

Urban travel time reliability at different traffic conditions

Zheng, Fangfang; Li, Jie; van Zuylen, H.J.; Liu, Xiaobo; Yang, Hongtai

DOI

[10.1080/15472450.2017.1412829](https://doi.org/10.1080/15472450.2017.1412829)

Publication date

2017

Document Version

Accepted author manuscript

Published in

Journal of Intelligent Transportation Systems: technology, planning, and operations

Citation (APA)

Zheng, F., Li, J., van Zuylen, H. J., Liu, X., & Yang, H. (2017). Urban travel time reliability at different traffic conditions. *Journal of Intelligent Transportation Systems: technology, planning, and operations*, 22 (1028)(2), 106-120. <https://doi.org/10.1080/15472450.2017.1412829>

Important note

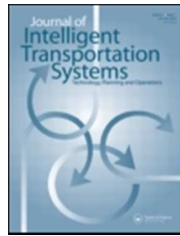
To cite this publication, please use the final published version (if applicable).
Please check the document version above.

Copyright

Other than for strictly personal use, it is not permitted to download, forward or distribute the text or part of it, without the consent of the author(s) and/or copyright holder(s), unless the work is under an open content license such as Creative Commons.

Takedown policy

Please contact us and provide details if you believe this document breaches copyrights.
We will remove access to the work immediately and investigate your claim.



URBAN TRAVEL TIME RELIABILITY AT DIFFERENT TRAFFIC CONDITIONS

Journal:	<i>Journal of Intelligent Transportation Systems: Technology, Planning, and Operations</i>
Manuscript ID	GITS-2015-0259.R3
Manuscript Type:	Travel Time Reliability
Date Submitted by the Author:	n/a
Complete List of Authors:	Zheng, Fangfang; Southwest Jiaotong University, School of Transportation and Logistics Li, Jie; Hunan University, Department of Traffic and Road Engineering, Civil Engineering College van Zuylen, Henk J.; Delft University of Technology, Transport and Planning; Liu, Xiaobo ; Southwest Jiaotong University, School of Transportation and Logistics Yang, Hongtai; Southwest Jiaotong University, School of Transportation and Logistics
Keywords:	Travel time, Reliability, Skewed distributions, Urban transportation, Cameras

SCHOLARONE™
Manuscripts

URBAN TRAVEL TIME RELIABILITY AT DIFFERENT TRAFFIC CONDITIONS

Fangfang Zheng^{1,2}, Jie Li^{*3}, Henk van Zuylen^{1,3,4}, Xiaobo Liu^{1,2} and Hongtai Yang^{1,2}

¹ School of Transportation and Logistics, Southwest Jiaotong University, No. 111. Erhuanlu
Beiyiduan, Chengdu, Sichuan, 610031, P.R. China.

²National-local Association Laboratory of Comprehensive Transportation Intelligentization,
Southwest Jiaotong University, No.111, Erhuanlu Beiyiduan, Chengdu, Sichuan, 610031,
P.R. China

³ Department of Traffic and Road Engineering, Civil Engineering College, Hunan University,
Lushan South Road, 410082 Changsha, Hunan Province, P.R. China

⁴ Department of Transport & Planning, Faculty of Civil Engineering and Geosciences, Delft
University of Technology, Stevinweg 1, 2628 CN Delft, The Netherlands

* Corresponding author

ABSTRACT

The decision making of travelers for route choice and departure time choice depends on the expected travel time and its reliability. A common understanding of reliability is that it is related to several statistical properties of the travel time distribution, especially to the standard deviation of the travel time and also to the skewness. For an important corridor in Changsha (P.R. China) the travel time reliability has been evaluated and a linear model is proposed for the relationship between travel time, standard deviation, skewness and some other traffic characteristics. Statistical analysis is done for both simulation data from a delay distribution model and for real life data from Automated Number Plate Recognition (ANPR) cameras. ANPR data give unbiased travel time data, which is more representative than probe vehicles.

The relationship between the mean travel time and its standard deviation is verified with an analytical model for travel time distributions as well as with the ANPR travel times. Average travel time and the standard deviation are linearly correlated for single links as well as corridors. Other influence factors are related to skewness and travel time standard deviations, such as vehicle density and degree of saturation. Skewness appears to be less well to explain from traffic characteristics than the standard deviation is.

Keywords: Travel time reliability, Skewness, Travel time standard deviation, Automated number plate recognition, Urban traffic.

INTRODUCTION

The reliability of travel time is an important characteristic of a trip. It reflects the quality of traffic operations both for freeways and urban networks. In the choice of routes, departure time, travel mode and destinations, travel time reliability plays a role at least as important as the expected travel time (Bates et al., 2001; Bogers, 2009). In certain situations, travelers seem to place a higher relative value on reducing travel time variability than on the mean travel time (Bates et al., 2001).

In order to quantify travel time reliability, a range of reliability measures have been proposed in the past decades, e.g., statistical range in the form of expected travel time plus/minus the standard deviation multiplied by a factor (Bates et al., 2001), 95th percentile (FHWA 2015), buffer index, planning time index, tardy trip measures (Lomax et al., 2003). Among all these measures, the standard deviation is most often used to represent variability and is included in the route choice utility function in studies of the value of reliability (Liu et al., 2004). Sen et al. (2001) proposed a mean-variance approach which employs the variance of travel time as the travel time reliability measure to investigate travelers' route choice behavior. Different methods to determine the value of reliability have been reviewed by e.g. Carrion and Levinson(2012) and De Jong and Bliemer (2015).

Mahmassani et al. (2012) analyzed the characteristics of the travel time reliability for an urban road network by establishing a linear regression model describing the relationship between the standard deviation of travel time per unit distance and the corresponding mean value. Van Lint et al.(2008) argued that the travel time distribution is often wide and skewed, particularly during the periods when congestion occurs, sets in or dissolves. Given a skewed distribution, applying classic measures based on the mean or variance of travel times may lead to a biased estimate of reliability. They suggested that skewness should be considered as another measure of unreliability. The importance of skewness is emphasized by Bogers

1
2
3 (2009). She showed that route choice in an experimental situation was especially determined
4
5 by the skewness of the travel time distribution.
6

7 There are large differences in the traffic processes that determine travel time reliability
8
9 between urban roads and freeways (Tu, 2008). In this article we focus on urban travel time
10
11 reliability. The travel time reliability (or variability) in urban networks has received a lot of
12
13 attention during the past years. With the development of various monitoring techniques, travel
14
15 times can be derived from different data sources (e.g., from Automatic Number Plate
16
17 Recognition data, GPS/mobile phone equipped floating car data, and Bluetooth). Different
18
19 statistical models such as Normal, Lognormal, Gamma and Weibull distributions (Al-Deek &
20
21 Emam 2006; Arroyo & Kornhauser, 2005; Pu, 2011) are applied to describe the travel time
22
23 variability. Due to the complexity of urban traffic conditions, a single distribution model
24
25 couldn't well represent the travel time distribution of an urban road. Guo et al. (2010)
26
27 proposed a mixed distribution model to capture multi-state traffic conditions for urban roads.
28
29 Chen et al. (2017) proposed a copula-based model to estimation path travel time for urban
30
31 arterial roads considering stochastic characteristics of segments. Yang et al. (2017) proposed a
32
33 Gaussian mixture model to estimate travel time distributions for urban arterial road. Apart
34
35 from modeling travel time variability with field data, Kim et al. (2013) employed traffic
36
37 simulation models to derive travel time distributions under different scenarios considering
38
39 various demand and supply uncertainty factors, such as weather, traffic incidents, work zones,
40
41 traffic control. In urban context, travel time variability can be further recognized in different
42
43 temporal scales. Robinson and Polak (2007) applied the K-Nearest Neighbor classification
44
45 method to characterize travel time variability using loop detector data. They disaggregated
46
47 travel time variability into three components: vehicle-to-vehicle, period-to-period and day-to-
48
49 day. In order to capture both the vehicle-to-vehicle and day-to-day variability in travel time
50
51 data, Kim and Mahmassani (2014) proposed a Gamma-Gamma mixture distribution model.
52
53
54
55
56

1
2
3 Based on their proposed model, the heterogeneity within these two variability types under
4
5 different weather conditions can be described as well.
6

7 Up to now, most research on urban travel time reliability was done with simulation models
8
9 to produce data for reliability analysis. Though Mahmassani et al. (2012; 2013) used both
10
11 simulated data and field GPS trajectory data to model travel time reliability, the investigation
12
13 with field data is rather limited. Moreover, the GPS data they used is only from a sample of
14
15 the total traffic on the network and no flow data is available in their study area. The question
16
17 is to what extent the derived relationship between the travel time variability and the network
18
19 flow or density deduced from GPS sample data can represent the real situation. With the
20
21 development of traffic monitoring systems, different field data sources including Automated
22
23 Number Plate Recognition (ANPR) camera data, GPS taxi data, loop detector data and signal
24
25 timing data are now available.
26
27

28 In (Zheng & van Zuylen, 2011), the authors derived an analytical model which describes
29
30 the travel time distribution for signalized roads. In that model the variation in travel time
31
32 between different vehicles is due to differences in arrival moment at the intersection and
33
34 variations in the arrival rate. Zheng et al. (2017) further extended the model to include also the
35
36 effect of spill back. Their model has been validated with respect to the travel time distribution
37
38 both with simulated data from VISSIM and real data from probe vehicles.
39
40

41 In this paper, firstly we give some observation for the use of simulation programs, probe
42
43 vehicle data and data from ANPR cameras. Then we apply the travel time distribution model
44
45 to derive two reliability measures: the standard deviation and the skewness of travel time. The
46
47 flow data from cameras and signal timing data extracted from the SCATS traffic control
48
49 system in Changsha are used as input to the travel time distribution model. We investigate the
50
51 relationship between the expected travel time and the standard deviation, as well as the effect
52
53 of changing traffic states on the travel time variability, i.e. to show the changes of the standard
54
55
56
57
58
59
60

1
2
3 deviation and the skewness during the day. Consecutively, field travel times are calculated
4
5 from ANPR data. The relationship between the mean travel time and the standard deviation is
6
7 shown. Also the connection between the travel time variability (e.g., the standard deviation,
8
9 skewness) and different traffic states is established. Finally, some discussion and conclusions
10
11 are provided.
12

13 14 ***SOME OBSERVATIONS REGARDING ANPR, SIMULATION AND PROBE VEHICLES*** 15

16
17 For the calculation of travel time reliability the travel time distribution on links, routes
18
19 and/or whole networks are needed. The source of the necessary data is often a micro
20
21 simulation program, speed measurements, probe vehicles or ANPR data. In the study reported
22
23 in this article we used data from a route in Changsha, the capital of Hunan province in China
24
25 (Figure 1), consisting of ANPR data, traffic volumes, and GPS data from 7200 taxis. These
26
27 data were collected for three days from 20, April 2015 to 22, April 2015. Several input
28
29 variables and parameters such as traffic flow rates, signal control plans and the saturation flow
30
31 rates have to be determined in order to derive the delay and travel time distributions. Here we
32
33 mainly use ANPR data to estimate travel time distributions, traffic flow rates, and saturation
34
35 flow rates for the study area. Before analyzing travel time data, the different empirical data
36
37 sources have been analyzed.
38
39
40

41 In Figure 1 the part of the network that is used for the travel time analysis is shown. It
42
43 consists of 9 intersections which are all provided with loop detectors located close to the stop
44
45 line on every lane. These detectors are a part of the traffic control system SCATS. The
46
47 intersections denoted with italic numbers have ANPR cameras, one camera per lane. Taxis
48
49 equipped with GPS devices send their position data every 30 seconds.
50
51
52
53

54 # Figure 1#
55
56
57

Analysis of the quality of the ANPR data

The ANPR cameras record the number plates of all vehicles passing the stop line. Lighting conditions appear to have an influence on the quality of the registrations. In the evening and early morning the failure rate of the cameras, in terms of missed number plates, is much larger than during the day time. Some number plates appear to be registered more than once at an intersection, sometimes by the same camera (up to 8%) and sometimes by adjacent cameras (up to 0.06%).

The ANPR cameras count traffic per lane, just as the loop detectors of the SCATS traffic control system do. The values from the cameras were in general close to the loop detector counts on the intersections in the study area. Since drivers do not always follow paths indicated by the lane marking on the intersection, they can 'escape' from being counted by the loop detectors or cameras. Especially left turning traffic is often miscounted.

Also the volumes of taxis counted from ANPR data (taxis have a special number plate and can be separately identified by the cameras) are close to those counted from the GPS taxi data.

An analysis of the volumes from ANPR cameras shows that some cameras did not perform well during these three days and at some intersections incidents have happened during one of the days. In the further analysis only intersections with regular and consistent data have been chosen.

Travel time measurement

For the travel time measurement, two data sources are available: ANPR and probe vehicles (taxis). A comparison was made for travel times measured from these two data sources. It appears that travel times measured from taxi GPS data can be rather different from the travel

1
2
3 times determined from ANPR data, as shown in Figure 2. The reason is probably that taxi
4
5 drivers are more experienced and thus faster than other drivers, but sometimes stop half way
6
7 on a road to let passengers alight or get in, or just to take a break. The records from taxis
8
9 stopping for more than 2 minutes or making a detour from a link have been removed. Such
10
11 elimination of outliers, i.e. vehicles stopping between two intersections for reasons that have
12
13 nothing to do with the traffic conditions, is also necessary for ANPR data. The outliers in
14
15 ANPR travel times are visible in the graph of travel times as function of the arrival time at the
16
17 end of a link. Normally travel times of two consecutive arriving cars are only slightly
18
19 different, with the exception of the transition between a car that just passes the end of the
20
21 green time and its follower. ANPR journey times that were more than twice the journey time
22
23 of the vehicle arriving before or after were considered as drivers who had some activities
24
25 during their journey between two cameras. About 5% of the journey times were identified as
26
27 outliers and removed. The elimination of outliers in the ANPR travel times is very important
28
29 to get a consistent statistical analysis.
30
31

32
33 The fact that during some time of the day (e.g. between 16:00 and mid-night) taxis drivers
34
35 appear to be much faster than the other drivers, makes it preferable to use ANPR data for the
36
37 measurement of travel time.
38
39
40

41 # Figure 2 #
42
43
44
45
46
47

48 ***Conclusions with respect to simulations and probe vehicles*** 49

50 A simulation represents aspects of real world traffic. Most simulations are calibrated and
51
52 validated on aspects like mean travel time and traffic volumes. In a study of travel time
53
54 reliability, the simulations should give travel time distributions which is proven to be valid.
55
56

1
2
3 Zheng et al. (2010, 2011, and 2015) explicitly show the validity of their travel time model
4 with respect to the distribution of travel time, both with measured real travel time data and
5 simulation data.
6
7

8
9 Another drawback of simulation is that certain aspects of reality are ignored. Saturation
10 flows, which have an important role in the urban traffic process, are assumed to be constant,
11 independent from time and traffic volume. In most articles about the application of simulation
12 programs the issue of saturation flow rates is not discussed at all, so that probably default
13 values of saturation flow rates are used. Based on these findings we firstly analyzed the travel
14 time reliability with a mesoscopic simulation program developed by Zheng (2011), which
15 gives validated travel time distributions. For this simulation study the traffic volumes that
16 have been measured in reality are used. The cycle times and green splits for the model
17 calculation were taken from the traffic control system SCATS. Afterwards the travel times
18 measured by ANPR cameras are analyzed. The probe vehicle data from the taxis are not used
19 because of the reasons mentioned above.
20
21
22
23
24
25
26
27
28
29
30
31
32

33 34 *MODELLING DELAY AND TRAVEL TIME DISTRIBUTIONS*

35
36
37 Microscopic simulation models try to represent the behaviour of traffic on a detailed level:
38 the behaviour of individual vehicles interacting with each other and responding to road
39 conditions and traffic management measures. For the purpose of evaluation of the traffic
40 situation, such simulations can provide the necessary characteristics; however, for the
41 optimization of the traffic system it is more effective to have a macroscopic model that gives
42 the relation between parameters of the traffic system, such as traffic volumes, the timing of
43 signals, and the performance, e.g. travel time.
44
45
46
47
48
49
50
51

52 A meta-model can be derived from microscopic simulation. An example is the model
53 developed by Webster (1958) to describe the macroscopic relation between traffic parameters
54
55
56

1
2
3 and signal timing and the delay. He developed a mathematical model consisting of three
4
5 terms:

- 6
7 1. A term that gives the delay for a continuous flow of vehicles, stopped during the red
8
9 phase when the queue builds up and crossing the stop line when the queue is released;
- 10
11 2. Since the intersection is also a capacity bottleneck, the second term in the delay model
12
13 describes the delay at a bottleneck with arrivals according to a Poisson statistics.
- 14
15 3. The third term is a correction, a rather complicated product of parameters that play a
16
17 role in the first two terms.
18

19
20 There are some disadvantages of meta-models because the validity of the model is restricted to a
21
22 certain range of the parameters. The Webster model is only valid for undersaturated conditions
23
24 and becomes infinite for fully saturated situations. The integration of the oversaturated and
25
26 undersaturated model has been developed by several researchers (e.g. Akcelik, 1988). All of
27
28 these models give a smooth transition between undersaturated and oversaturated conditions.
29

30
31 Fu and Hellinga (2000) continued in that line and developed an analytic expression for the
32
33 standard deviation of the delay, assuming stationary arrivals rates and zero initial queue. The
34
35 difficulty in applying a formula like the one derived by Fu and Hellinga (2000) and Akcelik
36
37 (1988) in practice is, that often the initial queue is not zero and that the queue is not always
38
39 growing but also shrinking. Although the mathematical model for the delay probability
40
41 distribution developed by Viti (2006) covers all these situations, it does not provide a closed
42
43 mathematical expression for the situation that flows and queues are changing over time.
44

45
46 From the examples mentioned above one can find that the most important parameters that
47
48 determine the delay and its standard deviation are the effective green to cycle time ratio, the
49
50 flow and saturation flow and the degree of saturation x . The offset between signal control on
51
52 different intersections is another important factor determining travel time and its standard
53
54 deviation. This is not taken into account in the studies mentioned above.
55

Another approach to determine the statistical properties of travel time is to use a mesoscopic model for the distribution of the delay. For the delay on an isolated intersection the distribution $P(W)$ of the delay (W) when there is no overflow queue (a remain queue at the start of the red phase) is given by (Van Zuylen and Viti, 2007; Zheng et al., 2010):

$$P(W) = \alpha\delta(W) + \beta, \quad 0 < W < t_r \quad (1)$$

where $\alpha = 1 - t_r / \{t_c(1 - q/s)\}$ and $\beta = \{t_c(1 - q/s)\}^{-1}$.

where t_c is the cycle time and t_r is the duration of the red phase; q is the flow of the arriving traffic and s is the saturation flow. The function δ is a distribution function defined as:

$$\delta(x) = 0 \text{ if } x \neq 0,$$

$$\delta(0) = \infty, \text{ and}$$

$$\int \delta(x - x_0)f(x)dx = f(x_0)$$

For this uniform delay distribution the expectation value and the standard deviation can be calculated:

$$E\{W\} = \int_0^{t_r} WP(W)dW = 0.5\beta t_r^2 = \frac{t_r^2}{2t_c(1 - q/s)} \quad (2)$$

$$\sigma\{W\} = \sqrt{E\{W^2\} - E^2\{W\}} \quad (3)$$

$$E\{W^2\} = \int_0^{t_r} W^2 P(W)dW = \frac{t_r^3}{3t_c(1 - q/s)} \quad (4)$$

$$\sigma\{W\} = E\{W\} \sqrt{\frac{4t_c(1 - q/s)}{3t_r} - 1} = E\{W\} \sqrt{\frac{2t_r}{3E\{W\}} - 1} \quad (5)$$

This shows that the standard deviation of the (uniform) delay for undersaturated conditions can be considered as a function of the expectation value and the duration of the red phase.

That means that also the standard deviation will become larger when the ratio of the traffic flow and saturation flow q/s becomes larger, e.g., closer to the value 1.

For larger values of q/s the uniform delay is only a small part of the real delay and the delay due to variations in the arrivals and oversaturation has to be included. The mathematical expression for the initial or overflow queue is the representation of a Markov process in which the distribution of the overflow queue length in a cycle depends on the distribution in the previous cycle and the probability distribution of the arrivals (Olszewski, 1990; Viti and van Zuylen, 2006; 2009, 2010).

Zheng and van Zuylen (2011; 2014) further extended the single intersection model to two intersection models which consider the signal coordination between the upstream intersection and the downstream intersection, and the overflow queue at the beginning of the red phase. The delay probability distribution function is given as:

$$P_d(W | n_0) = \alpha(n_0)\delta(W) + \sum_N \beta B(W, W_{2N+1}(n_0), W_{2N+2}(n_0)) \quad (6)$$

Where

$$\alpha = \max\left(\frac{st'_g - n_0 - 1}{qt_c} - \frac{t_r + \frac{(n_0 + 1)}{s}}{t_c(1 - \frac{q}{s})}, 0\right), \beta = \frac{1}{\tau_c(1 - \frac{q}{s})}, \quad (7)$$

$B(w, w_{2N+1}, w_{2N+2})$ is a box-shaped function with the property:

$$B(w, w_{2N+1}, w_{2N+2}) = \begin{cases} 1 & w_{2N+1} < w < w_{2N+2} \\ 0 & otherwise \end{cases} \quad (8)$$

W_{2N+1}, W_{2N+2} are delays at transition moments as shown in Figure 3;

n_0 is the overflow queue at the beginning of the red time;

t'_g is the 'effective' green time at the downstream intersection, which is calculated as the green time of the downstream intersection minus the mismatched green time between the upstream intersection and the downstream intersection due to bad coordination.

Figure 3

The next section uses the delay (travel time) distribution models as developed by van Zuylen and Viti (2007), Zheng and Van Zuylen (2010; 2011). Equations (1) to (8)) are used to determine the standard deviation and skewness of delays and travel times for a single intersection and two linked intersections. The leading principle in this article is that a relation is searched between the standard deviation and skewness and traffic parameters like flow, average or expected delay, volumes and signal control parameters. This is done by both simulation and empirical data. From the discussion above we can expect that the relevant parameters are $E[W]$, q/s , x , t_C , and t_r .

THE MODEL-SIMULATED STANDARD DEVIATION AND SKEWNESS

The calculations with the mesoscopic model are executed using the actual traffic variables for the corridor shown in figure 1. The data from the ANPR cameras were used for this purpose. The cycle times and green splits were obtained from the log files of the SCATS control system, but the offsets had to be estimated from the ANPR data. Traffic flow rates, saturation flow rates and signal timings are aggregated into 15 minutes time intervals starting from 7:00 AM until midnight. For each 15 min time interval, the delay distribution, expectation, standard deviation and skewness are computed by Equations (1 - 8). Since the cycle time of the traffic control was variable and in the order of 3 minutes, a shorter time interval would give too much influence of the control process on the aggregated traffic characteristics.

Figure 4 illustrates the correlation between the expectation and the standard deviation of delays calculated based on the delay distribution model (equations 1 - 8) using the measured

1
2
3 traffic flow rates and signal setting. Each 'star' in the figure represents the expectation vs. the
4
5 standard deviation for a 15 minutes time interval. The correlation coefficients (*R*-square) of
6
7 west bound links 50-113 (a –b), 113-51 (b – c), 51-24 (c – d), 24-54 (d – e) are large (>0.85),
8
9 which suggest that a strong linear relation exists between the expectation and the standard
10
11 deviation. These results confirm the findings by Mahmassani et al. (2013) who also found a
12
13 linear relation between the mean travel time and the standard deviation.
14
15
16
17

18 # Figure 4 #
19
20
21

22 If we try to find a similar relation for two linked intersections, the correlation is still visible
23
24 but becomes much weaker, as visible in the lower two graphs in Figure 4. This indicates that
25
26 the signal coordination between intersections has a significant influence on travel time
27
28 reliability.
29

30 Although the relation between the expected value of the travel time and the standard
31
32 deviation is consistent for all links, the regression coefficients differ per link.
33
34

35 The relation between the expectation value of travel times and skewness is shown in
36
37 Figures 5 and 6. It is clear that the skewness becomes less when the travel time becomes
38
39 larger, which means that for higher travel times the distribution of the travel times becomes
40
41 more symmetrical. However, when the degree of saturation becomes close to 1, i.e. larger than
42
43 0.8, the skewness increases with the increase of the expectation value as shown in Figure 6,
44
45 which indicates that travel times become more skewed with a longer tail to the right for heavy
46
47 traffic conditions.
48
49
50
51

52 # Figure 5 #
53
54
55
56
57
58
59
60

1
2
3 # Figure 6 #
4
5
6

7 Apparently the degree of saturation plays an important role in the skewness. Therefore, the
8 analysis of skewness is repeated with the degree of saturation as an explanatory variable.
9 Figure 7(a)(b) show the relation between the degree of saturation x and the skewness. Each
10 dot represents a skewness value with respect to a certain degree of saturation for a time
11 interval of 15 min. From Figure 7 (a), we can see that when the degree of saturation is low
12 (e.g., in free flow conditions), the skewness value is larger than zero which indicates that the
13 travel time distribution is right-skewed with a longer tail towards high travel time values. For
14 undersaturated situations (e.g. $x < 0.8$) the skewness decreases with the degree of saturation;
15 while for near saturated conditions (e.g. $x > 0.8$, Figure 7 (b)), the skewness increases with the
16 increase of the degree of saturation. This indicates that traffic becomes more uncertain near
17 saturated conditions, which is consistent with what we have found in the previous study
18 (Zheng and van Zuylen, 2010). No oversaturation ($x > 1$) was observed for the intersections
19 within the study corridor. The regression coefficient reflects how much the skewness will
20 decrease when the degree of saturation increases.
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38

39 # Figure 7 #
40
41
42
43

44 In the following section we analyze the travel times and travel time distributions as
45 estimated from the ANPR observations and determine the relations between traffic states and
46 the standard deviation and skewness.
47
48
49
50

51 ***TRAVEL TIME ANALYSIS FROM THE ANPR REGISTRATIONS*** 52 53 54 55 56 57 58 59 60

The number plate recognition data were used to determine travel times in the East – West direction (see figure 1) for traffic travelling on the Renmin road as follows:

- Intersection 50 to Intersection 113 (a to b)
- Intersection 113 to Intersection 51 (b to c)
- Intersection 51 to Intersection 24 (c to d)
- Intersection 24 to Intersection 54 (d to e)
- Intersection 54 to Intersection 59 (e to f)

The travel times over the day are shown in Figure 8. The data of Monday 20 April 2015 appear to be different from the other two days, Tuesday and Wednesday 21 and 22 April. This is probably a post-weekend / beginning of the week effect. These differences are very well visible on the link 113 – 51 (b-c), while on the following link, 51 – 24 (c – d) the difference is especially in the morning, while on link 24 – 54 (d – e) the difference is more in the afternoon.

Figure 8

The correlation between *TTSD* and skewness has been analyzed for every link for three days. Figure 9 gives the analysis for link 113 – 51 (b – c), triangle shaped dots represent data collected on 20th April, square dots are from 21st April, and asterisk shaped dots represent data collected on 22nd April respectively. The relation between the mean travel time *T* and the Travel Time Standard Deviation *TTSD* is assumed to have the form as:

$$TTSD = b + a*T \quad (9)$$

Figure 9#

1
2
3
4
5 The coefficients in the regression formula are slightly different for the different days and
6 there is a negative correlation ($R^2 = 0.908$) between the slope and constants. The analysis for
7 each link separately (see Table 1) shows that the regression parameters differ from link to link
8 and from day to day, while the square of the correlation coefficient R^2 varies between 0.6681
9 and 0.9187. It can be concluded that there is a relation between mean travel time T and
10 $TTSD$, but that the linear relation is not a generic linear function. However, if we analyze the
11 regression parameters a and b we can see that for 4 of the 5 links, these parameters have a
12 strong correlation with the link length. Only the link 113-51 (b –c) does not fit in this relation.
13
14
15
16
17
18
19
20
21

22 Ignoring the link 113-51, we can write the parameter a as $a = 0.403 - 0.0002 L$ while for b
23 we derived $b = -9.1885 + 0.0221 L$, where l is the length of the link. The R^2 is 0.815 for a and
24 0.9222 for b .
25
26
27

28 Although we analyzed only a small number of links, we can assume that there is a linear
29 relation between mean travel time and its standard deviation and that the parameters in that
30 linear relation depend on the length of the link.
31
32
33
34
35
36

37 # Table 1 #
38
39
40

41 ***Traffic density as explanatory variable***

42 The average traffic density of link i \hat{k}_i in time interval T is calculated as:
43
44
45

$$46 \hat{k}_i = \frac{\sum_{j=1}^n t_{ij}}{T} \quad (T = T_2 - T_1) \quad (10)$$

47
48
49
50
51 Where

52 t_{ij} : travel time of vehicle j on link i ;

53 T_1 and T_2 : start and end of the time interval.
54
55
56
57
58
59
60

1
2
3 The traffic density is calculated for all lanes of a link. Traffic densities on Monday 20
4 April were in general higher than on the other days. On that day the travel times were also
5 higher and density and mean travel time are related as visible in equation (10).
6
7
8
9

10 11 ***Degree of saturation*** 12

13 Previous research (e.g. Fu and Hellinga 2000) indicates that the degree of saturation is an
14 important characteristic of a link that determines the standard deviation of the travel time.
15

16
17 In this study, the degree of saturation is also estimated for every 15 minutes using the flow
18 rates, saturation flow rates determined with the ANPR data and the green time and cycle time
19 from the SCATS traffic control. The statistical analysis of the relation between *TTSD* and the
20 degree of saturation, saturation flow rate, traffic density, mean travel time and skewness has
21 initially be done using the Pearson correlation coefficient. The variation in the saturation flow
22 rates appears to have no significant relation with the variation in the *TTSD*. Density and travel
23 times have a significant correlation which is obvious from the way density is calculated by eq.
24 (10) and on most intersections skewness is also significantly related to *TTSD*. For the
25 skewness, the most important correlated factors are *TTSD*, degree of saturation (consistent
26 with the analysis of the model data in Figure 6) and Traffic density.
27
28
29
30
31
32
33
34
35
36
37
38

39 A further analysis has been executed with partial correlation analysis. In that analysis the
40 most important correlated parameter is first used in a linear regression. The remaining errors
41 are then analyzed to find possible correlations with the remaining variables. This analysis
42 method removes the effect of collinearity. Table 2 shows the result of this analysis. The role
43 of the degree of saturation appears not to be significant for most links (with the exception of
44 113-51) and also the explanatory value of the traffic density is relatively small (traffic density
45 is correlated with the mean travel time as can be seen in its definition in eq. 10).
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

Table 2

This analysis is further extended by a step wise linear regression. In that regression method the function to be estimated is

$$TTSD = a_1 \times T + a_2 \times S + a_3 \times k + b \quad (11)$$

Where:

S : Travel time skewness,

k : Traffic density,

b : Constant,

a_i : Coefficient of independent variable i .

The parameters are tested in every step of the regression whether their explanatory values for the residuals that remain from the previous regression step can be sufficiently explained by the remaining variables. Variables that don't contribute significantly to the quality of the regression are eliminated from formula (11). The results are shown in 3 and 4.

Table 3

Table 4

The adjusted R^2 represents the proportion of the total variation in the series that is explained by the linear regression model. Compared with R^2 , the adjusted R^2 eliminates the influence of dependent variables and series size on the coefficients.

The conclusion is that the mean travel time, $TTSD$ and travel time skewness S are mutually significantly related and that the traffic density plays a minor role in explaining the variations

of the standard deviation $TTSD$. Therefore, we can eliminate the traffic density from equation (11) as:

$$TTSD = a_1 \times T + a_2 \times S + b \quad (12)$$

Table 5 shows the regression coefficients and their estimation errors for every link and on the three dates. Coefficients a_1 of Link 50 - 113, 113 - 51 (a - b, b - c), and 24 - 54 (d - e) are rather consistent over different days and just varies between 0.35 and 0.2 for most days. However, coefficient a_1 of Link 51 - 24 (c -d) and 54 - 59 (e - f) fluctuates observably, with an upper boundary of 0.554, while the lower boundary is around 0.260.

The coefficient a_2 varies strongly over the days and differs per link.

Table 5

A next question is whether the regression coefficients are the same for different links. For the simple regression (eq. 9) it was shown that the regression coefficients depend on the link length. For the coefficients in eq. (12) we can find similar results. For the coefficients found for the three days together we can derive the following linear relations between the coefficients and the link length:

$$b = 0.0161 L - 8.0739 \quad R^2 = 0.6751 \quad (13)$$

$$a_1 = -0.0002 L + 0.4069 \quad R^2 = 0.9928 \quad (14)$$

$$a_2 = 0.0242 L - 7.2406 \quad R^2 = 0.8456 \quad (15)$$

1
2
3 Just as in the case of the simple regression we had to ignore the data from link 113 – 51 (b –
4
5 c), which are far from the linear relations.
6
7
8
9

10 ***THE TRAVEL TIME RELIABILITY ANALYSIS FOR A ROUTE***

11
12
13 In the previous section the travel time reliability analysis has been done for single links. In
14
15 this section travel time over a route of several links is analyzed. The full route from
16
17 intersection 50 (a) to intersection 59 (f) appears to have too few complete trips. Since very
18
19 few vehicles can be followed over these links before 6:00, the analysis period was confined to
20
21 the period 6:00 and 0:00. Figure 8 (f) shows the route travel time for three days.
22
23
24
25

26 The variation of travel time between different periods of the day and between days is rather
27
28 large. We will first analyze the travel time reliability within a time period, just as we did for
29
30 the single links. The partial correlations are shown in Table 6.
31
32
33
34

35 # Table 6#
36
37
38

39 For this route, negative correlation exists between skewness and mean travel time. That is
40
41 consistent with the results for undersaturated intersections in the model based analysis. The
42
43 degree of saturation of the four intersections is mostly between 0.7 and 0.9. Furthermore, the
44
45 traffic density and volumes have a significant correlation with the travel time, standard
46
47 deviation and skewness, which was not found for single links.
48
49

50 A stepwise linear regression of the Travel Time Standard Deviation (*TTSD*) as a function of
51
52 the mean travel time T gives:
53
54
55
56
57
58
59
60

$$TTSD = 0.120 \times T + 26.566 \quad (16)$$

This regression equation explains 44.5% of the variation of the *TTSD*. If the skewness *S* is also included in the regression formula, it becomes:

$$TTSD = 0.126 \times T + 10.369 \times S + 20.3 \quad (17)$$

COMPARISON WITH A LINK ON ANOTHER ROUTE

The analysis performed on the West bound links of the Renmin Road have been repeated on different links in the network. In general a similar relation between Travel time *T*, Skewness *S* and Travel time standard deviations *TTSD* is found with significant values for the coefficients a_1 , a_2 , and b in eq. (12). The relation between these coefficients and the link length is not well represented by eq. 13, 14 and 15. Probably the coefficients depend on more traffic characteristics than only the link length.

DISCUSSION AND CONCLUSIONS

Travel time (un)reliability can be characterized by two important quantities: the standard deviation of the travel time and the skewness. Most reliability studies concentrate on the *TTSD*, but several studies show that traveler's route choice and departure time behavior is determined also by the travel time skewness. For this reason the travel times of a route in Changsha have been analyzed with respect to mean travel time, *TTSD* and skewness. The analysis was aimed on travel time reliability within time periods of 15 minutes.

Two methods have been used for this study:

- A model based calculation of travel time distributions,

- Travel times obtained from Automated Number Plate Recognition cameras.

The model based reliability analysis gives results that are qualitatively consistent with the results for the real ANPR data. However, the regression coefficients from the model outcomes differ quantitatively from the ANPR outcomes. Also the regression of the ANPR measurements differs between links. Still there are significant features in the relation between travel time, travel time standard deviation and skewness. On single links *TTSD* is positively correlated with the mean travel time. On routes with several links this relationship is also found. The skewness is negatively correlated with the mean travel time and positively with *TTSD*. For the route the influence of volumes and density on travel time, standard deviation and skewness are significant.

The real travel times, obtained from the ANPR cameras are probably influenced by traffic management made by the traffic police in the field. Even though high degrees of saturation and high traffic densities occur, no spill back phenomena could be observed. In our two analysis methods we took this automatically into account because we used the data that came directly from the real traffic situation. Simulation programs that ignore the influence of traffic management measures probably give results that differ from the empirical data. The standard deviation of the travel time is dominated by the mean travel time.

The linear relationship between mean travel time and *TTSD* is not the same for every link and every day. There is some evidence that the regression parameters for a link depend linearly on the link length.

In the ANPR the taxis were removed because their travel times were not representative for the rest of the traffic. The remaining travel times contain outliers, travel times that are much longer than travel times of vehicles arriving just before or just after a vehicle. These are not representative for the traffic conditions because the drivers apparently had some activities to

1
2
3 do between the two observation sites. The elimination of these outliers changed the statistics
4
5 of the travel times considerably.
6

7 The consequences of the findings for practice is first of all that the improvement of the
8
9 travel time reliability has no apparent conflict with the reduction of delays, since both
10
11 characteristics are linearly related. Also the skewness and mean travel time optimization does
12
13 not have a conflict. Traffic management aimed at the reduction of travel time standard
14
15 deviation and skewness are expected to optimize the mean travel time as well. The study
16
17 reported in this article used only a small part of the available data. Only 7 intersections with
18
19 ANPR cameras have been analyzed, while the cameras are installed on 120 intersections in
20
21 Changsha. The main reason for this selection was that not all ANPR cameras worked
22
23 sufficiently well over longer time periods. That limitation made it possible to analyze in detail
24
25 the relation between travel time reliability and other traffic characteristics. Further research
26
27 will be done to identify the network wide travel time reliability, e.g. the reliability on origin –
28
29 destination basis. Furthermore the data will be used to analyze also the day to day and within
30
31 day travel time reliability.
32
33
34
35

36 *ACKNOWLEDGEMENT*

37
38

39 The authors thank Changsha Traffic Police for the SCATS and ANPR data and Changsha
40
41 Saiteng Electronic Co. Ltd. for providing the GPS data of the taxis. This work was also
42
43 supported by the National Science Foundation of China (NSFC) under project 51308475,
44
45 61673321 and 71671147, the Chengdu Science and Technology Commission under project
46
47 2015-RK00-00190-ZF and the Fundamental Research Funds for the Central Universities
48
49 under contract 2682015CX040.
50
51

52 *REFERENCES*

53
54
55
56
57
58
59
60

- 1
2
3 AI-Deek, H. and Emam, E.B. (2006). New Methodology for Estimating Reliability in
4
5 Transportation Networks with Degraded Link Capacities. *Journal of Intelligent*
6
7 *Transportation Systems*, 10:117-129.
8
- 9 Akcelik, R. (1988). The highway capacity manual delay formula for signalized intersections.
10
11 *ITE Journal*, 58(3):23-27.
12
- 13 Arroyo, S. and Kornhauser, A.L. (2005). Modeling Travel Time Distributions on a Road
14
15 Network. *Proceedings of the 84th TRB annual meeting*, Washington D.C.
16
- 17 Bates, J., Polak, J.W., Jones, P. and Cook, A. (2001). The valuation of reliability for personal
18
19 travel. *Transportation Research E*, 37:191-229.
20
- 21 Bogers, E.A.I. (2009). *Traffic Information and Learning in Day-to-Day Route Choice*.
22
23 *Dissertation*, Delft University of Technology, the Netherland.
24
- 25 Carrion, C. and Levinson, D. (2012). Value of travel time reliability: A review of current
26
27 evidence. *Transportation Research Part A: Policy*, 46(4):720-741.
28
- 29 Chen, M., Yu, G., Chen, P. and Wang, Y. (2017). A copula-based approach for estimating the
30
31 travel time reliability of urban arterial. *Transportation Research Part C*, 82: 1-23.
32
- 33 de Jong G.C. and Bliemer, M.C.J. (2015). On including travel time reliability of road traffic in
34
35 appraisal, *Transportation Research Part A; Policy* 73 80–95
36
- 37 Fu, L. and Hellinga, B. (2000). Delay Variability at Signalized Intersections. *Transportation*
38
39 *Research Record: Journal of the Transportation Research Board*, 1790:215-221.
40
- 41 FHWA, Federal Highway Administration. Travel Time Reliability: Making It There On Time,
42
43 All the Time. www.ops.fhwa.dot.gov/publications/tt_reliability/TTR_Report.htm. Accessed
44
45 October 2015.
46
- 47 Guo, F., Rakha, H. and Park, S. (2010). A Multi-State Travel Time Reliability Model. *TRB*
48
49 *89th annual meeting*, Washington D.C.
50
51
52
53
54
55
56
57
58
59
60

- 1
2
3 Kim, J., Mahmassani, H., Vovsha, P., Stogios, Y. and Dong, Y. (2013). Scenario-based
4 Approach to Analysis of Travel Time Reliability with Traffic Simulation Models.
5 *Transportation Research Record: Journal of the Transportation Research Board*, 2391:56-
6
7 68.
8
9
10
11 Kim, J. and Mahmassani, H.S. (2014). A finite mixture model of vehicle-to-vehicle and day-
12 to-day variability of traffic network travel times. *Transportation Research Part C:*
13 *Emerging Technologies*, 46:83-97.
14
15
16
17 Liu, H.X., Recker, W. and Chen, A. (2004). Uncovering the contribution of travel time
18 reliability to dynamic route choice using real-time loop data. *Transportation Research Part*
19 *A: Policy*, 38(2004):435-453.
20
21
22
23
24 Lomax, T., Schrank, D., Tyrners, S. and Margiotta, R. (2003). Selecting travel time reliability
25 measures. *Technical report*, Texas Transportation Institute, Texas, USA.
26
27
28
29 Mahmassani, H.S., Hou, T. and Dong, J. (2012). Characterizing Travel Time Variability in
30 Vehicular Traffic Networks: Deriving a Robust Relation for Reliability Analysis.
31 *Transportation Research Record: Journal of Transportation Research Board*, 2315:141-
32
33 152.
34
35
36
37 Mahmassani, H.S., Hou, T. and Saberi, M. (2013). Connecting Networkwide Travel Time
38 Variability and the Networkwide Fundamental Diagram of Traffic Flow. *Transportation*
39 *Research Record: Journal of the Transportation Research Board*, 2391:80-91.
40
41
42
43
44 Olszewski, P.S. (1990). Modelling of queue probability distribution at traffic signals. *in*
45 *Proceedings: the 11th International Symposium on Transportation and Traffic Theory*,
46
47 Tokyo.
48
49
50
51 Pu, W. (2011). Analytic Relationship Between Travel Time Reliability Measures.
52 *Transportation Research Record: Journal of the Transportation Research Board*,
53
54 2254:122-130.
55
56
57
58
59
60

- 1
2
3 Robinson, S. and Polak, J.W. (2007). Charaterizing the components of urban travel time
4 variability using the k-NN method. *86th TRB Annual meeting*, Washington D.C.
5
6
7 Sen, S., Pillai, R., Joshi, S. and Rathi, A. (2001). A Mean-Variance Model for Route
8 Guidance in Advanced Traveler Information Systems. *Transportation Science*, 35(1):37-49.
9
10
11 Tu, H. (2008). *Monitoring Travel Time Reliability on Freeways. PhD thesis, TRAIL Thesis*
12 *series*, Delft University of Technology, the Netherlands.
13
14
15 Van Lint, J.W.C., Van Zuylen, H.J. and Tu, H. (2008). Travel time unreliability on freeways:
16 Why measures based on variance tell only half the story. *Transportation Research Part A:*
17 *Policy and Practice*, 42(1):258-277.
18
19
20
21
22 Van Zuylen , H.J. and Viti, F. (2007). A Probabilistic Model for Queues, Delays and Waiting
23 Time at Controlled Intersections. *86th TRB annual meeting*, Washington D.C., U.S.
24
25
26 Viti, F. (2006). *The Dynamics and the Uncertainty of Delays at Signals. PhD thesis* , Delft
27 University of Technology, Delft.
28
29
30
31 Viti, F. and van Zuylen , H.J. (2006). Consistency of random queuing models at signalized
32 intersections. *In Proceedings: 85th TRB annual meeting*, Washington D.C., USA.
33
34
35 Viti, F., & van Zuylen, H.J. (2009). The dynamics and the uncertainty of queues at fixed and
36 actuated controls: A probabilistic approach, *Journal of Intelligent Transportation Systems*
37 13(1), 39-51
38
39
40
41 Viti, F. and Van Zuylen , H.J. (2010). Probabilistic models for queues at fixed control signals.
42 *Transportation Research Part B: Methodological*, 44:120-135.
43
44
45
46 Webster, F.V. (1958). Traffic signal settings. Road Research Laboratory London, Her Majesty
47 Stationary Office.
48
49
50 Yang, Q., Wu,G., Boriboonsomsin, K. and Barth, M. (2017). A novel arterial travel time
51 distribution estimation model and its application to energy/emissions estimation. *Journal of*
52 *Intelligent Transportation Systems*, pp.1-13.
53
54
55
56
57
58
59
60

1
2
3 <https://doi.org/10.1080/15472450.2017.1365606>

4
5 Zheng, F. and van Zuylen, H.J. (2010). Uncertainty and Predictability of Urban Link Travel
6
7 Time: A Delay Distribution Based Analysis. *Transportation Research Record: Journal of*
8
9 *the Transportation Research Board*, 2192:136-146.

10
11 Zheng, F. and van Zuylen, H.J. (2011). Modeling Variability of Urban Travel Times by
12
13 Analyzing Delay Distribution for Multiple Signalized Intersections. *Transportation*
14
15 *Research Record: Journal of the Transportation Research Board* 2259:80-95.

16
17 Zheng, F. and Van Zuylen , H.J. (2014). The Development and Calibration of a Model for
18
19 Urban Travel Time Distributions. *Journal of Intelligent Transportation Systems:*
20
21 *Technology, Planning, and Operations* 18(1):81-94.

22
23
24 Zheng, F., Van Zuylen, H.J., Liu, X.B. (2017). A Methodological Framework of Travel Time
25
26 Distribution Estimation for Urban Signalized Arterial Roads. *Transportation Science*, pp.1-
27
28 25. <https://doi.org/10.1287/trsc.2016.0718>

List of figures and tables

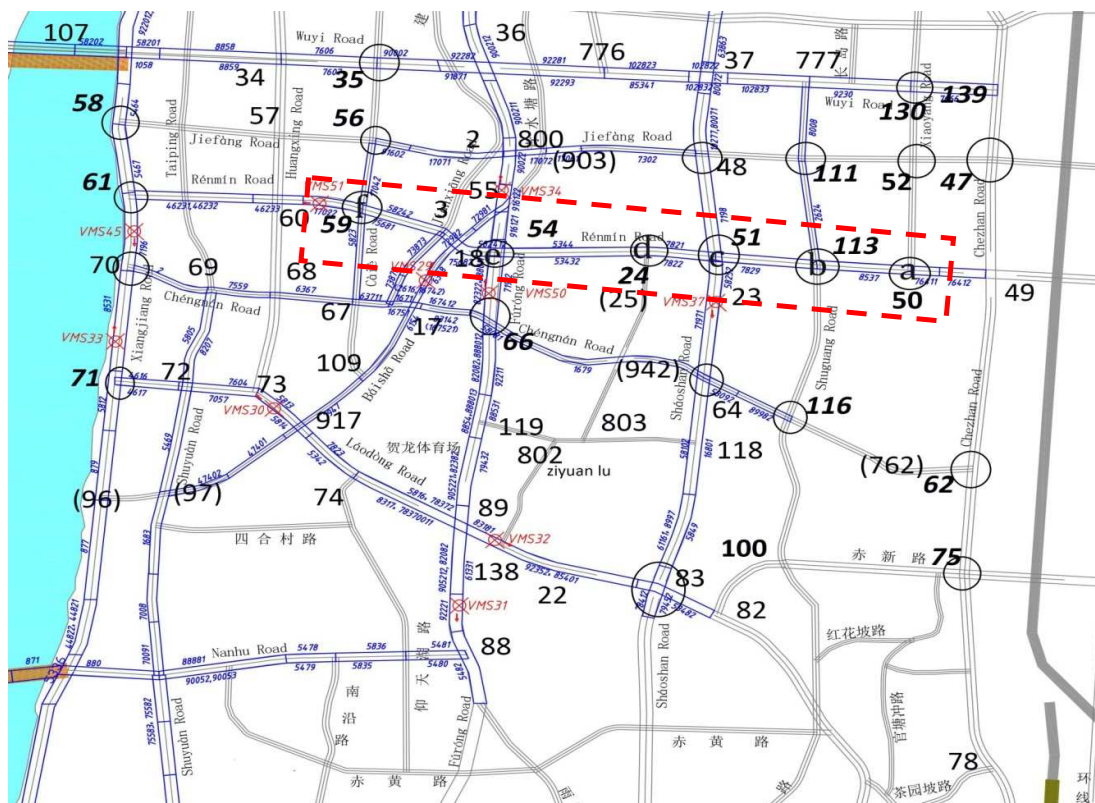
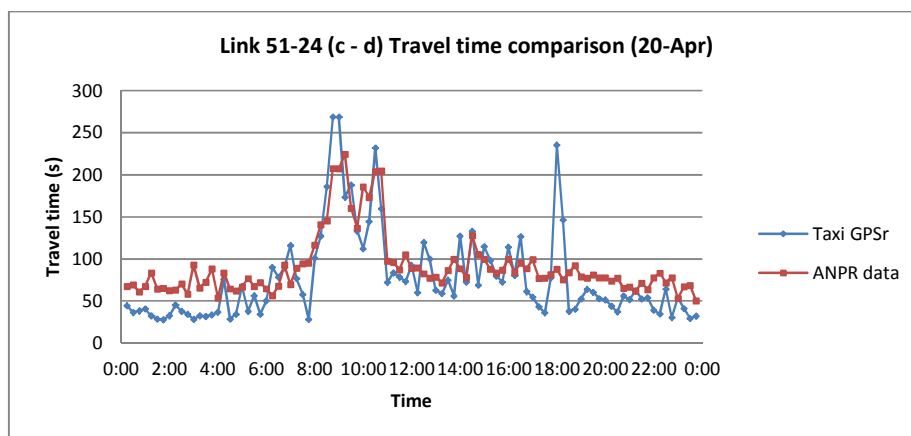
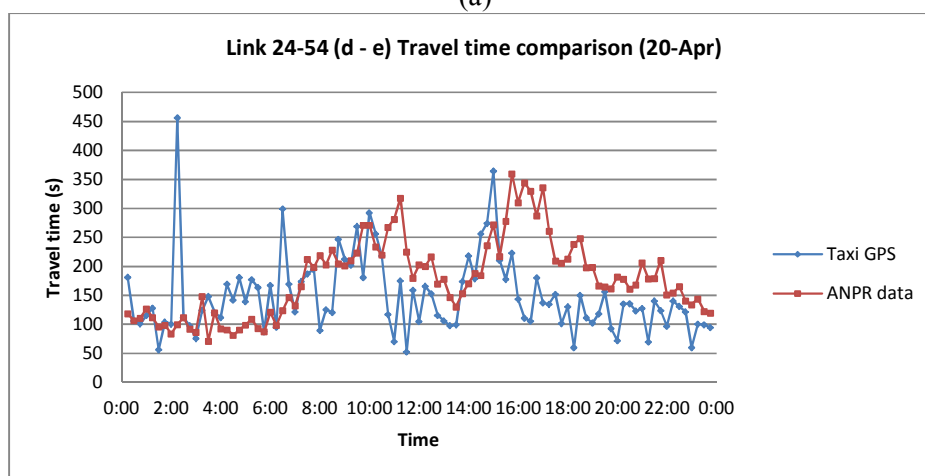


Figure 1 The network of Changsha for which the travel time distributions have been determined . The intersections with a number in *italics* have ANPR cameras. The area in the red dashed rectangle is the Renmin Road, where the travel times have been analyzed on the corridor 50 -59 (a - f)



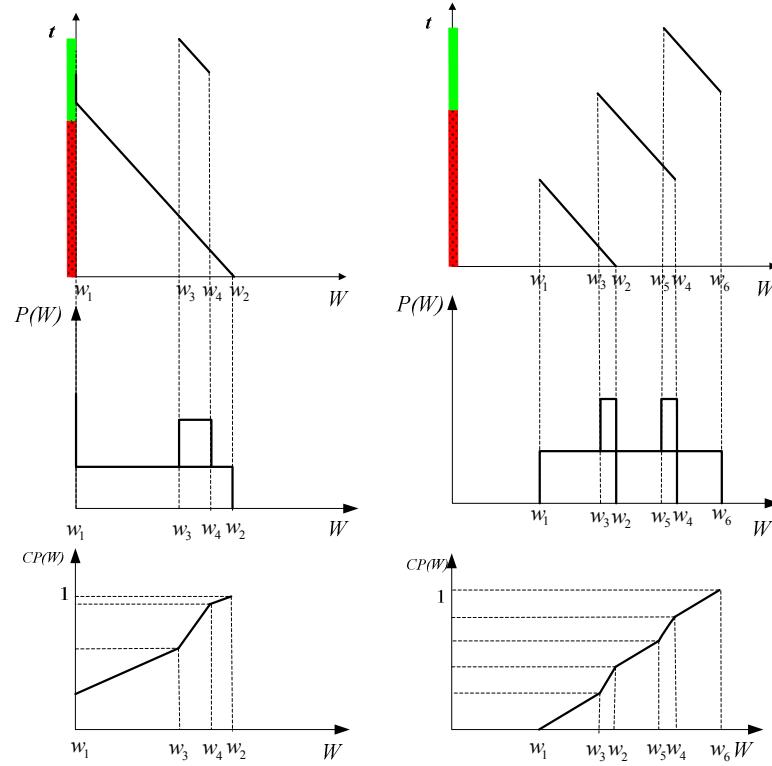
(a)



(b)

34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

Figure 2 Comparison of travel times as measured by taxi with GPS and by cameras.



(a) Undersaturated condition

(b) Oversaturated condition

Figure 3 Relationship between the arrival moment and the delay, delay probability distribution and cumulative distribution for both undersaturated and oversaturated conditions

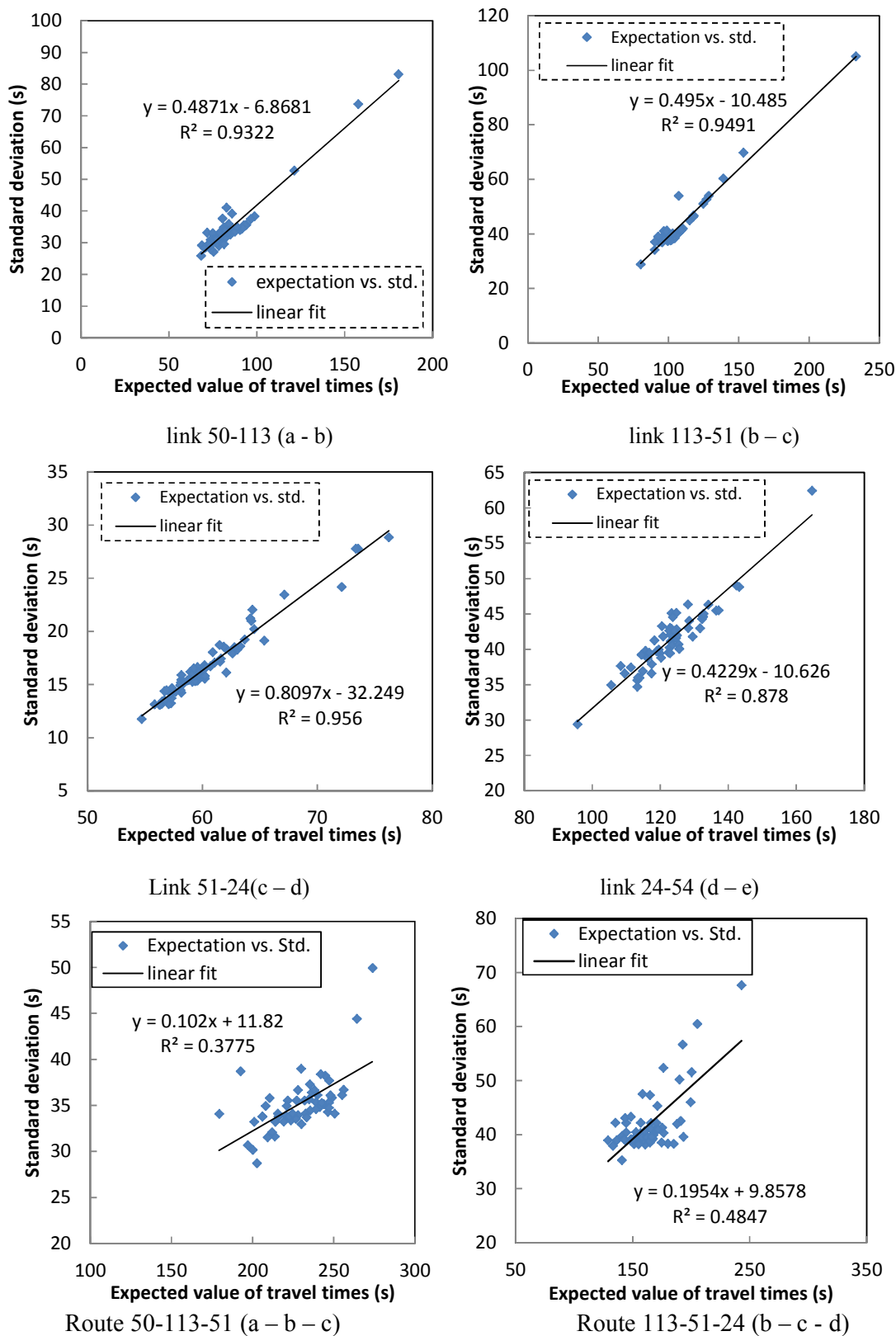


Figure 4 The relation between expectation value of travel time and its standard deviation for single links and routes with two coordinated intersections

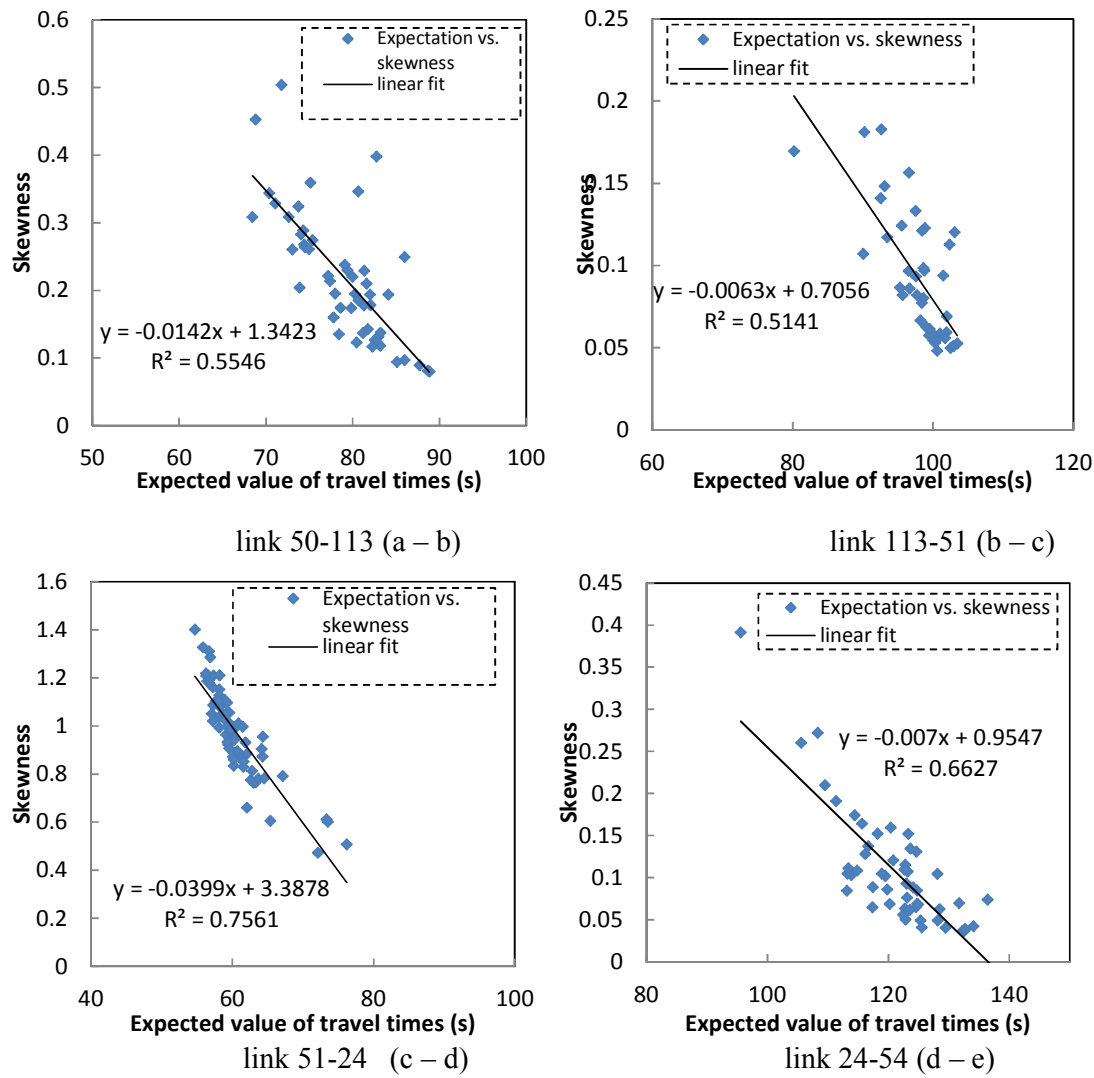


Figure 5 Relation between expectation value of the travel time and skewness for isolated intersections with a degree of saturation lower than 0.8

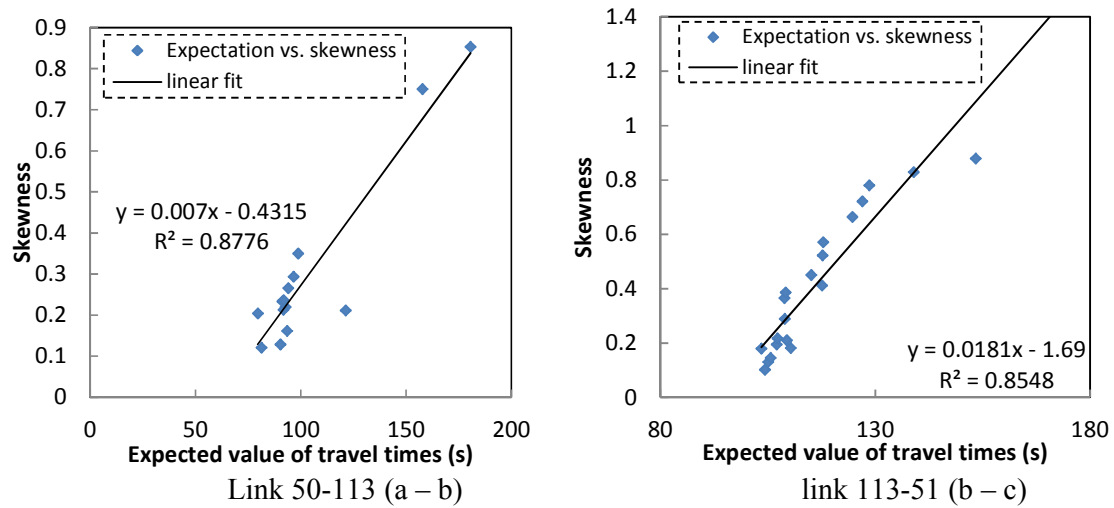
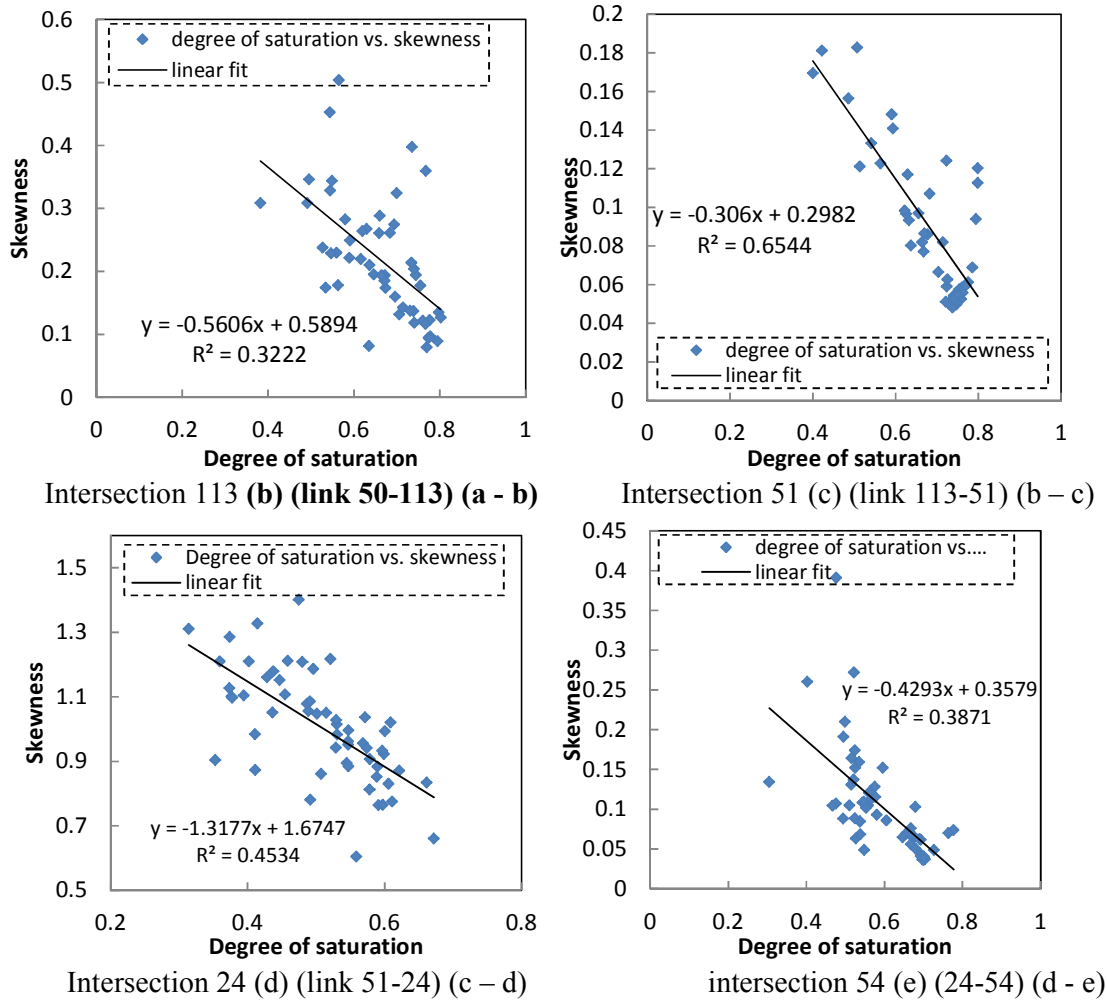


Figure 6 Relation between skewness and expectation value of the travel time for intersections with a degree of saturation > 0.8



(a) degree of saturation $x < 0.8$

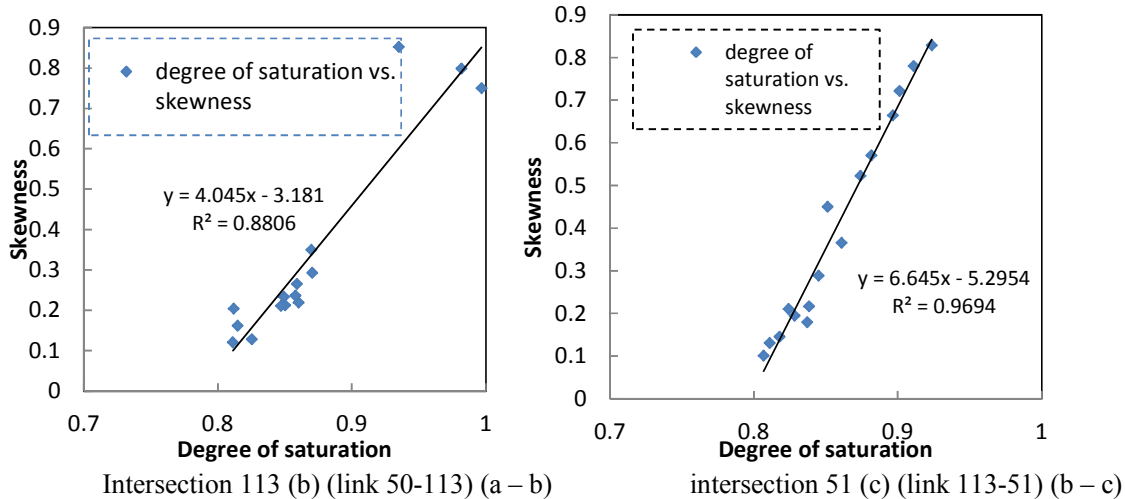
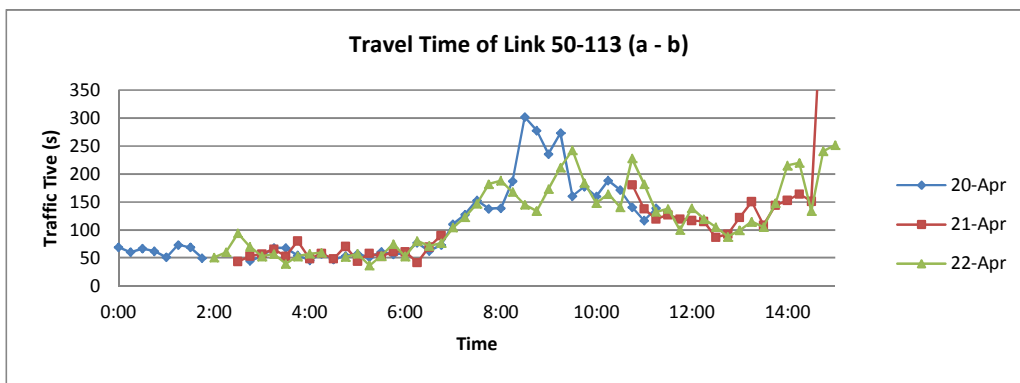
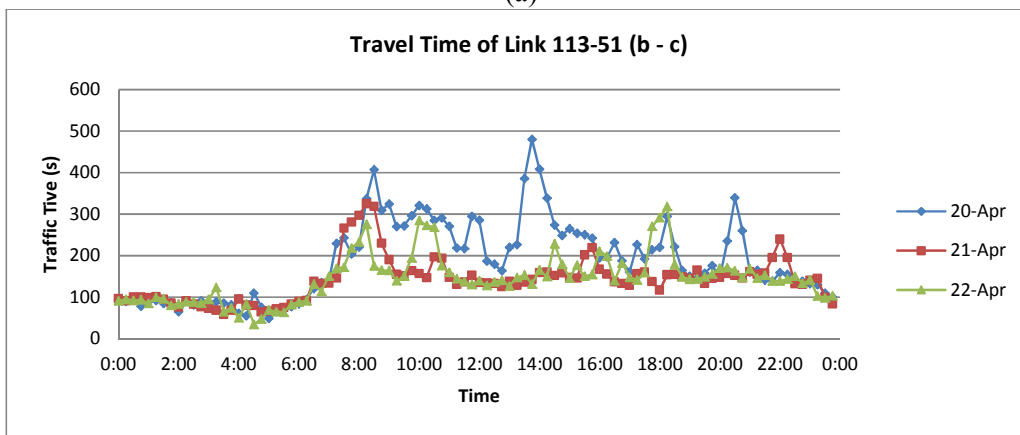


Figure 7 (b) Degree of saturation $x > 0.8$

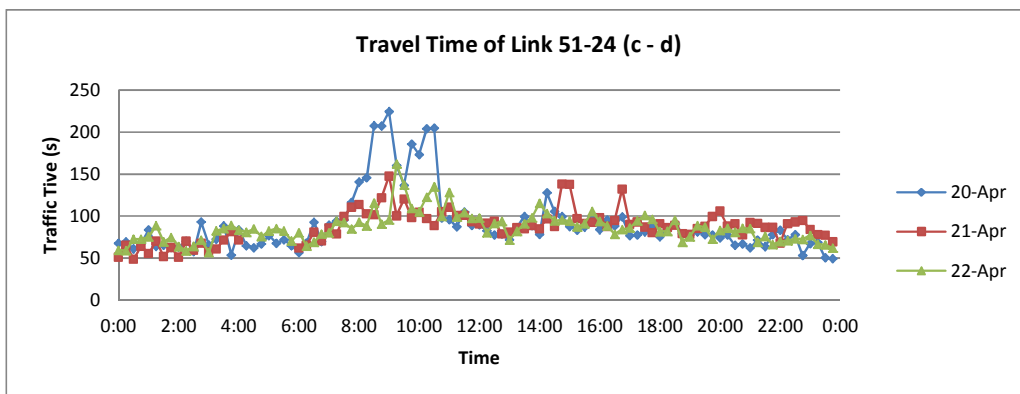
Figure 7 Relation between degree of saturation and skewness



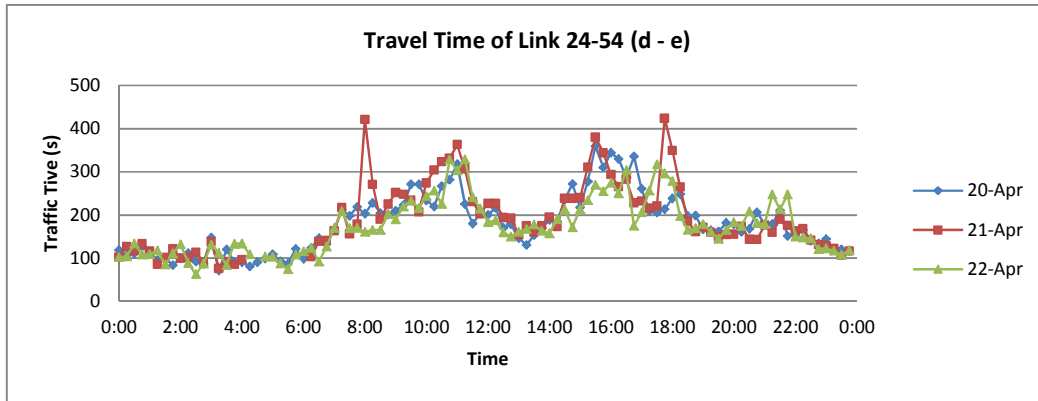
(a)



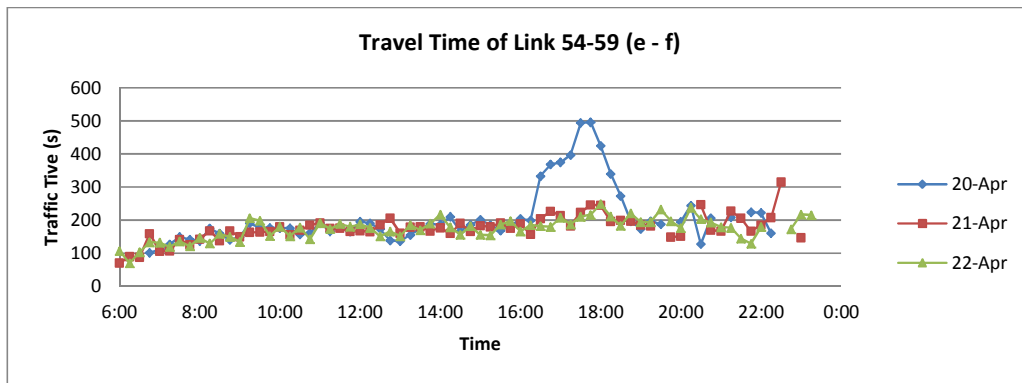
(b)



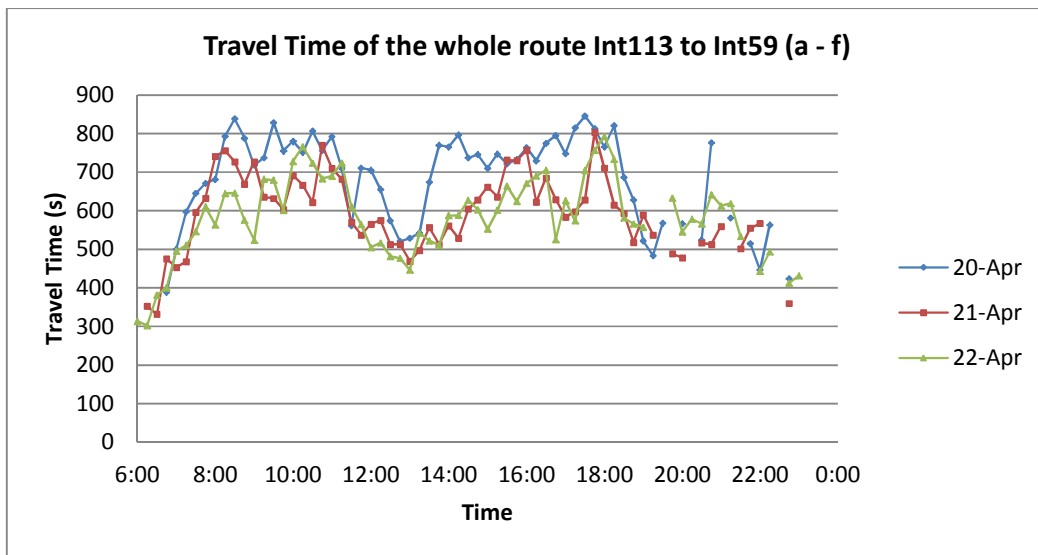
(c)



(d)

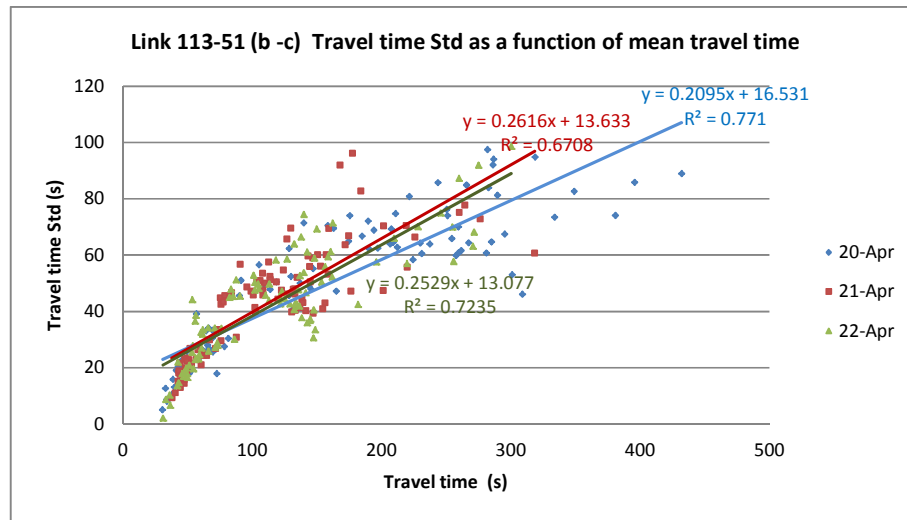


(e)



(f)

Figure 8 Travel times as function of the time of day and day of the week



20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

Figure 9 The graphical relation between TTSD and average travel time

Table 1 The parameters of a linear function used to describe the relation between travel time T and $TTSD$: $TTSD = a \times T + b$. Number is the number of recognized vehicles.

Link		50-113 (a - b)	113-51 (b - c)	51-24 (c - d)	24-54 (d - e)	54-59 (e - f)
Length (m)		449	486	326	718	671
Apr. 20 th	a	0.2800	0.2095	0.3050	0.2904	0.2468
	b	2.1846	16.531	0.3125	4.0841	9.6628
	R^2	0.9187	0.7710	0.7944	0.8765	0.7121
	Number	6937	11482	10005	7271	4362
Apr. 21 st	a	0.3515	0.2616	0.5337	0.2767	0.4219
	b	-2.6692	13.633	-13.532	7.655	-14.465
	R^2	0.9078	0.6708	0.7211	0.8582	0.7702
	Number	7549	10216	10541	7731	4670
Apr. 22 nd	a	0.2868	0.2530	0.4637	0.2952	0.3541
	b	4.2786	13.046	-9.2114	4.7014	-4.3405
	R^2	0.9078	0.7218	0.7161	0.8928	0.6681
	Number	7434	10457	10881	7355	4707
Integrated Data	a	0.3103	0.2243	0.3607	0.2862	0.271
	b	1.1674	16.145	-3.1195	5.6170	6.8523
	R^2	0.8661	0.7245	0.7102	0.8748	0.6883
	Number	21920	32155	31427	22357	13739

Table 2 Partial correlation analysis between Travel Time Standard Deviation (TTSD) / skewness resp. and other factors (3 days data)

Partial correlations between TTSD and other factors				
Link	Degree of saturation	Density	Travel Time	Skewness
50-113 (a – b)	.026	-.124	.673**	.383**
113-51 (b – c)	.304**	-.229**	.464**	.308**
51-24 (c – d)	.199*	-.117	.467**	-.161
24-54 (d – e)	.178*	-.179*	.632**	.573**
54-59 (e – f)	.065	-.005	.556**	.231*
Partial correlation between skewness and other factors				
Link	Degree of saturation	Density	Travel Time	TTSD
50-113 (a – b)	.011	-.093	-.230**	.383**
113-51 (b – c)	-.240**	.083	-.178**	.308**
51-24 (c – d)	.048	.020	-.138	-.161
24-54 (d – e)	-.102	.099	-.321**	.573**
54-59 (e – f)	.050	.397**	-.625**	.231*

** . Correlation is significant at the 0.01 level (2-tailed).

* . Correlation is significant at the 0.05 level (2-tailed).

Table 3 Coefficients in the multiple linear regression formula for *TTSD*

Link	Coefficient of travel time T		Coefficient of Skewness		Coefficient of density		Coefficient of Saturation flow rate		Constant		Adjusted R^2
	a_1	Std. Error	a_2	Std. Error	a_3	Std. Error	a_4	Std. Error	Constant	Std. Error	
50-113 (a – b)	.329	.014	7.443	1.452					-3.585	2.136	.814
113-51 (b – c)	.312	.041	4.396	.931	-.498	.145	30.995	6.649	2.288	4.758	.668
51-24 (c – d)	.361	.017							-3.329	1.301	.770
24-54 (d – e)	.255	.008	14.384	1.519					8.585	1.791	.862
54-59 (e – f)	.271	.019	5.789	2.058					3.162	4.417	.699

* Stepwise (Criteria: Probability-of-F-to-enter $\leq .050$, Probability-of-F-to-remove $\geq .100$).

Table 4 Stepwise linear regression of travel time skewness

Link	Coefficient of <i>TTSD</i>		Coefficient of <i>T</i>		Coefficient of <i>V/C</i>		Coefficient of <i>Density k</i>		Constant		Adjusted R^2
	a_1	Std. Error	a_2	Std. Error	a_3	Std. Error	a_4	Std. Error	Constant	Std. Error	
50-113 (a – b)	.022	.004	-.010	.001					.687	.102	.252
113-51 (b – c)					-1.382	.321			1.103	.244	0.075
51-24 (c – d)			-.016	.002					2.378	.133	.390
24-54 (d – e)	.022	.002	-.005	.001					-.153	.074	.343
54-59 (e – f)	.010	.004	-.013	.001			.018	.004	1.853	.140	.474

Table 5 Regression coefficients for equation (9) calculated for different days and different links

Link	Name	50-113 (a – b)		113-51 (b – c)		51-24 (c – d)		24-54 (d – e)		54-59 (e – f)	
	Length	448.77m		485.789m		325.92m		718.93m		671.16m	
Date	coefficient	value	Std	value	Std	value	Std	value	Std	value	Std
Apr. 20 th	b	.142	2.035	14.995	2.436	.915	1.966	3.287	1.899	5.780	5.955
	a_1	.291	.014	.216	.012	.302	.018	.283	.010	.260	.024
	a_2	2.692	1.964	2.785	1.780	-.346	.892	8.486	1.626	3.353	3.052
	R^2	.919		.772		.790		.906		.733	
Apr. 21 st	b	-5.268	2.085	12.506	2.811	-16.122	3.031	7.127	2.173	-15.609	4.183
	a_1	.361	.014	.269	.021	.554	.039	.257	.011	.421	.028
	a_2	3.539	1.519	1.426	1.725	1.056	.848	14.494	2.666	1.298	1.427
	R^2	.912		.666		.720		.892		.766	
Apr. 22 nd	b	-2.493	2.293	11.647	2.010	-2.841	3.005	2.211	1.730	.555	4.992
	a_1	.318	.015	.265	.015	.404	.036	.296	.009	.288	.034
	a_2	8.925	1.722	5.142	1.131	-1.963	.725	7.667	1.704	7.609	1.523
	R^2	.841		.767		.731		.918		.665	
3-day	b	-3.368	1.301	14.916	1.316	-1.084	1.407	4.291	1.115	3.287	1.899
	a_1	.331	.009	.231	.008	.347	.015	.279	.006	.283	.010
	a_2	5.987	1.042	2.888	.882	-.947	.493	9.428	1.117	8.486	1.626
	R^2	.883		.732		.712		.902		.906	

Table 6 Partial Correlations analysis of 3 links 113⇒51⇒24⇒54. Volume and density are averaged over the 3 links.

	TT_mean	TT_std	TT_skew	Volume	Density
TT_mean	1	.650**	-.236**	-	.89
TTSD	.650**	1	.405**	.522**	.9**
TT_skew	-.236**	.405**	1	.305**	-.398**
Volume	-.522**	.305**	-.327**	1	.0**
Density	.899**	-.398**	.230**	.761**	1

1
2
3 Dear editor
4

5 We have modified our article 'urban travel time reliability at different traffic conditions' (GITS-
6 2015-0259) according to your recommendations. We have added two references to publications in
7 your journal (by Yang and by Viti and van Zuylen) and a reference to a recently published article
8 (Zheng, F., Van Zuylen, H.J., Liu, X.B. (2017)). We have followed the guidelines for authors of your
9 journal.
10
11

12 Thank you for publishing our article.
13

14 Sincerely yours
15

16 Henk J. van Zuylen
17

18 (on behalf of all authors)
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60