TRAVEL TIME RELIABILITY DURING EVACUATION: THE IMPACT OF HETEROGENEOUS DRIVING BEHAVIOR

Huizhao Tu [1], Adam J. Pel [2], Hao Li [1,*], Lijun Sun[1]

[1]) Tongji University
School of Transportation Engineering
Key Laboratory of Road and Traffic Engineering of the Ministry of Education
Shanghai, P. R. China

[2]) Delft University of Technology
Faculty of Civil Engineering and Geosciences
Department of Transport and Planning
Delft, The Netherlands

[*]) *Corresponding author*
Cao'an Road 4800, JiaDing District, 201804 Shanghai, P. R. China
Tel. +86 21 6958 0417, Fax. +86 21 6958 3810
Email: haolitj@tongji.edu.cn

Word count:

Words:		4380
Tables:	3 x 250 =	750
Figures:	3 x 250 =	750
Total:		**5880**

Submitted for presentation and publication for the 91st annual meeting of the Transportation Research Board, 22-26 January 2012

ABSTRACT

Earlier studies have shown that driving behavior differs strongly at emergency conditions and normal traffic conditions. In this paper, we continue on these findings by investigating how these differences in driving behavior have an impact on travel time reliability. In particular, we focus on the effect of (relatively strong) heterogeneity in the driving behavior. To this end, the microscopic simulation framework S-Paramics is adapted accordingly, and applied to the emergency evacuation network of the Dutch city of Almere. This experimental setup allows a structured and in-depth analysis of the relationship between a number of driving behavior parameters and the emergent travel time reliability. The main findings from this study are thus insightful and directly applicable for evacuation planning and management studies. For instance, it is found that although a reduction in drivers' mean time-headway and minimum gap acceptance typically improves the overall evacuation time, at the same time this yields less reliable travel times. Also, the reliability of travel times decreases over time resulting in (much) less reliable travel times for those travelers who depart later. And finally, in general, heterogeneity in driving behavior strongly reduces travel time reliability.

INTRODUCTION

Major traffic accidents, extreme weather conditions, and natural and man-made disasters are a few examples of exceptional events that have a relatively small probability of occurring, yet tend to have a very large impact on the functioning of the transportation system. At the same time, there is a societal dependency on the well-functioning of the transportation system, in particular during emergency situations such as an evacuation. This dependency is emphasized by, for instance, the evacuations preceding hurricanes Katrina and Rita in the U.S. in 2005. Such mass evacuations are becoming increasingly more difficult and resource-consuming as the population and urban development of hazard-prone regions grow faster than the road infrastructure capacity [1],[2]. Furthermore, the success of an evacuation strongly depends on many factors, such as amount of warning time, public preparedness and response time, information and instructions dissemination procedure, evacuation shelters and routes, traffic conditions, dynamic traffic management measures, etc. [3],[4]. This complexity in the underlying processes and the multitude of factors influencing these processes can be dealt with via a model-based approach. An evacuation simulation model is then used for the analysis and planning of a large-scale emergency evacuation [5].

Evacuation analyses generally focus on traffic dynamics and the effect of traffic control measures in order to locate possible bottlenecks and predict evacuation times. For an adequate analysis, the travel behavior and driving behavior of evacuees needs to be modeled with sufficient realism. Prior studies have found that this travel behavior and driving behavior of evacuees differs strongly between evacuation conditions and normal traffic conditions (for travel behavior, see [6], for driving behavior, see [7]). This has led to a number of studies on the impact of these differences. For example, at macroscopic level, Pel et al. [8] considers the effects of expected changes in travelers' departure time and route choice, and road capacities and free speeds. While, at microscopic level, Tu et al. [9],[10] considers the effects of expected changes in mean driving behavior (relating to aspects such as headway, acceleration, reaction time, etc.) and heterogeneity among drivers.

Cova and Johnson [11] show that evacuation travel times strongly differ as to the location of a household (i.e., near or far from the exit) as well as the aggregate departure timing and number of available exits. However, a key factor that has not yet received enough attention is the issue of travel time reliability. That is, how do these behavioral changes that are to be expected during an evacuation situation affect the reliability of travel times. One reason why this is important is that, empirical observations suggest that evacuees show a bias towards using familiar routes and motorways, and that this can be ascribed to the perception of these roads being more reliable [12]. For instance, this is supported by the studies by Dow and Cutter [13] and Lindell and Prater [14] reporting high traffic volumes on the interstate motorways in the evacuations preceding respectively hurricane Floyd and hurricane Katrina despite the availability of alternative routes using rural roads. Also, it has been experimentally shown that the appreciation of reliable travel times leads to travelers departing earlier [15], while at the same time such an early peaked travel demand may worsen traffic conditions and yield a longer overall evacuation time [8],[16]. Finally, apart from these behavioral aspects, travel time reliability is generally considered a prominent performance indicator for transport systems [15],[17].

This paper investigates how the expected changes in driving behavior during evacuation conditions impacts the travel time reliability. The results, main findings, and discussions provided here are thus valuable for (I) better understanding the relationship between (heterogeneous) driving behavior and travel time reliability, (II) hypothesizing the impacts of the former on the overall evacuation process, and (III) formulating general recommendations for evacuation planning and management studies regarding how to deal with travel time reliability aspects. To this end, first, the next section reviews a number of studies on driving behavior during evacuation and summarizes the expected differences compared to normal driving behavior. The third section then introduces an appropriate measure to quantify travel time reliability. This measure is used in the following analyses of the impact of evacuation-styled driving behavior on the evacuation times and the travel time reliability. The (quantitative) analyses are conducted on the case study describing the evacuation of the Dutch city of Almere. The final section then concludes with a number of important findings and research implications for future evacuation studies.

DRIVING BEHAVIOR DURING EVACUATION

There is general consensus that the behavior of drivers under mentally demanding and emergency conditions differs from that expressed in normal conditions. This is supported by experimental and empirical findings (e.g., [18]–[23]). Nevertheless, the quantitative changes in driving behavior that can be expected during an evacuation are still subject to debate. Hence, in this paper, we conduct a sensitivity analysis on a range of parameter values (around a parameter set calibrated on normal driving behavior) reflecting the range of expected behavioral changes that are reported in the literature. The latter are shown in Table 1, presenting the observed or assumed changes in a number of driving behavior parameters.

TABLE 1 Expected changes in driving behavior during exceptional events

Parameter	Hamdar and Mahmassani [19]	Hoogendoorn [20]	Knoop et al. [21]	Hoogendoorn et al. [22]	Goodwin [23]
Speed (mean)	+	+	-	-	-
Speed variations	+	+	0	+	+
Acceleration / braking	+			-/+	
Headways (mean)	-	-		+	
Headway variations			+/-		
Reaction time variations			+	0	

Note: + and - indicate increase and decrease, respectively, in parameter values. 0 indicates no significant change. All in comparison to normal driving behavior.

A note can be made here that the exceptional event that is considered varies among the reported studies, yet all have similarities with the driving conditions during an evacuation and hence help in hypothesizing the behavioral adaptations of evacuees. In the study by Hamdar and Mahmassani [19] drivers are expected to exhibit anxious behavior due to the mentally demanding conditions during an evacuation. This is presumed to lead to higher speeds, acceleration, and braking, more emergency braking and rubber-necking, larger speed variations due to a share of the drivers freezing or slowing down, smaller headways, and sudden lane changes. Hoogendoorn [20] argues for similar driving adaptations during evacuation conditions, basing the expected changes on earlier behavioral observations in pedestrian evacuation experiments. The studies by Knoop et al. [21] and Hoogendoorn et al. [22] consider the behavioral changes of drivers passing an incident location. Here, Knoop et al. [21] shows from empirical observations that distraction and anxiety result in larger variations in reaction time and lower speeds, yielding lower capacities. Also, no significant changes were found in speed variations and capacity variations. Interestingly, the variations in the headway distribution were found to both increase and decrease (also depending on the lane). Hoogendoorn et al. [22] uses driving simulator experiments to investigate these behavioral changes around incident locations, finding that mean speeds and acceleration decrease, while variations in the speed and braking rate increases. Also, reaction time remains similar and mean headways increase, while the sensitivity to changes in the headway and the speed of the predecessor also increase (i.e., there is a larger "magnitude of the response"). Finally, Goodwin [23] considers adverse weather conditions, observing lower speeds, yet larger speed variation, combined yielding lower road capacities.

In the following analyses, we focus on the adaptations in (variations in) drivers' speeds, time headways and minimum gap distance.

TRAVEL TIME RELIABILITY

In spite of its clear importance as a policy criterion and performance indicator, there is no consensus yet on how to define and operationalize the notion of travel time reliability [24]. Indeed many different definitions for travel time reliability exist, and equally many different quantifiable measures for travel time reliability in a transportation network or corridor have been proposed (for a recent overview, see [24],[25]). What these measures have in common is that, generally speaking, they all relate to properties of the (day-to-day or within-day) travel time distribution, and in particular to the shape of this distribution. That is, the wider (or longer-tailed) this distribution is, the more unreliable travel time is considered. A large number of studies has thus been carried out on fitting distribution functions onto observed travel time distributions. Most commonly found are the Gamma distribution [26],[27], lognormal distribution [27],[28], and Weibull distribution [29]. Recently, Pu [30] showed that four different typical shapes in travel time distributions corresponding to the situation of free flow conditions, the onset of congestion, congested conditions, and the dissolving of congestion (earlier identified by

Van Lint et al. [24]), can be adequately captured by the lognormal distribution. Hence, the lognormal distribution is also used here in this paper to fit the simulated travel time distributions.

The general formula for the probability density function of the lognormal distribution is

$$f(x)=\frac{\exp\left(\frac{-\ln^2\left[(x-\theta)/m\right]}{2\sigma^2}\right)}{(x-\theta)\sigma\sqrt{2\pi}} \qquad x\geq\theta;m,\sigma>0 \tag{1}$$

where σ is the shape parameter, θ is the location parameter, and m is the scale parameter.

As mentioned earlier, there are a large number of different quantifiable measures for travel time reliability. These measures include, for instance, the percentile travel time, standard deviation, coefficient of variation, percent variation, skewness, buffer index, planning time index, frequency of congestion, failure rate, travel time index, etc. Van Lint et al. [24] argue that the travel time distribution is often wide and (left) skewed, particularly during congestion, and therefore propose a robust percentile-based reliability measure, referred to as the skew statistic. The skew statistic, λ^{skew}, is the distance between the 90th and 50th percentile travel time proportional to the distance between 50th and 10th percentile travel time (see [24]):

$$\lambda^{\text{skew}}=\frac{TT_{90}-TT_{10}}{TT_{50}-TT_{10}} \tag{2}$$

Here, TT_x denotes the x-th percentile in the travel time distribution. Thus, a small skew statistic indicates reliable travel times, while a large skew statistic indicates unreliable travel times. This way, the skew statistic captures not only the variations of travel times, but also the skewness of the travel time distribution.

By combining Equations (1) and (2), the skew statistic for the lognormal function is given by (for derivation, see [30]):

$$\lambda^{\text{skew}}=\exp(1.282\sigma) \tag{3}$$

where σ is the shape parameter value of the lognormal-distributed travel times. This established skew statistic will be adopted in this paper as an indicator of evacuation travel time (un)reliability while analyzing the impact of evacuation-styled heterogeneous driving behavior.

EXPERIMENTAL SETUP AND CASE STUDY APPLICATION

In the remainder of this paper, we investigate the travel time reliability (measured by the skew statistic introduced in the previous section) in case of an evacuation. To this end, we apply the expected changes in driving behavior (based on empirical observations reported in the literature, and discussed earlier) in the setting of a sensitivity analysis on the corresponding model parameters, to a model which has been calibrated on normal driving behavior. The adapted model (using the S-Paramics micro-simulation software) is then applied to the case study describing the evacuation of the Dutch city of Almere.

In the following, the experimental setup of the sensitivity analyses is explained and the case study application is described, after which the results and findings are presented.

Experimental Setup

In the adapted S-Paramics evacuation traffic simulation, the model parameters describing driving behavior (under evacuation conditions) are systematically varied to test their impact. A base model using the calibrated default parameter settings (describing normal driving conditions), as listed in Table 2, is used for reference.

As discussed earlier, prior studies suggest that mean speeds and variations in speeds may increase under evacuation driving conditions, while headways decrease and variations in headways may either increase or decrease (where the factors on which this depends are not clearly understood yet). Therefore, the experimental setup chosen here jointly varies the corresponding model parameters. We assess a 10 %, 20 %, and 30 % reduction in the parameter values which represent mean driving behavior, and a 10 % increase and 10 % decrease in the corresponding variances which are the indicator of the heterogeneity in driving behavior. An overview of the scenarios is given in Table 3. Note that in the adapted S-Paramics Microscopic Simulation, the variations in mean time headway and in minimum gap distance are assumed to follow a normal distribution.

TABLE 2 S-Paramics default parameter settings (for reference base model)

Parameter	Mean	Variance
Speed limit		
- motorways	120 km/h	---
- provincial roads	80 or 100 km/h	---
- urban roads	50 km/h	---
Acceleration	2.5 m/s^2	---
Time headway	1 s	0.2s
Minimum gap	2 m	0.4m

TABLE 3 Changes in parameter settings for evacuation driving behavior scenarios

		Variance		
		110%	100%	90%
Mean	100%	0C	0B	0A
	90%	1C	1B	1A
	80%	2C	2B	2A
	70%	3C	3B	3A

Case Study Description

For the regions in The Netherlands where coastal and/or river flooding can be considered conceivable, the provincial safety departments are required to prepare evacuation plans and to take appropriate precautionary measures related to the possible threat of flooding. Part of this task is to design a traffic evacuation plan for a number of larger municipalities. One of the Dutch cities in need of such a plan is Almere. With a population exceeding 180,000 inhabitants, the municipality is one of the medium-sized cities in the western Randstad area.

Here we choose a setting in line with the evacuation plans currently developed by the municipality in preparation for possible flood evacuation. The evacuation scenario anticipates (a threat of) a levee breach near the city of Lelystad, northeast of the city of Almere. The evacuation plan prescribes a staged departure of the different city areas, using two dedicated evacuation routes and restricting lane usage in order to prevent the occurrence of conflicts at junctions and merges (otherwise possibly resulting in lower outflow capacities). The staged departure of city blocks is achieved by aggregating the 276 postal code zones into 90 origin zones, and applying (mobile) road barriers to ensure a prioritized departure. The zones closest to the evacuation exit points are then allowed to depart first, after which the next-closest zones, and so forth. Each zone has a specific evacuation route and exit point, depicted in Figure 1 by the red evacuation route using motorway A6 leaving the area to the southwest, or the blue evacuation route using motorway A27 leaving the area to the southeast. In total, the staged departure lasts 10 hours (as this proved optimal in an earlier study [16]), yielding an estimated evacuation time of between 10.5 and 11 hours.

The Almere network and accompanying evacuation plan are implemented in the adapted S-Paramics microscopic simulation model (for details on the S-Paramics software, see [31]). The simulated road network covers an area of approximately 15 by 15 km and includes all motorways, main arterials, and collector roads within and around the city, see Figure 1. The road network, including all junctions, roundabouts, priority rules, and traffic lights, has been calibrated on aggregated traffic counts collected under 'normal' traffic conditions.

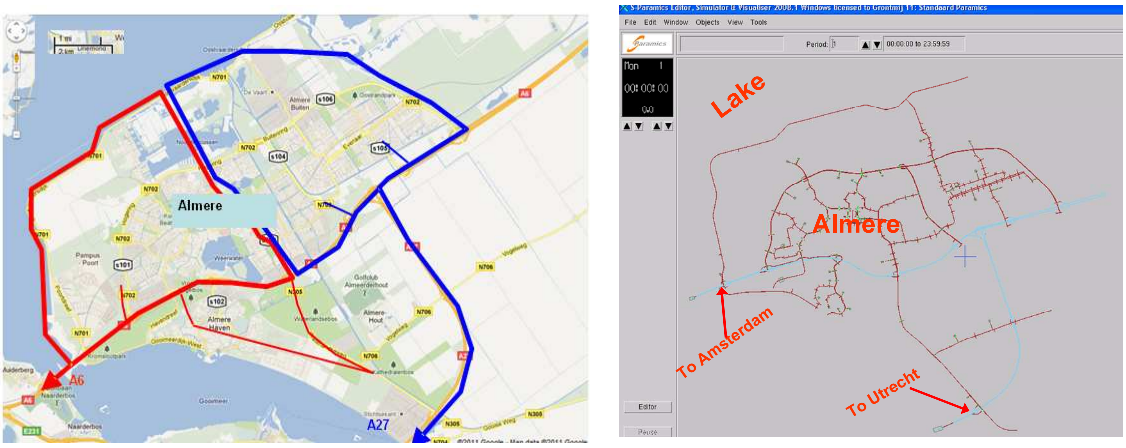

FIGURE 1 Almere evacuation network. Left: city map with main evacuation routes (source: Google Maps). Right: screenshot S-Paramics road network

Results and Findings

All twelve scenarios listed in Table 3 were simulated, where each scenario was run for 10 times so as to capture the stochasticity in the micro-simulations. Evacuees departing within the same time interval may experience different evacuation travel times, which directly forms a distribution of the experienced evacuation travel time for each departure time interval. Therefore, for each scenario, a lognormal distribution (following Equation (1)) was fitted to the individual evacuation travel times for all evacuees departing at a specific departure time interval within the staged 10 hour evacuation. The shape parameter value of the fitted lognormal functions was then used to compute the skew statistics reflecting the travel time reliability (following Equations (2), (3)). These skew statistics, representing the (evacuation) travel time unreliability, as a function of the departure time, are plotted for the various scenarios in Figures 2 and 3. Here, Figure 2 bundles the scenarios having the same mean parameter value, but different variances were tested, thus showing the impact of changes in heterogeneity. While Figure 3 bundles the scenarios having the same variance parameter value, but different mean values were tested, thus showing the impact of changes in overall average driving behavior.

Looking at the impact of heterogeneity of driving behavior (Figure 2), it is found that, generally speaking, a lower variation (scenarios 0/1/2/3A) yields more reliable travel times (as the values of skew statistic decreases are relatively lower), while a higher variation yields less reliable travel time as seen with scenarios 0/1/2/3C (as the values of skew statistic increases are relatively higher).

Also, the travel times on the evacuation routes tend to become more unreliable over time, resulting in (much) less reliable travel times for those travelers who depart later. This holds in particular for the situation in which time headways are shortest, as clearly observable from Figure 3 showing the impact of changes in mean driving behavior. Even further, it is noticed as well that the evacuation travel time unrealibility (i.e. the skew statistic value) starts to increase earlier (at about the evacuation time 5th or 6th hour) with the shorter mean headways than that (at about the evacuation time 8th or 9th hour) with the longer mean headways. All these are to be expected, since with short headways there is stronger driver interaction, in turn leading to more instable traffic flows, yielding a higher probability of traffic breakdown and a higher probability of earlier traffic breakdown in the network. Thereby it creates more variable (and hence less reliable) evacuation travel times and earlier start of the rise in the evacuation travel time unreliability.

Finally, interestingly, a reduction in drivers' mean time-headway and minimum gap acceptance is here shown to yield less reliable travel times, while in an earlier study [10] such a behavioral adaptation was shown to improve the overall evacuation time (note that these two observations may appear paradoxical, but are evidently not mutually exclusive).

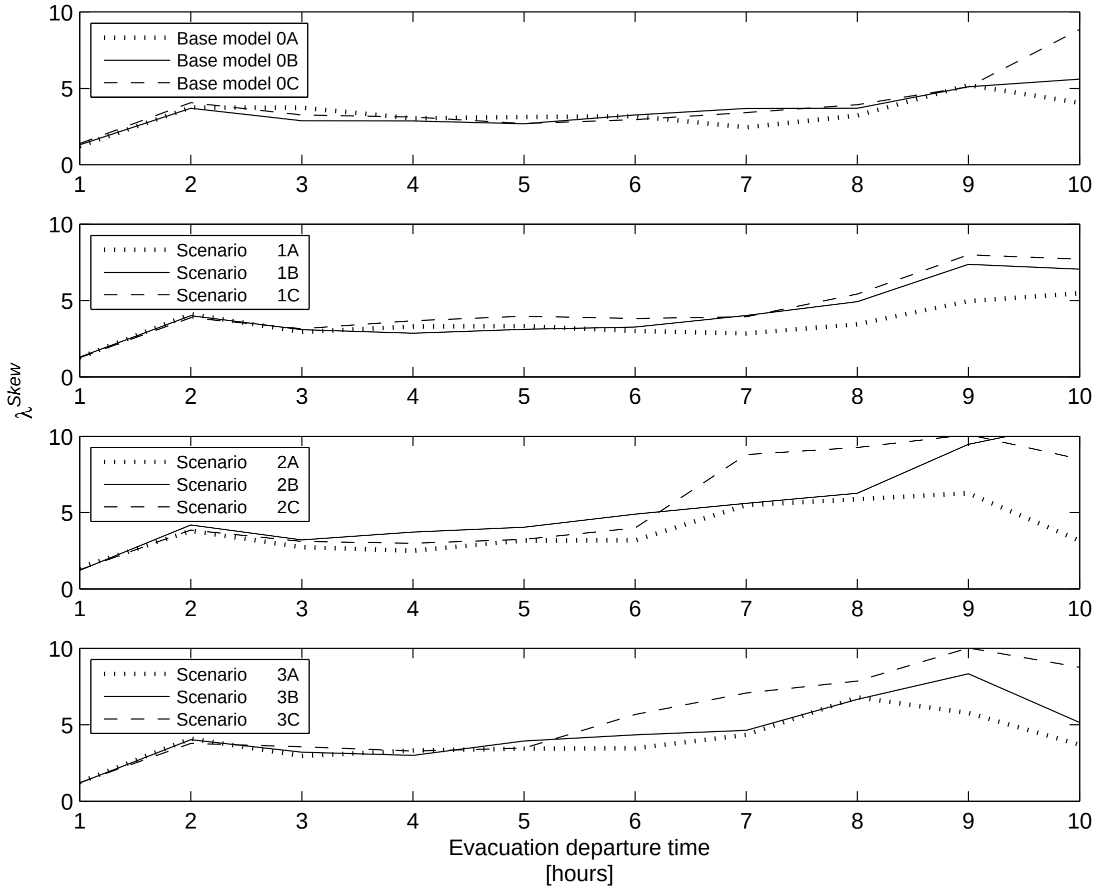

FIGURE 2 Travel time unreliability (skew statistic) over evacuation departure time; comparison of changes in *heterogeneity* of driving behavior

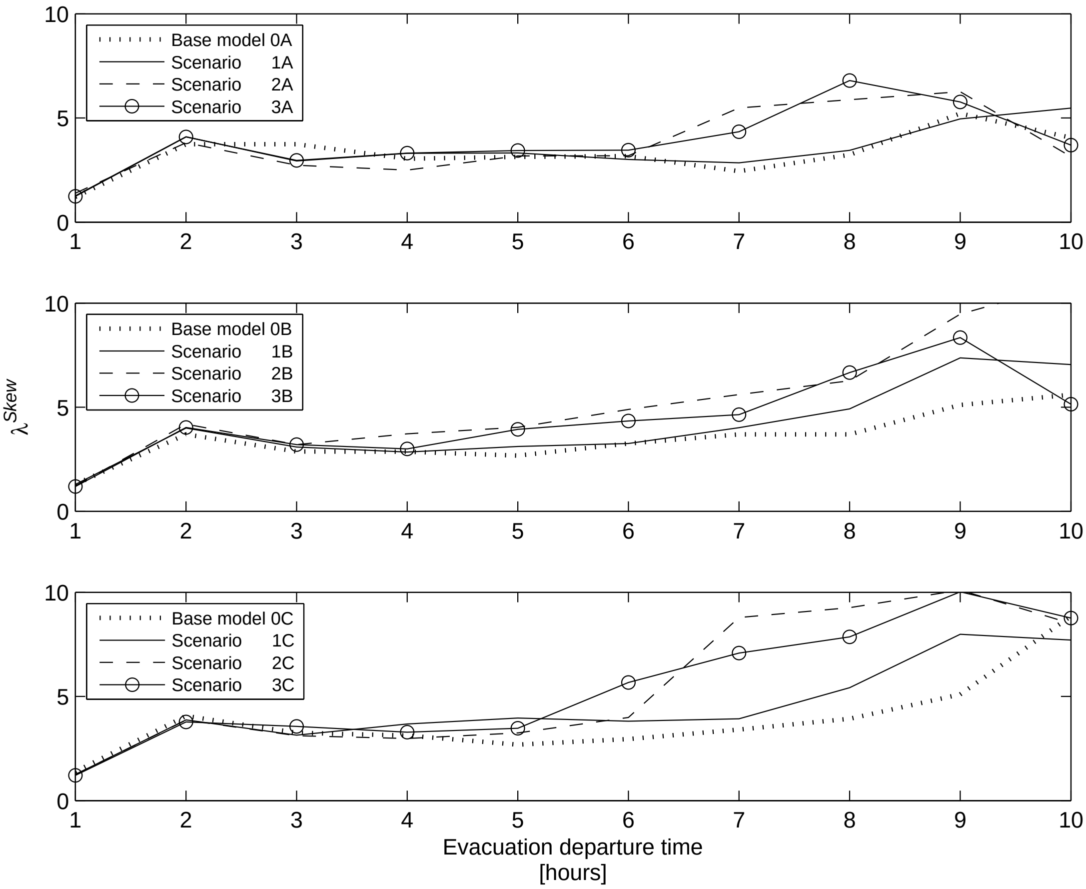

FIGURE 3 Travel time unreliability (skew statistic) over evacuation departure time; comparison of changes in *mean* driving behavior

CONCLUDING REMARKS

In this paper, we have shown how expected adaptations (as reported from empirical observations) in both mean driving behavior and the heterogeneity among drivers during evacuation conditions have an impact on the travel time reliability. The main findings from this study are thus insightful and directly applicable for evacuation planning and management studies.

First of all, it is found that although a reduction in drivers' mean time-headway and minimum gap acceptance typically improves the overall evacuation time, at the same time this yields less reliable travel times. This implies that anxious driving may indeed be beneficial for the evacuation process, yet worsens traffic conditions, and may also affect travelers' departure time and route choice decisions (not investigated here).

Second of all, shorter mean time-headways lead to a higher probability of earlier traffic breakdown in the network, thus resulting in a much earlier start of the rise in the evacuation travel time unreliability. It implies that more evacuees will experience more unreliable evacuation travel times and the overall service level from the reliability's perspective is then decreased.

Third of all, the reliability of travel times decreases over time resulting in (much) less reliable travel times for those travelers who depart later. This is expected to lead to more evacuees departing earlier on, which may yield a more peaked travel demand and as a consequence slow down the evacuation process.

And finally, in general, heterogeneity in driving behavior strongly increases travel time unreliability. It is therefore recommended to investigate the benefit of deploying traffic control mechanisms which aim at regulating the traffic flow and suppressing otherwise strong variations in drivers' speeds and headways.

ACKNOWLEDGEMENTS

This study has been supported by Shanghai Science and Technology Committee and Grontmij Nederland BV. The contents of the paper reflect the views of the authors who are responsible for the correctness and accuracy of the data presented.

REFERENCES

1. Plowman, T. Danger! Hurricane coming. *Planning* Vol. 67(12), 2001, pp. 16-21
2. Barrett, B., B. Ran and R. Pillai. Developing a Dynamic Traffic Management Modelling Framework for Hurricane Evacuation. *Transportation Research Record* Vol. 1733, 2000, pp. 115-121
3. Dash, N. and H. Gladwin. Evacuation Decision Making and Behavioral Responses: Individual and Household. *Natural Hazards Review* Vol. 8(3), 2007, pp. 69-77
4. Lindell, M.K. and C.S. Prater. Critical Behavioral Assumptions in Evacuation Time Estimate Analysis for Private Vehicles: Examples from Hurricane Research and Planning. *Journal of Urban Planning and Development* Vol. 133(1), 2007, pp. 18-29
5. Pel A.J. *Transportation Modelling for Regional Evacuations*. Doctoral dissertation, Delft University of Technology, Delft, The Netherlands, 2011
6. Pel, A.J., M.C.J. Bliemer and S.P. Hoogendoorn. A Review on Travel Behaviour Modelling in Dynamic Traffic Simulation Models for Evacuations. *Transportation* (in press – published online 28 January 2011, doi: 10.1007/s11116-011-9320-6)
7. Wolshon, B. Empirical Characterization of Mass Evacuation Traffic Flow. *Transportation Research Record* Vol. 2041, 2008, pp. 38-48
8. Pel, A.J., S.P. Hoogendoorn and M.C.J. Bliemer. Impact of Variations in Travel Demand and Network Supply Factors for Evacuation Studies. *Transportation Research Record* Vol. 2196, 2010, pp. 45-55
9. Tu, H., G. Tamminga, H. Drolenga, J. De Wit and W. Van der Berg. Evacuation Plan of the City of Almere: Simulating the Impact of Driving Behaviors on Evacuation Clearance Time. In S.P. Hoogendoorn, A.J. Pel, M.A.P. Taylor and H. Mahmassani (eds.) *1st International Conference on Evacuation Modeling and Management*, *Elsevier Procedia Engineering* Vol. 3, 2010, pp. 67-75
10. Tu, H., G. Tamminga, A.J. Pel and H. Drolenga. Sensitivity Analysis on Heterogeneity of Driving Behavior for Evacuation Studies and its Impacts on Traffic

Safety. *Proceedings of 13th IEEE Intelligent Transportation Systems Conference*, Madeira, Portugal, 2010

11. Cova, T.J. and J.P. Johnson. Microsimulation of Neighborhood Evacuations in the Urban-Wildland Interface. *Environment and Planning A* Vol. 34, 2002, pp. 2211-2229
12. Chiu, Y.C. and P.B. Mirchandani. Online Behavior-robust Feedback Information Routing Strategy for Mass Evacuation. *IEEE Transactions on Intelligent Transportation Systems* Vol. 9(2), 2008, pp. 264-274
13. Dow, K. and S.L. Cutter. Emerging Hurricane Evacuation Issues: Hurricane Floyd and South Carolina. *Natural Hazards Review* Vol. 3(1), 2002, pp. 12-18
14. Lindell, M.K. and C.S. Prater. Evacuation from Hurricane Katrina: Jefferson and St. Charles parishes. *Proceedings of National Hurricane Conference*, Orlando, FL, United States, 2006
15. Li, H., M.C.J. Bliemer and P.H.L. Bovy. Strategic Departure Time Choice in a Bottleneck with Stochastic Capacities. *Transportation Research Record* Vol. 2091, 2009, pp. 61-69
16. Tamminga, G., H. Tu, W. Daamen and S.P. Hoogendoorn. Influence of Departure Time Spans and corresponding Network Performance on Evacuation Time by Simulating Scenarios for the City of Almere, The Netherlands. *Proceedings of 90th Annual Meeting of the Transportation Research Board*, Washington DC, United States, 2011
17. Fosgereau, M. and A. Karlstrom. The Value of Reliability. *Transportation Research Part B: Methodological* Vol. 44(1), 2010, pp. 38-49
18. Ni, D. Challenges and Strategies of Transportation Modeling and Simulation under Extreme Conditions. *International Journal of Emergency Management*, 2006
19. Hamdar, S.H. and H. Mahmassani. From Existing Accident-free Car-following Models to Colliding Vehicles: Exploration and Assessment. *Transportation Research Record* Vol. 2088, 2008, pp. 45-56
20. Hoogendoorn, R.G. *State-of-the-art Driving Theory and Modeling in case of Adverse Conditions*. Internal report, Delft University of Technology, Delft, The Netherlands, 2010
21. Knoop, V.L., H.J. Van Zuylen and S.P. Hoogendoorn. Microscopic Traffic Behaviour near Accidents. In W.H.K. Lam, S.C. Wong and H.K. Lo (eds.) *Proceedings of the 18th International Symposium of Transportation and Traffic Theory*, Hong Kong, China. Springer, New York, United States, 2009, pp. 75-97
22. Hoogendoorn, R.G., S.P. Hoogendoorn, K. Brookhuis and W. Daamen. Mental Workload, Longitudinal Driving Behavior and adequacy of Car Following Models in case of Incidents in the Other Driving Lane. *Transportation Research Record* Vol. 2188, 2010, pp. 64-73
23. Goodwin, L. *Weather Impacts on Arterial Traffic Flow*. Technical Report, Mitretek Systems Inc., Falls Church, United States, 2004
24. Van Lint, J.W.C., H.J. Van Zuylen and H. Tu. Travel Time Unreliability on Freeways: Why Measures based on Variance tell only half the Story. *Transportation Research Part A: Policy and Practice* Vol. 42, 2008, pp. 258-277
25. Tu, H. *Monitoring Travel Time Reliability on Freeways*. Doctoral dissertation, Delft University of Technology, Delft, The Netherlands, 2008

26. Polus, A. A Study of Travel Time and Reliability on Arterial Routes. *Transportation* Vol. 8, 1979, pp. 141-151
27. Herman, R. and T. Lam. Trip Time Characteristics of Journeys to and from Work. In D.J. Buckley (ed.) *Proceedings of the 5th International Symposium of Transportation and Traffic Theory*, Sydney, Australia. Springer, New York, United States, 1974, pp. 57-85
28. Richardson, A.J. and M.A.P. Taylor. Travel Time Variability on Commuter Journeys. *High Speed Ground Transportation Journal* Vol. 6, 1978, pp. 77-79
29. Al-Deek, H. and E.B. Emam. New Methodology for Estimating Reliability in Transportation Networks with Degraded Link Capacities. *Journal of Intelligent Transportation Systems* Vol. 10, 2006, pp. 117-129
30. Pu, W. Analytic Relationships between Travel Time Reliability Measures. *Proceedings of 89th Annual Meeting of the Transportation Research Board*, Washington DC, United States, 2010
31. Druitt, S. An Introduction to Microsimulation. *Traffic Engineering and Control* Vol. 39(9), 1998, pp. 480-483