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Influence of Weather on Traffic Flow: an Extensive Stochastic Multi-effect Capacity and Demand Analysis

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Abstract

Traffic is affected by a wide range of variables. An influential and commonly occurring variable on traffic flow is the weather. Weather conditions affect both traffic demand as well as road capacity and in doing so also affect the traffic fluency, or rather the ability of traffic to maintain a certain level-of-service. In this contribution it is argued that the influence of weather should be considered holistically for simultaneous influence on both the demand and supply. Furthermore, a case is made to quantify such outcomes stochastically, as traffic is rarely in an average state, especially when considering such stochastic variables as the weather. This is backed up by an extensive data analysis into the effects of rain, snow, temperature and wind on road capacity, traffic demand and traffic fluency. This found the effects on the traffic fluency of rain to be limited due to a reduction in both capacity and demand on relevant days. The effect of cold temperatures was especially shown to affect traffic to a greater extent. Results from snowfall remained inconclusive due to limited observations.

*Keywords:*Traffic flow, Capacity estimation, Demand estimation, Weather effects

1. Introduction

It is well known that weather influences many dynamic processes in traffic flow on multiple levels (Agarwal et al., 2005, Böcker et al., 2013). In operational and tactical analysis, as well as in the planning thereof, there may often be requirements to consider the influence that weather effects have on traffic flow. Fluctuations in traffic flow on both an operational hour-to-hour as well as on a tactical day-to-day level need to be accurately considered. It has been shown that weather has an influence on both traffic demand and capacity and is therefore a key variable and one that should be closely considered. It is therefore important that strong methodologies exist that allow fluctuations in various weather effects to be determined for an entire traffic system and, furthermore, that a base quantification exists of the possible influences.

In past decades research has been performed on a number of separate weather conditions for their effects on both capacity as well as traffic demand, such as rainfall,

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snowfall, wind, temperature and mist (Böcker et al., 2013, Snelder and Calvert, 2015). In this research, we will focus on the first four weather conditions.

Precipitation, both in the form of rain and snow, has probably been most extensively researched out of all weather conditions. Research on the effects of rain on capacity is generally collected for large rain intensity intervals and is compared to dry weather conditions. Agarwal et al. (2005), Calvert and Snelder (2013), Cools et al. (2010), Hranac et al. (2006), Smith et al. (2004) & van Stralen et al. (2014) are just some who have estimated capacity reduction due to rain and have found varying values in different regions varying in general from 4-30% capacity reduction depending on intensity. Changes in traffic demand due to rain have also been found generally indicating a reduction in traffic demand in the region of 0-5% also depending on rain intensity in most cases (Chung et al., 2005, Hogema, 1996, Keay and Simmonds, 2005, Vukovic et al., 2013). Exact values for these references can be found in Snelder and Calvert (2015) and are also given in Appendix A.

The effect of snowfall on capacity reduction has been found to be in between 3-30% capacity reduction depending on the intensity (Agarwal et al., 2005, Hranac et al., 2006). The effects on traffic demand of snowfall are somewhat more pronounced than for rain and have been found by a number of researchers to be anywhere up to 50% (Al Hassan and Barker, 1999, Hanbali and Kuemmel, 1993).

Previous research into the effects of wind has widely remained inconclusive. In Kwon et al. (2013) no significant effects of wind were found on the capacity. Agarwal et al. (2005) also found limited effects of 2% at most for above 32 kph. Other research has also shown the effects to be limited. No conclusive research was found on the demand effects of high winds. However, it should also be noted that local wind conditions can lead to substantial decreases in capacity, such as on bridges or along a coastline.

The effects of cold temperatures were found to predominantly present for the more extreme temperatures and only really for freezing temperatures. In Agarwal et al. (2005) values of 2% capacity were found for temperatures down to -20 degrees Celsius and up to 10% for more extreme cold. Other research has confirmed the reduction for non-extreme temperatures to be limited or non-existent (Kwon et al., 2013). An overview of values found in literature for each of these weather conditions is given in Appendix A for both capacity reductions and demand changes.

In nearly all of these studies the results merely show a single value or a bandwidth in which the results fall. This is compared to a distribution for the capacity reduction, which would fit much better with the real stochastic nature of capacity. In previous research it has been argued that the influence of relevant variables should be considered as stochastically (Lorenz and Elefteriadou, 2001, Van Stralen et al., 2015). From the presented literature it is also clear that much work has already been performed in an attempt to quantify various weather effects. But what does become apparent from the literature overview is that each weather type is viewed for its influence on either capacity or on demand and rarely on the combination of both. Also, many studies show single values, rather than a distribution of values. This is a gap in literature that is not unimportant, as it is not just the demand or supply that influences traffic flow dynamics, but rather the combination thereof. Also, the stochastic character of both weather and traffic should not be presumed to be captured by single valued observations, but rather by the underlying distributions. This was considered previously in Van Stralen et al. (2015), however demand was estimated from a stated preference experiment and not observed, whereas here we introduce a methodology which extracts the influence of demand from data.

The main objective of this paper is to highlight the need to consider the influence of weather effects from both a supply and demand side and also the need to do this stochastically, to demonstrate a methodology to do this and finally give an extensive stochastic quantification of various weather effects on traffic using the methodology. In the rest of the paper sections 2 and 3 describe the inherent stochastic characteristics of road capacity and traffic demand respectively. In section 4 the general methodology for determining the effects of weather on traffic fluency are described. The extensive results of weather on traffic fluency for multiple weather effects are given in section 5. Finally these are discussed and conclusions are given in section 6.

2. Stochastic traffic dynamics

An important assumption in this paper is that traffic fluency, as a function of both capacity and traffic demand, is a stochastic entity. Traffic fluency in this contribution denotes the level-of-service or ability of traffic to flow rather than a quantitative value of flow, as is described in later in more detail. Also weather, and its influence on traffic, itself is a stochastic system. This is a rather trivial assumption to make on all accounts as the stochastic nature of all of these is obvious and has been easily shown in the past. This however does not prevent the presentation of these quantities to be considered as deterministic values, as is commonly done. In this research we also consider the stochastic influence on traffic and quantify this. In this section a description is given of the stochastic dynamics of both road capacity and traffic demand. Methods are also given which can be used to quantify these.

2.1 Stochastic Capacity

In traffic flow theory there are not many variables that are as fundamental as road capacity. In traffic flow the capacity of a road has a direct influence on the traffic state. There are various differing definitions of road capacity, each with a specific purpose and a specific manner of detection or calculation. Common capacity definitions relate to the traffic state, such as the undersaturated or breakdown, discharge, and nominal capacity. A distinction can also be made between deterministic and stochastic capacity estimation. Motorway capacity is traditionally regarded as a deterministic phenomenon where the largest observed flow value before breakdown is considered as the absolute capacity of a road. However, numerous researchers have shown that the maximum capacity of a motorway varies even when the external factors are constant (Brilon et al., 2005, Elefteriadou et al., 1995, Lorenz and Elefteriadou, 2001, Minderhoud et al., 1997, Persaud et al., 1998). This results from unpredictable behaviour of drivers on a microscopic level.

Traffic as a stochastic system produces stochastic capacities, and therefore consideration of capacity as stochastic entity makes more sense than as deterministic. In any case, a conventional deterministic capacity will often be derived from multiple stochastic capacity observations, and therefore stochastic capacity is more elementary and is considered here in greater detail.

Variations in capacity stem directly from stochastic driver behaviour, not only from individual drivers, but also between drivers. Furthermore, a drivers’ behaviour can also vary in time and space. The mathematical definition of capacity is directly linked to that of the traffic flow and is inversely proportionate to the average time headway of traffic. The capacity of a road is then the traffic flow for the smallest mean time headway before traffic flow breakdown, for breakdown capacity, or after, for discharge capacity. From the relationship between the time headway and flow, it is evident that there is a direct relationship between driver behaviour and capacity. As the actions of a driver are variable, therefore the ability of a driver to traverse a road at a certain time headway to their predecessor is also variable. Moreover, this ability is also subject to the prevailing conditions of both the driver and the driving conditions. Therefore, one can clearly derive that the capacity of a road is also subject to aggregation of these conditions.

There are a number of known factors that directly or indirectly influence road capacity. For some, (exploratory) quantitative research has been performed, for others the quantitative relationship is less well researched. Some known and researched variables are road works, environmental effects (i.e. weather), incidents, modal split, driver & vehicle population, large events, luminance, and various temporal variables (i.e. seasonal). There are also many other (unknown) variables that may have a (small) effect on capacity.

Uncertainty of road capacity in traffic flow has led to a growth in stochastic estimation methods that take (a part) of this uncertainty into account to improve accuracy and reliability of capacity estimations. In many methods, use is made of arbitrary stochastic variations in either or both the capacity and traffic demand. In some cases a distribution of capacity is considered, however in such a way that it does not always accurately resemble capacity variations in reality and therefore may introduce additional errors. A number of capacity estimation methods exist which make use of different assumptions and capture capacity values in different ways. For an overview of many of these methods, see Minderhoud et al. (1997), and more recently on stochastic methods: Geistefeldt and Brilon (2009). In this research use is made of the Product Limit Method (PLM) as described by (Brilon et al., 2005) and recommended in the mentioned capacity estimation reviews. The method is described in section 3.2.

2.2 Stochastic Traffic Demand

Traffic demand is arguably much more stochastic than that of road capacity. It is easily understood that the number of vehicles requiring use of infrastructure is subject to fluctuations, which can be compared with queuing theory at a general stochastic level, but more when the daily and inter-daily trends in demand are considered.

Estimation of traffic demand is a vast area of research for which each subdomain has a specific purpose. For economical purposes demand is often linked to elasticity's and given monetary value compared to a wide range of variables (Graham and Glaister, 2004). A far more relevant area of research for this contribution is that of origin-destination (OD) estimation. Here the goal is to link demand to an origin to give insight into local traffic demand. This is primarily performed in three ways: through large scale population surveys, through empirical observations of traffic flow, or through a combination of both (Bera and Rao, 2011). In this research we are interested in local demand variations and less so in explicit OD-relations. Furthermore the goal in relation to demand is to derive patterns from vast amounts traffic flow data, rather than population data. Therefore, methods that explicitly look at deriving demand from traffic flows are most suited. Within this category a distinction may be made between methods that consider the effects of congestion on demand estimations and those that do not consider congestion effects. In Bera and Rao (2011), among others, a detailed review of various OD-estimation methods is given.

The discussion between congested and uncongested estimation is an important one. When deriving demand, one may expect that traffic flow resembles demand where congestion is not present, as traffic has the ability to reach a road section more or less unhindered. When congestion is present a few effects occur that introduce a bias to this reasoning. Firstly traffic is delayed and is therefore dispersed over time so that traffic with identical demand in time arrives at a location at different times. A second effect is that traffic may reroute to avoid congestion leading to different travel times and also passing of other locations than expected without congestion. A third effect is that of departure time shifts. If some traffic is not bound to a set departure time, shifts in the departure time may occur as drivers attempt to reduce their travel times by avoiding congestion. So although demand estimation for one specific road section may seem trivial, there are external effects, such as congestion, that should not be ignored. These effects are taken into consideration in the developed method for the demand estimation to reduce a possible bias. The demand estimation method is described in section 3.3.

3. Methodology

3.1 Framework

The applied methodology makes use of a combined approach using some existing methodological elements from both traffic theory and data analysis, while introducing some effective new methods. Figure 1 gives a complete overview of the main parts of the methodological framework. On one side,a comprehensive capacity estimation is performed using the adapted Product Limit Method in which 25 bottleneck locations are considered during a three year period and from which capacity estimations are made in the test case. The capacity estimations also include a stochastic estimation of the probability of various capacity values. On the other side,an estimation is made of traffic demand following *a traffic cordon inflow* approach. This approach records the inflow of all traffic into a specific network area during a set time period and derives the traffic demand therefrom. In this research, a 142 location cordon is applied and considered during a 4 year period. Both the capacity and demand parts are fed with detailed traffic data with minute-to-minute accuracy for both the traffic flow and speed. Furthermore detailed hourly weather data is acquired for all periods indicating a wide range of weather conditions and their corresponding data. For capacity estimations a further source of data is available in the form of minute-to-minute radar data with an accuracy of approximately 1 kilometre, allowing specific capacity estimation, as capacity is moment-in-time observation. Finally, both the capacity and demand estimations are combined to give an estimation of the effect on traffic fluency. This is performed through a simple division of the change in capacity by the change in traffic demand, which means that if both variables change at the same rate, that the effect on traffic fluency will remain identical. While a lower capacity value may reduce traffic flow, a reduction in demand can counteract the ability of traffic to flow fluently. Therefore, only a combination of both gives an accurate estimation on the actual effect on traffic fluency. Note that *traffic fluency* here denotes the level-of-service or ability of traffic to flow rather than a quantitative value of flow. In the following subsections a more detailed description is given of the various parts of the methodology.

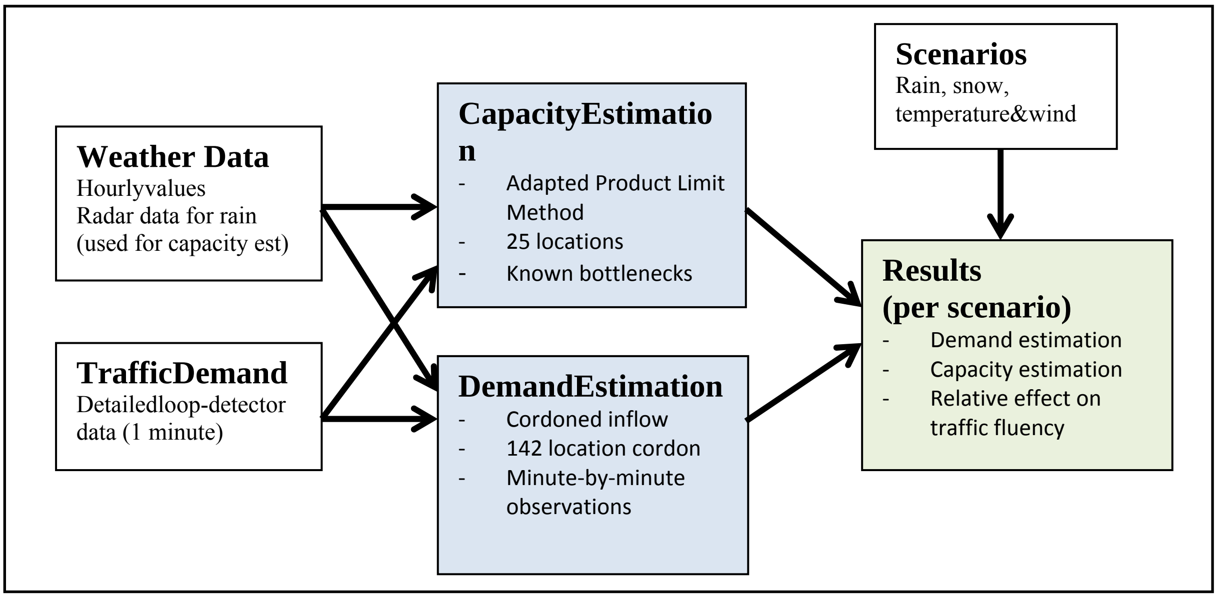

Figure 1. Applied framework

3.2 Capacity analysis

In this research, a stochastic capacity estimation method is applied that allows probability distributions of capacity to be constructed which envelop the full range of possible capacity values. The applied method is based on the Product Limit Method (PLM) as described by Brilon et al. (2005) and adapted from Kaplan and Meier (1958). Here we give a shorter description of the capacity estimation method.

The general methodology of data processing and capacity estimation follows the steps given below, and are explained in detail in this section:

Step 1. Bottleneck selection
Known freeway bottlenecks

Step 2. Traffic state detection
Flowing, Breakdown and Congestion

Step 3. Data filtering
Scenario based

Step 4. Capacity estimation
Stochastic breakdown and discharge capacity

Step 5. Distribution fitting
Distribution parameters

Step 1 is a simple selection of the motorway stretches and bottlenecks for which the capacity estimation are to be made. In section 4, the selected area and motorway stretches for the quantification in the research are given. Step 2 comprises of traffic state categorisation of large sets of traffic data over an extended time.

The traffic states upstream and downstream of each bottleneck location are recorded at a location as close to the bottleneck as possible. An aggregation level of 5-minute intervals is chosen to reliably capture traffic states without the period becoming too large. Three traffic states are defined in the labelling process: free flow traffic (F), breakdown conditions (B), and congested traffic (C). These are defined as (Brilon et al. 2005):

Free flow traffic (F): Traffic is in a free flow traffic state, defined in this research as a speed above 60 km/hr, in the considered time interval t and remains in a free flow traffic state in the following time interval t +1.

Breakdown conditions (B): Traffic is in an uncongested traffic state in the considered time interval t and is in a congested state in the following time interval t +1. In this research the congestion threshold is set to values below 60 km/hr for the entire 5-minute time period.

Congested traffic (C): Traffic is ina congested traffic state upstream of the active bottleneck in the considered time interval t, and remains in congested state in the following time interval t+1. Traffic flow downstream of the bottleneck is uncongested.

A threshold of 60 km/hr is applied as traffic breakdown on motorways generally results in a prompt drop in traffic speed from 70 km/hr to 50 km/hr, therefore the chance of erroneous labelling is reduced by using the 60km/hr threshold.

In step 3, data is filtered corresponding to scenarios using the labelling which filters the relevant traffic data during the considered period. The labelling is performed according to the characteristics of the defined weather condition scenarios. The scenarios in this research are given in section 4.2. Further details on the filtering and data labelling can be found in (Calvert and Snelder 2013). The results are a dataset based on a collective variable for that specific scenario. In this research, a distribution of the capacity is derived from the filtered data (step 4) and given for each scenario and each bottleneck location. In the Product Limit Method (PLM) as described by (Brilon et al. 2005) use is made of traffic flow observations in free flow traffic (F) and of breakdown traffic (B) observations. Using data of non-breakdown events (F), as censored data, that nevertheless are greater than traffic flows that have led to a breakdown improves ones ability to accurately determine a capacity distribution. The method makes use of a probability function which is used to estimate the probability of traffic breakdown, with the median being the presumed capacity with an uncertainty margin given by the shape of the distribution. Function G(q) is defined as the probability that a detected traffic flow value reaches a state of congestion. The method is described by two main equations:

$$G(q) = 1 - Prob(q_c \leq q) \tag{1}$$

$$G(q) = 1 - \prod_{q_i} \frac{K_{q_i} - 1}{K_{q_i}} \quad with\ q_i \in B \tag{2}$$

Where

K_{q_i} = total number of observations with traffic flow q_i larger than the congestion threshold flow q_c

B = set of breakdown observations

In previous research, it was shown that the Weibull distribution gives a good fit to probabilistic capacity distributions on freeways (Brilon et al., 2005, Brilon and Zurlinden, 2003). The Weibull distribution is similar to a Gaussian distribution in shape, but has a greater flexibility towards the extremities of the distribution. This allows for a greater power to fit empirical data. Weibull distributions make use of a scale and a shape parameters, and is defined as:

$$G(x) = 1 - e^{-\left(\frac{x}{\beta}\right)^{\alpha}} \text{ for } x \geq 0 \tag{3}$$

Where α = shape parameter
β = scale parameter

The authors are aware that other researchers have obtained good fits with other distribution types, however there is no evidence to prove that they generically perform better that the Weibull distribution. Therefore, the choice is dependent on the local traffic conditions and capacities and validity to fit them. The entire procedure produces for each scenario at each bottleneck location an empirical distribution and Weibull parameters which best fit the empirical distribution. An explicit example of the methodology can be found in (Brilon et al. 2005) and is therefore not given here.

3.3 3.3 Demand analysis

Calculation of changes in the traffic demand is performed through empirical data analysis of a cordoned area of a motorway network in a region. Maintaining a cordon around the entire network reduces external issues that may bias the demand results as previously described. Such biases may occur from rerouting to other parts of the same network or from certain areas of the network reacting differently to other areas. Although the approach cannot entirely rule out small disturbances, the approach substantially decreases the chances thereof. An example of the cordon used in this paper is given in Figure 2.

The total daily demand is calculated for a desired time period: starting at time t_s and ending at time t_e. It may be relevant for example for research to just collect demand during the morning peak period, as this gives a good indication of the total demand on that day. It should be noted that the traffic demand is not identical to the observed flow, as traffic may be delayed either in the considered network or in the approach to the network. To reduce this effect so that the actual demand resembles the measured flow, the times $t_s$and t_e should be chosen such that no or very limited congestion exists on the network and especially on the cut-off points of the network. For no or limited congestion it should be expected that most if not all traffic that demanded, has had the opportunity to enter the network.

The inflow into the network q_i, is collected at each inflow location i, and time moment t, into the network at both cut-off points on motorways as well as motorway junctions (if one is considering only a motorway network). The sum of all locations at a single time step t, gives the total inflow into the network, however this is not yet the demand as congestion delays the arrival of traffic in time. However, summation over time, for which no congestion is longer present and in which delayed vehicles have the chance to pass the detectors, allows a reliable estimation to be made of the demand. For a scenario k, on an arbitrary day d, the total demand $D_{k,d}$in a time period, $[t_s, t_e]$, is given by:

$$D_{k,d} = \sum_{t=t_s}^{t_e} \sum_{i} q_{i,t} \tag{4}$$

On its own the value of $D_{k,d}$ does not have any significant meaning, as a network or scenario can be arbitrarily chosen. Therefore, a demand $D_{k,d}$ is considered as part of a coherent scenario k for which the main scenario characteristics are kept identical. Careful selection of the scenario characteristics is important to be able to make a fair comparison between various days of $D_{k,d}$ within k. A careful consideration of the main variables, such as the type of day (week, weekend, holiday, etc.) or of other important characteristics should be made. Availability of all selected detection locations should also be consistent for all days that are to be compared to avoid inconsistent measurements in the collected demand. Once multiple days of a single scenario have been gathered, one may construct an empirical distribution of the observations of that scenario:

$$D_k = \{D_{k,1}, D_{k,2}, \dots, D_{k,n}\} \tag{5}$$

Here n denotes the number of observation days for the considered scenario. In most cases it will be desired to compare scenarios to gain insight into the effects of certain characteristics on the traffic demand. Therefore, a reference scenario should be defined that is considered as a 'neutral' scenario. For example, in the analysis in the following sections, dry weather conditions are considered as a base scenario which against other, sometimes overlapping, scenarios are compared. Comparison between the considered scenario, D_k, and the reference scenario, D_{kr}, is performed such that a ratio, r, between the scenarios is derived:

$$r = \frac{median(D_k)}{median(D_{kr})} \tag{6}$$

The calculated ratios are then applied for comparison between scenarios and as a strong indication of the effects that a scenarios has compared to the reference scenario. The applied parameters in this research are given in section 5.

3.4 Weather conditions

The previously described methods for capacity and demand estimation obviously must make use of data on weather and climatological conditions. For this, use is made of stationary weather stations administered by the Royal Netherlands Meteorological Institute (KNMI). The KNMI makes use of more than 30 high quality meteorological stations throughout The Netherlands which relay accurate and extensive hourly and daily data on wind, temperature, sunshine, radiation, precipitation, air pressure, visibility, humidity, and other categorical weather observations. The five weather stations in the considered area are shown in Figure 2. For each category, maximum and average hourly and daily values are collected as well as descriptive information relating to these values. Detailed information on the exact measurement apparatus and techniques can be found in KNMI (2014).

4. Quantification case setup

In the previous section the methodology for determination of the capacity and demand were presented. Here the applied characteristics of the methodology in this research are given. This starts with the locations and data sources and is followed by the considered weather scenarios.

4.1 Locations and data

Demand

Quantification of traffic demand is performed for an enclosed area of the motorway network in the west and central areas of The Netherlands, which includes the cities of The Hague, Rotterdam and Utrecht (see Figure 2). The total area is approximately 1200 square kilometres in size. At the 'cut-off' points on the motorways and on motorway entrances and junctions along each motorway data is collected of the total inflow with a minute accuracy from loop-detectors. The vast majority of all junctions were able to be analysed and totalled a total number of 142 locations. The data used for the demand calculations is taken from the years 2009-2013 (for 2013 only until June). The demand values are collected for two different periods. The first considers the demand throughout the whole day between 5 AM and 10 PM. The second only considers the demand during the morning peak period between 6 AM and 10 AM. A distinction is also made between the time of the day for which the weather classification is performed: either for just the morning or the entire day. This results in four demands per scenario: Day weather with morning or day demand, and Morning weather with morning or day demand. A further filtering is applied to the collected data. A minimum of 20 observations (days) are taken per scenario to sufficiently make an accurate estimate of the demand profile for that scenario.

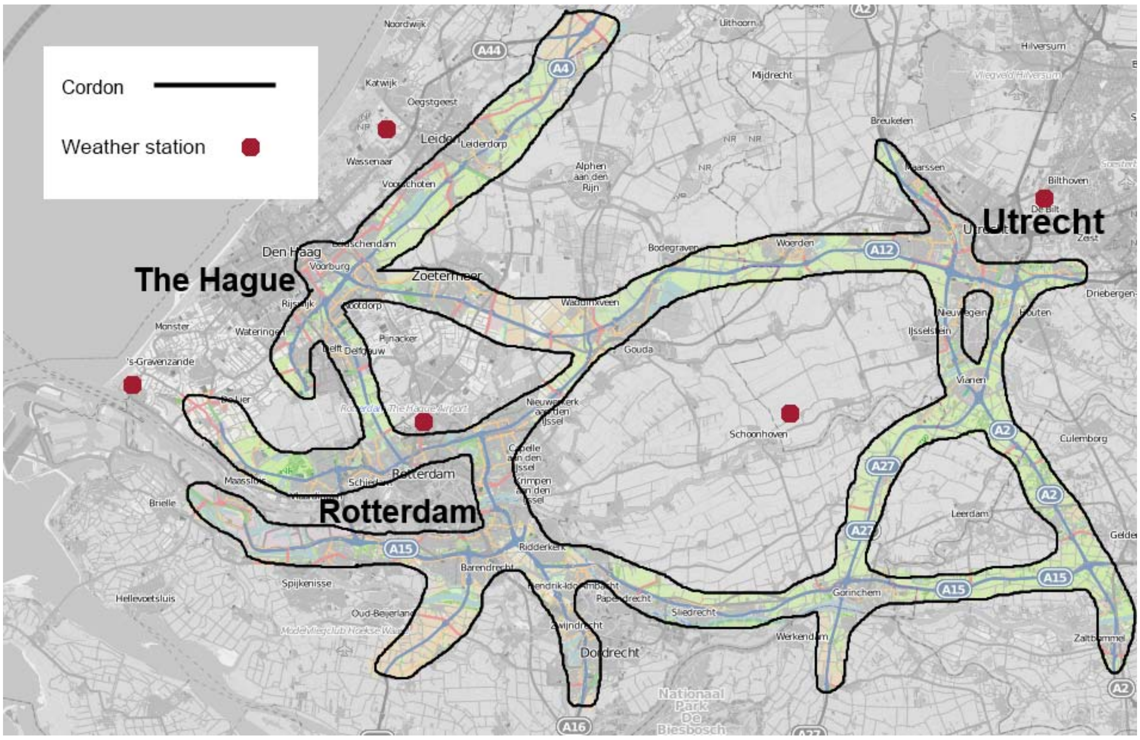

Figure 2. Considered network for the data analysis

Capacity

The capacity analysis is carried out in the same region of the Netherlands at known and proven bottleneck locations. In total 30 bottleneck locations were initially selected from which capacity data could be accurately collected through the use of double loop-detectors according to the previously described methods. Of these 30 locations, a further five locations were later rejected as the data was not consistently able to produce a sufficient number of reliable capacity estimations, leaving 25 locations that produced reliable and accurate capacity estimations. These included 20 2-lane motorway sections and five 3-lane sections. The data used for the capacity estimations is taken from the years 2007-2009. It was not easily possible to extend to later years as the data collection algorithm had changed for the later years, which may give undesired discrepancies in the data between the years.

4.2 Weather scenarios

In this research four main types of weather conditions are considered, namely rain, snow, temperature and wind. The focus is on each individual weather type separately, rather than a combination of various types in one scenario. This means that correlation is not explicitly considered between the results. An example could be that of snowfall that is recorded for temperatures below 2 degrees Celsius. While the scenario snow will overlap with low temperatures, the opposite will not necessarily be the case. Rather than search for causality, these are accepted in this research. It is a subject of later research to look closer at the specific correlations.

From these four conditions ten scenarios are defined. In each scenario the weather conditions are considered for the hours between 5 AM and 10 PM. This is also the period for which quantities are observed. For a day to be considered for a weather condition, the average value of that weather condition must be present for at least 3 hours during that day at, at least, three of the five weather stations. This last condition is almost always met due to the close proximity of the weather stations, and conditions are nearly identical on a day-to-day basis. As an example, if rain category 1.4-1.9 mm is considered, then this intensity must be found for at least 3 hours during the day. For the demand data, only the weather during the morning peak, the hours between 6 AM and 10 AM, are considered. For the morning demand only a single hour average needs to fit the relevant weather condition category. Furthermore, only data is considered for weekdays and for non-holiday days to avoid pollution of the data with possible trends from these day types. Seasonal trends are implicitly allowed, also due to the fact that the scenarios are explicitly correlated to certain seasons.

The scenarios are defined as:

1. Dry (Reference scenario)
2. Rain: 0-0.1 mm
3. Rain: 0.2-1.3 mm
4. Rain: 1.4-1.9 mm
5. Rain: >=2.0 mm
6. Snow: >0 mm
7. Temperature: <2C
8. Temperature: >=2C
9. Wind: <40 kph (<6 knots)
10. Wind: >=40 kph (>=6 knots)

For clarity, the data processing steps for the weather conditions are reiterated:

- The prevailing weather conditions for each day are labelled against that day according to the above scenario's and the described prerequisites. This is performed for both time windows: 6-10 AM and 5AM-10PM.
- The demand analysis and capacity analysis are performed for each day, as described in the previous sections per day.
- For each scenario the days that contain the relevant weather condition are viewed. The average of corresponding demand and capacity values over these days is taken and presented in the following section.

It is reiterated that the category values are hourly totals for rain and snow, and hourly averages for temperature and wind. In relation to precipitation this means that it is highly probable that higher values were found during that hour, but were averaged out. Therefore, we cannot speak of precipitation intensities, but rather of the quantity of precipitation. A conversion table is given in section 5.2 to allow global comparison of the results with other literature. It is presumed that travellers will perceive a day (or part of a day) to be of a certain weather category, rather than focus on a specific precipitation intensity at one single moment. This does not apply to the capacity estimates, as they are coupled to radar data that gives minute-to-minute and kilometre precise rain observations. This is necessary as the influence of precipitation cannot be average over an hour for capacity, as capacity observation is a 'moment-in-time' observation.

5. Results

5.1 Main results

The results of the entire analysis are shown in Table 1 for both the capacity effects and all demand calculations. The capacity results are shown per lane and considered for 2-lane and 3-lane motorways respectively, including the ratio compared to the reference scenario. The demand results are shown as a ratio compared to the reference scenario for each of the considered time window combinations for the demand.

The results for the capacity show that for an increasing quantity of rainfall the capacity of both 2- and 3-lane motorways fall with increasing rates. For a limited rainfall of under 1.4 mm in an hour the drop in capacity is limited to less than 2%. However, for the two greater categories, the drop in capacity is greater at 4-6% and 7% respectively. At the same time an increase in rainfall has an overall negative effect on the traffic demand. The effect for a wet day with less rainfall is nearly non-existent, while for higher rain quantities the drop in demand is around 4.5%. Interestingly, considering rainfall only during the morning peak period shows a greater drop in demand: approximately 1% and 4% for the lower rain categories, while up to 9% reduction is found for the 1.4-1.9 mm category. For the largest rain category insufficient data was available for the morning peak on the considered days to make an accurate prediction. It proved difficult to accurately determine the effect of snowfall using the available data with the described methodology. Locally, values could be derived, but a total trend from the dataset according to data-driven approach proved impossible due to a lack of snow observations. It was possible to derive an estimation of the effect on demand for days classed as ‘snowy’ in which a reduction in demand was found of 15-17%. For temperatures above 2 degrees Celsius no real difference is found in capacity, as may be expected, however a slightly lower demand is found albeit only 1%. The demand for temperature below 2 degrees does not drop, while the capacity is found to be nearly 7% lower for cold conditions. Although there is a small overlap with snow conditions, the vast majority of ‘cold’ observations are made under dry but cold weather conditions. The effect of windy weather on capacity is shown to be present but limited to 3-4%, while the demand on windy days is not found to substantially change.

Table 1. Capacity and demand influence of weather conditions

Scenario	**Capacity results**				**Demand results**			
	2-lane cap	***2-lane ratio***	***3-lane cap***	***3-lane ratio***	***Day weather AM demand ratio***	***Day weather Day demand ratio***	***AM weather AM demand ratio***	***AM weather Day demand ratio***
Reference (Dry)	2291	1.000	2243	1.000	1.000	1.000	1.000	1.000
Rain 0-0.1mm*	2287	0.998	2243	1.000	0.995	0.997	0.992	0.994
Rain 0.2-1.3mm*	2258	0.986	2233	0.996	0.994	0.998	0.988	0.993
Rain 1.4-1.9mm*	2153	0.940	2152	0.959	0.944	0.956	0.911	0.959
Rain >=2.0mm*	2132	0.931	2079	0.927	0.941	0.956	-	-
Snow >0mm	-	-	-	-	0.838	0.852	-	-
Temp <2C	2139	0.934	2091	0.932	1.000	1.000	1.000	1.000
Temp >=2C	2282	0.996	2237	0.997	0.989	0.987	0.989	0.987
Wind <40kph	2282	0.996	2253	1.004	0.999	1.000	0.996	0.999
Wind >40kph	2229	0.973	2153	0.960	0.999	1.000	0.999	1.000

** The method collects the rainfall rather than rain intensity. A conversion can be made for comparison to other data (see section 5.2)*

5.2 Rainfall-intensity transformation

To allow a comparison with other literature and data, a transformation can be made of the corresponding rainfall into the probable rain intensity which would be found in the same period. Note that this is rough transformation, but gives a general basis for order of magnitude comparisons. The corresponding values for rainfall versus rain intensity are found in table 2.

Table 2. Conversion table for rainfall versus rain intensity

Rainfall (mm in an hour)	Intensity (mm/h)
Rain 0-0.1mm	0-0.5 mm/h
Rain 0.2-1.3mm	0.5-5 mm/h
Rain 1.4-1.9mm	5-7 mm/h
Rain >=2.0mm	>7 mm/h

These are derived through consideration of two characteristics found in the data. These are the duration of rainfall in an hour, and the volatility of the rainfall (i.e. difference between the highest and lowest intensities). It was found that the volatility equates to a peak intensity in a range of 2-3 times the average rainfall when precipitation is actually falling. This hardly differs as a function of the total rainfall in an hour. Furthermore, a comparison was made between the duration of rainfall in an hour and the total rainfall in that hour. A duration correction factor is derived which indicates this relationship. For hours in which it rains for half the time a factor of 2 is given, for an hour in which it only rains for a third of the time the correction factor is 3, etcetera. Figure 3 shows the relationship found from the rain data and the derived equation. Application of both a volatility factor of approximately 2.5 and a duration correction factor according to Figure 3, gives the estimated values for the corresponding rain intensities in Table 2.

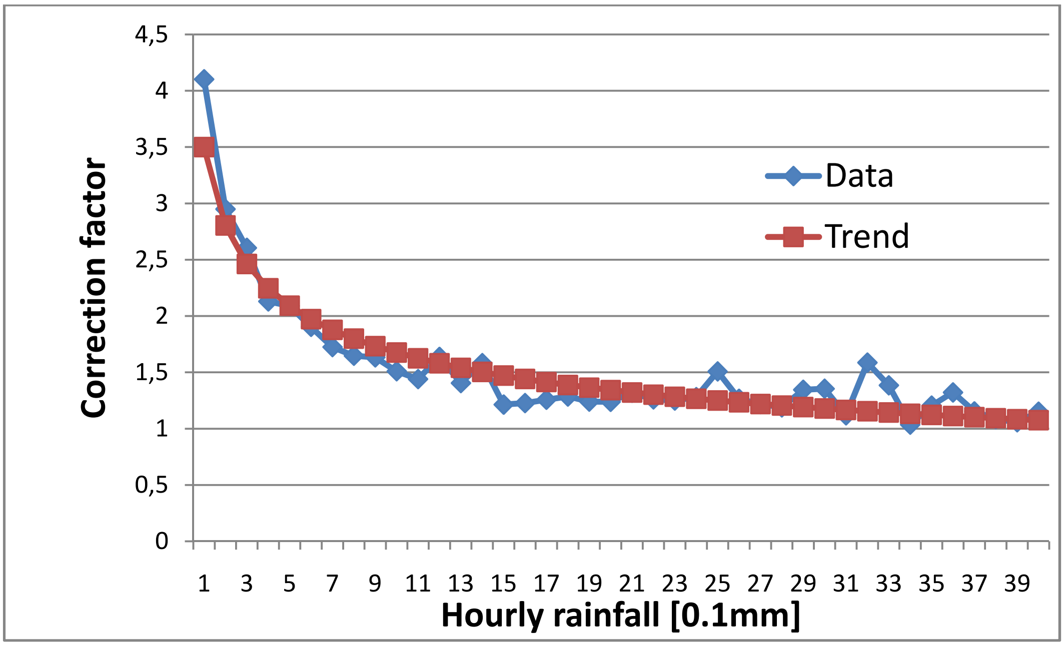

Figure 3. Rainfall duration correction factor

5.3 Stochastic results

For each of the scenarios the distributions of the results are given in Appendix B. The reference scenario is shown in Figure 4 as an example of the distributions. From the distributions it becomes apparent that the spread in the capacity distributions for each scenario do not show any substantial differences between scenarios. This can be easily derived from the shape parameter values (b-value) of the capacity Weibull distribution, which all in the range between 15-17. The distributions for the demand (on the left) are shown for the first considered demand window (Day weather with morning peak demand). The demand distributions are not significantly normally distributed. Maximum Likelihood analysis showed that the distributions best fitted a t-location scale distribution or a logistic distribution. The corresponding parameter values for the demand distributions are given in Appendix C. While each scenario has a different median value, again the general shape of each distribution is within a similar range, which indicates that stochasticity of demand, regardless of the scenario, exists within a certain range.

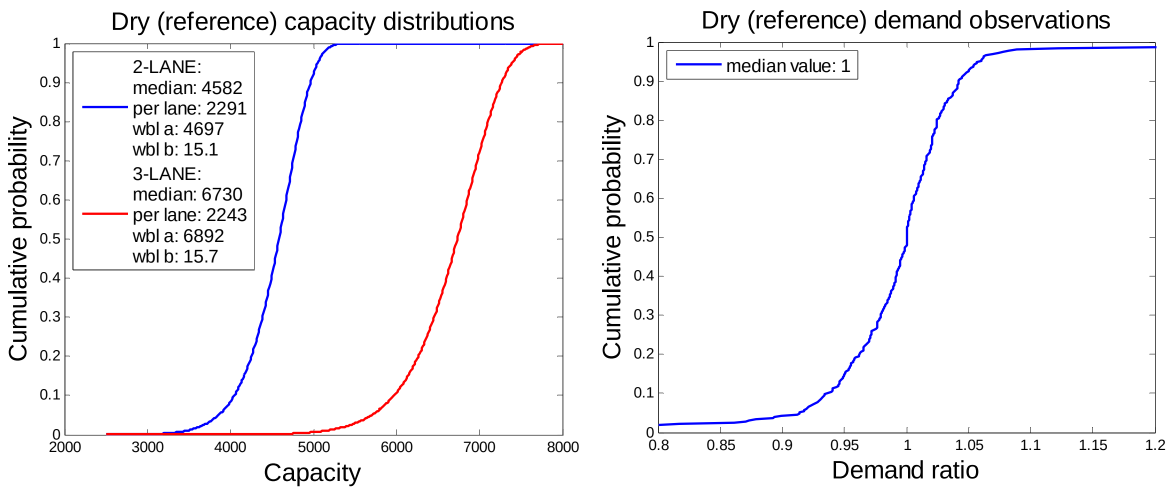

Figure 4. Capacity distributions (left) and demand distribution (right) for the reference scenario (dry)

5.4 Combined demand-capacity results

Although the effects of capacity changes and demand changes individually give an impression of the effect on traffic fluency, it is only when both are combined one can gain a true picture of the effect of a weather condition on traffic fluency and an indication of the level of service. If, for example, a scenario causes a reduction in capacity, but causes an even greater reduction to demand, traffic flow as a whole may benefit from this, while only considering capacity changes would suggest otherwise. Therefore, the combined capacity-demand results are shown in Table 3. This is done for the 2-lane motorway capacity estimations (although the difference between two or three lanes were near negligible). The ‘day weather condition’ and ‘peak hour weather conditions with peak morning demand’ are taken as representative reference demand estimation periods.

Table 3. Combined effect of weather on traffic fluency

Scenario	**Effect on traffic fluency (Capacity/Demand)**	
	2-lane capacity with Day weather& AM demand	***2-lane capacity with AM weather& AM demand***
Reference (Dry)	1.000	1.000
Rain 0-0.1mm*	1.003	1.006
Rain 0.2-1.3mm*	0.992	0.998
Rain 1.4-1.9mm*	0.996	1.032
Rain >=2.0mm*	0.989	-
Snow >0	-	-
Temp <2C	0.934	0.934
Temp >=2C	1.007	1.007
Wind <40kph	0.997	1.000
Wind >40kph	0.974	0.974

** The method collects the rainfall rather than rain intensity. A conversion can be made for comparison to other data (see section 5.2)*

Despite what the individual capacity and demand results say, the combined effect on traffic shows a different trend. The effect of rainfall has a limited negative effect on traffic fluency which remains for all rain categories below 2%. The effect of cold temperatures on traffic fluency is indicated to be one of the more important factors. Behind this lingers a maintained traffic demand, while the capacity is estimated to be lower resulting in a negative effect on traffic fluency as whole. This may also explain to a large extend some of the seasonal effects that are often observed during the winter months. Furthermore, the effect of high winds also shows an increased negative effect on traffic fluency, and that more so than rainfall, reaching a fall of 2.6%.

6. Conclusion & Discussion

In this contribution a methodology is presented that considers the combined effects of weather on traffic fluency though stochastic analysis of traffic demand and road capacity. The methodology is applied to give a quantitative insight into the stochastic effects of weather on traffic and to furthermore highlight the necessity of considering the effects simultaneously on both traffic supply and demand. The methodology allows both the capacity and demand to be calculated and combined to give an indication of the effects of weather on traffic. An extensive data-driven analysis is performed applying the described method in which the effects of rain, snow, temperature and wind are analysed for their influence on traffic. The analysis was performed for motorways in a large 1200 kilometre square area in the urbanised west of The Netherlands. The results show that increasing reductions of both capacity and demand are found for precipitation in the form of rainfall. Despite the reduction, the overall influence of rain on traffics ability to flow fluently is not substantially reduced. Insufficient data for the described approach meant that capacity estimation could not be made for snowfall, while a reduction in demand for snow was found of more than 15%. The influence of cold temperatures proved to be substantial on traffic fluency. Demand was found not to vary significantly, while capacity is reduced leading to a greater chance of a reduction in level-of-service of roads. Similarly high winds were found to also reduce the quality of traffic fluency, although at a lower level of approximately 2-3%.

A further quantification of the stochastic distributions of the results is derived for each weather scenario. This showed that the distribution shape of each weather type does not significantly differ and was found to yield similar shape-parameters when fitted for a Weibull distribution. The shapes of the demand distributions also showed a close resemblance and were found to adhere to a t-location-scale and logistic distributions. The resulting distributions may be used for a number of future purposes, such as application of uncertainty and sensitivity analysis both in data-analysis and modelling of traffic effects during weather to name two.

Further research following this contribution lies primarily in quantification of correlated weather effects on traffic flow, such as a combination of rain and high winds for example. Further research also lies in quantification of other weather effects as well as the development of a refined methodology for widespread data analysis of the effects of snow of traffic flow for limited observations.

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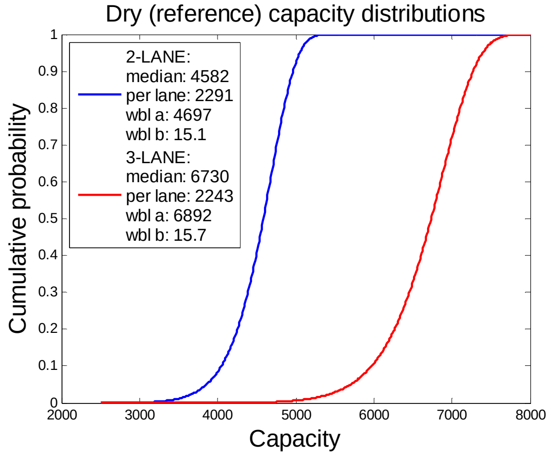
Appendix A: Literature overview weather effects on supply & demand

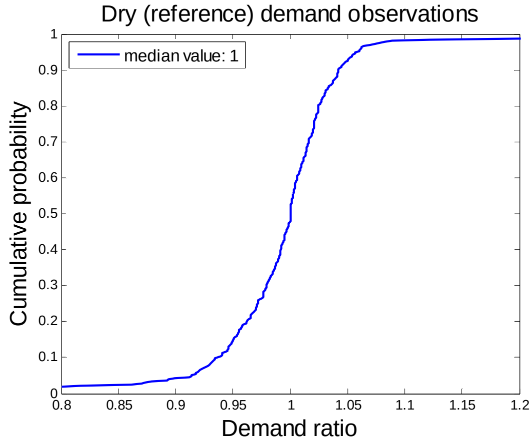
(adapted from Snelder and Calvert (2015))

Weather condition	*Source and location*	*Intensity (mm/h)*	*Capacity reduction*	*Demand effect*
Rain	Agarwal et al (2006), Minneapolis & St. Paul	0.25-6.35 >6.35	5%-10% 10%-17%	-
	Al Hassan and Barker (1999), Scotland	Heavy rain	-	-4.6%
	Calvert and Snelder (2012), Netherlands	For every 1 mm/h up to max 5 mm/h	1.9% per mm/h	-
	Chung et al. (2005), Tokyo Metropolitan expressway	0-1 1-10	4%-7% 8%-14%	-2% - -4% weekdays -4 - -14% weekend
	Hranac et al. (2006), Seatle, Baltimore, Minneapolis & St. Paul	<0.1 0.1-17	 10%-11%	-
	Keay and Simmonds (2005), Melbourne	-	-	-2% - -3%
	Smith et al. (2004), Virginia	0.25-6.35 >6.35	4%-10% 25%-30%	-
	Van Stralen et al. (2014), Netherlands	Light rain (0.01-1 mm) Heavy rain (>1 mm)	4% - 9% (ave 6%) 4% - 11% (ave 8%)	+2.3% -7.7%
	Vukovic et al. (2013)	> 2	-	-1.5%- -5%
Snow	Agarwal et al (2006)	0 – 1.3 1.5-12.7 12.7	3%-5% 6%-13% 19%-27%	-
	Al Hassan and Barker (1999)	-	-	-15%
	Hanbali and Kuemmel (1993)	<25 25–75 75–150 150–225 225–375	-	-7%– -17% -11%– -25% -18%– -43% -35%– -49% -41%– -53%
	Van Stralen et al. (2014)	-	-	-22% - -29%
Cold	Agarwal et al (2006), Minneapolis & St. Paul	>10 C 1-10 C 0- -20 C <-20 C	0% 1% 1.5% 6-10%	
	Kwon et al (2013) Toronto	2- -12 C	No significant change	
Wind	Agarwal et al (2006), Minneapolis & St. Paul	<16 kph 16-32 kph >32 kph	0% 1% 1-2%	
	Kwon et al (2013) Toronto	Up to 38 kph	No significant change	

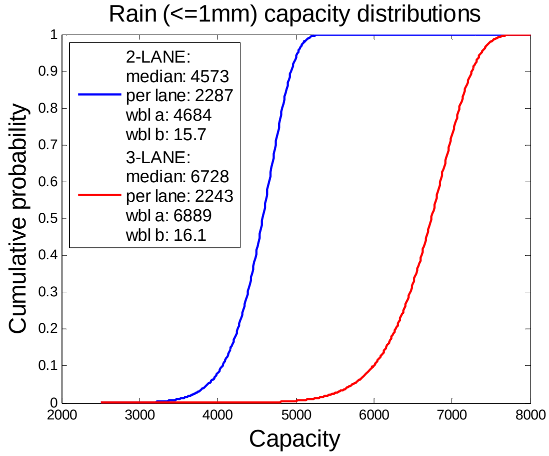
Appendix B: Stochastic results

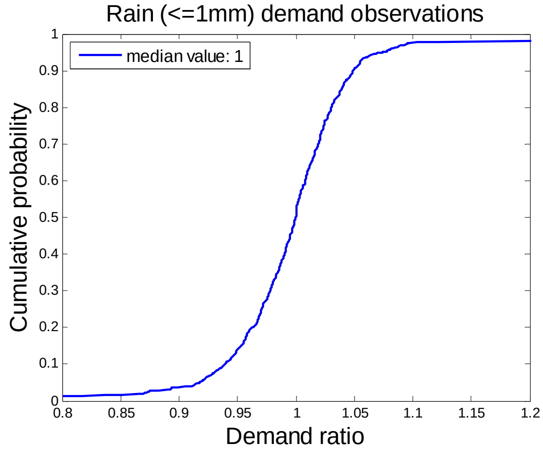
Reference (Dry)

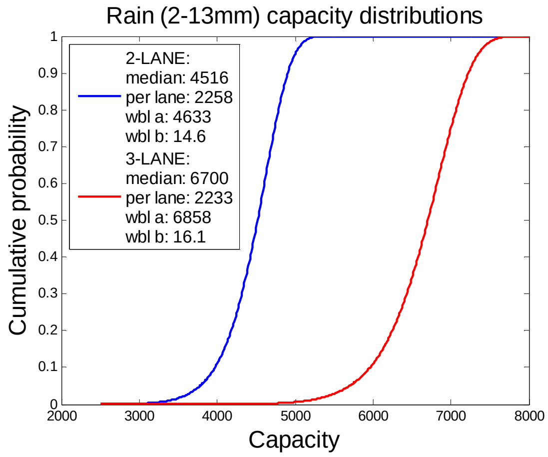


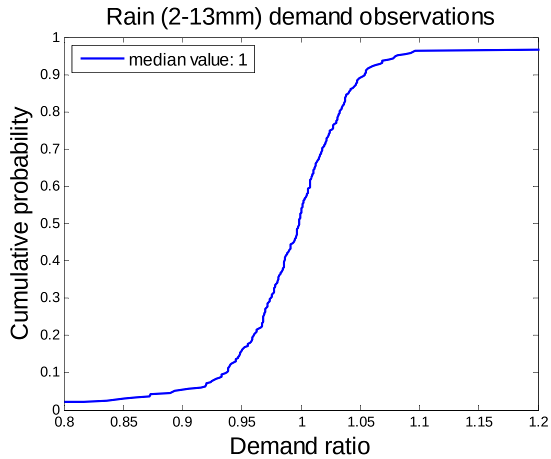


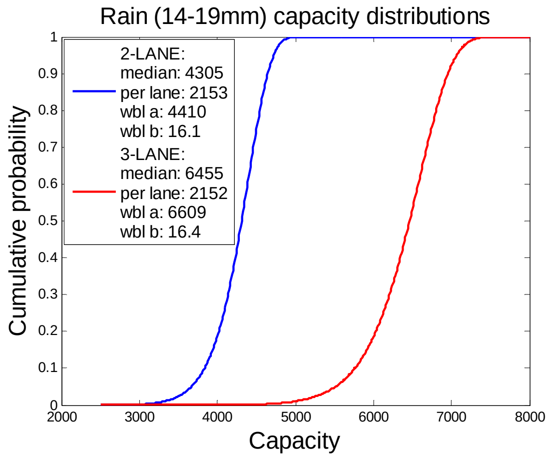
Rain

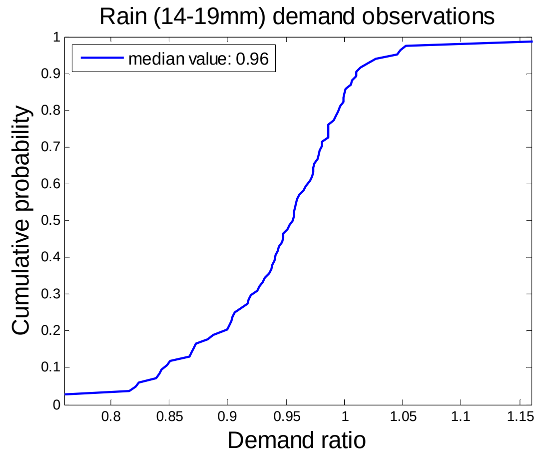


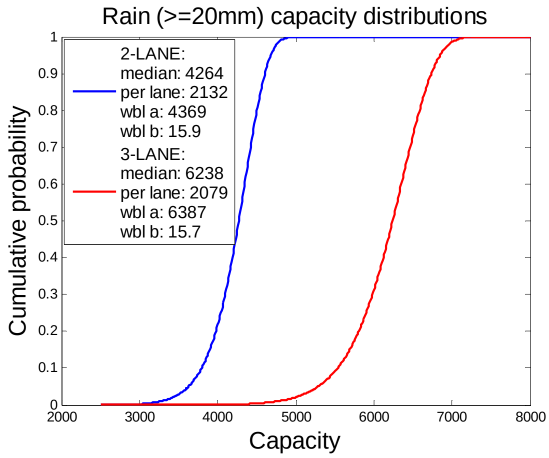


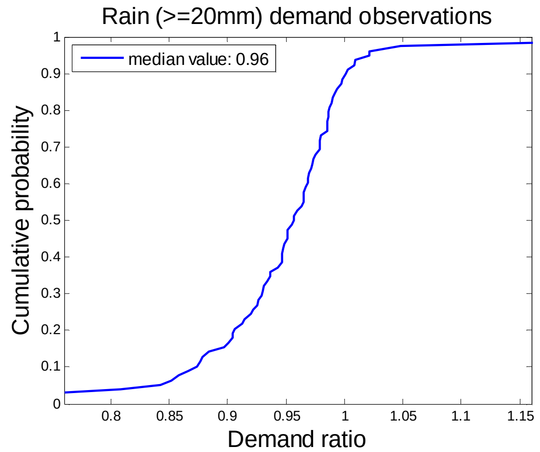




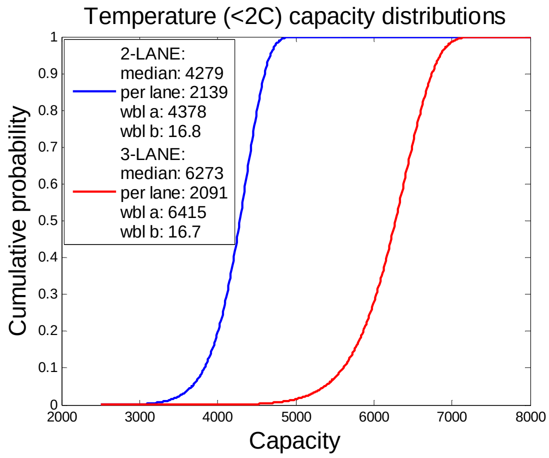


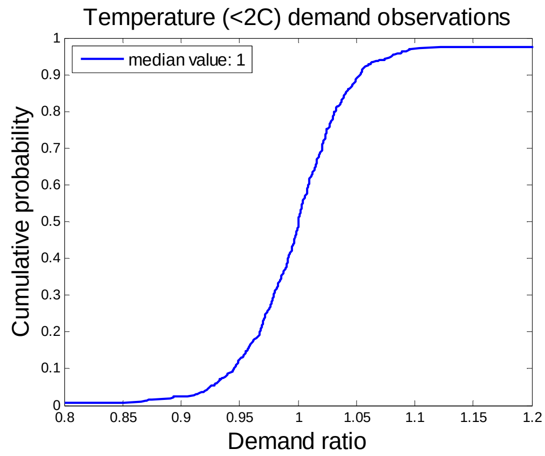


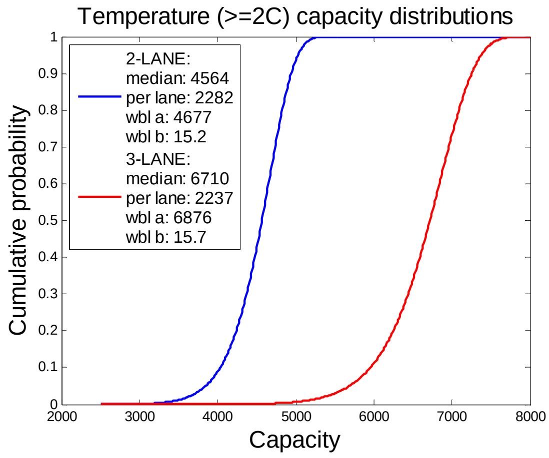


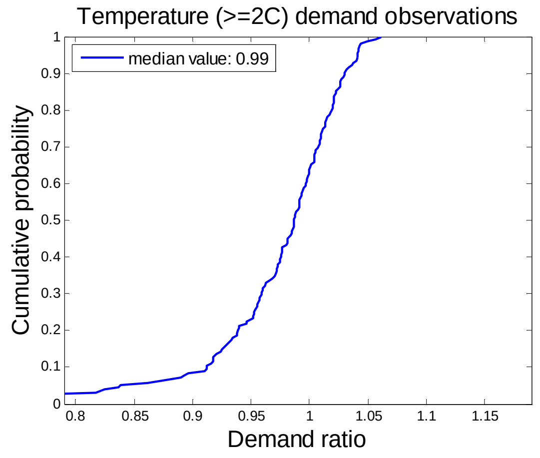


Temperature

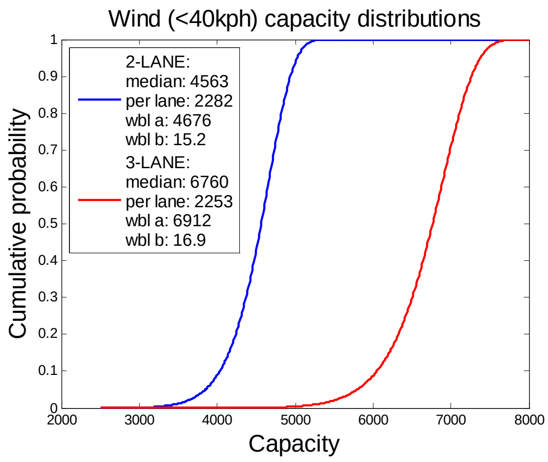


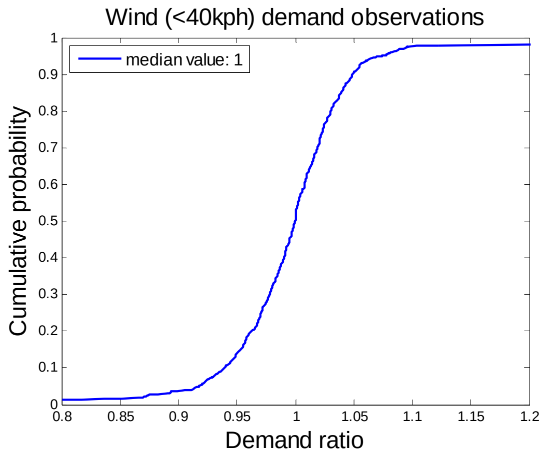


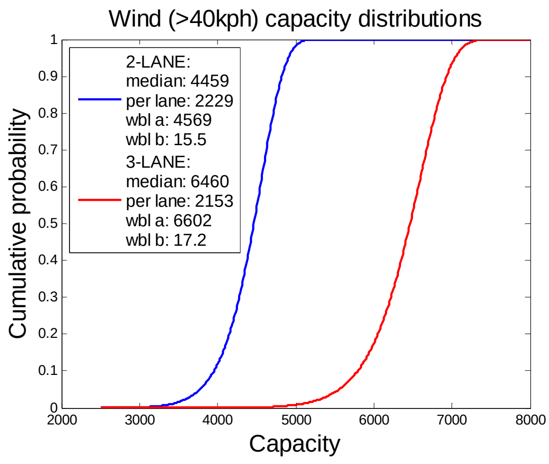

Temperature (>=2C) capacity distributions
2-LANE:
median: 4564
per lane: 2282
wbl a: 4677
wbl b: 15.2
3-LANE:
median: 6710
per lane: 2237
wbl a: 6876
wbl b: 15.7
Cumulative probability
Capacity

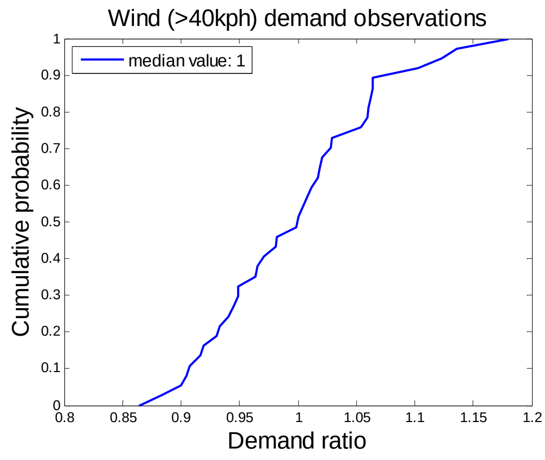

Temperature (>=2C) demand observations
median value: 0.99
Cumulative probability
Demand ratio

Wind


Wind (<40kph) capacity distributions
2-LANE:
median: 4563
per lane: 2282
wbl a: 4676
wbl b: 15.2
3-LANE:
median: 6760
per lane: 2253
wbl a: 6912
wbl b: 16.9
Cumulative probability
Capacity


Wind (<40kph) demand observations
median value: 1
Cumulative probability
Demand ratio


Wind (>40kph) capacity distributions
2-LANE:
median: 4459
per lane: 2229
wbl a: 4569
wbl b: 15.5
3-LANE:
median: 6460
per lane: 2153
wbl a: 6602
wbl b: 17.2
Cumulative probability
Capacity


Wind (>40kph) demand observations
median value: 1
Cumulative probability
Demand ratio

Appendix C: Demand distribution parameters

Scenario	Demand distribution fit: parameter values	
	t-location-scale [mu-sigma-nu]	*Logistic [mu-sigma]*
Reference (Dry)	[1.000 0.028 1.886]	[0.996 0.030]
Rain 0-1mm*	[0.997 0.034 2.115]	[0.996 0.034]
Rain 2-13mm*	[0.997 0.032 1.746]	[0.996 0.037]
Rain 14-19mm*	[0.954 0.046 2.236]	[0.948 0.043]
Rain >=20mm*	[0.957 0.035 1.815]	[0.951 0.038]
Snow >0	[0.849 0.051 2.663]	[0.841 0.043]
Temp <2C	[1.000 0.031 2.249]	[1.000 0.030]
Temp >=2C	[0.987 0.036 2.678]	[0.982 0.030]
Wind <40kph	[0.999 0.0312 2.111]	[0.998 0.031]
Wind >40kph	No best fit	[0.993 0.041]