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The influence of adverse weather conditions on probability of congestion on Dutch motorways

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Weather conditions are widely acknowledged to contribute to the occurrence of congestion on motorway traffic by influencing both traffic supply and traffic demand. To the best of our knowledge, this is the first paper that explicitly integrates supply and demand effects in predicting the influence of adverse weather conditions on the probability of occurrence of congestion. Traffic demand is examined by conducting a stated adaptation experiment, in which changes in travel choices are observed under adverse weather scenarios. Based on these choices, a Panel Mixed Logit model is estimated. Supply effects are taken into account by examining the influence of precipitation on motorway capacity. Based on the Product Limit Method, capacity distribution functions are estimated for dry weather, light rain and heavy rain. With the developed model to integrate the supply and demand effects breakdown probabilities can be calculated for any given traffic demand and capacity. The results show that rainfall leads to a significant increase in the probability of traffic breakdown at bottleneck locations. Interestingly the probability of a breakdown at these bottleneck locations is predicted to be slightly higher in light rain (98.7%) than in heavy rain (95.7%) conditions, which is the result of the higher traffic demand in light rain conditions. Based on the results presented in this paper, it can be recommended to always incorporate both supply and demand effects in the predictions of motorway breakdown probabilities due to adverse weather conditions to improve the validity of the predictions.

Keywords: *adverse weather conditions, modal shift, motorway capacity, motorway congestion probability, motorway traffic demand.*

1. Introduction

Congestion on motorways annually leads to serious economic damage. In the Netherlands alone, 68 million vehicle hours were lost due to congestion between May 2010 and April 2011 (TNO, 2011). Weather is widely acknowledged to contribute to the occurrence of congestion by both

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influencing supply and demand effects. Supply is influenced by weather conditions through a temporal reduction of capacity resulting from drivers allowing greater time headways. A well-known document about the effect of weather on traffic flow is the Highway Capacity Manual (Transportation Research Board, 2000). The manual suggests that capacity reduces up to 15% as a result of precipitation. Motorway capacity reduction is traditionally regarded as a deterministic phenomenon, but numerous researchers (Brilon et al., 2005; Elefteriadou et al., 1995; Lorenz and Elefteriadou, 2001; Minderhoud et al., 1997; Persaud et al., 1998) have shown that the maximum traffic flow on a motorway varies even when the external factors are constant. This results from unpredictable behaviour of drivers on the microscopic level.

Motorway traffic demand is also influenced by weather conditions, though this has received much less attention. In their literature review, Böcker et al. (2012) show that many studies have found effects of precipitation, temperature and wind on traffic demand. Call (2011), amongst others, found a large negative correlation (-0.30) between trip-making and snowfall by studying traffic count data. Car traffic demand reductions are also reported as a consequence of rainfall, for example by Al Hassan and Barker (1999) who found traffic reductions of 4% in Scotland by comparing traffic data with meteorological monthly variations. Whereas most studies show negative precipitation effects on trip generation, a Dutch study (Sabir, 2011) found a positive relationship between precipitation and car and public transport usage.

Lam et al. (2008) analysed demand and supply effects in adverse weather conditions on travel times on a road network. We are, however, not aware of any study that combines the effects of changes in motorway capacity and motorway traffic demand to examine the total effect of weather conditions on the probability of breakdown on motorways. An analysis solely based on the capacity reduction fails to take into account the demand change which can have a far greater impact on the breakdown probability than the capacity reduction itself. This could lead to incomplete conclusions regarding the motorway breakdown probability during adverse weather conditions. The aim of this paper is therefore to contribute to the literature by developing and applying a model that includes both supply and demand effects of adverse weather conditions on the probability of traffic breakdown on motorways. Traffic breakdown occurs when demand exceeds capacity which leads to congestion. To estimate this model, data are collected in the Netherlands. Demand effects are observed in a stated adaptation experiment, in which car drivers choose among a range of travel alternatives given presented weather conditions. Based on the observed choices, a Panel Mixed Logit model is estimated of which the results are presented and interpreted in this paper. Supply side effects are estimated using capacity distribution functions based on the Product Limit Method (Kaplan and Meier, 1958). The focus is on the influence of precipitation on motorway capacity. The demand and supply effects are then combined in a generic model that allows predicting breakdown probabilities for any given traffic demand and capacity.

2. Methodology

2.1 Motorway traffic demand and capacity

In this section, the relation between motorway morning peak traffic demand and motorway capacity is made explicit in order to link them later in the analysis. For the capacity analysis, a stochastic approach for capacity is used based on the following definition of capacity: “the rate of flow along a uniform freeway segment corresponding to the expected probability of breakdown deemed acceptable under prevailing traffic and roadway conditions in a specific direction” (Lorenz and Elefteriadou, 2001: 94). Applying the concept of stochasticity to the motorway capacity leads to a probability density function that describes the probability of breakdown given a certain traffic flow, for which an example is shown in Figure 1.

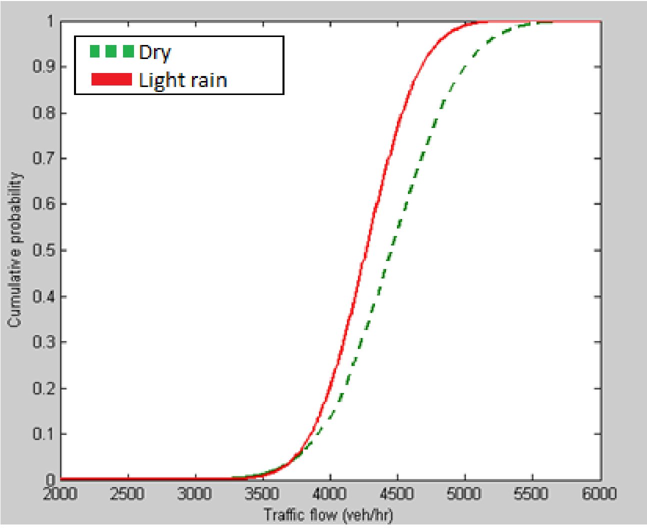


Figure 1. Breakdown probability at motorway A4 in dry and light rain conditions

The breakdown probability refers to the likelihood of the formation of congestion for a range of traffic flow values and is defined in more detail in the next subsections. Figure 1 shows the capacity distribution function at motorway A4 in 2007 in dry weather conditions (right line) and in light rain weather conditions (left line). Comparing the breakdown probability for a given traffic flow makes clear that the probability of breakdown is higher for light rain than for dry weather. In other words, the road capacity is lower for light rain than for dry weather. Traffic flow is largely determined by motorway travel demand, hence if traffic demand increases, traffic flow increases, which in turn increases breakdown probability. This makes clear that both motorway capacity and motorway traffic demand influence the probability of breakdown.

2.2 Capacity Analysis

The Product Limit Method (PLM) by Kaplan and Meier (1958) is used in the capacity analysis to arrive at probability breakdown functions, with adaptations as described by Brilon et al. (2005). This method considers traffic flow observations upstream of a bottleneck location. Measurement upstream of a bottleneck location takes into account that the free flow capacity in uncongested traffic flows differs from the discharge capacity in congested conditions, which is the result of the so-called capacity drop phenomenon. Amongst others, this was analysed by Chung et al. (2007), Regler (2004) and Zurlinden (2003). Consideration of only pre-breakdown traffic flows for capacity estimation is a major difference to other PLM implementations like Minderhoud et al. (1997) and Toorenburg (1986), which also consider discharge traffic flow observations.

Bottleneck location detection

The capacity estimation method relies on the occurrence of multiple breakdown observations to arrive at a reliable capacity distribution function based on a large dataset. Therefore, only static bottleneck locations with many congested morning peaks during the year are analysed in this study. The bottleneck locations are identified by analysing traffic data from double-induction loops present at the Dutch motorway network, which is known as the MONICA system (Dutch MONItoring CAsco). For all motorways included in MONICA, data is stored each minute regarding the average speeds (km/h), flows (veh/min) and possible lane closure. Data from the years 2007, 2008 and 2009 was available for the following Dutch motorways: A2, A4, A6, A9, A15, A16, A20, A27, A50, A58 & A59. Bottlenecks could be found by visually inspecting the local mean speed for a whole year.

We specified three criteria in order to include a static bottleneck location in the analysis. First, the induction loops at and around the bottleneck location should work properly. Second, congestion at the bottleneck location should not be initialized by spillback from a bottleneck downstream. Third, the bottleneck may not consist of a variable number of lanes over the day (for example peak hour lanes). In total fourteen bottleneck locations met all three requirements and were selected for the capacity analysis.

Categorization of the traffic flow observations

Observation intervals of five minutes are used, since this is considered a good compromise between reducing random fluctuations in the traffic flow and accuracy in the average intensity values (Brilon et al., 2005). Only observations within the morning peak period (6am-10am) are included in the analysis. Although most of the congestion during the morning peak occurs between 7 and 9 am, limiting the observations to this narrow period would fail to include all congestion effects during the morning peak. Other periods of the day are excluded, because the mode choice of the return trip is often the same as in the morning trip. In addition, observations of weekend days and vacation periods are excluded due to a lack of congestion. Each of the remaining five-minute traffic flow observations is categorized in either the Breakdown (*B*), Free-flow (*F*) or Congestion (*C*) category:

- Breakdown: If the observed flow in interval i is uncongested, but causes a breakdown in the following interval $i + 1$, then the traffic volume q_i observed in interval i is regarded as a realization of the capacity. As a congestions threshold we consider the average speeds: if these are lower than 60 km/h traffic is considered congested (Calvert and Snelder, 2013). An extra requirement for this observation is that during the preceding 6 observations (30 minutes) traffic needs to be uncongested to ensure uncongested flow before breakdown occurs.
- Free-flow: If the traffic flow is uncongested in interval i and in interval $i + 1$, we consider the traffic as free flow. The information obtained from this observation shows that the actual capacity in interval i may be greater than the volume q_i that is observed. This censored data is valuable for a correct quantification of the breakdown probability.
- Congestion: If traffic flow is congested both in interval i and in interval $i - 1$, traffic is considered congested. Since congested intervals cannot help determine capacity, congested interval are excluded from the capacity analysis.

After the observations are binned by category, these are coupled with rain data observations for the same period. The rain data are collected from a data feed of the Royal Netherlands Meteorological Institute (KNMI, 2011), which provides data for a grid pattern of 1 km by 1 km on a one-minute basis. The rain detection and intensity estimation is performed via advanced satellite images and has realized excellent accuracy during the latest years (Holleman, 2003; van Westrhenen, 2003). The one-minute rain intensity data is averaged to five-minute intervals and these intervals are mapped onto the road network with latitudinal and longitudinal coordinates, which is similar to the approach of Calvert and Snelder (2013).

Capacity distribution function estimation

The classified and filtered traffic observation intervals possess information regarding the average intensity and the average speed during that interval. With the information regarding the average speed, average intensity and the category of each observation interval, it is possible to estimate a distribution function for the free flow capacity using the Product Limit Method (Kaplan and Meier, 1958). Following Brilon et al. (2005) this leads to a free flow capacity distribution function of the bottleneck, estimated using the function:

$$F_c(q) = 1 - \prod_{i:qi \leq q} \frac{k_i - d_i}{k_i}; i \in \{B\} \quad (1)$$

Where:

$F_c(q)$ = capacity distribution function of traffic volume q (veh/h)

q_i = traffic volume in interval i (veh/h)

k_i = number of intervals with a traffic volume of $q \geq q_i$

d_i = number of breakdowns at a volume of q_i

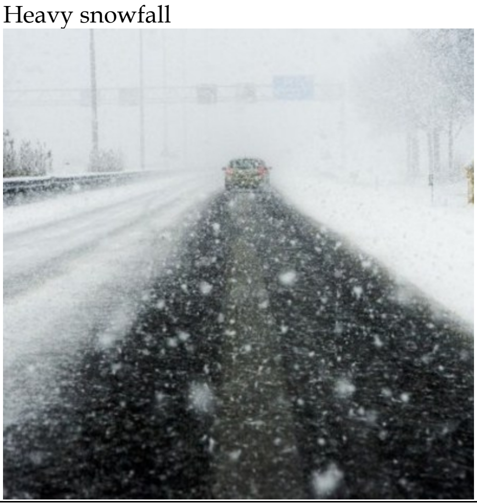
$\{B\}$ = set of breakdown intervals (intervals with classification B)

Eq. 1 gives a representation of a survival function, in which traffic flow is deemed to 'fail' upon the onset of congestion. For more details, see Brilon et al. (2005). The calculation is made for each breakdown interval observation. Each observed breakdown is normally used as one q_i-value, which leads to d_i always being equal to 1. The factor k_i is based on all B- and F- observations with a traffic volume (q) that is higher than the traffic volume at the breakdown observation (q_i). The points at the capacity distribution are thus B-observations, but in order to arrive at the probability of that certain point the F-observations are also included into the estimation.

2.3 Stated adaptation experiment

In this section, the stated adaptation experiment is described that was conducted to estimate the extent of traffic demand change due to adverse weather conditions. The reason for choosing a stated adaptation experiment is that loop detector data on a certain road section does not provide information regarding the trip purpose of the vehicles on that road section and the choices made by the travellers as a result of the weather. In addition, it is not feasible to count vehicles for every weather situation and forecast, since some aspects are related to extreme situations and therefore only occur a few times a year. While a stated adaptation experiment could be less accurate than loop detector data on a road section, the experiment allows to take both trip purpose and the effect of specific and rare weather situations into account. In this experiment, hypothetical weather situations are presented to respondents and for each situation they are requested to make a choice between six travel alternatives. An example is provided below:

What would you do if you had planned a utilitarian trip during the morning peak and the weather situation is as follows?

Current temperature	-5°C
Current weather	Heavy snowfall 
Weather forecast	The weather will improve during the day
Weather alarm	Icy roads alarm

1. Travel by car on the motorway in the morning peak
2. Travel by car, but avoiding the morning peak (before 06:00 or after 10:00am)
3. Travel by car, but avoiding the motorway

4. Travel by bicycle
5. Travel by public transport
6. Decide not to make the trip

In the following, first the construction of the weather conditions is discussed. This is followed by discussing how the trip purpose was included. Then, the data gathering procedure is described. Finally, attention is given to the model estimation procedure.

Selection of attributes
A first attribute that describes the weather conditions is *precipitation*, which reflects the current precipitation at the moment when the decision about a trip in the morning is made. *Precipitation* was included as many studies found significant effects of precipitation (rain and snow) on traffic demand (Böcker et al., 2012). This attribute consists of five levels, which are *dry weather*, *light rainfall*, *very heavy rainfall*, *light snowfall* and *heavy snowfall*. In order to mitigate effects due to different perceptions of precipitation conditions among the respondent, pictures are included for each of the precipitation levels in order to make the terms light and heavy more tangible. Light rainfall corresponds with rain intensity between 0 and 2mm/hour. Very heavy rainfall is a rain intensity of 2 mm/minute. Light snowfall resembles a snow intensity of 10-20mm/hour. Lastly heavy snowfall corresponds to 50mm/hour.

These figures are difficult to compare with the classification of the Royal Netherlands Meteorological Institute, since the classifications of the meteorological institute are based on rain intensities for a full day. The weather alarm for very heavy rain is issued if at least 75mm rain in 24 hours is predicted. The weather alarm for heavy snowfall is issued if at least 30mm snow per hour or 100mm snow per 6 hours is predicted.

We choose to add a heavy rain level as a result of the observation that the very heavy rain scenario is based on extreme rain intensity. In the very heavy rain level, respondents where shown a picture of rain during a severe rain shower which corresponded to an intensity of 2mm/minute. A rain intensity value based on interpolation between the light rain and very heavy rain level could be more representative for motorway traffic demand during heavy rainfall. This new heavy rain level is estimated by using part worth rain utilities with averaging the utility of light and heavy rain.

The second attribute is the *weather alarm* that is issued by the Royal Netherlands Meteorological Institute in case of extreme weather conditions. The hypothesis is that a weather alarm could reinforce traffic demand changes in adverse weather conditions. A weather alarm with code red is issued at most twelve hours in advance if the probability of the occurrence of an event is at least 90%. It is only issued if the affected region is at least 50 kilometres in length (KNMI, 2011). The following alarm codes are applied in this experiment: *code red for heavy rainfall* (at least 75mm in 24 hours), *code red for snow* (at least 30mm per hour or 100mm per 6 hours) and *code red for icy roads*. The final level is *no weather alarm*.

The third attribute is the *weather forecast.* The weather forecast is included in the experiment because it is expected that the weather forecast for the return trip influences the travel choice travellers make in the morning. As forecasts provided by the news broadcast generally do not provide very specific information regarding the weather during the coming day, rather general levels have been formulated for this attribute; during the day the weather conditions can: *improve*, *get worse* or *stay the same* as the current weather conditions.

Lastly, information regarding *temperature* was included. Although we did not expect significant effects of temperature on top of the already included attributes, this attribute was merely included for the sake of completeness and to avoid respondents guessing temperature levels based on the presented precipitation forms, which therefore reduces potential heterogeneity. The distinguished temperature values were *-5*, *+10* and *+25* degrees Celsius.

The selected attributes are combined using an efficient design to arrive at the weather condition descriptions. Priors were estimated from a pilot study with 30 respondents. To ensure that only logical weather combinations were constructed, several constraints were included. Examples of constraints that were added to the software are:

- If the temperature is 10 or 25 degrees, then the precipitation form cannot be snow
- If the current weather is dry and the weather is forecasted to stay the same or get better, then a weather alarm is not possible.

In total, 20 different weather situations were constructed. To limit the number of conditions shown to each respondent, weather conditions were blocked into two groups of 10 conditions. Each respondent was presented with only one of the blocks of 10 weather conditions.

Trip purpose

It is widely acknowledged that travel behaviour varies with trip purpose (Schwanen et al., 2001; Anable et al., 2005; Call, 2011). Those traveling for work related purposes may have more limited possibilities to adapt their travel plans than those traveling for recreational purposes. Therefore we distinguish two categories: utilitarian and recreational trips. Utilitarian trips consist of business, commuter and educational trips. Recreational trips are those trips related to visiting family or friends, grocery shopping, shopping, a day-out, going to sports etc.. For each of the presented weather conditions, respondents are asked to indicate their travel choice separately for utilitarian trips and for recreational trips, provided they typically travel for this purpose in a normal workweek. Hence, this procedure allows estimating separate models for utilitarian and recreational trips.

Questionnaire and sample

The stated adaptation experiment was included in an online questionnaire and was preceded by questions about socio-demographic characteristics and questions about typical travel behaviour of the respondents regarding motorway use. The latter involved questions about: the number of utilitarian and recreational trips respondents make in the morning peak of a normal workweek, the mode that is most often used for both purposes, the distance from home to work, the possibility to avoid the morning peak and the possibility to work at home. Respondents were randomly selected from an existing panel of respondents that fill out questionnaires on a regular basis. In total 342 respondents filled out the survey completely (response rate of 22%), of which 210 respondents only provided responses for utilitarian trips, 71 only for recreational trips and 61 respondents provided responses for both trip purposes. This resulted in 2710 observations for utilitarian trips and in 1320 observations for recreational trips. 48.2% of the respondents was male and 51.8% of the respondents was female. Comparing the normal transport mode with statistics reported by Statistics Netherlands (CBS, 2010) indicates that car users are slightly overrepresented and cyclists are underrepresented. From 1183 trips made by the respondents in the morning peak during a normal workweek 82.2% is utilitarian and 17.7% had a recreational purpose. This is similar to research from Ruimtelijk Planbureau (2006), which reported that utilitarian purpose accounts for 79% of the total motorway morning peak trips and recreational trips account for the other 21%. Given these results, we have a fairly high confidence in the sample being representative for the population.

Model estimation

Individual's preferences for choosing certain modes, routes and departure times can be expressed in utility. There are different models to estimate a utility function based on the answers of the respondents. In this paper the Multinomial Logit model (MNL), the Mixed Logit model and the Panel Mixed Logit model were compared. More information regarding stated choice can be found in Louviere et. al (2000) and for information with respect to the models to estimate the utility function we refer to Train (2003).

Effects coding is applied to code the attribute levels, hence, an estimated coefficient expresses the part-worth utility contribution of an attribute level to the utility of an alternative. The alternative specific constants are dummy coded, with the alternative 'not making this trip' chosen as the reference category. Hence, the estimated alternative constants denote the average utility derived from that alternative compared to 'not making the trip'. Effects coding resulted in four *current weather* indicator variables, two *weather forecast* and three *weather alarm* indicator variables. Preliminary analyses indicated that, as expected, *temperature* did not have any significant effects, and is therefore excluded from all models.

We expect that the choice for any alternative largely depends on the current and therefore the favourite travel options during the morning peak hours. This favourite option forms the basis of a segmentation for which the following groups were distinguished: motorway car group, non-motorway car group, public transport group and cyclist group. The number of respondents using public transport for recreational trips was too low to come to significant results. The public transport group was therefore excluded from the recreational trip analysis. The traveller groups were also effects coded and added to the constant of the utility function of each alternative, except for the 'not making a trip' alternative, which served as base alternative. The effects coding is presented in Table 1.

Table 1. Effects coding of the attribute levels and traveller groups

Current weather

estimated coefficients attribute levels	light rain	very heavy rain	light snow	heavy snow
light rain	1	0	0	0
very heavy rain	0	1	0	0
light snow	0	0	1	0
heavy snow	0	0	0	1
dry weather	-1	-1	-1	-1

Weather forecast

estimated coefficients attribute levels	worse forecast	better forecast
worse forecast	1	0
better forecast	0	1
similar forecast	-1	-1

Current weather

estimated coefficients attribute levels	rain alarm	snow alarm	icy roads alarm
rain alarm	1	0	0
snow alarm	0	1	0
icy roads alarm	0	0	1
no alarm	-1	-1	-1

Traveller groups utilitarian trips

estimated coefficients attribute levels	motorway car group	non-motorway car group	public transport group
motorway car group	1	0	0
non-motorway car group	0	1	0
public transport group	0	0	1
bicycle group	-1	-1	-1

Traveller groups recreational trips

estimated coefficients attribute levels	motorway car group	non-motorway car group
motorway car group	1	0
non-motorway car group	0	1
bicycle group	-1	-1

In addition, we tested for interaction effects between the groups and the weather attributes and we included in the model the interaction coefficients that were statistically significant. Hence, a statistically significant effect estimated for a group indicator means that the utility this group derives from that alternative differs from the average utility across all groups. This leads to the following alternative specific utility function:

$$U_j = \beta_{0j} + \sum_i \sum_m [\, \beta_{ij} X_i + \gamma_{mj} G_m + \alpha_{ijm} X_i * j_m \,] + \upsilon_{0j} + \varepsilon_j \tag{2}$$

Where:

U_j = the total utility derived from an alternative *j* (car using motorway, car avoiding morning peak, car avoiding motorway, bicycle, public transport, not making a trip)

X_i = effects coded indicator variables for the weather attributes (*i*=temperature, current weather, weather alarm, weather forecast)

G_m = grouping attribute indicating the most often chosen current alternative (*m*=motorway car group, non-motorway car group, public transport group and cyclist group)

X_i*G_m = interaction variables between attributes X_i and the groups G_m, denoting the group specific effects of weather variables X_i

β_{0j} = alternative specific constant to be estimated

β_{ij}'s = alternative specific effects of the weather variables to be estimated

Υ_{mj} = alternative specific effects of grouping variable on the alternative specific constants of the weather variables to be estimated

a_{ijm} = the interaction effects to be estimated, that denote the grouping variable's specific effects of weather variables on the alternatives

υ_{0j} = normally distributed standard deviation of the alternative specific constants to be estimated

ε_j = Gumbel distributed error term

The utility models were separately estimated for utilitarian and recreational travel behaviour in Biogeme (Bierlaire, 2003). First, a basic Multinomial Logit (MNL) model was estimated for utilitarian trips, which included only the alternative specific weather condition attributes, returned a Log-Likelihood value of -3882.16 and a Rho-square value of 0.200. After adding significant interactions of the current travel option with all coefficients, the log-likelihood considerably increases to -2005.48 and the Rho-square becomes 0.587, confirming that as expected the current travel option plays a big role in the choices among the alternatives, thus travellers who now use different travel modes make different choices in the experiment.

Next, a Panel Mixed Logit model was estimated to take the so called panel effect into account, the likely correlation in the choices observed for each respondent. More specifically, we assumed that the preferences for the alternative specific constants follow a normal distribution. Hence, a mean and a standard deviation for each alternative specific constant is estimated. This model is estimated by simulation for which error terms are drawn from a normal distribution, drawing a single error term for all the 10 choices observed for a single individual. This procedure results in more valid t-values as these are no longer based on the number of observations but on the number of respondents. Taking this panel effect into account further improved the Log-Likelihood towards -1386.50 and leads to a very high Rho-square value of 0.714. On top of that a shared error component was added to the three car alternatives to test if there is a significant correlation between the motorway alternatives. The shared error component, however, was insignificant, which means that the three car alternatives are uncorrelated.

For the recreational trips, the basic MNL model returns Log-Likelihood value of -2085.69 and Rho-square value of 0.118. Including the current mode choice indicators increases the Log-likelihood towards -1846.74. The Panel Mixed Logit model also resulted in a significant improvement of the model (Log-Likelihood = -1348.86) and results in a Rho-square value of 0.430.

Finally, some last notions need to be made about the model estimation. First, in each model, we started with the full set of coefficients and removed step by step all non-significant coefficients to finally arrive at a set of only statistically significant parameters. Secondly, the estimates of both utilitarian and recreational trip Panel Mixed Logit models did not change significantly when the number of draws was increased from 250 to 500 and are therefore considered to be stable. The presented models were estimated by applying 500 Halton draws.

3. Results

3.1 Capacity analysis

In this section, capacity is regarded under different weather scenarios. The first scenario is the reference case of dry weather. Secondly, the effect of light rain on motorway capacity is investigated by only analysing traffic flow intervals with precipitation intensities between 0.01 and 1 millimetre per hour. The third scenario is the heavy rainfall scenario, which includes all traffic flow intervals with precipitation intensities higher than 1 millimetre per hour. Unfortunately, analysis on the effect of snow on motorway capacity could not be conducted due to the limited days with snow within the examined years (2007, 2008 and 2009) and the absence of location specific snowfall data.

A cumulative normal distribution function is fitted to the resulting data in order to arrive at a complete capacity distribution function. The comparison of the capacity is made based on the median value of the capacity distribution functions (the median value denotes the tipping point for breakdown probability where it switches from most likely not to occur (<50%) to most likely to occur (>50%)). In stochastic capacity terms, it can be presumed as the 'representative' value. The results can be found in Table 2.

Light rainfall results in an average capacity reduction of 5.7% compared to dry weather. There is a significant difference in the capacity reduction at different bottleneck locations, with the capacity reductions ranging from 3.9% to 8.9%. In accordance with expectations, heavy rainfall, on average, leads to a higher capacity reduction than light rainfall for free flow capacity. This is a statistically significant difference, but the difference is rather small (5.7% vs. 8.1%) considering the fact that light rain only includes observations with rain intensities less than 1 mm/hour and heavy rain includes all observations equal or higher than 1 mm/hour. Compared to this difference, the difference in capacity between dry conditions and light rain is relatively large.

On the one hand it can be concluded that the median capacity reduction at a bottleneck location is similar at different time periods. The capacity reduction at a bottleneck location is very robust and does not change much over time. On the other hand, the differences in observations between different locations under equal conditions turn out to be relatively large: these vary between -3.7% and 11.1%. These differences may be caused by infrastructural differences between the various locations. Different road surfaces at the different locations may be an important candidate factor for explaining these differences, e.g. capacity reduction may be smaller on motorway sections with porous asphalt.

These results are in accordance with Cools et al. (2007), who found heterogeneity in the effect of rain on different traffic count locations and homogeneity of the rain effects on the upstream and downstream of the same location. Comparing the results obtained in the analysis with the findings from other studies leads to the conclusion that most other researchers have found capacity reductions that are within the same range as in this contribution (Agarwal et al., 2005; Maze et al., 2006; Chung et al., 2007) , increasing our confidence in the validity of our results.

Table 2. Comparison of the median capacity values in the different scenarios

			Dry		**Light rain**		**Heavy rain**	
motorway	Location pre-bottleneck (hecto-metre)	Location post-bottleneck (hector-metre)	Median Free flow capacity (veh/h)	Median Discharge capacity (veh/h)	Free flow capacity difference (%)	Discharge capacity difference (%)	Free flow capacity difference (%)	Discharge capacity difference (%)
A4R-2007	30.0	31.0	4452	3612	-4.2%	-6.6%	-10.3%	-5.3%
A4R-2008	30.0	31.0	4426	3624	-6.3%	-5.0%	-10.8%	-7.0%
A4L-2007	23.5	21.5	4368	3816	-3.9%	-4.1%		
A12R-2007	35.5	37.1	7173	5628			-7.3%	-5.1%
A12R-2008	68.1	68.7	4690	3864	-4.1%	-6.2%		
A15L1-2008	59.5	58.1	7267	6240	-4.4%	-6.9%		
A15L2-2007	80.9	80.1	4351	3768			-9.5%	-8.3%
A15L2-2008	80.9	80.1	4117	3792			-9.9%	-8.5%
A20R1-2007	31.0	31.9	6072	5460	-5.8%	-3.7%		
A20R1-2008	31.0	31.9	5939	5484			-7.5%	-7.7%
A20R2-2009	43.0	44.9	4205	3432			-11.0%	-4.2%
A20L-2007	32.2	31.2	6060	5268			-3.8%	-6.2%
A20L-2008	32.2	31.2	6064	5292			-3.7%	-6.3%
A20L-2009	32.2	31.2	6121	5388			-6.0%	-5.8%
A27L-2007	35.4	34.7	3938	3624			-6.1%	-5.0%
A27L-2008	35.4	34.7	3931	3624	-7.7%	-5.0%		
A50R-2007	156.3	157.5	4224	3516			-11.1%	-6.1%
A50L-2007	153.5	150.9	4181	3732	-8.9%	-7.1%	-8.1%	-9.0%
			Average		-5.7%	-5.6%	-8.1%	-6.5%
			Standard deviation		1.9%	1.3%	2.6%	1.5%

3.2 The estimated motorway travel demand model

The estimated parameters of both utilitarian and recreational trips Panel Mixed Logit models are presented in Table 3. As discussed before, all parameters are estimated alternative specific, hence, per model the table shows five sets of parameters. The alternative 'not making a trip' served as a base alternative and therefore has utility of zero by definition. If an alternative specific constant (ASC) or any other attribute is not listed, this means that its coefficient was not statistically significant and removed from the model. The presented standard deviations are the estimated standard deviations of the normally distributed ASC. All interaction effects of weather attributes and grouping attributes were estimated. As effects coding is applied, only L-1 coefficients are estimated for L attribute levels and M-1 interaction coefficients for M groups. The effects of the L-th attribute level or M-th group can be derived from the L-1 and M-1 estimated coefficients in such a way that the sum across all the effects of levels belonging to an attribute or group are equal to zero. The effect of the L-th attribute levels and M-th groups are presented in italics; as these values are not estimated, no t-values are presented for these results.

Table 3. The estimated Panel Mixed Logit utilitarian (a) and recreational (b) models

	Utilitarian trips	
	coefficient	t-value
Motorway		
no alarm	*1.40*	-
snow alarm	-0.57	-2.63
icy roads alarm	-0.82	-4.05
dry weather	*1.80*	-
light rain	2.20	6.61
light snow	-1.23	-6.63
heavy snow	-2.77	-12.49
motorway car group	4.69	16.77
public transport	-3.89	-4.75
bicycle group	*-0.80*	-
standard deviation constant	-3.61	-12.92
Avoid morning peak		
dry weather	*0.88*	-
heavy snow	-0.88	-3.68
standard deviation constant	-1.29	-6.68
Avoid motorway		
no alarm	*0.68*	-
rain alarm	0.55	2.62
icy roads alarm	-1.23	-3.74
dry weather	*1.08*	-
light rain	1.35	3.33
heavy snow	-2.43	-7.93
non-motorway car group	3.97	16.95
public transport group	-5.82	-4.76
bicycle group	*1.85*	-
standard deviation constant	-4.30	-11.76
Bicycle		
no alarm	*1.50*	-
icy roads alarm	-1.50	-4.10
dry weather	*7.54*	-
light rain	2.24	4.22
very heavy rain	-2.31	-3.70
light snow	-1.10	-2.87
heavy snow	-2.84	-4.95
motorway car group	-6.99	-7.02
bicycle group	*6.99*	-
motorway car group*very heavy rainfall	-3.53	-3.57
public transport group*very heavy rainfall	2.21	3.53
*bicycle group*very heavy rainfall*	*1.32*	-
standard deviation constant	-3.58	-7.09
Public transport		
dry weather	*-0.24*	-
light rain	1.13	3.05
heavy snow	-1.09	-3.46
motorway car group	-4.18	-8.00
non-motorway car group	-1.66	-3.34
public transport group	6.90	9.24
bicycle group	*-1.06*	-
public transport group*heavy snowfall	-1.08	-2.73
*bicycle group*heavy snowfall*	*1.08*	*-2.73*
standard deviation constant	3.06	9.29
Not making a trip		
ASC	0.00	reference
Log-likelihood	-1386.50	
Rho-square	0.714	

	Recreational trips	
	coefficient	t-value
Motorway		
ASC	-2.01	-7.24
no alarm	*1.19*	-
icy roads alarm	-1.19	-5.23
dry weather	*1.49*	-
light rain	1.74	5.14
very heavy rain	0.49	2.11
heavy snow	-2.24	-8.28
motorway car group	2.23	7.81
bicycle group	*-2.23*	-
standard deviation constant	2.38	-9.14
Avoid morning peak		
ASC	-0.78	-5.10
worse forecast	-0.56	-3.08
better forecast	0.61	3.55
similar forecast	*-0.05*	-
dry weather	*0.46*	-
light rain	0.90	3.05
heavy snow	-1.36	-5.85
standard deviation constant	1.15	9.50
Avoid motorway		
ASC	-2.99	-8.03
no alarm	*0.71*	-
icy roads alarm	-0.71	-2.92
dry weather	*0.71*	-
light rain	1.08	3.42
light snow	-1.47	-4.40
heavy snow	-1.79	-6.31
motorway car group	-2.48	-6.69
non-motorway car group	2.79	6.59
bicycle group	*-0.31*	-
standard deviation constant	3.78	7.86
Bicycle		
ASC	-2.72	-7.33
no alarm	*1.60*	-
snow alarm	-1.60	-4.06
dry weather	*0.50*	-
light snow	-0.72	-2.27
heavy snow	-2.07	-4.50
motorway car group	-1.78	-6.77
bicycle group	*1.78*	-
motorway car group*very heavy rainfall	1.24	4.24
*bicycle group*very heavy rainfall*	*-1.24*	-
standard deviation constant	-2.35	-11.99
Public transport		
ASC	-9.33	-4.31
standard deviation constant	-5.23	-5.26
Not making a trip		
ASC	0.00	reference
Log-likelihood	-1348.86	
Rho-square	0.430	

In the following, the main findings are briefly discussed and some examples of interpretations will be provided, starting with the utilitarian trips. The current weather generally has a larger impact on choice than the weather alarm and both variables affect choice much more than weather forecast. For example, a snow alarm has a much smaller effect on the choice for motorway than heavy snowfall at the decision moment (-0.57 vs. -2.77). Despite the smaller effect of weather alarm, travellers tend to take the advice of the KNMI to avoid travelling in extreme weather situations into consideration. Another interesting effect is that travellers derive a relative high disutility from heavy rain compared to light rain (e.g. a difference of 2.20 utility point for motorway utilitarian trips). The difference can be explained by the extreme rain intensity that was presented to the respondents in the stated adaptation experiment.

The utilitarian results show that none of the alternative specific constants is statistically significant, but that for every alternative at least one of traveller group constants is statistically significant. These user group specific constants are relatively large in the expected directions, which suggests that travellers more often choose for the alternative that is in line with their current revealed travel option during the morning peak hours. For example, considering the motorway alternative, which is on average most valued by the motorway user group (4.69), while it is very low valued by the public transport group (-3.89). In contrast, the public transport group highly prefers the public transport alternative (6.90). Furthermore, all estimated coefficients that denote standard deviations for the alternative specific constants were found to be statistically significant. This suggests that in addition to the differences in base preference of the different user groups and the effects of the weather alternatives, much heterogeneity exists with respect to alternatives base preferences.

Only a few interaction effects of weather attributes and the user groups were found to be statistically significant. Interesting interaction effects are observed for the bicycle alternative: during very heavy rainfall especially the utility the motorway group derives from the bicycle alternative is severely lower (-3.53), while bicycle's utility of both the public transport and bicycle group increases in those weather conditions (2.21, 1.32 respectively).

We now shift our focus to the recreational travel model and discuss some differences compared to the utilitarian travel model. The alternative (group specific) constants in the recreational travel model are all statistically significant and negative, which indicates that if one travels for recreational purposes, one more often choses for 'not making a trip' compared to travel for utilitarian purposes. Furthermore, the ASC of the 'avoiding the morning peak' alternative has a higher value than of the other alternatives, which indicates that this alternative is relatively more often chosen as a response to adverse weather conditions (in addition to not making the trip). Another noticeable result is the strong negative ASC for public transport. This suggests that travellers tend to avoid using public transport in adverse weather conditions if they travel for recreational purposes. This result is in accordance with findings from Tang and Thakuriah (2012). The reason for avoiding public transport in adverse weather conditions may be that in the last decade public transport performed very poorly in bad weather conditions resulting in large delays for many travellers, which has gained a lot of media attention.

3.3 Scenario analysis

In this section demand for motorway morning peak travel under several weather scenarios is calculated by applying the models presented in the previous section. Table 4 presents the choice probabilities for the six alternatives in the base scenario, separately for utilitarian and recreational travel and for the different user groups. The base scenario consists of dry weather, no weather alarm and forecasted similar weather. The number of respondents using public transport for recreational trips was too low to come to significant results and the public transport group was therefore excluded from the recreational trip analysis.

Table 4. Choice probabilities base scenario

		Motorway	Avoid morning peak	Avoid motorway	Bicycle	Public transport	Not making a trip
utilitarian trips	Car - motorway (n=136)	**74.5%**	1.7%	12.2%	10.9%	0.2%	0.5%
	Car- non motorway (n=72)	21.7%	2.4%	**52.2%**	21.7%	1.4%	0.7%
	Cyclists (n=28)	0.7%	0.0%	1.9%	**97.4%**	0.0%	0.0%
	Public transport (n=35)	5.1%	3.3%	1.7%	11.2%	**77.9%**	0.9%
recreational trips	Car - motorway (n=53)	**72.9%**	9.8%	2.0%	4.8%	0.0%	10.4%
	Car- non motorway (n=45)	25.3%	7.9%	**33.8%**	24.0%	1.4%	7.7%
	Cyclists (n=34)	8.7%	10.2%	7.9%	**61.5%**	1.6%	10.1%

In order to combine the predictions of utilitarian and recreational travel, we rely on research from (Ruimtelijk Planbureau, 2006), which shows the utilitarian trips account for 79% of the total motorway morning peak trips and recreational trips account for 21%. Hence, the separate predictions are weighted by these numbers. As the population distributions on the different user groups are unknown, we assume that user groups are distributed in the population as found in this sample (see table 4) and used the fraction of the group from the total amount of respondents as weights (e.g. utilitarian car-motorway group = $\frac{136}{271}$, car-non motorway group = $\frac{72}{271}$. The motorway traffic demand during the morning peak in the base scenario is indexed at 100 to make the relative difference between the different scenarios easier to interpret. The resulting motorway traffic demand in the different scenarios is shown in Table 5.

Table 5. Motorway morning peak traffic demand for different scenarios

Scenario	**Index**
Dry weather	100.0
Light rain	110.9
Heavy rain	105.5
Very heavy rain	100.0
Light snow	80.7
Heavy snow	77.9
Very heavy rain + rain alarm	84.1
Heavy snow + snow alarm	56.2
Heavy snow + icy roads alarm	54.0

The results show that the motorway traffic demand increases by 10.9% in light rainfall and by 5.5% in heavy rainfall. This is different compared to the 4% reduction in case of rainfall found by Al Hassan and Barker (1999) in Scotland. The difference could be explained by the modal shift of cyclists in the Netherlands during adverse weather conditions (Sabir, 2011). In case of very heavy rainfall the motorway traffic demand is the same as the base scenario. The other scenarios result in a decrease of motorway traffic demand compared to dry weather: 19.3% in case of light snowfall, and 22.1% in case of heavy snowfall. If a weather alarm is added, demand is reduced by 16.4% in case of very heavy rain and a rain alarm, by 43.8% in case of heavy snow and a snow alarm, and by 46.0% in case of heavy snow and icy road alarm. The snowfall figures are in accordance with the large negative correlation between highway traffic and snowfall found by

Call (2011) in the United States. In Scotland the traffic reduction of 10-15% with snow lying is slightly lower (Al Hassan and Barker, 1999).

3.4 Effect of precipitation on breakdown probability

A generic model is developed that provides information regarding the breakdown probability of traffic on all Dutch motorways. The developed model directly links the traffic supply with the traffic demand. Input necessary for predicting breakdown probability is the median capacity value and the traffic flow in the different precipitation scenarios. Since the breakdown probability is based on a normal distribution we are able to compute the standard deviation of the traffic flow from the median level. The standard deviation is computed for all bottleneck situations and scenarios, and the average of these values is taken. This results in corresponding traffic flow changes at one standard deviation of 8.6% for dry weather, 7.0% for light rainfall and 7.4% for heavy rainfall. Due to the different standard deviations for the different rain scenarios, one function and plot is made for each of the scenarios, which can be seen in Figure 2a-c.

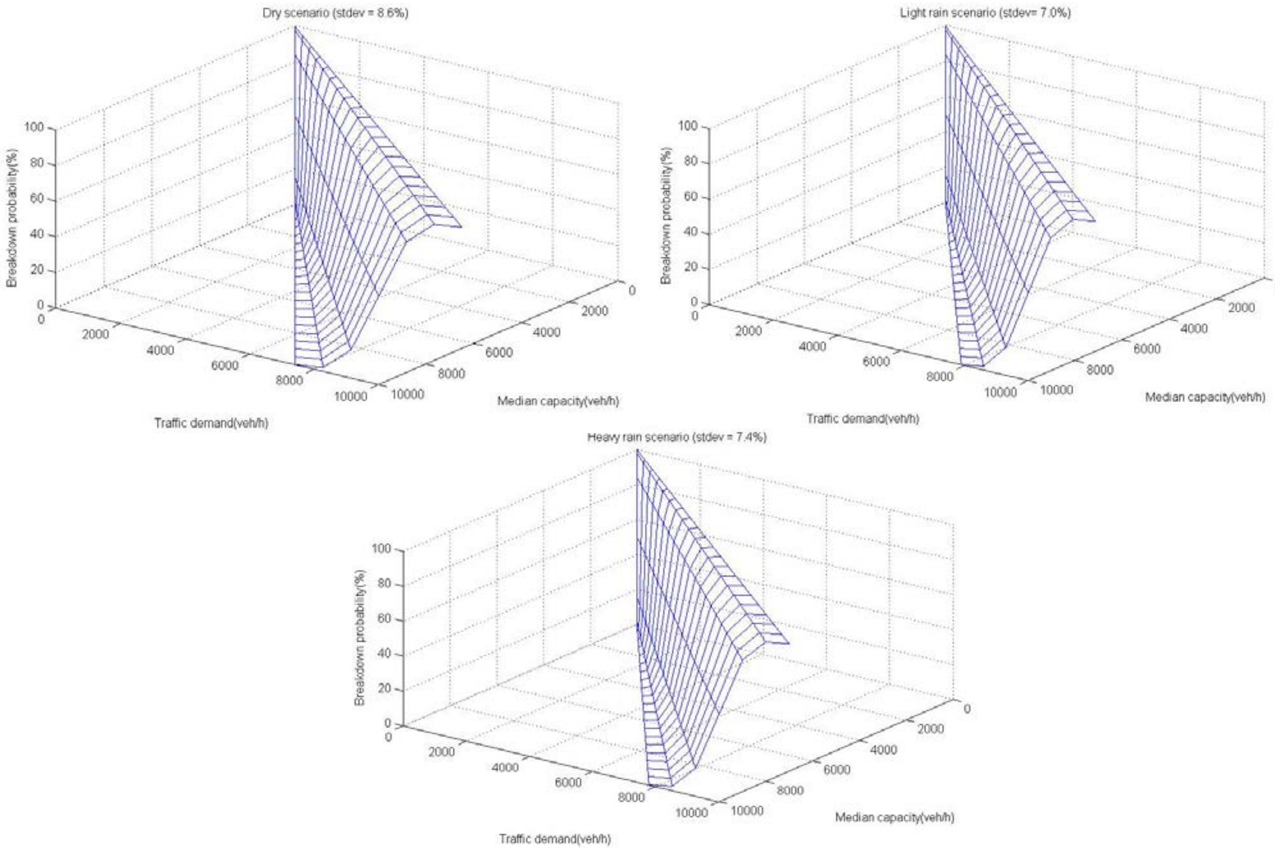


Figure 2. 3D-plot breakdown probability dry (a), light rain (b) & heavy rain (c) scenario

With the development of the three generic models, accurate breakdown probabilities can be calculated for any given traffic demand and median capacity. When the median capacity value of a certain bottleneck and the traffic demand are known, the intersection of this point with the function leads to the breakdown probability value. The resulting breakdown probability in the dry weather scenario can be used as a reference value. Inserting the adjusted traffic flow (reference traffic flow with the demand change) and the reduced median capacity into the model leads to a breakdown probability for a specific scenario for a specific motorway.

The traffic flow corresponding to the median capacity is used as a reference value. If the traffic flow is equal to the median capacity, this results in a breakdown probability of 50%. The traffic demand changes of +10.9% for light rain and +5.5% result in the traffic flow values per bottleneck location in these scenarios. The median capacity values for the bottleneck locations in the different scenarios are also presented. Furthermore, the average breakdown probability increases from 50% to 98.7% in light rain conditions. This is the result of the decreased capacity and an increasing traffic demand in this scenario. The range of breakdown probabilities for the different locations is between 98.1% and 99.9%, which can be explained by the different capacity reductions for the bottleneck locations. In the heavy rain scenario the average breakdown probability is increased from 50% to 95.7%. There is a larger range in the breakdown probability (between 88.2% and 98.8%) for the heavy rain scenario resulting from the relatively low breakdown probability on motorway A20L and A27L. The average probability of breakdown is lower than in the light rain scenario, while the average capacity reduction in the heavy rain scenario is larger than in the light rain scenario. This is the result of lower traffic demand in the heavy rain scenario compared to the light rain scenario.

4. Conclusions

This paper reports on the first study that incorporates both the motorway traffic demand change and the motorway capacity reduction in the estimation of the congestion probability as a result of adverse weather conditions. Motorway traffic demand is predicted by a Panel Mixed Logit model that was estimated from choices observed in a stated adaptation experiment that varied adverse weather conditions. To examine the influence of precipitation on motorway capacity, distribution functions were estimated for dry weather, light rain and heavy rain based on the Product Limit Method. With the development of a generic model based on a cumulative normal distribution, breakdown probabilities can be calculated for any given traffic demand and capacity.

Capacity reductions at single bottleneck locations are very robust and do not change significantly over the years. A plausible explanation is that differences in motorway characteristics cause the different capacity reductions. The road surface at the different locations may be an important factor in the reduction of motorway capacity. Future research needs to examine the effects of different road surfaces, so the road authorities are able to choose the type of road surface at the bottleneck locations that reduces capacity the least.

The most important result of the stated adaptation experiment is that the motorway traffic demand increases by 10.9% with light rainfall and by 5.5% in the heavy rainfall scenario as a result of the travel decisions of travellers. The small change on motorway traffic demand in the morning peak hours has a significant effect on the breakdown probability at the motorways.

Combining both traffic demand change and capacity reduction leads to the conclusion that rainfall leads to a significant increase in the probability of traffic breakdown at bottleneck locations. A breakdown probability of 50% in dry weather changes to an average breakdown probability of 98.7% in light rain and 95.7% in heavy rain conditions. The higher breakdown probability in light rainfall is caused by the higher traffic demand, mainly caused by cyclists switching to using car.

The integrated approach provides insights that a small change on motorway traffic demand in adverse weather conditions has a substantial effect on the breakdown probability at the motorways. An analysis solely based on the capacity reduction fails to take into account the demand change which can have a far greater impact on the breakdown probability than the capacity reduction itself. This would lead to incomplete conclusions regarding the motorway breakdown probability during adverse weather conditions. By adapting an integrated approach it was possible to develop a model that is able to more accurately predict the breakdown probability at bottleneck locations. The methodological implications of the model are that it can directly link the traffic supply with the traffic demand. The generic character of the model allows the effects of other events involving traffic demand changes on the breakdown probability on motorways to be analysed. One can for example think of the effect of closing certain motorways on the breakdown probability at other motorways, the effect of big events in certain cities that attract many visitors, the effect of breakdowns in public transport systems which force travellers to use the car, etc.. Furthermore, the finding that breakdown probabilities as a result of precipitation differ at different locations can be taken into account by road authorities in the decision to assign budgets to motorway improvement projects. Making more investments in the bottleneck locations at which rain leads to the biggest increase in breakdown probability could contribute to meeting the congestion reduction goals set by policy makers.

5. Discussion

The results from this study introduce a method to incorporate stochasticity and the influence of adverse weather conditions into traffic models. Due to its generic character the developed model can also be used to analyse the effect of other events involving traffic demand changes on the breakdown probability on motorways.

Road authorities could also use the specific breakdown probability results at the bottlenecks from this study to analyse the underlying factors for the different capacity reducing effects at different locations as a result of rainfall. A characteristic that should be taken into account in the analysis is the effect of porous asphalt versus normal asphalt on the breakdown probability. This way the probability of reaching the goals of reduction of congestion will increase.

The results of the travel demand study also provide some interesting insights for the Dutch meteorological institute that issues the weather alarm. The weather alarm has led to some debate over the past years. In 2010 the criteria for initiating a weather alarm were changed and in January 2013 the criteria had to be revised again. It can be concluded that the weather alarm still has a substantial effect on travellers.

The analysis in this study focused on congestion on freeways, whereas delays due to adverse weather conditions can also take place in the city centre. The delays in the city centre could unfortunately not be incorporated within the scope of this study, because data from traffic in the city was not available to us. During further research it could be interesting to include delays in the city centre.

The results obtained regarding the demand changes in this research have three limitations. Firstly, the results are based on stated behaviour instead of revealed behaviour. As common for stated research, stated behaviour may differ from actual behaviour. Moreover, the hypothetical weather situations may be differently interpreted by respondents. Secondly, the results of the travel behaviour analysis are average changes in motorway traffic demand. With the high importance of small changes in travel demand, investigating the effect of location specific rainfall on motorway traffic demand should be considered. Thirdly, there was no data available of the number of travellers in the different travel groups (car motorway, car non-motorway, public transport and bicycle). In this contribution the importance of the groups was based on the number of respondents of the groups in the sample. More valid data regarding the distribution of the groups in the population may increase the accuracy of the traffic demand predictions.

An analysis of the effect of snow on motorway capacity could provide a valuable addition. In order to come to sufficient breakdown observations on days with snowfall, it is advised to combine the traffic data from a longer time period at the same bottleneck location than applied in this paper. The snow analysis would be more accurate if reliable location specific snowfall information could be obtained. Lastly, it might be valuable to analyse whether the filtering algorithm can cope with breakdown observations at snow conditions.

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