Simulating the Impacts of Risk-Averse Vehicle Navigations on Network Traffic Flow under Travel Time Uncertainty*

Daisuke FUKUDA†

Transport Studies Unit, Tokyo Institute of Technology, Japan

Jiangshan MA

Shenzhen Urban Transport Planning Center, China

Kaoru YAMADA

Oriental Consultants Global Co., Ltd., Japan

Norihito SHINKAI

Regional Futures Research Center Co., Ltd., Japan

March 31, 2017

1 Introduction

Most of standard commercial vehicle navigation systems usually rely on fixed travel times as link weights while sophisticated algorithms appropriately can deal with stochastic travel times. Reliable routing considering travel time uncertainty would have a potential of providing additional benefits to drivers.

The basic concept of hyperpath (HP) that can be regarded as one of the risk-averse vehicle navigations is that "Do not put all eggs in one basket in an uncertain environment" and so that the actual routes are widely distributed (Figure 1) as traffic congestion becomes severe. The risk of delay due to the induced congestions would become lower and the traffic congestions at network level would also expected to be reduced. Based on the idea of "Optimal strategy" that is widely employed in frequency-based transit assignment by Spiess and Florian [1], Bell [2] proposed the optimal hyperpath search algorithm called "Hyperstar". Variant of algorithms under various conditions are further developed in Bell et al. [3], Ma et al. [5] and Ma and Fukuda [6].

One of the benefits for HP-based vehicle navigation for the society would be that *knock-on effect* [7] or *hunting* [8] in network might be mitigated or eliminated when many drivers are recommended to routes spread across a set of paths. The hyperpath-based route recommendation thus would have the potential

*This is a revised and enhanced version of the following conference paper and book chapter: (1) Yamada, K., Ma, J. and Fukuda, D.: Simulation analysis of the market diffusion effects of risk-averse route guidance on network traffic, *Procedia Computer Science*, Vol. 19, 874–881; (2) Fukuda, D., Ma, J., Yamada, K. and Shinkai, N.: Tokyo: Simulating hyperpath-based vehicle navigations and its Impact on travel time reliability, In Horni, A., Nagel, K. and Axhausen, K. (eds.), *The Multi-Agent Transport Simulation MATSim*, London, Ubiquity Press.

†Corresponding Author, Email: fukuda@plan.cv.titech.ac.jp

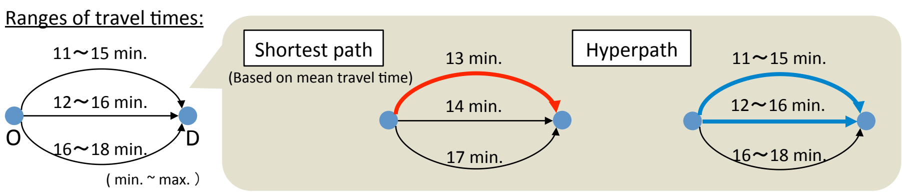

Figure 1: Concept of hyperpath under travel time uncertainty (1 OD – 3 routes example)

of reducing the congestion of the entire network because it might lead to the dispersion of vehicular traffic in an appropriate way. In this paper we examine how the market penetration of the hyperpath-based vehicle navigation would affect the entire network performances using MATSim (Horni et al. [4]).

2 Fundamental model of hyperpath-based navigation

Consider a network $G(I, A)$ where $I(|I| = n)$ and $A(|A| = m)$ denote the node and link sets, respectively. The travel time on a general link $a(i, j)$, is denoted by $\tau_a(t_i)$, where t_i is the arrival time at node i. Assume that $\tau_a(t_i)$ is bounded within $[\underline{\tau}_a(t_i), \overline{\tau}_a(t_i)]$, where the difference between $\underline{\tau}_a(t_i)$ and $\overline{\tau}_a(t_i)$ is the maximum delay when considering $\underline{\tau}_a(t_i)$ as the undelayed travel time. Given the origin r and the destination s, a traveler is supposed to form an *a priori* route plan over the travel time uncertainty.

Let us consider each intersection as a decision node. The drivers are supposed to make sequential link choices at each intersection with the strategy that minimizes the exposure to the maximum delay on the downstream links results in an inverse proportionality towards the maximum delay (Bell [2]):

$$P_{a|i} \equiv P_a \propto \frac{1}{\overline{\tau}_a(t_i) - \underline{\tau}_a(t_i)} \tag{1}$$

Then, the optimal strategy is described as minimization of the expected travel time by risk-averse drivers who fear the maximum delays on the adjacent downstream links. Because the distributions are unknown, the expected travel time is calculated based on subjective probabilities. The basic model can be established as a mathematical programming problem as follows:

$$\begin{aligned} &\min \sum_{a\in A} p_a \underline{\tau}_a(t_i) + \sum_{i\in I} p_i \tau_i(t_i) \\ &\text{s.t.} \begin{cases} \sum\limits_{a\in A_i^{+H}} P_a - \sum\limits_{a\in A_i^{-H}} P_a = \begin{cases} -1, & \text{if } i = s \\ 1, & \text{if } i = r \\ 0, & \text{others} \end{cases} \\ p_a = P_{a|i(a)} \cdot p_{i(a)}, \quad a \in A_i^{+H} \\ p_i = 1, \quad i \in \{r, s\} \end{cases} \end{aligned} \tag{2}$$

where t_i is the (anticipated) arrival time at node i, A_i^{+H} denotes the downstream attractive links of i involved in the optimal strategy, and $\tau_i(t_i)$ is the node traversal time against uncertainty using the average delay exposure to the maximum delays of the downstream links at a decision node i (Ma et al. [5]).

3 Day-to-Day Traffic Simulation

The basic structure of the simulation procedure is shown in Figure 2. Based on the network database and the traffic demand database, the main input files are created. A "network.xml" file contains information about network structure and attributes of each link in the network. A "plans.xml" file has information about daily action plan for each agent.

Dynamic network loading is then executed by using these input files and experienced travel times by agents are recorded for each link at each time slice. Based on the travel time information of the previous day, route recommendation of some part of drivers may be updated. Each agent can keep several plans and the plans for the next day is determined by the "plan selection strategy". Then, the dynamic network loading for the next day is executed by using the newly created plans. This procedure can be executed iteratively for several days. After each iteration, the file named "events.xml" and some other output files are created.

In this study, HP-based route recommendation is added as a new plan selection strategy together with the current strategy of choosing the shortest (single) path. For the implementation of hyperpath-based route recommendations, statistic maximum delay information for each link and time slice is required. This information is obtained from pre-simulations by using the same input data. Hyperpath algorithm is coded as an external route planning module in Python and the market share can be configured by setting the "ModuleProbability" item.

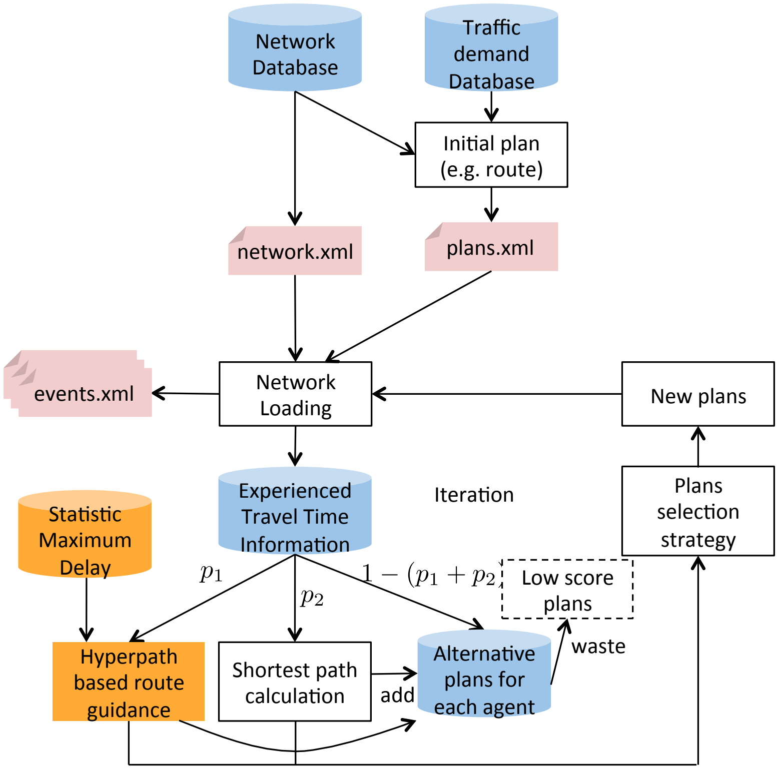

Figure 2: Simulation procedure with MATSim

4 Applications

4.1 A Sioux-Fall Network Case

We exogenously set the shares of each vehicle type (the one that follows HP-based navigation and the other one that follows shortest-path (SP) based navigation) and then conduct many simulation runs for traffic. In addition to the shares, four different total travel demand patterns are prepared by changing the number of agents and the dispersion of departure time (i.e. the standard deviation of departure times) as shown in Table 1.

For each case, 10 simulation runs are firstly executed without any HP-based route guidance drivers to obtain historical travel time distribution. Maximum delay in the last 5 days is then computed and used in the following main simulations with the market diffusion of HP-based navigated drivers. Figure 3 shows the network state (in terms of link speed) improvement with increase in the market share of HPs for 20% and 80%.

Figure 4 shows the fluctuation of network average travel time for 30 days simulation runs. Both average and standard deviation of travel times have the decreasing tendency when the share of HP-based route guidance is increased, which implies that the possibility that HP-based route guidance would be superior from the viewpoint of travel time saving and travel time reliability when seen the day-to-day patterns of average travel time particularly for large traffic demand (i.e. Case 4).

Table 1: Setting of some numbers for each case

	Case 1	Case 2	Case 3	Case 4
Number of agents (car drivers)	33,576	67,259	36,024	72,039
Average of departure time (at o'clock)	9:00	9:00	9:00	9:00
Standard deviation of departure time (in hour)	2	2	1	1

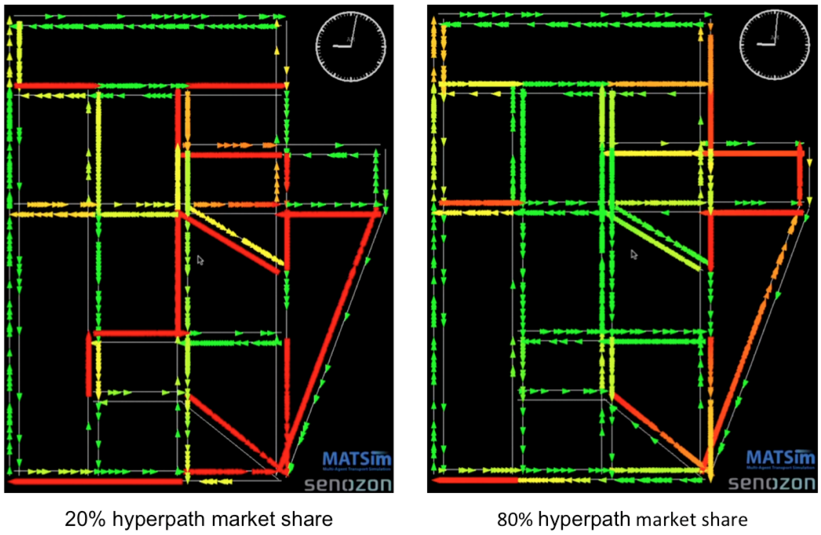

Figure 3: Link travel speeds for different levels of market penetrations (Case 4)

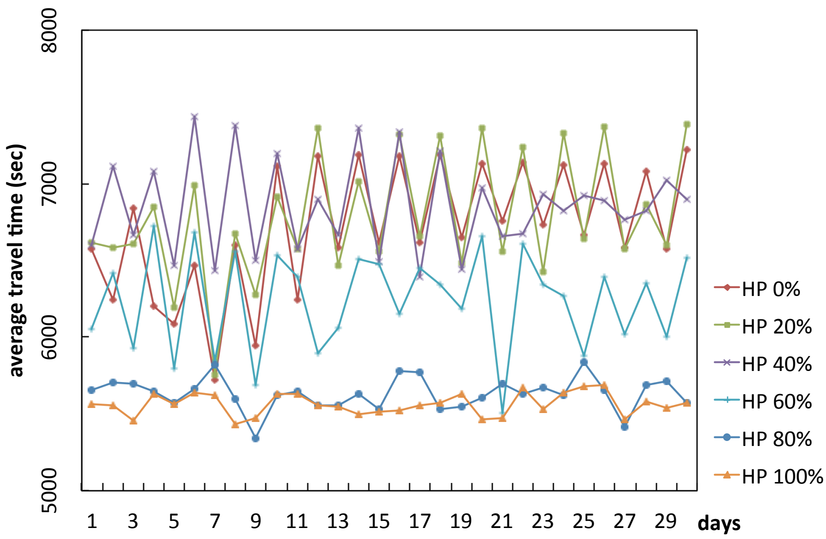

Figure 4: Variation of average travel time across 30 days for different levels of HP-based router diffusion

4.2 Tokyo's Arterial Case

We also analyze the simulation runs in Tokyo's large-scale arterial network with actual travel demand data. The target area is the traffic network of the downtown Tokyo which consists of 444,220 nodes and 177,971 links. We conduct five different cases of traffic simulations by changing the shares of HP-based drivers from 0% to 80% by 20%. The simulation runs are conducted for 30 days for each case to evaluate network-level travel-time savings as well as reliability.

The average travel time per unit length of the whole drivers for each day is plotted in Figure 5. There are high levels and large fluctuations in travel times particularly for the case where there are no HP-based drivers (HP = 0%, that is identical to SP = 100%).

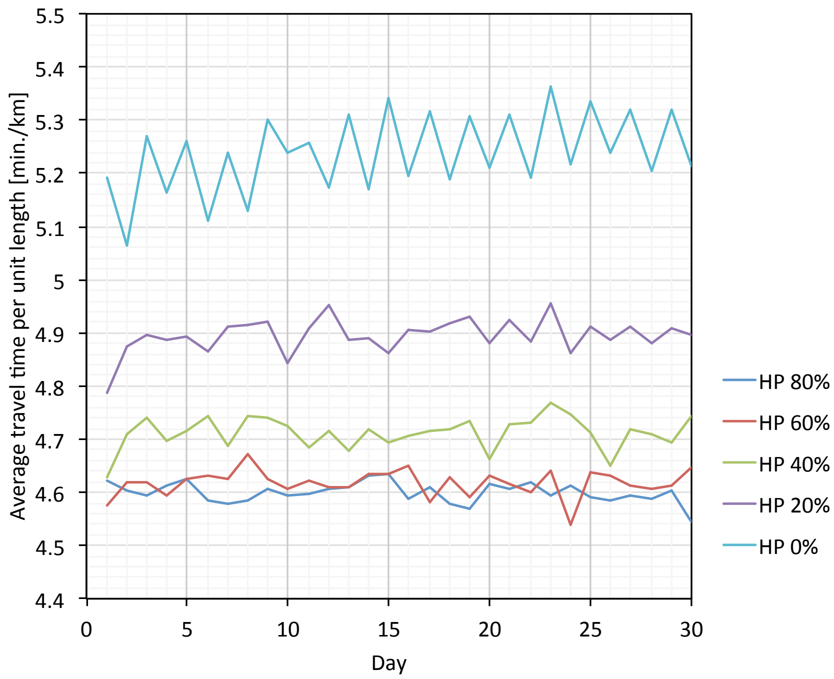

Figure 5: Average travel time per unit length for all vehicles

References

[1] Spiess, H. and Florian, M.: Optimal strategies: A new assignment model for transit networks, *Transportation Research Part B: Methodological*, Vol. 23 (2), 83–102, 1989

[2] Bell, M.G.H.: Hyperstar: A multi-path Astar algorithm for risk averse vehicle navigation, *Transportation Research Part B: Methodological*, Vol. 43 (1), 97–107, 2009.

[3] Bell, M.G.H., Trozzi, V., Hosseinloo, S.H., Gentile, G. and Fonzone, A.: Time-dependent hyperstar algorithm for robust vehicle navigation, *Transportation Research Part A: Policy and Practice*, Vol. 46 (5), 790–800, 2012.

[4] Horni, A., Nagel, K. and Axhausen, K. (eds.), *The Multi-Agent Transport Simulation MATSim*, London, Ubiquity Press, 2016.

[5] Ma, J., Fukuda, D. and Schmöcker, J.-D.: Faster hyperpath generating algorithms for vehicle navigation, *Transportmetrica*, Vol. 9 (10), 925–948, 2013.

[6] Ma, J. and Fukuda, D.: A hyperpath-based network generalized extreme-value model for route choice under uncertainties, *Transportation Research Part C: Emerging Technologies*, Vol. 59, 19–31, 2015.

[7] Park, K. and Bell, M. and Kaparias, I. and Bogenberger, K.: Learning user preferences of route choice behaviour for adaptive route guidance, *Intelligent Transport Systems, IET*, Vol. 1 (2), 159–166, 2009.

[8] Oguchi, T., Satoh, T, Katakura, M. and Shikata, S.: Analysis of traffic congestion and route choice behavior influenced by traffic information, *International Journal of ITS Research*, Vol. 1 (1), 75–82, 2003.