USING AN ACTIVITY-BASED FRAMEWORK TO DETERMINE THE EFFECTS OF A POLICY MEASURE ON POPULATION EXPOSURE TO NO_2

Evi Dons * (corresponding author)
VITO-MRG (Flemish Institute for Technological Research)
Boeretang 200
2400 Mol, Belgium
Tel: +32 14 33 51 90
Fax: +32 14 58 26 57
E-mail: evi.dons@vito.be

Carolien Beckx
VITO-TEM (Flemish Institute for Technological Research)
Boeretang 200
2400 Mol, Belgium
Tel: +32 33 14 59 58
Fax: +32 14 58 26 57
E-mail: carolien.beckx@vito.be

Theo Arentze
Urban Planning Group
Eindhoven University of Technology, PO Box 513
5600 MB Eindhoven, The Netherlands
Tel: +31 40 247 22 83
E-mail: T.A.Arentze@tue.nl

Geert Wets
Transportation Research Institute - Hasselt University
Wetenschapspark 5 bus 6
3590 Diepenbeek, Belgium
Tel: +32 11 26 91 11
Fax: +32 11 26 91 99
E-mail: Geert.wets@uhasselt.be

Luc Int Panis *
VITO-MRG (Flemish Institute for Technological Research)
Boeretang 200
2400 Mol, Belgium
Tel: +32 33 14 51 02
Fax: +32 14 58 26 57
E-mail: luc.intpanis@vito.be

* Also associated with:
Transportation Research Institute - Hasselt University
Wetenschapspark 5 bus 6
3590 Diepenbeek, Belgium

Submission date: July 31 2010
Word Count: 6*250 = 1500 + 5207= 6707

Submitted for presentation and publication to
Transportation Research Board
90th Annual Meeting
January 2011. Washington, D.C.

ABSTRACT

Few studies have modeled the effects of policy measures on population exposure. In this work we assess for the first time the impact of a policy measure on population exposure to NO_2 by using the activity-based model ALBATROSS. Activity-based (AB) models can be of great value in evaluating the effect of integrated policies and measures that have no obvious relation with transport or air quality at first sight.

The scenario considered in this study concerns changing the opening hours of shops and allows shopping earlier in the morning and later in the evening. Both emissions and population distribution of this policy measure can be derived from the activity-travel behavior predicted by the AB model. We found that widening opening hours changes the activity pattern of the adult population in the Netherlands. Approximately 6% more non-daily and 0.5% more daily shopping hours are predicted. The change in activity pattern results in more transport (+0.5% more vehicle kilometers driven). As a consequence of this, emissions and air pollutant concentrations were also altered. When matching the concentration maps with the dynamic population, we observe an increase in population exposure to NO_2. Absolute differences are small (up to 0.40 $\mu g/m^3$). On an average weekday NO_2 exposure increases by 0.15 $\mu g/m^3$. The relative change in exposure on an average weekday is 0.4%. In certain neighborhoods and on certain hours a more substantial increase can be observed.

INTRODUCTION

Numerous studies have already emphasized the importance of transport sources for exposure to air pollutants. Transport not only affects exposure of people living nearby but also those working or shopping in the vicinity. Often it is overlooked that participating to traffic also influences personal exposure and may entail health impacts (*1, 2*). Policy measures, e.g. introduction of congestion charging, changes in work duration, or facilitation of tele-working, are able to change an individual's activity pattern and the derived traffic participation. Will this impact population exposure as well?

The classical way of looking at exposure is by multiplying population density, based on residential addresses, with concentrations measured at a nearby fixed monitoring station (*3, 4*). When using this approach several unrealistic assumptions are made. Everyone in the population is assumed to be at their home location all the time. This may be true for approximately 70 to 80% of the time; but many researchers acknowledge that the short time spent in a non-residential microenvironment (e.g. in transport) may account for a large fraction of the accumulated exposure (*5, 6, 7*). Further, using concentrations measured at fixed monitoring stations to estimate personal exposure is unrealistic in a way that concentrations of air pollutants, especially traffic related pollutants like NO_2, differ substantially on a local scale. By using interpolation methods like universal and ordinary kriging, inverse distance weighting, land use regression or emission- and dispersion modeling, the spatial resolution can be improved.

A decade ago Shiftan (*8*) already explored the advantages of activity-based (AB) modeling for air-quality prediction purposes. An AB model basically predicts a diary for every individual in a population: which activities will be performed where and for how long and if a trip is involved which transport mode will be used (*9, 10*). By using an AB transportation model we can improve on both of the issues stated above: we can use dispersion modeling based on more accurate emission estimates of modeled trips and we can model the location of every individual for every hour of the day. This way a truly dynamic exposure analysis can be made by geographically matching hourly concentrations and hourly population densities. Moreover, we are able to differentiate between different subpopulations and different activities allowing a more detailed exposure analysis.

This methodology has the potential to provide valuable information for air pollution epidemiology (*11*) and policy purposes (*12*). To reduce population exposure to air pollution, policy makers can cut down emissions or lower concentrations. However to enable a durable change in population exposure, policy measures should affect the driving forces of the DPSIR framework (*13*). By changing the activity patterns, trips can become unnecessary. In our modeling framework, policy measures impact the AB model (and effects propagate further through the emission and dispersion model). As an example of this approach we present a scenario (widening of shop opening hours) and evaluate the effects of the scenario on population exposure using an AB model.

METHODOLOGY

The modeling framework consists of three models which run subsequently: the output of one model serves as the input of the following model. The three models used here are: the AB model ALBATROSS, the emission model MIMOSA and the dispersion model AURORA. This chain of models provides a flexible framework. It is possible to replace each of the models by a comparable model, e.g. substitute the AB model for the Netherlands with an AB model for a different region. An extensive description of the complete framework can be found in Beckx et al. (*5, 14*).

When calculating the effects of a scenario on population exposure, the modeling framework is run through twice: before the introduction of a policy measure and after the introduction of the policy measure. The outcome of the first model run is then compared to the results ex post.

Activity-Based Transportation Model

The AB transportation model ALBATROSS (an acronym for A Learning Based Transportation Oriented Simulation System) was used to predict activity-travel patterns for the Dutch population (*15, 16*). The model first establishes a synthetic population 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. Every adult inhabitant of the Netherlands (or more precisely, household head), is incorporated in the synthetic population. The 4-digit postal code area (4PCA) was chosen as the spatial unit for the ALBATROSS model.

Activity-travel schedules are then simulated for all the individuals by using decision trees representing each choice (e.g. a stochastic choice of activity type, duration of activity, choice of location, transportation mode involved, etc.). While making these decisions several constraints, e.g. institutional constraints and household constraints, are taken into account to make resulting activity diaries more realistic. We used the output of one run of the model representing one-day diaries across all days of the week of all people in the study area. Thus, the activity patterns should be representative for an entire week. Although ALBATROSS is a stochastic model we have used only one model run (implicitly assuming it to be a deterministic model) because the subsequent modeling steps are very computer intensive.

Presently, possible seasonal differences in weekly activity patterns are not captured by the model. To assess the traffic flows, we extract the Origin-Destination (OD) matrices from the simulated activity patterns. Predicted car trips for the entire population are assigned to a road network (‘Basisnetwerk’) by using an all-or-nothing assignment (shortest path in distance). Because ALBATROSS does not estimate freight traffic a more advanced network assignment taking into account capacities (or possible congestion) was not possible. Passenger car trip matrices were analyzed for different time periods, to account for intraday and intraweek differences in travel behavior, and for various trip motives with a focus on shopping.

Emission Model

Traffic flows are converted into vehicle emissions by applying the emission factor approach from the MIMOSA emission model following the procedure described by Beckx et al. (*17*). Hourly, geographically spread, emissions were calculated with a classical approach. MIMOSA belongs to the macroscopic `average speed emission models', that express emission and fuel consumption rates for each trip as a function of average speed. The model was adapted to calculate emissions and emission reduction scenarios for larger areas by Schrooten et al. (*18*). The emission factors used within the MIMOSA model are mostly based on the Copert-III report (*19*). For missing data (some specific pollutants and particulate matter (PM) emissions), emission functions from MEET (*20*) were applied and some data were extracted from experimental on-road measurements (*21*). In order to calculate the vehicle emissions for passenger car trips in the Netherlands, the latest MIMOSA version was extended with information regarding the Dutch vehicle park and road conditions (*17*). Further, the settings within the model were altered to benefit maximally from the information provided by the AB approach. These new characteristics make the model suitable for the emission estimations at the national level, on the basis of the output of an AB model. The basic version of MIMOSA predicts hourly traffic emissions based on peak-hour traffic flows. The time dependency of the emissions is ‘simulated’ using normalized factors expressing the fluctuations of the traffic flow as a function of the time of day, the day of the week, and the month of the year. By using an AB approach, hourly traffic flows are immediately provided on all 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. 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 (*22*). Link-specific traffic speeds were not derived from the all-or-nothing assignment but (to be consistent with Albatross) we used the same traffic speeds as used by the AB model to estimate travel time between different locations. These link-specific traffic speeds 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 derived by Arentze and Timmermans (*23*). By combining the hourly traffic volumes computed per road segment with fleet statistics and the corresponding emission factors, our final Dutch MIMOSA model calculates temporally and geographically distributed traffic emissions. The emissions presented in this study include hot and cold emissions of NO_x. 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.

Dispersion Model

In a next phase the emissions are converted into pollutant concentrations. For this purpose, the AURORA model is applied to simulate the dispersion and conversion of the emissions into concentrations. AURORA (Air quality modeling in Urban Regions using an Optimal Resolution Approach), is a deterministic 3-dimensional Eulerian model of the atmosphere. The model predicts how air pollutants are transported away from their source and mixed in the air. Physical changes and chemical reactions that generate secondary pollutants are also taken into account. The model's outputs are 3-dimensional concentration fields for the region of interest. We discuss the AURORA model briefly to enable understanding of our work but we refer the reader to De Ridder et al. (*24*) and Beckx et al. (*5*) for a full description of the model and its use in the environmental evaluation of transport scenarios.

Data requirements for AURORA are difficult to meet and include the specification of 3-D fields of relevant meteorological parameters, wind vector components, friction velocity, temperature, humidity, precipitation, radiation, cloud properties, and turbulent diffusion coefficients, among others. The emissions input required by the AURORA model consists of gridded two-dimensional emissions maps on an hourly basis. Local emissions from industry, shipping and building heating were obtained from the E-MAP GIS tool. E-MAP performs a spatial disaggregation of CORINEAIR/EMEP emission inventories by using spatial surrogate data. CORINAIR (Core Inventory of Air Emissions) collects, maintains, manages and publishes information on air emissions, by means of a European air emission inventory and database system (*25*). A good description of these auxiliary data sets can be found in Maes et al. (*26*). The annual emissions are distributed temporally according to monthly (January – December), daily (Monday – Sunday) and hourly (0h – 23h) correction factors. These factors are specific to each pollutant and emission sector, and hence reflect the different energy-use time patterns. Traffic related emissions were obtained from the previously ran ALBATROSS-MIMOSA model chain (also described in (*17*)). The remainder of the emissions for the Netherlands were taken from the national Dutch pollutant emission inventory (*27*), which distinguishes between various types of road transport and emissions. The Dutch emission inventory is available on a yearly basis, and has a geographic resolution of 5 x 5 km² that was transferred to the AURORA grid.

By using a dispersion model we produce high-resolution air quality maps for the Netherlands. However the air quality in the Netherlands is not only determined by emissions taking place in its territory, but also by air pollutants that are being emitted in the neighboring countries. These air pollutants were taken into account through the principle of nesting. This means that we start AURORA calculations covering a large domain at a low resolution and gradually focus on the region of interest at higher resolutions. The lateral boundary conditions of the model domain are always specified from the previous run (or from external data in the case of the outer domain). Three different resolution steps were taken for the AURORA modeling, starting with a domain at 30km resolution (2400 km x 1500 km) through 10 km down to 3km resolution. Only results from the 3-km resolution model domain will be discussed in this paper.

We have performed AURORA calculations for six months (March, April, May and September, October, November) for the year 2005 and the following pollutants were considered: NO_2, O_3 and PM10, because these pollutants are traffic related and important for human health. Only results for NO_2 during the month of April are discussed in this paper. We refer the reader to Beckx et al. (*5, 14, 17, 28*) for a more detailed description of the procedures followed for atmospheric modeling.

Integration of the Models

The goal of the modeling framework is to assess population exposure both in the base case, as well as in a scenario simulation. The predicted hourly NO_2-concentration field from the ALBATROSS-MIMOSA-AURORA modeling chain is combined with hourly information on people's whereabouts to calculate their exposure. By using the population information from the AB simulation, hourly population maps are simulated and dynamic exposure values can be estimated (Figure 1).

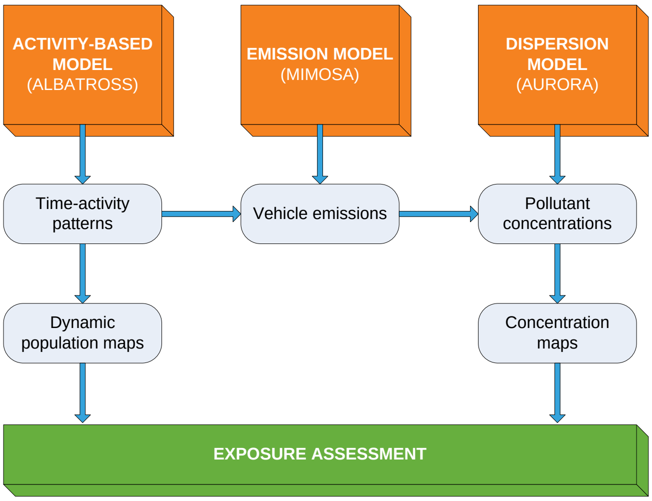

FIGURE 1 The exposure modeling framework (adapted from Beckx et al. (*28*))

Each step in the process was evaluated to assess the accuracy of the predictions. The predicted results from the AB emission modeling approach were compared with travel and emission values from the Dutch Scientific Statistical Agency whose data originates from other model simulations. Of course, 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. Moreover, uncertainties in both simulated and reported data are not looked at. Ideally, a validation method should therefore use measurements instead of simulation values, but the procedure of comparison with other models provides useful cross-validation. Because travel and emission measurements were not available on a national level (only concentration measurements are executed), the values from the Dutch Scientific Statistical Agency were therefore considered as an acceptable alternative for the validation of the base case travel and emission data. Modeled emissions and reported emission values demonstrate good correspondence. When comparing the simulated concentrations for the base case with measured values at Dutch monitoring stations, the index of agreement varies between 0.40 and 0.70 for NO_2 (*14*), which demonstrates that the AB air quality model chain is able to simulate the hourly concentration patterns in the Dutch study area with sufficient accuracy.

RESULTS AND DISCUSSION

The scenario considered here involves a widening of shop opening hours for daily and non-daily shopping as described in Table 1. Daily shopping also includes service related activities, like going to a post office or a hair dresser. The new opening hours are from 6 a.m. until 10 p.m. on weekdays and Saturdays, which allows shopping earlier in the morning and later in the evening. In ALBATROSS this is implemented by changing the institutional constraints in the scheduler. The shop opening hours-law, adopted in the Netherlands in 1996, interdicts retailers to open their shops between 10 p.m. and 6 a.m.. Municipalities can deviate from this law, e.g. by enabling shops to open on Sundays. These exceptions cannot be included in the ALBATROSS-scheme, although it is possible on a very limited scale to enable shopping on Sundays when this is indicated in the revealed preference diaries. Even though this law now stands for over a decade, discussions on shop opening hours are still open, making this a relevant policy scenario.

As a case study we model the difference in dynamic population and concentration, and the difference in population exposure for NO_2. We only consider the adult population of the Netherlands (approximately 10.5 million individuals).

TABLE 1 Shop opening hours for daily and non-daily shopping in the base case and in the widening scenario

Day	Base case		Widening scenario	
	Daily (hours)	Non-Daily (hours)	Daily (hours)	Non-Daily (hours)
Monday	08:00 – 20:00	13:00 – 18:00	06:00 – 22:00	06:00 – 22:00
Tuesday	08:00 – 20:00	09:00 – 18:00	06:00 – 22:00	06:00 – 22:00
Wednesday	08:00 – 20:00	09:00 – 18:00	06:00 – 22:00	06:00 – 22:00
Thursday	08:00 – 20:00	09:00 – 21:00	06:00 – 22:00	06:00 – 22:00
Friday	08:00 – 21:00	09:00 – 21:00	06:00 – 22:00	06:00 – 22:00
Saturday	08:00 – 20:00	09:00 – 17:00	06:00 – 22:00	06:00 – 22:00
Sunday	Closed	Closed	Closed	Closed

Results

Dynamic Population

The AB model ALBATROSS predicts an hourly population for every postal code area (4PC). During the day population is higher in city centers and lower in residential areas. At 4 a.m. the dynamic population approaches the residential population.

As a consequence of the scenario, the ALBATROSS model predicts approximately 6% more non-daily shopping hours and 0.5% more daily shopping. In a study of Jacobsen (*29*) an augmentation in weekly shopping time was observed as well, both from a simple model and from empirical findings. Schwanen (*30*) indicates that the shopping duration is affected by temporal constraints and the activity/travel episodes conducted before or after the shopping activity. The changes in activity patterns result in more transport hours; an increase of 0.5%. Since transport is the third most important ‘activity’, next to residential activities and working, a small relative increase will have a substantial effect on total kilometers driven (and corresponding emissions). Kilometers driven by car will mainly increase in the early morning and the evening.

On an average weekday, shifts are seen during the day (Figure 2). As expected, there will be more shopping in the morning and in the evening. This is offset by less time spent on in-home activities and on leisure. Between 8 a.m. and 5 p.m. there will be somewhat less shopping compared to the reference situation. Shifts between days of the week are rather limited. On Monday morning shops were closed in the base case whereas the scenario simulation allows shopping from 6 a.m. onwards. This leads to a shift between the hours of the day, but also to a shift between the days of the week.

Concerning the differences in shopping behavior between men and women, we found that in the reference situation and in the scenario women execute more shopping-activities than men. However, both men and women adapt quite similarly to the new opening hours and the same temporal pattern can be observed.

On Figure 4 (a) and 4 (b) the difference in population per postal code area is depicted for a random moment in time.

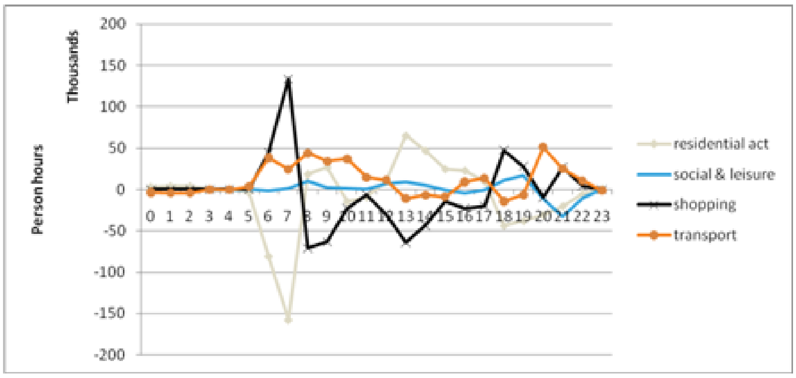

FIGURE 2 Difference in activity pattern between scenario and reference situation on an average weekday per hour of the day (on the x-axis the hours of the day are represented)

Hourly Concentrations

The ALBATROSS model predicted more kilometers driven by car in the shopping scenario; as a consequence emissions of road transport will rise (output of the MIMOSA-model) as well as the derived concentrations in ambient air (output of the AURORA-model). The activity pattern is assumed the same for every week of the year, but the meteorological conditions change so concentrations will differ from week to week.

The concentration maps use a raster overlaying the Netherlands, one grid cell being 9 km² (a total of 11439 grid cells). Figure 4 (c) and Figure 4 (d) show the differences in concentration levels between the scenario and the reference situation. Absolute differences are small as expected since not only traffic emissions will determine the concentration patterns.

Population Exposure

Population exposure to NO_2 is calculated by multiplying the dynamic population in each postal code area with the concentrations in the overlaying grid cell. This procedure is rather straightforward for most activities. For the activity 'in transport', we have allocated the hourly average NO_2 concentration measured in the Dutch traffic-related monitoring stations following the procedure established by Beckx et al. (*5*). Other authors have circumvented this problem by either ignoring the transport activity (*31*) or by assuming that the trajectory covered a straight line between origin and destination (*32*). All calculations were performed for all four weeks of April 2005.

Results show an increase in population exposure to NO_2 (Figure 3, Table 2). On an average weekday in April exposure increased with 0.15 µg/m³. Taking the week as a whole (including the weekend) lowers this number to 0.14 µg/m³. This number is relatively stable across the days of the week and across the weeks of April. There is an increase in exposure in the morning and a clear peak in the evening; this supports our hypothesis that the exposure difference is mostly due to an increase in kilometers driven by car. Keeping in mind the already higher exposure during peak hours, the scenario will only make this trend even more apparent. At night-time and on Sundays the difference between the base-situation and the scenario is small, which is a reassuring result (since no changes were made to the institutional constraints in these periods, results should be very similar). Tested over the 4 weeks of April the relative change in exposure on an average weekday is 0.4%. In certain neighborhoods and on certain hours a more substantial increase can be observed. In order to illustrate the variation in exposure geographically Figure 4 (e) and (f) respectively present exposure in two different study areas: the city of Amsterdam and the city of Rotterdam. Similar geographic illustrations can of course be presented for any other area in the Netherlands and for any other hour of the day or day of the week. For legibility reasons a random moment in time was selected and we zoomed in on two geographical areas.

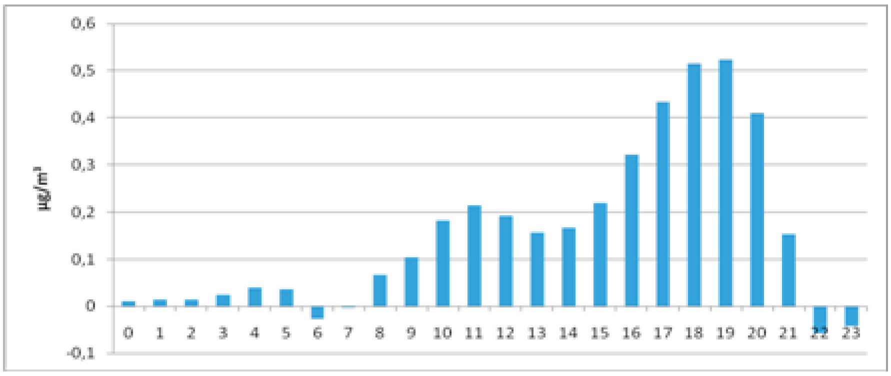

FIGURE 3 Difference in exposure between scenario and reference situation on an average weekday per hour of the day for April 2005 (on the x-axis the hours of the day are represented)

The increase in population exposure is statistically significant. The numbers in Table 2 are corrected for postal code areas with a low number of people residing there (less than 100) because a ratio of small values can cause inconsistent results.

TABLE 2 Difference in exposure between scenario and reference situation (April 2005) [µg/m³]

	Week 1	Week 2	Week 3	Week 4	Average April
Monday	0.1079	0.1599	0.1223	0.1441	0.1336
Tuesday	0.1163	0.1421	0.1323	0.1487	0.1348
Wednesday	0.1168	0.1662	0.1174	0.1232	0.1309
Thursday	0.1122	0.1741	0.1935	0.2165	0.1741
Friday	0.2113	0.1154	0.1852	0.2371	0.1873
Average weekday	0.1329	0.1515	0.1501	0.1739	0.1521
Saturday	0.1592	0.0881	0.1472	0.1696	0.1410
Sunday	0.0614	0.0657	0.0604	0.0677	0.0638
Average week	0.1265	0.1302	0.1369	0.1581	0.1379

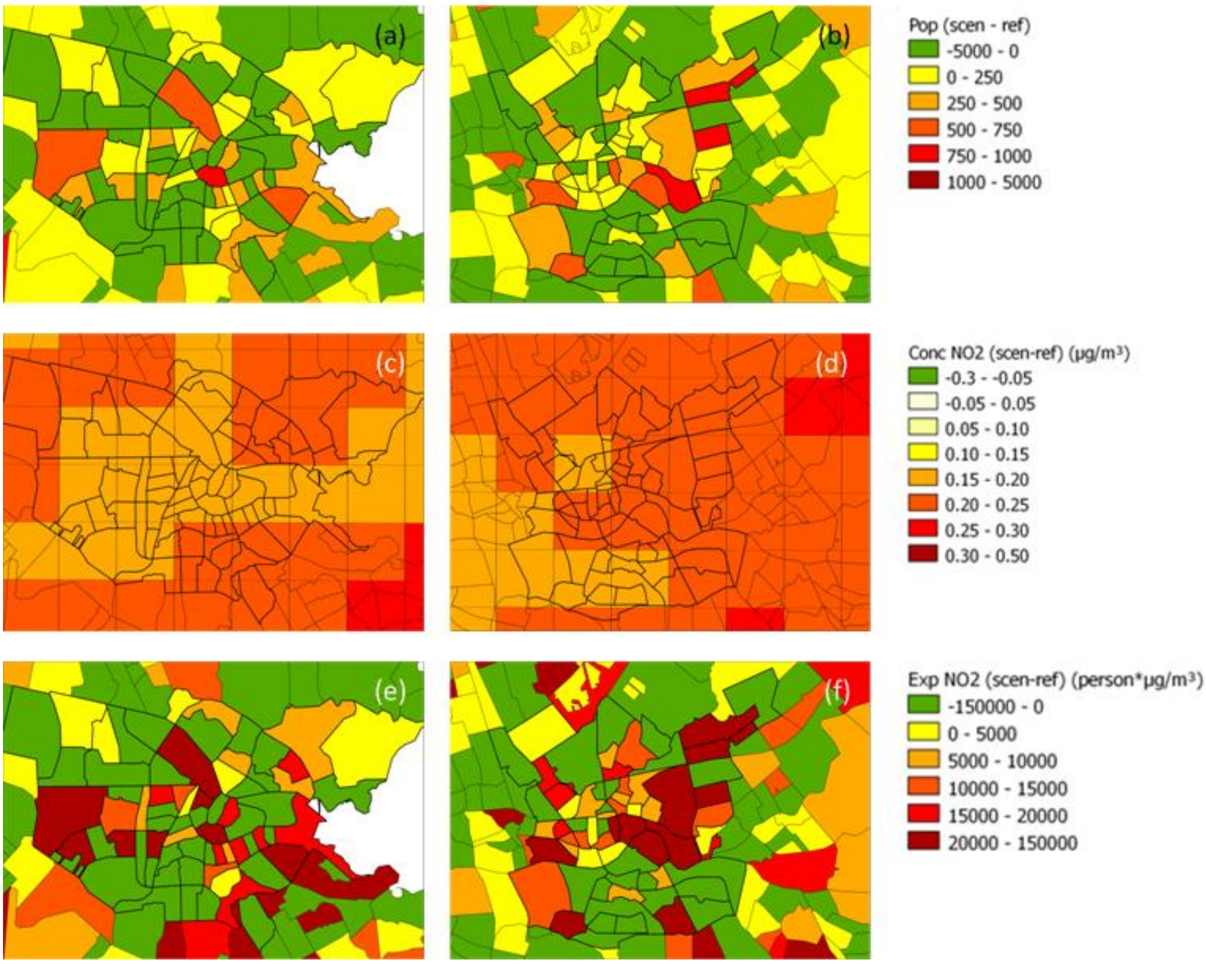

FIGURE 4 (a)-(f). Difference in population levels (a, b), ambient pollutant concentrations of NO_2 (c, d) and population exposure to NO_2 (e, f) between the scenario and the reference situation. The maps on the left side present the values for the city of Amsterdam, while the maps on the right side present the values for the city of Rotterdam, each time on an average Tuesday in April 2005 at 5 p.m.

Discussion

Since the early 1970s, the EU has been working to improve air quality and much progress has been made since then. However, air pollution continues to be a matter of concern. Several European, national or regional policy measures explicitly aim at lowering concentrations of harmful pollutants (e.g. through legislation or vehicle technology). There is a lack of awareness that many other measures, not explicitly focusing on air quality, will significantly impact exposure and health both in a positive and in a negative way. It may happen that expensive measures to cut emissions and lower concentrations are offset by initiatives from other policy makers who are not aware they are affecting air quality. Prolonging shop opening hours is such a measure that has an unintended negative side-effect on population exposure, although the effect is clearly limited.

AB transportation models are proven to be better in evaluating the effect of TDM (travel demand measures) and integrated policies because of their ability to incorporate secondary effects (*8*). Examples of TDM are traffic restraint measures, pricing mechanisms, telecommunication or high-occupancy vehicle lanes. Next to transportation measures, AB models are able to calculate the effects of certain scenarios having no obvious relation with transport or air quality. Institutional changes (e.g. changing working hours, changing shop opening hours) or demographical changes (e.g. ageing of the population (*33*), changing percentage of part-time workers, more one-adult households) can be assessed with an AB model, all being evolutions relevant to policy nowadays.

So far and to the best of our knowledge, there are hardly any papers on the modeled quantitative effects of policy measures on air pollutant concentrations, population exposure and health for larger geographical areas. One of the first papers of this sort looked at the effect of the Congestion Charging Scheme (CCS) in London (*34*) which affected an area with approximately 7 million inhabitants. This study only considered emissions and not concentration or population exposure. The health effects of the London CCS were assessed by Tonne et al. (*35*) and they found a decrease in population exposure to NO_2 in the Greater London area of 0.10 µg/m³; in the congestion charging zone the effect was larger (-0.73 µg/m³). A similar study on the Stockholm congestion charging found effects of -0.23 µg/m³ (population exposure to NO_x) (*36*). These resulting exposures are observed ex post; after the introduction of a policy measure. Our simulation is valuable in a way that measures can be assessed ex ante. This gives priceless information to governments who want to assess costs en benefits before a policy measure is introduced.

CONCLUSIONS AND FURTHER RESEARCH

To the best of our knowledge, this study is the first that has used an AB model to predict the impact of a policy measure on population exposure to an air pollutant. The chosen policy measure had, at least on first sight, nothing to do with traffic or air pollution, but nevertheless we showed that even these policy measures can have an impact: an increase in population exposure to NO_2 of 0.15 µg/m³ or 0.4% is associated with the widening of shop opening hours. Examples of other measures or scenarios that can be evaluated by such an approach are ageing of the population, tele-working, introduction of congestion charging, etc.

The modeling framework we developed showed useful to assess population exposure. The framework is flexible; e.g. the emission and dispersion model can be replaced by a different interpolation technique as long as there is a direct input from the AB model. However, given the complexity of the models and the computer run time, we suggest replacing the emission and dispersion model with a land use regression model (LUR-model). The challenge here will be to adequately incorporate a temporal dimension into the land use regression model.

Further, making the transition from population exposure to individual exposure is especially relevant when looking at health effects. In theory it is possible to use the simulated diaries on a disaggregated level to look into personal exposure instead of assessing population exposure, as we did in this paper.

ACKNOWLEDGEMENTS

We would like to acknowledge dr. ir. Karen Van De Vel and dr. Wouter Lefebvre from VITO for providing the concentration data for this study.

REFERENCES

1. McCreanor, J. et al. (2007). Respiratory effects of exposure to diesel traffic in persons with asthma. *The New England Journal of Medicine,* 357: 2348-2358.
2. Peters, A. et al. (2004). Exposure to traffic and the onset of myocardial infarction. *The New England Journal of Medicine,* 351: 1721-1730.
3. Kaur, S. et al. (2007). Fine particulate matter and carbon monoxide exposure concentrations in urban street transport microenvironments. *Atmospheric Environment,* 41: 4781-4810.
4. Sarnat, S. E. et al. (2009). An examination of exposure measurement error from air pollutant spatial variability in time-series studies. *Journal of Exposure Science and Environmental Epidemiology*: 1-12.
5. Beckx, C. et al. (2009). Disaggregation of nation-wide dynamic population exposure estimates in the Netherlands: Applications of activity-based transport models. *Atmospheric Environment,* 43 (34): 5454-5462.
6. Fruin, S. A. et al. (2004). Black carbon concentrations in California vehicles and estimation of in-vehicle diesel exhaust particulate matter exposures. *Atmospheric Environment International - North America,* 38: 4123-4133.
7. Piechocki-Minguy, A. et al. (2006). A case study of personal exposure to nitrogen dioxide using a new high sensitive diffusive sampler. *Science of The Total Environment,* 366: 55-64.
8. Shiftan, Y. (2000). The advantage of activity-based modelling for air-quality purposes: Theory vs practice and future needs. *Innovation,* 13 (1): 95-110.
9. Davidson, W. et al. (2007). Synthesis of first practices and operational research approaches in activity-based travel demand modeling. *Transportation Research Part A,* 41: 464-488.
10. McNally, M. G. *The activity-based approach*, http://escholarship.org/uc/item/5sv5v9qt. Accessed 2009.
11. Int Panis, L. (2010). New directions: Air pollution epidemiology can benefit from activity-based models. *Atmospheric Environment*, 44: 1003-1004.
12. Hatzopoulou, M., Miller, E. J. (2010). Linking an activity-based travel demand model with traffic emission and dispersion models: Transport's contribution to air pollution in Toronto. *Transportation Research Part D*.
13. EEA (1999). Environmental indicators: Typology and overview. Technical report no 25. European Environment Agency.
14. Beckx, C. et al. (2009). The contribution of activity-based transport models to air quality modelling: A validation of the ALBATROSS-AURORA model chain. *Science of The Total Environment,* 407 (12): 3814-3822.
15. Arentze, T. A., Timmermans, H. J. P. (2000). *ALBATROSS: A learning based transportation oriented simulation system*, European Institute of Retailing and Service Studies, Eindhoven, The Netherlands.
16. Arentze, T. A., Timmermans, H. J. P. (2004). A learning-based transportation oriented simulation system. *Transportation Research Part B: Methodological,* 38 (7): 613-633.
17. Beckx, C. et al. (2009). An integrated activity-based modelling framework to assess vehicle emissions: Approach and application. *Environment and Planning B: Planning and Design,* 36: 1086-1102.
18. Schrooten, L. et al. (2006). Costs and benefits of an enhanced reduction policy of particulate matter exhaust emissions from road traffic in Flanders. *Atmospheric Environment,* 40: 904-912.
19. Ntziachristos, L., Samaras, Z. *Copert-III (computer programme to calculate emissions from road transport). Methodology and emission factors (version 2.1), technical report 49,* http://lat.eng.auth.gr/copert/. Accessed 2000.
20. MEET (1999). *Methodology for calculating transport emissions and energy consumption,* Transport Research, Fourth Framework Programme, Strategic Research, DG VII.
21. Lenaers, G. et al. (2003). The realisation of an on-board emission measuring system serving as a R&D tool for ultra low emitting vehicles. *International Journal of Vehicle Design,* 31: 253-268.
22. CBS. *Emissies en parkemissiefactoren (emissions and park emission factors), analyses from the Statistical Office of the Netherlands ("Centraal Bureau voor de Statistiek"),* http://www.cbs.nl. Accessed 2000.

23. Arentze, T. A., Timmermans, H. J. P. (2005). *ALBATROSS 2.0: A learning based transportation oriented simulation system*, European Institute of Retailing and Services Studies, Eindhoven, The Netherlands.
24. De Ridder, K. et al. (2008). Simulating the impact of urban sprawl on air quality and population exposure in the German Ruhr area. Part I: Reproducing the base state. *Atmospheric Environment*, 42: 7059-7069.
25. EEA. *EMEP/CORINAIR emission inventory guidebook. Technical report no. 16/2007*, http://reports.eea.europa.eu/EMEPCORINAIR5/en/page-002.html. Accessed 2007.
26. Maes, J. et al. (2009). Spatial surrogates for the disaggregation of CORINAIR emission inventories. *Atmospheric Environment*, 43: 1246-1254.
27. PBL. *Pollutant release and transfer register*, www.emissieregistratie.nl. Accessed 2008.
28. Beckx, C. et al. (2009). A dynamic activity-based population modelling approach to evaluate exposure to air pollution: Methods and application to a Dutch urban area. *Environmental Impact Assessment Review*, 29 (3): 179-185.
29. Jacobsen, J. P., Kooreman, P. (2005). Timing constraints and the allocation of time: The effects of changing shopping hours regulations in the Netherlands. *European Economic Review*, 49: 9-27.
30. Schwanen, T. (2004). The determinants of shopping duration on workdays in the Netherlands. *Journal of Transport Geography*, 12: 35-48.
31. Hertel, O. et al. (2001). Human exposure to outdoor air pollution. *Pure and Applied Chemistry 73, IUPAC Technical Report*: 933-958.
32. Marshall, J. D. et al. (2006). Inhalation intake of ambient air pollution in California's south coast air basin. *Atmospheric Environment*, 40: 4381-4392.
33. Arentze, T. et al. (2008). More gray hair - but for whom? Scenario-based simulations of elderly activity travel patterns in 2020. *Transportation*, 35: 613-627.
34. Beevers, S. D., Carslaw, D. C. (2005). The impact of congestion charging on vehicle emissions in London. *Atmospheric Environment*, 39: 1-5.
35. Tonne, C. et al. (2008). Air pollution and mortality benefits of the London congestion charge: Spatial and socioeconomic inequalities. *Occupational and Environmental Medicine*, 65: 620-627.
36. Johansson, C. et al. (2009). The effects of congestions tax on air quality and health. *Atmospheric Environment*, 43: 4843-4854.