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Inter- and Intraday Variability of Flemish Travel Behavior

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Dedication

Dedicated to Tom Verachtert (°26/06/1982 - †12/04/2008)

The relevance of research in the field of transportation never seems more relevant than when a good friend dies in a traffic accident.

Quotations

Traveling is almost like talking with men of other centuries.
René Descartes

Travel is the frivolous part of serious lives,
and the serious part of frivolous ones.
Anne Sophie Swetchine

The individual has always had to struggle
to keep from being overwhelmed by the tribe.
Friedrich Nietzsche

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Mario Cools
November 20th, 2009

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Chapter 1

Introduction

1.1 Background

In today's society, mobility is one of the driving forces of human development. The motives for travel are not confined to work or educational purposes but reach across a spectrum of diverse goals. Mobility is more than a cornerstone for economic growth; it is a social need that offers people the opportunity for self-fulfillment and relaxation (Ministerie van Verkeer en Waterstaat, 2004). Governments recognize the significance of mobility as evidenced by the mobility plans that are formulated by government agencies at different policy levels - for example, at the European level, the European Commission's White Paper 'European Transport Policy for 2010: Time to Decide' (European Commission, 2001), and at the Belgian regional level, the 'Mobility Plan Flanders (Mobiliteitscel, 2001) - and by the transportation research that is directly or indirectly funded by governments.

Due to a variety of reasons ranging from the intrinsic appeal of automobiles, urban sprawl, increasing demands of the labor market with regard to employees' flexibility and mobility, increasing female participation in labor, to a decline in traditional household structures, the previous century was characterized by an extraordinary growth in car use that has continued into the current century (Haustein & Hunecke, 2007). As a result, in today's society, cars play a dominant role in the travel behavior of people, causing serious environmental (e.g. greenhouse-emissions such as CO_2, methane, NO_x; noise, odor annoyance and acid precipitation), economic (e.g. use of non-renewable energy sources; and loss of time due to congestion) and societal (e.g. health problems such as cardiovascular and respiratory diseases; traffic casualties;

community severance and loss of community space) repercussions (Steg, 2003). Rising concerns over these increasingly intolerable externalities have generated particular interest in how transport policies might at least moderate the negative effects.

To support policy makers, traffic and transportation models can be used to make better long-term decisions. On an international level, activity-based models have become the norm to model travel behavior (a more detailed description of the different types of transportation models is given in Section 4.1 of this dissertation). The most important characteristic of these models is that the travel behavior of persons or families is a product of the activities that they wish or have to perform, procuring a more realistic description and a better understanding of people's travel behavior. Because of these advantages, researchers and policy makers in the United States have switched from conventional models to activity-based models. Although this trend is most visible in the United States, the same evolution can be noticed in Europe. It is within this context that an activity-based modeling framework for Flanders, denoted as '*FEATHERS (Forecasting of Evolutionary Activity-Travel of Households and their Environmental RepercussionS)*', is developed.

As mentioned in the previous paragraph, governments require reliable predictions of travel behavior, traffic performance, and traffic safety to support long-term decisions. Therefore, a better understanding of the events that influence travel behavior and traffic performance will lead to better forecasts and consequently policy measures that are based on more accurate data. Such improved information would allow policy makers to provide more precise travel information and formulate more efficient travel demand management (TDM) strategies, so that an important goal, more acceptable and reliable travel times (Ministerie van Verkeer en Waterstaat, 2004), could be achieved.

Events such as special holidays (e.g. Christmas, New Year's Day), school holidays (e.g. in July and August), socio-demographic changes, and weather can have an influence on mobility in different ways, as is illustrated by Figure 1.1 (Egeter & van de Riet, 1998). First, they can affect the travel market, in which the demand for activities and the supply of activity opportunities in space and time result in travel patterns. Second, these events can have an influence on the transport market, in which the demanded travel patterns and the supply of transport options come together in a transport pattern that assigns passenger and goods trips to vehicles and transport services. Finally, these events can have an effect on the traffic market, in which the required transport patterns are confronted with the actual supply of infrastructure and the associated management systems, resulting in the actual use of infrastructure as revealed by traffic patterns.

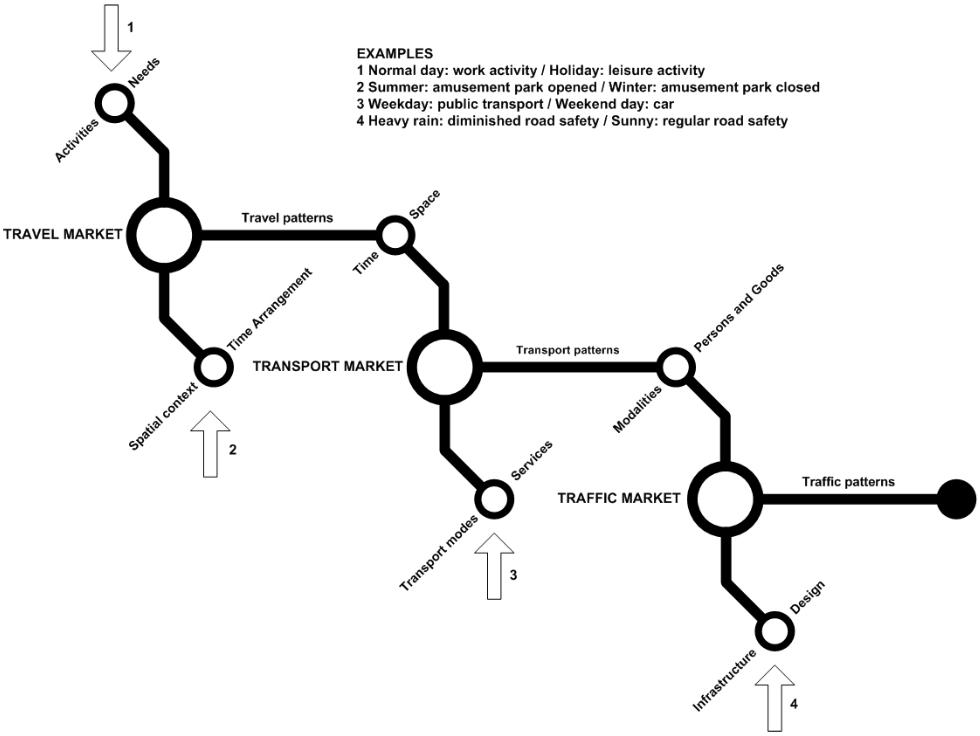

Figure 1.1: Three-market model and examples of influences on mobility

As the list of examples (Figure 1.1) shows, people may perform different activities during holidays than during on ordinary days. During holidays, people go to the beach, for example, whereas on regular days, they go to work. Another example indicated in Figure 1.1 involves the closing of amusement parks during winter. People wishing to visit such a park during winter will do something else instead, for instance, go ice skating. These are merely two examples of how holidays and seasonal effects influence the activities that people pursue and, in turn, how these activities have an impact on the travel market. A third example shows how mode choice can be influenced by the type of day, which can have an impact on the transport market, and the fourth example demonstrates how the environment can have an impact on the traffic market. The list of examples given in Figure 1.1 is not restrictive but is meant to exemplify how the three markets and hence mobility can be influenced by various events.

1.2 Outline of the dissertation

In the remainder of this introductory chapter, the title of the thesis '*Inter- and intraday variability of Flemish travel behavior*' is elucidated, and the general structure of the dissertation is illuminated. When the title is unraveled, it is immediately clear that the term 'travel behavior' is a very broad and generic term. Therefore it is needed to clearly confine the scope of travel behavior within the context of this thesis. A first refinement is the geographical context: the study investigates the travel behavior of people living in Flanders (the Dutch speaking region of Belgium). Figure 1.2 displays the location of Flanders (marked in red) within the global and European context.

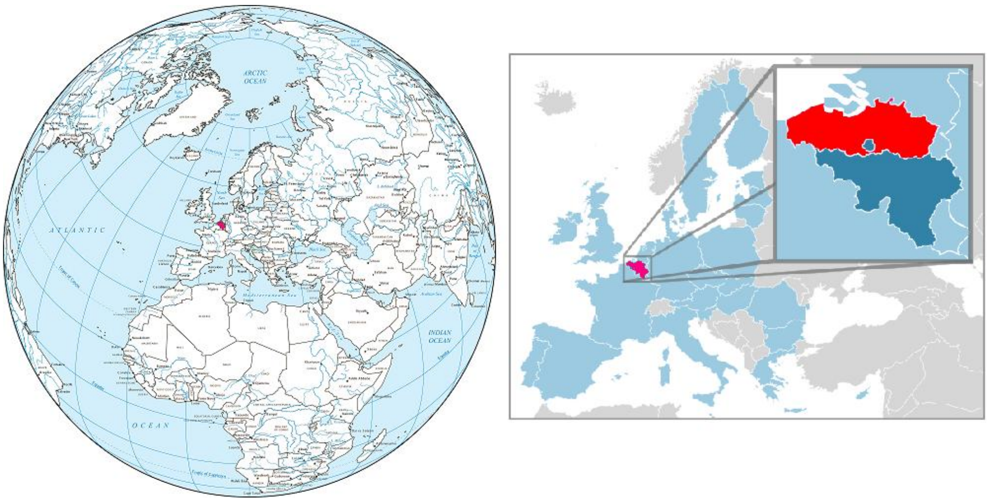

Figure 1.2: Geographical location of Flanders

Secondly, the focus lies on two specific characteristics of travel behavior, namely its inter- and intraday variability. Interday variability refers to the variability between days, operationalized by investigating the impact of temporal effects (e.g. day-of-week effects and holiday effects) on different key indicators (such as daily traffic intensity and daily travel times). A fine example illustrating interday variability is provided in Figure 1.1: the fact that people may perform other activities during holidays than during regular days, will definitely result in different travel and transport patterns. Intraday variability refers to the variability within one day and will be analyzed by looking at the impact of socio-demographics and by assessing factors influencing time-of-day decisions. A good example is the postponement of a planned trip due to adverse weather conditions to a moment later that day.

A third delineation of this dissertation is the range of facets that are disentangled. After all, travel is a complex and multifaceted phenomenon entailing '*decisions*'[1]concerning timing, transport mode, travel party, and route chosen. In particular, the research reported in this thesis focuses on the analysis of revealed traffic patterns (i.e. daily traffic counts), daily travel time expenditures, and stated behavioral adaptations due to external events. In addition to the travel facets, the analyses particularly focus on two external events influencing mobility, namely (public) holidays and (adverse) weather conditions.

The dissertation is divided into two main parts, as is visualized by Figure 1.3. In the first part, the impact of holidays and weather conditions on Flemish travel behavior is examined. Chapter 2 deals with holiday effects. First, the impact of holidays on daily traffic intensities (the revealed traffic pattern) is assessed (Section 2.1). Afterwards, the influence of holidays on daily travel time expenditure is investigated (Section 2.2). Chapter 3 tackles the effect of (adverse) weather conditions. In Section 3.1 attention is paid to the effect on daily traffic counts, whereas in Section 3.2 the focus lies on behavioral adjustments in response to weather conditions.

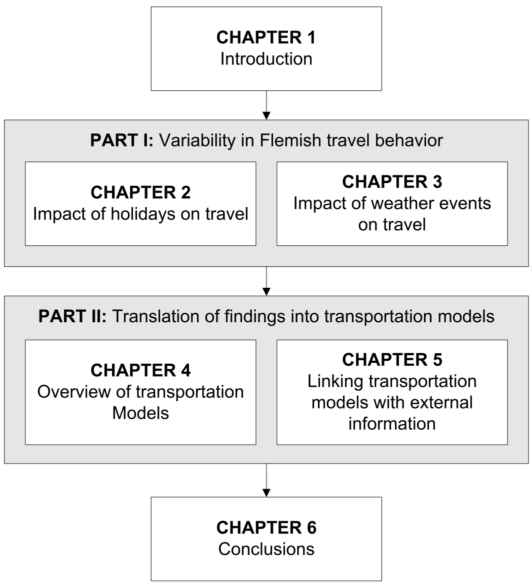

Figure 1.3: Schematic overview of the structure of the thesis

[1] The term '*decisions*' in this context does not imply that the decision maker deliberately considers all possible alternatives; the decisions can be purely habitual or being directed towards a specific choice alternative.

In the second part, the findings of the first part (the effects of holidays and weather events on travel behavior) are translated into transportation models. First (in Chapter 4), an overview of existing transportation models is provided . This overview focuses on the increased behavioral realism that could be observed in transportation models (Section 4.1). In the second part of this Chapter (Section 4.2), the need for developing state-of-the-art transportation modeling frameworks will be investigated by assessing the quality of origin-destination-matrices derived from household activity travel surveys.

In Chapter 5 the background of transportation models is used to link the observed holiday and weather effects directly and indirectly with the transportation models. A numerical example is provided to elucidate the suggested approaches.

To conclude the thesis, the final chapter recapitulates the most important findings of the dissertation, formulates recommendations for transportation planners and modelers, and provides suggestions for further research.

Part I

Variability in Flemish travel behavior

Chapter 2

Impact of holidays on travel

The research reported in this chapter is mainly based on Cools* et al. *(2007a), Cools* et al. *(2007b), Cools* et al. *(2009a) and Cools* et al. *(2010a).

In this chapter, the effect of holidays on the daily mobility of Flemish households is analyzed. Recall from the introduction that events such as public holidays (e.g. Christmas, New Year's day) and school holidays (e.g. in July and August) can have an influence on mobility in different ways, as was illustrated by Figure 1.1.

First, in Section 2.1, the impact of holidays on daily traffic counts[1]is investigated. Afterwards, the focus is turned to travel behavior itself. More precisely, the impact on daily travel times[2]will be thoroughly examined.

2.1 Impact of holidays on revealed traffic patterns

This first section examines the impact of holidays on daily traffic counts. First, some general background on the modeling of traffic counts is provided. Then, the data that are used in the analysis is described. Afterwards, the statistical methodology is explained. Finally, the results are discussed and some general conclusions are formulated.

Reliable predictions of travel behavior, traffic performance and traffic safety are

[1]The daily traffic counts are an indicator of the revealed traffic patterns, the final output from the three-market model (Figure 1.1)

[2]The daily travel times are specific features of the transport pattern, the output of transportmarket of the three-market model (Figure 1.1)

essential requirements for governments to lead an efficient policy. Policy tools like advanced traveler information systems (ATIS), advanced traffic management systems (ATMS) and control strategies such as ramp metering depend on the quality of forecasts of traffic volumes (Park, 2002). Therefore, a deeper understanding of the events that affect traffic performance will improve the quality of the predictions and consequently policy measures can be based upon more accurate data.

A good overview of the different techniques that exist to investigate the variability in daily traffic counts is provided by Han & Song (2003) and Van Arem *et al.* (1997). A first category that can be distinguished are time series models, which can be further divided into Box and Jenkins techniques, smoothing techniques, Kalman filtering theory and spectral analysis. Early applications of Box and Jenkins techniques in the field of traffic forecasting were implemented by Ahmed & Cook (1979) and Nihan & Holmesland (1980). More advanced techniques have more recently been applied, including ARIMA(X) (Auto-Regressive Integrated Moving Average Models with Intervention X-variables (Williams & Hoel, 2003)), Seasonal ARIMA models (Williams, 2001) and Kohenen enhanced ARIMA (KARIMA) models (Van Der Voort *et al.*, 1996), and multivariate approaches such as the multivariate state space approach (Stathopoulos & Karlaftis, 2003) and vector autoregressive and dynamic space time models (Kamarianakis & Prastacos, 2003, 2005). The first application of Kalman filtering theory within the field of traffic flow forecasting can be attributed to Okutani & Stephanedes (1984). Xie *et al.* (2007) also used the Kalman filter to forecast traffic volumes, but now with discrete wavelet decomposition.

Neural network models are the second category of techniques that can be identified. Smith & Demetsky (1994) were among the first that applied the technique in the domain of traffic flow forecasting. A performance evaluation of neural networks was made by Yun *et al.* (1998). Time-delay neural networks (Vlahogianni *et al.*, 2007), dynamic neural networks using a resource allocating network (Chen & Grant-Muller, 2001), and Bayesian combined neural networks (Zheng *et al.*, 2006) appear to be valuable neural network modeling examples.

Other techniques that are used for predicting traffic volumes include non-parametric models (Smith *et al.*, 2002; Lam *et al.*, 2006), cluster-based methods (Danech-Pajouh & Aron, 1991; Weijermars & van Berkum, 2005), principal component analysis (Lakhina *et al.*, 2004), pattern recognition (Kim *et al.*, 2007), fuzzy set theory (Li *et al.*, 2006) and support vector machines (Zhang & Xie, 2008).

The main objectives in this section are the unraveling of the variability in daily traffic counts, the identification and comparison of holiday effects at different site locations, the prediction of future traffic volumes, and the validation of the suggested modeling framework. The cyclicality in the daily traffic data will be explored using spectral analysis. To quantify holiday effects and predict future traffic counts, autoregressive integrated moving average models with explanatory variables (ARIMAX) and seasonal autoregressive integrated moving average models with explanatory variables (SARIMAX) will be the main statistical model approaches envisaged. Note that the combination of a regression model with ARIMA or SARIMA errors raises the opportunity to build a model with desirable statistical properties, and thus to minimize the risk or erroneous model interpretation (Van den Bossche *et al.*, 2004).

2.1.1 Data

Daily traffic data

The aggregated daily traffic counts originate from minute data coming from single inductive loop detectors, collected in 2003, 2004 and 2005 by the Vlaams Verkeerscentrum (Flemish Traffic Control Center). Four traffic count locations are investigated, displayed in Figure 2.1. The first two are located on the E314 Highway, a highway that is one of the entranceways of Brussels, and thus excessively used by commuters. The detectors in Gasthuisberg (Leuven, Belgium) are used to analyze the upstream traffic counts on this highway. The detectors in Herent (Leuven, Belgium) are used to analyze the downstream traffic counts. The second two traffic count locations are located on the E40 Highway, a highway that is one of the accesses to the Belgian seashore, and thus typified by leisure traffic. Both the upstream and downstream traffic counts are analyzed by data coming from detectors in Zandvoorde (Belgium). To refine the attractiveness of the Belgian seashore, it is noteworthy to mention that Belgium has a moderate maritime climate.

The loop detectors minutely generate four statistics: the number of cars driven by, the number of trucks driven by, the occupancy of the detector and the time-mean speed of all vehicles (Maerivoet, 2006). Adding up the number of cars and trucks for all lanes in a specific direction, i.e. two lanes for all four traffic count locations under study, yields a total traffic count for each minute. Although single loop detectors can distinguish between cars and trucks, it was decided to use the aggregate of both car and truck traffic to analyze the impact of holidays, as the distinction between cars and trucks is made by means of an algorithm which has an inferior performance during congested periods.

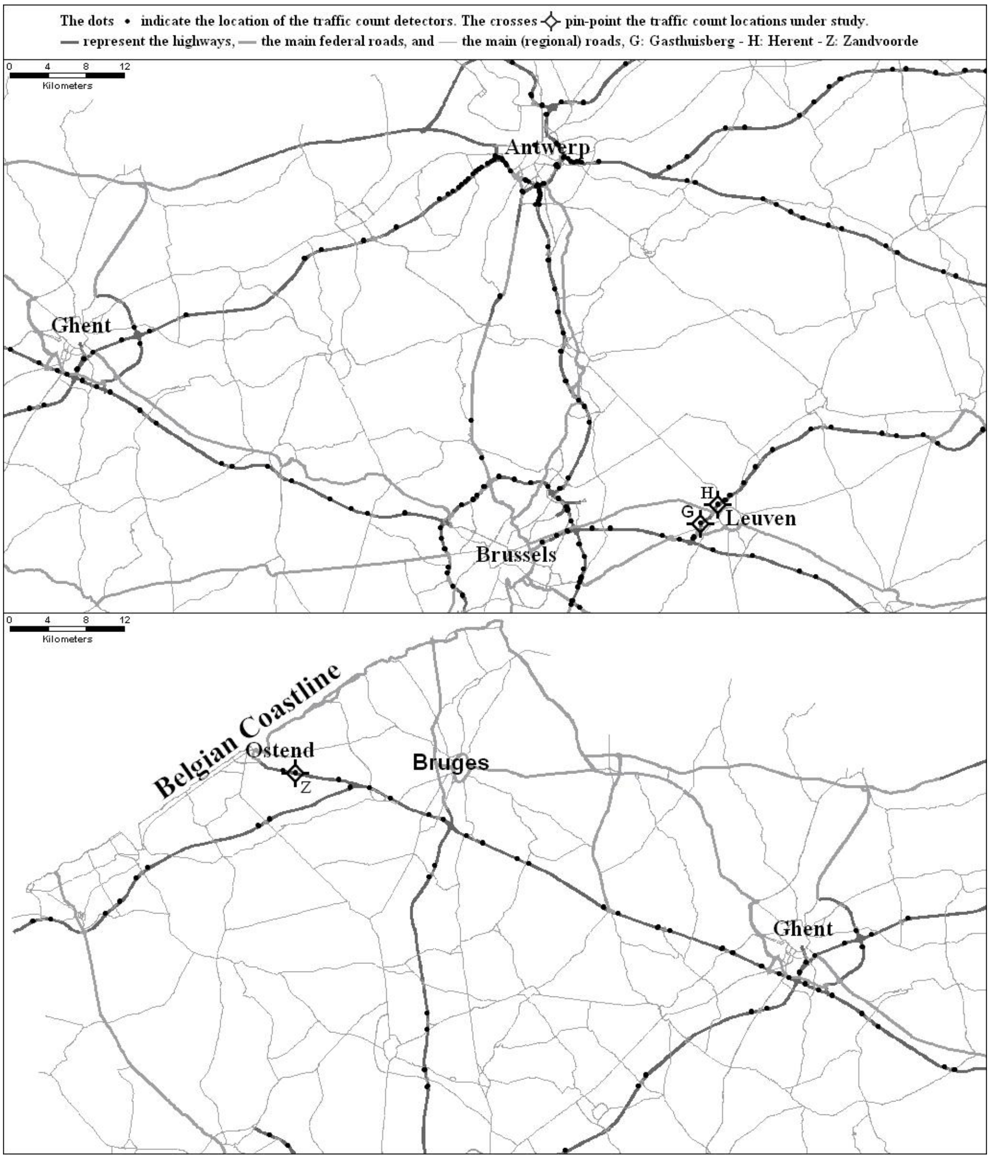

Figure 2.1: Geographical representation of the traffic count locations under study

Tackling missing data

The aggregation on daily basis of these minute data can only be done when there are no missing data that day. When some, or all of the minute data are missing, a defendable imputation strategy must be applied. About half of all the days that were analyzed, contained no missing data, as is shown in Table 2.1. Obviously, for these days no imputation strategy needed to be applied. This, however means that for the other half, there were some (41.78%) or a lot (7.84%) of the minute count data missing. When at least two hours of data, so at least 120 of the 1440 data points, were available, an imputation strategy was applied which extends the "reference days"-method proposed by Bellemans (2003). When there were fewer than 120 data points available in a day, a more general imputation strategy was applied.

Table 2.1: Missing data analysis upstream traffic Herent and corresponding imputation strategy

Quality Assessment	Number of days	% of all days	Imputation strategy
No minutes missing	552	50.36%	no strategy
1-60 minutes missing	342	31.20%	strategy 1
61-240 minutes missing	48	4.38%	strategy 1
241-720 minutes missing	68	6.20%	strategy 1
721-1320 minutes missing	32	2.92%	strategy 1
1321-1439 minutes missing	3	0.27%	strategy 2
Entire day missing	51	4.65%	strategy 2
Total	1096	100.00%	

Imputation strategy 1

Bellemans (2003) assumed in his work the existence of an a priori known reference day that is representative of the day for which missing values have to be estimated. The imputed value is then calculated by scaling the reference measurement so that it corresponds to the traffic dynamics of the day under study. In Bellemans (2003), the scaling factor was the fraction of the measurement and the reference measurement in the previous minute.

The imputation strategy applied in this dissertation uses the ideas of the reference days and the use of a scaling factor. The new measurements $x_{new}(t)$ are calculated in the following way:

$$x_{new}(t) = \delta x_{ref}(t), \tag{2.1}$$

where $x_{ref}(t)$ is the reference measurement and δ the scaling factor. For determining the reference measurement, 21 reference days (7 days for each of 3 holiday statuses) were used. For each reference day, the reference measurements were defined as the average of the modus, median and mean of the available days that corresponded to the reference day. The average of these three measures of central tendency was taken, because each of them has its own unique attributes (central location, robustness, highest selection probability), and favoring one could obscure model interpretation. The scaling factor δ is calculated as follows:

$$\delta = \frac{\sum\limits_{t=1}^{1440} d_t}{\sum\limits_{t=1}^{1440} m_t}, \tag{2.2}$$

where

$$d_t = \begin{cases} \frac{x(t)}{x_{ref}(t)} \Leftrightarrow x\left(t\right) \text{ not missing} \\ 0 \Leftrightarrow x\left(t\right) \text{ missing} \end{cases} \tag{2.3}$$

and

$$m_t = \begin{cases} 1 \Leftrightarrow x\left(t\right) \text{ not missing} \\ 0 \Leftrightarrow x\left(t\right) \text{ missing} \end{cases} \tag{2.4}$$

In the above equations, $x(t)$ is the measurement at minute t and $x_{ref}(t)$ the reference measurement at minute t.

Imputation strategy 2

For the above described imputation strategy, a scaling factor was required to match the reference measurement to the day under study. When all or almost all of the data points are missing, the scaling factor could not be calculated. In this case, the missing values are replaced by the reference measurements, which is equivalent to setting the scaling factor equal to 1.

Evaluation of implemented imputation strategies

Circumspection is essential when applying imputation strategies, as imputation processes encompass the risk of distorting the distributions of the data, and thus biasing the results. The magnitude of the risk must be indicated and potential patterns of the missing data need to be analyzed.

When the risk of distortion of the data is addressed, a thorough look at the minute data places the risk in the correct context. Of the 1578240 minutes (1096 days multiplied by 1440 minutes a day) that were aggregated on a daily basis, 140860 minutes (8.93%) were missing. Communication errors (e.g. due to system failures) account for 135654 minutes (8.60%) of missing data. The remaining 5206 minutes (0.33%) were due to other reasons such as physical errors of the loop detectors, disturbances in the electronic systems of the substations and inaccurate measurements.

When the imputation strategies are evaluated on the daily level, a first observation is that 81.56% (50.36% + 31.20%) of the days contains at least 95.83% (more than 1380 of the 1440 data points) of the data points that day. Thus, the imputation strategy has nearly no effect on these days. For the days (4.65% + 0.27%) that contained nearly no information (less than 120 of the 1440 data points available), just a measure of central tendency was used as imputed value, taking into account the day type (which day of the week and holiday or not). For 10.58% (4.38% + 6.20%) of the days between 50% and 95.83% of the data points were available, so the scaling factor used for the imputation strategy was still based upon a reliable amount of data. Only for 2.92% of the days, less than 50%, but at least 8.33% of the data points were available. It might be judged that here the imputation strategy could result in significantly distorted values. Different imputation strategies could be applied to this part of the data to assess the effect of the chosen strategy. However, since it is only a very small part of the entire data set, it was judged not to have a significant impact on the remainder of the study.

It is important to stress that the imputation strategies applied use a measure of central tendency that takes into account the day of week and the holiday status. Thus, the significance of these variables (day of week, holiday status) is not affected by the choice of the measure of central tendency. It is fair to recapitulate and infer that the implemented imputation strategies had no significant distorting effect on the results or conclusions.

Plot of the data

The following figure visualizes the aggregated daily traffic count data, taking into account the imputation strategies that were implemented. A similar pattern is visible over the three years. A drop in the number of passing vehicles at the beginning and end of each year is noticed, and during summer holidays, the intensity of daily traffic clearly is lower than during the other months.

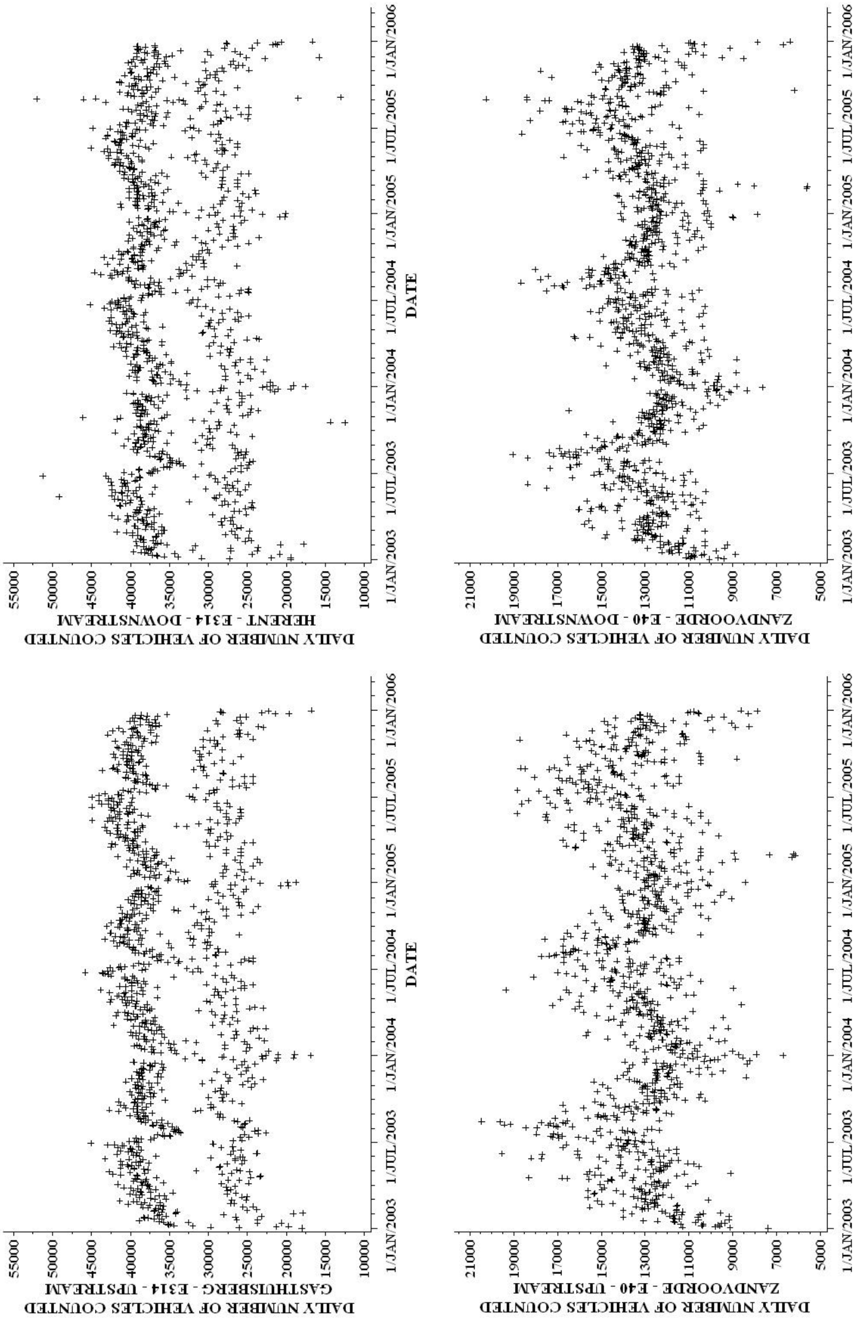

Figure 2.2: Time plots of daily up- and downstream traffic counts for two highways

Next the different interventions[3]will be briefly summarized.

Holiday effect

To assess the effect of holidays on traffic counts, it is necessary to identify which holidays occur in Belgium. The following holiday occasions were considered: Christmas vacation, spring half-term, Easter vacation, Labor Day, Ascension Day, Whit Monday, vacation of the construction industry (three weeks, starting the second Monday of July), Our Blessed Lady Ascension, fall break (including All Saints' Day and All Souls' Day), and finally Remembrance Day. Note that the national holiday, occurring on July 21, is included in the vacation of the construction industry. To evaluate the effect of all these holidays, the adjacent weekends, were considered to be a holiday too. For holidays occurring on a Tuesday or on a Thursday, respectively the Monday and weekend before, and the Friday and weekend after, were also defined as a holiday, because often people have a day-off on those days, and so have a leave of several days, which might be used to go on a long weekend or on a short holiday. To model the effect of the above described holidays a dummy variable was created; "normal" days were coded zero, and holidays were coded one.

Day effects

Next to the holiday effects, also day-of-week effects are envisaged. Six dummy variables are created in order to model the day-of-week effect. Note that in general it is necessary to create $k - 1$ dummy variables to analyze the effect of a categorical variable with classes (Neter *et al.*, 1996). It was chosen to represent the first six days of the week (Monday until Saturday) by respectively one dummy each, equal to one for the day the dummy represents, and zero elsewhere. Representing the first six days by six dummies entails that the remaining day, the Sunday, is treated as a reference day, implying that for all traffic counts that were collected on a Sunday, the corresponding six dummies are coded zero.

2.1.2 Statistical methodology

Special emphasis is laid on the investigation of cyclicality in the daily traffic data and on the identification and comparison of holiday effects at different site locations. To get prior insight in the cyclic patterns present in the daily traffic counts, spectral analysis provides the required framework to highlight periodicities in the data

[3]In time series analysis, explanatory variables are often called 'interventions'.

(Brocklebank & Dickey, 2003).

For forecasting daily traffic counts, two modeling philosophies are explored. The basic principle of the first philosophy is the fact that consecutive traffic counts are correlated, and that therefore present and future values can be (partially) explained by past values. SARIMA-models are fitted as this type of models is extremely suitable for taking into account seasonality in the data (Makridakis *et al.*, 1997).

The second philosophy is the regression philosophy. The basic premise of this approach is the idea that the dependent variable, in this study the daily traffic counts, could be explained by other variables. Notwithstanding, the linear regression model only yields interpretable parameter estimates when different underlying assumptions are satisfied. Since correlation between error terms is present, two accommodations to the classical linear regression model, namely the ARIMAX-model, sometimes referred to as the Box-Tiao-model, and the SARIMAX-model, are investigated. The latter models are capable of taking into account dependencies between error terms. The remainder of this section provides a brief recapitulation of underlying mathematical theory of the proposed time series models. For an introduction on time series techniques, the reader is referred to Shumway & Stoffer (2000). In Yaffee & McGee (2000), and Brocklebank & Dickey (2003) a comprehensive overview of how to fit time series models using the statistical software SAS, is given.

Spectral analysis

Spectral analysis is a statistical approach to detect regular cyclical patterns or periodicities. In spectral analysis the data are transformed with a fine Fourier transformation and decomposed into waves of different frequencies (Tian & Fernandez, 1999). The Fourier transform decomposition of the series x_t is:

$$x_t = \frac{a_0}{2} + \sum_{k=1}^{m} [a_k \cos(w_k t) + b_k \sin(w_k t)], \tag{2.5}$$

where t is the time subscript, x_t are the data, n is the number of observations in the series, m is the number of frequencies in the Fourier decomposition ($m = \frac{n}{2}$ if n is even; $m = \frac{n-1}{2}$ if n is odd), a_0 is the mean term ($m = \frac{n-1}{2}$), a_k are the cosine coefficients, b_k are the sine coefficients, and w_k are the Fourier frequencies ($w_k = \frac{2\pi k}{n}$).

Functions of the Fourier coefficients a_k and b_k can be plotted against frequency or against wave length to form periodograms, estimates of a theoretical quantity called a spectrum. The amplitude periodograms, also referred to as the periodogram ordinates, can then be smoothed to form spectral density estimates. The weight function used for the smoothing process, $W()$, is often called the spectral window. The following simple triangular weighting scheme will be used to produce a weighted moving average estimate for the spectral density of the series: $\frac{1}{64\pi}, \frac{2}{64\pi}, \frac{3}{64\pi}, \frac{4}{64\pi}, \frac{3}{64\pi}, \frac{2}{64\pi}, \frac{1}{64\pi}$.

SARIMA modeling

SARIMA modeling is a time series technique that accommodates ARIMA modeling to take into account seasonality in the data. It is an approach that tries to predict current and future values of a variable by using a weighted average of its own past values. If the series Y_t is modeled as a SARIMA $(p, d, q) \times (P, D, Q)_s$ process, then the model is given by:

$$\phi(B)\,\Phi(B^s)\,(1-B)^d(1-B^s)^D Y_t = \theta(B)\,\Theta(B^s)\,e_t, \tag{2.6}$$

where s is the length of the periodicity (seasonality); $\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - ... - \phi_p B^p$ is the non-seasonal autoregressive (AR) operator of order p and $\phi_1, \phi_2, ..., \phi_p$ the corresponding non-seasonal AR parameters; $\Phi(B^s) = 1 - \Phi_1 B^s - \Phi_2 B^{2s} - ... - \Phi_P B^{Ps}$ the seasonal AR operator of order P and $\Phi_1, \Phi_2, ..., \Phi_P$ the equivalent seasonal AR parameters; $\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - ... - \theta_q B^q$ the non-seasonal moving average (MA) operator of order q and $\theta_1, \theta_2, ..., \theta_q$ the associated non-seasonal MA parameters; $\Theta(B^s) = 1 - \Theta_1 B^s - \Theta_2 B^{2s} - ... - \Theta_Q B^{Qs}$ the seasonal MA operator of order Q and $\Theta_1, \Theta_2, ..., \Theta_Q$ the corresponding seasonal MA parameters; $(1-B)^d$ the non-seasonal differencing operator of order d to produce non-seasonal stationarity of the d-th differenced data (usually $d = 0$, 1, or 2); and finally $(1-B^s)^D$ the seasonal differencing operator of order D to produce seasonal stationarity of the D-th differenced data (usually $D = 0$, 1, or 2). In the above model equation B^i is used as a backshift operator on Y_t, and is defined as $B^i(Y_t) = Y_{t-i}$.

Note that a SARIMA-model is only valid when the series satisfies the requirement of weak stationarity. This requirement is fulfilled when the mean value function is constant and does not depend on time, and when the variance around the mean remains constant over time (Shumway & Stoffer, 2000). A transformation, like taking the logarithm or the square root of the series, often proves to be a good remedial measure to achieve constancy in the variance of the series (Neter *et al.*, 1996). To achieve stationarity in terms of the mean, it is sometimes required to difference the original series. Successive changes in the series are then modeled instead of the original series. Therefore in its most general form, as represented above, the SARIMA model includes a seasonal and non-seasonal differencing operator.

ARIMAX and SARIMAX modeling

In contrast with purely modeling a series Y_t as a combination of its past values, the regression approach tries to explain the series Y_t with other covariates. Attention is needed when the classical linear regression approach is applied to time series, as the assumption of independence of the error terms is often violated because of autocorrelation (the error terms being correlated among themselves). The transgression of this assumption increases the risk of erroneous model interpretation, because the true variance of the parameter estimates may be seriously underestimated (Neter *et al.*, 1996).

ARIMAX and SARIMAX models provide the required modeling frameworks to rectify the problem of autocorrelation by describing the error terms of the linear regression model by respectively an ARIMA(p, d, q) and SARIMA$(p, d, q) \times (P, D, Q)_s$ process. Formally the ARIMAX and SARIMAX models can be represented by the following equations:

$$Y_t = \beta_0 + \beta_1 X_{1,t} + \beta_2 X_{2,t} + ... + \beta_k X_{k,t} + \frac{\left(1 - \theta_1 B - \theta_2 B^2 - ... - \theta_q B^q\right)}{\left(1 - \phi_1 B - \phi_2 B^2 - ... - \phi_p B^p\right)} \varepsilon_t, \quad (2.7)$$

$$Y_t = \begin{array}{l} \beta_0 + \beta_1 X_{1,t} + \beta_2 X_{2,t} + ... + \beta_k X_{k,t} + \\ \frac{\left(1-\theta_1 B-\theta_2 B^2-...-\theta_q B^q\right)\left(1-\Theta_1 B^s-\Theta_2 B^{2s}-...-\Theta_Q B^{Qs}\right)}{\left(1-\phi_1 B-\phi_2 B^2-...-\phi_p B^p\right)\left(1-\Phi_1 B^s-\Phi_2 B^{2s}-...-\Phi_P B^{Ps}\right)} \varepsilon_t \end{array} \quad (2.8)$$

the first being the formal representation of the ARIMAX model, the latter of the SARIMAX model, where Y_t is the t-th observation of the dependent variable, $X_{1,t}$, $X_{2,t}$, ..., $X_{k,t}$ the corresponding observations of the explanatory variables, β_0, β_1, β_2, ..., β_k the parameters of the regression part, and where ϕ_1, ϕ_2, ..., ϕ_p, Φ_1, Φ_2, ..., Φ_P, θ_1, θ_2, ..., θ_q and Θ_1, Θ_2, ..., Θ_Q are the weights for the non-seasonal and seasonal autoregressive terms and moving average terms. The remaining error terms ε_t are assumed to be white noise. Note that for clarity of the formulae the differencing operators were left out of the equations.

The parameters of the ARIMAX and SARIMAX models are estimated using Maximum Likelihood. Studies, comparing least squares methods with maximum likelihood methods for this family of models, show that maximum likelihood estimation gives more accurate results (Brocklebank & Dickey, 2003). The likelihood function is maximized via nonlinear least squares using Marquardt's method (SAS Institute Inc., 2004a). When differencing of the error terms is required to obtain stationarity, all dependent and independent variables should be differenced (Van den Bossche *et al.*, 2004).

Model evaluation

In order to compare the different types of models that are considered, and to make comparisons between the models for upstream and downstream traffic intensity on the one hand, and between the models for different highways on the other hand, objective criteria are needed to determine the performance of the models (Makridakis *et al.*, 1997). To determine the appropriateness of the models and to substantiate the validity of the proposed modeling framework, the following criteria were considered: the Akaike Information Criterion (AIC), the Mean Square Error (MSE) and the Mean Absolute Percentage Error (MAPE). Only the last criterion can be applied for comparing models of different traffic count locations. By constructing the models on a training data set containing the first 75% of the observations, the remaining 25% of the observations make up a validation or test data set. This test data set can then be used to assess the forecasting performance of the models, by calculating the MSE and MAPE for the predictions for this test data set. The choice of these percentages is arbitrary, but common practice in validation studies (see e.g. Wets *et al.* (2000)).

The following three formula define the three criteria that are considered:

- AIC $= -2log(likelihood) + 2p$
- MSE $= \frac{\text{SSE}}{(n-p)}$
- MAPE $= \left(\sum_i \left| \frac{\hat{Y}_i - Y_i}{Y_i} \right| \times 100 \right) \Big/ n,$

with p the number of parameters in the model, n the number of observations and SSE the sum of all squared errors. Models with lower values for these criteria are considered to be the more appropriate ones (Akaike, 1974).

To evaluate the predictive strength of the proposed models, and more precisely to test whether the differences in MAPE for the different models are significant, the following statistical testing procedures are used: the Friedman test and the Wilcoxon signed-rank test (Smith *et al.*, 2002). The predictions (test data) of the different forecasting methods are ranked, and based on these ranked predictions the nonparametric repeated measures tests are performed. The Friedman test evaluates the null hypothesis that three or more related samples are from the same population, and so is used to assess whether the MAPEs for the different approaches are equal or not. The Wilcoxon signed-rank test evaluates the null hypothesis that two related samples have the same distribution. This test is adopted to test whether pairwise differences in MAPE are significant or not.

2.1.3 Results

In this (sub)section, the results are presented, the parameter estimates of the models are interpreted, and the different models are compared with each other. First, the periodicities in the data are highlighted. Then, the results of the three model approaches are provided, and their performances are carefully assessed. Finally, the models for upstream traffic count data and downstream traffic count data are compared for the two highways, and then differences in variability between the two highways are discussed.

Spectral analysis

Prior insight in the cyclic patterns present in the daily traffic counts can be obtained by looking at the results of the spectral analysis presented in Figure 2.3. This figure displays the spectral density estimates against the periods. From this figure is it clear that for three of the four traffic count locations the spectral density reaches a local maximum in period 3.5 and a global maximum in period 7. This global maximum can be interpreted as a weekly recurring pattern in the traffic data. For the remaining traffic count location (E40, Downstream) only a local maximum in period 7 is attained. Note that the other maxima (in periods 2.33 and 3.5) also contribute in explaining weekly cyclicality, as repetition of these patterns also yields a weekly pattern. In addition to the weekly periodicity, differences between the two highways can be highlighted: the weekly structure accounts for almost all variability on the E413 highway (typified by commuting traffic), whereas weekly patterns only partially explain the variability on the E40 highway (characterized by leisure traffic).

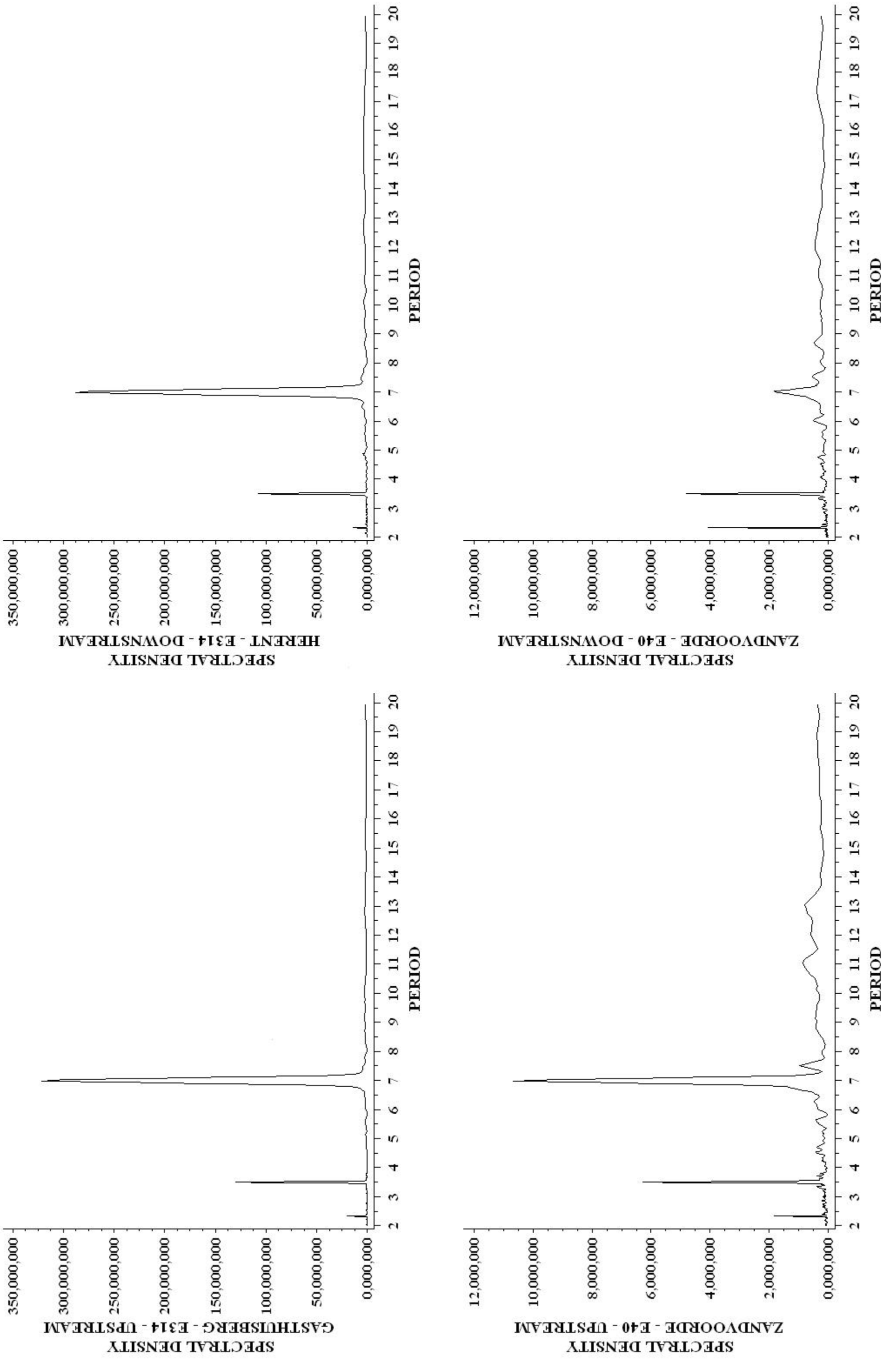

Figure 2.3: Spectral analysis of daily up- and downstream traffic counts for two highways

SARIMA modeling

For all four traffic count locations it was required to develop the corresponding SARIMA models on differenced data in order to obtain stationarity. A thorough investigation of the autocorrelation function and the partial autocorrelation function of the residuals was required, to evaluate which Autoregressive (AR) and Moving Average (MA) factors were required for the model building process. The following SARIMA models were obtained using the AIC as selection criterion:

1. E314, Upstream (Gasthuisberg): SARIMA $(1,1,1) \times (1,0,1)_7$
2. E314, Downstream (Herent): SARIMA $(2,0,1) \times (0,1,1)_7$
3. E40, Upstream (Zandvoorde): SARIMA $(1,1,1) \times (1,1,2)_7$
4. E40, Downstream (Zandvoorde): SARIMA $(0,1,2) \times (1,1,1)_7$

The estimates for these final obtained SARIMA models for the four traffic count locations can be formally represented by the following equations:

1. $(1-B)\,Y_t = \frac{(1-0.812B)\left(1-0.999B^7\right)}{(1-0.349B)(1-B^7)}\varepsilon_t$
2. $\left(1-B^7\right)Y_t = \frac{(1-0.775B)\left(1-0.994B^7\right)}{(1-1.256B+0.304B^2)}\varepsilon_t$
3. $(1-B)\left(1-B^7\right)Y_t = \frac{(1-0.926B)\left(1-1.593B^7+0.598B^{14}\right)}{(1-0.485B)(1-0.700B^7)}\varepsilon_t$
4. $(1-B)\left(1-B^7\right)Y_t = \frac{\left(1-0.457B-0.324B^2\right)\left(1-0.978B^7\right)}{(1-0.077B^7)}\varepsilon_t$

The above described models all contain seasonal and non-seasonal moving average factors, and addition seasonal and/or non-seasonal autoregressive factors are included if required. Notice that if these models were worked out completely, also other autoregressive and moving factors would play a role. Investigation of the SARIMA models draws immediate attention to the seasonality in the data: a seven-day cyclicality seems to predetermine daily traffic counts. This can be seen from the fact that a seasonal difference operator (taking the 7-th order difference) is included in three of the four models and that the seasonal autoregressive and moving average (SARMA) factors for the first model (E314, Upstream) are very close or equal to one. Moreover, other SARMA factors play an important role, indicating that traffic counts can be explained by weekly cyclic patterns.

ARIMAX and SARIMAX modeling

Like for the SARIMA modeling approach also for the ARIMAX and SARIMAX modeling approaches it was necessary to develop a model on differenced data to achieve (weak) stationarity; and the intercept was dropped from the equations to attain realistic interpretations. Recall that when differencing is applied, the intercept is interpreted as a deterministic trend, and this interpretation is not always realistic (Pankratz, 1991). The final error terms obtained in the four models were accepted to be 'white noise' according to the Ljung-Box Q*-statistics (Ljung & Box, 1978). Parameter estimates for the ARIMAX and SARIMAX models are shown in Table 2.2. The standard errors (S.E.), and values of the significance tests are provided as well. The estimates of the (S)ARIMA parameters are not shown, as they serve as a remedial measure for autocorrelation, and because focus lies on the interpretation of the regression part of the models. No day-of-week effects were included in the SARIMAX models, as seasonal differencing of the day-of-week variables would yield variables having a zero variance, and thus the model estimation would become infeasible. For the traffic count site location counting upstream traffic on the E314 highway (Gasthuisberg), it would have been feasible to include day-of-week effects, as no seasonal difference operator was used in this model. Nonetheless, when day-of-week effects were included, the seasonal AR and MA parameters were not significant and the model unfolded into the ARIMAX model.

From Table 2.2 one can see that the day-of-week effects are significant for all four traffic count locations: all six individual day-of-week dummy variables were significant on three of the four locations, whereas on the remaining traffic count location (E40 Downstream) half of the day-of-week dummy variables turned out to be significant. Note that the spectral analysis also pinpointed this contrast between the latter location and the rest. This could be partially explained by the fact that in general on Sundays the lowest traffic counts are observed compared to other days, whereas on this particular site location, on Sundays the intensity rates peak due to traffic generated from people returning home from their leisure trip to the seashore area. Furthermore, the analysis revealed that the holiday effects are only significant for the traffic count locations on the E314 highway. For the traffic count locations on the E40 highway the holiday effects were not significant. Therefore, for these leisure locations the parameter estimates for both the ARIMAX model including holiday effects (a) and the ARIMAX model without holiday effects (b) are presented in Table 2.2. For the SARIMAX models only the models including the holiday effects are displayed, as the models without holiday effects are obviously the SARIMA models described in the previous section.

Table 2.2: Parameter estimates for the ARIMAX and SARIMAX models

Parameter	Estimate	S.E.	t-value	p-value	Estimate	S.E.	t-value	p-value
	E314 Upstream (Gasthuisberg)				E314 Downstream (Herent)			
	$ARIMAX\ (1,1,1)$				$ARIMAX\ (1,1,1)$			
Holiday	-4197	295	-14.2	<0.001	-3863	351	-11.0	<0.001
Monday	9203	256	36.0	<0.001	9011	308	29.3	<0.001
Tuesday	10832	293	37.0	<0.001	10548	362	29.2	<0.001
Wednesday	11522	303	38.1	<0.001	11022	378	29.2	<0.001
Thursday	11311	301	37.6	<0.001	10863	376	28.9	<0.001
Friday	11983	291	41.2	<0.001	11028	359	30.7	<0.001
Saturday	1390	252	5.5	<0.001	1428	303	4.7	<0.001
	$SARIMAX\ (1,1,1)\times(1,0,1)_7$				$SARIMAX\ (2,0,1)\times(0,1,1)_7$			
Holiday	-4219	290	-14.6	<0.001	-3839	351	-10.9	<0.001
Parameter	Estimate	S.E.	t-value	p-value	Estimate	S.E.	t-value	p-value
	E40 Upstream (Zandvoorde)				E40 Upstream (Zandvoorde)			
	$ARIMAX\ (1,1,2)^a$				$ARIMAX\ (3,1,1)^a$			
Holiday	-196	164	-1.2	0.234	95	143	0.7	0.504
Monday	933	126	7.4	<0.001	-193	112	-1.7	0.086
Tuesday	1121	158	7.1	<0.001	-398	135	-3.0	0.003
Wednesday	1370	164	8.3	<0.001	-473	131	-3.6	<0.001
Thursday	1651	163	10.1	<0.001	-222	131	-1.7	0.089
Friday	3119	156	20.0	<0.001	-107	134	-0.8	0.424
Saturday	738	124	6.0	<0.001	-2122	110	-19.3	<0.001
	$ARIMAX\ (1,1,2)^b$				$ARIMAX\ (3,1,1)^b$			
Monday	963	124	7.8	<0.001	-207	110	-1.9	0.059
Tuesday	1155	155	7.5	<0.001	-416	133	-3.1	0.002
Wednesday	1406	162	8.7	<0.001	-491	129	-3.8	<0.001
Thursday	1680	162	10.4	<0.001	-237	129	-1.8	0.066
Friday	3147	154	20.4	<0.001	-121	132	-0.9	0.362
Saturday	737	124	6.0	<0.001	-2122	110	-19.3	<0.001
	$SARIMAX\ (1,1,1)\times(1,1,2)_7$				$SARIMAX\ (0,1,2)\times(1,1,1)_7$			
Holiday	-178	161	-1.1	0.269	50	135	0.4	0.711

Model comparison

When the performance of the different modeling philosophies is assessed, it is clear from Table 2.3 that all three model approaches perform reasonably well in explaining the variability of daily traffic counts: the three criteria that are based on the training data (AIC, MSE and MAPE) favor different modeling approaches suggesting that the three model approaches tested are valid approaches for investigating daily traffic counts. Concerning forecasting of daily traffic counts the ARIMAX models outperformed the SARIMA and SARIMAX models on three locations based on the two criteria that are based on the test data (MSE and MAPE) and for the fourth location (E314 Downstream) only small differences in performance are observed. This suggests that when the focus is put on forecasting, the use of the ARIMAX model approach should be preferred.

Besides, forecasting on the E314 yields more reliable results than on the E40 highway: MAPEs of 7.12% and 8.24% are observed for respectively upstream and downstream traffic for the E314 highway, whereas on the E40 highway only percentages of 10.07% and 9.16% were attained for the best models. This finding matches perfectly with the results from the spectral analysis, namely that the weekly structure accounts for almost all variability on the E314 highway (typified by commuting traffic), while weekly patterns only partially explain the variability on the E40 highway (characterized by leisure traffic). The superior forecasting on the E314 highway is also evidenced by Figure 2.4: the predictions of the daily traffic counts on the E314 highway (upper plots) are much closer to the actual values than the ones on the E40 highway (lower plots).

Table 2.3: Criteria for model comparisons ($\star$ best model according to the criterion)

	Training data			Test data	
	AIC	MSE	MAPE	MSE	MAPE
E314 Gasthuisberg (Upstream)					
SARIMA $(1,1,1) \times (1,0,1)_7$	15275.0	6,654,557	5.37%	17,877,684	8.85%
ARIMA(X) $(1,1,1)$	$\star$15074.8	$\star$5,451,893	$\star$4.90%	$\star$10,380,923	$\star$7.12%
SARIMA(X) $(1,1,1) \times (1,0,1)_7$	15116.6	5,515,467	5.06%	18,557,140	10.18%
E314 Herent (Downstream)					
SARIMA $(2,0,1) \times (0,1,1)_7$	15387.0	8,905,383	6.05%	16,779,060	9.13%
ARIMA(X) $(1,1,1)$	15383.8	$\star$7,939,285	$\star$5.82%	14,453,314	8.46%
SARIMA(X) $(2,0,1) \times (0,1,1)_7$	$\star$15295.4	7,994,919	5.84%	$\star$13,501,012	$\star$8.24%
E40 Zandvoorde (Upstream)					
SARIMA $(1,1,1) \times (1,1,2)_7$	$\star$13883.0	1,440,592	6.67%	3,883,197	11.92%
ARIMA(X) $(1,1,2)$ with holiday	13978.7	$\star$1,433,216	$\star$6.59%	$\star$3,246,433	10.11%
ARIMA(X) $(1,1,2)$ no holiday	13978.2	1,433,935	6.60%	3,296,933	$\star$10.07%
SARIMA(X) $(1,1,1) \times (1,1,2)_7$	13883.8	1,440,650	6.67%	3,948,399	12.14%
E40 Zandvoorde (Downstream)					
SARIMA $(0,1,2) \times (1,1,1)_7$	$\star$13661.1	1,101,579	6.06%	3,025,826	9.67%
ARIMA(X) $(3,1,1)$ with holiday	13775.2	1,090,283	5.91%	3,052,143	9.24%
ARIMA(X) $(3,1,1)$ no holiday	13753.7	$\star$1,089,540	$\star$5.89%	$\star$3,003,765	$\star$9.16%
SARIMA(X) $(0,1,2) \times (1,1,1)_7$	13662.9	1,102,956	6.07%	3,017,484	9.59%

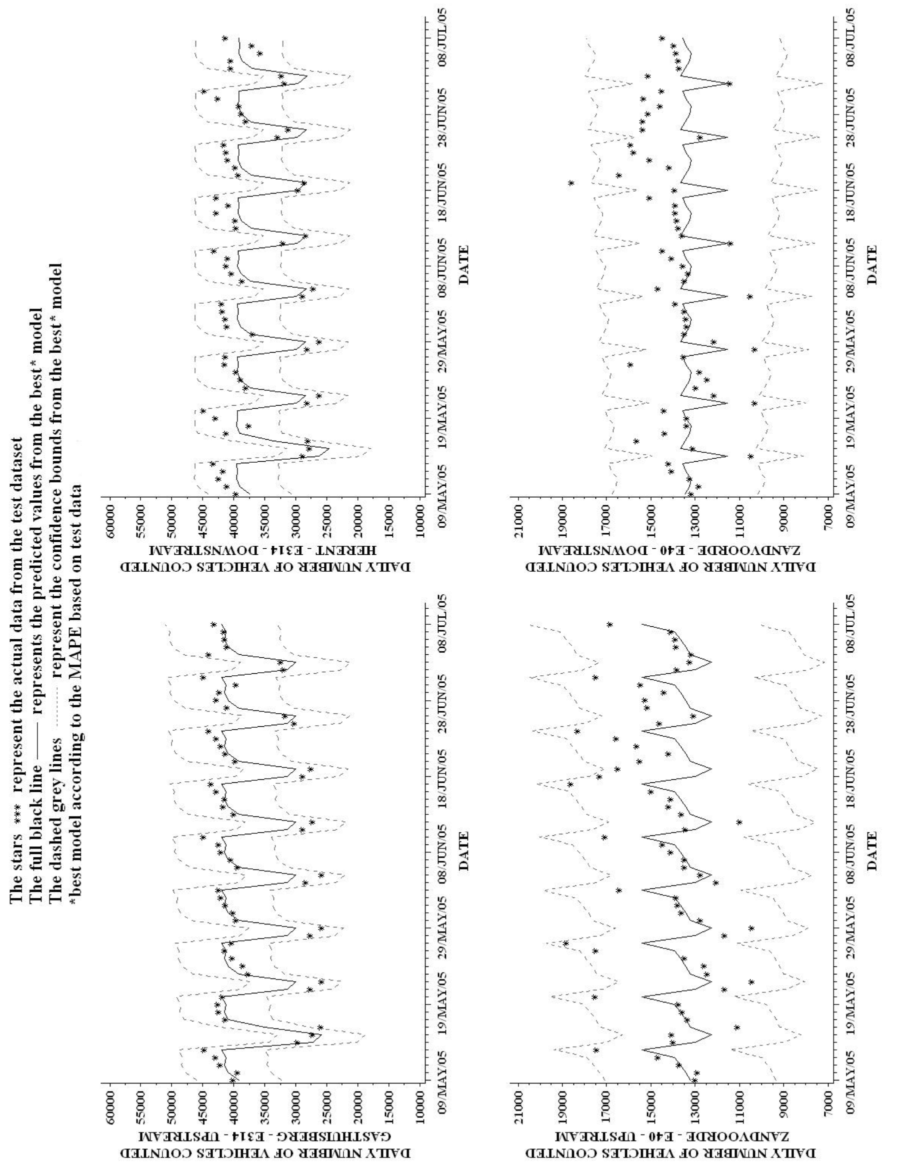

Figure 2.4: Daily traffic counts and their predicted values and confidence bounds

When the statistical testing procedures are used to assess the predictive value of the models, the Friedman tests all indicate that significant differences in MAPE exist. For three of the four locations the corresponding p-values are below 0.01. For the models for downstream traffic on the E40 highway, the differences are only borderline significant (p-value equals 0.046). Note that for this location the MAPEs based on the test data set are indeed much closer to each other, when compared to the other locations. When the differences are tested in pairwise comparison, accounting for multiple testing, significant differences can be found between most of the MAPEs, except for the models predicting downstream traffic on the E40 highway.

The sundry techniques all highlighted a weekly cyclic behavior on all four locations. Yet, holiday effects turned out to have only a significant impact on the upstream and downstream traffic of the E314 highway. For the traffic count locations on the E40 highway no significant holiday effects were retrieved. Nevertheless, further elaboration on this insignificance of the holiday-effect is worthwhile, since the daily travel time expenditure on commuting is clearly lower on holidays than on regular days (Cools *et al.*, 2007b)[4]. So, one can conclude that for the E40 traffic count locations, the decrease in the number of vehicles due to fewer commuting traffic on holidays is compensated by an increase in the number of vehicles due to leisure traffic, which is shown by the non-significant effect of holidays on the sum of all traffic, as considered here. The simultaneous analysis of travel goals and traveling itself (traffic counts) therefore seems an interesting avenue for further research.

The comparison of upstream and downstream traffic count locations yields quite diverse results for the locations on the E314 highway and the locations on the E40 highway (Table 2.2). For the first highway, upstream and downstream traffic seem to yield very comparable findings; significant lower traffic counts during the weekend and during holidays and maximum levels of traffic intensity on Wednesdays and Fridays. Controversially, the upstream and downstream traffic locations on the E40 show quite divergent results; upstream traffic seems to top on Fridays and is least intense on Sundays, whereas downstream traffic reaches the maximum on Sundays. This discrepancy between upstream and downstream can be (partially) explained by the fact that people make a weekend trip to the seashore, starting their leisure trip on Friday evening, and returning home on Sunday.

[4]An elaborated discussion concerning the effect of holidays on travel time expenditure is provided in Section 2.2.

2.1.4 Discussion and generalization of the results

Three modeling approaches, namely SARIMA, ARIMAX and SARIMAX were considered to predict daily traffic counts. These different modeling techniques, as well as the spectral analysis, pointed out the significance of the day-of-week effects: weekly cycles seem to determine the variation of daily traffic flows. The comparison of day-of-week effects or seasonal effects and holiday effects at different site locations revealed that all three modeling approaches perform reasonably well in explaining the variability of daily traffic counts, favoring the ARIMAX model, when the focus is on forecasting daily traffic counts. Results revealed that the ARIMAX and SARIMAX modeling approaches are valid frameworks for identification and quantification of possible influencing effects. Nonetheless, the explicit incorporation of day-of-week effects in ARIMAX yields additional insight for policy decision makers. The technique provided the insight that holiday effects play a noticeable role on highways that are excessively used by commuters, whereas holiday effects have a more ambiguous effect on highways typified for their leisure traffic.

The results generalize the findings of Cools *et al.* (2007a) who used multiplicative Holt-Winters exponential smoothing[1], ARIMA modeling[2] and Box-Tiao modeling[3] to disentangle the variability in the upstream traffic of the E314 highway. Cools *et al.* (2007a) concluded that weekly cycles determined the variation of daily traffic flows, that daily traffic flows turned out to be lower in the weekends than during the week, and that traffic flows were significantly lower during holidays[4]. One of the limitations of this study was that the analysis was done on a very specific location.

The results can help policy makers to fine-tune current policy measures. The performance of policy tools like advanced traveler information systems (ATIS) and advanced traffic management systems (ATMS) can be improved. An example are

[1]The multiplicative Holt-Winters exponential smoothing model accommodates the simple exponential smoothing model - simple exponential smoothing is a way of forecasting future observations, by producing a time trend forecast, in which the parameters are allowed to change gradually over time, and recent observations are given more weight than observations further in the past (Yaffee & McGee, 2000) - to account for regular seasonal fluctuations, by combining a time trend with multiplicative seasonal factors (SAS Institute Inc., 2004a).

[2]ARIMA modeling is a simplification of SARIMA modeling in which all seasonal factors are removed from the formula.

[3]Box-Tiao modeling is a synonym for ARIMAX modeling. The corresponding methodology is discussed in Section 2.1.2.

[4]Concerning modeling performance Cools *et al.* (2007a) concluded that when forecasting of daily traffic flows is required, the Box-Tiao model appears to be an approach that performs reasonably well. Furthermore, they ascertained that smoothing techniques, like the Holt-Winters Exponential Smoothing model, are to be avoided for predictions with a large forecast horizon.

online calendars pinpointing the days with high expected traffic volumes. Travelers can use the information provided, reschedule and/or adapt their planned travel trips. A second example is to focus policy actions such as carpooling initiatives on the most traffic intense days. For the upstream traffic for the E40 highway for instance, focus should be put on stimulating alternatives for the Friday traffic. The examples illustrate that the findings of this study contribute to achieving an important goal, namely the policy keystone 'more acceptable and reliable travel times'.

Further generalization of the results is possible, when more traffic patterns of other parts of the road network are analyzed. Modeling of daily traffic counts on secondary roads, and simultaneous modeling of different traffic counts locations is certainly an important pathway for further research. A key challenge will be the simultaneous modeling of both the underlying reasons of travel, and revealed traffic patterns.

2.2 Impact of holidays on daily travel time expenditure

In this section, the effect of holidays on travel behavior will be assessed by investigating the impact on daily travel times. Before the detailed analysis of the influence on daily travel times is examined, first an 'exploratory' assessment of this impact is provided.

2.2.1 Impact on daily travel times: a first assessment

In this (sub)section, travel time expenditure in Flanders (the Dutch speaking part of Belgium) is investigated. The focus is put on the time spent on commuting, with commuting trips being defined as school- and work-related[5]trips. Travel behavior researchers have regained interest in the travel time budget (the daily travel time expenditure) in the context of activity-based and time use research in travel behavior modeling (Banerjee *et al.*, 2007). The notion of a constant travel time budget is thoroughly discussed in literature (van Wee *et al.*, 2006).

Data

The data that will be used for the analysis stem from a household travel survey in Flanders that was carried out in 2000 (Zwerts & Nuyts, 2004). The focus of this survey was to investigate the travel behavior of the people living in the Flanders area. Using stratified clustered sampling, 3,028 households were queried about their travel behavior. All household members older than 6 (in total 7,625 persons) had to report the trips they made during a particular day, yielding information about 21,031 trips. Since commuting was the primary motive for travel, as can be seen from Table 2.4, focus is laid on the investigation of daily time expenditure on commuting.

Daily commuting time

The daily commuting time is calculated by adding up the time spent on school- or work-related travel. Both the trips to the work/school locations and the trips back home were considered to be commuting trips. For this calculation all the respondents, that made at least one trip during the survey period (not necessarily a commuting trip), were considered. Figure 2.5 displays the distribution of the daily commuting

[5]Work-related or commuting trips also include trips related to applications for vacancies and trips related to moonlighting.

Table 2.4: Categorization of trips according to trip motive

Trip motives	Nr. of trips	% of trips
Commuting	5633	26.80%
Shopping	4323	20.50%
Leisure	2992	14.20%
Non-commercial visits	2432	11.60%
Drop-off and Pick-up	2187	10.40%
Services (GP, Bank)	863	4.10%
Walking, Touring	732	3.50%
Business visits	506	2.40%
Other	1386	6.60%
Total number of trips	*21054*	*100.00%*

times. Note that more than half of the respondents did not commute at all. The average time that the respondents spent on commuting (including zeros of non-commuters) was about 21 minutes.

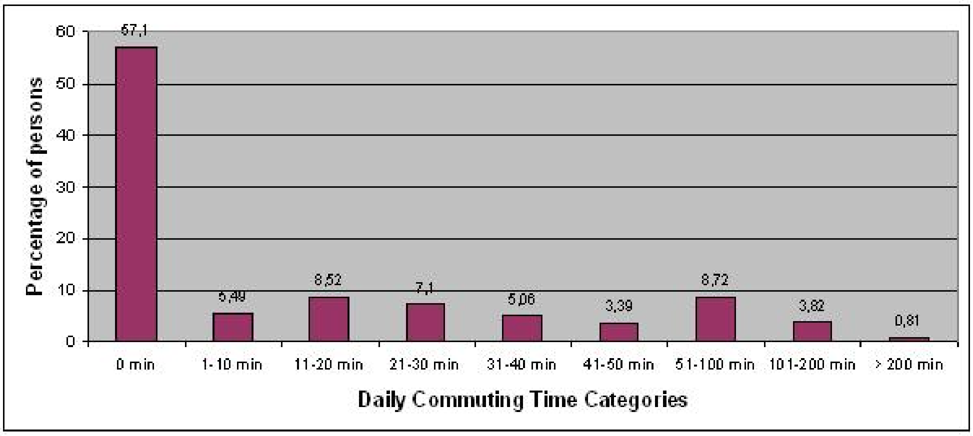

Figure 2.5: Distribution of Daily Commuting Time (non-commuters included)

Socio-demographics

Socio-demographic variables are commonly used in models that predict travel time (Frusti *et al.*, 2002; Sall & Bhat, 2007). The following variables are used for the analysis: age, sex, and employment status. When Table 2.5 is explored it can be seen that daily commuting first increases with age, reaches its maximum at age category 35-44 and declines when people reach their retirement age. Daily commuting team seems to be much higher for males than for females and obviously the professionally active population spends more time on commuting than the inactive population.

Day-effects

Next to the demographic variables, also some day-effects are used for the analysis.

Day-of-week effect

Agarwal (2004) showed that there exists a significant difference between travel behavior on a weekday and travel behavior on a weekend day. This difference is further unraveled by Sall & Bhat (2007) demonstrating a significant day-of-week effect. For the analysis the day-of-week effect is represented in a categorical variable with seven categories; the first category corresponding to a Monday, the last to a Sunday.

Holiday effect

Liu & Sharma (2006a) and Cools *et al.* (2007a) indicated the importance of incorporating holiday effects into travel behavior models. To evaluate the significance of holidays on daily commuting time a special holiday variable is created, consisting of three categories: “normal days”, “holidays” and “summer holidays”. The following holidays are taken into account: Christmas vacation, spring half-term, Easter vacation, Labor Day, Ascension Day, Whit Sunday, Whit Monday, vacation of the construction industry (three weeks, starting the second Monday of July), Our Blessed Lady Ascension, fall break (including All Saints’ Day and All Souls’ Day), and finally Remembrance Day. Note that for all these holidays, the adjacent weekends, were considered to be a holiday too. For holidays occurring on a Tuesday or on a Thursday, respectively the Monday and weekend before, and the Friday and weekend after, were also defined as a holiday, because often people have a day-off on those days, and thus have a leave of several days, which might be used to go on a long weekend or on a short holiday (Cools *et al.*, 2007a). The days in July and August that were not in the above holiday list were labeled as “summer holidays”.

Table 2.5: Descriptive statistics of the socio-demographic variables

	Daily commuting time (in min.)		
Variable	Mean	St. Deviation	Nr of obs.
Age			
6-12	12.38	22.27	550
13-15	23.10	29.19	242
16-24	28.26	40.73	788
25-34	28.76	46.40	844
35-44	29.07	50.38	1169
45-54	25.43	52.39	1074
55-64	11.44	35.43	786
65+	1.41	12.59	608
Sex			
Male	26.05	50.58	3134
Female	16.53	31.90	2919
Employment status			
Housekeeping	0.68	5.89	401
Unemployed	2.57	10.57	179
Retired	1.33	15.16	881
Disabled	1.47	6.53	97
Pupil, Student	20.16	32.96	1348
Worker	31.04	48.93	912
Employee	33.29	53.71	1335
Executive	42.14	58.73	448
Liberal Profession	14.00	23.77	67
Self-Employed	24.43	46.13	261
Other, Non-Occupational	4.52	14.08	25
Other, Occupational	19.64	28.22	28

Transportation preferences

A final group of variables that is used for the analysis is the use of public transport services. The following transport services were considered: the use of the scheduled service bus, the use of the tramway service and use of the railroad system. As can be noted from Table 2.6, more than half of the respondents never use buses or trams. The use of trains is slightly more popular.

Table 2.6: Descriptive statistics for the use of public transport services

	Number of respondents using (% of respondents)					
Frequency	Bus		Tram		Train	
Daily	204	(3.59%)	85	(1.55%)	194	(3.46%)
A few times a week	289	(5.08%)	159	(2.90%)	158	(2.82%)
A few times a month	474	(8.34%)	280	(5.11%)	313	(5.58%)
A few times a year	1626	(28.60%)	1476	(26.96%)	2885	(51.44%)
Never	3093	(54.40%)	3475	(63.47%)	2058	(36.70%)

Methodology

Two modeling approaches are used for the analysis of daily travel time expenditure, namely the Poisson regression approach and the classical linear regression approach. The Poisson regression approach is defended by arguing that time expenditure can never take negative values. The classical linear regression approach can be justified by claiming that there is a widespread and continuous range of values that travel time expenditure can adopt. This wide range is also witnessed from Figure 2.5. Comparing linear regression models with Poisson regression models is not a straightforward task. Therefore an objective criterion is constructed to compare the two types of models.

Exploratory data analysis: Regression tree

To get prior insight into the data, a regression tree is built through a process known as binary recursive partitioning. This is an iterative process of splitting up the data into two partitions, and then splitting up further each of the branches. The algorithm chooses the split that partitions the data into two parts so that it minimizes the sum of the squared deviations from the mean in the separate parts. This splitting (or partitioning) is then applied to each of the new branches. The process continues until a saturated tree is grown. A tree is saturated in the sense that the nodes subject to further division cannot be split (Therneau & Atkinson, 1997). The terminal nodes are then recombined or "pruned" upwards to an optimal size tree. The degree of pruning is determined by cross-validation using a cost-complexity function that balances the apparent error rate with the tree-size. The optimal tree is the tree that corresponds to the complexity parameter that gives a minimum cost for the new data (Breiman *et al.*, 1984). Since no separate test sample was available, V-fold cross-validation was used as an alternative. A specified V-value determines the number of random sub samples, as equal in size as possible, which have been formed from the learning sample. The binary tree is then computed V times, each time leaving out one of the sub samples from the calculations. Then the sub sample that was not used in the calculations serves as a test sample for cross-validation (CV). Afterwards the CV costs computed for each of the V test samples are averaged to give the V-fold estimate of the CV cost.

'Classical' linear regression

The classical linear regression approach is a modeling philosophy that tries to explain the dependent variable with the help of other covariates. Formally, the multiple linear regression model can be represented by the following equation:

$$Y_i = \beta_0 + \beta_1 X_{i,1} + \beta_2 X_{i,2} + ... + \beta_{p-1} X_{i,p-1} + \epsilon_i, \tag{2.9}$$

in which Y_i is the i-th observation of the dependent variable, $X_{i,1}$, $X_{i,2}$, ..., $X_{i,p-1}$ the corresponding observations of the explanatory variables, β_0, β_1, β_2, ..., β_{p-1} the parameters, which are fixed, but unknown, and in which ϵ_i is the unknown random error. Estimates for the unknown parameters can be obtained by classical estimation techniques. If b_0, b_1, b_2, ..., b_{p-1} are the estimates for the parameters, then the estimated value for the dependent variable Y_i is given by:

$$\hat{Y}_i = b_o + b_1 X_{i,1} + b_2 X_{i,2} + ... + b_{p-1} X_{i,p-1}. \tag{2.10}$$

The following assumptions are made about the explanatory variables and the error terms.

- The error terms must be uncorrelated with the explanatory variables. If one of the explanatory variables is correlated with the error terms, it means that that covariate is correlated with unmeasured variables that are influencing the dependent variable.

- The assumption of homoskedasticity: the error terms must have the same variance for all values of the explanatory variables. Thus the predicted values of the independent variable must be equally good for all values of the explanatory variables.
- The values of the error terms have to be independent of one another. Non-independence leads to autocorrelation. This occurs when unmeasured variables are systematically similar between some pairs of observations.
- The error terms must be normal distributed for small sample sizes. If the error terms are not normally distributed, the parameter estimate is also usually not normally distributed and thus the desirable characteristics of a normally distributed estimate would no longer be true. For large sample sizes, under the Central Limit Theorem the estimate is asymptotically normal distributed and thus have the desirable characteristics (Lumley *et al.*, 2002).
- Absence of multicollinearity. The estimated parameter coefficients will be unstable and unreliable if explanatory variables are highly correlated. In the presence of multicollinearity, the effect of a single explanatory variable cannot be isolated, as the regression coefficients are quite uninformative and their confidence intervals very wide.

When these assumptions are satisfied, the estimators for the parameters are BLUE (Best Linear Unbiased Estimators). Otherwise some remedial measures, like transformations, are required (Neter *et al.*, 1996).

Poisson regression

Explaining a dependent variable by means of other covariates is also the hands-on approach in Poisson regression. Instead of assuming independent normal distributed error terms like the classical linear regression approach, the Poisson regression technique is based on the assumption that the dependent variable is Poisson distributed. Formally, the model can be represented in the following way:

$$log(E[Y_i]) = \beta_0 + \beta_1 X_{i,1} + \beta_2 X_{i,2} + ... + \beta_{p-1} X_{i,p-1} \tag{2.11}$$

or equivalently:

$$E[Y_i]) = exp(\beta_0 + \beta_1 X_{i,1} + \beta_2 X_{i,2} + ... + \beta_{p-1} X_{i,p-1}), \tag{2.12}$$

where $E[Y_i]$ is the expected value of the i-th observation of the dependent variable, $X_{i,1}$, $X_{i,2}$, ..., $X_{i,p-1}$ the corresponding observations of the explanatory variables, and β_0, β_1, β_2, ..., β_{p-1} the parameters (Agresti, 2002). Estimates of the unknown parameters are obtained by maximizing the log likelihood using a ridge-stabilized Newton-Raphson algorithm (SAS Institute Inc., 2004b).

The assumption of a Poisson distribution entails that the mean and variance of the presumed Poisson distributed variable must be (quasi-)equal. When the variance is significantly higher there is a problem of overdispersion. Potential overdispersion is taken into account by using the deviance as a dispersion parameter. Note that function obtained by dividing the log-likelihood function by the dispersion parameter is not a legitimate log-likelihood function, but a quasi-likelihood function. Nevertheless, most of the asymptotic theory for log-likelihoods also applies to quasi-likelihoods (McCullagh & Nelder, 1989).

Model comparison criterion

Comparing linear regression models with Poisson models is not a straightforward task. An objective criterion is needed to assess the performance of the two model approaches. Starting point is the determination coefficient (R^2) that is used in linear regression. This R^2 can be defined as the squared value of the Pearson correlation between the predicted values and the dependent variable. However, the Pearson correlation requires that the predicted values and the dependent variable are bivariate normally distributed. In classical linear regression this assumption is fulfilled when the residuals are normally distributed, but for Poisson models this assumption seems inappropriate. Therefore the Spearman correlations, which are non-parametric correlation estimates, form a more defendable basis for a comparison criterion. The new criterion, the Spearman Determination coefficient (Ψ^2), is defined as the square of the Spearman Correlation coefficient between the predicted and real values of the dependent variable. Formally the Spearman Determination coefficient can be represented in the following way:

$$\Psi^2 = \left(1 - \frac{6 \sum_i d_i^2}{n\left(n^2 - 1\right)}\right)^2, \tag{2.13}$$

where d_i is the difference between each rank of corresponding predicted and real values, and where n equals the number of observations (Cohen & Cohen, 1984).

Results

Exploratory data analysis

The regression tree that is built through binary recursive partitioning is given in Figure 2.6. This tree is the pruned tree that takes into account a complexity parameter (cp) of 0.02548, minimizing the cost for new data. This cost was calculated by cross validation using 10 subsamples. Note that if fewer than 10 cross validations had been used, the error rate of the tree could have been seriously overestimated (Breiman *et al.*, 1984).

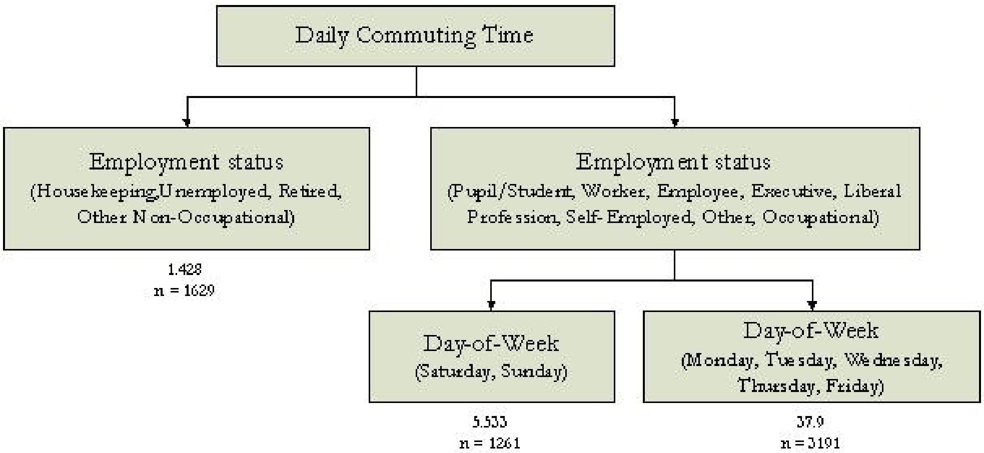

Figure 2.6: Binary regression tree for the daily commuting time

Figure 2.6 reveals that the employment status is the most important discriminator in explaining daily commuting time. As expected, the active population spends more time on commuting than their inactive counterpart. Next to the employment status, also day-of-week effects seem to determine the daily communing time: during weekends people spend less time on going to work/school than during weekdays. Quite obviously this can be explained by the fact that most people only work during weekdays.

Linear regression

The variables that were used in the final linear regression model, together with their likelihood ratio (LR) statistics are displayed in Table 2.7. From this table it can be seen that all three categories of variables (socio-demographic variables, day effects and transportation preferences) contribute significantly to the unraveling of daily travel time. The age effect, although insignificant, was kept in the model, because of the significant interaction effect between sex and age. Remind that p-values of interaction effects only have a valid interpretation when also the main effects are included in the model (Neter *et al.*, 1996).

Table 2.7: LR Statistics (Type 3) For Linear Regression

Variable	DF	Chi-Square	P-value
Holiday	2	57.51	<0.0001
Day-of-week	6	138.12	<0.0001
Interaction Holiday/Day-of-week	12	32.19	0.0013
Age	7	5.45	0.6051
Sex	1	21.57	<0.0001
Interaction Age/Sex	7	52.28	<0.0001
Employment Status	11	239.50	<0.0001
Scheduled service bus	4	53.12	<0.0001
Tramway service	4	18.54	0.0010
Railroad system	4	118.79	<0.0001

Table 2.8 shows the parameter estimates for the Linear Regression model. These Linear Regression parameter estimates can be interpreted as additive effects. If for instance the parameter estimates for Workers and Employees are compared, then the additive effect of being an employee instead of a worker can be calculated by a simple subtraction: 29.3025 - 25.9094 = 3.3931. This means that on average employees spend 3.3931 minutes more on daily commuting time than workers do, given that they share the same characteristics for the other variables.

By examining Table 2.8, it is obvious that the active population spends more time on commuting than the inactive population. The higher the position within a company, the more daily time is spent on commuting. Correspondingly, executives spend most time on commuting. Also important to notice is that people who use public transport (bus, train, tram) commute longer than the ones who seldom or never use public transport (20 up to 33 minutes longer).

Table 2.8: Parameter estimates for linear regression model

Parameter	Estimate	Parameter	Estimate	Parameter	Estimate
Intercept	-20.2705	*Age & Sex*		*Employment status*	
Holiday & Day-of-week		Male, 6-12	-1.1889	Employee	29.3025
Regular day, Monday	29.9273	Male, 13-15	3.8782	Executive	34.3036
Regular day, Tuesday	32.1461	Male, 16-24	3.5454	Liberal profession	11.3672
Regular day, Wednesday	26.8283	Male, 25-34	7.3532	Self-employed	18.5779
Regular day, Thursday	30.9206	Male, 35-44	13.5726	Other, non-occupational	7.2682
Regular day, Friday	25.0761	Male, 45-54	11.8088	Other, occupational	18.3512
Regular day, Saturday	1.7512	Male, 55-64	6.8192	*Use of schedules service bus*	
Regular day, Sunday	0.0000	Male, 65+	3.4970	Daily	23.5018
Holiday, Monday	19.2130	Female, 6-12	1.5222	A few times a week	3.3912
Holiday, Tuesday	23.9021	Female, 13-15	7.5432	A few times a month	2.2725
Holiday, Wednesday	19.6896	Female, 16-24	4.8481	A few times a year	0.8242
Holiday, Thursday	9.4924	Female, 25-34	-2.3521	Never	0.0000
Holiday, Friday	14.9622	Female, 35-44	-5.0870	*Use of tramway service*	
Holiday, Saturday	1.0133	Female, 45-54	-3.4375	Daily	19.5191
Holiday, Sunday	-2.5585	Female, 55-64	-0.3207	A few times a week	-0.7410
Summer Holiday, Monday	13.4156	Female, 65+	0.0000	A few times a month	1.9913
Summer Holiday, Tuesday	13.6732	*Employment status*		A few times a year	0.7206
Summer Holiday, Wednesday	12.2422	Housekeeping	5.9466	Never	0.0000
Summer Holiday, Thursday	18.4244	Unemployed	0.0000	*Use of train*	
Summer Holiday, Friday	16.4569	Retired	0.5872	Daily	30.9260
Summer Holiday, Saturday	-1.5522	Disabled	-0.9767	A few times a week	14.9523
Summer Holiday, Sunday	3.6116	Pupil, Student	14.1228	A few times a month	-3.3527
		Worker	25.9094	A few times a year	-1.1999
				Never	0.0000

Table 2.8 also gives the parameter estimates of the total effects for respectively day-of-week and holiday status, and age and sex. Note that these total effects are calculated by adding up the parameter estimates for both main effects and the interaction effect. From the table it can be seen that during holidays, summer holidays and weekends people spend much less time on commuting than during normal weekdays. Furthermore, the parameter estimates displayed in Table 2.8 indicate that young females (06-24) commute longer than their peer males, whereas older males (25+) commute longer than their female counterparts.

Poisson regression

Table 2.9 displays the variables that were used in the Poisson regression model. To facilitate comparison between the two types of models, the same variables were taken into account as the linear regression model. From this table, one may observe that all three categories of variables (socio-demographic variables, day effects and transportation preferences) play a significant role in the interpretation of daily travel time. Contrary to the linear regression model, the main age effect has a significant meaning in the Poisson regression model.

Table 2.9: LR Statistics (Type 3) For Poisson Regression

Variable	DF	Chi-Square	P-value
Holiday	2	54.85	<0.0001
Day-of-week	6	492.48	<0.0001
Interaction Holiday/Day-of-week	12	31.33	0.0018
Age	7	43.87	<0.0001
Sex	1	34.17	<0.0001
Interaction Age/Sex	7	90.00	<0.0001
Employment Status	11	836.44	<0.0001
Scheduled service bus	4	65.62	<0.0001
Tramway service	4	20.20	0.0005
Railroad system	4	124.08	<0.0001

The parameter estimates for the Poisson Regression model are shown in Table 2.10. These parameter estimates should be interpreted as multiplicative effects. Take as an example the parameter estimates for workers and employees. The multiplicative effect of being an employee instead of a worker can then be calculated in the following way: exp(2.3989 - 2.2852) = exp(0.1137) = 1.1204. This means that employees commute on average 1.1204 times longer (in terms of duration) than workers.

From Table 2.10 it can also be seen that the occupationally active people quite logically spend more time on commuting than occupationally inactive people. The higher the position people hold within a company, the more daily time they spend on commuting. Hence, similar results are obtained when compared to the classical regression model.

Another point that requests attention is the fact that people who use public transport (bus, train, tram) commute 1.52 (=exp(0.4205-0)) up to 1.88 (=exp(0.5533+0.0789)) times longer than the ones who seldom or never use public transport. Interesting is that these parameter estimates could be seen as approximations of the travel time factors, which are defined as ratios of the time spent covering a certain trajectory using public transport to the time spent using a car. When these approximations are compared to the total travel time factor of 1.7 reported in the Flemish Mobility Plan (Mobiliteitscel, 2001), one can conclude that the approximations work reasonably well and provide a more thorough look at the subject of travel time factor.

The parameter estimates of the total effects for respectively day-of-week and holiday status, and age and sex are also given in Table 2.10. Bear in mind that these total effects are calculated by adding up the parameter estimates for both main effects and the interaction effect. Table 2.10 illustrates the fact that during holidays, summer holidays and weekends people spend much less time on commuting than during normal weekdays. From this table one can also notice that young females (06-24) commute longer than their peer males, whereas older males (25+) commute longer than their female counterparts.

Table 2.10: Parameter Estimates For Poisson Regression Model

Parameter	Estimate	Parameter	Estimate	Parameter	Estimate
Intercept	-3.6835	*Age & Sex*		*Employment status*	
Holiday & Day-of-week		Male, 6-12	2.4047	Employee	2.3989
Regular day, Monday	2.2280	Male, 13-15	2.8718	Executive	2.4739
Regular day, Tuesday	2.2954	Male, 16-24	2.9321	Liberal profession	1.5340
Regular day, Wednesday	2.1652	Male, 25-34	2.9882	Self-employed	2.0230
Regular day, Thursday	2.2726	Male, 35-44	3.1630	Other, non-occupational	0.7433
Regular day, Friday	2.0943	Male, 45-54	3.1886	Other, occupational	1.9887
Regular day, Saturday	0.4598	Male, 55-64	3.1480	*Use of schedules service bus*	
Regular day, Sunday	0.0000	Male, 65+	2.7993	Daily	0.6008
Holiday, Monday	1.8591	Female, 6-12	2.5902	A few times a week	0.1356
Holiday, Tuesday	2.0467	Female, 13-15	3.0582	A few times a month	0.0811
Holiday, Wednesday	1.9151	Female, 16-24	2.9675	A few times a year	0.0346
Holiday, Thursday	1.3858	Female, 25-34	2.6980	Never	0.0000
Holiday, Friday	1.6647	Female, 35-44	2.4991	*Use of tramway service*	
Holiday, Saturday	0.2392	Female, 45-54	2.5815	Daily	0.4205
Holiday, Sunday	-0.3137	Female, 55-64	2.6078	A few times a week	0.0531
Summer Holiday, Monday	1.5434	Female, 65+	0.0000	A few times a month	0.0657
Summer Holiday, Tuesday	1.6203	*Employment status*		A few times a year	0.0694
Summer Holiday, Wednesday	1.5729	Housekeeping	-1.1669	Never	0.0000
Summer Holiday, Thursday	1.8369	Unemployed	0.0000	*Use of train*	
Summer Holiday, Friday	1.7334	Retired	-0.2939	Daily	0.5533
Summer Holiday, Saturday	0.1621	Disabled	-0.5122	A few times a week	0.4600
Summer Holiday, Sunday	0.5161	Pupil, Student	1.8745	A few times a month	-0.1808
		Worker	2.2852	A few times a year	-0.0789
				Never	0.0000

Model comparison

When the linear regression model is compared with the logistic regression model it is important to acknowledge that both model approaches yield consistent findings. One of the most important variables in explaining differences in daily commuting time is employment status. Also Craviolini (2006) stressed the importance of this social status. Next to the employment status, the other socio-demographic variables that were taken into account, namely age and sex, were contributing significantly in explaining variability in daily commuting time. These findings are coherent with international literature on this subject (Bhat & Misra, 1999; Kapur & Bhat, 2007). Findings concerning the significant day-of-week effects and holiday effects were harmonious with the results reported in Lockwood *et al.* (2005) and Cools *et al.* (2007a).

Table 2.11 shows the Spearman Determination coefficient (Ψ^2) that can be used to assess the performance of the two model approaches. From this table one can see that this coefficient is higher for the Poisson regression and consequently one can conclude that Poisson regression modeling is the approach to be preferred when trying to explain daily commuting time. The fact that the linear regression model yielded both negative and positive values for daily commuting time predictions, whereas the Poisson regression model only yielded positive values, favors the Poisson regression even more.

Table 2.11: Spearman Determination coefficient (Ψ^2)

Model Type	Spearman Correlation	Ψ^2 (Psi-square)
Poisson regression	0.66395	0.441
Linear regression	0.62344	0.389

Conclusions and further research

The analyses show that socio-demographics, day-effects and transportation preferences contribute significantly to the explanation of variability in daily commuting time. Both the linear regression approach and the Poisson regression approach yielded findings that were consistent with international literature. When the performance of the two model approaches is evaluated, the Spearman Determination Coefficient favors the Poisson regression approach.

On of the most marked results of this study is the fact that people who often use public transport (buses, trams or trains) spend more time on commuting than their counterparts who avoid using public transport services. An important question that could be raised is why these people still choose in favor of public transport: because of ease, comfort, safety? A stated-preference research might give an answer to this. Since commuting trips consume the largest part of travel time expenditure, it is essential that policy makers acknowledge these findings. An essential step for stimulating the modal split, and thereby trying to achieve reliable travel times and environmental goals, such as the Kyoto norms, is the continuation of investments in public transport. Only when "acceptable" travel times are achieved by the public transport services, the general public will consider switching their transport mode. So choosing for those investments that reduce public transport travel times is a key challenge for policy makers.

It was evidenced that the multiplicative effects of the transportation preferences form good approximations of the travel time ratios. Thus, the reported Poisson methodology offers a framework that can be used to fine-tune policy measures.

In the next Section, other types of travel time expenditure (e.g. daily travel time expenditure on shopping or leisure) are analyzed to realize a deeper understanding of Flemish travel behavior. Moreover, other covariates, such as degree of urbanization, are included to illuminate the insights in travel behavior even further.

2.2.2 Impact on daily travel times: differentiation by trip motive

Background

An increased environmental awareness has shifted the focus of travel demand modeling towards the activity-based modeling approach (Kitamura & Bhat, 1999), as will also be comprehensively discussed in Chapter 4. Jovicic (2001) distinguished three steps in the evolution of travel demand modeling approaches. The first generation models were developed in the late 1950s, a period characterized by a rapid increase in car use. In order to assess major investments in road infrastructure four-step models were developed to make long term projections of travel demand. These models assumed that travel is the result of four consecutive steps, namely trip generation, trip distribution, mode choice and route choice.

The second generation models became widely applied in the 1980s and 1990s. Disaggregate trip-based demand models, commonly referred to as discrete choice models (Ben-Akiva & Lerman, 1985), turned the focus to the travel needs of a single person. The third and last generation models that Jovicic (2001) distinguished are the activity-based travel demand models. These models predict travel behavior as a derivative of activities. Nowadays, dynamic activity-based models, taking into account short-term adaptations (e.g. Joh *et al.* (2001), van Bladel *et al.* (2009)) and long-term learning due to key events (e.g. Verhoeven *et al.* (2005), Verhoeven *et al.* (2006)) and annually recurring events (e.g. Cools *et al.* (2007a)), could be seen as a fourth generation of travel demand models.

As already highlighted earlier in this dissertation, governments require reliable predictions of travel behavior in order to lead an efficient policy and achieve environmental goals, such as the Kyoto norms. A better understanding of travel behavior will lead to better forecast and thus policy measures can be fine-tuned based on more accurate data. In this Section, therefore the impact of holidays on travel time expenditure in Flanders (the Dutch speaking part of Belgium) is investigated. As emphasized in the previous Section, travel behavior researchers have regained interest in the travel time budget (the daily travel time expenditure) in the context of activity-based and time use research in travel behavior modeling (Banerjee *et al.*, 2007).

Relevance of investigating holiday effects on travel time expenditure

The importance of a thorough examination of the effect of holidays on travel time expenditure is underlined by Liu & Sharma (2006b) and Cools *et al.* (2007a) stressing the need to incorporate holiday effects in travel behavior models. First, holiday effects can influence both the demand for activities (e.g. during regular days the demand for work activities is much larger than during periods in which most people plan their holiday) and the supply of activity opportunities in space and time (e.g. opening hours of amusement parks are often prolonged during holiday periods). Second, holidays can affect the supply of available transport options (e.g. during summer holidays, extra trains/plains are scheduled to transfer people to popular holiday destinations). Finally, they can influence the supply of infrastructure and their associated management systems (e.g. during the summer holiday period, the police often enforces driving in groups in order to limit traffic congestion).

State-of-the art literature concerning holiday effects mainly focused on two items, namely on the effects of holidays on traffic counts (e.g. Liu & Sharma (2006a), Liu & Sharma (2008)) and on traffic safety (e.g. Keay & Simmonds (2005), Van den Bossche *et al.* (2006)). The impact on the underlying reasons of travel behavior, namely the activities people perform and the trips made, are seldom investigated. Therefore, this study discusses the effect of holidays on the trips made, and in particular the focus is devoted to the attribute travel time.

Importance of examining travel time expenditure differentiated by trip motive

When travel time expenditure is investigated, it is necessary to acknowledge the importance of differentiating travel time expenditure by trip motive. First, commuting (which is defined as work and school related trips), although being the main reason for performing trips, only accounts for 26.8% of all trips (Zwerts & Nuyts, 2004). Thus, solely focusing on commuting trips would neglect almost three quarters of all trips reported. By analogy with this argument also the concentration of the analysis solely on shopping (20.5% of all trips) or leisure trips (14.2% of all trips) is to be avoided.

Second, the differentiation provides the opportunity to analyze the travel time expenditure on non-commercial visit trips and drop-off and pick up trips. Since international research on travel time expenditure mainly focuses on commuting, shopping and leisure trips, insight in the underlying patterns of non-commercial visit trips and drop-off and pick-up trips, together responsible for 22% of all trips, can yield a more thorough understanding of travel behavior.

Third, the differentiation by trip motive can trigger a refinement of the underlying relationships between travel behavior and explanatory factors. By dividing the travel time expenditure into trip motive dependant subparts, more complex relationships can be implicitly modeled: differentiation makes it feasible to incorporate explanatory factors that have an increasing/decreasing effect on subpart, and have an opposite effect, a substitution effect or no effect at all on other subparts.

Overview of the data

In line with the preliminary analyses presented before, similar variables are used for the more profound analyses discussed in this section.

Sample correspondence to the population

Exactly as in the preliminary assessment, the data that are used for the analysis presented in this Section also stem from the household travel survey in Flanders that was carried out in 2000 (Zwerts & Nuyts, 2004). Recall that the focus of this survey was to investigate the travel behavior of the people living in the Flanders area. In order to guarantee an optimal correspondence between the survey sample composition and the population the observations in the sample are weighed. The weights were calculated by matching the marginal distributions of the sample with the marginal distributions of the population. Age, sex and civil state were the basis for this matching process.

Travel time expenditure by purpose

The daily travel time expenditure for each trip motive is calculated by adding up the time spent on the trips related with the specific motive. Both the trips to the activity locations and the trips back home were considered. Table 2.12 displays the distribution categories for the travel time expenditure, differentiated by trip motive. From this table one can see that commuting is the most performed travel activity (it has the smallest number of zeros), followed by shopping and leisure trips. Non-commercial visit trips (denoted in Table 2.12 as visits) and drop-off and pick-up trips (abbreviated as drop-off) still play an important role, however, contributing together for an extra 11 minutes of average daily travel time expenditure. In addition to different overall means, also the means excluding zeros are tabulated. Striking are the large discrepancies between these two measures of central tendency, suggesting the need for a modeling approach that explicitly takes into account the excess of zeros.

Table 2.12: Distribution categories for travel time expenditure, differentiated by travel motive

Descriptive measure	Commuting	Shopping	Leisure	Visits	Drop-off
Distribution category					
0 min	62.1 %	70.1 %	78.3 %	81.4 %	86.9 %
1-10 min	4.7 %	8.3 %	4.8 %	4.3 %	3.2 %
11-20 min	7.6 %	8.0 %	5.0 %	4.3 %	3.2 %
21-30 min	6.6 %	5.2 %	2.9 %	3.4 %	2.1 %
31-40 min	4.5 %	2.7 %	2.0 %	1.9 %	1.3 %
41-50 min	3.1 %	1.5 %	1.5 %	0.9 %	0.9 %
51-100 min	7.5 %	3.4 %	3.2 %	2.9 %	2.0 %
$>$ 100 min	4.0 %	1.0 %	2.3 %	0.9 %	0.5 %
Central tendency					
Mean (with 0's)	18.5 min	8.9 min	10.7 min	6.7 min	4.3 min
Mean (without 0's)	48.9 min	29.8 min	49.5 min	35.8 min	33.0 min

Temporal effects

The first category of explanatory variables that are used in the analysis are temporal effects. The first temporal effect that is considered is the day-of-week effect. Agarwal (2004) showed that there exists a significant difference between travel behavior on a weekday and travel behavior on a weekend day. This difference is even further unraveled by Sall & Bhat (2007) and Schwanen (2004) demonstrating a significant day-of-week effect. For the analysis the day-of-week effect is represented by a categorical variable with seven categories; the first category corresponding to a Monday, the last to a Sunday.

The focus of the analyses lie on the second temporal effect, namely the holiday effect. To evaluate the significance of holidays on daily travel time expenditure, the same special holiday variable is created as in the section discussing the preliminary assessment of holiday effects on commuting time, consisting of the following three categories: "normal days", "holidays" and "summer holidays". Correspondingly, the following holidays are taken into account: Christmas vacation, spring half-term, Easter vacation, Labor Day, Ascension Day, Whit Sunday, Whit Monday, vacation of the construction industry (three weeks, starting the second Monday of July), Our Blessed Lady Ascension, fall break (including All Saints' Day and All Souls' Day), and finally Remembrance Day. As noted before, the adjacent Mondays and Fridays, and adjacent weekends were considered to be a holiday too. The remaining days in July and August were labeled as "summer holidays". From Table 2.13 one can see that the time spent on commuting is considerably lower during holidays when compared to regular days, while travel time expenditure on leisure trips is portentously higher during holiday periods. Concerning shopping, non-commercial visit[1] and drop-off and pick-up[2] trips, less pronounced differences can be observed.

Socio-demographics

Next to the temporal effects, also demographic variables are considered for the analysis, as they are commonly used in models that predict travel time (Gould & Golob (1997), Frusti *et al.* (2002), Lanzendorf (2002), Sall & Bhat (2007)). The following variables are considered for the analyses: age, sex, employment status, living conditions and degree of urbanization. An exploratory analysis of the most dominant

[1] In the remainder of the text the term 'non-commercial visit trips' will be denoted by 'visits' or 'NCVI'.

[2] In the remainder of the text the term 'drop-off and pick-up trips' will be denoted by drop-off''or 'DOPU'.

Table 2.13: Mean travel time expenditure according to trip motive

Explanatory Variable	Commuting	Shopping	Leisure	Visits	Drop-off
Holiday					
No holiday	21.9 min	8.6 min	8.3 min	5.8 min	4.6 min
Holiday	11.3 min	9.6 min	15.7 min	8.7 min	3.4 min
Summer holiday	12.8 min	9.4 min	16.6 min	6.9 min	4.2 min
Age					
6-12	10.8 min	5.3 min	14.4 min	5.4 min	2.1 min
13-15	21.0 min	3.8 min	12.1 min	5.5 min	1.0 min
16-24	27.1 min	6.1 min	13.4 min	6.5 min	3.3 min
25-34	27.7 min	8.8 min	9.9 min	6.8 min	6.9 min
35-44	28.0 min	8.8 min	10.7 min	4.5 min	7.7 min
45-54	24.0 min	10.7 min	10.4 min	6.5 min	5.2 min
55-65	10.0 min	12.4 min	13.4 min	8.8 min	3.2 min
65+	1.0 min	10.1 min	6.5 min	8.6 min	1.6 min
Sex					
Male	24.0 min	7.5 min	12.5 min	6.4 min	4.5 min
Female	13.4 min	10.2 min	9.1 min	7.0 min	4.2 min
Employment status					
Housekeeping	0.6 min	15.3 min	9.6 min	7.4 min	5.4 min
Unemployed	1.7 min	15.5 min	6.3 min	5.3 min	7.2 min
Retired	0.6 min	10.3 min	8.6 min	8.6 min	2.1 min
Disabled	1.1 min	9.1 min	8.8 min	5.4 min	1.4 min
Pupil, student	18.6 min	4.8 min	13.8 min	5.7 min	2.0 min
Worker	30.5 min	7.8 min	8.1 min	5.6 min	5.9 min
Employee	31.7 min	10.0 min	11.8 min	6.6 min	6.7 min
Executive	42.0 min	8.6 min	11.9 min	5.8 min	5.9 min
Liberal profession	15.5 min	5.2 min	18.5 min	8.1 min	4.5 min
Self-employed	20.3 min	6.1 min	11.6 min	2.9 min	6.0 min
Overall	*18.5 min*	*8.9 min*	*10.7 min*	*6.7 min*	*4.3 min*

socio-demographical variables, shown in Table 2.13, reveals that the daily time spent on commuting first increases with age, reaches its maximum at age category 35-44 and declines after people reach their retirement age. Daily commuting time seems to be higher for males than for females and obviously the professionally active population spends more time on commuting compared to the inactive population. A similar conclusion was also formulated in Section 2.2.1. Table 2.13 also provides preliminary insight into the travel time spent on shopping trips; the travel time increases with age and females spend more travel time on shopping trips than males. When employment status is considered, it could be noticed that the inactive population spends more travel time on shopping than the active one. The overall picture for travel time spent on the three other categories of trips is less striking. Yet, one could notice that travel time spent on drop-off and pick-up trips is noticeably higher in the middle age group (25-54) and that travel time spent on leisure is higher for males than for females, and is remarkably lower for the oldest age category (65+).

Transportation preferences

The final group of variables that is used for the analysis is the frequency of using different transport modes. The following transport modes were considered: the use of the scheduled service bus and tramway service, categorized in people who never, occasionally (a few times a year or month) and frequently (weekly or more often) use this service, the use of the railroad system (same categorization), the daily use of a bicycle (dummy variable which equals one if the respondent uses the bicycle daily) and the daily use of a motorcycle (cf. daily bicycle use). Reports concerning the Flemish travel survey (Zwerts & Nuyts, 2004) revealed that more than half of the respondents never use buses or trams. The use of trains seemed to be slightly more popular. In addition to the different transportation uses also the possession of a driving license is considered for the analysis. For an interpretation of the impact of transportation preferences the reader is referred to Subsection 2.2.2.

Methodology

Zero-inflated Poisson regression

The main modeling approach that is used for the analysis is the zero-inflated Poisson (ZIP) regression approach. This modeling framework uses a zero-inflated Poisson distribution to deal with the excess of zeroes. The approach assumes that the population consists of two types of individuals. The first type gives a Poisson-distributed count, which may be zero, whereas the second type always gives a zero count. This assumption can be supported by the inherent contrast between travelers and non-travelers, which could explain the discrepancies between the means incorporating and disregarding zeros, identified in the previous section. The choice for the ZIP regression approach implies that the three types of travel time expenditures will be treated as count variables. The comparison of a linear regression and Poisson regression model for predicting commuting times revealed that the Poison regression model explained more of the variability in travel time expenditure on commuting (Section 2.2.1). Therefore, the accommodation of a Poisson model that takes into account the inherent contrast between travelers and non-travelers certainly is a defensible approach.

The zero-inflated Poisson distribution has two parameters; the mean of the Poisson distribution λ_i and the proportion of the individuals of the second type (the non-travellers) ω_i. Formally, the zero-inflated Poisson distribution can be represented in the following way (Lambert, 1992):

$$\Pr(Y_i = k) = \begin{cases} \omega_i + (1-\omega_i)\, e^{-\lambda_i} & \text{for } k = 0 \\ (1-\omega_i)\, \frac{e^{-\lambda_i}\lambda_i^k}{k!} & \text{for } k > 0 \end{cases}, \tag{2.14}$$

in which both the probability ω_i and the mean number λ_i depend on covariates. For the covariate matrices $\mathbf{B}$ and $\mathbf{G}$ of the models discussed in this section, the parameters $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ satisfy the following equations:

$$\begin{cases} \log(\boldsymbol{\lambda}) = \mathbf{B}\boldsymbol{\beta} \\ \operatorname{logit}(\boldsymbol{\omega}) = \log(\boldsymbol{\omega}/(1-\boldsymbol{\omega})) = \mathbf{G}\boldsymbol{\gamma} \end{cases}. \tag{2.15}$$

Estimates for the unknown parameters are obtained by maximizing the log likelihood using a ridge-stabilized Newton-Raphson algorithm (SAS Institute Inc., 2004b). The log-likelihood function for the zero-inflated Poisson distribution is given by:

$$\sum_{i=1}^{n} l_i, \quad l_i = \begin{cases} w_i \log\left[\omega_i + (1-\omega_i)\, e^{-\lambda_i}\right] & k = 0 \\ w_i \left[\log(1-\omega_i) + k\log(\lambda_i) - \lambda_i - \log(k!)\right] & k > 0 \end{cases}, \tag{2.16}$$

in which n is the number of observations and w_i the weights calculated by matching the marginal distributions of the sample with the marginal distributions of the population.

Model performance assessment

To assess the appropriateness of the zero-inflated Poisson distribution, the Van den Broek score test for testing zero inflation relative to a Poisson distribution (Van den Broek, 1995) will be performed. The statistic is based on a comparison of the actual zeros to those predicted by the model:

$$S = \frac{\left[\sum_{i=1}^{n}\left\{\frac{I(y_i=0)-p_{0i}}{p_{0i}}\right\}\right]^2}{\sum_{i=1}^{n}\left\{\frac{1-p_{0i}}{p_{0i}}\right\} - n\bar{y}}, \tag{2.17}$$

in which S is the score, $I(y_i = 0)$ is an indicator function that is one if a given observation equals zero, and zero otherwise; p_{0i} the probability of a zero for observation i under the null distribution (regular Poisson distribution), $\bar{y}$ the mean of the observations and n the number of observations. Note that the probability is allowed to vary by observation. The S-score is assumed to follow a chi-squared distribution with one degree of freedom.

Next to computing the score test, also two model selection criteria, that balance model fit against model parsimony, will be tabulated. The first measure is the corrected Akaike information criterion ($AICC$), given by:

$$AICC = -2LL + 2p\frac{n}{n-p-1}, \tag{2.18}$$

in which p is the number of parameters estimated in the model, n the number of observations and LL the log likelihood evaluated at the value of the estimated parameters (SAS Institute Inc., 2004b). A second, yet similar measure is the Bayesian information criterion (BIC) defined by:

$$BIC = -2LL + p\log(n). \tag{2.19}$$

The $AICC$ and BIC are useful criteria in selecting among different models, with smaller values representing better models. For an extensive discussion about the use of $AICC$ and BIC with generalized linear models the reader is referred to Simonoff (2003).

Results

Overall results

The variables that were used in the final zero-inflated Poisson regression models, together with their likelihood ratio (LR) statistics are displayed in Table 2.14. From this table, it can be seen that all three categories of variables (socio-demographic variables, temporal effects and transportation preferences) contribute significantly to the unraveling of daily travel time. The final models also take into account interdependencies between trips, as the travel time spent on a certain type of trip, significantly influences the likelihood of performing other trips, as well as the travel time of these other trips, especially in the case of commuting trips.

Concerning the covariates in the Poisson regression part of the model, one could note that the holiday effect, the day-of-week effect, age, sex, employment status, degree of urbanization, the use of buses and trams, the use of trains, and the indicator of making other types of trips play a significant role in all five models. Notice that the main of effect of sex is not significant in the model predicting the travel time spent on non-commercial visit trips; nonetheless it remained in the model because of the highly significant interaction effect with age. Remind that p-values of interaction effects only have a valid interpretation when also main effects are included in the model (Neter *et al.*, 1996). With respect to the covariates in the zero-inflation part of the model, one could observe that only the time spent on other types of trips is significant in all five models. Except for the covariate driving license, all other explanatory variables representing transportation preferences were left out of the zero-inflation part in order to prevent convergence problems in the estimation procedure.

For the five different types of trips considered, each time the best model was chosen using the $AICC$ and BIC model selection criteria. The corresponding values for these criteria are displayed in the second part of Table 2.14. The necessity of using a zero-inflated Poisson model rather than an regular Poisson model is formally tested using the Van den Broek score test. For all five models the corresponding p-value is smaller than 0.001 indicating that a zero-inflated Poisson distribution seriously outperforms a regular Poisson distribution for these models.

Table 2.14: Likelihood ratio (LR) statistics for the zero-inflated Poisson regression models

Selected variables	DF*	Commuting		Shopping		Leisure		NCVI		DOPU	
		Chi^2	p-value	Chi^2	p-value	Chi^2	p-value	Chi^2	p-value	Chi^2	p-value
Model predicting λ											
Holiday	2	84.2	<0.001	7.7	0.021	2052.4	<0.001	83.0	<0.001	67.8	<0.001
Day-of-week	6	401.0	<0.001	95.8	<0.001	615.2	<0.001	286.5	<0.001	129.5	<0.001
Age	7	1291.7	<0.001	330.2	<0.001	664.9	<0.001	472.1	<0.001	208.1	<0.001
Sex	1	15.4	<0.001	46.2	<0.001	70.3	<0.001	0.0	1.000	49.6	<0.001
Interaction Age*Sex	7	1388.2	<0.001	238.7	<0.001	896.9	<0.001	140.6	<0.001	164.4	<0.001
Employment status	9	845.1	<0.001	383.5	<0.001	1534.4	<0.001	218.1	<0.001	470.9	<0.001
Living conditions	4	- - -	- - -	223.6	<0.001	1164.2	<0.001	104.8	<0.001	64.9	<0.001
Degree of urbanization	3	120.0	<0.001	219.9	<0.001	863.0	<0.001	131.9	<0.001	188.7	<0.001
Uses of bus/tram	2	931.8	<0.001	497.6	<0.001	117.2	<0.001	189.6	<0.001	9.3	0.009
Uses of trains	2	3272.5	<0.001	29.1	<0.001	27.6	<0.001	116.8	<0.001	41.5	<0.001
Daily use of motorcycle	1	86.0	<0.001	- - -	- - -	99.3	<0.001	31.6	<0.001	100.3	<0.001
Daily use of bicycle	1	341.4	<0.001	- - -	- - -	- - -	- - -	17.8	<0.001	- - -	- - -
Driving license	1	30.0	<0.001	- - -	- - -	211.4	<0.001	69.5	<0.001	- - -	- - -
Other type of trips made	1	1911.8	<0.001	927.4	<0.001	7125.9	<0.001	455.6	<0.001	222.8	<0.001

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Selected variables	DF*	Commuting		Shopping		Leisure		NCVI		DOPU	
		Chi^2	p-value	Chi^2	p-value	Chi^2	p-value	Chi^2	p-value	Chi^2	p-value
Model predicting ω											
Holiday	2	218.3	<0.001	- - -	- - -	6.4	0.041	23.6	<0.001	- - -	- - -
Day-of-week	6	909.1	<0.001	136.5	<0.001	204.8	<0.001	120.6	<0.001	- - -	- - -
Age	7	- - -	- - -	17.5	0.014	15.5	0.030	- - -	- - -	57.8	<0.001
Sex	1	11.7	<0.001	22.3	<0.001	30.5	<0.001	- - -	- - -	9.1	0.003
Employment status	9	1400.6	<0.001	68.1	<0.001	29.2	<0.001	- - -	- - -	22.2	0.008
Living conditions	4	- - -	- - -	- - -	- - -	14.3	0.006	- - -	- - -	99.8	<0.001
Degree of urbanization	3	- - -	- - -	- - -	- - -	- - -	- - -	9.3	0.025	- - -	- - -
Driving license	1	- - -	- - -	17.9	<0.001	7.8	0.005	- - -	- - -	32.8	<0.001
Time spent on other types of trips	1	357.4	<0.001	89.4	<0.001	60.3	<0.001	92.1	<0.001	28.3	<0.001
Performance measure											
AICC		75489		46880		70572		34979		26908	
BIC		75908		47344		71088		35378		27366	
Score-test (p-value)		<0.001		<0.001		<0.001		<0.001		<0.001	

* DF: Degrees of freedom, - - - indicates that the variables is not included in the final model

Commuting time

The parameter estimates of the zero-inflated Poisson regression model for predicting travel time expenditure on commuting are shown in Table 2.15. A distinction has to be made between the parameters in the model predicting the mean response λ and the parameters for estimating the probability of the zero-inflation ω. The parameters of the Poisson part of the zero-inflated Poisson model (λ) should be interpreted as multiplicative effects. Take as an example the parameter estimates for daily users of a motorcycle. Then the multiplicative effect of being a daily motorcycle user instead of a non-(daily) motorcycle user can be calculated in the following way: exp(-0.422-0) = exp(-0.422) = 0.643. This means that the commuting time of daily motorcycle users is only 64.3% of the commuting of non-(daily) motorcycle users, given that they share the same characteristics for all the other variables. The parameters of the logistic part of the zero-inflated Poisson model (ω) could be seen as log odds ratio multiplicative effects. Take as an example the parameter of the time spent on other type trips: an increase of one minute travel time spent on other type trips has as a consequence that the odds of non-commuting (a zero for travel time expenditure on commuting trips) equal exp(0.016) = 1.02 times the odds of commuting.

Table 2.15: ZIP regression parameter estimates for travel time expenditure on commuting

Parameter	Estimate	Parameter	Estimate	Parameter	Estimate	Parameter	Estimate
Poisson Model λ							
Intercept	-5.735	*Sex & Age*		*Employment status*		*Urbanization*	
Holiday		Male, 25-34	9.238	Retired	0.329	Metropol. area	-0.155
Regular day	0.000	Male, 35-44	9.346	Disabled	-0.117	Urban area	0.018
Holiday	-0.061	Male, 45-54	9.367	Pupil, Student	0.224	Suburban area	-0.049
Summer Hol.	-0.120	Male, 55-64	9.278	Worker	0.341	Rural area	0.000
Day-of-week		Male, 65+	9.459	Employee	0.477	*Motorcycle use*	
Monday	0.204	Female, 6-12	8.523	Executive	0.541	Yes	-0.442
Tuesday	0.140	Female, 13-15	9.165	Liberal prof.	0.199	No	0.000
Wednesday	0.116	Female, 16-24	9.137	Self-employed	0.207	*Bicycle use*	
Thursday	0.166	Female, 25-34	8.976	*Bus/tram use*		Yes	-0.143
Friday	0.158	Female, 35-44	8.890	Frequently	0.337	No	0.000
Saturday	-0.026	Female, 45-54	8.818	Occasionally	0.125	*Driving license*	
Sunday	0.000	Female, 55-64	9.078	Never	0.000	Yes	0.081
Sex & Age		Female, 65+	0.000	*Train use*		No	0.000
Male, 6-12	8.550	*Employment status*		Frequently	0.531	*Other trips*	
Male, 13-15	8.954	Housekeeping	0.384	Occasionally	-0.038	Yes	-0.293
Male, 16-24	9.099	Unemployed	0.000	Never	0.000	No	0.000

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Parameter	Estimate	Parameter	Estimate	Parameter	Estimate	Parameter	Estimate
Zero inflation ω							
Intercept	4.950	*Day-of-week*		*Sex*		*Employment status*	
Holiday		Wednesday	-3.080	Female	0.000	Worker	-3.782
Regular day	0.000	Thursday	-3.120	*Employment status*		Employee	-3.871
Holiday	1.241	Friday	-3.135	Housekeeping	1.182	Executive	-4.157
Summer Hol.	1.466	Saturday	-0.628	Unemployed	0.000	Liberal prof.	-2.750
Day-of-week		Sunday	0.000	Retired	0.906	Self-employed	-2.738
Monday	-3.197	*Sex*		Disabled	0.452	*Time other*	0.016
Tuesday	-3.303	Male	-0.290	Pupil, Student	-3.375		

Hol.: Holiday, prof.: profession, Metropol.: Metropolitan, Time other: Time spent on other trips

When certain covariates are used for modeling both the mean response λ and the probability of zero-inflation ω, the assessment of the overall effect is not straightforward. When both parameters support the same conclusion, the multiplicative effect of the Poisson parameter is elevated by the zero-inflation parameter. Take as an example the comparison between regular days and days within the summer holiday period: the parameters of the Poisson model indicate that the average commuting time on a regular day is 1.13 (=exp(0+0.120) times the commuting time during a day within the summer holiday period, and this effect is enlarged by the zero-inflation part indication that the odds of commuting are 4.33 for regular days compared to summer holidays. On the other hand, when both parameters support opposite effects, the assessment of the overall effect remains inclusive. Consider for instance the difference between Saturdays and Sundays: the Poisson parameters indicate that the commuting time on Sundays is 1.03 (=exp(0+0.026) times the commuting time on Saturdays, whereas the zero-inflation parameters indicate that the odds of commuting on a Saturday versus a Sunday are 1.87.

Examination of the temporal effects provides the insight that the traditional organization of modern society in 5-day workweeks predominates the travel time expenditure on commuting: the likelihood of commuting and the average time spent on commuting are considerably larger during weekdays than during weekend days. This finding is consistent with the results reported by Bhat & Misra (1999) and Sall & Bhat (2007), who indicated the importance of incorporating day-of-week effects to account for variability in travel times. Furthermore, the travel time expenditure is significantly lower during holidays and summer holidays.

Investigation of the socio-demographic effects points out that males have a higher propensity to commute than females. Furthermore, males (25+) commute longer than their female counterparts. This can be explained by persistence of the traditional role patterns: taking care of children still is most frequently done by females, and correspondingly females adjust home and work locations better to one another. When employment status is considered, it can be seen that the occupationally active population quite logically has a higher likelihood to commute and spends more time on commuting than occupationally inactive people. Interesting is the fact that the higher the position people hold within a company, the more daily time they spend on commuting and the higher the probability of commuting. Consequently, executives spend most time on commuting.

Final conclusions that can be drawn from exploring the parameter estimates are the fact that frequent users of public transport (bus, train) commute up to 1.7 times longer than people who seldom or never use public transport. Daily users of a motorcycle spend on average 35.7% less time on commuting than non-(daily) users. Also noteworthy is the significant interdependency of travel time expenditure on the remainder of the travel time budget: people making other kinds of trips commute on average 25.4% less than people who only make commuting trips, and moreover the chance of commuting decreases when other types of trips are made. This is a consequence of the substitution effect caused by the travel time frontier, the intrinsic maximum amount of time that people are willing to allocate for travel (van Wee *et al.*, 2006; Banerjee *et al.*, 2007).

Time spent on shopping trips

The parameter estimates of the zero-inflated Poisson regression model for predicting the travel time expenditure on shopping trips are displayed in Table 2.16. Recall the distinction between the parameters in the model predicting the mean response λ and the parameters for estimating the probability of the zero-inflation ω. For the analysis no distinction was made between daily and non-daily shopping, as only one-day trip diary data were available. The analysis of the temporal effects yields the conclusion that in general the time spent on shopping trips is lower during holidays than during regular days. Saturday appears to be the most preferred day for performing shopping trips: the likelihood of performing shopping trips, as well as the travel time expenditure exceed those of the other days. This can be accounted for by the fact that on Saturdays there are fewer work-related obligations, and more available time to perform non-work related activities. The importance of incorporating temporal effects to account for differences in travel time variability is also acknowledged by Srinivasan & Guo (2003) and Habib & Miller (2006).

Table 2.16: ZIP regression parameter estimates for travel time expenditure on shopping trips

Parameter	Estimate	Parameter	Estimate	Parameter	Estimate	Parameter	Estimate
Poisson Model λ							
Intercept	3.628	*Sex & Age*		*Employment status*		*Urbanization*	
Holiday		Male, 6-12	0.417	Housekeeping	-0.070	Metropol. area	-0.186
Regular day	0.000	Male, 13-15	-0.309	Unemployed	0.000	Urban area	-0.159
Holiday	-0.034	Male, 16-24	-0.193	Retired	-0.166	Suburban area	-0.014
Summer Hol.	-0.001	Male, 25-34	-0.131	Disabled	-0.365	Rural area	0.000
Day-of-week		Male, 35-44	0.032	Pupil, Student	-0.392	*Bus/tram use*	
Monday	0.021	Male, 45-54	0.033	Worker	-0.008	Frequently	0.408
Tuesday	0.036	Male, 55-64	0.087	Employee	-0.017	Occasionally	0.088
Wednesday	0.040	Male, 65+	-0.045	Executive	-0.036	Never	0.000
Thursday	0.079	Female, 6-12	0.242	Liberal prof.	-0.366	*Other trips*	
Friday	0.008	Female, 13-15	0.337	Self-employed	0.008	Yes	-0.299
Saturday	0.141	Female, 16-24	0.139	*Living conditions*		No	0.000
Sunday	0.000	Female, 25-34	-0.224	Alone	0.000		
Train use		Female, 35-44	-0.063	With children	-0.045		
Frequently	0.136	Female, 45-54	0.024	With partner	-0.038		
Occasionally	0.054	Female, 55-64	0.023	P. & Children	-0.188		
Never	0.000	Female, 65+	0.000	Other	-0.505		

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Parameter	Estimate	Parameter	Estimate	Parameter	Estimate	Parameter	Estimate
Zero inflation ω							
Intercept	0.889	*Age*		*Sex*		*Employment status*	
Day-of-week		6-12	-0.136	Male	0.313	Worker	0.839
Monday	0.045	13-15	0.007	Female	0.000	Employee	0.538
Tuesday	-0.001	16-24	-0.132	*Employment status*		Executive	0.719
Wednesday	-0.250	25-34	-0.548	Housekeeping	-0.030	Liberal prof.	1.026
Thursday	-0.269	35-44	-0.430	Unemployed	0.000	Self-employed	1.253
Friday	-0.375	45-54	-0.382	Retired	0.301	*Time other*	0.004
Saturday	-1.018	55-64	-0.437	Disabled	0.600		
Sunday	0.000	65+	0.000	Pupil, Student	0.825		

Hol.: Holiday, prof.: profession, Metropol.: Metropolitan, Time other: Time spent on other trips

P. & Children: With partner and children

Exploration of the socio-demographic effects reveals that females have a much larger propensity to perform shopping trips than males (odds ratio equals 1.37), which can be explained by the fact that household related activities are primarily performed by females (Schlich *et al.*, 2004). The assessment of the effect of age is not that straightforward. Notwithstanding, adults in the age category 25-64 have the largest probability of performing shopping trips. When the effect of employment status is evaluated, it can be seen that the finding of Gould & Golob (1997), indicating that the occupationally active population spends less travel time on shopping than occupationally inactive people, is more variegated in this study: on the one hand occupationally active people have a decreased likelihood of performing shopping trips, on the other hand - when they do make the trip - they spend more time than occupationally inactive people. Although the overall effect remains inconclusive, an important finding is that people with a liberal profession are less likely to perform shopping trips (irrespective of self-employed people) and have a clearly lower travel time (28% less than executives) than other occupationally active people.

Other conclusions that can be formulated are the fact that people living in non-traditional living conditions spend considerable less time on shopping trips. This can be explicated by the fact that shopping trips for people living in 'other' living conditions such as rest homes and institutions are performed by personnel of these organizations instead of by the individuals themselves. Next, one can infer that the degree of urbanization has a decreasing impact on travel time expenditure on shopping trips. A possible reason is the increased number of shopping locations in a more urban context. Furthermore, one could ascertain the interdependence of shopping trips and other kind of trips. This is again a consequence of the travel time frontier. Note that the interdependency of shopping trips and work trips was also incorporated by Lee & Timmermans (2007).

Time spent on leisure trips

The parameter estimates of the zero-inflated Poisson regression model for predicting the travel time expenditure on leisure trips are shown in Table 2.17. Examination of the temporal effects indicates that both the travel time expenditure on leisure trips and the odds of making these trips are higher during holiday periods and weekends. This can again be explained by the traditional organization of modern society: during weekends and holidays more time is available to perform leisure activities.

Table 2.17: ZIP regression parameter estimates for travel time expenditure on leisure trips

Parameter	Estimate	Parameter	Estimate	Parameter	Estimate	Parameter	Estimate
Poisson Model λ							
Intercept	3.481	*Sex & Age*		*Employment status*		*Bus/tram use*	
Holiday		Male, 35-44	0.546	Pupil, Student	0.601	Frequently	-0.162
Regular day	0.000	Male, 45-54	0.646	Worker	0.606	Occasionally	-0.110
Holiday	0.361	Male, 55-64	0.941	Employee	0.917	Never	0.000
Summer Hol.	0.415	Male, 65+	0.371	Executive	0.844	*Train use*	
Day-of-week		Female, 6-12	0.709	Liberal prof.	1.162	Frequently	-0.065
Monday	-0.056	Female, 13-15	0.735	Self-employed	1.125	Occasionally	0.046
Tuesday	0.110	Female, 16-24	0.485	*Living conditions*		Never	0.000
Wednesday	-0.253	Female, 25-34	0.685	Alone	0.000	*Motorcycle use*	
Thursday	-0.161	Female, 35-44	0.544	With children	-0.581	Yes	-0.978
Friday	0.066	Female, 45-54	0.512	With partner	-0.154	No	0.000
Saturday	-0.036	Female, 55-64	0.505	P. & Children	-0.385	*Driving license*	
Sunday	0.000	Female, 65+	0.000	Other	0.971	Yes	-0.292
Sex & Age		*Employment status*		*Urbanization*		No	0.000
Male, 6-12	0.485	Housekeeping	0.738	Metropol. area	0.506	*Other type trips made*	
Male, 13-15	0.593	Unemployed	0.000	Urban area	0.100	Yes	-0.783
Male, 16-24	0.909	Retired	0.734	Suburban area	0.189	No	0.000
Male, 25-34	0.369	Disabled	1.042	Rural area	0.000		

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Parameter	Estimate	Parameter	Estimate	Parameter	Estimate	Parameter	Estimate
Zero inflation ω							
Intercept	1.064	*Sex*		*Living conditions*		*Employment status*	
Holiday		Male	-0.408	Alone	0.000	Worker	0.350
Regular day	0.000	Female	0.000	With children	0.148	Employee	-0.029
Holiday	-0.111	*Age*		With partner	0.210	Executive	-0.092
Summer Hol.	-0.264	6-12	-0.898	P. & Children	0.369	Liberal prof.	-0.338
Day-of-week		13-15	-0.643	Other	2.029	Self-employed	0.393
Monday	1.161	16-24	-0.936	*Employment status*		*Driving license*	
Tuesday	1.349	25-34	-0.607	Housekeeping	-0.033	Yes	-0.363
Wednesday	1.186	35-44	-0.624	Unemployed	0.000	No	0.000
Thursday	0.971	45-54	-0.430	Retired	0.137	*Time other*	0.005
Friday	0.617	55-64	-0.366	Disabled	0.813		
Saturday	0.293	65+	0.000	Pupil, Student	-0.207		
Sunday	0.000						

Hol.: Holiday, prof.: profession, Metropol.: Metropolitan, Time other: Time spent on other trips

P. & Children: With partner and children

Investigation of the socio-demographic effects reveals that males have a higher propensity to perform leisure trips and in general spend more time on leisure trips than females, which was also demonstrated by Schlich *et al.* (2004). People in the age category 65+ have the smallest likelihood to execute leisure trips and also spend the least time on leisure trips. This can be accounted for by the fact that people aged 65+ are more likely to have physical disabilities limiting the opportunity to perform leisure activities. People living together with other people have a clearly lower probability and lower travel time expenditure on leisure than people living alone. Coupling constraints clearly seem to play an important role here. Besides, the importance of incorporating land use and density variables, denoted by Bhat & Gossen (2004), is also evidenced in this study: in metropolitan and urban areas significantly more time is spent on leisure trips than in rural areas. Finally, the interdependency of travel time expenditures on differently motivated trips can also be observed for leisure trips.

Time spent on non-commercial visit (NCVI) trips

The assessment of the parameter estimates for the zero-inflated Poisson regression model for predicting the travel time expenditure on non-commercial visit trips, shown in Table 2.18, points out that people are more likely to make non-commercial visits during holidays than during regular days. Nonetheless, this effect is abated by the finding that travel time expenditure on these trips is lower during holidays than during regular days. With respect to the day-of-week effects, one can conclude that during weekend days, and in particular on Sundays, the propensity of making non-commercial visit trips surpasses all other days. Moreover, the travel time expenditure on non-commercial visits on Sundays transcends the expenditures on other days, with disregard of Mondays, on which the likelihood of making non-commercial visit trips is significantly lower.

Table 2.18: ZIP regression parameter estimates for travel time expenditure on NCVI trips

Parameter	Estimate	Parameter	Estimate	Parameter	Estimate	Parameter	Estimate
Poisson Model λ							
Intercept	3.430	*Sex & Age*		*Employment status*		*Urbanization*	
Holiday		Male, 45-54	0.062	Housekeeping	0.353	Metropol. area	-0.044
Regular day	0.000	Male, 55-64	0.070	Unemployed	0.000	Urban area	0.052
Holiday	-0.065	Male, 65+	0.024	Retired	0.292	Suburban area	-0.141
Summer Hol.	-0.063	Female, 6-12	-0.297	Disabled	0.038	Rural area	0.000
Day-of-week		Female, 13-15	-0.185	Pupil, Student	0.443	*Train use*	
Monday	0.045	Female, 16-24	-0.310	Worker	0.265	Frequently	-0.235
Tuesday	-0.142	Female, 25-34	-0.076	Employee	0.290	Occasionally	0.060
Wednesday	-0.112	Female, 35-44	-0.325	Executive	0.224	Never	0.000
Thursday	-0.027	Female, 45-54	-0.014	Liberal prof.	0.727	*Bicycle use*	
Friday	-0.244	Female, 55-64	-0.191	Self-employed	0.130	Yes	-0.062
Saturday	-0.034	Female, 65+	0.000	*Bus/tram use*		No	0.000
Sunday	0.000	*Living conditions*		Frequently	0.328	*Driving license*	
Sex & Age		Alone	0.000	Occasionally	0.052	Yes	0.244
Male, 6-12	-0.227	With children	-0.063	Never	0.000	No	0.000
Male, 13-15	-0.485	With partner	-0.021	*Motorcycle use*		*Other trips*	
Male, 16-24	-0.426	P. & Children	-0.040	Yes	-0.522	Yes	-0.262
Male, 25-34	-0.197	Other	0.577	No	0.000	No	0.000
Male, 35-44	-0.337						

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Parameter	Estimate	Parameter	Estimate	Parameter	Estimate	Parameter	Estimate
Zero inflation ω							
Intercept	0.668	*Day-of-week*		*Day-of-week*		*Urbanization*	
Holiday		Monday	0.935	Friday	0.713	Metropol. area	-0.165
Regular day	0.000	Tuesday	1.015	Saturday	0.412	Urban area	-0.226
Holiday	-0.285	Wednesday	0.820	Sunday	0.000	Suburban area	-0.018
Summer Hol.	-0.326	Thursday	1.100	*Time other*	0.006	Rural area	0.000

Hol.: Holiday, prof.: profession, Metropol.: Metropolitan, Time other: Time spent on other trips

P. & Children: With partner and children

When the socio-demographic effects are investigated, it can be noted that older people spend more travel time on non-commercial visit trips than younger people, as also demonstrated by Tacken (1998). When the sex effect is unraveled, one can observe that young females (13-45) spend more time on non-commercial visit trips than their male peers, whereas older females (45+) spend less time than their male counterparts. A thorough look at the employment status indicates that the occupationally active population spends more time on visit trips than occupationally inactive people. A final finding is the significant interdependency of non-commercial visits trips and other types of trips. Note that the relevance of this interrelationship was also underlined by Ettema *et al.* (2007a).

Time spent on drop-off and pick-up (DOPU) trips

The final parameters that are interpreted are the ones of the zero-inflated Poisson regression model for predicting the travel time expenditure on pick-up and drop-off trips, shown in Table 2.19. The analysis of the temporal effects yields the conclusion that in general more time on pick-up and drop-off trips is spent during summer holidays. Controversially, during general holidays, like for instance Whit Sunday and Whit Monday, considerably less time is spent on pick-up and drop-off trips. This is an indication that during these general holidays, all members of the households perform activities together and consequently also make their trips together.

Table 2.19: ZIP regression parameter estimates for travel time expenditure on DOPU trips

Parameter	Estimate	Parameter	Estimate	Parameter	Estimate	Parameter	Estimate
Poisson Model λ							
Intercept	3.979	*Sex & Age*		*Employment status*		*Bus/tram use*	
Holiday		Male, 35-44	0.079	Pupil, Student	-0.353	Frequently	0.077
Regular day	0.000	Male, 45-54	0.233	Worker	-0.032	Occasionally	0.044
Holiday	-0.074	Male, 55-64	0.007	Employee	-0.089	Never	0.000
Summer Hol.	0.148	Male, 65+	0.226	Executive	-0.401	*Train use*	
Day-of-week		Female, 6-12	0.001	Liberal prof.	-0.484	Frequently	-0.155
Monday	0.121	Female, 13-15	-0.146	Self-employed	-0.347	Occasionally	0.062
Tuesday	0.047	Female, 16-24	0.086	*Living conditions*		Never	0.000
Wednesday	0.011	Female, 25-34	-0.403	Alone	0.000	*Motorcycle use*	
Thursday	0.019	Female, 35-44	-0.272	With children	-0.164	Yes	-0.921
Friday	0.180	Female, 45-54	-0.124	With partner	-0.271	No	0.000
Saturday	0.065	Female, 55-64	-0.317	P. & Children	-0.147	*Other trips*	
Sunday	0.000	Female, 65+	0.000	Other	-0.545	Yes	-0.265
Sex & Age		*Employment status*		*Urbanization*		No	0.000
Male, 6-12	-0.181	Housekeeping	-0.051	Metropol. area	0.264		
Male, 13-15	-0.286	Unemployed	0.000	Urban area	0.018		
Male, 16-24	0.169	Retired	-0.409	Suburban area	-0.107		
Male, 25-34	0.081	Disabled	-0.162	Rural area	0.000		

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Parameter	Estimate	Parameter	Estimate	Parameter	Estimate	Parameter	Estimate
Zero inflation ω							
Intercept	2.870	*Sex*		*Employment status*		*Living conditions*	
Age		Male	0.326	Employee	0.536	Other	0.655
6-12	-1.346	Female	0.000	Executive	0.257	*Driving license*	
13-15	-0.969	*Employment status*		Liberal prof.	0.481	Yes	-0.977
16-24	-1.011	Housekeeping	0.510	Self-employed	0.495	No	0.000
25-34	-1.524	Unemployed	0.000	*Living conditions*		*Time other*	0.003
35-44	-1.224	Retired	0.261	Alone	0.000		
45-54	-0.760	Disabled	1.592	With children	0.289		
55-64	-0.780	Pupil, Student	0.454	With partner	0.449		
65+	0.000	Worker	0.695	P.& Children	-0.622		

Hol.: Holiday, prof.: profession, Metropol.: Metropolitan, Time other: Time spent on other trips

P. & Children: With partner and children

Investigation of the socio-demographic effects points out that females and people belonging to younger age-classes (<45) have a higher probability of making drop-off and pick-up trips than males and people belonging to the older age groups. Furthermore, persons living alone clearly spend more time on drop-off and pick up trips than people living together. Another conclusion that can be drawn is that lower degrees of urbanization coincide with lower levels of travel time expenditure on drop-off and pick-up trips. Concerning the likelihood of making drop-off and pick-up trips, one could observe that the possession of a driving license significantly increases the probability of making a drop-off and pick-up trip. Finally, one could derive a significant relationship between travel time expenditure on other type of trips. Note that this interrelationship was found to be highly significant for all types of trips.

Conclusions and further research

It has been shown that socio-demographics, temporal effects and transportation preferences contribute significantly to the unraveling of variability in daily travel time expenditure. In particular it has been illustrated that holidays have a non-ignorable impact on daily travel behavior. The zero-inflated Poisson regression models, which were used to accommodate the Poisson models to the portentous excess of zeros caused by non-travelers, yielded findings that were in accordance with international literature.

It is essential that the findings reported in this paper are acknowledged and translated into transportation models. An explicit incorporation of the effect of public holidays in travel demand models will most likely result in more precise travel demand forecasts, and consequently policy makers can develop and fine-tune their policy measures on more precise assumptions.

From a methodological point of view, further research should assess the need for accommodating over-dispersion in zero-inflated models. A possible framework tackling both over-dispersion and the excess of zeros in the zero-inflated negative binomial approach. A comparison of zero-inflated Poisson regression models with zero-inflated negative binomial regression models would provide a thorough assessment. In addition, it would be worthwhile to compare the suggested modeling approach with the classical techniques such as Tobit models and hazard-based duration models. Inclusion of social interaction variables (Schlich *et al.*, 2004) and spatial variables (Baumeler *et al.*, 2005) in the analyses could further intensify the understanding of differences in travel time expenditure. Moreover, the use of multi-day data can improve the analysis even further by for instance differentiating random and routine behavior (Bhat *et al.*, 2004b). Triangulation of both quantitative (e.g. statistical analysis) and qualitative methods (e.g. mental models (Hannes *et al.*, 2009) or Q-methodology (Cools *et al.*, 2009b)) seems a solid roadway for further illumination of the underpinnings of travel behavior.

Chapter 3

Impact of weather events on travel

The research reported in this chapter is mainly based on Cools* et al. *(2008), Cools* et al. *(2010b) and Cools* et al. *(2010e).

3.1 Impact of weather events on revealed traffic patterns

3.1.1 Background

A clear insight into how weather conditions influence traffic is essential for policy makers. This is underlined by policy issues which are often related with adverse weather events such as increased fuel consumption and economic losses due to traffic delays. Day-to-day weather conditions such as fog and precipitation can reduce travel demand, for instance when drivers postpone or cancel discretionary activities, but can also have an increasing effect when travel modes are shifted from slow modes (walking, cycling) towards motorized vehicles (Hranac *et al.*, 2006). At the network level, adverse weather events increase the uncertainty in system performance, resulting for instance in a network capacity reduction ranging from 10 to 20% in heavy rain (De Palma & Rochat, 1999).

Figure 3.1 displays the conceptual framework of the interplay between weather conditions, traffic flow, traffic speed and road safety (Koetse & Rietveld, 2009). Take as an example heavy rain conditions during which drivers might reduce their travel speed, and as a consequence also have a reducing effect on road capacities and corresponding traffic flows. There might be also a direct decrease in traffic flow resulting from people canceling their trips. The resulting reduction in traffic flow and traffic speed could decrease the accident severity, but slippery roads on the other hand could increase the accident frequency. This example illustrates the long recognized proposition that road accidents are the consequence of an interaction between behavioral, environmental and technological factors. A change in any of these factors could prevent an accident from occurring (Levine *et al.*, 1995; Edwards, 1996).

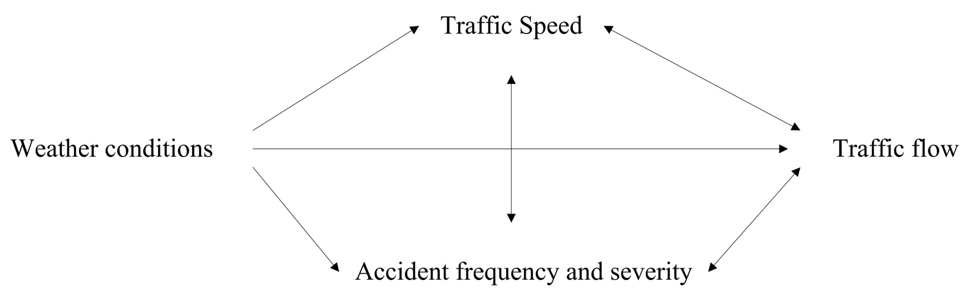

Figure 3.1: Relationship between weather, road safety, traffic speed and traffic flow (Koetse & Rietveld, 2009)

The rise of advanced traffic management systems (ATMS) provides transportation agencies the opportunity to implement traffic management strategies that could limit weather-related side-effects on traffic operations (Zhang *et al.*, 2005b). A solid understanding of the impact of various weather conditions on roadside crash frequency and traffic flow serves a good knowledge base for developing these strategies (Shankar *et al.*, 2004; Smith *et al.*, 2004).

The assessment of weather impacts on traffic intensity (the daily number of vehicles passing a specific location) is of significant value to travel demand modelers. Khattak & De Palma (1997) reported that adverse weather conditions cause important changes in travel decisions: mode changes, changes in departure time and diversions to alternate route, were reported as the most prevalent behavioral adaptations.

The investigation of weather effects on traffic intensity is also important from a road safety point of view, because traffic intensity, commonly referred to as exposure in traffic safety literature, is noted as the first and primary determinant of traffic safety

(Van den Bossche *et al.*, 2005). Injury accidents are nearly proportionally related with exposure (Fridstrøm *et al.*, 1995), evidencing the strong relationship between traffic flow conditions and the likelihood of traffic accidents (Golob *et al.*, 2004).

Summarizing, weather events can affect two predominant traffic variables: traffic flow/traffic demand and traffic safety (Maze *et al.*, 2006). In the following (sub)sections the focus will lie on on the first predominant traffic variable, namely traffic flow. The main objective is to test the hypothesis whether weather conditions uniformly alter daily traffic flows in Belgium, or in other words to test whether the road usage on a particular location determines the size of the effects. The formal testing of this hypothesis is a contribution which allows policy makers to assess the appropriateness of global versus local traffic management strategies. In addition, a secondary goal is to validate findings in international literature within a Belgian context.

The remainder of this introductory section will address the specific weather variables that influence traffic flows, traffic demand and traffic safety. Afterwards the data will be described and the employed methodology will be addressed. In the final part of Section 3.1 the results will be presented and an elaboration on their relevance to transport policy will be provided, some general conclusions formulated and avenues for further research indicated.

Influence of weather on traffic flows and traffic demand

Weather can affect traffic volumes and traffic demand in different ways, including diversions of trips to other modes or other paths, or even cancelations of trips (Maze *et al.*, 2006). Bos (2001) indicated that in the Netherlands heavy rain accompanies a smaller number of cyclists, whereas mild winters and warm summers have an increasing effect on bicycle use. A similar relationship was found by Nankervis (1999) who examined the effect of both (short-term) weather conditions and (long-term) seasonal variation patterns on bicycle commuting patterns among students in the temperate climate of Melbourne, Australia. He found that cycle commuting was affected by long-term, climatic conditions as well as daily weather conditions. Guo *et al.* (2007) reported that temperature, rain, snow and wind all influence transit ridership of the Chicago Transit Authority: good weather increases ridership, whereas bad weather has a diminishing effect. Guo *et al.* (2007) also stress that not only the transit ridership is influenced by weather, but also vehicle running and dwell times are affected, as well as the cost of operation. In Brussels, Belgium, on the other hand, the transit agency reported higher levels of transit ridership during adverse weather (Khattak & De Palma, 1997).

From various studies on the effect of rain, snow and fog on traffic operations, it has become clear that adverse weather can significantly reduce not only capacity but also operating speeds on roadways, resulting in congestion and productivity loss (Agarwal *et al.*, 2006; Datla & Sharma, 2008). When the effect of precipitation on traffic operations is explored, almost all studies indicate that speed and capacity are negatively influenced (Stern *et al.*, 2003; Unrau & Andrey, 2006). Hanbali & Kuemmel (1993) found traffic volume reductions on highways away from the major urban centers in the United States ranging from 7% to 56% depending on the intensity of the snowfall. Maze *et al.* (2006) found comparable reductions in traffic volume on Interstate 35 in the northern rural Iowa ranging from 7% to 80% during snowstorms. In contrast, during rainstorms traffic volumes were reduced by less than 5%. According to Smith *et al.* (2004), who analyzed the effect of precipitation on traffic intensity in Hampton Roads, Virginia, highway capacity is reduced by a range from 4 to 10% during light rain (intensity of 0.01- 6.35 mm/h) and a range from 25 to 30% during heavy rain (intensity higher than 6.35 mm/h).

When the focus in turned to highway speeds, Ibrahim & Hall (1994) found reductions in speed of respectively 2 and 3 km/h during light rain and light snow, and decreases in speed of 5 to 10 km/h during heavy rain, and 38 to 50 km/h during heavy snow. The reductions tend to be larger for precipitation amounts (Keay & Simmonds, 2005). Other factors worthwhile investigating are visibility (fog), wind speed, sunshine hours and temperature, the last two associated with slight increases in traffic activity (Hassan & Barker, 1999).

Influence of weather on traffic safety

Most literature on effects of weather on traffic safety focuses on the impact of rain and wet conditions, and snow and slippery road surfaces on collision risk, collision frequency and injury and fatality rates (Andrey *et al.*, 2003b). Precipitation in the form of rainfall and snowfall generally results in an increasing number of accidents (Keay & Simmonds, 2005; Brijs *et al.*, 2008). Andrey *et al.* (2001, 2003a) report an augmentation of collision risk from 50 up to 100 percent during precipitation. Notwithstanding, the effect of precipitation is multifaceted: larger effects of rainfall are observed in autumn than during spring and an increased impact is noted after dry spells (Keay & Simmonds, 2006). Withal, divergent results are found when discussing snowfall. In Denmark, for example, snowfall has a tempering effect on the number of injury accidents (Fridstrøm *et al.*, 1995), whereas Zhang *et al.* (2005a) found a significantly increased risk under snow conditions. Snowstorms on rural Iowa

Interstates dramatically exacerbate crash rates by 13 times during moderate-intensity snowstorms and by 25 times in high-intensity snowstorms (Maze *et al.*, 2006). The severity of snowstorms is influenced by the duration, intensity and wind speed (Qin *et al.*, 2006).

Next to precipitation, also other weather conditions are relevant in investigating traffic safety, for instance high winds, fog and sunshine radiation and duration, having a negative impact on traffic safety (Edwards, 1998; Hermans *et al.*, 2006). The fact that the relationship between weather events and traffic safety is not always clear hampers the formulation of general research findings, especially when it is acknowledged that certain human manoeuvres before a collision may have a significant impact on whether weather is a contributing factor (Golob & Recker, 2003).

3.1.2 Description of the traffic and weather data

To assess the impact of weather conditions on traffic intensity, and in particular to test the hypothesis that the road usage on a particular location determines the size of the effects of weather conditions on traffic intensities, the upstream and downstream traffic of three traffic count locations (represented by black squares in Figure 3.2) were considered. Weather conditions on these traffic count locations were approximated by the events recorded in the nearest available weather stations (represented by grey circles in Figure 3.2).

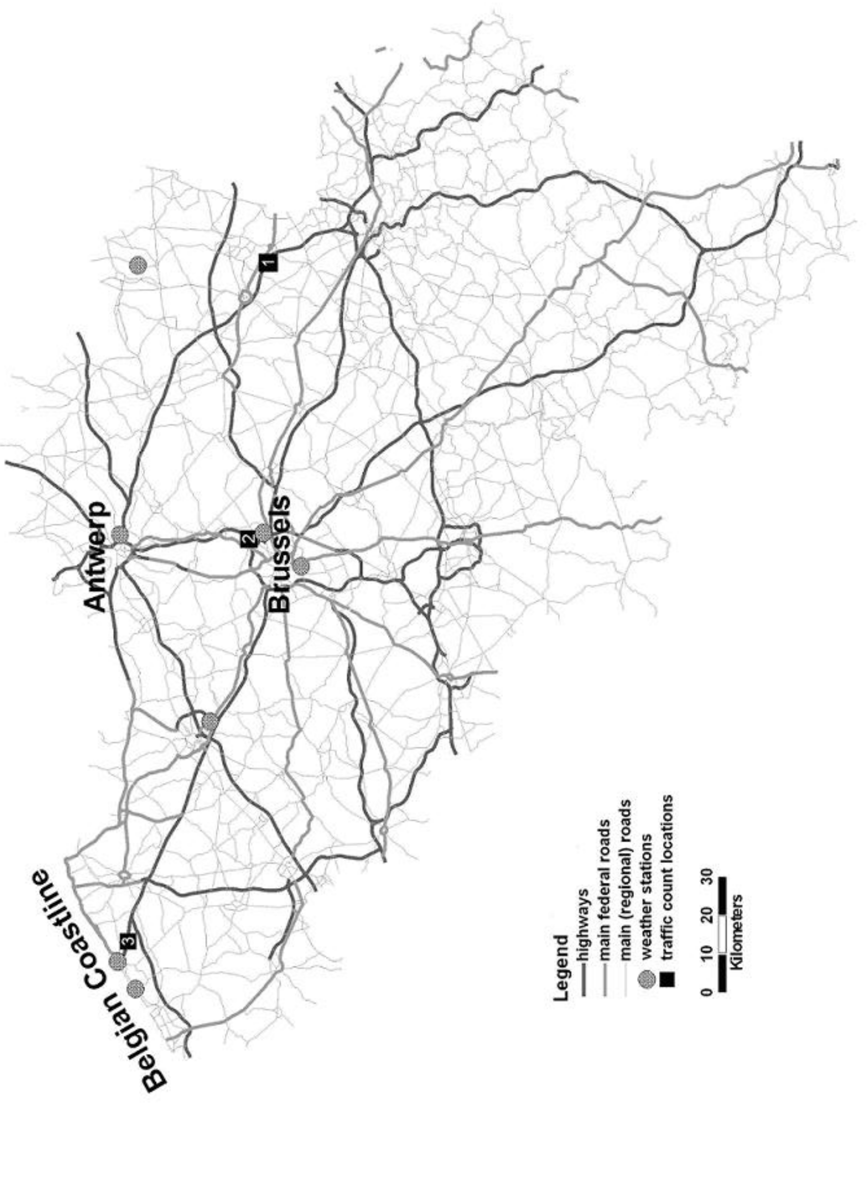

Figure 3.2: Representation of the traffic count locations and weather stations under study

Dependent variables: traffic intensity data

The traffic intensity data originate from minute data coming from single inductive loop detectors, collected in 2003 and 2004 by the Vlaams Verkeerscentrum (Flemish Traffic Control Center). Minutely, the loop detectors generate four statistics: the number of cars driven by, the number of trucks driven by, the occupancy of the detector (the percentage of time that the detector is "occupied" by vehicles) and the time-mean speed of all vehicles (Maerivoet, 2006). Adding up the number of cars and trucks for all lanes in a specific direction, yields a total traffic count for each minute. The aggregation on a daily basis of all 1440 minutely total traffic counts then results in a single daily traffic intensity measure. Note that this aggregation on a daily level also filters away the noise caused by random fluctuations due to potential in accuracies of single loop detector counts. For a general discussion about the quality of traffic counts derived from single loop detectors the reader is referred to Chen *et al.* (2003) and Weijermars & van Berkum (2006).

As indicated earlier, upstream (towards the location of interest) and downstream (away from the location of interest) traffic intensity of three traffic count locations (displayed as black numbered squares in Figure 3.2) are investigated. The first location is a traffic count location measuring upstream and downstream highway traffic from Hasselt, a provincial city with a population of about 70 000 people. The highway were these upstream and downstream traffic counts are measured is characterized by 2 lanes in each direction, used both for commuting and leisure traffic. The second traffic count location is situated on one of the entranceways of Brussels, the capital of Europe and thus an important location in terms of job opportunities. At the location of the traffic counts, the highway consists of 3 lanes in each direction, excessively used by commuters. The last location is based on one of the access highways (3 lanes in each direction) to the Belgian seashore, and thus typified by leisure traffic. Note that the speed limit on all these locations was equal to 120 km/h.

Independent variables

Weather data

Data concerning weather events were recorded by the Royal Meteorological Institute of Belgium (KMI). These data originate from Automatic Weather Stations (AWS) equipped with a Present Weather Sensor (PWS). In addition to the PWS, these AWS are also equipped with a ceilometer, an anemometer, a temperature sensor, a hygrometer and rain gauges. Weather events on the relevant traffic count locations were approximated by the events recorded in the most nearby (available) weather stations. The following variables were recorded and considered for the analysis: daily precipitation (expressed in 1/10 mm; all 24 hourly measurements from rain gauges are aggregated to a daily level), conditions of hail, snow and thunderstorm (a dummy variable indicating the presence of the weather event during the day under study was created for each of these weather events; the weather types were derived from the PWS, and enriched with data from the SAFIR lightning detection system), average and maximum cloudiness (expressed in eights; the average and maximum of all 24 hourly measurements was calculated; the degree of cloudiness was derived from the ceilometer), minimum, maximum and average temperature (expressed in °C; the minimum, maximum and average from all 24 hourly averages were tabulated), maximum hourly wind speed (expressed in m/s; the maximum of all 24 hourly averages was taken), sunshine duration (expressed in minutes; all 24 hourly durations were added up) and duration of diminished visibility due to fog (a dummy variables was created indicating that the day under study at least a few minutes the visibility was smaller than 200m).

In general, Belgium has a temperate maritime climate influenced by the North Sea and Atlantic Ocean, with cool summers and moderate winters. There is little variation in climate from region to region, although the marine influences are less inland. Rainfall is distributed throughout the year with a dryer period from April to September. Specific information about the meteorological conditions for the years 2003 and 2004 are provided in Table 3.1.

Temporal effects

Next to the different weather conditions that will be used to (partially) explain the variability in traffic counts, it is also necessary to incorporate temporal effects. In the previous chapter it was indicated that day-of-week effects and holiday effects contribute significantly to unraveling differences in daily traffic intensity. Analogously to the previous chapter, a dummy variable was created for the following holidays: Christmas vacation, spring half-term, Easter vacation, Labor Day, Ascension Day, Whit Monday, vacation of the construction industry (three weeks, starting the second Monday of July), Our Blessed Lady Ascension, fall break (including All Saints' Day and All Souls' Day), and finally Remembrance Day. It should be noted that for all these holiday occasions, the adjacent weekends were considered to be a holiday. Similarly, for holidays occurring on a Tuesday or on a Thursday, respectively the

Table 3.1: Meteorological conditions in 2003-2004

Parameter of the weather conditions	Value
Average maximum wind speed (m/s)	6.5
Average minimum temperature (°C)	6.7
Average mean temperature (°C)	10.8
Average maximum temperature (°C)	14.8
Average sunshine duration (min/day)	307.2
Average cloudiness (eights)	4.7
Average precipitation (1/10 mm/day)	18.8
Number of days with precipitation / year	172.5
Number of days with hail / year	9.3
Number of days with snow / year	18.2
Number of days with thunderstorm / year	22.7
Number of days with reduced visibility / year	12.2

Monday and weekend before and the Friday and weekend after were also defined as a holiday. A second holiday dummy variable was created for the summer holidays (excluding holidays in the above-mentioned holiday list). As a result, for normal days both dummy variables were coded zero.

Next to these holiday effects, also day-of-week effects were taken into account. As there are seven days in a week, the first six days (Monday until Saturday) were each represented by a dummy, equal to 1 for the days they represent and zero elsewhere. For the reference day (Sunday), all six dummies were coded zero.

3.1.3 Methodology

To develop an understanding of the effects of weather on traffic intensity, some basic descriptive statistics will be provided. For the continuous variables the Spearman correlation between traffic intensity and the weather variables will be calculated. Unlike the traditional Pearson product-moment correlation, the Spearman rank correlation is a non-parametrical technique, robust for deviations of normality. Technically, the

Spearman rank correlation is computed in the following way:

$$\rho = 1 - \frac{6 \sum_i d_i^2}{n\left(n^2 - 1\right)}, \tag{3.1}$$

in which d_i is the difference between each rank of corresponding pair of values, and in which n equals the number of observations (Cohen & Cohen, 1984). For the categorical variables the group means are provided.

The main modeling philosophy envisaged is the classical linear regression approach. This modeling approach tries to explain a dependent variable with the help of other covariates. Formally, the multiple linear regression model can be represented by the following equation (Neter *et al.*, 1996):

$$Y_i = \beta_0 + \beta_1 X_{i,1} + \beta_2 X_{i,2} + ... + \beta_{p-1} X_{i,p-1} + \varepsilon_i, \tag{3.2}$$

in which Y_i is the i-th observation of the dependent variable, $X_{i,1}$, $X_{i,2}$, ..., $X_{i,p-1}$ the corresponding observations of the explanatory variables, β_0, β_1, β_2, ..., β_{p-1} the parameters, which are fixed, but unknown, and in which ϵ_i is the unknown random error. Estimates for the unknown parameters can be obtained by classical estimation techniques. When all underlying assumptions of the classical linear regression model are satisfied, the estimators for the parameters are BLUE (Best Linear Unbiased Estimators). Otherwise some remedial measures, like transformations, are required (Neter *et al.*, 1996).

Since autocorrelation is present between traffic counts, ignorance of this problem would increase the risk of erroneous model interpretation. To accommodate for this risk, Newey-West heteroskedasticity and autocorrelation consistent (HAC) covariance matrices are used for the estimation process. The Newey-West covariance matrix estimator is given by:

$$\hat{\mathbf{\Sigma}}_{\mathbf{NW}} = \left(\mathbf{X'X}\right)^{-1} \hat{\mathbf{\Omega}} \left(\mathbf{X'X}\right)^{-1}, \tag{3.3}$$

with the estimated error variance ($\hat{\mathbf{\Omega}}$) defined as:

$$\hat{\mathbf{\Omega}} = \frac{N}{N-k} \left\{ \sum_{i=1}^{N} e_i^2 x_i x'_i + \sum_{v=1}^{q} \left(\left(1 - \frac{v}{q+1} \right) \sum_{i=v+1}^{N} \left(x_i e_i e_{i-v} x'_{i-v} + x_{i-v} e_{i-v} e_i x'_i \right) \right) \right\} \tag{3.4}$$

with N the number of observations, k the number of regressions, e_i the least square residual and q the truncation lag representing the number of autocorrelations used in evaluating the dynamics of the ordinary least squares residuals e_i (Newey & West, 1987). Note that the use of HAC covariance matrices does not change the point estimates of the parameters, but only the estimated standard errors (Zeileis, 2004).

To ensure that all parameter estimates are stable and reliable, the models should be checked for multicollinearity. In the presence of multicollinearity (high correlation between explanatory variables) the effect of a single explanatory variable can not be isolated, as the regression coefficients are quite uninformative and confidence intervals very wide. As a consequence, the individual estimated coefficients should be interpreted with caution, since only imprecise information can be derived from the regression coefficients (Van den Bossche *et al.*, 2004). Variance Inflation Factors (VIF) are used as a diagnostic tool to assess the level of multicollinearity. These VIF-factors measure how much the variances of the estimated regression coefficients are inflated as compared to when the predictor variables are not linearly related. The largest VIF-value among all predictor variables is used as an indicator of the severity of multicollinearity. A maximum VIF-value exceeding 10 indicates that the stability and reliability of the parameter estimates are questionable (Neter *et al.*, 1996).

3.1.4 Results

Validation of findings in international literature within Belgian context

Direction of the weather effects

A first indication of the direction of the weather effects is given by the sign of the Spearman rank correlations (Table 3.2) and by the group means of the different categorical weather variables (Table 3.3). Bad weather conditions such as precipitation, cloudiness and wind speed are negatively correlated with traffic intensity, whereas good weather conditions such as temperature and sunshine duration are positively correlated. When the group means of the different categorical weather indicators are compared, ambiguity is found in the direction of hail, fog and thunderstorm effects: on some locations traffic intensity increases in the presence of these weather conditions, on other locations it decreases. In contrast, the impact of snow is univocal: snow decreases traffic intensity on all traffic count locations.

A more thorough estimation of the direction of weather effects is obtained by the heteroskedasticity and autocorrelation consistent linear regression models. Estimates for the variables that were used in the location-specific models, their corresponding standard errors and values for the significance tests, and the VIF-factors are displayed in Table 3.4. The VIF-factors (all smaller than 10) assure that the parameter estimates are stable and reliable. The intercepts and temporal effects (day-of-week effects and holiday effects) are omitted from this table, since this section focuses mainly on

Table 3.2: Spearman rank correlations between traffic intensity and continuous predictors

Weather condition	Down Hasselt	Up Hasselt	Down Brussels	Up Brussels	Down Seashore	Up Seashore
Cloudiness (Mean)	⋆ -0.15	⋆ -0.18	⋆ -0.09	⋆ -0.10	⋆ -0.37	⋆ -0.33
Cloudiness (Max)	⋆ -0.17	⋆ -0.20	⋆ -0.09	⋆ -0.10	⋆ -0.34	⋆ -0.29
Precipitation	⋆ -0.10	⋆ -0.13	⋆ -0.14	⋆ -0.12	⋆ -0.26	⋆ -0.25
Temperature (Mean)	⋆ 0.17	⋆ 0.23	0.02	0.04	⋆ 0.56	⋆ 0.52
Temperature (Max)	⋆ 0.20	⋆ 0.27	0.05	0.07	⋆ 0.61	⋆ 0.57
Temperature (Min)	⋆ 0.13	⋆ 0.18	-0.01	0.01	⋆ 0.45	⋆ 0.42
Wind speed (Max)	-0.06	⋆ -0.09	⋆ -0.11	⋆ -0.09	⋆ -0.26	⋆ -0.25
Sunshine duration	⋆ 0.15	⋆ 0.20	⋆ 0.11	⋆ 0.13	⋆ 0.45	⋆ 0.42

⋆ indicates p-value < 0.05, $n = 731$

Table 3.3: Group means of traffic intensity by presence of weather condition

Weather condition	Presence	Down Hasselt	Up Hasselt	Down Brussels	Up Brussels	Down Seashore	Up Seashore
Hail	Yes	18642	18273	57068	53830	11519	11707
	No	18173	17984	53382	50439	12902	13210
Thunderstorm	Yes	18791	18457	52225	49770	13339	13756
	No	18135	17953	53588	50599	12859	13161
Snow	Yes	17045	16765	51313	47745	11080	11188
	No	18267	18078	53615	50699	12933	13245
Reduced visibility (Fog)	Yes	17488	17548	50290	46889	13361	13626
	No	18214	18010	53597	50660	12863	13170

assessing the impact of weather conditions on traffic intensity and because the impact of temporal effects has been reported in the previous chapter. The estimated weather effects are consistent with international literature addressing the impact of weather conditions on traffic intensity (Kyte *et al.*, 2001; Maze *et al.*, 2006; Datla & Sharma, 2008): rainfall, snowfall and wind speed significantly decrease traffic volumes, whereas temperature has a noticeable increasing effect. Comparable results are obtained in the overall model, of which the results are displayed in Table 3.5 (a more elaborate discussion concerning the overall model is provided further on in this section).

Table 3.4: Parameter estimates (HAC) for weather effects

Weather condition	Estimate	Standard Error	T-value	P-value	VIF
1. Location-specific model for downstream traffic in Hasselt					
Precipitation	-3.0	1.3	-2.33	0.020	1.22
Cloudiness (Mean)	-57.3	28.6	-2.01	0.045	1.30
Temperature (Max)	84.2	8.1	10.40	<0.001	1.33
Wind speed (Max)	-55.0	23.1	-2.38	0.018	1.15
2. Location-specific model for upstream traffic in Hasselt					
Precipitation	-2.9	1.3	-2.20	0.028	1.22
Cloudiness (Mean)	-55.4	26.7	-2.08	0.038	1.30
Temperature (Max)	84.0	7.4	11.42	<0.001	1.33
Wind speed (Max)	-66.2	21.3	-3.11	0.002	1.15
3. Location-specific model for downstream traffic in Brussels					
Hail	2085.7	804.2	2.59	0.010	1.06
Snowfall	-2358.4	1077.0	-2.19	0.029	1.19
Precipitation	-13.4	3.9	-3.43	0.001	1.27
Temperature (Max)	106.7	26.9	3.96	<0.001	1.97
Wind speed (Max)	-170.1	59.7	-2.85	0.005	1.20
Sunshine duration	1.5	0.7	-2.08	0.038	1.68
4. Location-specific model for upstream traffic in Brussels					
Hail	2020.1	805.9	2.51	0.012	1.06
Snowfall	-3049.8	1025.2	-2.97	0.003	1.19
Precipitation	-11.6	3.5	-3.35	0.001	1.27
Temperature (Max)	93.3	25.8	3.62	<0.001	1.97
Wind speed (Max)	-126.4	54.6	-2.32	0.021	1.20
Sunshine duration	1.9	0.7	2.78	0.006	1.68

Table continued on the following page

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Weather condition	Estimate	Standard Error	T-value	P-value	VIF
5. Location-specific model for downstream traffic in seashore area					
Precipitation (Dum)	-437.2	89.1	-4.91	<0.001	1.50
Cloudiness (Mean)	-152.1	21.2	-7.19	<0.001	1.40
Temperature (Max)	129.4	7.3	17.67	<0.001	1.26
Wind speed (Max)	-49.3	13.9	-3.56	<0.001	1.22
Visibility (<200m, Dum)	615.0	278.6	2.21	0.028	1.03
6. Location-specific model for upstream traffic in seashore area					
Precipitation (Dum)	-308.1	105.9	-2.91	0.004	1.53
Cloudiness (Mean)	-217.2	26.5	-8.20	<0.001	1.41
Temperature (Max)	148.5	8.7	17.01	<0.001	1.26
Wind speed (Max)	-62.3	17.0	-3.66	<0.001	1.24
Visibility (<200m, Dum)	642.5	220.3	2.92	0.004	1.05

Table 3.5: Parameter estimates (HAC) for the overall model

Weather condition	Estimate	Standard Error	T-value	P-value	VIF
Hail	2.734	0.831	3.29	0.001	1.06
Snowfall	-3.822	0.945	-4.04	<0.001	1.18
Precipitation	-0.019	0.004	-5.38	<0.001	1.20
Wind speed (Max)	-0.418	0.062	-6.74	<0.001	1.32
Cloudiness (Mean)	-1.639	0.160	-10.26	<0.001	2.53
Cloudiness (Mean) Hasselt	1.403	0.220	6.37	<0.001	5.85
Cloudiness (Mean) Brussels	1.500	0.208	7.21	<0.001	5.83
Cloudiness (Mean) Seashore	0.000	n.a.	n.a.	n.a.	n.a.
Temperature (Max)	1.034	0.071	14.60	<0.001	4.05
Temperature (Max) Hasselt	-0.619	0.090	-6.86	<0.001	7.46
Temperature (Max) Brussels	-0.792	0.092	-8.64	<0.001	7.00
Temperature (Max) Seashore	0.000	n.a.	n.a.	n.a.	n.a.

n.a.: not applicable (Seashore location used as reference category)

A final overview of the estimated directions between weather conditions and traffic intensity is provided in Table 3.6. Recapitulating one can conclude that snowfall, precipitation, cloudiness and wind speed clearly have a decreasing effect on traffic intensity, whereas temperature and hail increase traffic volumes. Note that whereas snowfall and rain have a decreasing effect on traffic intensity, hail has an increasing effect. The decreasing effect of snowfall and rain may perhaps be explained by the diminished capacity of the highway network, caused by a reduction in speed, whereas the increasing effect of hail might be attributed to the shift towards the car as travel mode due to the unfavorable weather conditions. Finally, there is also some evidence that reduced visibility due to fog and longer sunshine duration increase traffic intensity.

Table 3.6: Summary of relationships between weather conditions and traffic intensity

Weather conditions	Down Hasselt	Up Hasselt	Down Brussels	Up Brussels	Down Seashore	Up Seashore	Overall model
Hail	0	0	+	+	0	0	+
Snowfall	0	0	−	−	0	0	−
Precipitation	−	−	−	−	−	−	−
Temperature (Max)	+	+	+	+	+	+	+
Wind speed (Max)	−	−	−	−	−	−	−
Sunshine duration	0	0	+	+	0	0	0
Reduced visibility	0	0	0	0	+	+	0
Cloudiness (Mean)	−	−	0	0	−	−	−
R-square	0.79	0.69	0.86	0.85	0.65	0.67	0.72

Magnitude of the weather effects

Next to the direction it is also important to assess the magnitude of the weather effects. A first insight is obtained by looking at the Spearman rank correlations (Table 3.2). The highest correlations with traffic intensity are found for maximum temperature and maximum cloudiness and amount of precipitation. Most striking are the considerably larger correlations of weather conditions at the seashore traffic count location.

An overall model was estimated to quantify the influence of weather conditions on traffic intensity. To accommodate for differences in magnitude of the traffic volume between the six traffic count locations (e.g. the magnitude of the traffic volume of downstream traffic in Brussels is almost three times the magnitude of the traffic volume of downstream traffic in the seashore area), the percentages of the traffic volumes, relative to their location specific mean, were modeled instead of the absolute numbers. In order to obtain a parsimonious model, and based on the homogeneity observed in the location-specific models, upstream and downstream traffic locations were combined to estimate interaction effects between weather conditions and traffic count location. Estimates for the weather conditions and corresponding significance tests of this overall model are provided in Table 3.5. Since relative traffic intensity numbers were modeled instead of absolute numbers, the parameter estimates can be directly interpreted as the percentage of change in traffic intensity. When it snows for instance, traffic intensity will on average be 3.822 percent lower than during fine weather.

Dependence of the effects of different weather conditions on the road usage

A first indication that the effects of various weather conditions differ among highways with a divergent road use are the clearly higher correlations (in absolute terms) between weather events and traffic intensity on the seashore highway when compared to the other locations. In contrast to these differences between locations, weather impacts are quite homogeneous when downstream and upstream (denoted as 'down' and 'up') intensities of the same locations are compared.

A similar conclusion can be drawn after investigation of the parameter estimates of the location-specific models: the impact of weather conditions is clearly more homogeneous (size of the effect and similar significant weather variables) between upstream and downstream traffic at a certain location, than between different locations. The heterogeneity (different effect sizes and different significant weather variables) between different locations can be (partially) explained by the underlying travel motives of the road users using these highways. Highways typified by their leisure traffic can be affected more easily than highways that are excessively used by commuters. Underlying reason is the relatively high invariability of work activities (work activities are mandatory activities which can not be easily skipped) compared to the flexibility of adapting leisure activities (leisure activities are non-mandatory and consequently changed more freely).

The hypothesis of dependence of the effects of different weather conditions on the road usage is substantiated by the significant interaction terms in the overall model between location and temperature on the one hand, and between location and cloudiness on the other hand. This underlines the necessity for policy makers to formulate local traffic management strategies next to global strategies.

3.1.5 Conclusions and further research

In this section the impact of various weather conditions on traffic intensity has been investigated. The most striking result for policy makers is the heterogeneity of the weather effects between different traffic count locations, and the homogeneity of the weather effects on upstream and downstream traffic at a certain location. Consequently, traffic management strategies that minimize weather-related side-effects on traffic operations must adopt an approach that takes into account local weather effects.

The results in this section also indicated that precipitation, cloudiness, and wind speed have a clear diminishing effect on traffic intensity, whereas maximum temperature and hail significantly increase traffic intensity. These significant impacts of weather conditions on traffic intensity underline the necessity of incorporating weather conditions in future traffic safety research not only in a direct way, but also indirectly by modeling the effects of weather conditions via traffic intensity. Because of the previously discussed inherent relationship between traffic intensity, weather and traffic safety, the results support the recommendation to develop location specific traffic safety policies next to a global country-wide strategy.

Further generalizations of the findings are possible by studying weather effects on local roads and by shifting the scope towards travel behavior. Linking travel behavior research, traffic flow modeling, and safety research by simultaneously modeling of weather conditions, traffic intensity rates, collision risk and activity travel behavior is certainly a key challenge for further research.

3.2 Impact of weather events on travel behavior

A deeper understanding of how various weather conditions affect traffic is essential for policy makers. This is stressed by policy issues which are often related with adverse weather events such as increased fuel consumption, economic losses due to traffic delays, and higher traffic counts. At the network level, adverse weather events increase the uncertainty in system performance, resulting for instance in a network capacity reduction ranging from 10 to 20% in heavy rain (De Palma & Rochat, 1999). Maze *et al.* (2006) reported that weather events affect three predominant traffic variables: travel demand, traffic safety and the traffic flow relationship. This section focuses on the impact of weather on travel demand.

Weather can influence travel demand in different ways, including diversions of trips to other modes or other paths, or even cancelations of trips (Maze *et al.*, 2006). Day-to-day weather conditions such as fog and precipitation can decrease travel demand, for instance when drivers postpone or cancel discretionary activities (e.g. leisure activities), but can also have an increasing effect when travel modes are shifted from slow modes (walking, cycling) towards motorized vehicles (Hranac *et al.*, 2006). Mode changes, changes in departure time and diversions to alternate route, were reported by Khattak & De Palma (1997) as the most prevalent behavioral adaptations. Bos (2001) indicated that in the Netherlands heavy rain reduces the number of cyclists, whereas mild winters and warm summers increase bicycle use. van Berkum *et al.* (2006) noted that the reduction in bicycle use during heavy rain accompanies a modal shift from bicycle to car (either driver or passenger). A similar result was found by Nankervis (1999), who examined the effect of both (short-term) weather conditions and (long-term) seasonal variation patterns on bicycle commuting patterns among students in the temperate climate of Melbourne, Australia: cycle commuting was affected by long-term, climatic conditions as well as daily weather conditions. According to Guo *et al.* (2007) temperature, rain, snow and wind all influence transit ridership of the Chicago Transit Authority: good weather increases ridership, whereas bad weather has a diminishing effect. Guo *et al.* (2007) also stressed that next to transit ridership, also vehicle running and dwell times, as well as the cost of operation, are affected by weather. In Brussels (Belgium) on the other hand, the transit agency reported higher levels of transit ridership during adverse weather (Khattak & De Palma, 1997).

The main objectives of this section are to test the hypothesis that the type of weather influences the likelihood of a change in travel behavior (e.g. assessing whether more people change their transport mode during snow than during periods of fog) and to assay whether the changes in travel behavior due to weather conditions are dependent on the trip purpose (e.g. examining whether due to snowy weather more people cancel their leisure and shopping trips than school/work related trips). To this end, a stated adaptation study was conducted in Flanders (Dutch speaking region of Belgium).

The remainder of this section is organized as follows. Section 3.2.1 addresses the methodology that has been used throughout the research, followed by a descriptive analysis of the behavioral adaptations enticed by weather conditions in Section 3.2.2. Section 3.2.3 provides the results and corresponding discussion of the statistical analysis of the two hypotheses. Finally, some general conclusions will be formulated and avenues for further research indicated.

3.2.1 Methodology

A stated adaptation approach

The data needed to address the main research questions were collected by means of a stated adaptation experiment. Different definitions about stated adaptation experiments can be found in the literature (Lee-Gosselin, 1996; Faivre D'Arcier *et al.*, 1998; Janssens *et al.*, 2009). In this dissertation, stated adaptation experiments are regarded as an alternative to the more widely used stated preference and choice experiments. The main difference between stated adaptation and stated preference and choice experiments is the task posed to the respondents. In stated preference experiments, respondents are requested to indicate their preference to sequentially presented attribute profiles. In stated choice experiments, respondents are shown choice sets of two or more attribute profiles and are asked to choose the profile they like best (or alternatively allocate some fixed budget among the profile). In stated adaptation experiments, respondents are asked to indicate if and how they would change their behavior considering experimentally varied attribute profiles, typically representing scenarios, in this case the different weather conditions.

In total 586 respondents completed the stated adaptation survey, which was administered both on the Internet (13.3%) and via a traditional paper-and-pencil questionnaire (86.7%). The choice for this dual mode administration was made to remedy the sample bias that is introduced when only an internet-based data collection is conducted. After all, previous studies have demonstrated that some socio-economic classes of society, like older-age and lower-education groups, may be more reluctant towards using computer-assisted instruments for the data collection (Hayslett & Wildemuth, 2004; Couper *et al.*, 2007). In total 90 behavioral adaptations in response to different weather conditions were queried; the frequencies of 5 travel behavior changes in response to 6 weather conditions were surveyed, and this was repeated for 3 types of trips. An elaboration on these different items will be provided in the following subsections.

Weather conditions

The following weather conditions were considered: cold temperature (defined as temperatures below freezing (0° C, 32° F), abbreviated as 'cold'), warm temperature (defined as temperatures above 28° C (82.4° F), abbreviated as 'warm'), snow/freezing rain, heavy rain/thunderstorm (abbreviated as 'rain'), fog and storm/heavy wind. Note that in Section 3.1 it was reported that these weather conditions had a significant impact on daily traffic intensities measured on Belgian highways. Therefore, the decision was made to analyze the impact of these weather conditions on the underlying travel behavior. To provide a better understanding of how frequent these weather events occur, various weather-related measures are provided in Table . In addition, it is noteworthy to mention that in general, Flanders has a moderate maritime climate.

Table 3.7: Weather parameters measured in Uccle[1] (nearby Brussels, Belgium)

Parameter	2007	2008	Normal[2]
Average wind speed (m/s)	3.3 3.4	3.7	
Sunshine duration (h)	1472.0	1449.0	1554.0
Average temperature (°C)	11.5	10.9	9.7
Average maximum temperature (°C)	15.3	14.6	13.8
Average minimum temperature (°C)	7.8	7.2	6.7
Absolute maximum temperature (°C)	30.9	31.0	31.7
Absolute minimum temperature (°C)	-6.8	-6.1	-8.9
Number of freezing days (min $<$ 0°C)	27.0	37.0	47.0
Number of wintry days (max $<$ 0°C)	1.0	0.0	8.0
Number of summery days (max $\geq$ 25 °C)	23.0	25.0	25.0
Number of heat wave days (max $\geq$ 30°C)	2.0	1.0	3.0
Average relative atmospheric humidity (%)	80.0	77.0	81.0
Total precipitation (mm)	879.5	861.5	804.8
Number of days with measurable precipitation ($\geq$ 0.1 mm)	204.0	209.0	207.0
Number of days with thunderstorm	94.0	95.0	94.0

1 Source: Royal Meteorological Institute (2009)

2 Normal: long-term meteorological average (1971-2000)

Changes in travel behavior

The stated adaptation questionnaire was subdivided into three parts, corresponding to the three types of trips that were considered for the analysis. These three types of trips correspond to the categories of most commonly performed trips according to the Flemish travel behavior survey (Zwerts & Nuyts, 2004); namely commuting (work/school), shopping and leisure trips. Equivalent questions were asked in each part: for a certain behavioral change, the respondents had to indicate how often (never, in 1-25% of the cases, in 26-50% of the cases, or in more than 50% of the cases) they make a certain change in travel behavior for each of the six weather conditions. The following changes in travel behavior changes were queried: (i) a change in transport mode, (ii) a change in timing of the trip (postponement/advancing of the trip to a later/earlier moment the same day), (iii) a change in the location where the activity (work/school, shopping or leisure) will be performed, (iv) elimination of the trip by skipping the activity (trip cancellation), and (v) a change in the route of the trip. To illustrate the questionnaire style, Figure 3.3 displays the question concerning the postponement/advancing of work/school-related trips to a later/earlier moment the same day.

Do you postpone or advance your work/school-related trip to a later/earlier moment the same day due to any of the following weather conditions?

Mark the answer that corresponds mostly to your situation. Only ***one*** *answer is possible for* ***each weather condition****.*

	No, never	Yes, occasionally (<25% of the cases)	Yes, sometimes (<50% of the cases)	Yes, usually (>50% of the cases)
Cold temperature	○	○	○	○
Snow/freezing rain	○	○	○	○
Heavy rain/thunderstorm	○	○	○	○
Fog	○	○	○	○
Warm temperature	○	○	○	○
Storm/heavy wind	○	○	○	○

Figure 3.3: Stated adaptation question concerning postponement/advancing work/school-related trip.

Statistical analyses

In order to guarantee an optimal correspondence between the survey sample composition and the Flemish population, the observations in the sample are weighted. The weights were calculated by matching the marginal distributions of the sample with the marginal distributions of the population. Age, sex and civil state were the basis for this matching process. Recall that the main objectives of this section are to test the hypothesis that the type of weather determines the likelihood of a change in travel behavior and to assay whether the changes in travel behavior due to weather conditions are associated with the trip motive. To test these hypotheses, independence tests will be performed.

To test independence (this is the null hypothesis) between two multinomial (categorical) variables one could use the Pearson statistic Q_p, which is defined by the following equation:

$$Q_p = \sum_{i=1}^{k} \sum_{j=1}^{l} \frac{(n_{ij} - \hat{\mu}_{ij})^2}{\hat{\mu}_{ij}}, \tag{3.5}$$

in which n_{ij} is the observed frequency in cell (i,j), calculated by the multiplying the observed chance by the sample size, and $\hat{\mu}_{ij}$ is the expected frequency for table cell (i,j). When the row and column variables are independent, Q_p has an asymptotic chi-square distribution with $(k$ - 1$)(l$ - 1$)$ degrees of freedom (Agresti, 2002).

3.2.2 Descriptive analysis of the changes in travel behavior

Before elaborating on the formal testing of the main hypothesis in Section 4, in this section a descriptive analysis of the behavioral adaptations enticed by weather conditions is provided. First, the changes in commuting (work/school) related trips are discussed. Afterwards, behavioral alterations of shopping trips are examined. Finally, a closer look is taken at the adaptations in leisure trips. To improve readability, conditional probabilities of people making behavioral adaptations are displayed rather than absolute numbers.

Changes in commuting trips

For the commuting (work/school) trips, the percentages of respondents making a certain travel behavior change are displayed in Table 3.8. When the different weather conditions are compared, it is immediately clear that snow has the largest impact on commuting trips. Especially time-of-day decisions (postponing the trip to a later moment) are common practice: more than one person out of two appears to postpone his/her trip in the presence of snow. Next to the timing of the trip, also the route taken is considered to be changed by almost half of the respondents. This major impact of snow on travel behavior is also revealed on the network. Take as an example Hanbali & Kuemmel (1993) who found traffic volume reductions on highways away from the major urban centers in the United States ranging from 7% to 56% depending on the intensity of the snowfall.

Extreme temperatures (both cold and warm temperatures) appear to have the least impact on commuting behavior, whereas storms, fog and heavy rain appear to have an effect mainly on the timing of the trip: people appear to postpone their trips until more favorable weather conditions apply.

When the focus is turned to behavioral changes, it is immediately clear that the work/school location is the least frequently changed. Obviously the main reason is the fact that the locations of work and school sites are relatively fixed. Nonetheless, telecommuting alternatives, satellite offices and e-learning are opportunities making location changes feasible. The most prevalent changes in commuting behavior are changes in the timing of the trip and changes in the route chosen. A possible reason is the fact that people are trying to avoid traffic jams by diverging the paths and departure times of their trips.

Changes in shopping trips

The percentages of respondents making a certain travel behavior change for shopping trips are displayed in Table 3.9. Similarly to commuting trips, the most conspicuous finding from the comparison of the different weather conditions is the fact that snow has the largest impact on shopping trips. Especially time-of-day changes (trip postponements) and trip cancelations are standard: about 70% of the respondents postpone their shopping trip, and the same percentage even cancels their shopping trip.

Next to the effect of snow, also the effects of heavy rain, and heavy winds/storms are very striking: about 60% of the respondents postpone and around half of them cancel their shopping trips during periods of heavy rain, and slightly less pronounced about half of the respondents postpone their shopping trips during stormy periods, whereas 45% cancels their shopping trips.

The comparison of extreme temperatures provides the insight that more people change their transport mode for shopping trips during warm temperatures (above 28° C), than during cold temperatures (below freezing). One explanation could be that people are more enticed to use slow modes (walking, cycling) during highly favorable

Table 3.8: Frequencies of changes in work/school trips due to weather

Change	Frequency	Cold	Snow	Rain	Fog	Warm	Storm
	Never	93.8%	75.8%	84.8%	94.6%	81.6%	86.8%
Mode	1-25%	4.4%	14.6%	7.9%	3.7%	10.5%	8.1%
Change	26-50%	0.9%	2.6%	1.4%	0.1%	4.4%	0.9%
	>50%	0.9%	7.0%	5.9%	1.6%	3.5%	4.2%
	Never	89.5%	47.8%	70.3%	74.0%	94.4%	74.9%
Time-of-day	1-25%	6.0%	23.7%	17.0%	13.7%	2.8%	14.9%
Change	26-50%	2.5%	9.2%	6.9%	6.9%	1.5%	4.7%
	>50%	2.0%	19.3%	5.8%	5.4%	1.3%	5.5%
	Never	96.6%	86.6%	94.4%	97.5%	97.0%	93.3%
Location	1-25%	2.2%	8.4%	3.3%	1.3%	2.0%	4.1%
Change	26-50%	0.6%	3.0%	1.0%	0.5%	0.8%	1.1%
	>50%	0.6%	2.0%	1.3%	0.7%	0.2%	1.5%
	Never	96.2%	75.4%	93.8%	95.3%	89.0%	92.6%
Trip	1-25%	3.4%	19.4%	5.0%	4.3%	10.1%	6.1%
Cancelation	26-50%	0.4%	4.1%	0.2%	0.4%	0.9%	0.7%
	>50%	0.0%	1.1%	1.0%	0.0%	0.0%	0.6%
	Never	90.5%	56.4%	85.0%	85.4%	96.4%	87.1%
Route	1-25%	6.3%	26.7%	9.9%	10.0%	2.4%	8.4%
Change	26-50%	1.8%	9.8%	2.5%	1.5%	0.9%	2.7%
	>50%	1.4%	7.1%	2.6%	3.1%	0.3%	1.8%

weather conditions. This is in line with the results of Bos (2001) who found an increase in bicycle use during warm summers.

The most prevalent changes in shopping related travel behavior are trip postponements and trip cancelations. Extreme weather conditions appear to cause serious changes in the activities people want to perform. When the overall results of shopping trips are compared with commuting trips, a considerable larger percentage of people changes their shopping related travel behavior than their commuting behavior. This can be explained by the fact that it is much easier to postpone/cancel discretionary activities as opposed to mandatory activities, which is also observed on the Flemish highway network (Cools *et al.*, 2008).

Table 3.9: Frequencies of changes in shopping trips due to weather

Change	Frequency	Cold	Snow	Rain	Fog	Warm	Storm
	Never	91.5%	78.2%	85.6%	91.9%	79.7%	86.8%
Mode	1-25%	5.2%	11.2%	6.0%	4.4%	10.2%	6.5%
Change	26-50%	1.4%	3.4%	2.2%	0.8%	4.9%	1.6%
	>50%	1.9%	7.2%	6.2%	2.9%	5.2%	5.1%
	Never	80.2%	29.4%	41.8%	59.9%	80.0%	47.7%
Time-of-day	1-25%	13.1%	28.2%	24.1%	19.2%	13.0%	22.8%
Change	26-50%	3.9%	16.9%	13.6%	11.4%	4.2%	13.7%
	>50%	2.8%	25.5%	20.5%	9.5%	2.8%	15.8%
	Never	86.8%	54.0%	68.4%	72.2%	83.7%	69.3%
Location	1-25%	7.4%	20.6%	12.6%	11.9%	10.5%	13.7%
Change	26-50%	2.8%	9.4%	10.7%	8.8%	2.6%	10.0%
	>50%	3.0%	16.0%	8.3%	7.1%	3.2%	7.0%
	Never	86.7%	31.9%	48.4%	64.4%	82.6%	55.0%
Trip	1-25%	7.1%	33.7%	29.3%	20.4%	13.3%	23.3%
Cancelation	26-50%	3.0%	14.5%	11.6%	8.8%	2.7%	11.6%
	>50%	3.2%	19.9%	10.7%	6.4%	1.4%	10.1%
	Never	93.1%	58.8%	81.7%	80.6%	93.3%	81.7%
Route	1-25%	4.5%	23.2%	11.0%	11.3%	4.7%	10.7%
Change	26-50%	1.4%	10.3%	3.7%	4.8%	0.5%	4.6%
	>50%	1.0%	7.7%	3.6%	3.3%	1.5%	3.0%

Changes in leisure trips

For the final category of trips that were considered, namely leisure trips, the percentages of respondents making a certain travel behavior change are shown in Table 3.10. Yet again snowy weather has the largest impact. Similar to shopping trips, trip postponements and trip cancelations are the most frequent change in travel behavior: about 65% of the respondents postpone their leisure trip, and the same number cancels their leisure trip.

Apart from the effect of snow, heavy rain, and heavy wind/storms are also clearly influencing leisure-related travel behavior: about 45% of the respondents postpone and a similar percentage cancel their leisure trips during periods of heavy rain or periods with heavy wind. The effect of extreme temperature on leisure trips is very similar to the effect on shopping trips: more people alter their transport mode for leisure trips during warm temperatures, than during cold temperatures. The resemblances between shopping and leisure trips are further underlined when the most prevalent changes in leisure trips are discussed: trip postponements and trip cancelations are also the most frequent performed changes in leisure related travel behavior. The homogeneity between the behavioral changes concerning and leisure trips and shopping trips can be explained by the fact that both leisure and shopping activities are discretionary activities. As noted earlier, these activities are much more flexible, and consequently easier to adapt than mandatory activities such as school and work.

Table 3.10: Frequencies of changes in leisure trips due to weather

Change	Frequency	Cold	Snow	Rain	Fog	Warm	Storm
	Never	89.9%	74.4%	83.9%	87.3%	77.3%	85.6%
Mode	1-25%	7.7%	13.5%	8.9%	8.1%	11.7%	8.7%
Change	26-50%	1.2%	3.8%	3.1%	3.5%	6.4%	3.0%
	>50%	1.2%	8.3%	4.1%	1.1%	4.6%	2.7%
	Never	85.3%	35.1%	54.3%	61.8%	85.3%	58.6%
Time-of-day	1-25%	10.5%	30.9%	26.1%	21.3%	11.5%	20.1%
Change	26-50%	2.0%	15.0%	12.7%	9.2%	2.0%	13.0%
	>50%	2.2%	19.0%	6.9%	7.7%	1.2%	8.3%
	Never	83.3%	70.9%	75.1%	81.5%	83.9%	74.1%
Location	1-25%	9.9%	14.1%	11.3%	9.3%	10.0%	13.1%
Change	26-50%	2.8%	6.5%	6.3%	5.3%	3.3%	6.5%
	>50%	4.0%	8.5%	7.3%	3.9%	2.8%	6.3%
	Never	79.3%	35.6%	56.1%	66.1%	82.2%	55.3%
Trip	1-25%	14.4%	34.0%	24.2%	20.2%	13.9%	23.5%
Cancelation	26-50%	4.1%	13.8%	9.6%	8.0%	3.0%	12.1%
	>50%	2.2%	16.6%	10.1%	5.7%	0.9%	9.1%
	Never	92.8%	55.1%	76.4%	78.6%	94.3%	76.9%
Route	1-25%	4.4%	24.4%	13.9%	13.5%	3.6%	12.4%
Change	26-50%	2.1%	11.9%	5.9%	4.5%	1.2%	6.9%
	>50%	0.7%	8.6%	3.8%	3.4%	0.9%	3.8%

3.2.3 Statistical analysis of the changes in travel behavior

The descriptive results in the previous section gave a clear indication that changes in travel behavior in response to weather conditions are dependent on the type of weather condition. Moreover, the results suggested that the behavioral changes were strongly dependent on the underlying activity. In this section, these two hypotheses are formally tested using Pearson chi-square independence tests. First, the statistical analysis of the hypothesis that the type of weather determines the likelihood of a change in travel behavior is provided. Afterwards, an elaboration on the test of the hypothesis that changes in travel behavior due to weather conditions are dependent on the trip purpose is given. Note that multiple testing is accounted for by lowering the significance level in a Bonferroni-like approach.

Dependence of changes in travel behavior on type of weather

For each activity (trip purpose), the dependency between the change in travel behavior and the type of weather was formally tested. Table 3.11 shows the chi-square values, degrees of freedom (DF) and corresponding significance levels of the different tests. First, for each activity, the dependency between all travel behavior changes and weather conditions was tested. Afterwards, the dependencies of the specific travel behavior changes and weather conditions were assessed.

A first conclusion that can be drawn from Table 3.11 is the fact that all behavioral changes are highly depending on the type of weather (the null hypothesis of independence is rejected for all behavioral changes with a p-value smaller than 0.001). Similar to the preliminary conclusions drawn from the descriptive results, for work/school related trips, trip postponement (time-of-day change) and route changes are the strongest depending on the weather type, whereas for shopping and leisure trips, the relationship is the most significant (higher chi^2-value, same degrees of freedom) for trip postponements and trip cancelations. Although highly significant (p-value smaller than 0.001) the interdependence between changes in travel behavior and type of weather was smallest for location and mode changes.

Recall that the number of degrees of freedom is calculated by multiplying the number of rows minus one by the number of columns minus one. For the dependence of specific travel behavior changes on weather conditions the independence test followed a chi-square distribution with 15 degrees of freedom: 4 frequencies (the number of people who would never change their behavior, and respectively the ones that change their behavior in 1-25%, 26-50% and more than 50% of the cases) minus one multiplied by 6 weather conditions minus one. Since the underlying assumption of the independence test (minimum 80% of the cells expected counts should be at least equal to 5) was not fulfilled for the hypothesis test that assessed the relationship between trip cancelations of commuting trips and weather conditions, an alternative independence test was tabulated by combining the three categories of people that change their behavior. As a result the number of degrees of freedom for this test was smaller than for the other test, as could be noticed from Table 3.11.

Table 3.11: Dependence of behavioral changes on weather

Trip Purpose	Behavioral Change	Chi^2	DF	Signif. [1]
Work/School	All Changes	1185.75	95	⋆⋆⋆
	Mode Change	138.71	15	⋆⋆⋆
	Time-of-day Change	409.05	15	⋆⋆⋆
	Location Change	81.12	15	⋆⋆⋆
	Trip Cancelation [2]	174.79	5	⋆⋆⋆
	Route Change	362.56	15	⋆⋆⋆
Shopping	All Changes	1728.89	95	⋆⋆⋆
	Mode Change	92.24	15	⋆⋆⋆
	Time-of-day Change	542.97	15	⋆⋆⋆
	Location Change	235.69	15	⋆⋆⋆
	Trip Cancelation	555.65	15	⋆⋆⋆
	Route Change	302.34	15	⋆⋆⋆
Leisure	All Changes	1456.24	95	⋆⋆⋆
	Mode Change	107.92	15	⋆⋆⋆
	Time-of-day Change	522.45	15	⋆⋆⋆
	Location Change	62.85	15	⋆⋆⋆
	Trip Cancelation	405.26	15	⋆⋆⋆
	Route Change	357.76	15	⋆⋆⋆

1 Significance: ⋆ p-value < 0.05, ⋆⋆ p-value < 0.01, ⋆⋆⋆ p-value < 0.001

2 Estimated using reduced answer possibilities (Yes/No)

Dependence of changes in travel behavior on trip purpose

To test the dependence of changes in travel behavior on activity type (trip purpose), first independence tests are performed on an aggregate level (aggregation over all travel behavior changes). Table 3.12 displays the chi-square values, degrees of freedom (DF) and corresponding significance levels of these tests.

In line with the tests assessing the dependence of changes in travel behavior on the type of weather, also for the dependence of changes in travel behavior on trip purpose confirm the preliminary conclusions drawn from the descriptive results: the extent to which people adapt their travel behavior is strongly dependent (all p-values smaller than 0.001) on the trip purpose. This dependence appears to be the largest for periods of heavy rain, snow and heavy wind. For extreme temperatures these dependency appears to be smaller (lower chi-square value and same number of degrees of freedom), yet still highly significant.

Table 3.12: Dependence of behavioral changes on trip purpose (aggregate level)

Weather	Behavioral Change	Chi^2	DF	Signif. [1]
All Types	All Changes	2180.35	238	⋆⋆⋆
Cold	All Changes	165.69	38	⋆⋆⋆
Snow	All Changes	473.46	38	⋆⋆⋆
Rain	All Changes	550.80	38	⋆⋆⋆
Fog	All Changes	382.66	38	⋆⋆⋆
Warm	All Changes	144.80	38	⋆⋆⋆
Storm	All Changes	462.94	38	⋆⋆⋆

1 Significance: ⋆ p-value < 0.05, ⋆⋆ p-value < 0.01, ⋆⋆⋆ p-value < 0.001

In order to further investigate the dependence of the changes in travel behavior on trip purpose a more detailed analysis is performed: for all six weather conditions, the dependence of the specific behavioral changes on trip purpose was investigated. Different conclusions could be drawn from this disaggregate analysis. First, one could note that for all weather conditions time-of-day changes (trip postponements), location changes and trip cancelations were significantly depending on trip purpose (p-values all smaller than 0.01 and for location changes even all smaller than 0.001). In addition, all behavioral changes in response to fog and heavy wind/storm were statistically significantly depending on the trip purpose (p-values all smaller than 0.05).

A thorough look at the effect of cold and warm weather, as well as snow, provides the insight that the extents to which people change their mode or route in response to these weather conditions are not depending on the trip purpose. Furthermore, inspection of Table 3.13 reveals that for all weather conditions (except warm weather) the highest dependency of behavioral changes on trip purpose was found for trip cancelations. A possible reason explaining this contrast with warm weather conditions is the fact that all other weather conditions are considered to be unfavorable weather conditions, whereas high temperatures may be considered as favorable, at least for some part of the population.

3.2.4 Conclusions and avenues for further research

In this section the hypothesis of dependence of changes in travel behavior on type of weather on the one hand, and the hypothesis of dependence of changes in travel

Table 3.13: Dependence of behavioral changes on trip purpose (disaggregate level)

Weather	Behavioral Change	Chi^2	DF	Signif. [1]
Cold	Mode Change	9.03	6	n.s.
	Time-of-day Change	21.24	6	$\star\star$
	Location Change	50.88	6	$\star\star\star$
	Trip Cancelation	79.41	6	$\star\star\star$
	Route Change	5.12	6	n.s.
Snow	Mode Change	5.07	6	n.s.
	Time-of-day Change	49.55	6	$\star\star\star$
	Location Change	143.46	6	$\star\star\star$
	Trip Cancelation	271.33	6	$\star\star\star$
	Route Change	4.06	6	n.s.
Rain	Mode Change	9.93	6	n.s.
	Time-of-day Change	129.11	6	$\star\star\star$
	Location Change	120.21	6	$\star\star\star$
	Trip Cancelation	275.88	6	$\star\star\star$
	Route Change	15.68	6	$\star$
Fog	Mode Change	42.05	6	$\star\star\star$
	Time-of-day Change	30.06	6	$\star\star\star$
	Location Change	126.67	6	$\star\star\star$
	Trip Cancelation	170.08	6	$\star\star\star$
	Route Change	13.80	6	$\star$
Warm	Mode Change	5.41	6	n.s.
	Time-of-day Change	54.24	6	$\star\star\star$
	Location Change	58.03	6	$\star\star\star$
	Trip Cancelation [2]	11.59	2	$\star\star$
	Route Change [2]	5.15	2	n.s.
Storm	Mode Change	13.15	6	$\star$
	Time-of-day Change	97.85	6	$\star\star\star$
	Location Change	104.97	6	$\star\star\star$
	Trip Cancelation	225.54	6	$\star\star\star$
	Route Change	21.42	6	$\star\star$

1 Significance: $\star$ p-value < 0.05, $\star\star$ p-value < 0.01, $\star\star\star$ p-value < 0.001

2 Estimated using reduced answer possibilities (Yes/No)

behavior on trip purpose (activity type) on the other hand were formally tested. Both the results from the descriptive analysis and the Pearson chi-square independence tests confirmed that indeed the type of weather condition matters, and that the changes in travel behavior in response to these weather conditions are highly dependent on the trip purpose.

Whereas the majority of the papers in international literature focus on traffic safety and traffic flows, this dissertation contributes to the literature by looking at the actual underlying travel behavior by means of a multifaceted stated adaptation approach. The clear dependence of behavioral adjustments on activities (trip purposes) provides policy makers with a deeper understanding of how weather conditions affect traffic. The value of this contribution is stressed by weather related policy issues such as increased fuel consumption, economic losses due to traffic delays, and higher traffic counts.

The findings in this section are consonant with international literature and provide a solid base for further analysis of weather-related policy measures, such as for instance whether extreme weather conditions cause last minute changes in travel mode and the assessment whether high quality bus shelters do make differences in last minute mode changes. Further generalizations of the findings are possible by shifting the scope towards revealed travel behavior and by braking down the modal changes to different transport modes. Triangulation of both stated and revealed travel behavior on the one hand, and traffic intensities on the other hand, is certainly a key challenge for further research.

Part II

Translation of findings into transportation models

Chapter 4

The need for transportation models

The research reported in this chapter is mainly based on Cools* et al. *(2010c).

As outlined in the introduction, in the second part of this dissertation, the effects of holidays and weather events on travel behavior are translated into transportation models. In particular, the accommodation of transportation to behavior dynamics based on learning allow for the incorporation of effects such as holiday effects and weather effects. In this Chapter, first, an overview of transportation models is provided, whereby the focus is put on the increase in behavioral realism. Afterwards, a dilation on the framework of "travel behavior dynamics based on learning" is provided. Finally, the need for transportation models is underlined by assessing the quality of origin-destination (OD)-matrices derived from household activity-travel surveys by means of a Monte Carlo experiment.

4.1 An increased behavioral realism in transportation models

4.1.1 Towards an increased behavioral realism

Due to an increased environmental awareness, current travel demand models pursue higher levels of behavioral realism. Four periods can be distinguished in this evolution of travel demand modeling approaches: the origin of conventional four-step models, the development of tour-based models, the evolution towards the activity-based approach, and the rise of integrated dynamic modeling frameworks.

The first period, the late 1950's, is a period typified by a steep increase in car use. During this period, trip-based models were developed to make long term projections of travel demand in order to assess major investments in road infrastructure. These first generation models assumed that travel is the result from four consecutive steps, namely trip generation (prediction of the total number of trips generated and attracted to each zone in the study area), trip distribution (partitioning of the predicted trips between all origin-destination pairs), mode choice (assessment of the transport mode for each trip) and route choice (assignment of trips to particular routes on the transport network) (Jovicic, 2001).

From the mid 1970's until the 1990's, the focus shifted towards the travel needs of a single person. The original four-step models were replaced by theories about utility maximizing behavior and individual choice behavior. Discrete choice models such as multinomial logit models and more advanced statistical techniques (e.g. nested logit and probit models) formed the core of so-called tour-based systems (Daly *et al.*, 1983; Ben-Akiva & Lerman, 1985). In the tour-based model, trips are explicitly connected in tours, i.e. chains that start and end at the same home or work base. This is done by introducing spatial constraints and by directions of movement.

From the mid 1990's and early 2000's, activity-based travel demand models became a rising modeling paradigm. The basic premise of these third generation models is the fact that travel behavior is a derivative from the activities that an individual performs (Jovicic, 2001). The intellectual roots of this model paradigm are the contributions of Hägerstrand (1970), Chapin (1974) and Fried *et al.* (1977). Hägerstrand (1970) has put forward the time-geographic approach that characterizes a list of constraints on activity participation. Chapin (1974) has identified patterns of behavior across time and space. Fried *et al.* (1977) have dealt with the social structure and the question of why people participate in activities. These contributions came together in a study of Jones *et al.* (1983), in which activities and travel behavior were integrated. This was the first initial attempt to model complex travel behavior.

Current dynamic activity-based models, such as Aurora and Feathers (Joh *et al.*, 2004; Arentze *et al.*, 2006), taking into account different forms of learning, and integrated land-use activity-based models, such as URBANSIM (Waddell, 2002; Waddell *et al.*, 2003) and CEMUS (Eluru *et al.*, 2008; Lin *et al.*, 2008) could be seen as a fourth generation of travel demand models.

Figure 4.1 shows the (conceptual) relationship between the behavioral realism captured in transportation models and the computation complexity. As the figure shows, the cost in terms of model complexity increases exponentially as the models advances, whereas the benefits in terms of behavioral realism are increasing at a decreasing rate. For activity-based models to have the required behavioral realism, they need to be theoretically sound, and at a sufficient resolution to explain policy impacts. The ideal activity-based model should consider activity participating along a continuous time dimension capturing time use and allocation behavior with explicit consideration of constraints by the spatial, temporal, and social dimension, accounting for interdependency among individual in the households, among trips, and trip chaining. To better understand activity behavior there is a need to analyze also the context of the activities including the why, when, with whom, and the duration and sequence of those activities. It also requires a detailed understanding of how households and individual acquire and assimilate information about their opportunities for activity participation and travel options, how this information is used to determine time allocation for activities and travel, and whether the attributes of activity episodes are determined jointly or sequentially (Shiftan & Ben-Akiva, 2006).

4.1.2 Motivations for using activity-based models

Disadvantages of four-step models

Conventional four-step (trip-based) models are limited due to the fact that although the models may be estimated at the individual or household level, the application of the models require to be done at the (traffic analysis) level. Therefore, several drawbacks coincide with four-step models (Davidson *et al.*, 2007):

- The models cannot keep linkages between the travel decisions of members of a single household. Yet, research has shown that interactions among family members, whether coordinating the use of household vehicles, sharing household responsibilities or performing joint activities, often affects and in many cases largely determine people's travel.

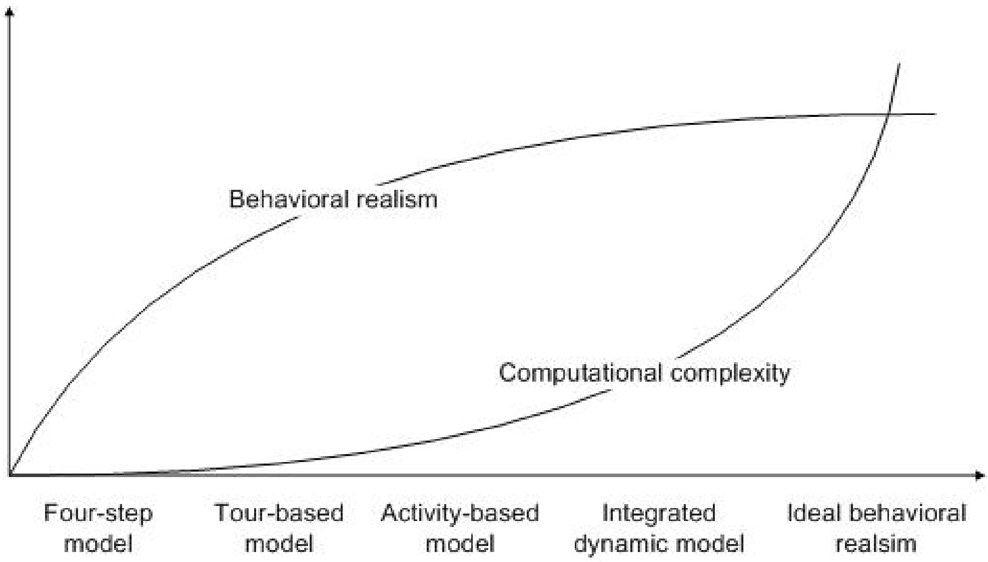

Figure 4.1: Behavioral realism and computational complexity in travel demand models

- The models do not predict consistent choices for a single person across all travel decisions. Although the four-step model paradigm implies that travel decisions are made sequentially, in fact it cannot model these decisions as conditioned by prior choices. This has resulted in inconsistencies and it also precludes the models from examining complex yet common mode choice behavior, such as when two or more people are carpooling towards work, but return back home by different and separate means.
- The models cannot incorporate disaggregate time of day travel decisions, which are important for predicting the effect of congestion relief policies. Prediction of the time of day for travel must necessarily be based upon the individual's time-space constraints and examined within the context of his/her daily activity schedule. Only in this fashion can a feasible set of schedule choices be constructed, and by extension it is by examining how different policies affect this choice set that the effect of congestion relief policies be realistically studied.

So one can conclude that four-step models suffer from multiple aggregation errors (Walker, 2005; Davidson *et al.*, 2007):

- *Spatial aggregation*: All trip origins and destinations within a given zone are modeled as if they are located at the same point in space.

- *Demographic aggregation*: All households within a given zone are treated as identical, or, at best, segmented along a few dimensions such as income, household size and car ownership.

- *Temporal aggregation*: Typically, only two or three periods of the day are considered (e.g. AM peak hour, PM peak hour, off-peak), and the proportion of trips made in each period is treated as constant and not sensitive to changes in traffic congestion or other factors.

Advantages of activity-based models

When describing activity-based models, three important and positive features can be highlighted. The first positive feature is that the model core is an *activity-based platform*. This implies that modeled travel is derived within the general framework of the daily activities undertaken by households and persons, including in-home activities, intra-household interactions, time allocation for activities and many other aspects pertinent to activity analysis, but typical missing in convention four-step models.

The second desirable property is the tour-based structure, in which the tour - a closed chain of trips starting and ending at the base location (home or workplace) - is used as the base unit of modeling travel instead of a trip. This structure preserves a consistency across trips included into the same tour.

The third favorable feature is the fact that the models use micro-simulation modeling techniques that are applied at the fully-disaggregate level of persons and households. Explicitly modeling of a full lists of households in stead of zonal strata of households with identical attributes avoids numerous aggregation biases that arise in the conventional modeling framework. It allows for more realistic and consistent linkages across travel choices made by the individuals in a course of a day. Three major advantages coincide micro-simulation (Vovsha *et al.*, 2002):

1. substantial savings in the calculation of multidimensional fractional-probability arrays,

2. explicit formulation of various chained decisions and time-space constraints on individual travel behavior,

3. explicit modeling variability of travel demand rather than average values.

4.1.3 Operational activity-based platforms

After having discussed the evolution towards and motivation for activity-based modeling approaches in the previous sections, this section will focus on operational activity-based platforms and some of their main characteristics. Henson *et al.* (2009) distinguish ten different activity-based paradigms, displayed in Table 4.1. Note that only nine paradigms are displayed in Table 4.1 as the paradigms ‘Psychometric Hazards Risk’ and ‘Psychometric Cognitive’ are merged into the category ’Psychometric’.

Table 4.1: Activity-based model paradigms

Model	Cellular Automata	Constraint-based	Computational Process Models	Data-Statistical Distribution	Econometric Utility-Based	Frame-work	Micro-Simulation	Operations Research	Psychometric
ADAPTS[1]			X			X			
Adler & Ben-Akiva[2]				X					
Alam-PSEM[3]				X					
ALBATROSS[4]			X				X		
AMOS[5]		X					X		
AURORA[6]		X			X				
CARLA[7]		X							
CATGW[8]					X				
CEMDAP[9]					X		X		
CentreSIM - medoid[10]				X					
CentreSIM - regional[11]				X					
COBRA[12]					X				
COMRADE[13]									X
DEMOS[14]				X			X		
FAMOS[15]		X	X				X		
FEATHERS[16]		X	X		X		X		
GISICAS[17]		X	X						X
HAPP[18]		X						X	
Hayes-Roth[19]			X						X
ILUTE[20]			X		X		X		
Jakarta[21]					X		X		

Table continued on the following page

Table continued from the previous page

Model	Cellular Automata	Constraint-based	Computational Process Models	Data-Statistical Distribution	Econometric Utility-Based	Frame-work	Micro-Simulation	Operations Research	Psychometric
Kawakami & Isobe[22]		X		X					
LATP/DATS[23]		X		X			X		
MASTIC[24]		X		X					
MatSIM[25]					X		X		
MERLIN[26]			X				X		
MIDAS[27]					X		X		
MORPC[28]				X			X		
NYBPM[29]				X			X		
PATRICIA[30]				X	X				
PCATS[31]		X			X				
PESASP[32]		X							
PETRA[33]				X					
Portland[34]				X					
PUMA[35]		X			X				
RAMBLAS[36]		X		X			X		
San Francisco[37]				X			X		
SCHEDULER[38]		X	X			X			X
SIMAP[39]				X			X		
SMART[40]						X			
SMASH[41]			X		X				
STARCHILD[42]		X			X				

Table continued on the following page

Table continued from the previous page

Model	Cellular Automata	Constraint-based	Computational Process Models	Data-Statistical Distribution	Econometric Utility-Based	Frame-work	Micro-Simulation	Operations Research	Psychometric
TASHA[43]			X	X	X		X		
Tel Aviv[44]					X				
TRANSIMS[45]	X						X		
Vause[46]			X						
VISEM[47]				X					
Wen & Koppelman[48]				X					

1: Auld & Mohammadian (2009), 2: Adler & Ben-Akiva (1979), 3: Alam & Goulias (1999), 4: Arentze *et al.* (2000) and Arentze & Timmermans (2004)

5: Kitamura *et al.* (1996), 6: Timmermans *et al.* (2001) and Joh *et al.* (2004), 7: Jones *et al.* (1983), 8: Bhat & Singh (2000), 9: Bhat *et al.* (2004a)

10: Pribyl & Goulias (2005), 11: Kuhnau & Goulias (2003), 12: Wang & Timmermans (2000), 13: Ettema *et al.* (1995), 14: Sundararajan & Goulias (2003)

15: Pendyala *et al.* (2005), 16: Arentze *et al.* (2006), 17: Kwan (1997), 18: Recker (1995) and Gan & Recker (2008), 19: Hayes-Roth & Hayes-Roth (1979)

20: Salvini & Miller (2005), 21: Yagi & Mohammadian (2008), 22: Kawakami & Isobe (1989), 23: Ma (1997), 24: Dijst & Vidakovic (1997)

25: Balmer *et al.* (2006), 26: van Middelkoop *et al.* (2004), 27: Goulias & Kitamura (1992), 28: Vovsha *et al.* (2003), 29: Vovsha *et al.* (2002)

30: Borgers *et al.* (2002), 31: Kitamura (1997), 32: Lenntorp (1976), 33: Fosgerau (2002), 34: Bowman *et al.* (1998), 35: Ettema *et al.* (2007b)

36: Veldhuisen *et al.* (2000b) and Veldhuisen *et al.* (2000a), 37: Jonnalagadda *et al.* (2001), 38: Gärling *et al.* (1989), 39: Kulkarni & McNally (2001)

40: Stopher *et al.* (1996), 41: Ettema *et al.* (1996) and Joh *et al.* (2008), 42: Recker *et al.* (1986) and Recker *et al.* (1986b)

43: Miller & Roorda (2003), and Roorda *et al.* (2008), 44: Shiftan & Ben-Akiva (2006), 45: Rilett (2001) and Nagel *et al.* (2003), 46: Vause (1997)

47: Fellendorf *et al.* (1997), 48: Wen & Koppelman (2000)

Next to the different modeling philosophies underlying the activity-based modeling frameworks, the models can also be categorized based on the behavioral units the spatial and temporal resolution. Two characteristics of the behavioral units that are modeled are of crucial important: the groups modeled (i.e. workers, college students, adults, partial households, or entire households) and the decision makers (i.e. individuals, households, specific groups, workers, or homogeneous population groups). For an extended discussion of the different activity-based modeling approaches, the reader is referred to Henson & Goulias (2006), Henson *et al.* (2009) and Goulias (2009).

4.1.4 Travel behavior dynamics based on learning

As noted in Section 4.1.1 current dynamic activity-based models, such as Feathers (Arentze *et al.*, 2006), taking into account different forms of learning could be seen as a fourth generation of travel demand models. In particular, Feathers integrates two types of travel behavior dynamics, namely travel behavior dynamics based on learning and travel behavior dynamics based on short-term adaptations. For the translation of the findings reported in the first part of this dissertation, the dynamics based on learning are of particular interest. Further clarification provided in this Section are for the largest part based on Janssens *et al.* (2007).

The learning framework within Feathers was developed with a multi-agent modeling approach in mind: in the model, individuals and households are represented as "agents". These agents act on the basis of behavioral principles and mechanisms. They are assumed to hold beliefs about their environment. They have plans and agendas, learn about the environment and the consequences of their behavior and hence can adapt to changing circumstances and to ineffective behavior. The framework is based on the Aurora model (Joh *et al.*, 2004), which simulates the (re)scheduling of activities and related travel across the day, and principles of learning and adaptation in non-stationary, uncertain urban and transportation environments, with mechanisms for implementing schedules.

The multi-agent simulation starts with the creation of a synthetic population. It is assumed that each agent schedules his activities across various time horizons. The scheduling of activities is a function of the utility derived from conducting activities, reflecting amongst others the nature of the activity (mandatory versus discretionary), and the priority of conducting an activity as a function of its history. Furthermore, it is assumed that at the start of the day, every agent has a set of (partly) scheduled activities that he plans to conduct during that day. This schedule is based on a mental processing of the plan, based on previous experiences with the environment. However, because the environment and the transportation system are inherently uncertain, the actual implementation of the activity-travel schedule may deviate from the plan, implying that some activities may need to be rescheduled. That is, the duration of certain activities may need to be changed or other choice facets of the schedule (destination, route, etc) need adjusting, or one of more planned activities should be dropped altogether and rescheduled for another day.

Agents will learn about their environment based on the deviation between planned and actual schedules. They will develop beliefs about travel times along links and paths in the transportation network, and they will experience new potential destinations and update their beliefs about the attributes of the destinations. With increasing experience, they will learn about the conditions under which certain states of the system are more likely, and we assume that in order to better understand and make sense of the world around them, these cognitions will be adjusted as part of conditional learning processes.

It is assumed that agents build up their beliefs by learning in a variety of ways. First, it is presumed that when implementing their activity schedules, agents will learn about the attributes or states of their environment (e.g. travel times) from experiences. Experiences with respect to the state of a variable will change the subjective probabilities and hence the agent's beliefs. If the actual situation is consistent with outcomes perceived as most probable, uncertainty in beliefs will be reduced and the individual will be more confident in predicting outcomes on future occasions. In contrast, if outcomes are contrary to expectations, uncertainty will increase and difficulty of prediction and perceived value of information of future events increases. This type of learning is denominated as "attribute learning". Secondly, it is postulated that agents have an inherent desire to make sense of the world around them. One of the mechanisms involved is to identify the conditions that allow them to explain away differences in attributes of the environment. This type of learning is called "conditional learning". For example, differences in travel times can be explained in terms of day of the week, departure time, weather conditions, an accident, etc. Note that these conditions correspond to the events unraveled in the first part of this dissertation. The condition set is not necessarily constant over time, but may grow or shrink. Learning about changes in the condition set is named "condition learning". The incorporation of only the last two forms of learning (conditional and condition learning) would imply that only after a substantial amount of personal experiences, agents will have gained sufficient knowledge about their environment. Therefore, it is postulated that agents also are capable of "analogue" learning and reasoning: they draw inferences about attributes of certain objects in analogy to other similar objects. In addition, agents will be actively or passively exposed to information, and hence learn from such information. Such learning is not based on own personal observations and experiences, but on information provided by external sources (news media, information sources). Finally, in addition to these personal styles of learning, it is presupposed that agents learn from being part of a social network: they learn from word of mouth from members of their social network. The learning dynamics are implemented within the Feathers framework by means of Bayesian updating (Janssens *et al.*, 2007).

Bayesian updating is used for these various forms of learning. For example, as for attribute learning, due to non-stationarity, an agent will experience different travel times on successive occasions for the same trip. We assume that agents mentally classify travel times into a set of states, and develop beliefs (subjective probabilities) about the occurrence of these states.

4.2 Monte Carlo sample size experiment

In the modern cosmopolite society, travel is a cornerstone for human development, both for personal and commercial reasons: travel is not only regarded as one of the boosting forces behind economic growth, but is also seen as a social need providing people the opportunity for self-fulfillment and relaxation. As a result of the continuous evolution of modern society (e.g. urban sprawl, increasing female participation in labor, decline in traditional household structures), transportation challenges have accrued and have become more complex (Haustein & Hunecke, 2007). Consequently, combating environmental (e.g. greenhouse-emissions such as CO_2, methane, NOx; noise, odor annoyance and acid precipitation), economic (e.g. use of nonrenewable energy sources; and the time lost due to congestion) and societal (e.g. health problems such as cardiovascular and respiratory diseases; traffic casualties; community severance and loss of community space) repercussions is a tremendous task (Steg, 2003).

To support policy makers in addressing these externalities, quality data are required for the design and management of transportation systems and policies (TRB Committee on Travel Survey Methods, 2009). To this end, during the last four decades, large amounts of money have been spent on collecting household and person-based data. For most metropolitan areas, the largest part of planning budgets (an estimated $7.4 million per year) was devoted to the conduct of household and person travel surveys (Stopher *et al.*, 2008). The data collected by these surveys are used for a wide variety of applications, including traffic forecasting (an overview of different transportation models was given in the previous section), transportation planning and policy, and system monitoring (TRB Committee on Travel Survey Methods, 2009).

The main objective of this section is to assess the quality of origin-destination matrices derived from travel surveys. Mark that origin-destination matrices are core components in both traditional four-step and modern activity-based travel demand models. A sample size experiment is set up to estimate the precision of the OD-matrices given different sampling rates. Thus, an assessment of the appropriateness of travel surveys for deriving origin-destination relations can be made. Note that different types of travel surveys exist: Cambridge Systematics (1996) distinguished seven different commonly used types of surveys (household activity/travel surveys; vehicle intercept and external surveys; transit onboard surveys; commercial vehicle surveys; workplace and establishment surveys; hotel/visitor surveys; and parking surveys). Each of these survey types provides a unique perspective for input into travel demand models. In this section, the term 'travel survey' is confined to the first category, namely the household activity/travel surveys.

In a household activity/travel survey, respondents are queried about their household characteristics, the personal characteristics of the members of the household, and about recent activity/travel experiences of some or all household members. For most regions, household activity/travel surveys remain the best source of trip generation and distribution data, and therefore, are an important building block for travel demand models. In addition to model building purposes, these surveys are also used to survey specific target populations (such as transit users and non-users), to assess the potential demand and level of public support for major infrastructure projects, and to create a deeper understanding of travel behavior in the region (Cambridge Systematics, 1996). For a more elaborate discussion concerning travel surveys the reader is referred to TRB Committee on Travel Survey Methods (2009), Cambridge Systematics (1996) and Tourangeau & Ghadialy (1997). Recent trends in household travel surveys are discussed by Stopher & Greaves (2007).

The remainder of this section is organized as follows. Section 4.2.1 provides an extended discussion on the set-up of the sample size experiment. The relationship between sampling rates and the precision of a general statistic (i.e. the proportion of the commuting population) is highlighted in the first part of Section 4.2.2. The second part of Section 4.2.2 provides the results and corresponding discussion of the statistical analysis of the main sample size experiment. Finally, some general conclusions will be formulated and avenues for further research indicated.

4.2.1 Set-up of the sample size experiment

As mentioned in the introduction, the main goal is the assessment of the quality of original-destination matrices derived from household activity/travel surveys and, consequently, providing an answer to the question of how large sample size is required to provide accurate OD-information in a region. To this end a Monte Carlo experiment is set up to estimate the precision of the OD-matrices given different sampling rates. A Monte Carlo experiment involves the use of random sampling techniques and computer simulation to obtain approximate solutions to mathematical problems. It involves repeating a simulation process, using in each simulation a particular set of values of random variables generated in accordance with their corresponding probability distribution functions (Rubinstein, 1981). A Monte Carlo experiment is a viable approach for obtaining information about the sampling distribution of a statistic (in this case the precision of an origin-destination matrix) of which a theoretical sampling distribution may not be available due to the complexity. Monte Carlo simulation is generally suitable for addressing questions related to sampling distribution, especially when a) the theoretical assumptions of the statistical theory are violated; b) the theory about the statistic of interest in weak; or c) no theory exists about the statistic of interest (Fan *et al.*, 2000). The last is the case in this study (i.e. the precision of OD-matrices given different sampling rates).

The Monte Carlo experiment reported in this section focuses on commuting (i.e. work and school related) trips made in Belgium. The 2001 census data will be used for the experiment. In particular, the census queried information about the departure and arrival times and locations of work/school trips (when applicable) for all 10,296,350 residents. For different sampling rates, ranging from one (the full population) to a millionth, 2,000 random stratified samples were drawn (2,000 for each sampling rate). Note that this number of samples is common in transportation oriented simulation experiments (e.g. Patel & Thompson (1998) or Awasthi *et al.* (2009)). To ensure that the persons in the samples were geographically distributed in the country, the sample was stratified by geographical area: three nested stratification levels were taken into account, namely province, district and municipality. The sample was proportionately allocated to the strata. In other words, the sample in each stratum was selected with the same probabilities of selection (Groves *et al.*, 2004).

For each sample, the proportion of persons making commuting trips was calculated, and three corresponding (morning commute) origin-destination-matrices (OD-matrices) were composed: one OD-matrix on municipality level (589 by 589 matrix), one OD-matrix on district level (43 by 43 matrix), and one on provincial level (11 by

11 matrix). A side-note has to be made for the latter OD-matrix on provincial level: actually there are only 10 provinces in Belgium, but the Brussels metropolitan capital area (accounting for about 1/10 of the entire population) was treated as a separate province. The correspondence of the sample proportion and sample OD-matrices with the population (census) proportion and OD-matrices was then tabulated.

The correspondence between the sample and the population is assessed by using the Mean Absolute Percentage Error (MAPE) and an accommodated version of the MAPE. The MAPE is the mean of the Absolute Percentage Errors (APE) and is calculated by:

$$MAPE_{ij} = \sum_i \sum_j APE_{ij} \Big/ N, \tag{4.1}$$

with

$$APE_{ij} = \left| \frac{A_{ij} - E_{ij}}{A_{ij}} \right| \times 100, \tag{4.2}$$

in which A_{ij} is the population count for the morning commute from origin i to destination j, E_{ij} the sample count (scaled up to population level) for this morning commute, and N the total number of origin-destination cells. Despite its widespread use, the MAPE has several disadvantages. Armstrong & Collopy (1992) for instance, argued that the MAPE is bounded on the low side by an error of 100% (origin-destination counts are all positive integers), but there is no bound on the high side. In response to this comment, Makridakis (1993) proposed a modified MAPE (MDAPE), which is often referred to as SAPE (smoothed absolute percentage error) or SMAPE (symmetric mean absolute percentage error). This modified MAPE (MDMAPE) is given by:

$$MDMAPE_{ij} = \sum_i \sum_j MDAPE_{ij} \Big/ N, \tag{4.3}$$

with

$$MDAPE_{ij} = \left| \frac{A_{ij} - E_{ij}}{(A_{ij} + E_{ij})/2} \right| \times 100. \tag{4.4}$$

Although this modification accommodates the above described problem, it treats large positive and negative errors very differently (Goodwin & Lawton, 1999). Therefore, in this dissertation, a new accommodation of the MAPE is proposed, named the Mean Censored Absolute Percentage Error (MCAPE). This new statistic takes into account the above described comments by limiting the positive values to a maximum of 100. Mathematically, the MCAPE is given by the following formula:

$$MCAPE_{ij} = \sum_i \sum_j CAPE_{ij} \Big/ N, \tag{4.5}$$

with

$$CAPE_{ij} = \min\left\{100, \left|\frac{A_{ij} - E_{ij}}{A_{ij}}\right| \times 100\right\}. \tag{4.6}$$

When A_{ij} in the above formulae would be equal to zero, the different criteria would be undefined. This has been remedied by equalizing the APE_{ij}, MDAPE_{ij} and CAPE_{ij} to zero in these occasions. After all, when the true population count equals zero (no person in the full population corresponds to the considered origin-destination pair) the up-scaled sample count also equals zero, and thus the true zero is correctly estimated.

The correspondence between the sample proportion (p) of persons making commuting trips and population proportion (π) is calculated by simply calculating the Absolute Percentage Error (APE):

$$APE = \left|\frac{\pi - p}{\pi}\right| \times 100. \tag{4.7}$$

No accommodation of this APE was required, as the population proportion (π) was equal to 62.59 percent, and consequently the APE could not exceed 100.

To recapitulate, for each sampling rate, 2000 MAPE values and MCAPE values are calculated for the OD-matrix on municipality level, for the OD-matrix on district level, and for the OD-matrix on province level. In addition 2000 APE values are computed for the commuting proportion. For each of these sets of 2000 values, the 2.5^{th} percentile, the 5^{th} percentile, the 95^{th} percentile and the 97.5^{th} percentile was calculated. The k^{th} percentile is that value x such that the probability that an observation drawn at random from the population is smaller than x, equals k percent (Good, 2006). The 2.5^{th} percentile and 97.5^{th} percentile are used to construct the 95% percentile interval which will be illustrated graphically as lower and upper bounds for the median. The 5^{th} percentile and 95^{th} percentile will be displayed in the corresponding tables because one is most often only interested in the one-sided alternative. In addition, the median (the 50^{th} percentile) and the arithmetic mean are also computed.

To guarantee that the Monte Carlo experiment is really estimating the precision of the OD-matrices in function of different sample rates, rather than in function of other (unobserved) effects, one could take a look at the different sources of errors and biases in surveys. Groves (1989) distinguished different sources of inaccuracy in surveys, of which an overview is given in Figure 4.2. Since in this experiment the true population values are known, and samples are drawn under ideal circumstances (no response bias, no selection bias, no observation errors, no non-response and perfect coverage), the resulting variations in the experiment are only a consequence of the sampling variance (indicated with a gray box, framed with a tick black line in Figure 4.2). So, as intended, the relationship between different sample sizes and the precision/accuracy (sample variance) of the quantities under study are investigated.

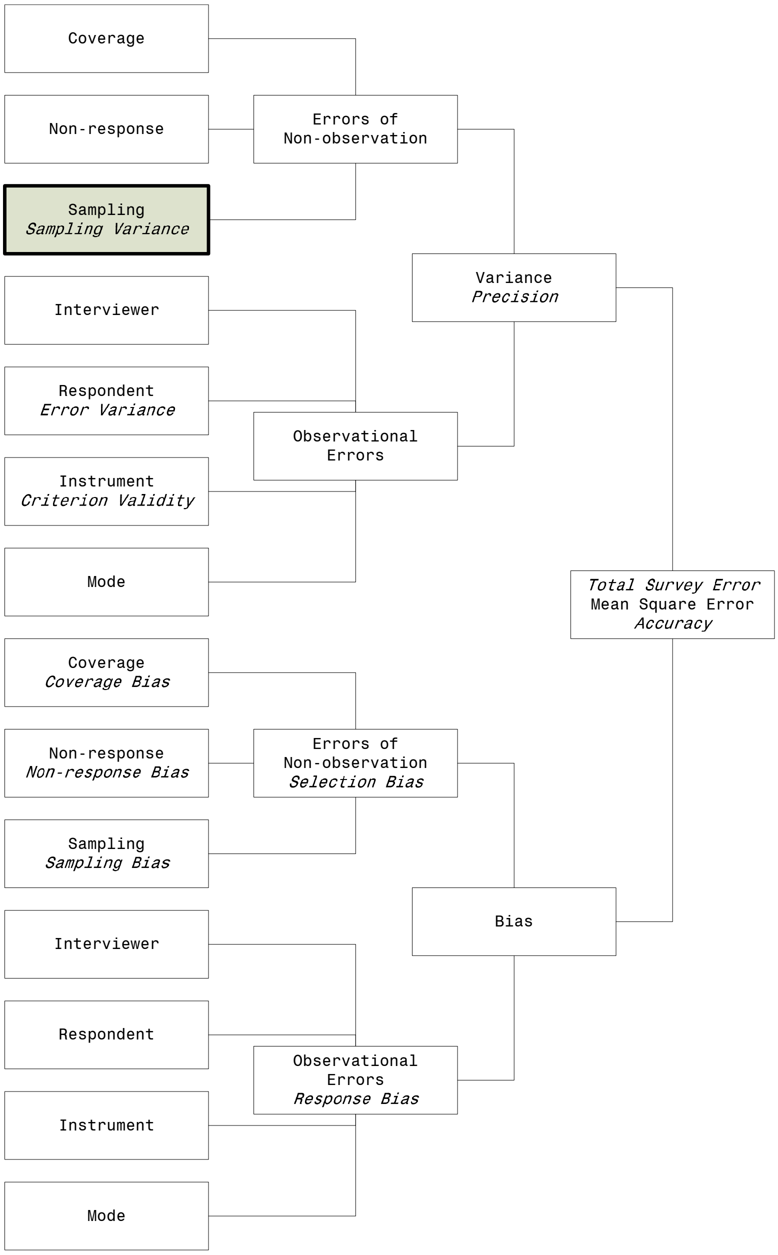

Figure 4.2: Potential sources of the total survey error

4.2.2 Results

Proportion of the commuting population

Before elaborating on the quality of OD-matrices in the second part of this Section, in this first part, an assessment of the appropriateness of travel surveys for deriving traditional indices, such as the mean number of trips made or the mean number of activities performed by individuals/households, or the proportion of the population making work/school related trips, the last being subject of the Monte Carlo experiment, is made. For traditional indices such as the mean number of trips made / activities performed by individuals/households, classical sample size calculations can be used to determine optimal sample sizes. Cools *et al.* (2009c), for instance, calculated the required number of households for a household activity survey using the following formula:

$$n \geq \frac{z^2 p\,(1-p)}{md^2}, \tag{4.8}$$

with n the sample size, p the sample (survey) proportion, md the maximal deviation and z the z-value of the desired confidence interval. For the most 'safe' case (i.e. p = 0.5), a maximal deviation of 2% and a confidence level of 95% would require a minimum of at least 2,401 households. This example illustrates that for aggregate indices, such as the proportion of the commuting population, a clear theory exists and Monte Carlo simulation is not per se required. Notwithstanding, an investigation of the relationship between sampling rates and precision (sample variance) is still valuable, and especially contributes to the literature when the focus is turned to the different percentiles that are examined.

Results from the Monte Carlo experiment for the proportion of commuters in the population are graphically displayed in Figure 4.3 and numerically represented in Table 1. From Figure 4.3 a clear relationship between the Absolute Percentage Error (APE) and the sampling proportion is visible. As expected, the additional improvement in precision decreases as the sampling rate increases: for instance the increase in precision (decrease in APE) from a sampling rate of one millionth (base-10 logarithm of the sampling proportion equals minus 6) to one hundred-thousandth (base-10 logarithm equals minus 5) is considerably larger than the increase in precision from a sampling rate of one thousand to one hundred. This is especially so for the upper bound of the 95% percentile interval (97.5$^{\text{th}}$ percentile).

The results also show that when the full population is sampled, an absolute precision is obtained (absence of all variation). By definition this result should be obtained. When an average deviation of 5 percent is considered acceptable, a sample rate be-

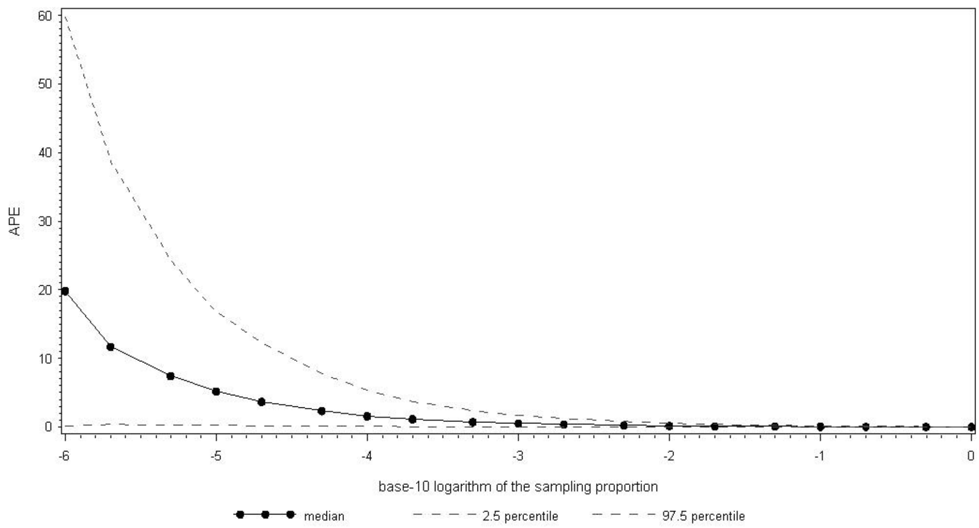

Figure 4.3: Relationship between absolute percentage error and sampling rate for commuting proportion

tween 1 and 2 hundred-thousandth is required (5 percent lies between the mean values 4.293 and 6.083). On the other hand, from the median value one could conclude that in 50% of the cases the maximal deviation (APE) is smaller than 5.192 percent. A more cautions approach entails the use of the 95^{th} percentiles. Suppose that only in 5% of the cases the APE was allowed to exceed 2, than a sampling rate of about 5 ten-thousandth would be required, which roughly corresponds to sampling 5000 persons.

Table 4.2: APE-Statistics for the commuting proportion given different sampling rates[1]

Sampling Rate	Mean	P5	Median	P95
0.000001	20.270	1.670	19.826	46.744
0.000002	13.915	1.096	11.684	34.377
0.000005	8.642	0.659	7.412	21.509
0.000010	6.083	0.474	5.192	14.849
0.000020	4.293	0.343	3.671	10.618
0.000050	2.741	0.213	2.317	6.793
0.000100	1.879	0.137	1.574	4.586
0.000200	1.330	0.097	1.140	3.219
0.000500	0.853	0.072	0.723	2.097
0.001000	0.602	0.052	0.508	1.485
0.002000	0.430	0.040	0.362	1.054
0.005000	0.269	0.022	0.227	0.659
0.010000	0.190	0.015	0.160	0.462
0.020000	0.129	0.010	0.109	0.313
0.050000	0.080	0.007	0.067	0.197
0.100000	0.053	0.004	0.045	0.132
0.200000	0.034	0.003	0.029	0.082
0.500000	0.016	0.001	0.013	0.038
1.000000	0.000	0.000	0.000	0.000

[1] 'P' stands for the percentile, e.g. P5 stands for the 5$^{\text{th}}$ percentile

Precision of Origin-Destination Matrices

In this part of the result section, an assessment of the appropriateness of household activity/travel surveys for deriving OD-matrices is made. Recall that a Monte Carlo simulation is particularly suitable for addressing the questions concerning the distribution of the precision of these OD-matrices, as no real theoretical background of this distribution exists. First, attention will be paid to OD-matrices at municipality level. Afterwards, the focus is laid on OD-matrices at district and provincial level.

OD-matrices at municipality level

Before expanding on the results of the Monte Carlo experiment, it is important to mention that the true OD-matrix (OD-matrix composed from the full population) is a very large and sparse matrix: of the 346,921 origin-destination pairs (589 times 589), 77.8% are zero-cells. As zero-cells in the full population are by definition correctly predicted by taking a sample from this population, the actual overall precision is significantly boosted by the sparseness of the true OD-matrix. Therefore, the decision was made to present the results based on the 76,882 non-zero-cells. To derive the values that include the zero-cells, one only needs to divide the MAPE and MCAPE values by 4.512 (= all cells / (all cells - zero-cells)).

Inspection of Table 4.3 reveals immediately that no accurate OD-matrices are obtained at municipality level, even if zero-cells are taken into account: a survey that would query half of the population still would have an average absolute percentage error of 11.99 percent when zero-cells are included and correspondingly of 54.11% when only the actual predictions (non-zero-cells) are taken into account. This clearly indicates that the direct derivation of origin-destination matrices from household activity/travel surveys should be avoided. Notwithstanding, origin-destination matrices derived from household activity/travel surveys are very valuable: even a simple gravity model with the inverse squared distance as deterrence function, taking into account the productions and attractions derived from the surveys, already results in a clear improvement of the OD-matrices. This is certainly a plea for travel demand models that incorporate the behavioral underpinnings of destination choices (activity location choices) given a certain origin, like for instance models that make use of space-time prisms, e.g. Pendyala *et al.* (2002), and models that combine data from different sources, such as data integration tools, e.g. Nakamya *et al.* (2007). In addition, OD-matrices derived from travel surveys form a good basis for OD-matrices derived from traffic counts: as multiple OD-matrices can be derived from the same set of traffic counts, OD-matrices derived from travel surveys provide a good basis

Table 4.3: MAPE and MCAPE for OD-matrices derived at municipality level

Sampling	MAPE				MCAPE			
Rate	Mean	P5	Median	P95	Mean	P5	Median	P95
0.000001	205.996	100.902	115.559	753.493	100.000	100.000	100.000	100.000
0.000002	200.992	102.528	129.575	754.266	100.000	100.000	100.000	100.000
0.000050	199.861	109.279	155.540	431.119	99.999	99.998	99.999	100.000
0.000010	199.089	116.768	175.588	352.896	99.997	99.995	99.997	99.999
0.000020	198.647	127.682	187.707	304.125	99.994	99.992	99.994	99.996
0.000050	198.338	148.261	194.723	259.440	99.977	99.972	99.977	99.981
0.000100	199.452	160.661	198.325	243.313	99.927	99.919	99.927	99.936
0.000200	197.459	170.778	196.746	226.279	99.784	99.769	99.784	99.798
0.000500	195.930	178.611	195.344	215.156	99.414	99.391	99.414	99.437
0.001000	193.624	181.284	193.511	206.508	98.999	98.973	98.999	99.026
0.002000	190.182	181.664	189.982	199.411	98.393	98.360	98.392	98.427
0.005000	183.425	177.916	183.465	188.907	97.033	96.990	97.033	97.077
0.010000	175.654	171.907	175.659	179.551	95.352	95.298	95.353	95.407
0.020000	164.993	162.373	165.044	167.739	92.797	92.730	92.798	92.865
0.050000	145.263	143.745	145.271	146.836	87.514	87.424	87.515	87.598
0.100000	124.970	124.078	124.960	125.866	81.369	81.273	81.369	81.469
0.200000	99.172	98.724	99.169	99.631	72.293	72.193	72.294	72.392
0.500000	54.108	54.089	54.108	54.128	54.108	54.089	54.108	54.128
1.000000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

for constraining the matrices derived from traffic counts (Abrahamsson, 1998). A thorough look at Table 4.3 also reveals that when half the population is sampled, the values for the MAPE and MCAPE are the same. This can be explained by the fact that when using half of the population none of the 2000 samples has a MAPE higher than 1.

When the general tendency of the precision of the OD-matrices derived from travel surveys is discussed, Figures 4.4 and 4.5 provide a clear insight in the relationship between the precision and the sampling rate. From Figure 4.4 one could clearly see that the median MAPE first increases when samples are becoming larger, and then starts to decrease. The increase in median MAPE for the smallest sampling rates can be accounted for by the fact that more cells are seriously overestimated on average, whereas the maximum underestimations are bounded by 100%. This effect is filtered out by using the MCAPE, as could be seen from Figure 4.5; a clear decreasing relationship is visible here. Next to the difference in relationships between the MAPE and MCAPE, one could also observe a clear difference between the percentile interval for the MAPE and the percentile interval for the MCAPE. By condensing the APE to a maximum of one (i.e. the CAPE), almost all variability around the median value is filtered out: the 2.5^{th} and 97.5^{th} percentiles almost coincide with the median values in case of the MCAPE.

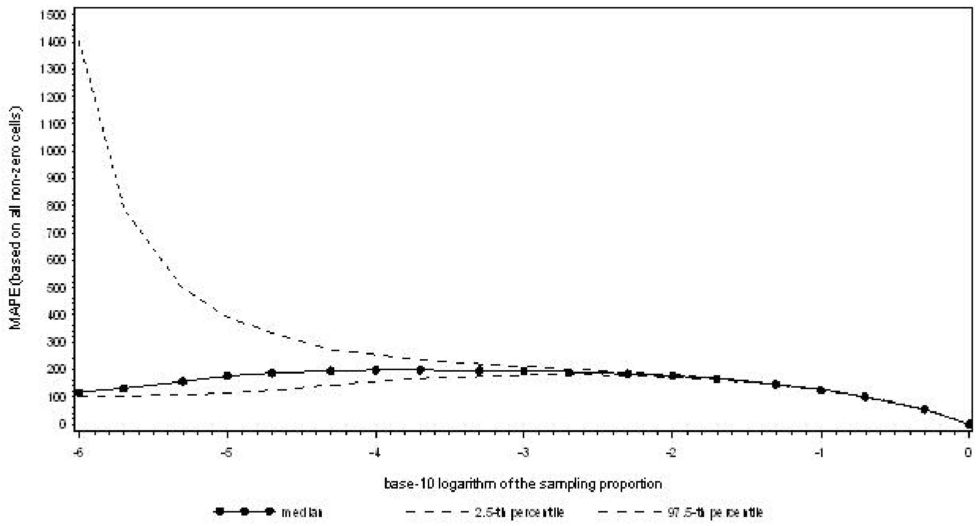

Figure 4.4: Relationship between MAPE and base-10 logarithm of the sampling rate

When this decreasing pattern of the MCAPE (Figure 4.5) is compared to the one of the proportions (Figure 4.3), a clear contrast can be seen between in the tendency: whereas the pattern for proportion is a convex decreasing function, for the OD-matrices this is a concave decreasing function. This difference in pattern, as well as the difference in precision, can be explained by the fact that proportions are aggregate indices, and that surveys are extremely suitable for capturing these aggregate figures, whereas in OD-matrices all individual information is used.

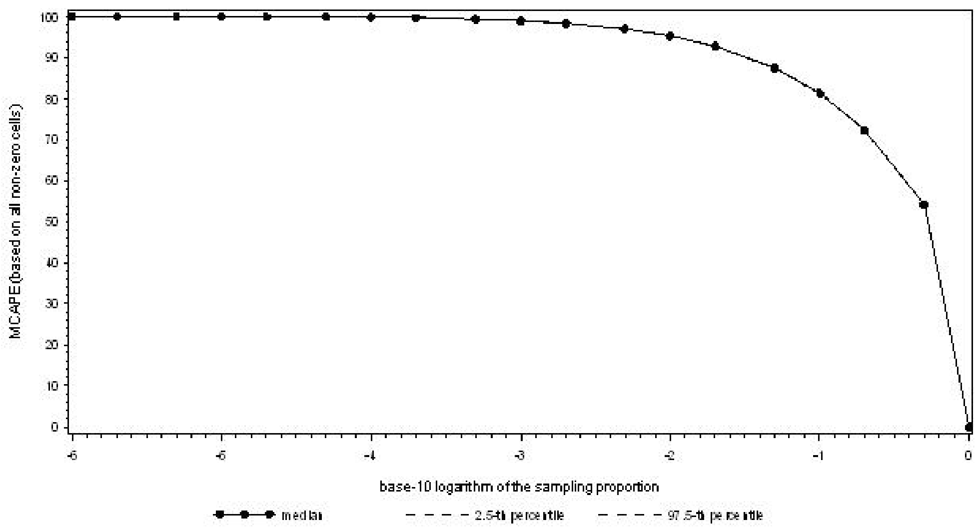

Figure 4.5: Relationship between MCAPE and base-10 logarithm of the sampling rate

OD-matrices at district level

Similar to the true OD-matrix at municipality level, the true OD-matrix at district level (43 by 43) comprises a non-negligible amount of zero-cells. Nonetheless, the number of non-zero-cells is considerably smaller: 10.4% of the 1,849 origin-destination pairs are zero-cells. Recall that zero-cells in the full population are by definition correctly predicted by taking a sample from this population. Therefore, similar to the previous paragraph, the results are based on the 1,657 non-zero-cells. The values that include the zero-cells can be calculated by dividing the MAPE and MCAPE values by 1.116.

A thorough look at Table 4.4 shows that also at district level no accurate OD-matrices can be derived. Even if zero-cells are included in the calculations, surveying half of the population would result in an average absolute percentage error of 22.25 percent (24.832 divided by 1.116). When compared to the results of OD-matrices derived at municipality level, the results including the zero-cells are worse at district level than at municipality level (an average MAPE of 22.25 percent versus one of 11.99 percent). This is due to the fact that at municipality level a much larger share (77.8 percent versus 10.4 percent) of zero-cells is automatically correctly predicted. In contrast, when the results of only the non-zero-cells are compared, the precision of the OD-matrices derived at district level is higher than the precision of the OD-matrices derived at municipality level. This result confirms that predictions on a more aggregate level are more precise.

A visual representation of the relationship between the precision of the OD-matrices derived at district level and the sampling rate is provided in Figures 4.6 and 4.7. Inspection of Figure 4.6 reveals a pattern very similar to the one observed in Figure 4.4: the MAPE first increases when samples are becoming larger, and then starts to decrease. Recall that the increase in median MAPE for the smallest sampling rates can be accounted for by the fact that more cells are seriously overestimated on average, whereas the maximum underestimations are bounded by 100%. By analogy with the results at municipality level, this effect is filtered out by using the MCAPE, as could be noticed from Figure 4.7. Moreover, the relationship between the MCAPE and sampling proportion is a concave decreasing function, similar to the relationship between the MCAPE and sampling rate at municipality level.

Table 4.4: MAPE and MCAPE for OD-matrices derived at district level

Sampling	MAPE				MCAPE			
Rate	Mean	P5	Median	P95	Mean	P5	Median	P95
0.000001	171.196	100.978	110.178	299.050	99.996	99.987	99.993	100.000
0.000002	206.097	101.875	113.822	385.419	99.937	99.869	99.937	100.000
0.000050	197.675	104.054	121.673	442.676	99.716	99.589	99.717	99.841
0.000010	200.483	105.752	127.559	481.848	99.352	99.174	99.351	99.535
0.000020	191.212	108.363	136.036	417.340	98.750	98.524	98.749	98.970
0.000050	186.436	111.940	145.249	383.240	97.578	97.331	97.572	97.860
0.000100	187.614	114.861	152.048	359.850	96.444	96.145	96.449	96.738
0.000200	177.715	118.461	156.391	307.348	94.788	94.416	94.791	95.131
0.000500	172.565	122.683	160.022	274.422	92.023	91.596	92.027	92.443
0.001000	164.271	124.944	157.032	230.024	89.557	89.113	89.557	90.004
0.002000	154.307	123.783	150.441	196.883	86.232	85.711	86.228	86.753
0.005000	138.952	118.396	137.611	164.985	81.028	80.476	81.014	81.605
0.010000	124.538	110.153	123.828	141.608	75.874	75.224	75.874	76.529
0.020000	109.048	99.198	108.610	120.450	69.540	68.823	69.548	70.242
0.050000	85.890	80.198	85.743	92.146	59.623	58.825	59.617	60.407
0.100000	67.276	63.761	67.238	70.863	50.649	49.818	50.645	51.482
0.200000	48.653	46.789	48.640	50.602	40.040	39.253	40.042	40.890
0.500000	24.832	24.110	24.826	25.529	24.832	24.110	24.826	25.529
1.000000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

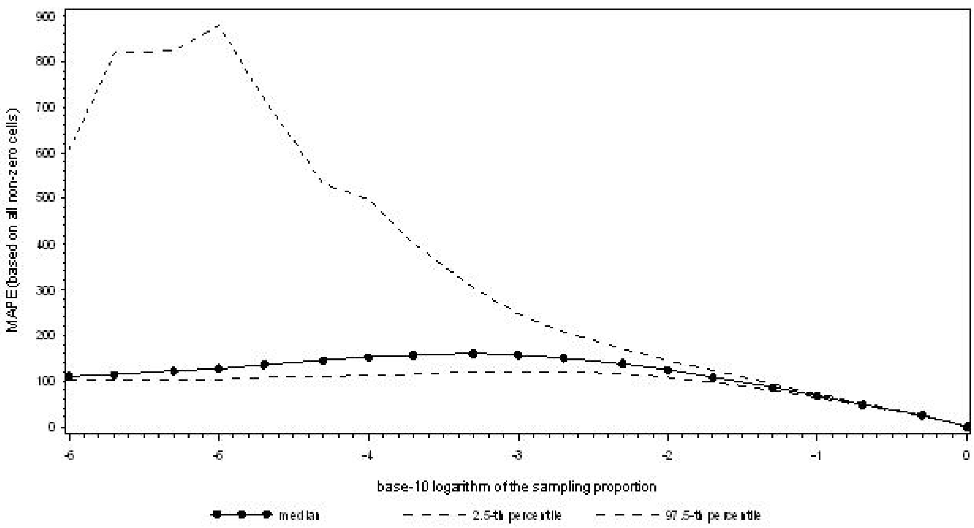

Figure 4.6: Relationship between MAPE and base-10 logarithm of the sampling rate

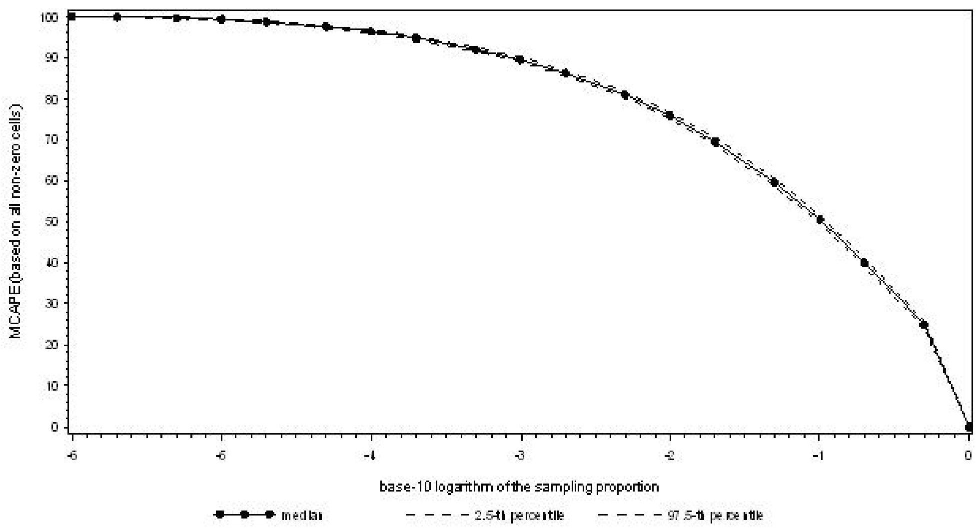

Figure 4.7: Relationship between MCAPE and base-10 logarithm of the sampling rate

OD-matrices at provincial level

In contrast to the true OD-matrices at municipality and district level, the true OD-matrix at provincial level (11 by 11) only comprises non-zero-cells. Examination of Table 4.5 reveals that at provincial level, barely any accurate OD-matrices can be derived. Nonetheless, in contrast to the results at municipality and district level, for the largest sample sizes acceptable results are obtained: sampling half of the population would result in average absolute percentage error of 3.4 percent, and surveying one fifth of the population results in an average absolute percentage error of 7.4%. Results from Table 4.5, also confirm that predictions related with a more aggregate level are more precise. Notwithstanding, results at provincial level confirm the finding unraveled at the lower levels (municipality and district) that the direct derivation of origin-destination matrices from household activity/travel surveys should be avoided.

Table 4.5: MAPE and MCAPE for OD-matrices derived at provincial level

Sampling	MAPE				MCAPE			
Rate	Mean	P5	Median	P95	Mean	P5	Median	P95
0.000001	176.769	99.263	107.557	394.608	99.063	98.121	99.098	100.000
0.000002	203.155	97.373	116.674	433.429	97.457	96.026	97.482	98.892
0.000050	181.113	96.627	126.086	350.822	95.265	93.815	95.268	96.704
0.000010	168.445	98.339	127.604	348.163	93.433	92.038	93.444	94.797
0.000020	168.536	99.464	128.362	360.363	91.485	90.201	91.460	92.835
0.000050	151.833	95.531	121.858	311.175	86.839	84.890	86.849	88.801
0.000100	139.293	89.910	117.180	260.735	81.456	78.907	81.492	83.867
0.000200	122.260	83.171	109.350	199.592	75.496	72.706	75.491	78.216
0.000500	102.579	73.950	95.857	153.082	66.131	63.291	66.100	68.976
0.001000	86.550	65.717	82.586	121.220	58.695	55.863	58.703	61.425
0.002000	70.179	55.819	67.913	91.566	50.581	47.480	50.567	53.506
0.005000	50.419	42.091	49.683	61.219	40.069	37.270	40.045	42.948
0.010000	37.062	31.187	36.759	44.062	31.583	28.460	31.522	34.604
0.020000	26.160	22.031	25.987	30.902	23.833	20.970	23.816	26.754
0.050000	16.138	13.530	16.044	19.084	15.566	13.331	15.566	17.840
0.100000	11.165	9.297	11.150	13.148	11.018	9.271	11.021	12.841
0.200000	7.417	6.252	7.374	8.784	7.404	6.243	7.370	8.721
0.500000	3.449	2.903	3.440	4.050	3.449	2.903	3.440	4.050
1.000000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

The visualization of the relationship between the precision of the OD-matrices derived at provincial level and the sampling proportion is shown in Figures 4.8 and 4.9. Harmonious with the relationships between the sample rate and the precision of the OD-matrices at municipality and district level, the MAPE first increases when samples are becoming larger, and then starts to decrease (Figure 4.8). Again, the use of the MCAPE filters out this effect. In contrast to the results at municipality and district level, the relationship between the precision and the MCAPE reveals an s-shaped decreasing function: for the smallest sampling rates the relationship is concave decreasing, similar to the OD-matrices at municipality and district level; but for the larger sampling rates the relationship is a convex decreasing function. Moreover, the 95 percentile interval is much wider than for the OD-matrices at less aggregated levels. The most important reasons for this are the degree of sparseness and size of the matrix: for the less aggregate levels (municipality and district level), a lot of the variability of the precision is taken away by the large amounts of (zero-)cells.

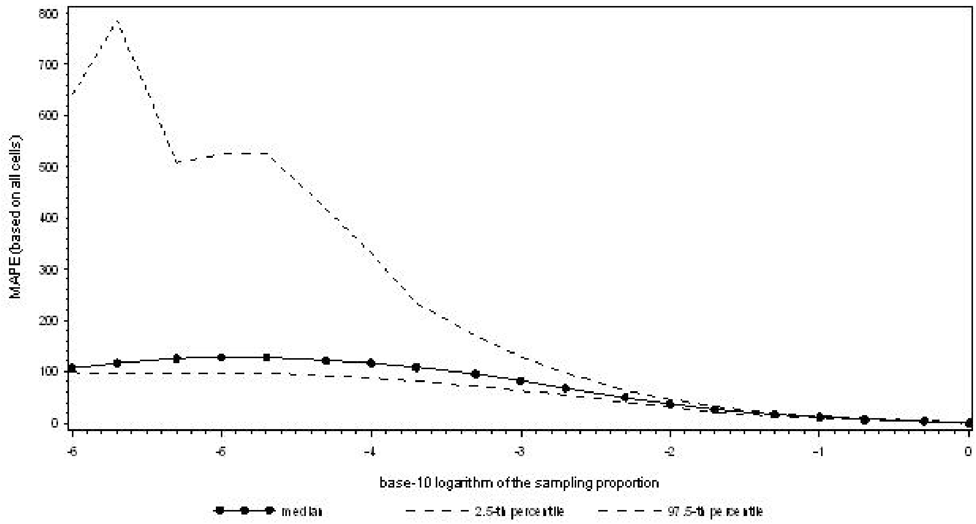

Figure 4.8: Relationship between MAPE and base-10 logarithm of the sampling rate

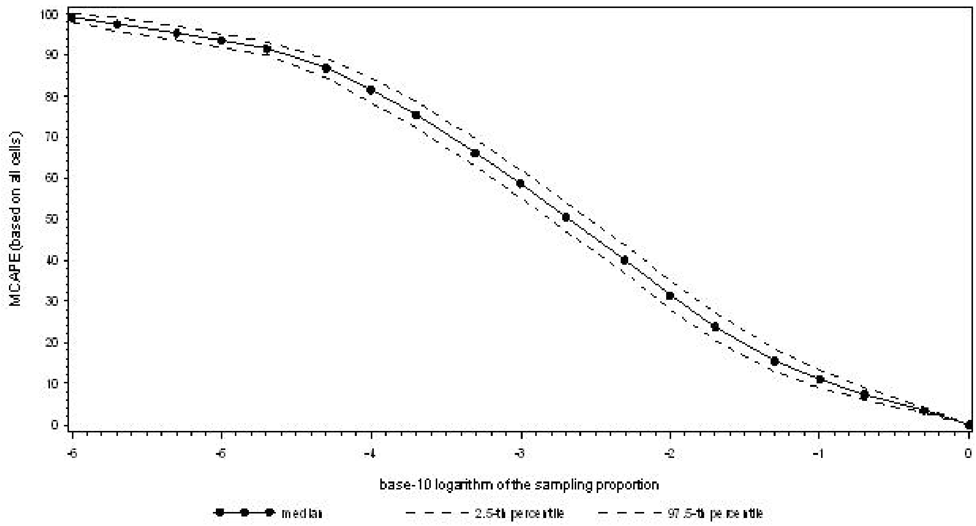

Figure 4.9: Relationship between MCAPE and base-10 logarithm of the sampling rate

4.2.3 Conclusions

In this section, an assessment of the quality of origin-destination matrices derived from household activity/travel surveys was made. The results showed that no accurate OD-matrices can be directly derived from these surveys. Only when half of the population is queried, an acceptable OD-matrix is obtained at provincial level. Therefore, it is recommended to use additional information to better grasp the behavioral realism underlying destination choices. This is certainly a plea for travel demand models that incorporate the behavioral underpinnings of destination choices (activity location choices) given a certain origin. Moreover, matrix calibration techniques could seriously improve the quality of the matrices derived from these household activity/travel surveys. In addition, it is recommended to collect information about particular origin-destination pairs by means of vehicle intercept surveys rather than household activity/travel surveys, as these vehicle intercept surveys are tailored for collecting specific origin-destination data. Mark that the results presented in this paper do not negate the value of travel surveys as was shown with the example of deriving the commuting population, but indicate that sophistication is needed in how the data are employed.

A second important finding is that traditional methods to assess the comparability of two origin-destination matrices could be enhanced: the MCAPE index that was proposed has clear advantages over the traditional indices. The most important being the fact that the MCAPE filters out the noise created by the asymmetry of the traditional criteria. Therefore, when dissimilarities between different OD-matrices are investigated, the use of the MCAPE index next to traditional criteria is highly recommended.

An important avenue for further research is the investigation of the relationship between the variability in the outcomes of travel demand models and underlying survey data. Triangulation of both travel demand modeling and small area estimation models could prove to a pathway for success. An empirical investigation of the effect of sampling proportions in household activity/travel surveys on final model outcomes would further illuminate the quest for optimal sample sizes. A thorough examination of the minimum required sampling rate of a household travel survey such that trip distribution models such as a gravity model could help fill in the full trip table certainly is an important step in further analyses. Model complexity and computability will certainly be key challenges in this pursuit.

Chapter 5

Linking transportation models with external information

The research reported in this chapter is mainly based on Cools* et al. *(2010d).

Although modern activity-based travel demand models have clear theoretical advantages over conventional four-step models[1] - the most important ones are the fact that all basic travel decisions can be applied in a disaggregate fashion, the explicit linkages between the travel decisions of members of a single household, the consistent choices for a single person across all travel decisions and the disaggregate way of handling the time-of-day of travel decisions - conventional models still dominate the travel demand modeling paradigm (Vovsha *et al.*, 2005; Walker, 2005). Davidson *et al.* (2007) highlighted several reasons that explain the acceptance of and resistance to more sophisticated model frameworks. They can be broadly categorized as the degree of resistance to new modeling technology and the size of encouragement forces. The reasons include the size of the public agency, the size of the jurisdiction, the level of institutional history and the level of state support for travel demand forecasting. Davidson *et al.* (2007) also stressed that in order to reinforce the transition from conventional models towards activity-based models, it is imperative that the objective theoretical advantages of activity-based models are better explained to practitioners and communicated more actively.

This chapter focuses on a concern that stems from misunderstanding and mistrust by practitioners. Although researchers have acknowledged the advantages of an exhibited behavioral realism to policy analysis, many practitioners question the advantages of activity-based models over conventional four-step models in terms of replication of traffic counts, as it is in many respects easier to adjust a conventional travel demand model to fit base level traffic counts exactly than an activity-based micro-simulation model (Davidson *et al.*, 2007). In this regard, it is important to stress the distinction between static model accuracy in terms of the replication of the base-year observed data, and the responsive properties of the model that are related to the quality of the travel forecasts for future and changed conditions, as these two model properties do not necessarily coincide. Therefore, in this chapter, different techniques are highlighted that actively link activity-based models in particular, and travel demand models in general, with traffic counts in order to achieve the desired responsive properties - the model being sensitive to demographic changes and policy measures - of the travel demand models as well as the replication of traffic counts. Note that proper calibration[2] is a crucial step in simulation models as findings based on inappropriately calibrated models could be misleading and even erroneous (Park & Qi, 2005). An overview of new calibration and validation standards, as well as best practice examples for travel demand modeling, is provided by Schiffer & Rossi (2009). Bare in mind that the calibration of an activity-based model is not unlike calibrating a conventional four-step model (Walker, 2005). A thorough example of the calibration of a conventional four-step model with traffic counts is provided by Cascetta & Russo (1997). For an excellent example concerning the calibration of an activity-based travel demand model (i.e. the Sacramento activity-based travel demand model) the reader is referred to Bowman *et al.* (2006).

The remainder of the text is organized as follows. Section 5.1 provides an outline of the suggested techniques that are implemented in a practical example, which are thoroughly discussed in Section 5.2. Finally, some general conclusions and avenues for further research are indicated.

[1]A more elaborate discussion of advantages of activity-based travel demand models was provided in Section 4.1.2

[2]Dowling *et al.* (2004) define calibration as '*the adjustment of model parameters to improve the model's ability to reproduce traffic performance characteristics*'.

5.1 Linkages between activity-based models and traffic counts

There are two possible approaches to link activity-based models in particular, and travel demand models in general, with traffic counts, namely an indirect and a direct approach. The first approach tries to incorporate findings, based on the analysis of traffic counts, into the model components of the activity-based models. The second approach calibrates the model parameters of the activity-based model in such way that the model replicates the observed traffic counts (quasi-)perfectly (less than 5% error on average). The following subsections will elaborate and further clarify the two methods of linking activity-based models with traffic counts.

5.1.1 Indirect linkage

The 'indirect linkage'-approach tries to identify events that affect travel behavior and resulting traffic patterns. Analysis of traffic counts for instance can be used to identify effects of holidays and weather events (Cools *et al.*, 2007a). These traffic swaying events can then be used to alter the impedance functions used in route choice modules. When events such as holidays and weather conditions are identified, their impact on travel behavior can even be further elucidated by analyzing activity diary data. Utility functions that express the propensity of performing certain activities - note that basically the utility functions of all elements of the activity-pattern generation can be modified in this way - can then explicitly incorporate explanatory variables to account for the events that were analyzed. In this regard, activity-diary collection tools that integrate geographical information logging, such as the PARROTS-tool (Bellemans *et al.*, 2008) provide the required data to perform detailed analysis, for instance on route choice. It can be expected that the explicit incorporation of events that account for the variability in revealed traffic patterns and their underlying reasons, will result in both an improved responsiveness of the activity-based model and a better replication of traffic counts.

5.1.2 Direct linkage

The 'direct linkage'-approach tries to fine-tune the model parameters of the activity-based (AB) model in such a way that the model-based traffic counts correspond maximally to the observed ones on the network. Calibration opportunities exist at four levels (Figure 5.1): the data level, the model level, the OD-matrix level and the assignment level.

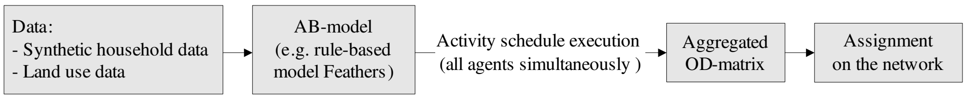

Figure 5.1: Four levels of calibration opportunities

Two approaches can be followed when considering calibration at the data level: a 'crude' approach, in which data (personal/household information, zonal information) is altered in order to achieve a better correspondence to the benchmark measures, and a 'fine' approach in which agents (individuals or households) are weighted. The first approach immediately raises questions concerning the validity and the credibility: adjusting fields or adding or deleting records undermines the validity of the model and should be avoided. The latter approach attributes weights to the different agents. For the practical example discussed in Section 5.2, the weights are chosen to be natural numbers (including zero) such that these weights correspond to exact counterparts in the real population. Fractional weights like 0.8 or 1.2 would also have been feasible, but the interpretation of these weights would be a probability of this agent to have an exact counterpart in the real population (0.8 would correspond to a change of 80% of having an exact counterpart in the real population, and 1.2 would be interpreted as 80% chance of having one counterpart in the real population, 20% of having two counterparts in the real population). The use of weights can be defended by the fact that there exist groups of individuals with similar travel behavior that can be captured in representative activity patterns (RAPs). By using these RAPs, the complete activity-generation can be performed in a hands-on manner (Kulkarni & McNally, 2001). McNally (1998) and Wang (1996) have even further advocated the use of RAPs by showing that RAPs are relatively stable over conventional planning horizons (up to 10 years). So weighting agents seems to be a worthwhile path to follow. Notwithstanding, the weighting procedure can become computationally very intensive as the number of possible weights increases with the number of simulated agents.

A second calibration possibility arises at the model level. The activity schedule generation could be altered in such a way that the obtained OD-matrix reproduces optimally the observed traffic counts. One solution to achieve this optimal state is an 'updating'-process which alters the scheduling rules that are derived from the available travel survey data. In addition, zone-specific rules can be introduced: for instance increasing the probability of certain destination choices, or increasing the probability of performing a certain activity. In that way, the production and attraction of these zones can be fine-tuned. When different forecasting scenarios are desired, it is necessary to keep the updated rules that were defined by the updating-process in the baseline year. In that manner the AB-model is constructed in a consistent way. Hence, linking activity-based models with traffic counts by making behavioral adjustments (altering rules) might prove to be a valid way of overcoming practitioners' mistrust.

The OD-matrix level is the third level at which calibration opportunities arise. The OD-matrix is obtained by the simultaneous activity schedule execution of all agents. This OD-matrix can then be bench-marked in function of the screen-line counts. Different techniques exist to estimate OD-matrices from traffic counts. In practice, most models assume or require that a target OD-matrix is available. This target OD-matrix (the OD-matrix resulting from the activity-based model) is a crucial part of prior information. In statistical approaches, the target OD-matrix is typically assumed to stem from a sample survey and is regarded as an observation of the "true" OD-matrix. The observed set of traffic count data may also be assumed to be an observation of the "true" traffic count data, and therefore (small) deviations between estimated counts and observed counts may be accepted. So the purpose of the calibration process is to find an OD-matrix which produces "small" differences between the estimated link flows and the observed flows. Three modeling philosophies are postulated in the transportation literature (Abrahamsson, 1998): traffic modeling based approaches, statistical inference approaches and gradient based solution techniques.

The traffic assignment module is the last level where calibration is possible. Obviously the way of attributing origin-destination flows to the network plays a crucial role in how well the model-based traffic counts correspond to the benchmark measures. Ortúzar & Willumsen (2001) classify traffic assignment methods according to their treatment of congestion (inclusion of capacity restraints) and their treatment of differences in objectives and perceptions by agents (inclusion of stochastic effects).

5.2 Practical example

In this Section, a practical example is worked out to exemplify the different options of the 'direct-linkage'-approach. The example is a numerical example that illustrates the linkages at all three levels.

5.2.1 Example: Hasselt and surrounding municipalities

The first illustration is a numerical example provided to further illuminate the 'direct linkage'-approach. The study area for this numerical example is Hasselt, a Belgian city of about 70,000 residents, and its surrounding municipalities. Activity-travel information derived from census data, from the Flemish travel survey and from the origin-destination (OD) matrix assigned in the multi-modal travel demand model Flanders, is combined to generate a simulated "true" population and its corresponding travel behavior. The data from this true population is assumed to be unbiased and precise. For generating the "true" representative activity patterns (RAPs) at population level, people are supposed to perform activities in a predefined order: first, people perform a work or school activity, then they go shopping, afterwards they perform a leisure trip, and finally, they perform other type of activities. In addition to this predefined order, it is presumed that people perform a specific type of activity at most once (the exact chances to perform a specific activity are given in the upper part of Table 5.1). Furthermore, it is assumed that residents return home after their last activity.

To focus on the general ideas behind the different calibration techniques presented, and to reduce model complexity, route choice modeling (traffic assignment) and mode choice modeling were not taken into account. Consequently, the practical example focuses on the first three levels of calibration. Assuming perfect knowledge about these aspects procures the property that the quality of the output of the (activity-based) travel demand model is completely related to the aggregated OD-matrix resulting from the individual activity patterns. In addition, owing to the perfect knowledge of these aspects, traffic counts on the different roads form an identity match to the origin-destination flows. Note that the assumption of perfect knowledge about origin-destination relationships nowadays become a more viable option. When privacy issues are carefully addressed, data from a mobile phone network can be used to derive origin-destination patterns (Giannotti & Pedreschi, 2008). Results from Caceres *et al.* (2007) and González *et al.* (2008) indicate that extracting OD-information from mobile phone records has great potential and is much more cost-efficient that those generated with traditional techniques.

As complete information about all activity-patterns seldom is available, the starting point for the calibration exercises is a 2.5% stratified random sample of the "true" population (municipality is taken as the stratification variable). The lower part of Table 5.1 provides more information about the 2.5% sample: the number of residents in each municipality, as well as the municipality specific propensities to perform different

Table 5.1: Number of residents and propensities of activity participation

	"True" population					
Municipality	No. of residents	% Work	% School	% Shopping	% Leisure	% Other
1: Hasselt	70,584	29.59%	14.22%	33.28%	27.94%	25.92%
2: Diepenbeek	17,874	34.30%	30.49%	30.47%	25.30%	23.47%
3: Kortessem	8,153	33.83%	16.39%	33.88%	19.66%	21.59%
4: Alken	11,090	27.92%	17.60%	37.76%	25.35%	24.82%
5: Nieuwerkerken	6,685	28.02%	17.71%	41.74%	22.03%	22.11%
6: Herk-De-Stad	11,874	32.52%	21.32%	35.20%	21.10%	23.61%
7: Lummen	13,874	31.38%	16.38%	37.03%	21.19%	21.77%
8: Heusden-Zolder	31,017	24.54%	17.95%	32.19%	24.18%	23.63%
9: Zonhoven	20,060	30.06%	17.57%	31.42%	24.32%	24.79%
10: Genk	64,095	25.35%	18.32%	28.77%	25.85%	23.79%
	Sample					
Municipality	No. of residents	% Work	% School	% Shopping	% Leisure	% Other
1: Hasselt	1,765	28.90%	13.88%	32.52%	30.71%	25.89%
2: Diepenbeek	447	35.35%	27.07%	30.43%	23.27%	23.94%
3: Kortessem	204	35.78%	14.22%	31.37%	25.98%	21.57%
4: Alken	277	29.96%	18.41%	36.82%	24.55%	23.83%
5: Nieuwerkerken	167	23.95%	20.36%	40.72%	23.35%	20.96%
6: Herk-De-Stad	297	32.32%	18.86%	36.03%	21.55%	22.56%
7: Lummen	347	28.82%	20.46%	35.73%	24.50%	20.46%
8: Heusden-Zolder	775	24.13%	16.52%	33.29%	25.81%	21.16%
9: Zonhoven	502	30.88%	22.71%	34.06%	26.89%	26.10%
10: Genk	1,602	27.47%	17.04%	28.34%	25.22%	23.78%

activities, are displayed.

Table 5.2 presents the OD-matrix obtained from aggregating the individual activity persons from all people in the population (upper part of the Table 5.2) and the sample (lower part of the Table 5.2). The OD-information from the sample is scaled up to the population level for comparison purposes. A side-note has to be made concerning the "true" population origin destination matrix. When the origin-destination flows of this matrix are compared to flows really observed in practice, the population OD-matrix overestimates the flows observed in practice. This is due to the fact that all residents from the municipalities in this practical example are assumed to perform their activities within the entire study area.

The absolute percentage difference (APE) between the true population and the sample is displayed in the lower part of Table 5.2. Many of these APEs are larger than 5% indicating that some extra calibration is needed to improve the correspondence with the "true" observed values. The absolute percentage is defined as:

$$APE = \begin{cases} \frac{abs\left(T_{ij}^{pop} - T_{ij}^{sa}\right)}{T_{ij}^{pop}} & \text{if } T_{ij}^{pop} > 0 \\ 0 & \text{if } T_{ij}^{pop} = T_{ij}^{sa} = 0 \\ \text{infinity value} & \text{if } T_{ij}^{pop} = 0, T_{ij}^{sa} > 0 \end{cases}, \tag{5.1}$$

in which T_{ij} represents the number of trips from municipality i to municipality j, pop indicates that the flow corresponds to the population, and sa that the flow corresponds to the sample. A possible infinity value could be one, indicating that you are of the target by 100%. Such an infinity value has to be defined, as many calculations are infeasible when values are divided by zero (and as a result mathematically equal to infinity). Since the "true" population OD-matrix contains no zero cells, no infinity value had to be defined in the practical example.

Table 5.2: OD-matrices retrieved from the "true" population and the sample

					"True" population					
From\to	1	2	3	4	5	6	7	8	9	10
1	130,888	8,142	2,692	8,239	2,620	4,580	2,899	5,270	7,108	8,928
2	8,299	22,167	1,292	744	163	283	306	825	1,281	7,682
3	2,715	1,310	8,704	522	111	106	88	137	227	1,125
4	8,278	731	518	11,780	723	656	273	322	515	673
5	2,591	151	117	721	7,052	1,683	305	219	184	335
6	4,637	318	109	648	1,614	14,892	1,852	732	316	555
7	2,891	304	95	260	308	1,907	19,398	3,272	652	783
8	5,220	837	149	314	232	721	3,281	46,967	2,953	1,960
9	7,224	1,290	241	530	175	311	673	2,915	22,160	5,621
10	8,623	7,792	1,128	711	360	534	795	1,975	5,744	112,725
					Sample					
From\to	1	2	3	4	5	6	7	8	9	10
1	132,800	8,440	3,120	7,600	2,440	4,960	3,120	5,440	7,440	8,240
2	8,520	21,680	800	840	160	440	320	1,160	1,160	7,160
3	3,040	880	9,480	640	40	200	120	280	320	1,160
4	7,920	840	600	11,240	600	600	240	200	400	640
5	2,560	160	40	680	7,000	1,520	240	280	320	280
6	4,800	440	200	600	1,600	14,280	1,720	600	240	680
7	3,200	360	160	240	320	1,760	19,560	2,720	480	1,160
8	5,240	1,160	240	120	240	600	2,880	46,200	3,760	2,000
9	7,560	1,200	400	640	320	240	520	3,400	23,400	6,040
10	7,960	7,080	1,120	680	360	560	1,240	2,160	6,200	112,920
					Absolute Percentage Difference					
From\to	1	2	3	4	5	6	7	8	9	10
1	1.5%	3.7%	15.9%	7.8%	6.9%	8.3%	7 .6%	3.2%	4.7%	7.7%
2	2.7%	2.2%	38.1%	12.9%	1.8%	55.5%	4.6%	40.6%	9.5%	6.8%
3	12.0%	32.8%	8.9%	22.6%	64.0%	88.7%	36.4%	104.4%	41.0%	3.1%
4	4.3%	14.9%	15.8%	4.6%	17.0%	8.5%	12.1%	37.9%	22.3%	4.9%
5	1.2%	6.0%	65.8%	5.7%	0.7%	9.7%	21.3%	27.9%	73.9%	16.4%
6	3.5%	38.4%	83.5%	7.4%	0.9%	4.1%	7.1%	18.0%	24.1%	22.5%
7	10.7%	18.4%	68.4%	7.7%	3.9%	7.7%	0.8%	16.9%	26.4%	48.2%
8	0.4%	38.6%	61.1%	61.8%	3.5%	16.8%	12.2%	1.6%	27.3%	2.0%
9	4.7%	7.0%	66.0%	20.8%	82.9%	22.8%	22.7%	16.6%	5.6%	7.5%
10	7.7%	9.1%	0.7%	4.4%	0.0%	4.9%	56.0%	9.4%	7.9%	0.2%

Calibration at the data level

The goal of weighting agents is to procure the highest possible resemblance between the observed traffic counts on the network and the predicted traffic counts by the activity-based model. In the non-calibrated model all agents are equally weighted (weights equal to the inverse of the sample size). By iteratively altering the weights, an optimal correspondence can be found using meta-heuristics (a meta-heuristic is a general algorithmic framework that can be used to guide heuristic methods to search for feasible solutions to different optimization problems). Two different approaches can be distinguished when agents have to be weighted. The first approach weights the agents before their activity pattern is generated. Since agents are duplicated before the activity patterns are generated, the activity patterns of the replicated agents - created by the weights - can differ from the ones of the "true" agents. As a consequence, the convergence of the iterative process of weighting persons and calculating the activity patterns of the "agents" and their replicates is not necessarily satisfied. The second approach solves this convergence problem by weighting the activity patterns instead of the agents themselves. Take for example a resident in Hasselt, who only performs a work activity in Diepenbeek. From Table 5.2 one can see that if this persons weight would be decreased, both the estimated OD-flows from Hasselt to Diepenbeek and Diepenbeek to Hasselt would be reduced, and as a result be closer to the "true" OD-flows for the population.

To illustrate the calibration of OD-matrices at the data levels, the second approach, the weighting of activity patterns, is followed. The RAPs of the residents in the sample are weighted using the algorithm displayed in Figure 5.2. Note that the algorithm that is implemented includes an element originating from tabu search meta-heuristics, namely the concept of a tabu list. A tabu list is a short-term memory where, in this case, the persons whose weights have been altered, are stored (Glover, 1990). The tabu list ensures that these weights are not altered multiple times within the same iteration, and consequently preventing situations like for instance the repetitive increasing and decreasing of the weight of a specific person. Two versions of the algorithm were implemented. The first one changed the weights by adding or subtracting one. The second one altered the weights by increasing or reducing the weights by a random number between one and ten, reducing the risk of converging towards the same saddle point (i.e. the same (sub)-optimum). A safeguard was included, procuring non-negative weights.

The estimated OD-matrices are provided in Table 5.3. The mean absolute percentage error (MAPE) of the estimated matrix using the first algorithm equals 2.12%, whereas the second matrix has a MAPE of 2.02%. From Table 5.4 one could notice that for two cells in both matrices the APE is higher than 0.5. This is due to the fact that the very few people are traveling between these two locations (Kortessem and Nieuwerkerken), and in line with this, that the persons in the sample traveling between these locations, also travel between other uncommon OD-pairs (Kortessem - Herk-De-Stad and Kortessem - Lummen). This underlines the importance of including a stop criterion in the algorithms to avoid an endless computation.

Table 5.3: OD-matrices calibrated using weighted RAPs

					Algorithm 1					
From\to	1	2	3	4	5	6	7	8	9	10
1	132,196	8,181	2,702	8,194	2,594	4,608	2,871	5,298	7,044	8,855
2	8,291	21,972	1,282	738	160	285	304	817	1,269	7,751
3	2,688	1,319	8,781	526	32	107	88	138	225	1,130
4	8,241	738	513	11,715	716	650	271	325	517	670
5	2,567	160	46	727	7,038	1,667	302	217	185	338
6	4,611	315	107	654	1,630	14,762	1,842	739	314	559
7	2,915	307	95	262	311	1,896	19,585	3,240	648	777
8	5,179	845	148	311	234	714	3,309	46,563	2,959	1,955
9	7,263	1,302	242	525	174	314	676	2,887	22,286	5,565
10	8,592	7,730	1,118	704	358	530	788	1,993	5,787	113,222
					Algorithm 2					
From\to	1	2	3	4	5	6	7	8	9	10
1	132,173	8,223	2,712	8,160	2,610	4,584	2,874	5,306	7,038	8,873
2	8,332	21,987	1,282	744	160	285	304	818	1,284	7,720
3	2,695	1,323	8,728	526	40	111	88	138	226	1,120
4	8,227	724	514	11,814	718	650	271	324	519	667
5	2,601	160	40	718	6,985	1,670	303	219	185	337
6	4,610	315	111	654	1,630	14,906	1,859	729	313	557
7	2,905	304	95	262	311	1,920	19,570	3,240	657	779
8	5,182	844	148	314	232	714	3,307	46,870	2,966	1,942
9	7,273	1,302	239	527	175	313	667	2,896	22,292	5,565
10	8,555	7,734	1,126	709	357	531	800	1,979	5,769	113,457

Table 5.4: Absolute percentage errors (calibration using weighted RAPs)

	Algorithm 1									
From\to	1	2	3	4	5	6	7	8	9	10
1	1.00%	0.48%	0.37%	0.55%	0.99%	0.61%	0.97%	0.53%	0.90%	0.82%
2	0.10%	0.88%	0.77%	0.81%	1.84%	0.71%	0.65%	0.97%	0.94%	0.90%
3	0.99%	0.69%	0.88%	0.77%	71.17%	0.94%	0.00%	0.73%	0.88%	0.44%
4	0.45%	0.96%	0.97%	0.55%	0.97%	0.91%	0.73%	0.93%	0.39%	0.45%
5	0.93%	5.96%	60.68%	0.83%	0.20%	0.95%	0.98%	0.91%	0.54%	0.90%
6	0.56%	0.94%	1.83%	0.93%	0.99%	0.87%	0.54%	0.96%	0.63%	0.72%
7	0.83%	0.99%	0.00%	0.77%	0.97%	0.58%	0.96%	0.98%	0.61%	0.77%
8	0.79%	0.96%	0.67%	0.96%	0.86%	0.97%	0.85%	0.86%	0.20%	0.26%
9	0.54%	0.93%	0.41%	0.94%	0.57%	0.96%	0.45%	0.96%	0.57%	1.00%
10	0.36%	0.80%	0.89%	0.98%	0.56%	0.75%	0.88%	0.91%	0.75%	0.44%
	Algorithm 2									
From\to	1	2	3	4	5	6	7	8	9	10
1	0.98%	0.99%	0.74%	0.96%	0.38%	0.09%	0.86%	0.68%	0.98%	0.62%
2	0.40%	0.81%	0.77%	0.00%	1.84%	0.71%	0.65%	0.85%	0.23%	0.49%
3	0.74%	0.99%	0.28%	0.77%	63.96%	4.72%	0.00%	0.73%	0.44%	0.44%
4	0.62%	0.96%	0.77%	0.29%	0.69%	0.91%	0.73%	0.62%	0.78%	0.89%
5	0.39%	5.96%	65.81%	0.42%	0.95%	0.77%	0.66%	0.00%	0.54%	0.60%
6	0.58%	0.94%	1.83%	0.93%	0.99%	0.09%	0.38%	0.41%	0.95%	0.36%
7	0.48%	0.00%	0.00%	0.77%	0.97%	0.68%	0.89%	0.98%	0.77%	0.51%
8	0.73%	0.84%	0.67%	0.00%	0.00%	0.97%	0.79%	0.21%	0.44%	0.92%
9	0.68%	0.93%	0.83%	0.57%	0.00%	0.64%	0.89%	0.65%	0.60%	1.00%
10	0.79%	0.74%	0.18%	0.28%	0.83%	0.56%	0.63%	0.20%	0.44%	0.65%

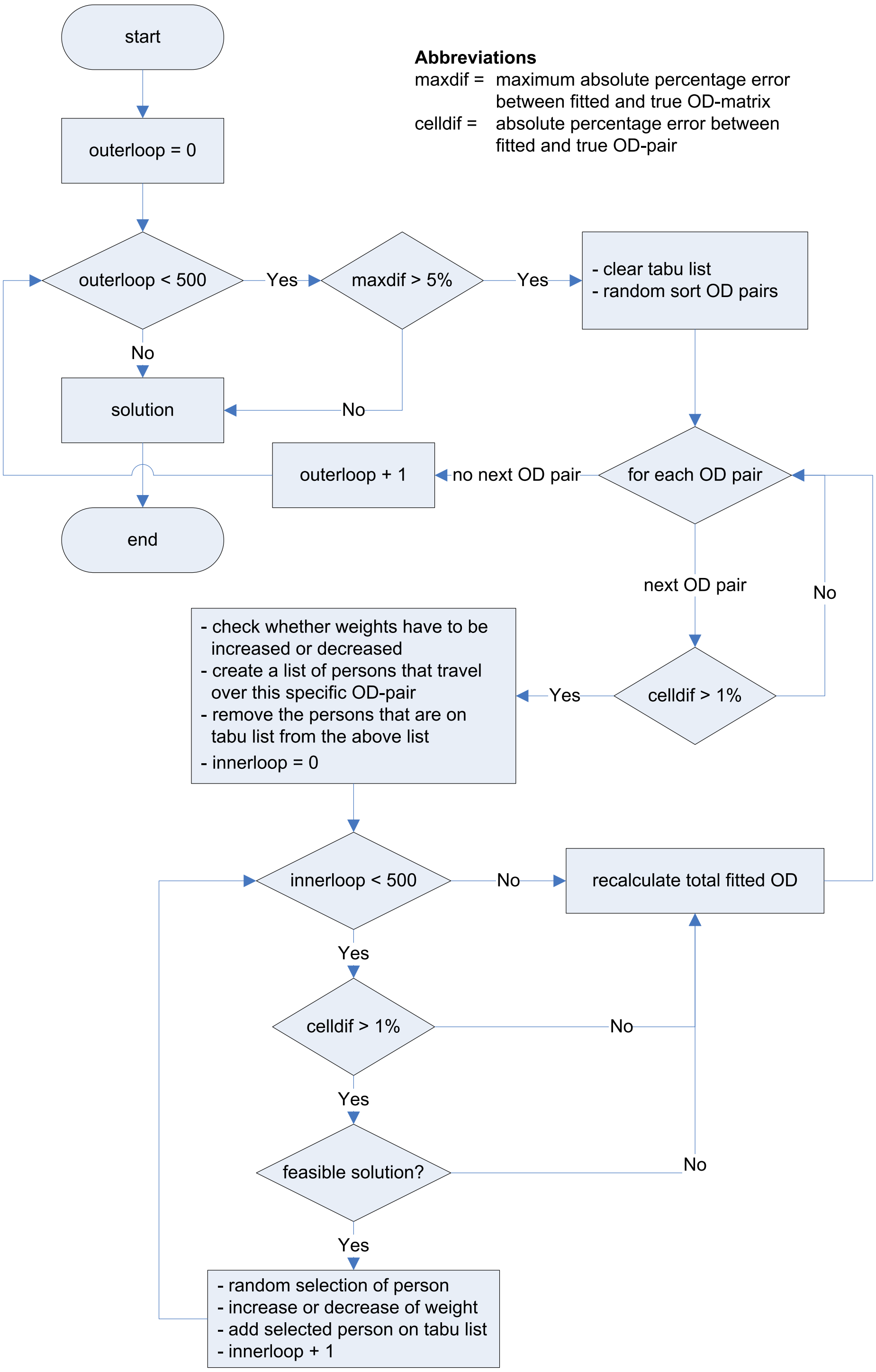

Figure 5.2: Calibration algorithm to weight representative activity patterns

Calibration at the model level

The basic model that will be calibrated, first predicts activity chains for all persons (the proportions of the different activity chains have been fixed to the population proportions), and then predicts the locations where the different activities will be performed. Note that the proportions of the different activity chains have been fixed to the population proportions. This reassures discrepancies between the "true population" OD matrix, and the calibrated OD-matrix are only due to differences in destination choices (location probabilities). Therefore, at the model-level, the activity schedule generation could be altered by iteratively updating the probabilities of certain destination choices (related to their respective activity purposes). The adjustment of the model parameters is straightforward in this case as only one dimension is considered at the time (i.e. the location probabilities). After all, the other parameters (such as the chances of performing certain activities) are kept constant. For real activity-based models in practice, a chain of interlinked choices with feedbacks are modeled, and consequently multiple parameters have to be changed simultaneously. This would seriously augment the complexity of the model, but the basic framework elucidated in this chapter, still could be used.

The updating process will attain a quasi-perfect match when the updated sample probabilities of the destination choices are equal to the unknown population probabilities. Nonetheless, a full search of the solution space (investigating all possible combinations of location probabilities for the different activities) is not a feasible option, as the number of possible combinations approaches infinity. The number of possible combinations can be computed as follows:

$$(1/\,(1 \text{ - precision of location probability}))^{\text{number of activities} \times \text{number of municipalities}},$$

which for the first practical example discussed in this chapter (applying a precision of 1%) would yield a total number of possible combinations of 10^{500} (approximating infinity). Therefore, an algorithm that explores the solution space for a 'good' solution instead of the optimal solution, should be implemented.

In order to calibrate the activity-based travel demand model, and to ensure convergence of optimization algorithms, it is essential that the variability caused by the activity-generation process is reduced as much as possible. Stability of the activity-generation can be assured by taking averages over multiple (activity-generation) runs, so that differences between the estimated OD-matrix and the true population OD-matrix are not the result of random variations, but of the altered location probabilities. However, guaranteeing the stability of the activity generation diminishes the performances, as computation times are significantly increased. The algorithm that is used is shown in Figure 5.3.

Table 5.5 presents the OD-matrix and corresponding APEs for the model-based calibration results. From these results, one could see that here is a decrease in the mean absolute percentage error from 20.27% in the up-scaled sample OD-matrix to 6.29% in the model-calibrated OD-matrix (after 100 iterations). Nevertheless, as multiple activity-generations are required in each step of the algorithm, model-based calibration is the most computer intensive calibration option, favoring other calibration techniques.

Table 5.5: Model-based calibrated OD-matrix and corresponding APEs

					Model-based calibrated OD-matrix					
From\to	1	2	3	4	5	6	7	8	9	10
1	131,667	8,088	2,822	8,140	2,553	4,634	2,970	5,391	7,071	8,617
2	8,307	21,901	1,153	783	178	319	331	909	1,211	7,554
3	2,830	1,188	8,814	554	98	126	107	183	258	1,174
4	8,159	759	543	11,487	690	623	234	265	544	711
5	2,506	172	101	689	7,063	1,665	303	236	220	355
6	4,692	341	124	628	1,591	14,879	1,815	682	324	615
7	2,972	333	107	228	312	1,843	19,266	3,149	635	857
8	5,306	918	190	263	235	685	3,188	46,990	3,064	2,044
9	7,154	1,241	269	545	224	321	631	3,014	21,894	5,772
10	8,359	7,706	1,208	699	367	597	856	2,063	5,844	112,689
					Model-based calibrated APEs					
From\to	1	2	3	4	5	6	7	8	9	10
1	0.60%	0.66%	4.84%	1.21%	2.54%	1.17%	2.44%	2.30%	0.52%	3.48%
2	0.10%	1.20%	10.78%	5.24%	9.20%	12.84%	8.28%	10.18%	5.44%	1.66%
3	4.24%	9.34%	1.27%	6.19%	11.41%	18.55%	21.97%	33.58%	13.51%	4.33%
4	1.43%	3.88%	4.83%	2.49%	4.56%	5.08%	14.29%	17.70%	5.63%	5.65%
5	3.27%	14.13%	13.68%	4.48%	0.16%	1.05%	0.77%	7.76%	19.38%	5.97%
6	1.19%	7.34%	14.07%	3.09%	1.45%	0.09%	2.00%	6.83%	2.64%	10.81%
7	2.79%	9.43%	12.28%	12.44%	1.19%	3.36%	0.68%	3.75%	2.66%	9.45%
8	1.65%	9.64%	27.74%	16.14%	1.15%	5.04%	2.84%	0.05%	3.76%	4.27%
9	0.96%	3.80%	11.62%	2.77%	27.81%	3.22%	6.29%	3.38%	1.20%	2.69%
10	3.06%	1.11%	7.12%	1.69%	1.85%	11.86%	7.67%	4.46%	1.74%	0.03%

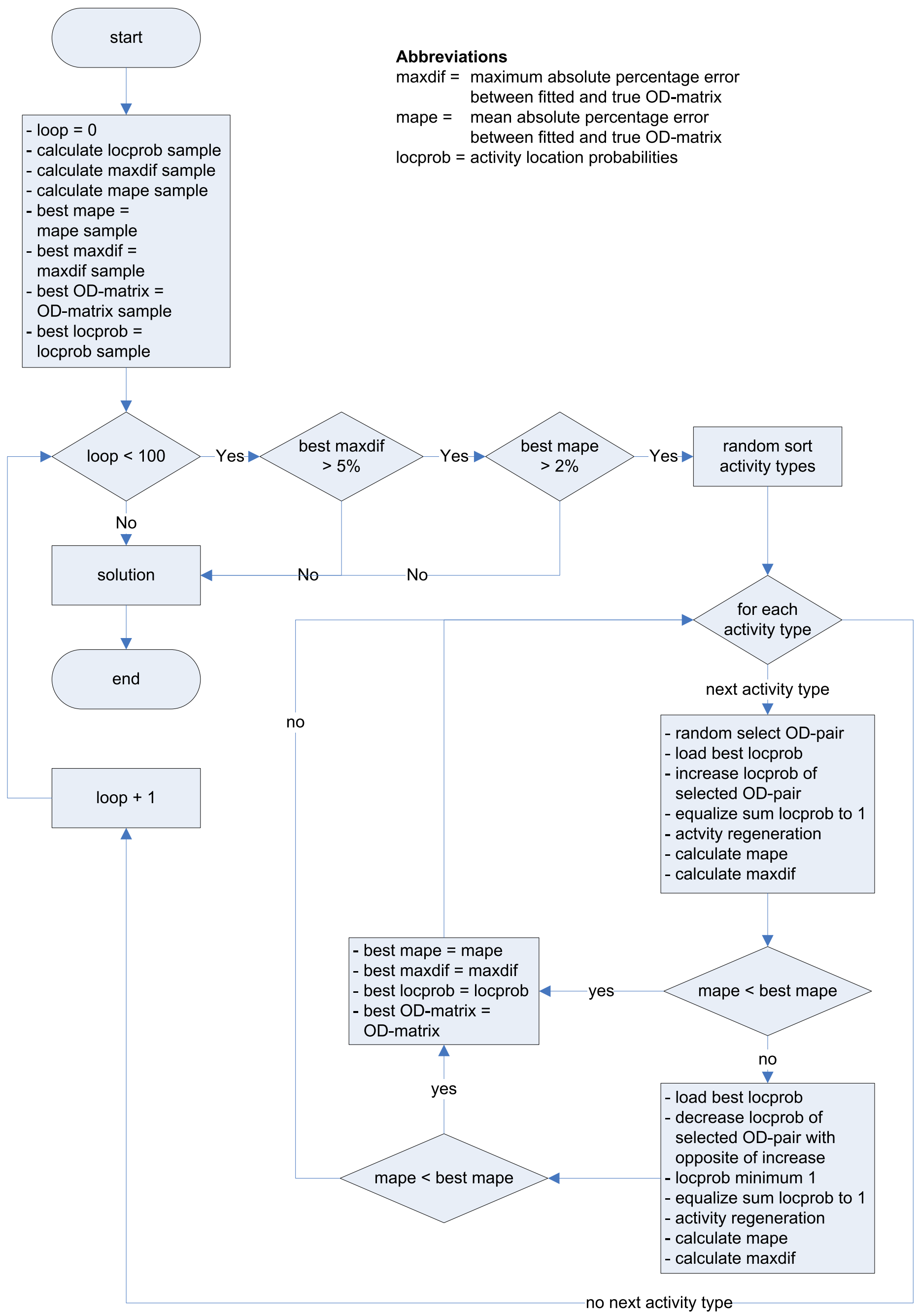

Figure 5.3: Calibration algorithm to adjust activity location probabilities

Calibration at the matrix level

The third level of calibration tackled in this section is the matrix level. Recall that perfect knowledge about route choice and mode choice is assumed, and that an identity match is presumed between traffic counts and origin-destination flows. Therefore the calibration at the matrix level, like the two previous calibration levels discussed, is illustrated using OD-pair information. The reader is referred to Abrahamsson (1998) for a thorough literature review concerning the calibration of OD-matrices using traffic counts. Three situations are explored in order to calibrate the survey OD-matrix.

Perfect Knowledge about Inter-Zonal Traffic

In the first situation, it is assumed that "perfect" knowledge is available about all inter-zonal traffic flows, but that information about intra-zonal traffic is only available at survey level. Let $P_i = \sum_j T_{ij}$ be the number of trips originating from municipality i (production), $A_j = \sum_i T_{ij}$ the number of trips arriving in municipality j (attraction), and T_{ij} the number of trips from zone i to zone j. Then the intra-zonal traffic flows $T_{ij,i=j}$ could be approached by the following formula:

$$T_{ij,i=j} = \lambda \left(P_i^{est} - P_i^{*,pop}\right) + (1-\lambda)\left(A_j^{est} - A_j^{*,pop}\right), \qquad (5.2)$$

in which $\lambda \in [0,1]$ expresses the relative importance that is given to the number of trips originating in a municipality, compared to the number of trips arriving in a municipality, in which *est* indicates that the quantity is derived from the estimated (survey) OD-matrix, and *pop* indicates that the quantity is derived from the population "true" OD-matrix. The asterisk underlines that the fact that the intra-zonal traffic flows are not included in the population row ($P_i^{*,pop} = \sum_{j,j\neq i} T_{ij}^{pop}$) and column totals ($A_j^{*,pop} = \sum_{i,i\neq j} T_{ij}^{pop}$). As it is often assumed that production is estimated more accurately than attraction (Ortúzar & Willumsen, 2001), in this practical example three times more confidence is placed in the estimation of productions than in the estimation of attractions. So the intra-zonal origin-destination flows are calculated by:

$$T_{ij,i=j} = 0.75\left(P_i^{est} - P_i^{*,pop}\right) + 0.25\left(A_j^{est} - A_j^{*,pop}\right). \qquad (5.3)$$

The resulting OD-matrix is given in the upper part of Table 5.6. Note that when it is assumed that the activity-travel pattern of people begin and end in the home location (like it is the case for the practical applications described in this chapter), the number of trips originating from a municipality equals the number of trips arriving in that municipality. In this case the choice of is irrelevant. From Table 5.7 it is clear that only the intra-zonal trips are altered (APEs for inter-zonal trips equal zero).

Growth Factor Modeling (Furness Iteration)

The second situation considers the case in which two OD-matrices (one on population level and one derived from the sample) are available. Information from these OD-matrices can be combined using growth factor modeling. One option is to take the cell information from the population (e.g. retrieved from GPS tracks) and the trip totals (column and row totals of the OD-matrix) from the survey. A second option is the reverse, namely taking the cell information from the survey, and the trip totals from the population. To illustrate the technique, the first option is implemented. This option is the more realistic one, as in practice precise OD-pair information can be derived using cell phone information at fairly low costs, whereas surveys capture well the total travel demand. The doubly constrained growth factor model is estimated using Furness iterations. Formally, the number of trips from municipality i to j (T_{ij}) is calculated as follows:

$$T_{ij} = t_{ij} \times a_i \times b_j, \tag{5.4}$$

in which t_{ij} is the number of trips (in the population OD-matrix), and in which a_i and b_j are balancing factors. These balancing factors are a set of correction coefficients which are appropriately applied to the cell entries in each row or column. The iterative procedure starts with setting all b_j equal to one. In the second step, the a_i are solved for b_j to satisfy the trip production constraint (row totals of the cell entries of the population OD matrix have to equal the productions derived from the survey). Subsequently, in the third step, the b_j are solved for the a_i, calculated in the previous step, to satisfy the trip attraction constraint (column totals of the cell entries of the population OD matrix have to equal the attractions derived from the survey). Then, the OD matrix is updated. This consecutive calculation of a_i and b_j is repeated until convergence is achieved (both the production and attraction constraints are satisfied). The procedure yields the matrix presented in the middle of Table 5.6, the corresponding APEs in Table 5.7.

"Perceived Precision" Updating

The third and final situation that is explored to illustrate potential calibration options at the data level, describes the case in which an outdated population-based OD-matrix, as well as a recent matrix derived from the sample are available. The procedure is an adaptation of the Bayesian updating procedure discussed by Ather-

Table 5.6: OD-Matrices Calibrated Using Matrix Level Possibilities

Situation 1: Perfect Knowledge about Inter-Zonal Traffic										
From\to	1	2	3	4	5	6	7	8	9	10
1	133,122	8,142	2,692	8,239	2,620	4,580	2,899	5,270	7,108	8,928
2	8,299	21,365	1,292	744	163	283	306	825	1,281	7,682
3	2,715	1,310	9,819	522	111	106	88	137	227	1,125
4	8,278	731	518	10,591	723	656	273	322	515	673
5	2,591	151	117	721	6,774	1,683	305	219	184	335
6	4,637	318	109	648	1,614	14,379	1,852	732	316	555
7	2,891	304	95	260	308	1,907	19,488	3,272	652	783
8	5,220	837	149	314	232	721	3,281	46,773	2,953	1,960
9	7,224	1,290	241	530	175	311	673	2,915	24,740	5,621
10	8,623	7,792	1,128	711	360	534	795	1,975	5,744	112,618
Situation 2: Growth Factor Modeling (Furness Iteration)										
From\to	1	2	3	4	5	6	7	8	9	10
1	132,854	8,085	2,839	8,008	2,606	4,556	2,925	5,294	7,449	8,984
2	8,241	21,536	1,333	707	159	275	302	811	1,313	7,563
3	2,863	1,352	9,535	527	115	110	92	143	247	1,176
4	8,046	695	523	10,964	688	625	264	310	517	648
5	2,577	147	121	687	6,871	1,640	302	216	189	330
6	4,611	309	113	617	1,573	14,513	1,831	720	325	548
7	2,919	301	100	251	305	1,886	19,468	3,268	679	783
8	5,243	822	155	302	228	710	3,278	46,688	3,062	1,952
9	7,569	1,322	262	532	180	319	702	3,023	23,972	5,839
10	8,677	7,671	1,179	685	355	526	796	1,967	5,967	112,457
Situation 3: "Perceived Precision" Updating										
From\to	1	2	3	4	5	6	7	8	9	10
1	131,207	8,192	2,763	8,132	2,590	4,643	2,936	5,298	7,163	8,813
2	8,336	22,086	1,210	760	162	309	308	881	1,261	7,595
3	2,769	1,238	8,833	542	99	122	93	161	242	1,131
4	8,218	749	532	11,690	702	647	267	302	496	667
5	2,586	152	104	714	7,043	1,656	294	229	207	326
6	4,664	338	124	640	1,612	14,790	1,830	710	303	576
7	2,942	313	106	257	310	1,882	19,425	3,180	623	846
8	5,223	891	164	282	233	701	3,214	46,839	3,087	1,967
9	7,280	1,275	267	548	199	299	647	2,996	22,367	5,691
10	8,512	7,673	1,127	706	360	538	869	2,006	5,820	112,758

Table 5.7: Absolute Percentage Errors (Calibration Using Matrix Level Possibilities)

From\to	1	2	3	4	5	6	7	8	9	10
Situation 1: Perfect Knowledge about Inter-Zonal Traffic										
1	1.71%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
2	0.00%	3.62%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
3	0.00%	0.00%	12.81%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
4	0.00%	0.00%	0.00%	10.09%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
5	0.00%	0.00%	0.00%	0.00%	3.94%	0.00%	0.00%	0.00%	0.00%	0.00%
6	0.00%	0.00%	0.00%	0.00%	0.00%	3.44%	0.00%	0.00%	0.00%	0.00%
7	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.46%	0.00%	0.00%	0.00%
8	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.41%	0.00%	0.00%
9	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	11.64%	0.00%
10	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.09%
Situation 2: Growth Factor Modeling (Furness Iteration)										
From\to	1	2	3	4	5	6	7	8	9	10
1	1.50%	0.70%	5.46%	2.80%	0.53%	0.52%	0.90%	0.46%	4.80%	0.63%
2	0.70%	2.85%	3.17%	4.97%	2.45%	2.83%	1.31%	1.70%	2.50%	1.55%
3	5.45%	3.21%	9.55%	0.96%	3.60%	3.77%	4.55%	4.38%	8.81%	4.53%
4	2.80%	4.92%	0.97%	6.93%	4.84%	4.73%	3.30%	3.73%	0.39%	3.71%
5	0.54%	2.65%	3.42%	4.72%	2.57%	2.55%	0.98%	1.37%	2.72%	1.49%
6	0.56%	2.83%	3.67%	4.78%	2.54%	2.54%	1.13%	1.64%	2.85%	1.26%
7	0.97%	0.99%	5.26%	3.46%	0.97%	1.10%	0.36%	0.12%	4.14%	0.00%
8	0.44%	1.79%	4.03%	3.82%	1.72%	1.53%	0.09%	0.59%	3.69%	0.41%
9	4.78%	2.48%	8.71%	0.38%	2.86%	2.57%	4.31%	3.70%	8.18%	3.88%
10	0.63%	1.55%	4.52%	3.66%	1.39%	1.50%	0.13%	0.41%	3.88%	0.24%
Situation 3: “Perceived Precision” Updating										
From\to	1	2	3	4	5	6	7	8	9	10
1	0.24%	0.61%	2.65%	1.29%	1.15%	1.38%	1.27%	0.54%	0.78%	1.28%
2	0.44%	0.37%	6.35%	2.15%	0.31%	9.25%	0.76%	6.77%	1.57%	1.13%
3	2.00%	5.47%	1.49%	3.77%	10.66%	14.78%	6.06%	17.40%	6.83%	0.52%
4	0.72%	2.49%	2.64%	0.76%	2.84%	1.42%	2.01%	6.31%	3.72%	0.82%
5	0.20%	0.99%	10.97%	0.95%	0.12%	1.61%	3.55%	4.64%	12.32%	2.74%
6	0.59%	6.39%	13.91%	1.23%	0.14%	0.68%	1.19%	3.01%	4.01%	3.75%
7	1.78%	3.07%	11.40%	1.28%	0.65%	1.28%	0.14%	2.81%	4.40%	8.02%
8	0.06%	6.43%	10.18%	10.30%	0.57%	2.80%	2.04%	0.27%	4.55%	0.34%
9	0.78%	1.16%	11.00%	3.46%	13.81%	3.80%	3.79%	2.77%	0.93%	1.24%
10	1.28%	1.52%	0.12%	0.73%	0.00%	0.81%	9.33%	1.56%	1.32%	0.03%

ton & Ben-Akiva (1976). This procedure updates information using the following formulae:

$$\vartheta_{updated} = \frac{\frac{\vartheta_{prior}}{\sigma^2_{prior}} + \frac{\vartheta_{updating}}{\sigma^2_{updating}}}{\frac{1}{\sigma^2_{prior}} + \frac{1}{\sigma^2_{updating}}} \text{ and } \sigma^2_{updated} = \frac{1}{\frac{1}{\sigma^2_{prior}} + \frac{1}{\sigma^2_{updating}}}, \tag{5.5}$$

with ϑ the mean of the investigated quantity and σ the variance of the mean of that quantity. As the OD-cells in an OD-matrix are fixed numbers, of which the variance is seldom reported, one could replace the mean of the quantity by the OD-flow and reformulate the formulae in terms of perceived precision (ψ) instead of variance of the mean (since the precision increases as the variance decreases). This perceived precision can for instance be obtained via expert knowledge. The formulae then take the form of the following equations:

$$T^{new}_{ij} = \frac{\frac{T^{pop}_{ij}}{(1-\psi^{pop})} + \frac{T^{sa}_{ij}}{(1-\psi^{sa})}}{\frac{1}{(1-\psi^{pop})} + \frac{1}{(1-\psi^{sa})}} \text{and} \psi^{new} = 1 - \frac{1}{\frac{1}{(1-\psi^{pop})} + \frac{1}{(1-\psi^{sa})}}. \tag{5.6}$$

For the practical example discussed in this chapter the perceived precision of the population OD-matrix is set equal to 99% and the one of the sample OD-matrix equal to 95%. Note that the updated OD-matrix then has a precision of 99.17%. The updated OD-matrix is shown in the lower part of Table 5.6. For reasons of completeness and comparability with other calibration techniques, the APEs for this method are also presented (Table 5.7), even though interpretation of these specific APEs is meaningless, as the premise of this example was outdated population data.

3.4 Discussion of Proposed Techniques

An interesting issue of calibration to traffic counts is the fact that the traffic counts themselves are uncertain. Uncertainty can be tackled in the data-level and model-level based calibration by adjusting the converge criterion, i.e. absolute percentage errors (called 'fitness values' by Park & Qi (2005)). When choosing between the different techniques suggested in this paper, three key issues have to be taken into account: computational complexity, data availability and sensitivity to policy issues.

The most computer intensive method was the model-based calibration, requiring 14 days of computation on a computer with a Core 2 Duo 2.10 GHz CPU and 4GB RAM. This large computation time was due to the fact that the calibration at this level involves running the full simulation model ((Toledo *et al.*, 2003; Jha *et al.*, 2004; Toledo *et al.*, 2004). In comparison, the iterative procedure for calibration at the date level took about 1 day, and the matrix-level techniques only required a few seconds of computation (the latter techniques did not include iterative optimization techniques). Note that the computation times of the iterative procedures could be decreased by using more efficient optimization algorithms, such as genetic algorithms (Park & Qi, 2005) and golden section search (Zhang & Levinson, 2004).

Next to the computational complexity, the available target data will definitely will influence the suitability of the different techniques. The largest amount of target data are required for the model-based calibration, since for each subpart of the model, target information is necessary.

Finally, the influence of the calibration techniques on the sensitivity of the model to policy measures is of high importance. This sensitivity depends on how the base year calibration manipulations (i.e. calibrations weights) are transferred towards future predictions. Further research on the policy sensitivity of the different approaches should be a key priority for further research.

5.3 Conclusion and further research

In this Section, different possibilities for linking travel demand models in general, and activity-based models in particular, with traffic counts and precise OD-matrix information are highlighted and illustrated by means of an example. The discussed techniques provide the framework to overcome one of the main concerns of practitioners, namely the disadvantage of activity-based models over conventional four-step models in terms of the replication of traffic counts. The practical examples revealed that there is not a single roadway to success in calibrating activity-based models, but that different options exist in fine-tuning the activity-based model. Therefore, a careful assessment of the available options is needed to determine which choices have to be made. A step-wise procedure, combining elements of the different proposed solutions, is to be recommended.

Notwithstanding, it is important to recognize some open issues and avenues for further research. First, it is not always appropriate to assume that traffic counts are completely correct. In reality, differences may relate to sampling bias, variability in travel, imperfect counts, assumptions about non-passenger cars (e.g. freight traffic) and external traffic, and unreliability in model facets. Setting up some belief-structure might increase the responsiveness of the activity-based model. Second, the OD-matrix calibration that optimizes the correspondence between estimated and observed screen-line counts could negatively impact the correspondence to other measures such as vehicle miles traveled. Therefore, formulation of a multi-objective calibration method is a key challenge. Third, in most cases in practice, travel demand models are validated and tested against hour-specific counts. The same methodology can be applied in this case: modeled trip tables must be compared to counts for each time-of-day period. The challenge herein, exists in consolidating the time-of-day specific adjustments into a set of activity-generation, location and schedule adjustments. Finally, further testing the calibration possibilities within a real activity-based travel demand modeling environment would further provide empirical evidence of the proposed frameworks. In particular, the investigation of how the policy sensitivity of an activity-based model is affected by the different approaches should be a key priority for further research.

Chapter 6

Conclusions

In this final chapter, the main conclusions that evolved from this research are epitomized and avenues for further research are highlighted.

6.1 Main conclusions

In the first part of the dissertation, the impact of holidays and weather conditions on Flemish travel behavior was examined. First, the variability in daily traffic intensities (the revealed traffic pattern) was assessed. In particular, the focus was turned to the investigation of holiday effects and to weekly recurring cycles. Three modeling approaches, namely SARIMA, ARIMAX and SARIMAX, were considered for the prediction of the daily traffic counts. These different modeling techniques, as well as the spectral analysis, pointed out the significance of the day-of-week effects: weekly cycles seem to determine the variation of daily traffic flows. The comparison of day-of-week effects or seasonal effects and holiday effects at different site locations revealed that all three modeling approaches perform reasonably well in explaining the variability of daily traffic counts, favoring the ARIMAX model, when the focus is on forecasting daily traffic counts. Moreover, results pointed out that the ARIMAX and SARIMAX modeling approaches are valid frameworks for identification and quantification of possible influencing effects. Nonetheless, results showed that the explicit incorporation of day-of-week effects in ARIMAX yields additional insight for policy decision makers. The technique provided the insight that holidays play a noticeable role on highways that are excessively used by commuters, whereas they have a more ambiguous effect on highways typified for their leisure traffic. These results could help policy makers to fine-tune current policy measures. An example is to focus policy actions such as carpooling initiatives on the most traffic intense days. A specific example for the E40 highway for instance, is the stimulation of alternative travel modes for the Friday traffic. These examples illustrate that the findings of this study contribute to achieving an important goal, namely the policy keystone 'more acceptable and reliable travel times'.

Secondly, the influence of holidays on daily travel time expenditure was investigated by using data that stem from the 2000 Flemish household travel survey. Results from both the preliminary analysis[1]as well as the results from the zero-inflated Poisson model showed that socio-demographics, temporal effects and transportation preferences significantly contribute to the unraveling of variability in daily travel time expenditure. In particular it has been illustrated that holidays have a non-ignorable impact on daily travel behavior. The zero-inflated Poisson regression models, which were used to accommodate the Poisson models to the portentous excess of zeros caused by non-travelers, yielded findings that were in accordance with international literature. It is essential that policy makers acknowledge these findings. The accommodation of activity-based models to the new insights allows policy makers to fine-tune their policy measures in an attempt to achieve important political goals such as reliable travel times and environment goals like the Kyoto norms.

Next to the investigation of holiday effects, variability in Flemish travel behavior was assessed by examining the effect of weather conditions on travel behavior. First, the impact of various weather conditions on traffic intensity was investigated. The most striking result for policy makers is the heterogeneity of the weather effects between different traffic count locations, and the homogeneity of the weather effects on upstream and downstream traffic at a certain location. Consequently, traffic management strategies that minimize weather-related side-effects on traffic operations must adopt an approach that takes into account local weather effects. The results also indicated that precipitation, cloudiness, and wind speed have a clear diminishing effect on traffic intensity, whereas maximum temperature and hail significantly increase traffic intensity. These significant impacts of weather conditions on traffic intensity underline the necessity of incorporating weather conditions in future traffic safety research not only in a direct way, but also indirectly by modeling the effects of weather conditions via traffic intensity. Because of the previously discussed inherent relationship between traffic intensity, weather and traffic safety, the results support the recommendation to develop location specific traffic safety policies next to a global

[1]Recall that simple linear regression and Poisson regression, using a scale parameter for remedying over-dispersion, were used as preliminary analysis techniques to examine daily travel time expenditure.

country-wide strategy.

Secondly, the effect of weather conditions was studied by focusing on the underlying activity-travel behavior. In particular, the hypothesis of dependence of changes in travel behavior on type of weather on the one hand, and the hypothesis of dependence of changes in travel behavior on trip purpose (activity type) on the other hand were formally tested. To this end, a stated adaptation study was conducted in Flanders (Dutch speaking region of Belgium). In total 586 respondents completed the survey. Both the results from the descriptive analysis and the Pearson chi-square independence tests confirmed that indeed the type of weather condition matters, and that the changes in travel behavior in response to these weather conditions are highly dependent on the trip purpose. Whereas the majority of the papers in international literature focus on traffic safety and traffic flows, this dissertation contributed to the literature by looking at the actual underlying travel behavior by means of a multifaceted stated adaptation approach. The clear dependence of behavioral adjustments on activities (trip purposes) provides policy makers with a deeper understanding of how weather conditions affect traffic. The value of this contribution is stressed by weather related policy issues such as increased fuel consumption, economic losses due to traffic delays, and higher traffic counts.

In the second part of the dissertation it was shown how the findings of the first part (the effects of holidays and weather events on travel behavior) could be integrated in the context of transportation models. First, it was shown that weather conditions and holidays can be integrated in transportation models using the concept of 'conditional learning'. 'Conditional learning' is the identification by agents of conditions that allow the agents to explain differences in attributes of the environment, such as differences in travel times that could be explained in terms of type of day (holiday versus regular working day), weather conditions, etc.

Next to the concept of conditional learning, an assessment of the quality of origin-destination matrices (a key component in both traditional four-step and modern activity-based models) derived from household activity/travel surveys was made. The results showed that no accurate OD-matrices can be directly derived from these surveys. Only when half of the population is queried, an acceptable OD-matrix is obtained at provincial level. Therefore, it is recommended to use additional information to better grasp the behavioral realism underlying destination choices. This is certainly a plea for travel demand models that incorporate the behavioral underpinnings of destination choices (activity location choices) given a certain origin. Moreover, matrix calibration techniques could seriously improve the quality of the matrices derived from these household activity/travel surveys. In addition, it is recommended to collect information about particular origin-destination pairs by means of vehicle intercept surveys rather than household activity/travel surveys, as these vehicle intercept surveys are tailored for collecting specific origin-destination data. A second important finding is that traditional methods to assess the comparability of two origin-destination matrices can be enhanced: the MCAPE index that was proposed has clear advantages over the traditional indices, the most important being the fact that the MCAPE filters out the noise created by the asymmetry of the traditional criteria. Therefore, when dissimilarities between different OD-matrices are investigated, the use of the MCAPE index in addition to traditional criteria is highly recommended.

In the final chapter, different possibilities for linking travel demand models in general, and activity-based models in particular, with traffic counts and precise OD-matrix information were highlighted and illustrated by means of an example. The discussed techniques provided the framework to overcome one of the main concerns by practitioners, namely the disadvantage of activity-based models over conventional four-step models in terms of the replication of traffic counts. The practical examples revealed that there is not a single roadway to success in calibrating activity-based models, but that different options exist in fine-tuning the activity-based model. Therefore, a careful assessment of the available options is needed to determine which choices have to be made. A step-wise procedure, combining elements of the different proposed solutions, can be recommended.

6.2 Avenues for further research

This dissertation concludes with highlighting different avenues for further research.

6.2.1 Holiday effects

Further generalizations of the effects of holidays on daily traffic counts are possible, when more traffic patterns of other parts of the road network are analyzed. Modeling of daily traffic counts on secondary roads, and simultaneous modeling of different traffic count locations is certainly an important pathway for further research. A suggested approach could be the combination of a clustering technique and a vector modeling approach. In order to increase the understanding of differences in travel time expenditure and further isolate the effect of holidays, it is necessary for further research to incorporate social interactions and spatial variables. Multi-day data can improve the analysis even further by for instance differentiating random and routine behavior. Triangulation of both quantitative (e.g. statistical analysis) and qualitative measures (e.g. mental models) seems a solid roadway for further illumination of the underpinnings of travel behavior. A key challenge will be the simultaneous modeling of both the underlying reasons of travel, and revealed traffic patterns.

6.2.2 Weather conditions

Pathways for further research on the effect of various weather conditions include the investigation of weather effects on local roads and the shift of scope towards underlying travel behavior. Linking travel behavior research, traffic flow modeling, and safety research by simultaneous modeling of weather conditions, traffic intensity rates, collision risk and activity travel behavior is certainly an important issue for further research. In particular, integration of both stated and revealed travel behavior on the one hand, and traffic intensities on the other hand, could produce valuable insights in the effect of weather conditions.

6.2.3 Sampling error

Concerning transportation models, an important avenue for further research is the investigation of the relationship between the variability in the outcomes of travel demand models and underlying survey data. An empirical investigation of the effect of sampling proportions in household activity/travel surveys on final model outcomes would further illuminate the quest for optimal sample sizes. Model complexity and computability will certainly be key challenges in this pursuit.

6.2.4 Calibration

The final roadways for further research indicated in this dissertation, are the ones related with the suggest approaches for calibrating transportation models. Some of the open issues include the following. First, it is not always appropriate to assume that traffic counts are completely correct. In reality, differences may relate to sampling bias, variability in travel, imperfect counts, assumptions about non-passenger cars, and unreliability in model facets. Setting up some belief-structure might increase the responsiveness of the activity-based model. Second, the OD-matrix calibration that optimizes the correspondence between estimated and observed screen-line counts could negatively impact the correspondence to other measures such as vehicle miles traveled. Therefore, formulation of a multi-objective calibration method is a key challenge. Third, in most cases in practice, travel demand models are validated and tested against hour-specific counts. The same methodology can be applied in this case: modeled trip tables must be compared to counts for each time-of-day period. Here the challenge consists of consolidating the time-of-day specific adjustments into a set of activity-generation, location and schedule adjustments. Finally, further testing the calibration possibilities within a real activity-based travel demand modeling environment would enhance empirical evidence of the proposed frameworks.

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Samenvatting

Inleiding

In de hedendaagse samenleving domineert 'koning auto' ons verplaatsinggedrag met ernstige ecologische en socio-economische gevolgen. Toenemende bezorgdheid over deze steeds ernstig wordende gevolgen heeft bijzondere interesse gewekt in hoe verkeersmaatregelen deze neveneffecten op zijn minst kunnen temperen.

Om beleidsmakers te ondersteunen met het nemen van beslissingen werden/worden diverse transport modellen ontwikkeld. Het is in deze context dat het activiteitengebaseerde raamwerk Feathers (Engelstalig acroniem voor 'voorspellen van evolutionair activiteiten- en verplaatsingsgedrag van huishoudens en de bijhorende ecologische repercussies) werd ontwikkeld. Bovendien kan een diepgaander begrip van de gebeurtenissen die activiteiten- en verplaatsingsgedrag beïnvloeden leiden tot betere voorspellingen en bijgevolg kunnen beleidsmaatregelen worden ondersteund door meer betrouwbare gegevens.

Om een meer verfijnd inzicht te krijgen in het Vlaamse verplaatsingsgedrag, wordt in dit doctoraat de interdagvariabiliteit (de variabiliteit tussen verschillende dagen) en de intradagvariabiliteit (de variabiliteit in een dag) van het Vlaams verplaatsingsgedrag onderzocht. Aangezien 'verplaatsingsgedrag' een zeer generieke term is, is het noodzakelijk om zeer nauwkeurig af te lijnen welke deelaspecten onderzocht worden. In dit doctoraat ligt de klemtoon op de analyse van gereleveerde verkeerspatronen (verkeerstellingen), dagelijkse verplaatsingstijden en verplaatsingsafstanden en op aangegeven gedragsveranderingen als antwoord op weerscondities en vakantiedagen.

Dit doctoraat is opgesplitst in twee delen. In het eerste deel wordt de impact van vakantiedagen en diverse weeromstandigheden onderzocht. In het tweede deel, wordt aangeduid hoe bevindingen op basis van o.a. verkeerstellingen kunnen vertaald worden naar transportmodellen.

Vakantie-effecten

De impact van vakantiedagen op de dagelijkse mobiliteit van Vlaamse huishoudens wordt onderzocht door enerzijds de impact van vakantiedagen op dagelijkse verkeerstellingen te analyseren, en anderzijds door de impact op dagelijkse verplaatsingstijden diepgaander te bestuderen.

Bij het bestuderen van de verkeerstellingen werden diverse modelleertechnieken aangewend om dagelijkse verkeerstellingen te voorspellen. De diverse benaderingen (waaronder (S)ARIMA(X)-modellen en spectrale analyse) onderstreepten de significantie van 'dag-van-de-week'-effecten: wekelijkse cycli bepalen in belangrijke mate de variatie in dagelijkse verkeersstromen. De vergelijking van 'dag-van-de-week'-effecten of seizoenseffecten en vakantie-effecten op verschillende tellocaties toonde aan dat de (S)ARIMA(X)-modellen redelijk goed de variabiliteit in dagelijkse verkeerstellingen kunnen verklaren. Bovendien bleek dat de (S)ARIMAX-modellen geldige benaderingen zijn om effecten zoals vakantie-effecten te kwantificeren. Naar beleidsrelevantie toe, verschafte de ARIMAX modellen het meeste inzicht: de expliciete opname van 'dag-van-de-week' effecten leverde het inzicht op dat vakantiedagen een belangrijke impact hebben op autosnelwegen die in hoofdzaak gebruikt worden door pendelaars, terwijl vakantiedagen een meer ambigu effect hebben op autosnelwegen getypeerd door recreatief verkeer. Verdere veralgemening van het effect van vakantiedagen op dagelijkse verkeerstellingen is mogelijk wanneer andere delen van het wegennetwerk worden geanalyseerd: het modelleren van verkeerstellingen op het onderliggende wegennet en het simultaan schatten van verschillende tellocaties is zeker een belangrijke piste voor verder onderzoek.

Naast het bestuderen van de impact van vakantiedagen op dagelijkse verkeerstellingen werd ook de impact van vakantiedagen op dagelijkse verplaatsingstijden (bevraagd tijdens het Onderzoek Verplaatsingsgedrag 2000) grondiger onderzocht. Gebruikmakend van zogenaamde 'zero-inflated Poisson'-regressiemodellen, die het opblazen van nullen, veroorzaakt door mensen die zich niet verplaatsen, expliciet in rekening nemen, werden relaties blootgelegd in overeenstemming met de internationale literatuur: socio-demografische en temporele effecten, alsook transportvoorkeuren dragen in niet geringe mate bij tot het verklaren van de variabiliteit in dagelijkse verplaatsingstijden. In het bijzonder werd er aangetoond dat vakantiedagen een niet te verwaarlozen effect hebben op het dagelijkse verplaatsingsgedrag. Om nog meer verfijnde conclusies te kunnen trekken, is het noodzakelijk dat in verder onderzoek ook sociale interacties en variabelen die het ruimtelijke aspect beschrijven, mee in rekening worden genomen. Meerdaagse gegevens kunnen bovendien de analyses nog verder verfijnen door onderscheid te maken tussen spontaan en routinematig gedrag. Triangulatie van zowel kwantitatieve (bijvoorbeeld statistische analyses) als kwalitatieve modellen (bijvoorbeeld mentale modellen) kunnen een mogelijke weg bieden om de wortels van verplaatsingsgedrag nog verder te onthullen. Een van de grootste uitdagingen zal zeker het simultaan modelleren zijn van zowel de onderliggende verplaatsingsmotieven als de resulterende verkeerspatronen.

Weerscondities

Naast het bestuderen van het effect van vakantiedagen, werd ook de impact van diverse weersomstandigheden bestudeerd. Eerst werd het effect op de verkeersintensiteit onderzocht. Het meest beleidsrelevante resultaat van deze analyse is de heterogeniteit van weerseffecten tussen diverse tellocaties, en de homogeniteit van weerseffecten stroomopwaarts en stroomafwaarts op dezelfde tellocatie. De resultaten toonden ook aan dat neerslag, bewolking en windsnelheid een duidelijk dempend effect hebben op verkeersintensiteit, terwijl maximumtemperatuur en hagel de verkeersintensiteit beduidend verhogen. Deze significante impact van weersomstandigheden onderstreepten de noodzaak om in toekomstig verkeersveiligheidsonderzoek weersvariabelen niet alleen op een directe wijze, maar ook op een indirecte wijze te modelleren.

Ten tweede werd het effect van diverse weersomstandigheden bestudeerd door te kijken naar het onderliggende activiteiten-verplaatsingsgedrag. In het bijzonder werd de hypothese van (on)afhankelijkheid van gedragsveranderingen van weerscondities getest, en werd de hypothese van (on)afhankelijkheid van gedragsveranderingen van het verplaatsingsmotief (activiteittype) ook formeel getest met behulp van een 'stated adaptation' experiment. De resultaten bevestigden dat het type weerconditie inderdaad een rol speelt, en dat de gedragsveranderingen als antwoord op diverse weerscondities zeer afhankelijk zijn van het motief (activiteit) van de verplaatsing.

Prioritaire pistes voor verder onderzoek naar weerseffecten zijn de analyses van de effecten van weersomstandigheden op lokale wegen en het verder verschuiven van de focus naar het onderliggende verplaatsingsgedrag. In het bijzonder kan de integratie van 'stated' en 'revealed' verplaatsingsgedrag aan de ene kant, en verkeersintensiteiten aan de andere kant, waardevolle beleidsrelevante inzichten leveren.

Integratie in transportmodellen

In het tweede deel van dit doctoraat werd getoond hoe de bevindingen van het eerste deel (effecten van vakantiedagen en weersomstandigheden) kunnen worden geïntegreerd in de context van transportmodellen. Eerst werd geïllustreerd hoe deze effecten kunnen worden geïntegreerd, gebruik makend van het concept van 'conditioneel leren'; de identificatie door de 'agents' van diverse condities die hen toelaat om verschillen in omgevingsattributen te verklaren, zoals verschillen in verplaatsingstijden die kunnen verklaard worden door het type dag (reguliere werkdag versus vakantiedag), weersomstandigheden, etc.

Als aanvulling op het 'conditioneel leren'-concept, werd de kwaliteit van herkomst-bestemmingsmatrices (één van de meest belangrijke modelcomponenten van zowel traditionele vierstapsmodellen als moderne activiteitengebaseerde modellen), afgeleid van huishoudenquêtes die het activiteiten/verplaatsingsgedrag bevragen, beoordeeld. De resultaten toonden aan dat geen accurate herkomst-bestemmings (HB)-matrices kunnen worden afgeleid van deze enquêtes. Enkel wanneer op zijn minst de helft van de populatie wordt bevraagd, kan een aanvaardbare HB-matrix worden verkregen op provinciaal niveau. Daarom is het aangewezen om bijkomende informatie te gebruiken die beter het onderliggende gedrag bevat bij bestemmingskeuzes. Dit is zeker een pleidooi voor het gebruik van transportmodellen die de onderliggende factoren van bestemmingskeuzes integreren. Bovendien kunnen technieken voor matrixcalibratie de kwaliteit van de afgeleide HB-matrices sterk verbeteren.

Een tweede belangrijke bevinding is dat traditionele methoden om HB-matrices te vergelijken kunnen worden verfijnd: de MCAPE index die voorgesteld werd heeft duidelijke voordelen ten opzichte van de traditionele indices; het meest belangrijke is het feit dat de MCAPE de ruis wegfiltert die gecreëerd wordt door de asymmetrie van traditionele criteria.

Een belangrijke piste voor verder onderzoek is de studie van het verband tussen de variabiliteit in de modelresultaten van de transportmodellen en de onderliggende enquêtedata. Een empirisch onderzoek naar het effect van steekproefproporties op de finale modelvoorspellingen zal verder de zoektocht naar optimale enquêtegroottes verhelderen. Hierbij zullen modelcomplexiteit en berekenbaarheid grote uitdagingen zijn.

Matrix-kalibratie

In het laatste hoofdstuk (het besluitende hoofdstuk niet meegeteld) werden verschillende mogelijkheden om transportmodellen te linken met precieze HB-matrix informatie toegelicht en geïllustreerd aan de hand van een voorbeeld. De voorgestelde technieken bieden een raamwerk om één van de grootste bekommernissen van practici, namelijk het nadeel van activiteitengebaseerde modellen ten opzichte van conventionele modellen wat betreft het repliceren van verkeerstellingen, te overwinnen. Het praktische voorbeeld onthulde dat er meerdere kalibreermogelijkheden zijn om (activiteitengebaseerde) transportmodellen fijn af te stemmen. Daarom is een zorgvuldige beoordeling van de beschikbare mogelijkheden nodig om te bepalen welke keuzes gemaakt moeten worden.

Het is belangrijk om enkele randopmerkingen te maken bij de kalibreertechnieken. Ten eerste is het niet altijd aangewezen om te vooronderstellen dat verkeerstellingen volledig correct zijn. In werkelijkheid kunnen verschillen ontstaan tussen de echte en de gemeten waarde die te wijten zijn aan selectievertekening ('sampling bias'), variabiliteit in verkeer, onjuiste tellingen, assumpties over voertuigen zonder passagiers en onbetrouwbaarheid in diverse modelfacetten. Het opzetten van een 'belief'-structuur kan mogelijk de gevoeligheden van het model aan diverse stimuli zoals beleidsmaatregelen verbeteren. Ten tweede kan de OD-matrixkalibratie die de overeenstemming tussen geschatte en geobserveerde verkeerstellingen optimaliseert, een negatieve impact hebben op de accuraatheid van andere maatstaven zoals de afgelegde afstand. De ontwikkeling van een 'multi-objective' kalibratiemethode is daarom een cruciale uitdaging. Ten derde, in de meeste praktijkgevallen worden transportmodellen gevalideerd en getest met uurwaarden in plaats van dagwaarden. Dezelfde methodiek kan worden aangewend in dit geval: gemodelleerde HB-tabellen moeten vergeleken worden met tellingen voor elk van de verschillende tijdsperiodes. De uitdaging bestaat hierin om tijdsspecifieke aanpassingen te vertalen naar een reeks aanpassingen in het genereren van activiteiten en aanpassingen in bestemmingskeuzes. Tenslotte kunnen verdere empirische testen van de kalibreermogelijkheden met een volledig activiteitengebaseerd model de vereiste validatie bieden van de voorgestelde methodieken.