestion.

p	0	0.25	0.5	1
Travel cost [$]	7.6	11.3	12.0	11.9
Schedule delay cost [$]	2.2	3.2	3.4	3.3
Travel time [min.]	25.0	37.4	40.0	39.8
Change in consumer surplus [$]	0	-1.9	-2.3	-2.1
Congestion index [%]	28.9	55.4	60.8	65.0
Mileage [10^6km]	56.5	59.8	60.2	59.8
Early arrivals [%]	49.5	48.2	48.1	46.1
Late arrivals [%]	29.7	34.7	35.0	36.5

A second set of experiments is performed on the Sioux Falls network with $50,000$ individual trips. The compensation χ introduced above for travel *time* variability can be extended to the compensation of generalized travel *cost* variability. Generalized travel costs C_i are recorded for T =300 iterations The monetarization of uncertainty is computed as follows:

$$\chi_\theta = \frac{1}{\theta} \ln \left\{ \frac{1}{T} \sum_{i=1}^{i=T} e^{\theta C_i} \right\} - \frac{1}{T} \sum_{i=1}^{i=T} C_i$$

Incidents are introduced during the T iterations with same level of probability p. Several runs are performed for values of p ranking from 0 to 1. Fig. 1 presents the results of the evaluation of χ_θ as a function of the level of risk aversion θ. The range of θ is based on the results from an empirical survey conducted in the Paris area.

4 Conclusion

This study demonstrates that dynamic traffic simulations can be used to evaluate the cost of uncertainty corresponding to a given level of incidents. This evaluation is fundamental to the designers and managers of ATIS since it gives a benchmark of the potential benefit that can be expected with such technologies. The results confirm the intuition that in the extreme cases where incidents are very rare or very frequent, the potential for ATIS is very limited.

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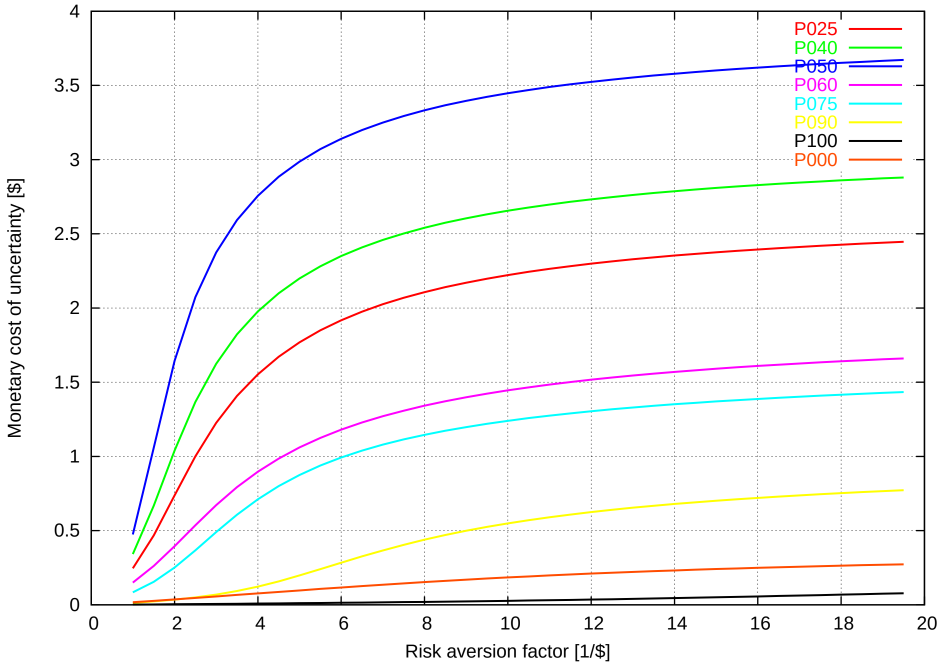
Figure 1: Monetarization of uncertainty. Measurements for different probability p of occurrence of incidents.



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