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MACROSCOPIC TRAVEL TIME RELIABILITY DIAGRAMS FOR FREEWAY NETWORKS

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ABSTRACT

Travel time reliability is considered to be one of the key indicators of transport system performances. The knowledge on the mechanisms of travel time unreliability enables the derivation of explanatory models with which travel time reliability could be predicted and utilized in traffic management. Inspired by the Macroscopic Fundamental Diagram (MFD), describing the relationship between production (average flow completing their trips) and vehicle accumulation (average density) in a traffic network, this paper investigates a so-called Macroscopic travel time (un)Reliability Diagram (MRD), relating the travel time (un)reliability to the network accumulation. The potential of the MFD relation lies in the fact that it characterizes the state of an entire traffic network with just two (production, accumulation) or three (adding spatial variability of accumulation) state variables. Likewise, the MRD describes the network travel time reliability as a function of just one independent state variable (network accumulation). Empirical analyses are performed to investigate the variability in MFD as seen in scatters and to show the travel time (un)reliability in relation to the network accumulations. Traffic data from Dutch freeway networks are employed to facilitate the analyses. It is found with the MRD on different freeway networks that a critical travel time (un)reliability accumulation exists, below which network accumulation has little or even no impacts on travel time (un)reliability and above which the accumulation has significant impacts on travel time (un)reliability. It is also found that the critical travel time (un)reliability accumulation is in general lower than the critical MFD accumulation. These findings provides insights for the road authorities in how to make tradeoffs between the maximum production and the travel time reliability in traffic management.

INTRODUCTION

Travel time reliability is considered to be one of the key indicators for the performance of transport systems[1, 2]. The increased attention for travel time reliability in the past decade has inspired many research efforts in this subject (e.g.[3-12]). Travel time reliability has significant impacts on travelers' mode, route and departure time choice decisions, particularly for trips, such as journey-to-work, of which time constraints (e.g. arrival time) may impose significant penalties to an individual[3, 7]. Yet, travel time is random in nature and the unreliability of travel time is hardly predictable. Understanding the causal relationships between travel time reliability and, for example, demand or supply characteristics allows one to derive explanatory models with which travel time (un)reliability can be predicted and become an integral part in traffic planning and design. Looking at the causes of travel time (un)reliability[8], a rough distinction can be made into two categories which both can cause a breakdown: demand variation and supply (capacity) variation. However, a key question is which causes of travel time (un)reliability can be identified and how can these be used to derive explanatory models with which travel time reliability can be predicted. A few studies have been conducted to investigate the factors affecting travel time reliability (e.g.[6, 9, 12]). Tu et al.[12], for example, investigated the impact of traffic flow on travel time reliability using risk assessment techniques and found that the critical travel time reliability flow is much lower than the capacity. The main drawback to use flow is that the flow is a local measurement of freeway networks, which can not reflect the overall traffic state of the freeway network and its relation with travel time (un)reliability. Thus, there is a need to investigate the relationship between travel time (un)reliability and network traffic state, such that it could be used for network management and traffic controls aiming to optimizing network travel time reliability.

In the past few years the macroscopic fundamental diagram (MFD) has become an important tool to evaluate the overall network performance[13], which describes the network production (average flow out of the network) as a (concave) function of the network accumulation (the amount of vehicles present in the network). Inspired by the MFD, this paper proposes a similar approach that describes travel time (un)reliability on a network as a function of network accumulation. The results, main findings, and discussions provided here may be valuable for (I) better understanding the macroscopic diagram between freeway network accumulation and network travel time (un)reliability, and (II) formulating general recommendations for traffic management of freeway networks. To this end, the next section firstly reviews a number of studies on travel time reliability measures and on causes of travel time (un)reliability. The third section then summarizes the research on the MFD and proposes Macroscopic travel time (un)Reliability Diagram (MRD) to reflect the relationship between travel time (un)reliability and the overall traffic state of freeway networks. The fourth section describes the empirical analyses on MRD, which are conducted using the data of Dutch freeway networks. The final section then concludes with a number of findings and research implications for future travel time reliability studies.

TRAVEL TIME RELIABILITY

Travel Time Reliability Measures

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[8]. Indeed many different definitions[14] 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[8, 15]). In most cases, travel time reliability is defined as some function or metric derived from the distribution of travel time. 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[16, 17], lognormal distribution[17, 18], and Weibull distribution[19]. In Susilawati et al.[20] a Burr Type XII distribution for travel time variability is proposed on urban roads. Pu[21] 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 (these were identified earlier by Van Lint et al.[8]) can be adequately captured by the lognormal distribution. There are a large number of different quantifiable measures for travel time reliability, which could be derived from either estimated or actually measured travel time distributions. These measures include, 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. What these measures have in common is that, in general, they all relate to properties of the (day-to-day or within-day) travel time distributions, and particularly to the shape of the distribution. That is, the wider (or longer-tailed) this distribution is, the more unreliable travel time is considered. One of the key problems is that these measures are highly inconsistent. In Van Lint et al.[8], for example, this inconsistency is demonstrated with a selection of 8 commonly used indicators for travel time reliability applied to a large database of real data. The consequence of this inconsistency is that policy evaluations may use different reliability metrics rather than commonly accepted assessment criteria. This may lead to ambiguous evaluations, but also to a fundamental difficulty in using such (inconsistent) travel time unreliability measures in ex ante studies as a means to choose between planning and design alternatives.

Recently, Tu et al.[12] proposed a new travel time reliability measure, in which the travel time reliability of a trip does not just depend on the uncertainty (variability) of travel times, but also on the instability of travel times (i.e. the instability of the prevailing traffic conditions). On the basis of a large empirical dataset, they established a novel travel time reliability model for freeways using risk assessment techniques by synthesizing both reliability concepts (uncertainty and instability). Traffic breakdown, the indicator of the instability of travel times, is treated as the risk, whereas travel time variability, the indicator of the uncertainty of travel times, is considered as the consequence of this risk. Thereby, the travel time unreliability is the sum of the products of the consequences (i.e. variability) and the corresponding probabilities of breakdown. The same measure of travel time reliability will be used in this paper.

Causes of Travel Time (Un)Reliability

Recent literature show various opinions on factors that should be considered the main driving forces behind travel time variability (or unreliability). These studies are either simulation-based or based on real data. Nicholson and Du[22] show by means of a static network equilibrium model that travel time variability is proportional to both capacity and inflow variability. For a given (fixed) link capacity, the variability in link travel time is due to link flow variation, while for a given (fixed) link flow, the variability in link travel time is due to variation in the link capacity. They note that travel time variability, in reality, can arise from both sources, and that it is not always an easy matter to identify the separate effects of flow and capacity variations. Chen et al.[23] define travel time reliability in terms of the probability a trip can be made within a particular time and assume stochastic link capacities, which are uniformly distributed between some upper and a lower bound value. On a small test network they use Monte Carlo methods and again (static) network equilibrium methods to analyze amongst other things the sensitivity of travel time reliability to fluctuations in link capacities. They conclude that travel time reliability decreases as the demand level increases, which "is no surprise since traffic congestion grows as a result of higher demand". Chen et al.[23] also show that the sensitivity of path travel time reliability to individual link capacity fluctuations differs largely. Capacity variations on one link may have a huge impact on path travel time variability, while capacity variations on other links may not affect travel time reliability more than marginally. In a slightly different fashion, using analytical techniques instead of Monte Carlo methods, Clark and Watling[4] evaluated a small network under stochastic demand and degrading link capacities. Also they find that network travel time reliability decreases as capacity decreases for a given demand level.

Causes of travel time reliability have also been investigated based on empirical data. For example, Kwon et al.[9] use an empirical, data-driven method to quantify the contribution of various factors (e.g. traffic incidents, weather, work zones, special events, bottleneck) on the travel time reliability. They concluded that traffic accidents contributed 15.1% during AM and 25.5% during PM, among others, and most of the remaining reliability came from the recurrent bottlenecks. Tu et al.[6] define three traffic regimes by two so-called critical inflows (critical transition inflow and critical capacity inflow, which are both lower than capacity): fluent traffic, transition traffic and capacity traffic. On the basis of a large empirical dataset, we investigate the relationship between flow and travel time reliability and conclude that travel time variability is hardly related to the variability of flow in the fluent traffic and capacity traffic (hyper-congested regime), whereas it is positively correlated with flow variability in transition traffic. However, inflow used in our earlier work[6] exclusively denotes vehicles entering the studied freeway section at the upstream entry of the main carriageway, which does not include the flow of on- of off-ramps along the roadway section. Therefore, inflow can not reflect the overall traffic state of freeway networks. In this context, a traffic state indicator of freeway networks needs to be introduced, with which its relationship to travel time (un)reliability can be studied.

MACROSCOPIC FUNDAMENTAL DIAGRAMS

Our idea on MRD is stimulated by the well-known Macroscopic Fundamental Diagrams (MFD)[13, 24, 25]. Furthermore, we explore the variability in MFD, which relates to our travel time (un)reliability. Thus, this section provides an overview on MFD which is the basis of our MRD. MFD describes structural relationships between production and accumulation in a traffic network, indicating a deterioration of network performance when the accumulation of traffic exceeds a certain threshold. The accumulation is the number of vehicles in the network. Geroliminis and Daganzo[24, 26] have proven that MFD exist in urban networks, revealing the relation between the average flow and accumulation in the network, as well as a correlation between the average flow and the outflow of the network. The outflow is also called trip completion rate, reflecting the rate at which trips reach their destinations. Whereas a conventional link fundamental diagram relates local flow to density, the MFD can be understood as an average link fundamental diagram over an entire network which implies that the relationship represented by the MFD also incorporates route choice behavior (network dynamics). When only a few vehicles use the network, the network is in a free flow state, the outflow is low and it is almost proportional to the amount of vehicles traveling in this network. With the increase of the number of vehicles, the outflow rises up to a maximum. Like the critical density in a link fundamental diagram, the value of corresponding critical accumulation when maximum outflow is reached is also an important parameter. As the number of vehicles further increases, the production now no longer increases due to the capacity drop and spillback effects. If vehicles continue to enter the network, this will result in a network state where vehicles block each other and the outflow actually decreases. Hence, macroscopic feedback control strategies were introduced with the aim to keep accumulation at a level at which outflow is maximized for areas with high density of destination[27]. Geroliminis and Daganzo[24] further showed the existence of MFD using real data collected from Yokohama, the second biggest city in Japan, under the assumption that the collected data is homogenous in terms of congestion occurrence.

Jiyang et al.[28] have researched on impact factors that influence the shape of MFD using a microscopic simulation model. Focusing on the MFD for the freeway area, the causes for scatters and changes in the MFD have been investigated. Ramp-metering has a direct impact on the shape of MFD. It is found that the uneven onset and resolving of congestion is the direct reason for scatters, which is consistent to the one of Daganzo’s[29]. The rapidly changing traffic demand drastically affects the shape of MFD because the performance of congested network will be affected. Daganzo and Geroliminis[29] stressed that the MFD exists in ‘regularity conditions’ (a slow-varying and distributed demand, a redundant network ensuring that drivers have many route choices and that most likes are on many desirables routes and a homogeneous network with similar type of links) and analyzed the connection between the network structure and a network’s MFD for urban neighborhoods controlled in part by traffic signals. They also emphasized that networks with an uneven and inconsistent distribution of congestion may exhibit significant scatter on their MFD because of rapidly changing demands. However, a comparison between a weekday and a weekend day showed similar results, implying that the MFD is not sensitive to demand. Geroliminis and Sun[30] show that the spatial distribution of density/occupancy in the network is one of the key components that affect the scatter of an MFD and its shape. This is furthermore discussed and confirmed in recent work by Saberi and Mahmassani[31], which also discuss the dynamics. A more elementary work on this topic is presented by Daganzo et al.[32].

Recent works by Buisson and Ladier[25], Geroliminis and Sun[30], Jiyang et al.[28], and Cassidy et al.[33] have explored MFD for freeway networks, by using real data[30, 33] and simulation data[28]. Buisson and Ladier[25], for example, explored the impact of heterogeneity on the existence of a MFD by relaxing some of the homogeneity assumptions made by Daganzo, using loop detector data collected in Toulouse, a medium-size French city. A large scatter was found along the line of MFD, the causes of which were attributed to: 1) Different types of road (freeway versus urban roads). 2) Distance between detectors and traffic signals in the urban network. 3) The on-set and resolving of congestion. Jiyang et al.[28] used the freeway data generated from computer simulation and found that hybrid networks give a scattered MFD of freeway networks. Cassidy et al.[33] analyzed the vehicle trajectories from two freeway stretches of modest physical lengths and concluded the MFD can be estimated using data from ordinary loop detectors. In this paper, on the basis of the empirical traffic data, we investigate the relation between the accumulation of freeway networks and travel time (un)reliability providing valuable insight into travel time reliability macroscopic diagram.

MACROSCOPIC TRAVEL TIME RELAIBILITY DIAGRAMS

The aim of this paper is to identify traffic state indicators that can be used to investigate how the travel time unreliability in freeway networks vary with the overall network traffic state. Inspired by the MFD, the Macroscopic travel time Reliability Diagrams (MRD) is proposed and established to demonstrate the relationship between the traffic state of freeway networks and travel time (un)reliability. A few key variables with MRD will be defined in this section.

Travel Time Reliability

In this paper, we use the same travel time reliability measure as proposed by Tu et al.[12]:

$$TTUR = \left(1 - P_r^{br}\right) \times TTUC^f + P_r^{br} \times TTUC^c \qquad (1)$$

in which

P_r^{br} Probability of traffic breakdown on route r,

$TTUC^f$ Travel time uncertainty before traffic breakdown (i.e. in free flow conditions),

$TTUC^c$ Travel time uncertainty after traffic breakdown (i.e. in congested conditions).

This travel time reliability model provides a new measure accounting for the risks caused by traffic breakdown (the instability of traffic flow) and the associated travel time uncertainty. Travel time unreliability depends on the probability that traffic breaks down and the consequences (travel time uncertainty, *TTUC*) of such a traffic breakdown. *TTUC* is quantified by the difference between the 90th percentile travel time and the 10th percentile travel time. $TTUC^f$ refers to the percentile travel time per unit space in free flow conditions and $TTUC^c$ refers to the percentile travel time per unit space due to transitions until the congestion dissolves[12]. The instability is quantified by the probability of traffic breakdown P^{br}. The *section traffic breakdown* is defined as a reduction of average speed of a section within one time interval from a high level down below a threshold of 70 km/h and *traffic breakdown of a route* occurs in case of at least one section on the route breaks down (for the detail, please refer to Tu et al.[12]).

Macroscopic Fundamental Diagram

The MFD for freeway networks used in this paper is proposed by Daganzo[13], which relates 'production' (the product of average flow and network length) and 'accumulation' (the production of density and network length, network flow). Denote by i and l_i a road section between loop detectors and its length; and by q_i the flow on each section, by v_i the speed on each section. Then, the macroscopic variables 'production' (weighted average flow) Q^w and 'accumulation' A_i can be calculated based on data measured by ordinary loop detectors as follows:

$$Q^w = \frac{\sum_i q_i \times l_i}{\sum_i l_i}$$
$$A = \sum_i k_i \times l_i = \sum_i \frac{q_i}{v_i} \times l_i \tag{2}$$

If there is inhomogeneous congestion, then scatters are found on the MFD[25, 33]. In this paper, the network accumulation is classified into groups (1…n) with an accumulation-bin ΔA. When plotting the MFD, the 10th percentile, 50th percentile and 90th percentile value in each class, denoted as $Q^{W_n}_{10\text{th}}$, $Q^{W_n}_{50\text{th}}$, $Q^{W_n}_{90\text{th}}$ could be presented respectively to show the variation in the network accumulation as seen in scatters. Each network accumulation class n corresponds to a weighted average flow $Q^{W_n}_{10\text{th}}, Q^{W_n}_{50\text{th}}, Q^{W_n}_{90\text{th}}$, and the associated weighted average flows in each group, as illustrated in Eq.(3):

$$\begin{aligned}
A \quad &= \left\{\frac{1}{2}\Delta A, \frac{3}{2}\Delta A, \ \dots\ , \frac{2\text{n-1}}{2}\cdot\Delta A\right\} \\
&\qquad \updownarrow \qquad \updownarrow \qquad\quad \updownarrow \\
Q^W_{10th} &= \left\{Q^{W_1}_{10th},\ Q^{W_2}_{10th},\ \cdots\ ,\ Q^{W_n}_{10th}\right\} \\
Q^W_{50th} &= \left\{Q^{W_1}_{50th},\ Q^{W_2}_{50th},\ \cdots\ ,\ Q^{W_n}_{50th}\right\} \\
Q^W_{90th} &= \left\{Q^{W_1}_{90th},\ Q^{W_2}_{90th},\ \cdots\ ,\ Q^{W_n}_{90th}\right\}
\end{aligned} \tag{3}$$

In this paper, for a given network accumulation A, the 10th percentile, 50th percentile and 90th percentile network production will be presented.

Macroscopic Travel Time Reliability Diagram

The network accumulation will be the indicator of the traffic state of freeway networks and travel time unreliability will be computed by the integration of both travel time uncertainty and instability. Thus, MRD can be formulated as follows:

$$TTUR = f\left(A\right) \tag{4}$$

in which

TTUR Travel Time UnReliability

A Network Accumulation

CASE STUDY ANALYSIS

Case Study and Data Description

In order to empirically illustrate the macroscopic travel time unreliability diagram on freeway networks developed in this paper, a network consisting of freeways, provincial roads and an urban network in the South-west of the Netherlands as shown in **Figure 1** is selected to facilitate the applications. Detailed freeway traffic data (named Monica data) were collected to estimate the travel time uncertainty and the instability at a given inflow level on a route. The freeway traffic data are obtained from Regiolab-Delft[34, 35]. The traffic monitoring system of the study area in Regiolab-Delft gets its traffic data from dual loop detectors situated every 400-500 meters along the freeway that collect the traffic data (flow and speed) aggregated for every 1-minute time interval. It is known that short aggregation intervals (e.g., 1 minute) cause much noise and long aggregation intervals (e.g. 1-hour) ignore the phenomenon of the flow stochasticity. In order to measure reliable flows in this paper, the raw 1-minute aggregate Monica data are processed into 10-minute aggregate speed and flow observations, for the year 2004.
Before the data are used for analysis, they are pre-processed to tackle the missing data by using simple imputation interpolation method[15], which employs interpolation in both the spatial and the time directions, given the route is equipped with detectors $\boldsymbol{d} \in \{1,...,\boldsymbol{D}\}$ and a database of measurement U from these detectors in periods $\boldsymbol{p} \in \{1,...,\boldsymbol{P}\}$ is available. The location of each detector is denoted by $\boldsymbol{x}_d$. Suppose that no data are available at a detector *d* during the time period *p*, the spatial interpolation procedure we employed to fill in this gap is according to:

$$\boldsymbol{U}^{space}\left(\boldsymbol{d},\boldsymbol{p}\right) = \begin{cases} \boldsymbol{U}\left(\boldsymbol{d}+\boldsymbol{d}_a,\boldsymbol{p}\right) & \boldsymbol{d}+\boldsymbol{d}_a \le \boldsymbol{D} \\ \boldsymbol{U}\left(\boldsymbol{d}-1,\boldsymbol{p}\right) + \dfrac{\boldsymbol{x}_d}{\boldsymbol{x}_{d+n}-\boldsymbol{x}_{d-1}}\boldsymbol{U}\left(\boldsymbol{d}+\boldsymbol{d}_a,\boldsymbol{p}\right) & 1<\boldsymbol{d}<\boldsymbol{D} \\ \boldsymbol{U}\left(\boldsymbol{d},\boldsymbol{p}-1\right) & \textbf{\textit{otherwise}} \end{cases} \tag{5}$$

in which $\boldsymbol{U}\left(\boldsymbol{d}+\boldsymbol{d}_a,\boldsymbol{p}\right)$ is the first available measurement in the spatial direction (d_a, the adjacent loop detector; *n*, spatial steps between d_a and *d*). Similarly, in the time direction we can repair gap with

$$U^{time}(d,p)=\begin{cases}U(d,p+p_a) & p+p_a\le P\\ U(d,p-1)+\dfrac{1}{k+1}U(d,p+p_a) & 1<p<P\\ U(d,p-1) & otherwise\end{cases} \quad (6)$$

in which $U(d,p+p_a)$ is the first available measurement in the time direction (time step *k+1*). We will fill in the gap with minimum of both interpolates (implying the maximum constant of traffic throughput (flows) and travel time (speeds), that is

$$U^*(d,p)=\min\left(U^{space}(d,p),U^{time}(d,p)\right) \quad (7)$$

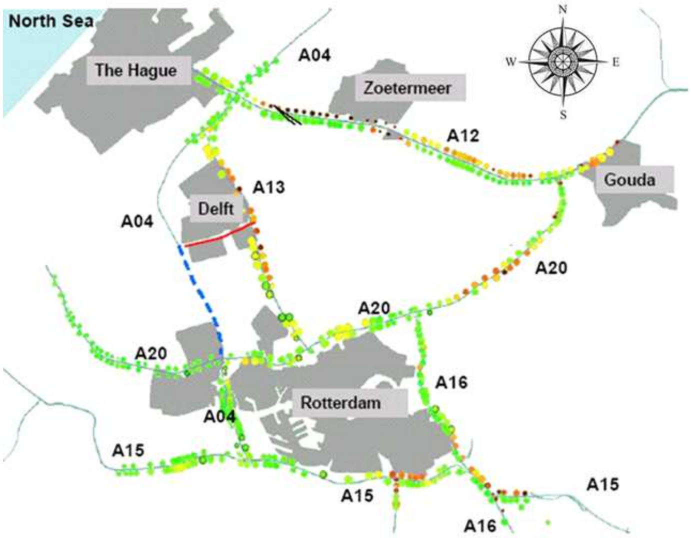


Figure 1 Regiolab-Delft traffic monitoring system in The Netherlands

As the Regiolab-Delft server does not directly measure travel time data on the freeway networks, travel times are estimated with the 'Piecewise Linear Speed Based' (PLSB) trajectory algorithm[36] for every departure time period of 10 minutes. This PLSB method reconstructs vehicle trajectories and hence mean travel times based on time series of speed and volume measurements on consecutive detector locations along a route. The characteristics of the PLSB method is the fact that trajectories are constructed based on the assumption of vehicle speeds are piecewise linear along a road section between detectors (and continuous at section boundaries) rather than piecewise constant (and discontinuous at section boundaries) speeds. During each departure time period, a record is stored with the mean travel time per unit length for vehicles departing in this period and inflow in vehicles per hour per lane during that period. Given sufficiently dense detector spacing – about 2 dual loop detectors per kilometer – the resulting travel time estimates compared with the travel times data from floating cars are almost unbiased and the residual errors exhibit small variance (in the order of 5%)[36]. The travel time used in this paper is concerned with the route-level dynamic estimated mean travel time on 10-minute aggregate.

Three routes (freeway corridors) are selected from Regiolab-Delft, as shown in **Table 1**. The routes are on average (approximately) 16.7 km long, ranging from 15.5 km to 17.3 km.

Table 1 Description of three freeway corridors

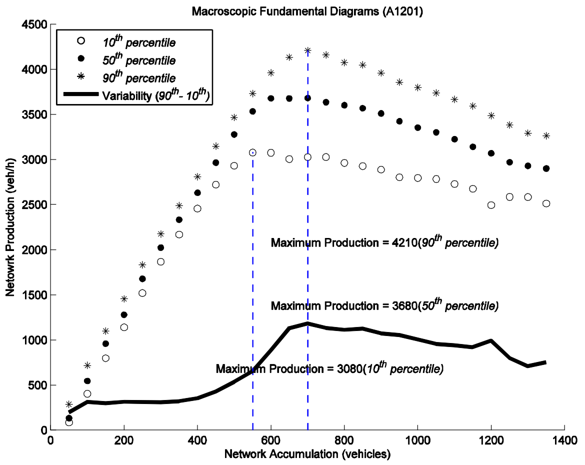
Code	Freeway	Route length (m)	N. of Lanes
A1201	A12	17,280	2
A1211	A12	15,520	2
A2001	A20	17,325	2

Results and Findings

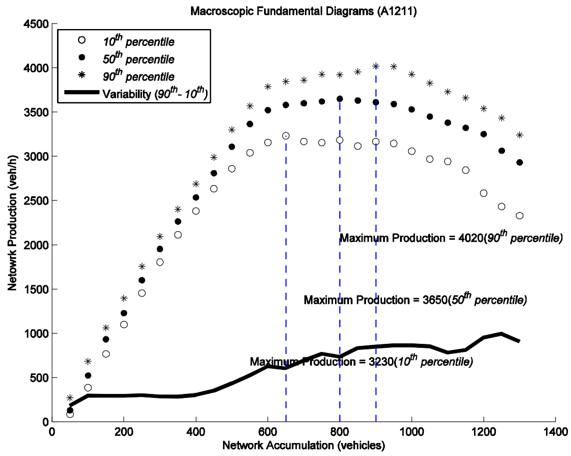
Figure 2 demonstrates the example of the MFDs on freeway networks. The accumulation and the production (weighted average flow) are calculated by Eq.(2). The two variables of accumulation and production shown in **Figure 2**, ,are grouped and averaged over the whole year (see Eq.(3)). The associated , 10^{th} percentile, 50^{th} percentile, 90^{th} percentile productions and the variability in productions (i.e. the 90th percentile value of productions minus the 10th percentile value) for a given accumulation group are calculated and presented as well. It is shown that the production increases with rising accumulation in the beginning and the scatter in productions for a given accumulation is low. At a certain moment, network production starts to decrease and the scatter in productions is high. The network accumulation reaches the region that the production is varied, leading to unreliable travel times. At very high level of accumulation, the variability in productions does not significantly increase as seen with the solid line of variability in productions, but the unreliability of travel times continues increasing due to the fact that the probability of traffic breakdown at such a high level of accumulation continues increasing as shown in **Figure 3**.

Figure 3 illustrates the estimated relationships between the corridor travel time unreliability (travel time unreliability is calculated/estimated using Eq.(1) by Tu et al.[12]) and the network accumulation on the three freeway networks based on the empirical data. As can be seen in the graph, the travel time unreliability increases with rising accumulations. Similar trends of travel time unreliability over accumulations are observed from the analyses on the three corridors. It appears that there is a certain critical MRD accumulation, above which, the travel time unreliability increases more dramatically than that below the critical MRD accumulation.

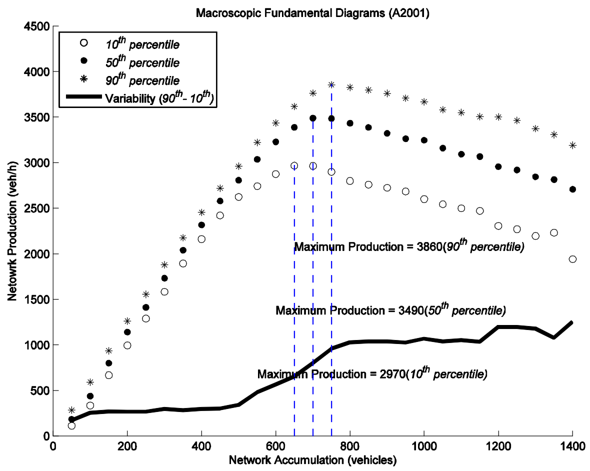
Table 2 lists the critical MFD accumulation (for maximum production) and the critical MRD accumulation (for travel time reliability). The critical MFD network accumulations on the basis of the 10^{th} percentile, 50^{th} percentile and 90^{th} percentile MFD are given as well. As can be seen in **Table 2**, the lower percentile productions, the lower the critical accumulations are. It is noticed as well that the critical MRD accumulation are about 500, 550, 600 for A1201, A1211 and A2001, respectively. On average, the critical MRD accumulation is 10% lower than the critical MFD accumulation with the 10^{th} percentile production, 25% lower with the 50th percentile production and 29% lower with the 90th percentile production. Thus, it is found that the critical MRD accumulation is in general lower than the critical MFD accumulation.



(a) MFD (A1201) (one line missing)



(b) MFD (A1211)



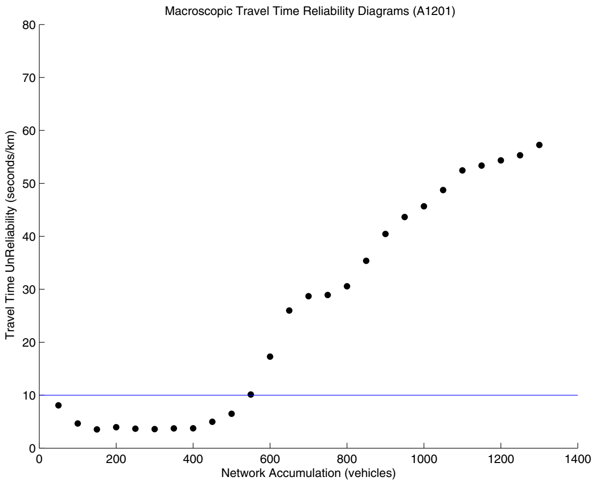
(c) MFD (A2001)

Figure 2 Macroscopic fundamental diagrams:
(a) A1201
(b) A1211
(c) A2001

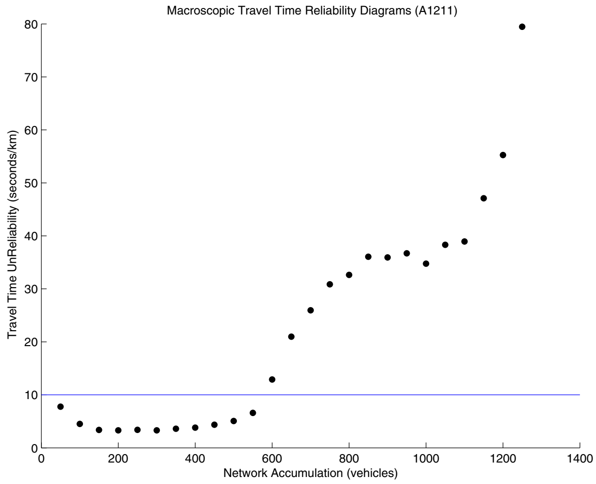
Note: the blue dashed lines indicate the critical accumulations with the maximum (percentile) productions.

Table 2 Macroscopic Travel Time Reliability Diagrams Evaluation

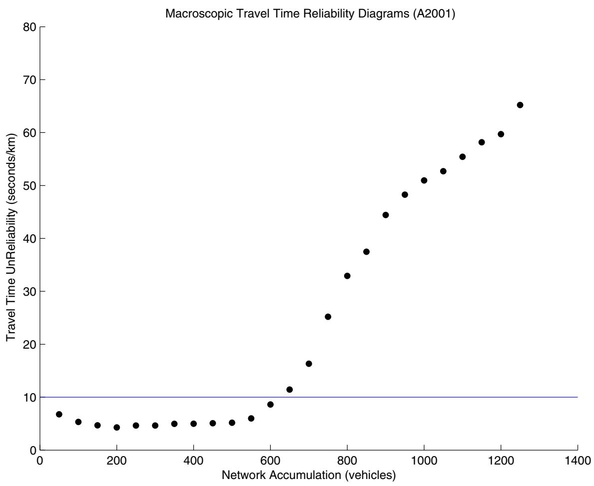
Freeway code	Critical network accumulation for maximum production (vehicles)			Maximum production (veh/h)			Critical network accumulation for MRD (vehicles)
	10th	50th	90th	10th	50th	90th	
A1201	550	700	700	3080	3680	4210	500
A1211	650	800	900	3230	3650	4020	550
A2001	650	700	750	2970	3490	3860	600



(a) MRD (A1201)



(b) MRD (A1211)



(c) MRD (A2001)

Figure 3 Macroscopic travel time Reliability Diagrams (MRD):
(a) A1201
(b) A1211
(c) A2001

Discussions

Travel time reliability has become a crucial indicator of network performances. Based on our studies on MRD, it is found that travel times becomes already significantly unreliable at a lower critical network accumulation than the critical MFD accumulation. The consequence is that there appears to be a tradeoff between travel time reliability and network flow efficiency (network flow throughput/production). From the latter point of view, the network flow throughput should be as large as possible. However, the price one has to pay is that under such conditions, travel times have already become fairly unreliable, due to the high probability of traffic breakdown. A traffic break down and subsequent recovery will lead to non-homogeneous situations[31, 37]. This is also visible by the increase of the bandwidth of the MFD. As soon as the MRD starts to increase, the variability of the MFD increases.

MRD is a new tool that is similar to MFD and could be utilized for network performance evaluations. If these findings turn out to be generally applicable, traffic practitioners and researchers may use this accumulation-based travel time unreliability model in a number of ways. For instance, it is a tool to monitor travel time unreliability on freeway networks on the basis of historical traffic data. In turn, the network traffic management limiting the inflow of (sub-) networks to ensure that the accumulation remains below the critical MFD accumulation might result in high probability of traffic breakdown and unreliable travel times in the networks. The goal of the network traffic management should be the tradeoff between the maximum production and the travel time reliability. MRD with the critical travel time (un)reliability accumulation could support the practitioners in network management and traffic controls, ensuring high travel time reliability.

CONCLUDING REMARKS

In this paper, we developed the MRD (Macroscopic travel time Reliability Diagram), which describes the relationship between the traffic state of freeway networks (network accumulation) and travel time (un)reliability. Firstly, it is found that in general there is a similar trend of travel time (un)reliability in relation to network accumulations, on the basis of analyses of MRD on different freeway networks. The travel time unreliability increases with rising accumulations, which implies that the indicator of network traffic state, i.e. accumulations, could be an explanatory variable for travel time unreliability. Secondly, there exists a critical MRD accumulation, below which network accumulation has little or even no impacts on travel time reliability and above which the accumulation has a positive correlation with travel time unreliability. For purposes of guaranteeing reliable travel times, the inflow should be controlled and restricted to a certain accumulation level. Thirdly, compared to MFD the critical MRD accumulations are in general lower than the critical MFD accumulations in all different percentile MFDs as presented in the paper. It implies that the tradeoffs between network flow efficiency and travel time reliability should be taken into account in the decision making on (corridor) traffic management. These main findings provides intuitive insights into the travel time (un)reliability in relation to network traffic state, which are meaningful and applicable for the traffic planning and management studies for road authorities.

Besides the findings, the developed travel time unreliability model in relation to network accumulations has potential practical relevances and substantial contributions in the assessment and optimization of dynamic traffic management measures. It shows that the accumulation is not only useful in flow optimizations, but also in the reliability enhancement.

In future research, it is interesting to investigate whether the MRD could be fitted into a function, for instance a BPR (a travel time function[38], in which travel time increases monotonically with flow)-like travel time (un)reliability function or other types of functions. The fitted MRD functions then could be used in the *ex ante* evaluations.

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