An integrated activity-based modelling framework to assess vehicle emissions: approach and application

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Abstract. Owing to the richer set of concepts which are involved in activity-based transportation models, the potential advantages of an activity-based approach for air quality purposes have been recognized for a long time. However, models that have been developed along these lines are still scarce. In this research the activity-based model ALBATROSS was used in combination with the emission model MIMOSA to assess the travelled distances and the mobile source emissions produced by passenger cars in the Netherlands. The fact that this approach is based on hourly travel and emission values, rather than on aggregated results or peak hour values, a common practice within other traditional models, is an important added value. The predicted values seem to correspond well with the reported values from the Dutch Scientific Statistical Agency. Predictions for travelled distances overestimated the reported values by approximately 8%. Predictions for emissions of nitrogen oxide, carbon dioxide, volatile organic compounds, and particular matter differed by 16%, 11%, 9%, and 3%, respectively, from the officially reported values. This paper is novel in the sense that it both reports on the applied methodology and presents the practical results from a case study of the activity-based emission modelling approach.

1 Introduction

The rapid economic development in most Western countries has led to a quasi-linear growth in the yearly number of vehicle miles travelled since the 1970s (European Commission, 2001). Advances in technology (eg the European directives 91/441/EEC, 94/12/EC, and 98/69/EC) have played, and will continue to play, a role in managing the emissions associated with vehicular transport, but the increasing number of vehicle miles travelled substantially offsets the emissions reduction achieved through advances in technology. As such, one of the key challenges of modern policy making consists of promoting a sustainable transportation system, with the primary aim of preventing the negative effects of the transportation system on environment and health. Many transportation control measures (TCMs), including transportation demand management (TDM) strategies specifically focusing on the driving forces of the problem, have therefore been defined to counter the rise in vehicle emissions and energy consumption due to increased travel.

In the US the Clean Air Act Amendments (CAAA) and the Intermodal Surface Transportation Efficiency Act of 1991 (ISTEA) have, in combination, defined a broad range of TCMs and have established procedures and requirements for integrating those

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TCMs, such as flexible work hours, congestion and parking charges, ridesharing, signal prioritization, and the expansion of public transport into transportation and environmental planning (Recker and Parimi, 1999). Also, in Europe, similar initiatives have been established to examine the potential impact of policy measures, such as telecommuting, congestion pricing, and no-drive days (eg Emmerink et al, 1995; Priemus, 1995). However, because of the limited data available to predict the travel effects of combined (or even individual) TCM strategies and the inadequacy of conventional trip-based models to forecast changes in travel behaviour, the value of these TCMs is often uncertain and the subject of controversy (Páez and Scott, 2007). The lack of interactions among individual and household travel decisions in response to TCMs lies at the heart of the failings of conventional trip-based models to provide adequate measures of their potential impact. This kind of model focuses on individual trips, with the spatial and temporal interrelationships between all trips being ignored. Further, these conventional approaches tend to focus on peak hour values, and use time factors to derive the other hourly values. These kinds of assumptions limit the possibilities for the use of these trip-based models for policy impact analysis.

In the early 1990s the US Department of Transportation supported four projects to examine how transportation planning models could and should be improved to address properly both the impacts of new transportation technologies and the need for real policy sensitivity, particularly relative to air quality considerations (Spear, 1996). Three of the four proposals recommended that the former trip-based methodologies be replaced by *activity-based* approaches. The activity-based model framework is based on the premise that travel is derived from the need to pursue various personal or household activities (Ettema and Timmermans, 1997). Under this premise, an individual's daily pattern of activities is modelled in its entirety, as a function of his or her role in the household, and is influenced by various constraints, including time availability, access to alternative travel modes, coordination with other household members, etc. By assuming the 'activity', instead of the 'trip', as the basic unit for transportation analysis and prediction, and incorporating such constraints as interpersonal dependencies among household members, this activity-based approach concurs better with the actual decision-making process. However, although the potential advantages of an activity-based approach for air quality purposes have been recognized from the beginning (eg Spear, 1996), and have been reiterated more recently (eg Beckx et al, 2005; 2007; Shiftan, 2000; see also section 2.2), to the best of our knowledge, models that have been developed along these lines are still scarce (eg Hatzopoulou et al, 2007; see also section 2.1).

The aim of this paper is to make a contribution to this line of research by proposing a comprehensive activity-based emission modelling framework. For this purpose, the activity-based model ALBATROSS (Arentze and Timmermans, 2000a; 2005) was applied to microsimulate activity patterns and to assess the vehicle emissions for base year conditions in the Netherlands. Furthermore, by converting the predicted travel behaviour into emissions, this approach focuses on temporal emission estimates instead of aggregated daily or yearly emission values. The model's ability to replicate base year travel behaviour and emission assessment with good accuracy and precision was verified in this study by comparing the travel emission results with officially reported Dutch values.

The remainder of this paper is organized as follows. In the next section, an overview of activity-based emission models is given and the most important conceptual and theoretical advantages of the activity-based modelling approach for air quality purposes are highlighted. Next, the development of an activity-based emission modelling framework for base year conditions in the Netherlands is described, using

the activity-based model ALBATROSS (a learning-based transportation-oriented simulation system) to assess people's travel behaviour and the emission model MIMOSA for emission calculation. In the fourth section some results of this application are presented and compared with reported values. Finally, the paper discusses the results and concludes by addressing some important aspects of this application and future research applications.

2 The activity-based approach to emission modelling
2.1 State of the art in activity-based emission modelling frameworks
Activity-based approaches aim to predict which activities are conducted, where, when, for how long, with whom, and, if travel is involved, the transport mode used. Good overviews of the activity-based modelling approach and descriptions of the main characteristics of activity-based models can be found in Ettema and Timmermans (1997), McNally (2000), and Timmermans et al (2002). In order to summarize the most important features of activity-based modelling, we would like to cite the work of McNally (2000), who has nicely listed five themes which characterize the activity-based modelling framework:
(1) travel is derived from the demand for activity participation;
(2) sequences or patterns of behaviour, and not individual trips are the relevant unit of analysis;
(3) household and other social structures influence travel and activity behaviour;
(4) spatial, temporal, transportation, and interpersonal interdependencies constrain activity and travel behaviour;
(5) activity-based approaches reflect the scheduling of activities in time and space.

Over the last years, several research teams have focused on building activity-based models of transport demand (eg Arentze and Timmermans, 2005; Bhat et al, 2004; Kulkarni and McNally, 2000; Miller and Roorda, 2003; Pendyala and Kitamura, 1998; Vovsha et al, 2002). Partial and fully operational activity-based microsimulation systems include the microanalytic integrated demographic accounting system (MIDAS), the activity – mobility simulator (AMOS), the prism constrained activity-travel simulator (PCATS), synthetic daily activity-travel patterns (SIMAP), the comprehensive econometric microsimulator for daily activity-travel patterns (CEMDAP), ALBATROSS, Florida's activity mobility simulator (FAMOS), the travel activity scheduler for household agents (TASHA), and other systems developed and applied to varying extents in Portland, Oregon, San Francisco, and New York.

However, although the advantages of an activity-based approach for air quality purposes are well known (see section 2.2), models that have been developed along these lines are still scarce. Perhaps the most ambitious project in this field of research is TRANSIMS, the transportation analysis and simulation system (Rickert and Nagel, 2001). TRANSIMS was developed at the Los Alamos National Laboratory as part of the multitrack Travel Model Improvement Program (TMIP). The TRANSIMS project is a major effort to develop new integrated transportation and air quality forecasting procedures to satisfy the CAAA and the ISTEA. The detailed simulation in TRANSIMS, in comparison with simplistic and unrealistic aggregate link cost functions used in conventional models, provides increased accuracy in the prediction of environmental impacts (eg emissions) and travel times. An important disadvantage of this microsimulation approach is the large amount of data required to make accurate predictions on this detailed space – time level. Given the fact that a lot of policy questions do not require such a time-consuming microscopic analysis, and that detailed analyses are not suited for very large study areas, less-detailed emission estimations are desirable. Moreover, TRANSIMS is somewhat limited regarding the

prediction of activity patterns. Activity schedules of simulated individuals are drawn from activity datasets, and hence the model, on that level, is insensitive to changed space–time conditions that may be involved in applications.

In Recker and Parimi (1999) a microscopic activity-based framework is developed to analyze the potential impacts of TCMs on vehicle emissions. Although this approach is very useful in estimating the upper bounds of certain policy measures in reducing vehicle emissions, their framework falls short of actually forecasting changes in travel behaviour. In Shiftan (2000) the first application of a real activity-based model in the US was examined in an evaluation of the advantages of the Portland activity-based model for emissions and air quality analyses against the use of a traditional four-step model. Afterwards, this research was explored further, and the transportation and air quality impacts of four travel demand strategies were evaluated with the Portland activity-based model (Shiftan and Suhrbier, 2002). By predicting a wider range of impacts and taking indirect effects into consideration, the activity-based approach proved to be very useful in estimating some important variables for emission estimation.

The most recent accomplishment in this line of research concerns the integration of the Canadian version of the Mobile6.2 emission model with the travel demand modelling capabilities of TASHA (Hatzopoulou et al, 2007). This study provides an initial attempt at quantifying vehicle emissions in the Greater Toronto Area. Unfortunately, both the Portland study and the Canadian study demonstrate the advantages of the activity-based approach for the analysis of TCMs, but do not carry out an independent benchmark based on external information of the predicted emissions.

2.2 Advantages of an activity-based approach for air quality purposes
The previous section highlighted the different models that dealt with both activity-based approaches and emission analyses. Despite the limited application areas adopted so far, the approach does provide considerable theoretical advantages for emission and air quality studies. In this section the main benefits of using an activity-based approach for air quality purposes are presented.

2.2.1 *Transportation information*
The accuracy of emissions and air quality estimates can be no better than the underlying transportation information (Int Panis et al, 2001; 2004). Owing to the richer set of concepts which are involved in activity-based transportation models, the estimate of some important transportation variables can be improved by using an activity-based approach (Shiftan, 2000). Vehicle energy use and emissions depend not only on distance and the driving speed, but also on the number of trips, the time between them, and whether the engine was hot or cold when started (Recker and Parimi, 1999). The activity-based prediction of trips as parts of a tour can identify whether a trip is a cold or a hot start. Furthermore, an activity-based model, by predicting which activities are conducted, where, when, for how long, with whom, and the transport mode involved, gives information about other transportation variables, such as vehicle miles of travel, travel mode, and occupancy rates for auto modes, travel according to time of day, and time/location of starts. These variables have been identified by Cambridge Systematics Inc. (2001) as relevant and important for emission analysis. More information about these advantages can be found in Shiftan (2000).

2.2.2 *Temporal travel and emission analysis*
In most traffic air pollution studies which aim at a temporal differentiation of traffic emissions, either hourly traffic counts are used (eg Ghenu et al, 2008) or the emission model applies normalized distribution factors expressing the time dependency of traffic

with respect to peak values (eg Schrooten et al, 2006). A consequence of this time factor approach is that similar variations in traffic flows are assumed over the entire region and local characteristics are usually not taken into account. An activity-based approach, however, does not work with time-consuming traffic counts nor peak hour predictions, but simulates entire activity-travel schedules covering a complete day, and takes into account local variations in travel behaviour. Extraction of the simulated travel information and conversion with emission factors will therefore provide temporal travel and emission values more accurately.

2.2.3 Activity-based policy measures

Governments today are considering several traffic policy measures to reduce the negative effects of increasing mobility on the environment. Since the demand for transportation is the principal driver behind the environmental problem of traffic air pollution, the impacts of TDMs is examined thoroughly. However, for a number of TDMs, such as congestion pricing, promoting telecommuting activities, and stimulating car pooling, the impact on the environment is not straightforward to determine. Current transportation forecasting models use the 'trip' (usually a vehicular trip) as the basic unit of analysis and prediction. Consequently, by starting with the trip, these transportation models are unable to address explicitly issues related to activities (eg telecommuting, teleshopping, and trip-chaining behaviour). Activity-based models, on the other hand, are able to evaluate the impact of these measures on travelers' responses, and, owing to this, the impact on travel behaviour and air quality can be better assessed.

2.2.4 Secondary effects

One of the main advantages of the activity-based modelling system is its ability to consider the secondary effects of TCMs (Pendyala and Kitamura, 1998; Shiftan and Suhrbier, 2002). Secondary effects are adjustments to the activity pattern that have to be made in response to the primary effect. For instance, a public transport subsidy may make a commuter change his or her mode from drive alone to public transport; this is the primary effect of the TCM. However, because the commuter no longer drives to work, there can be no stop on the way back to do the shopping. Therefore, upon returning home, he or she takes the car and drives to a nearby store. This is the secondary effect. In such cases the environmental advantages of this TCM may be limited, and the reduction of the work auto trip is partially offset by a new shopping auto trip. Owing to the considered constraints and household interactions, an activity-based approach is most suited to deal with these secondary effects (Shiftan, 2000).

2.2.5 Exposure assessment

Conventional exposure studies (eg Bae et al, 2007) take into account variations of the emission source, but typically assume static receptor conditions. According to this approach the receptors (ie the people) are considered to be always at home and, therefore, only exposed to pollutants at their home address. Attempts at dynamic exposure assessments are very rare and often focus on long time scales (eg De Ridder et al, 2006). However, when temporal information is available both on the sources (ie the emissions) and on the receptors of the air pollution, a dynamic exposure procedure can be established. An activity-based approach takes into account that people move during the day and therefore are exposed to pollutants at different locations and different moments. More information about the advantages of an activity-based approach for exposure assessments can be found in Beckx et al (2005).

3 Methodology
To illustrate the activity-based approach for emission evaluation, the activity-based model ALBATROSS was applied to assess the vehicle emissions in the Netherlands. This section presents the different components of the activity-based emission modelling framework and describes the data that were used to validate the model results.

3.1 The activity-based model ALBATROSS
The activity-based model ALBATROSS was developed for the Dutch Ministry of Transportation, Public Works, and Water Management as a transport demand model for policy impact analysis. ALBATROSS is a computational process model that relies on a set of decision rules, which are extracted from activity diary data, and dynamic constraints on scheduling decisions in order to predict activity-travel patterns (Arentze and Timmermans, 2000a; 2000b; 2002; Arentze et al, 2003). The model is able to predict which activities are conducted, when, where, for how long, with whom, and the transport mode involved.

The activity scheduling agent of ALBATROSS is the core of the system which controls the scheduling processes. The scheduling model of ALBATROSS 2.0 and higher, which generates a schedule for each individual and each day, consists of four major components, as displayed in figure 1 (Anggraini et al, 2007). The first model component generates a work activity pattern consisting of one or two work episodes, their exact start time, the duration of each episode, and their location. It also predicts the transport mode to the work activity. The second component determines the part of the schedule related to secondary fixed activities, such as bring/get activities and business. It determines which types of activities are conducted that day, the number of episodes of each activity that occur, their start time, and duration. Furthermore, it also identifies possible trip linkage to the work activity and predicts the location of each episode. The third component concerns the scheduling of flexible activities. Almost similar to the previous component, it predicts activity types, the number of episodes of each activity type, the start time and duration of each episode, and the location of each episode. The additional prediction of the sequence of activities and possible trip-chaining links between activities are also part of this stage. Finally, the last model component predicts the transport mode used for each tour (except for the work activity, for which the transport mode is known as the outcome of an earlier decision). These main components assume a sequential decision process in which key choices are made and predefined rules delineate choice sets and implement choices made in the current schedule. Interactions between individuals within households are to some extent taken into account by developing the scheduling processes simultaneously and alternating decisions between the persons involved. ALBATROSS does not represent activity schedules of children explicitly. More information about the detailed working of this model and other computational process models can be found in Arentze and Timmermans (2005) and Anggraini et al (2007).

In this case study ALBATROSS was used to simulate activity schedules for individuals within the Dutch population. The model was estimated on approximately 10 000 person-day activity diaries collected in the period 1997 – 2001 in a selection of regions and neighbourhoods in the Netherlands. The synthetic population, representing 30% of the households in the Netherlands, was created with iterative proportional fitting (IPF) methods, using demographic and socioeconomic geographical data from the Dutch population in base-year (2000) and attribute data of a sample of households originating from a national survey including approximately 67 000 households. A synthetic population of 30% yields results that are virtually identical to a simulation of the whole population, but significantly reduces the time needed for the computations.
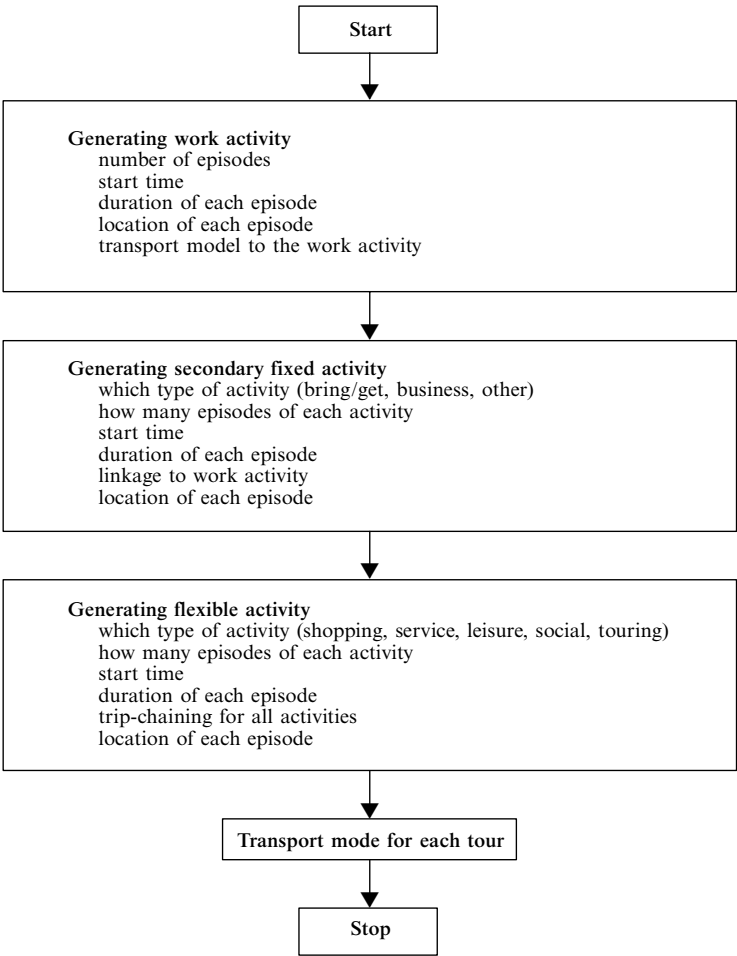
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                          │    Start     │
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┌─────────────────────────────────────────────────────────────┐
│  Generating work activity                                     │
│      number of episodes                                       │
│      start time                                               │
│      duration of each episode                                 │
│      location of each episode                                 │
│      transport model to the work activity                     │
└────────────────────────────┬──────────────────────────────────┘
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┌─────────────────────────────────────────────────────────────┐
│  Generating secondary fixed activity                          │
│      which type of activity (bring/get, business, other)      │
│      how many episodes of each activity                       │
│      start time                                               │
│      duration of each episode                                 │
│      linkage to work activity                                 │
│      location of each episode                                 │
└────────────────────────────┬──────────────────────────────────┘
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│  Generating flexible activity                                 │
│      which type of activity (shopping, service, leisure, social, touring) │
│      how many episodes of each activity                       │
│      start time                                               │
│      duration of each episode                                 │
│      trip-chaining for all activities                         │
│      location of each episode                                 │
└────────────────────────────┬──────────────────────────────────┘
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Figure 1. Schematic representation of the main steps of the ALBATROSS process model (source: Anggraini et al, 2007).

Activity schedules were generated for each individual within this synthetic population using the scheduling process in ALBATROSS, as described before.

3.2 Trip prediction and traffic assignment with TransCAD
In the following step, origin–destination (OD) matrices, based on a subdivision of the Netherlands into 1308 zones, were extracted from the activity schedules predicted by the ALBATROSS model. As the focus in this study is on passenger car trips, only OD matrices from car trips were considered. Furthermore, trip matrices were analyzed for different time periods, to account for intraday and intraweek differences in travel behaviour, and for various trip motives.

After multiplying the matrices by the inverted sample fraction, the trip matrices, representing the travel behaviour of the whole Dutch population, were assigned to a road network by using a standard 'all-or-nothing' traffic assignment algorithm embedded in the software package 'TransCAD', a GIS platform designed for use by transportation professionals to store, display, manage, and analyze transportation data (Caliper, 2004). After the traffic assignment procedure, detailed traffic information, taking into account intraday and intraweek differences in traffic flow and information about the trip motive, was present for all the car passenger trips in the Netherlands.

3.3 The emission model MIMOSA

Total emission values, hourly emissions, and geographically spread emissions were calculated with MIMOSA, a macroscopic emission model originally developed to calculate the emissions for the Antwerp region (Belgium). Later the model was extended further and improved by Lewyckyj et al (2004) to calculate emissions and emission reduction scenarios for larger areas in Belgium (eg Schrooten et al, 2006). MIMOSA belongs to the 'average speed emission models', expressing emission and fuel consumption rates for each trip as functions of average speed. The emission factors used within the MIMOSA model were partially extracted from experimental data collected by on-road measurements (Lenaers et al, 2003), as well as from the Copert-III report (Ntziachristos and Samaras, 2000). For missing data [some specific pollutants, particulate matter (PM) emissions], emission functions from MEET (1999) were applied. Within the model four major vehicle categories can be distinguished [passenger cars, light-duty vehicles (LDV), heavy-duty vehicles (HDV), and motorcycles and mopeds] with further subcategories depending on the age of the vehicle and its cylinder capacity for the passenger cars. Furthermore, a distinction can be made between four fuel types [gasoline, diesel, liquefied petroleum gas (LPG), and two-stroke gasoline], with lead and sulphur contents depending on the year of the simulation.

In order to calculate the vehicle emissions for passenger car trips in Netherlands, as aimed at in this study, the latest MIMOSA version was extended with information regarding the Dutch vehicle park and road conditions. Further, the settings within the model were altered to benefit maximally from the information provided by the activity-based approach. Its characteristics, which are described in the next paragraphs, make the model suitable for the emission estimations at the national level, on the basis of the outcome of an activity-based model.

The basic version of MIMOSA calculates geographically distributed hourly traffic emissions based on peak-hour (17:00–18:00) mobility data from a Flemish road traffic model. The time dependency of the emissions is simulated using normalized distribution factors expressing the fluctuations of the traffic flow as a function of the hour of the day, the day of the week, and the month of the year. By using this approach a uniform traffic flow variation is assumed in the entire study area. However, by using an activity-based approach instead of this peak-hour approach, hourly traffic flow information is immediately provided on all considered road segments. In this study we have therefore replaced the uniform traffic flow method from the basic MIMOSA model with an advanced traffic simulation procedure, allowing geographic and temporal differences in traffic flow.

Further, since the activity-based approach used in this study focuses on personal travel behaviour, only the characteristics of the passenger cars were taken into account. On the basis of statistical information on the Dutch vehicle park (including data from traffic counts and vehicle registration actions), the MIMOSA vehicle park composition was determined per road type (CBS, 2000).

Concerning the final emission calculation, the model uses a 'static' macroscopic approach—that is, hourly average speeds per road segment are combined with emission factors to calculate the emissions per road segment and per hour. Link-specific traffic speeds were not derived from the all-or-nothing assignment. Owing to a lack of information on freight transport, the estimated speeds would be unreliable. Instead, and to be consistent, we used the same traffic speeds as used by the activity-based model to estimate travel time between different locations. The link-specific traffic speeds used refer to an average speed over the course of a day and were estimated for the Dutch road network according to expert assessment at the level of individual links;

they are applied in ALBATROSS to estimate network distances and travel times according to mode between different activity locations (Arentze and Timmermans, 2005). By combining the hourly traffic volumes computed per road segment with fleet statistics and the corresponding emission factors, the final Dutch MIMOSA model calculates temporally and geographically distributed traffic emissions. The results for five pollutants, considered as major air pollutants in air quality studies, are presented in this study. Owing to the characteristics of the emission validation data (see next section), nonexhaust emissions were not calculated. The emissions presented in this study therefore only include hot, cold, and evaporative emissions. Cold-start emissions were calculated on the basis of information on the trip length and the ambient temperature. Short trips, carried out with cold engines, result in higher emissions. Evaporative VOC (volatile organic compound) emissions were obtained only for the running losses—that is, vapour losses generated in gasoline tanks during vehicle operation—which are significant at high ambient temperatures. Ambient temperature data for the model year was included to calculate these evaporative emissions.

3.4 Validation data
The (activity) travel values and emissions from the activity-based approach were compared with reported values originating from other (independent) travel surveys to examine the accuracy of this innovative approach. In this study we used data from the Dutch National Travel Survey (NTS) and the Dutch Scientific Statistical Agency (CBS) to perform a validation test.

Although the Dutch NTS uses trip diaries (as opposed to activity diaries), this travel survey has very similar survey characteristics to the activity-based survey (no holiday trips, no freight trips, no vehicle kilometres in other countries, no vehicle kilometres of foreigners), and is executed yearly to gain more insights into the travel behaviour of the Dutch population. The travel results from the year 2000 survey were used for comparison. This survey includes trip diaries of more than 100 000 persons and results were reweighted to compensate for the underrepresentation and overrepresentation of certain groups—for example, degree of urbanization, age, and journeys. More information about the NTS in the Netherlands can be found in Van Evert and Moritz (2000), and on the Dutch road safety website (SWOV, 2000).

The emission results from the activity-based modelling approach were compared with reported emission values provided by the CBS. These emission results have been published yearly by this statistical agency since 1990 and provide good insights into the emissions of passenger cars. The values are obtained in cooperation with other environmental and traffic institutes by multiplying gathered activity data (vehicle kilometres and fuel consumption) with corresponding vehicle fleet emission factors. The emission results from the year 2000, including hot emissions, cold emissions, and evaporative emissions, were used for comparison (CBS, 2000). Nonexhaust emissions—for example, PM emissions caused by abrasion or resuspension—were not included in the figures used for the validation of our emission estimates.

4 Results
In this section the results of the activity-based modelling approach for base-year conditions in the Netherlands are presented and the model outcome is validated against travel and emission results from other studies.

4.1 Model outcome
4.1.1 Synthetic population data
Using IPF methods, a synthetic population procedure was established in order to simulate a population representing 30% of the Dutch population in the base year.

The individual and household characteristics of this synthetic population are presented in tables 1, 2, and 3. In total the synthetic population consists of approximately 3 million individuals and 2 million households. Each individual is characterized by his or her gender and work status, whereas each household is characterized by the household composition, the age of the youngest child (if present), and the age of the head of the household.

Table 1. Characteristics of the synthetic population at the individual level.

	Total	Gender		Work status		
		male	female	no work	part-time	full-time
Number	3 121 1667	1 544 367	1 577 300	1 719 059	333 418	1 069 190

Table 2. Household characterization according to composition of the household

	Total	Household composition [a]				
		S-0W	S-1W	D-0W	D-1W	D-2W
Number	1 938 224	363 335	391 446	446 383	462 958	274 102

[a] S-0W: single, no work; S-1W: single, one works; D-0W: double, no work; D-1W: double, one works; D-2W: double, two work.

Table 3. Household characterization according to age of the household members.

	Age of youngest child (years)				Age of household head (years)			
	no child	<6	6–12	>12	<25	25–44	44–64	>64
Number	1 396 129	262 383	154 292	125 420	65 155	868 378	569 958	434 733

4.1.2 Trip analysis

The ALBATROSS model simulated activity schedules for every individual within the synthetic population. The predicted trip matrices for the whole population were then assigned to a Dutch road network (*Basisnetwork*), using standard traffic assignment algorithms from the software package TransCAD. By means of example, figure 2 presents the road network file with the resulting traffic flows for an average weekday. This figure gives more insights into the study area and the geographic location of zones with high traffic intensities.

The higher traffic intensities (up to 150 000 vehicles per traffic link) near the larger cities such as Amsterdam, Rotterdam, and Utrecht, can be easily distinguished from the map. The peripheral roads, on the other hand, tend to have smaller traffic loads (see figure 2).

4.1.3 Emission estimates

On the basis of the modelled traffic flows, the emission model MIMOSA calculated traffic emissions produced by different vehicle types. The results for five major air pollutants: carbon dioxide (CO_2), nitrogen oxide (NO_x), VOCs, sulphur dioxide (SO_2), and PM are presented in table 4. Fuel type and vehicle size were used to segregate the passenger cars and their emissions into different categories.

The large vehicle types, both petrol and diesel, seem to be responsible for most of the emitted pollutants. The smaller vehicles, on the other hand, represent the smallest amount of vehicle emissions. Comparing diesel vehicles with petrol vehicles, we can see that both fuel types have approximately an equal share in the production of CO_2 and
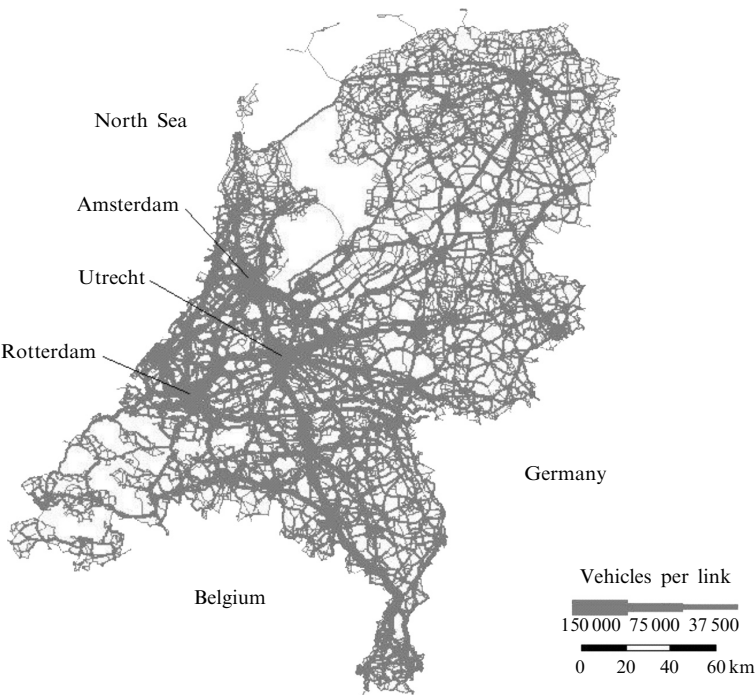
Figure 2. Geographic map of the study area (the Netherlands) with the simulated traffic flows per traffic link for an average weekday in the base year.

Table 4. Total modelled emissions for base year conditions according to vehicle type.

Vehicle type		Emissions ($\times 10^6$ kg)				
fuel type	vehicle size	CO_2	NO_x	VOCs	SO_2	PM
Petrol	small	1 273.05	6.15	8.73	0.04	0.06
	medium	3 153.29	11.01	14.31	0.10	0.10
	large	4 479.60	16.34	13.30	0.14	0.08
Diesel	small	903.70	4.41	0.52	0.18	0.47
	medium	2 329.36	9.26	1.16	0.39	1.04
	large	5 825.49	17.41	1.31	0.74	1.17
LPG		1 327.76	5.63	4.65	0.00	0.05
Total		19 292.25	70.21	43.97	1.59	2.97

Note. VOCs: volatile organic compounds; PM: particulate matter; LPG: liquefied petroleum gas.

NO_x emissions. Concerning the other pollutants, the petrol vehicles are responsible for most VOC emissions, and the diesel vehicles emit most of the SO_2 and PM emissions.

4.2 Model validation
In this section the simulated traffic flows and emission estimates are compared with reported values in order to validate the accuracy of the integrated model results. A critical discussion of the observed differences can be found in section 5.

In figures 3(a) and 3(b) the hourly distances travelled are presented for weekdays and weekend, respectively. Both the predicted values from the activity-based modelling procedure, and the reported values from the NTS are presented. In figure 3(a) the morning and evening traffic peaks can be easily distinguished from both curves.
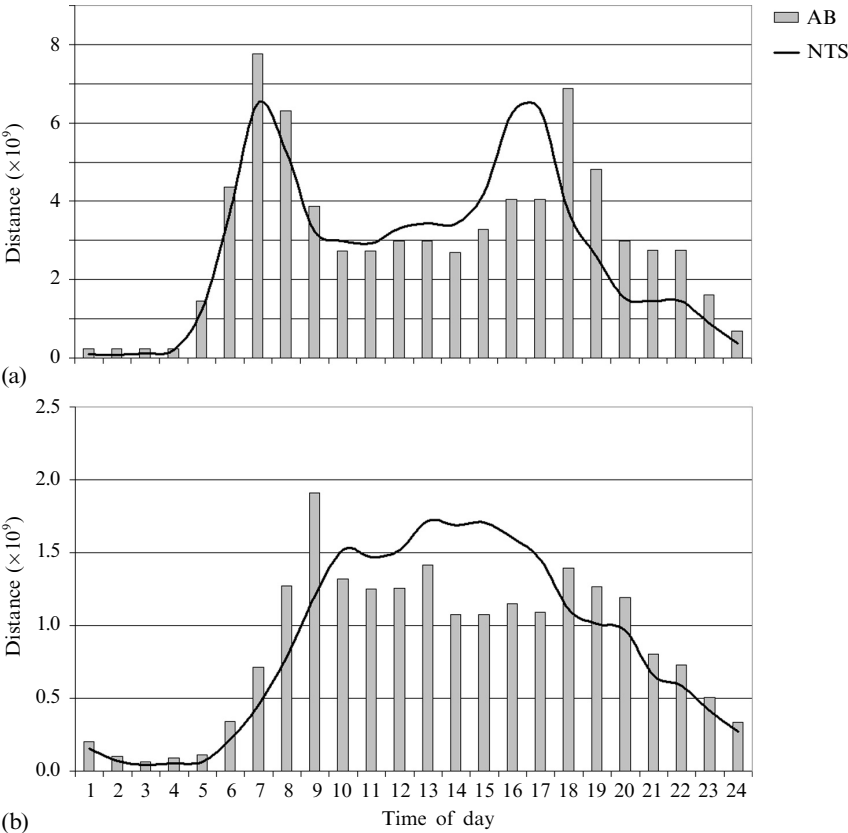
Figure 3. Hourly distances travelled on (a) weekdays, and (b) the weekend, in the year 2000: predicted activity-based (AB) values versus reported Dutch National Transport Survey (NTS) values (SWOV, 2000).

Both approaches have similar predictions for the morning peak, simulating a traffic peak around 7 am, but differ in their predictions for the evening peak. According to the activity-based approach, the evening peak occurs at 6 pm, whereas the largest NTS peak occurs one hour earlier. In figure 3(b) the variation in travelled distances during the weekend in the year 2000 is presented. According to the activity-based prediction, distances travelled during the daytime remain rather constant, with the exception of one small peak at 9 am. The NTS curve shows a larger amount of travelled distance during the day, but does not predict a traffic peak during the weekend. The predicted travelled distances during the early morning and the late evening seem to correspond well with the NTS values.

By aggregating the results from the traffic assignment procedure and extrapolating the values for a whole year, the total travelled distance during a whole year was calculated. In table 5 the calculated value is presented next to the reported travelled distance value from the NTS, which represents the total number of travelled kilometres by passenger car during the base year. The relative difference between both values is less than 10%.

Since the CO_2 emissions are highly related to the number of kilometres travelled, a small overestimate in the amount of CO_2 emissions can be expected. In table 6 the deferences between predicted and reported total emission values for the base year are presented. Relative differences vary between 3% and 26% for PM and SO_2, respectively.

Table 5. Total travelled distance according to noncommercial vehicle travel in the Netherlands in the year 2000.

	Travelled distance ($\times 10^9$ km)
Modelled travelled distance	93.3
Reported travelled distance [a]	85.9
Relative difference (%)	8.6

[a] SWOV (2000).

Table 6. Total vehicle emissions for the year 2000: predicted versus reported values.

	Emissions ($\times 10^6$ kg)				
	CO_2	NO_x	VOCs	SO_2	PM
Modelled results	19 292.25	70.21	43.97	1.59	2.97
Reported results [a]	17 346.00	60.10	40.35	1.26	2.88
Relative difference (%)	11.22	16.71	8.98	26.30	3.21

[a] CBS (2000).

Note. VOCs: volatile organic compounds; PM: particulate matter.

The CO_2 predictions differ by approximately 11% from the reported CBS emission values, NO_x emissions are overestimated by 17%, and the VOCs are overestimated by 9%.

5 Conclusions and discussion

In this paper we report on the use of an activity-based model for the assessment of mobile source emissions. We have combined the activity-based model ALBATROSS with the environmental model MIMOSA to assess the total amount of vehicle emissions produced by passenger cars in the Netherlands and the distribution of emissions across space and time. By converting the predicted travel behaviour into emissions and by comparing the results with values from the Dutch Scientific Statistical Agency, we have verified the model's ability to replicate base-year travel behaviour and emission assessment with good accuracy.

Regarding the temporal variation in travel behaviour, the activity-based predictions corresponded well with the reported NTS results. Both the timing and the magnitude of the morning traffic peak were predicted with good accuracy by the activity-based model. The prediction for the evening peak on weekdays slightly differed from the NTS values, but the overall picture of the temporal variation turned out very well. On weekends the small morning peak predicted at 9 am was not reproduced by the NTS simulations. A possible explanation is that churchgoing is overestimated by the activity-based approach, owing to the fact that a religious region in the Netherlands was somewhat oversampled in the activity survey used for this version of ALBATROSS. The feasibility of modelling the temporal variation in travelled distance, instead of using only peak-hour information, is an important improvement compared with most other travel studies (eg Schrooten et al, 2006), which often work with time factors to derive hourly information from one peak-hour value. When the traffic flows fluctuate differently throughout the study area, this activity-based approach will certainly be a better option.

Concerning the distance travelled, the activity-based approach overestimated the total travelled distance by approximately 8%, compared with the NTS values. This overestimate can be attributed to the characteristics of the survey. The activity-based

survey uses activity diaries to gather activity and travel data in a very comprehensive way. Respondents are asked to report every performed activity, together with information about the time, the location, travel model, etc. The NTS survey, on the other hand, works with travel diaries, for which respondents need to fill in information only about their travel behaviour. Previous research has already indicated that the trip-diary method often underestimates the amount of trips (SWOV, 2000). Small, short trips are frequently underreported by the respondents in the NTS method, whereas these trips are much better reported in the activity-diary method. This underreporting in the NTS method can explain the difference from the activity-based results.

The results of the emission assessments varied between pollutants. For the CO_2 emissions the estimated value differed approximately 11% from the reported value. Since the CO_2 emission value is correlated mainly with the estimated amount of kilometres, this difference can be explained by the overestimate in vehicle kilometres travelled. The SO_2 emissions differed 26% from the published value. Given that these SO_2 emissions are based on a fixed ratio of sulphur in the fuel, this result indicates that the emission model overestimated the sulphur content in the fuel. The sulphur content of the fuel is subject to national standards, changing every few years, so this is an acceptable explanation of this difference. The predictions for NO_x, VOC, and PM differed from their reported counter values by 16%, 9%, and 3%, respectively. Considering the fact that we overestimated the vehicle kilometres, compared with the NTS values, these relative differences are quite small and the number of PM emissions is probably still underestimated.

Of course, there are some qualifications to our research that need to be discussed. First of all, the 'static' emission factor approach used in this study is a possible subject of discussion. This state approach assumes hourly stable traffic conditions and, at first sight, ignores the local dynamics in driving patterns and street characteristics which influence emissions (De Vlieger, 1997; De Vlieger et al, 2000). However, the average speed emission factors do take into account the characteristics of the underlying driving patterns, on the basis of the estimated average speed and the location of the specific road (urban, rural, or highway) (Ntziachristos and Samaras, 2000). Therefore, this emission-factor-based approach is widely used in the modelling of traffic-related emissions (eg Jensen et al, 2001; Lin and Lin, 2002; Salles et al, 1996; Xia and Shao, 2005), with its accuracy depending very much on the reliability of traffic data (traffic volume and velocity, temporal and spatial variations, vehicle composition, etc) and the choice of emission factors (Kumari, 2008).

Another issue is the use of an all-or-nothing traffic assignment to distribute the traffic over the network. This kind of assignment is a simplification of the real traffic patterns, since it does not take into account redistributions at peak-hour situations, unlike the more advanced equilibrium assignment. However, since this study does not include information on freight traffic and only focuses on passenger cars, the more advanced procedure would not improve the model outcome, and an all-or-nothing procedure is therefore justified. If hourly freight data are available, together with link-specific capacity information, future research can include the emission assessment of all road traffic on the basis of a more advanced traffic assignment procedure.

Finally, one can argue about the validation method itself. The predicted results from the activity-based emission modelling approach were compared with travel and emission values from the Dutch Scientific Statistical Agency, whose data originate from other model simulations. A good agreement between both values does not automatically indicate a good representation of the real situation, and only states the similarity between both models. Ideally, a validation method should comprise the use of measurements instead of simulation values, but the procedure of comparison with

other models provides useful cross-validation (eg Int Panis et al, 2006; Schrooten et al, 2008). Since travel and emission measurements were not available on a national level (only concentration measurements are executed), and as the values from the Dutch Scientific Statistical Agency are considered to be an acceptable alternative in travel and emission studies, we decided to compare our model results with these reported values. In ongoing research we will model pollutant concentration (on the basis of the emissions presented here) that can be compared with air quality measurements.

As already stated in the introduction, the validation test in this research was an essential first step: if a model is unable to replicate its base-year behaviour, then it has little hope of forecasting the future adequately. On the basis of the results of this research we can conclude that the activity-based modelling approach is able to reproduce base-year conditions with sufficient accuracy. The use of an activity-based travel model will therefore put a new perspective on the research of policy measures, with advantages for air quality purposes and policy evaluations. Future studies will certainly involve the use of an activity-based model for the evaluation of different policy measures on travel behaviour and vehicle emissions, and will include the simulation of concentrations that can be used for validation purposes.

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