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A dynamic activity-based population modelling approach to evaluate exposure to air pollution: Methods and application to a Dutch urban area

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ABSTRACT

Recent air quality studies have highlighted that important differences in pollutant concentrations can occur over the day and between different locations. Traditional exposure analyses, however, assume that people are only exposed to pollution at their place of residence. Activity-based models, which recently have emerged from the field of transportation research, offer a technique to micro-simulate activity patterns of a population with a high resolution in space and time. Due to their characteristics, this model can be applied to establish a dynamic exposure assessment to air pollution.

This paper presents a new exposure methodology, using a micro-simulator of activity–travel behaviour, to develop a dynamic exposure assessment. The methodology is applied to a Dutch urban area to demonstrate the advantages of the approach for exposure analysis. The results for the exposure to PM_{10} and $PM_{2.5}$, air pollutants considered as hazardous for human health, reveal large differences between the static and the dynamic approach, mainly due to an underestimation of the number of hours spent in the urban region by the static method.

We can conclude that this dynamic population modelling approach is an important improvement over traditional methods and offers a new and more sensitive way for estimating population exposure to air pollution. In the light of the new European directive, aimed at reducing the exposure of the population to $PM_{2.5}$, this new approach contributes to a much more accurate exposure assessment that helps evaluate policies to reduce public exposure to air pollution.

1. Introduction

Reducing air pollution has been on the agenda of policy makers for several decades, especially in the US and Europe. A long list of consecutive initiatives, often of an international nature, has been taken to reduce emissions of key pollutants. Successful policies were implemented for pollutants such as Pb and SO_2. Air pollutions levels in large parts of Europe are now much lower than they were 10 or even 50 years ago, but levels in many other countries (e.g. India and China) have increased. Nevertheless air pollution keeps worrying European policy makers. Levels of particulate matter (PM) in the Po valley, Ruhr area and The Netherlands remain among the highest in the world and ozone levels are often exceeded in many countries each summer.

Epidemiological studies have consistently indicated a link between current levels of air pollution and public health. Ozone and PM are thought to be the key drivers although knowledge on the causal links between exposure to an air pollution mixture and resulting health effects remains sketchy. However, studies throughout the world have shown that any short term 10 μg/m^3 increase in PM_{10} levels increases the mortality rate on the next day by 0.6% (Nawrot et al., 2007) and long term exposure to PM is considered to be responsible for a significant fraction of cardiovascular mortality and lung cancers among non-smokers (Pope and Dockery, 2006).

Traditionally, most epidemiological research has focused on relating health endpoints in entire populations with pollutant concentration data from a small number of fixed site monitoring stations. Recent studies have highlighted that important differences in emissions and concentrations can occur over the day and between different sites within the same urban area (e.g. Corburn, 2007). This is especially true for transport related pollutants such as $PM_{2.5}$ and Ultrafine Particles (UFP) (Int Panis et al., 2006; Int Panis and Beckx,

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2007). Several studies have tried to demonstrate that vehicle exhaust related air pollution is more harmful than PM_{10} in general and that proximity to busy roads is linked to health impacts (e.g. Beelen et al., 2008; Brugge et al., 2007). These new insights have made policy makers aware of the fact that it is *exposure* of people that should be reduced in order to reduce health effects. The latest European directive on air quality (2008/50/EC) has therefore introduced new standards for $PM_{2.5}$, mentioning for the first time a reduction of the *exposure* to air pollution. On one hand there is a specific ECO ('Exposure Concentration Obligation') of 20 µg $PM_{2.5}/m^3$ in urban areas (where most people live) to be reached by 2015. On the other hand the average exposure of people in urban areas to $PM_{2.5}$ should be reduced by up to 20% between 2010 and 2020 depending on the current level of exposure.

Since previous air quality directives (e.g. 1999/30/EC; 96/62/EC) only focused on the reduction of concentration limit values, the recent focus on exposure means that new scientific methodologies to estimate exposure more accurately should be devised. Exposure has traditionally been calculated by multiplying population densities with concentrations at different geographical scales. While concentration data from models is often available at high temporal and spatial resolution, the population data is usually based on static administrative address data. According to this static exposure approach the receptors (i.e. the people) are considered to be always at home and, therefore, only exposed to pollutants at their home address (Friedrich and Bickel, 2001). This approach is only sufficient for rough assessments at the national level. Any assessment focusing at urban or suburban scales (consistent with the new European legislation) should take into account that people are often exposed to air pollution at different sites, other than their home address, during the day. To establish an improved assessment of human exposure, however, it is necessary to model peoples' activity–travel behaviour during the day. The traditional four-step transport models, modelling the travel behaviour only on peak-hour moments, cannot be considered. Other attempts at dynamic exposure assessments, taking into account that people "move", are scarce and often focus on long time scales (e.g. Borrego et al., 2006a; De Ridder et al., 2008a,b) or adopt a microenvironment approach (e.g. Borrego et al., 2006b) to take into account that people are exposed to air pollution at places different from their home address. A micro-simulation model of activity–travel behaviour on the other hand is able to simulate temporal population maps of people present in a study area during all stages of the day and does not only assume a limited number of microenvironments. By combining these simulated population data with pollution data, a dynamic exposure procedure can be established. Models adopting this kind of activity–travel strategy have recently emerged from travel behaviour research: the activity-based models.

In this paper we present a new methodology to estimate exposure to air pollution using population data from an activity-based transport model combined with air quality data from a dispersion model. We demonstrate the validity of the methodology by applying it to a major city in The Netherlands as a case study. The remainder of this paper is organized as follows. In the next section, a description of the activity-based dynamic population modelling approach is given and the advantages of using this approach for air quality purposes are highlighted. Next, the methodology to use an activity-based model for accurate exposure assessments is presented together with a description of the data. In the fourth section the methodology is illustrated with results from a case study in the Netherlands. Results from dynamic exposure assessments in an urban area are compared to static exposure estimates to indicate the differences and, accordingly the usefulness, of the new approach presented here. Finally, the paper discusses the results and concludes with some important aspects of this application and topics for future research applications.

2. The activity-based population modelling approach for exposure analysis

In this section we will briefly describe the characteristics of the activity-based modelling approach and highlight the advantages of this approach for exposure analysis.

2.1. The activity-based approach

The activity-based approach emerged in the 1970s in reaction to changes in the transportation policy environment. Since the conventional four-step trip-based approach lacked a valid representation of underlying travel behaviour, activity-based models were developed to improve travel behaviour analysis. Activity-based approaches aim at predicting, for the individuals of an entire population, which activities are conducted, where, when, for how long and with whom. If two consecutive activities are planned in different locations, travel is involved and the activity-based model will also predict the transport mode. The most important features of activity-based modelling can be found in McNally (2000), who has listed 5 themes which characterize the activity-based modelling framework:

(i) Travel is derived from the demand for activity participation;
(ii) sequences or patterns of behaviour, and not individual trips are the relevant unit of analysis;
(iii) household and other social structures influence travel and activity behaviour;
(iv) spatial, temporal, transportation and interpersonal interdependencies constrain activity/travel behaviour;
(v) 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. Partial and fully operational activity-based micro simulation systems include the Micro-analytic Integrated Demographic Accounting System (MIDAS) (Goulias and Kitamura, 1996), CEMDAP (Bhat et al., 2004), Prism Constrained Activity–Travel Simulator (PCATS) (Kitamura and Fujii, 1998), SIMAP (Kulkarni and McNally, 2000), ALBATROSS (Arentze and Timmermans, 2000, 2004, 2005), Florida's Activity Mobility Simulator (FAMOS) (Pendyala et al., 2005), the Travel Activity Scheduler for Household agents (TASHA) (Miller and Roorda, 2003), and other systems using a nested-logit framework (Bowman and Ben-Akiva, 2001) developed and applied to varying extents in Portland, Oregon, San Francisco and New York (e.g., Vovsha et al., 2004).

2.2. Advantages of the activity-based approach for air quality purposes

The activity-based approach does not only provide detailed information on travel behaviour, but also provides useful information for air quality purposes. Due to the richer set of concepts which are involved in activity-based modelling (information on travel by time of day, exact time between trips, vehicle miles travelled,…) the estimate of some important transportation and emission variables could be improved by using an activity-based approach. Several authors already described the advantages of the activity-based approach for emission analysis in previous publications (e.g. Shiftan, 2000). However, models that have been developed along these lines are still scarce (e.g. Beckx et al., in press; Hatzopoulou et al., 2007; Shiftan and Suhrbier, 2002), mainly due to the lacking of an operational activity-based model.

In addition to the advantages for emission analysis, the activity-based approach also provides useful information for detailed exposure analyses (Beckx et al., 2005). The activity-based model simulates the activity–travel behaviour from individuals within a population, covering an entire day (not only peak hour) and an entire study area (not only microenvironments). These characteristics allow for the establishment of a more realistic exposure assessment using an activity-based model to simulate peoples travel behaviour.

3. Data and methods

To illustrate the advantages and opportunities of a dynamic exposure approach, the activity-based model 'ALBATROSS' was applied to the Netherlands. In this section the applied method and necessary data for this procedure are described.

3.1. Population data

The activity-based model ALBATROSS, A Learning-Based Transportation Oriented Simulation System, was developed in 2000 for the Dutch Ministry of Transportation, Public Works and Water Management as a transport demand model for policy impact analysis. It 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, to predict activity–travel patterns (Arentze and Timmermans, 2000, 2004). The model is able to predict for an entire population which activities are conducted, when, where, for how long, with whom, and the transport mode involved.

In Fig. 1 the scheduling agent of ALBATROSS, consisting of four major components, is presented (Anggraini et al., 2007). The scheduling module generates the activity schedules of the individuals in each household within the study area and each day. 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(s) used to get to the location(s) of the work activity. The second component determines the part of the schedule related to secondary fixed activities such as bring/get activities, business and others. It determines which types of activity are conducted that day, the number of episodes of each activity that occur, their start time and duration. Furthermore, it also identifies its 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, number of episodes of each activity type, the start time and duration of each episode as well as the location of each episode. The additional prediction of 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 where 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.

As a result of the scheduling process in ALBATROSS activity–travel patterns are established for all the adult individuals within the study area. ALBATROSS does not represent activity schedules of children explicitly. Consecutive hourly cross sections of the modelled population will result in a representation of a dynamic population. 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). Validation studies of the scheduling process of ALBATROSS are described in Arentze and Timmermans (2000) and Arentze et al. (2003).

The ALBATROSS model is estimated on approximately 10,000 person-day activity-diaries collected in the period of 1997–2001 in a selection of regions and neighbourhoods in the Netherlands. In a sub application of the model, a synthetic population was created with iterative proportional fitting (IPF) methods, using demographic and socio-economic geographical data from the Dutch population and attribute data of a sample of households originating from a national survey including approximately 67,000 households.

For the present study, a synthetic population representing residential information for 30% of the households in the Netherlands was created. This population was extrapolated in a next step to represent the total Dutch residential information (approximately 11 million adult inhabitants) and considered as the 'static population' for further exposure analyses. In a next step, the dynamic population was generated by simulating activity schedules for each individual within the synthetic population using the scheduling process in ALBATROSS as described above. Consecutive cross sections of this modelled population will result in a representation of a dynamic population. The 4-position postcode area (PCA) was chosen as the spatial unit for the database and time steps of one hour were chosen as the appropriate time unit. There are 3987 4-position PCA's in the Netherlands with an average size of approximately 880 ha. The dynamic population of the Netherlands will therefore consist of hourly population maps with every individual assigned to one of the 3987 PCA's in the study area.

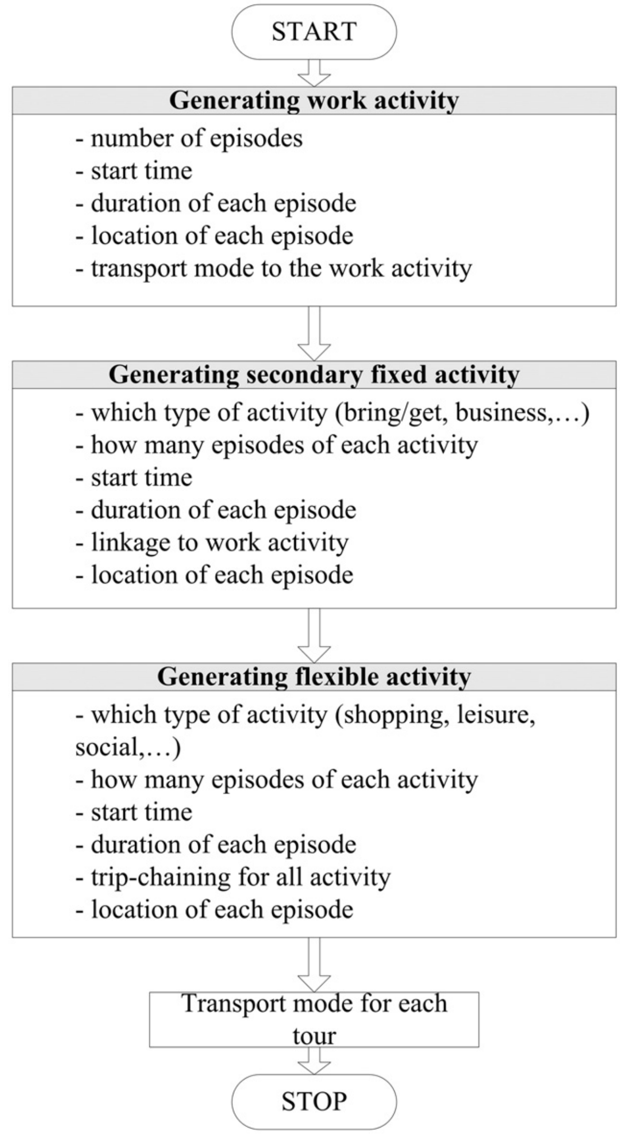

Fig. 1. Schematic representation of main steps of the ALBATROSS process model. Source: Anggraini et al. (2007).

3.2. Air pollution data

Concentration information for the Netherlands was provided by the Eulerian grid model AURORA, standing for "Air quality modelling in Urban Regions using an Optimal Resolution Approach" (Mensink et al., 2001). The model uses a nested approach in order to downscale large-scale meteorological and air quality fields down to more detailed location levels and was applied successfully in previous air quality and exposure studies in the cities of Antwerp and Ghent in Belgium, as well as Budapest in Hungary and the Ruhr area in Germany. The model input consists of terrain data (orography, land use, road networks, remote sensing), meteorological fields, and detailed emission data. The emissions from the passenger travel also originate from the activity-based modelling procedure by assigning the simulated motorized trips to a road network and converting these traffic flow into emissions (see Beckx et al., in press for more details on this study). This procedure has important advantages over older methods that were riddled with uncertainty (Int Panis et al., 2001, 2004). More information about the dispersion modelling procedure used by AURORA can be found in Mensink et al. (2001).

The output results of the modelling procedure consist of detailed hourly concentration maps. Grid cell sizes of 3 by 3 km were used to model hourly PM_{10} and $PM_{2.5}$ concentrations. By means of example the concentration data for the month of April 2005 were used for further analysis. Previous studies already demonstrated that exposure to PM_{10} and $PM_{2.5}$ is linked with cardio-respiratory health effects and even with mortality (e.g. Atkinson et al., 2001; Beelen et al., 2008; Le Tertre et al., 2002). Therefore, in this study, we choose to consider only PM_{10} and $PM_{2.5}$ concentration values for exposure analysis.

3.3. Exposure assessments

By combining the population data (Section 3.1) with the air quality data (Section 3.2) two different exposure assessments can be established: a static and a dynamic exposure assessment. In Fig. 2 the methodology for both approaches is presented schematically. On the one hand, by combining the static (synthetic) population with the hourly concentration information, static hourly exposure estimates can be made. In this static method, applied by most conventional exposure studies, people are considered to be only exposed to concentrations at their home address. On the other hand, the combination of the dynamic population maps, provided by the scheduling process in ALBATROSS, with the concentration information will result in dynamic hourly exposure assessments. In this case, people are considered to move through the day and therefore they will be exposed to concentrations at their respective locations. Both the static and the dynamic approach are performed in a GIS environment since population information as well as concentration information is available on a geographic level. Static and dynamic exposure estimates can be finally compared to examine the impact of using a different methodological approach on exposure evaluations. Observed differences are only due to differences in the population modelling approach since modelled concentration data have been kept identical for both approaches.

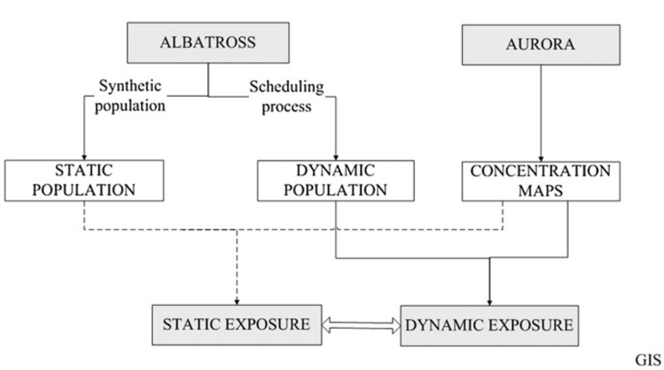

Fig. 2. Schematic representation of the applied methodology.

4. Results

4.1. Population

As already stated in Section 3 activity–travel schedules were generated for all the individuals from the Dutch adult population. However, to present the population (and exposure) results more clearly in this paper, only the results for one specific location in the Netherlands will be presented here. The Dutch population information from the ALBATROSS model was therefore reduced to represent only the population present at a specific location: the city centre of Utrecht. The selection for this location out of all the Dutch urban areas was made arbitrary.

4.1.1. The Utrecht city centre

The Utrecht city centre is an urban area in the centre of The Netherlands. It is the fourth largest city of The Netherlands with a population of over 0.25 million. It is an attractive city to live, work, shop, or recreate which causes a large inflow of people during the day. This is enhanced by the fact that the old historical centre and the cities central location tends to attract people from a large area for these purposes. The city centre of Utrecht (the inner part of the city) counts 9 PCA's with postcode areas varying from 46 ha to 115 ha and covering a total area of approximately 800 ha. This city centre was selected to illustrate the developed methodology.

4.1.2. Dynamic population results

Hourly cross-sections of the population present in the Utrecht city centre were first made to examine the in- and outflow of people in this region. Fig. 3 presents the variation in population during an average Monday for the Utrecht area. Results for other weekdays yield similar results. Population dynamics in the weekend differ from the travel behaviour on weekdays due to the larger amount of flexible (non-work) activities compared to weekdays. At 4 a.m. the dynamic approaches the residential population. During the day (at 10 a.m., 12 p.m. and 16 p.m.) more people tend to travel to Utrecht, resulting in an increase of the population during the day.

4.2. Air pollution

As a result of the AURORA dispersion modelling, hourly concentration maps for PM_{10} and $PM_{2.5}$ were available for the Netherlands for the month of April in 2005. In a GIS environment the 3 by 3 km concentration grid cells were analyzed for the study area: the Utrecht city centre. PM_{10} concentrations in Utrecht in April 2005 ranged from 6 µg/m^3 to 138 µg/m^3. Concentrations for $PM_{2.5}$ varied between 6 µg/m^3 and 227 µg/m^3 in the modelled month. Considering the variation in concentrations between the different locations, concentration differences of more than 50 µg/m^3 were reported for both PM_{10} and $PM_{2.5}$.

4.3. Exposure

As explained in Section 3.3 static and dynamic exposure estimates were calculated by combining population data and concentration information. For the Utrecht area, two kinds of exposure analyses were made on the static and dynamic population data: a calculation of the total exposure in the study area and an analysis of the exposure hours (i.e. the total number of hours spent in or above a certain concentration).

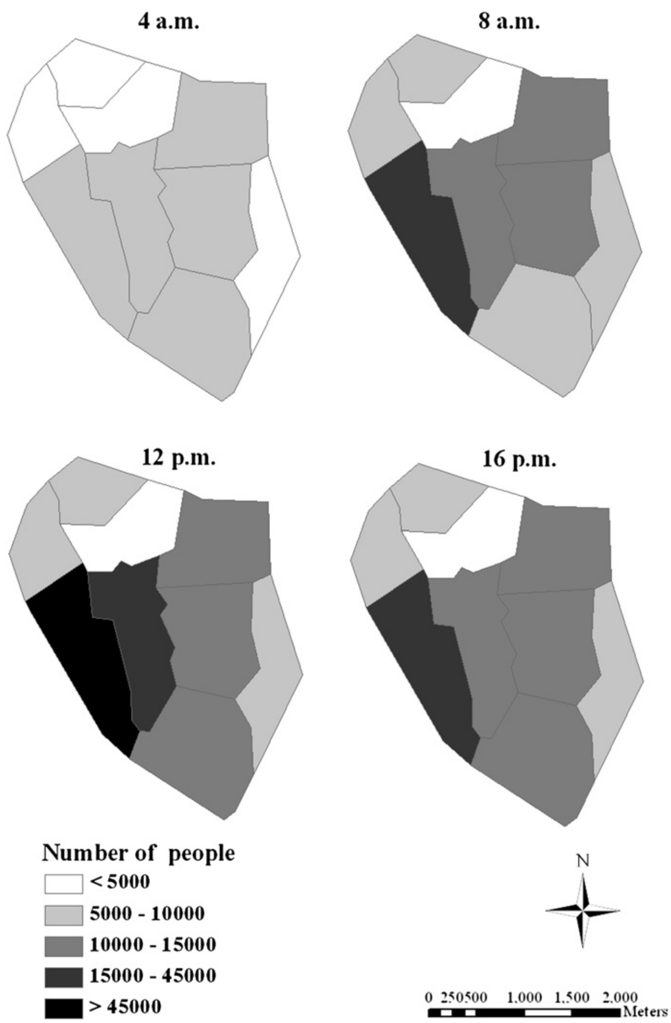

Fig. 3. Geographic presentation of the number of people present in the Utrecht city centre on an average Monday at four different points in time: 4 a.m., 8 a.m., 12 p.m. and 16 p.m.

The first exposure analysis in the Utrecht area concerned the calculation of total hourly exposure estimates by multiplying, for each hour, the number of people in each PCA with the corresponding concentration level. By summing all the exposure values per hour, a total exposure for the Utrecht city centre was calculated both for the static and the dynamic exposure approach. The relative difference in total exposure on weekdays between the static and the dynamic approach is presented in Fig. 4. This figure is the same for all pollutants since it actually represents the relative population difference for the two approaches. Hence, Fig. 4 also represents the relative in- or outflow in the Utrecht PCA's during an average weekday, compared to the static population. Between 9 a.m. and 16 p.m. the relative difference between static and dynamic estimates amounts more than 100%, meaning that the Utrecht population more than doubles during a weekday compared to the (static) residential information. At night, the number of people estimated by the dynamic exposure method approaches the number of residents used in the static method. Consequently differences between the total exposure estimates are smallest at night.

The second analysis concerns the amount of hours that people are exposed to certain concentrations. For this analysis, the number of people exposed each hour to a concentration was calculated for both the static and the dynamic approach. Each hour spent by a person at a certain concentration, was expressed as a 'personhour'. In Figs. 5 and 6 the cumulative number of personhours spent above a certain concentration of PM_{10} or $PM_{2.5}$ respectively is expressed for both the static and the dynamic approach. Both graphs represent exposure assessments for the month of April.

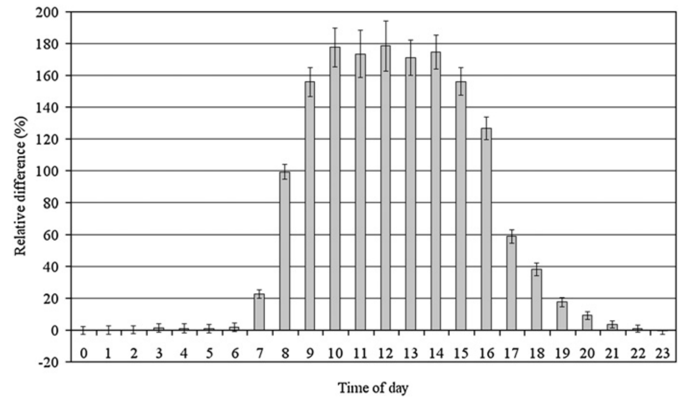

Fig. 4. Relative difference between static and dynamic total exposure estimates on weekdays for the city of Utrecht.

On both figures one can clearly see that the total number of hours spent in the Utrecht area is higher for the dynamic approach than for the static approach. According to the static approach approximately 35 million hours are spent in the Utrecht city centre in the month of April. The dynamic approach, on the other hand, simulates approximately 52 million hours spent in the Utrecht city centre. Apparently, the dynamic approach simulates an increase of the population in the study area during the day, confirming the graph in Fig. 4. Further, the difference between static and dynamic exposure estimates was also examined for certain concentration threshold values. Concerning PM_{10}, the hours spent at concentrations higher than 40 µg/m^3 were analyzed. This limit value was chosen because it is applied in the European Union as a threshold value for annual average PM_{10} concentrations. As illustrated in Fig. 5 approximately 6.5 million hours in the month of April were spent at concentrations above this limit value according to the static approach, whereas the dynamic approach simulated more than 7 million hours spent above 40 µg/m^3. In Fig. 6 the exposure to $PM_{2.5}$ was examined in a similar way. According to the new EU air quality directive (2008/50/EC), EU member states are also obliged to bring $PM_{2.5}$ exposure levels below 20 µg/m^3 by 2015 in urban areas. Therefore, the exposure to concentrations above 20 µg $PM_{2.5}$/m^3 was also examined. The static exposure approach predicted roughly 22 million hours spent at

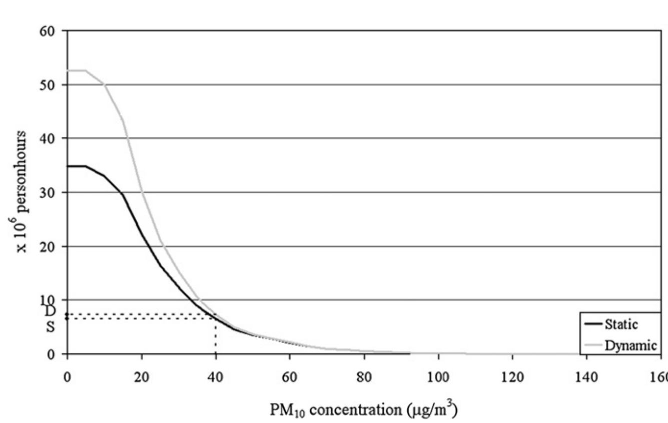

Fig. 5. Personhours spent above a certain PM_{10} concentration level in the Utrecht city centre in April 2005 (S-static = 6.50 million personhours and D-dynamic = 7.34 million personhours for PM_{10} concentrations ≥ 40 µg/m^3).

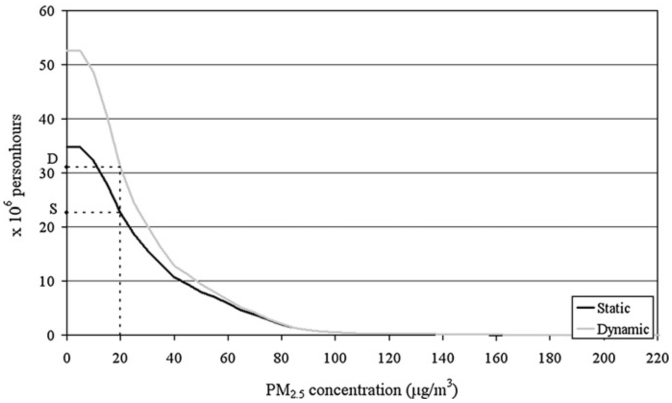

Fig. 6. Personhours spent above a certain $PM_{2.5}$concentration level in the Utrecht city centre in April 2005 (S-static = 22.60 million personhours and D-dynamic = 30.99 million personhours for $PM_{2.5}$ concentrations ≥ 20 μg/m^3).

concentrations above this limit value. Using the dynamic approach on the other hand, we estimate that more than 30 million hours were spent at concentrations above 20 μg $PM_{2.5}$/m^3.

5. Conclusions and future directions

In this paper we reported on the use of an activity-based model for the assessment of population exposure to air pollution. Hourly population information from the activity-based model ALBATROSS was combined with hourly concentration data from the AURORA dispersion model to calculate the dynamic exposure of people living in an urban area in the Netherlands. This dynamic approach opposes the traditional, static exposure approach where people are implicitly assumed to be always at their residential address. Dynamic exposure estimates for the month of April 2005 were compared with static exposure results to gain insights into to the impact of performing a dynamic population modelling approach on the exposure analysis in an urban area. Results demonstrated large differences between static and dynamic exposure estimates, especially during the day. According to the dynamic approach a large number of people tend to travel to the urban area during the day whereas the static approach works with a constant number of people during the day, explaining the lower exposure estimates for the static approach.

Regarding the analysis on PM concentration thresholds, both approaches (static and dynamic) simulate the exceeding of these values in the month of April. The PM_{10} threshold of 40 μg/m^3 was exceeded with 6.50 and 7.34 million personhours by the static and dynamic approach respectively. This means that, according to the dynamic approach, more than 7 million hours in April were spent at a PM_{10} concentration above 40 μg/m^3. For $PM_{2.5}$ approximately 22 and 31 million hours were spent above the concentration limit of 20 μg/m^3 for the static and dynamic approach respectively. The results of these analyses are very important for policy purposes since the real exposure of people to air pollution (and hence also the impact of the exposure) tends to be different than based on traditional analyses. Under the New EU Air Quality Directive (2008/50/EC) EU Member States are required to reduce exposure to $PM_{2.5}$ in urban areas by an average of 20% by 2020 based on 2010 levels. Good exposure assessments, taking into account the exposure of people at locations different than their home address, are necessary to ensure a realistic impact analysis of this measure. In this study the relative difference of the hours spent at $PM_{2.5}$ concentrations above 20 μg/m^3 differed already more than 20% between the static and dynamic approach.

Of course, one can argue the analysis method and especially the threshold values chosen in this study (40 μg/m^3 for PM_{10} and 20 μg/m^3 for $PM_{2.5}$). Official PM_{10} threshold values only exist on daily or yearly basis whereas $PM_{2.5}$ thresholds are only imposed on annual averaged concentrations. However, this kind of approach is also used and approved in other exposure studies (e.g. Borrego et al., 2006b) where the exposure to PM_{10} is evaluated by examining hourly exposure estimates. In the study presented here, we do not intend to draw direct conclusions on the health impacts of the exposure estimates but only want to indicate the large error that is associated with the traditional static exposure approach. Since the results of the dynamic exposure analysis in the Utrecht area revealed significant differences on an hourly time scale, large differences can also be expected on larger time scales.

Based on the results of this research we can conclude that the activity-based modelling approach offers the opportunity to perform a detailed, dynamic analysis of exposure to air pollution. Considering the fact that these dynamic exposure assessments take the real activity–travel behaviour into account, this accomplishment can lead to a much more sensitive policy impact analysis than previously performed studies (based on static exposure estimates). Given the characteristics of the activity-based model, we encourage to use this approach for the evaluation of different policy measures on both travel behaviour and exposure estimates. Further, since the activity-based approach does not only provide information on the location of the people but also on aspects like their gender or the performed activity, future research will allow far more detailed analyses of the exposure to air pollution.

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References

Anggraini R, Arentze T, Timmermans H. Modelling car allocation decisions in automobile deficient households. Proceedings of the European Transport Conference, Noordwijkerhout, The Netherlands; 2007.

Arentze T, Timmermans H. ALBATROSS: A Learning-Based Transportation Oriented Simulation System. Eindhoven, The Netherlands: European Institute of Retailing and Services Studies; 2000.

Arentze T, Timmermans H. ALBATROSS: A Learning-Based Transportation Oriented Simulation System. Transp Res Part B Methodol 2004;38:613–33.

Arentze T, Timmermans H. ALBATROSS 2.0: A Learning-Based Transportation Oriented Simulation System. Eindhoven, The Netherlands: European Institute of Retailing and Services Studies; 2005.

Arentze T, Hofman F, Timmermans H. Reinduction of ALBATROSS decision rules with pooled activity–travel diary data and an extended set of land use and cost-related condition states. Transp Res Rec 2003;1831:230–9.

Atkinson RW, Anderson HR, Sunyer J, Ayres J, Baccini M, Vonk JM, et al. Acute effects of particulate air pollution on respiratory admissions. Results from APHEA 2 project. Am J Respir Crit Care Med 2001;164:1860–6.

Beckx C, Broekx S, Janssens D. Activity-based policies to reduce human exposure to traffic air pollution. Proceedings of the 32nd International "Transportation Research Colloquium. Antwerp, Belgium, vol. 7. 2005. p. 1955–72.

Beckx, C., Arentze, T., Int Panis, L., Janssens, D., Vankerkom, J., Wets, G. An integrated activity-based modelling framework to assess vehicle emissions: approach and application. Environ and Plan B in press.

Bhat CR, Guo J, Srinivasan S, Sivakumar A, Pinjari A, Eluru N. Activity-Based Travel-Demand Modeling for Metropolitan Areas in Texas: Representation and Analysis Frameworks for Population Updating and Land-Use Forecasting, Report 4080-6, prepared for the Texas Department of Transportation; 2004.

Borrego C, Martins H, Tchepel O, Salmim L, Monteiro A, Miranda AI. How urban structure can affect city sustainability from an air quality perspective. Environ Model Softw 2006a;21:461–7.

Borrego C, Tchepel O, Costa AM, Martins H, Ferreira J, Miranda AI. Traffic-related particulate air pollution exposure in urban areas. Atmos Environ 2006b;40:7205–14.

Bowman JL, Ben-Akiva ME. Activity-based disaggregate travel demand model system with activity schedules. Transp Res Part A 2001;35:1-28.

Beelen R, Hoek G, van den Brandt P, Goldbohm R, Fischer P, Schouten L, et al. Long-term effects of traffic-related air pollution on mortality in a Dutch cohort (NLCS-AIR study). Environ Health Perspect 2008;116:196–202.

Brugge D, Durant J, Rioux C. Near-highway pollutants in motor vehicle exhaust: a review of epidemiologic evidence of cardiac and pulmonary health risks. Environ Health 2007;6:23.

Corburn J. Urban land use, air toxics and public health: assessing hazardous exposures at the neighbourhood scale. Environ Impact Asses Rev 2007;27:145–60.

De Ridder K, Lefebre F, Adriaensen S, Arnold U, Beckroege W, Bronner C, et al. Simulating the impact of urban sprawl on air quality and population exposure in the German Ruhr area. Part I: reproducing base state. Atmos Environ 2008a;42:7059–69.

De Ridder K, Lefebre F, Adriaensen S, Arnold U, Beckroege W, Bronner C, et al. Simulating the impact of urban sprawl on air quality and population exposure in the German Ruhr area. Part II: development and evaluation of an urban growth scenario. Atmos Environ 2008b;42:7070–7.
Friedrich R, Bickel P. Environmental External Costs of Transport. Berlin: Springer Verlag; 2001.
Goulias KG, Kitamura R. A dynamic model system for regional travel demand forecasting. In: Golob TF, Kitamura R, Long L, editors. Panels for Transportation Planning: Methods and Applications. Boston: Kluwer Academic Publishers; 1996. p. 321–48.
Hatzopoulou M, Miller EJ, Santos B. Integrating vehicle emission modelling with activity-based travel demand modelling: a case study of the Greater Toronto Area (GTA). Paper presented at the 86th Annual Meeting of the Transportation Research Board, Washington DC; 2007.
Int Panis L, Beckx C. Trucks driving at night and their effect on local air pollution. Proceedings of the European Transport Conference, Noordwijkerhout, The Netherlands, vol. 1. 2007. p. 1–9.
Int Panis L, De Nocker L, De Vlieger I, Torfs R. Trends and uncertainty in air pollution impacts and external costs of Belgian passenger car traffic. Int J Veh Des 2001;27:183–94.
Int Panis L, De Nocker L, Cornelis E, Torfs R. An uncertainty analysis of air pollution externalities from road transport in Belgium in 2010. Sci Total Environ 2004;334:287–98.
Int Panis L, Broekx S, Liu R. Modelling instantaneous traffic emission and the influence of traffic speed limits. Sci Total Environ 2006;371:270–85.
Kitamura R, Fujii S. Two computational process models of activity–travel behavior. In: Garling T, Laitila T, Westin K, editors. Theoretical Foundations of Travel Choice Modeling. Oxford: Elsevier Science; 1998. p. 251–79.
Kulkarni A, McNally MG. An Activity-Based Microsimulation Model for Generating Synthetic Activity–Travel Patterns: Initial Results. Center for Activity Systems Analysis, University of California; 2000. http://repositories.cdlib.org/itsirvine/casa/UCI-ITS-AS-WP-00-3.
Le Tertre A, Medina S, Samoli E, Forsberg B, Michelozzi P, Boumghar A, et al. Short-term effects of particulate air pollution on cardiovascular diseases in eight European cities. J Epidemiol Community Health 2002;56:773–9.
McNally MG. The activity-based approach. Center for Activity Systems Analysis Paper UCI-ITS-AS-WP-00-4, University of California; 2000. http://repositories.cdlib.org/itsirvine/casa/UCI-ITS-AS-WP-00-4.
Mensink C, De Ridder K, Lewyckyj N. Computational aspects of air quality modelling in urban regions using an optimal resolution approach. In: Margenov S, Wasniewski J, Yamalov P, editors. Large-Scale Scientific Computing, vol. 2179. Lect Notes in Comput Sci; 2001. p. 299–308.
Miller E, Roorda MJ. A prototype model of 24-hour household activity scheduling for the Toronto Area. Transp Res Rec 2003;1831:114–21.
Nawrot TS, Torfs R, Fierens F, De Henauw S, Hoet PH, Van Kersschaever G, et al. Stronger associations between daily mortality and fine particulate air pollution in summer than in winter: evidence from a heavily polluted region in western Europe. J Epidemiol Community Health 2007;61:146–9.
Pendyala RM, Kitamura R, Kikuchi A, Yamamoto T, Fujji S. FAMOS: Florida activity mobility simulator. Proceedings of the 84th Annual Meeting of the Transportation Research Board, Washington DC; 2005.
Pope CA, Dockery DW. Health effects of fine particulate air pollution: lines that connect. J Air Waste Manage Assoc 2006;56:709–42.
Shiftan Y. The advantage of activity-based modelling for air-quality purposes: theory vs practice and future needs. Innovation 2000;13:95-110.
Shiftan Y, Suhrbier J. The analysis of travel and emission impacts of travel demand management strategies using activity-based models. Transportation 2002;29:145–68.
Vovsha P, Bradley M, Bowman JL. Activity-based travel forecasting in the United States: progress since 1995 and prospects for the future. Proceedings of the Conference on Progress in Activity-Based Models. Maastricht; 2004.

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