Otto Hänninen

Probabilistic Modelling of $PM_{2.5}$ Exposures in the Working Age Population of Helsinki Metropolitan Area

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Department of Environmental Health
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Otto Hänninen

A C A D E M I C   D I S S E R T A T I O N

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TIIVISTELMÄ (ABSTRACT IN FINNISH)

Pienhiukkaset ovat vuosittain osasyynä satoihin tuhansiin kuolemantapauksiin Euroopassa. Pyrittäessä vähentämään ilmansaasteiden haittoja ensisijaisena keinona on yleinen ilmanlaadun parantaminen ja päästöjen vähentäminen, mutta vähentämistoimet voidaan kohdentaa monin eri tavoin. On selvää, että terveyden kannalta parhaaseen tulokseen päästään vähentämällä nimen omaan väestön altistusta tehokkaasti.

Ilmanlaadun ajallisen ja paikallisen vaihtelun lisäksi altistukseen vaikuttavat väestön ajankäyttö, erityisesti liikenteessä ja toisaalta sisätiloissa vietetty aika. Liikenteessä päästölähteiden läheisyys nostaa päästöjen vaikutusta altistukseen, sisällä oleskeltaessa puolestaan rakennukset suodattavat melko suuren osan ulkoilman pitoisuuksista. Toisaalta oma merkityksensä sisällä tapahtuvaan altistukseen on sisälähteillä, jotka joissain tapauksissa voivat kohottaa sisäilman pitoisuudet kertaluokkia korkeammaksi kuin pitoisuudet ulkona.

Tässä työssä kehitettiin väestön altistusten arviointiin soveltuva simulointimalli, jonka avulla voidaan vertailla erilaisten ympäristönsuojelutoimenpiteiden vaikutusta väestön altistukseen. Malli kuvaa testilaskentojen mukaan väestön altistuksen vaihtelua hyvin ja mallin virheet jäävät väestötutkimusten otantavirheitä pienemmiksi lukuun ottamatta aivan korkeimpia altistustasoja. Mallin soveltuvuutta erilaisten toimenpiteiden vertailuun testattiin tarkastelemalla uudenaikaisten ilmanvaihtojärjestelmien tarjoamaa mahdollisuutta alentaa altistusta ulkoilman pienhiukkasille. Olettaen, että koko rakennuskannassa pääkaupunkiseudulla käytettäisiin tulevaisuudessa koneellista ilmanvaihtoa suodattimineen tavalla, joka on jo käytössä 1990-luvulla rakennetuissa toimistorakennuksissa, voitaisiin altistusta ulkoilman pienhiukkasille laskea 27 % vuosien 1996-97 tasosta. Suuruusluokaltaan tämä vastaa paikallisen liikenteen pakokaasupäästöjen vaikutusta. Rakennusten ilmanvaihdon kehittäminen vaikuttaa lisäksi kaukokulkeutuneisiin hiukkasiin.

Mallin vastaavuus mittauksiin testatuissa tapauksissa oli siis hyvä ja mallin osoitettiin soveltuvan erilaisten tulevaisuuskuvien vertailuun. Altistuksen arviointia ja mallien käyttöä osana ympäristöpolitiikan kehittämistä tulee lisätä.

Asiasanat: pienhiukkaset, altistuminen, mallintaminen, ilman saastuminen, terveysvaikutukset, kaupunkiväestö, simulointi, sisäilma, ilmanvaihtojärjestelmät, tutkimus

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ABSTRACT

Fine particles are associated with hundreds of thousands annual deaths and significant increase in morbidity in Europe. Improvement of air quality and reduction of air pollution emissions are identified as the primary goals, but environmental policies can be targeted in different ways. It is clear, that optimal protection of public health is achieved by policy options reducing population exposures effectively. Besides air quality and associated temporal and spatial variability, the most important factor affecting exposures is population mobility. In traffic environments the proximity of emissions increases exposures, while in indoor environments concentrations of particles entering from outside are reduced by the building shell. Presence of indoor sources, however, may result in indoor concentrations orders of magnitude higher than outdoors.

In the current work a population exposure model was developed to compare the impact of alternative future policy scenarios on population exposures. Comparison with measurements showed that the model predicts the exposures and their variability well. The model errors were smaller than the statistical errors caused by random population sampling in an exposure study, apart from the highest few percentiles. Model applicability to policy evaluation was demonstrated by modelling the potential of ventilation systems equipped with effective particle filters to reduce exposures. Assuming the whole Helsinki metropolitan area building stock would be equipped with such mechanical ventilation systems that is already used in office buildings built in 1990's, the overall population exposure to ambient particles was reduced by 27 %. This is in the order of the effect of local traffic tailpipe emissions, which would have to be completely removed to achieve a similar net effect. Besides, building ventilation system affects also long-range transported particles.

Model correspondence with measurements was good and the model applicability to practical policy options comparison was demonstrated. The general conclusion of the work is that exposure assessment, using models when necessary, should be incorporated with development of effective environmental policies.

Subject terms: air pollution, air pollution, indoor, air pollutants, environmental, ventilation, evaluation studies, urban population, particle size

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Young scientific thoughts grow from the fertile ground laid down by experience. For this I want to express my highest gratitude to my supervisors. My former university teacher, the head of the Air Research Laboratory, **Professor Matti Jantunen, Ph.D.,** gathered an international network for the current study and made it possible to put the latest achievements in exposure science into unequalled use in Europe. **Decan Juhani Ruuskanen, Professor, Ph.D.,** my teacher already in the late '80s in the University of Kuopio, provided his gentle and peaceful sense of reality and approving attitude in a most constructive way. **Dr. Erik Lebret, Ph.D.,** Head of the Unit of Environmental Epidemiology, RIVM, brought in expertise in exposure modelling, and his professional touch kept my work on track.

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The opportunity to study and work together with **Kimmo Koistinen** for two decades is a corner stone of this work. Together we have faced challenges from university to business and science, and he has been my closest workmate and friend, for which I want to thank him.

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Kuopio, June 2005

Otto Hänninen

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ABBREVIATIONS AND DEFINITIONS

These non-comprehensive definitions describe of the use of the terms in the current context.

AirPEX	Air Pollution Exposure model developed in RIVM (Freijer *et al*., 1998).
BS	Black Smoke. An optical measure of the blackness of a filter sample. Associated typically with diesel exhausts.
CA	California. A western state in the U.S.
CD-ROM	Compact Disk Read Only Memory. A CD-disk, typical capacity 650 MB.
CHAD	Consolidated Human Activity Database, a population time-activity database combined from several U.S. studies (McCurdy *et al*., 2000).
CIDB	Combined International Database; the main results from all centres. Available in MS-Access versions 95, 97, and 2000.
CO	Colorado. A state in the U.S.
CO	Carbon monoxide. Toxic gas emitted from incomplete combustion processes.
DOS	Disk Operating System by Microsoft, Inc. A personal computer operating system popular in the 1980's.
Direct mode	Exposure modelling in the current work using directly microenvironment concentration distributions (as opposed to *nested* mode).
EADB	*EXPOLIS* Access Database. The local database used for local data entry and management in each *EXPOLIS* centre. MS-Access version 95.
EC	European Community.
ED-XRF	Energy dispersive X-ray fluorescence (see also XRF).
EPA	U.S. Environmental Protection Agency.
ETS	Environmental Tobacco Smoke. Air pollution (PM, nicotine, CO, etc.) originating from different forms of burning tobacco products to which smoking and non-smoking subjects are exposed in the environment. The total tobacco smoke exposure of active smokers is significantly higher than their ETS exposure, created by themselves and fellow smokers.
EU	European Union.
EXPOLIS	Air Pollution Exposure Distributions within Adult Urban Populations in Europe –study. A multi-centre study conducted in seven cities in 1996-2000 (Jantunen *et al*., 1998).
GerES	German Exposure Survey. A German exposure research program (Seifert *et al*., 2000).
GIS	Geographical Information System. A computer software environment for handling spatially oriented data. E.g. MapInfo.
GPS	Global Positioning System, a satellite network and atomic clock based system for accurate real-time measurement of geographical locations.
GSM	Global System for Mobile Communications (originally Groupé System Mobile), a cellular telephone system.
H^+	Hydrogen ion. Cause of acidity.
HAPEM	Hazardous Air Pollutant Exposure Model by U.S. EPA.
HEDS	Human Exposure Database System, developed by U.S. EPA NERL.
Helsinki	Unless otherwise specifically indicated, the current work refers with this to the Helsinki metropolitan area, consisting of cities Helsinki, Espoo, Kauniainen, and Vantaa. Total population approximately 1 million.
IN	Indiana. A state in the U.S.

KTL	Finnish Public Health Institute (*Kansanterveyslaitos*; www.ktl.fi).
MB	Megabyte. A measure of computer memory device storage capacity. Defined alternatively as 1.000.000 bytes or 2^{20} (1.048.576) bytes depending on the source.
ME	Multilinear Engine. A type of principal component analysis (Paatero and Hopke, 2003).
MEM	Microenvironment monitor. A sampling device that is positioned in a specific micro-environment, typically a (room in the) residence, school, or workplace of the subject.
NC	North Carolina. An eastern state in the U.S.
NERL	National Exposure Research Laboratory of U.S. EPA.
Nested mode	Exposure modelling in the current work using ambient levels to model microenvironment concentrations (as opposed to *direct* mode).
NHEXAS	An exposure research program in 1990's in the U.S. (Clayton *et al*., 2002).
NJ	New Jersey. An eastern state in the U.S.
NO_2	Nitrogen dioxide. An air pollutant.
NV	Nevada. A state in the U.S.
NY	New York. An eastern state in the U.S.
O_3	Ozone. An air pollutant produced by photochemistry in the atmosphere.
ON	Ontario. An east-central province in Canada.
PAH	Polycyclic aromatic hydrocarbons.
PC	Personal Computer. A microprocessor-based computer dedicated to a single user. Originally developed by IBM, Inc. in 1982.
PCA	Principal Component Analysis. A statistical modelling technique.
PCP	Pentachlorophenol.
PEM	Personal exposure monitor. A sampling device that is carried by the subject.
PM, PM_{10}, $PM_{2.5}$	Particulate matter (with aerodynamic cut size diameter smaller than 10, 2.5 µm). Particles consisting of solid and liquid materials, suspended in the air.
PMF	Positive Matrix Factorization. A type of principal component analysis (Hopke *et al*, 2003)
pNEM	Probabilistic version of U.S. EPA National Exposure Model (NEM, Law *et al*. 1997)
PTEAM	Particle-TEAM study, Riverside, CA, U.S. (Özkaynak *et al*., 1996)
p-value	A statistical measure for the probability of an outcome being caused by mere chance.
r^2	Coefficient of determination. A statistical estimate for the fraction of variance being attributable to the independent variable(s) in a regression model.
RIVM	The Dutch Institute for Public Health and the Environment (*Rijksinstituut voor Volksgezondheid en Milieu*; www.rivm.nl)
RSP	Respirable suspended particles. Particulate matter suspended in the air capable of penetrating the respiratory system. Particle size defined differently in different sources, upper limit varying typically from 3.5 to 10 µm.
SD	Standard deviation. A statistical measure of variability of values in a data set.
SHAPE	Simulation of Human Activity and Pollutant Exposure, a probabilistic exposure model developed by Ott *et al*. (1988).
SHEDS	Stochastic Human Exposure and Dose Simulation model by U.S. EPA NERL (Burke *et al*., 2001).
SOP	Standard operating procedure. A quality assurance procedure and document.
TAD, TMAD	Time-(microenvironment-)activity diary. A diary filled by study subjects to record their locations and activities.

TEAM	Total Exposure Assessment Methodology –research program in U.S., started in 1980's.
THEES	Total Human Environmental Exposure Study conducted in Phillisburg, NJ in 1980's (Lioy *et al*. 1990).
THERdbASE	Total Human Exposure Database and Simulation Environment by U.S. EPA NERL (Pandian *et al*., 1990).
TN	Tennessee. A state in the U.S.
TSP	Total Suspended Particles. Particulate matter suspended in air, regardless of the particle size (i.e. including coarse particles up to tens of micrometers).
TX	Texas. A southern state in the U.S.
UK	United Kingdom, consisting of Great Britain and Northern Ireland.
U.S.	United States of America.
VA	Virginia. An eastern state in the U.S.
VOC	Volatile Organic Compounds. A heterogeneous group of innumerable volatile organic compounds, boiling points varying from 50-100°C to 240-260°C (WHO, 1989).
VT	Vermont. An eastern state in the U.S.
WA	Washington. A western state in the U.S.
WHO	World Health Organization of the United Nations.
XRF	X-ray fluorescence spectrometry. An analysis technique for determination of the elemental composition of samples of airborne PM.

MATHEMATICAL SYMBOLS

E	Time-weighted average exposure level [µg m^{-3}]
f	Fraction of time (spent in an microenvironment) [unitless]
C	Concentration [µg m^{-3}]; using subscripts: *a* ambient (outdoors) *ai* ambient originating particles in indoors *ig* indoor generated particles in indoors *i* indoor concentration (sum of ambient originating and indoor generated levels)
F_{inf}	Infiltration factor [unitless]; ratio of C_{ai} and C_a; using superscripts *S* sulphur-containing particles $PM_{2.5}$. fine particles
P	Penetration factor [unitless]
k	Decay rate (indoors) [h^{-1}]
a	Air exchange rate [h^{-1}]
V	Volume (of an indoor space, e.g. apartment) [m^3]
Q	Emission rate (source strength) [µg h^{-1}]
t	time [h]
β_0	Regression constant
β_1	Regression slope; using superscripts *S* sulphur-containing particles $PM_{2.5}$. fine particles

ORIGINAL PUBLICATIONS

This thesis is based on the following seven original articles, published in four peer reviewed scientific journals. The articles are referred in the text by Roman numerals I-VII.

I Jantunen, M.J., Hänninen, O.O., Katsouyanni, K., Knöppel, H., Künzli, N., Lebret, E., Maroni, M., Saarela, K., Srám, R., Zmirou, D., 1998. **Air pollution exposure in European cities: The *EXPOLIS*-study**. *Journal of Exposure Analysis and Environmental Epidemiology* 8 (4): 495-518.

II Kruize, H., Hänninen, O.O., Breugelmans, O., Lebret, E., Jantunen, M., 2003. **Description and demonstration of the *EXPOLIS* simulation model: Two examples of modeling population exposure to particulate matter**. *Journal of Exposure Analysis and Environmental Epidemiology* 13 (2): 87-99.

III Hänninen, O.O., Kruize, H., Lebret, E., Jantunen, M., 2003. ***EXPOLIS* Simulation Model: $PM_{2.5}$ Application and Comparison with Measurements in Helsinki**. *Journal of Exposure Analysis and Environmental Epidemiology* 13 (1): 74-85.

IV Hänninen, O.O., Lebret, E., Ilacqua, V., Katsouyanni, K., Künzli, N., Srám, R., Jantunen, M.J., 2004. **Infiltration of ambient $PM_{2.5}$ and levels of indoor generated non-ETS $PM_{2.5}$ in residences of four European cities**. *Atmospheric Environment*, 38 (37): 6411-6423.

V Hänninen, O.O., Lebret, E., Tuomisto, J.T., and Jantunen, M.J., 2005. **Characterization of Model Error in the Simulation of $PM_{2.5}$ Exposure Distributions of the Working Age Population in Helsinki, Finland**. *JAWMA*. 55: 446-457.

VI Hänninen, O.O., Palonen, J., Tuomisto, J., Yli-Tuomi, T., Seppänen, O., Jantunen, M.J., 2005. **Reduction potential of urban $PM_{2.5}$ mortality risk using modern ventilation systems in buildings**. *Indoor Air*. In press (published as *OnlineEarly*).

VII Hänninen, O.O., Alm, S., Katsouyanni, K., Künzli, N., Maroni, M., Nieuwenhuijsen, M.J., Saarela, K., Srám, R., Zmirou, D., Jantunen, M.J., 2004. **The *EXPOLIS* Study: Implications for exposure research and environmental policy in Europe**. *Journal of Exposure Analysis and Environmental Epidemiology*, 14: 440-456.

CONTENTS

1. INTRODUCTION

A glimpse for perspective. Since prehistoric times it's been known to man that the smoke from flames is irritating – anyone who ever sat in front of an open fire outdoors knows that it makes your eyes bleed and throat sore; it has never been news that air pollution is bad for health. The three major factors that have increased exposures to air pollution during the last millenniums are urbanization, industrialization, and the drastic increase of traffic. Urbanization started well in the first millennium before Christ. Growth of the cities during the following two millennia gradually increased the problems of pollution. Industrialization boomed towards the end of the second millennium, starting in the 18th and 19th centuries, but still in those days, merely domestic heating was a significant problem for air quality; a fireplace existed in almost every room of every inhabited building. Photographs from late 19th and early 20th century taken over towns during days when heating was needed, demonstrate the poor state of air quality of that time. The third major step in worsening the air pollution was taken so late as early in the 20th century by the wide acceptance of the use of combustion engine.

The air pollution problem peaked in unfavourable meteorological conditions in places like Meuse Valley, Belgium (Dec. 1-5, 1930, 60 deaths), Donora, Pennsylvania, U.S., (Oct. 27-30, 1948, 20 deaths), and finally in London, UK, (Dec. 5-9, 1952, 3000 excess deaths, added to the one thousand of normally expected ones for such a period) (Bell and Davis, 2001). Severe wide-spread public health effects during these extreme air pollution episodes, including death of thousands, demonstrated beyond any doubt the acute harmfulness of modern air pollution to human health.

Fighting air pollution. In the next decades successful programs were launched to control air pollution, first in the developed world, and then towards the end of the century also globally. Political groups were founded targeting environmental protection in contrast to the struggle between the social classes in the beginning of the century. International collaboration started to fight global pollution and agreements were made to implement new low emission technologies.

Sulphur dioxide was one of the main pollutants that the emission abatement programs focused on in the 1970's. Emissions in many countries were dropped by tens of percents by the end of the century despite of increasing production and energy consumption, but globally the sulphur emissions continued to grow (Lefohn et al., 1999). Since the 1970's strict emission reduction requirements have been set for the auto industry, turning the tailpipe emissions into a slowly lowering trail in spite of the continuously increasing number of vehicles and kilometres. So by the end of the century the developed world had conquered the problem of air pollution – or had it?

The problem persists. After the London episode air quality monitoring has become standard practice in all cities and towns with more than hundred thousand inhabitants in the developed world. Together with the ever-increasing number of details of data collected by health authorities from populations of hundreds of millions, the accumulating data from these air quality monitoring networks has made it possible to study the effects of air pollution on human health with unforeseen sensitivity. During the last decade of the 20th century it became evident that even the prevailed relatively low levels or air pollution were still significantly associated with mortality and other health consequences in urban populations of the developed world. The number of premature deaths associated with air pollution was estimated to be tens of thousands annually in North America (Pope et al., 2002;Pope et al., 1995;Dockery et al., 1993) and in Europe (Samoli et al., 2005;Katsouyanni et al., 2001;Katsouyanni et al., 1997). The most significant association has been repeatedly found for particulate matter (PM), especially fine particles ($PM_{2.5}$) (WHO, 2002;Ezzati et al., 2002).

At the same time that the developed world realized that air pollution is an additional risk factor that increases the statistical probability of death and other adverse health effects caused primarily by cardio-vascular and respiratory diseases, the role of exposure as the actual causal link in the chain from emissions to the health effects became more clearly acknowledged (Ott, 1995). Health effects really having causal connections with the air pollution must be caused by the actual exposures of the affected individuals. Therefore reductions in the health risks must occur via reductions in the exposures – and sometimes emission-based policies have shown to have only negligible effects on exposures (Jantunen, 1998).

Particles originate from a number of different sources, including energy production, industry, vehicles, resuspension of dust, natural sources, and many sources indoors. In terms of emission tons the indoor sources are typically negligible, but their effect on indoor concentrations may be remarkable. Together with the fact that urban populations spend a majority of their time indoors makes the indoor exposures significant, and in some cases totally dominating. In the beginning of the current decade it became obvious that the health effects of ambient and indoor generated pollution should be considered separately (Wilson et al., 2000). The concentrations caused by these do not correlate with each other; the particles have different chemical and physical compositions, presumably different toxicities, and definitely very different controlling options. Consequently, the questions that have risen to a central role in the public health protection concerning particulate matter pollution are:

- Are all particles (equally) harmful?
- What kinds of particles are (more) harmful?
- To whom are they (most) harmful?
- How to reduce the harmful exposures of sensitive population groups efficiently?

Effective public health protection policies must be based on a clear understanding of population exposures and the underlying factors, including microenvironment concentrations and population time-activity (Lioy, 1990). Optimal reduction of exposures can then be achieved by comparing alternative control strategies in terms of costs and exposures. Comparison of hypothetical policy options is really possible only by using models (Ott, 1995;Seifert, 1995;Lioy, 1991;Ryan, 1991;Ott, 1985). Requirements for the reliability of such models, when used in selecting expensive and potentially invasive and limiting policies, are high. Such models must be carefully evaluated against experimental data in existing setups, including a thorough peer review before the models are applied. This is exactly what the current work is about.

2. AIMS OF THE DISSERTATION

The overall objective of the current doctoral dissertation work was to develop and evaluate a modelling methodology for the estimation of urban population exposures to fine particulate matter in current and future scenarios, including hypothetical scenarios supporting policy options evaluation. The work uses $PM_{2.5}$ data from Helsinki for these purposes.

The specific steps required meeting this overall objective include the following tasks. The original articles that tackle each task in detail are listed in parentheses.

1. Design and carry out a population-based exposure study to collect data on urban population exposure levels, microenvironment concentrations, and population time-activity for development and validation of a probabilistic exposure simulation model (**I**),

2. Develop a conceptual model and supporting software framework for implementing probabilistic exposure models (**II**),

3. Create data analysis methods to estimate model inputs from measured variables, including partitioning of microenvironment concentrations into ambient and indoor generated fractions and analysis of infiltration factors, and selection of appropriate population groups for time-activity modelling (**III**, **IV**, **V**),

4. Study the accuracy of the simulation model by comparing model results with the measured personal exposure distributions in a random population sample (**II, III**, **V**),

5. Clarify the concepts of model evaluation by differentiating between the concepts of model error and assessment of uncertainty (**V**) and discuss the use of independent data,

6. Demonstrate the use of a simulation model in a policy relevant setup by applying it for a selected exposure reduction scenario (**VI**), and

7. Discuss development of effective environmental policies by using exposure analysis and models (**VII**).

3. BACKGROUND

Focus shift from emissions to exposures. Environmental policies are facing new integration and optimization challenges in the 21st century. Health effects which have a causal relationship with air pollution must be caused by the actual personal exposures of the affected individuals (Spengler and Soczek, 1984;Duan, 1982;e.g. Ott, 1982). During the past decade it became clear that straightforward emission reductions are not always cost-effective means to reduce public health risks – in fact they can be costly and yet very ineffective. Perhaps the best-known example of this is the benzene exposure case in Northern California (Jantunen, 1998;Ott, 1995). In the early 1990's the San Francisco Bay Area Air Quality Management District considered that of all ambient air pollutants benzene was contributing the largest risk to the Bay area residents. The Board called for a 50 % reduction in benzene emissions from the largest industrial point sources. However, a source apportionment of the benzene exposures revealed that only 25 % of the exposures were of ambient origin, and only 3 % originated from the point sources. Majority of the exposures came from traffic, tobacco smoke, and various indoor sources and the 50 % reduction in point source emissions yielded only an indistinguishable 1.5 % reduction in the population's exposure and corresponding cancer risk.

The Exposure Paradox. The association between ambient PM pollution and health was observed in epidemiological studies using air quality monitoring data from fixed outdoor sites to describe population exposures. Personal exposures are, however, modified by individual behaviour, time spent in traffic, and especially the indoor environments visited. Many studies have confirmed that personal exposures correlate poorly with ambient levels measured at fixed monitoring sites (Alm et al., 2001;Koistinen et al., 2001;Oglesby et al., 2000;Pellizzari et al., 1999;Wallace, 1996;Morandi et al., 1988;Spengler et al., 1985;Sexton et al., 1984). At first, this was seen as a major objection to the epidemiological finding itself, before it was realized that the health effects associated with fixed station levels are those caused by the particles of ambient origin. Fixed urban background monitoring stations represent well the average population exposures to these particles (Wilson et al., 2000). Other particles, not correlating with the ambient levels, may then have health effects of their own (Mage, 2001;Wilson et al., 2000), but due to the methodological difficulties in assessing these, the toxicities of indoor generated particles – except for ETS (e.g. Zhang et al., 2005) – are still largely unknown.

The main conclusion from these findings is the fact that urban populations are exposed to a large variety of different kinds of particles from different sources; the particles may have different toxicities, and different sources certainly have different control mechanisms. Therefore it is important to assess these exposures separately (Ott, 1995;Sexton et al., 1995a;Wallace, 1993;Girman et al., 1989).

Understanding the underlying source and exposure factors associated with the health effects is crucial for the success in both exposure modelling and in public health risk management. On the population level there are dozens of time-activity factors, and factors that affect local microenvironment concentrations, that together create the individual exposure levels. Some major milestones in the particulate matter exposure analysis studying these factors are reviewed in the following section.

3.1. Population-Based Exposure Research

During 1980-2000 a number field studies were conducted first in the U.S. and later in Europe to collect population-based data for exposure analysis. The following reviews some of the studies that either had a profound contribution to exposure analysis for particulate matter, the design of the current work, or that have been progressing parallel to our study. Some of these studies, which have either preceded the current study and influenced its design, or have been conducted parallel or later to it, are summarized in Table 1 in chronological order and compared with *EXPOLIS*. The studies are identified primarily by the project acronym (if available; otherwise by location or primary researcher).

The reviewed studies can be classified into two categories: (i) those focusing on total exposures of pollutants having multiple routes of entry into the human body, including besides inhalation also dietary and skin exposures. From the point of view of the current work, some of these studies (e.g. TEAM, NHEXAS, GerES, see definitions and details below) have been significant in terms of developing concepts and methods for population exposure assessment. The second category (ii) includes studies of inhalation exposures focusing more or less on particulate matter.

Important exposure concepts developed along the two active decades of population exposure research include exposure distributions, intra- and inter-personal variation, source apportionment, ambient and indoor sources, microenvironment assessment and modelling, indoor-outdoor relationships, and infiltration of particles. Many of these concepts are directly utilized in the modelling in the current work.

Northern America. Early milestones in PM exposure research were set in late 1970's and early 1980's. One of these was the Harvard Six Cities study, a successful long-term research project that produced one of the most significant epidemiological findings on the association between ambient PM and health (Dockery et al., 1993). As a small part of this project, also the indoor-outdoor relationships of respirable particles (RSP) were studied using data from 68 residences over one-year period (Dockery and Spengler, 1981). Somewhat later a similar study was conducted in Suffolk and Onondaga counties in the New York State ERDA –study (Koutrakis et al., 1992), where $PM_{2.5}$ measurements, now including 16 elemental constituents, were conducted in 178 residences. Both of these studies were used to develop models for the indoor-outdoor relationship of particles (see modelling details in **IV**).

One of the important aspects studied in the 1980's was the relationship of short-term and long-term exposures. When short-term exposure measurements are conducted on a population sample, the observed variance of personal exposures includes two components: inter-personal variance (i.e. variance in exposures of different subjects during the same day) and intra-personal variance (variance of exposures of the same persons over different days). This issue was tackled in the Waterbury, Kingston-Harriman, and Phillisburg studies (Table 1). Exposures to respirable suspended particles (RSP) were measured in Waterbury (VT) using 48 subjects (Sexton et al., 1984). Each subject was sampled every other day for two weeks, giving information on the intra-personal day-to-day variation. In Kingston and Harriman (TN) the size of the population sample was 97 (Spengler et al., 1985). In this study RSP personal exposures were monitored for three non-consecutive days together with simultaneous residential indoor concentrations. The longitudinal variation of personal exposures to PM_{10} was studied also in the THEES study in Phillisburg (NJ) (Lioy et al., 1990). The population sample was rather small (14) and not randomly selected, but residential indoor and outdoor concentrations and personal exposures were followed from day to day for a two-week period. Thus the results formed a 14x14 matrix of person days, allowing for analysis of the inter- and intra-day variances of the personal exposures and their relationships to ambient PM_{10} levels.

Table 1. Summary of design features of selected exposure studies focusing on particulate matter (in chronological order from left to right).

	Kingston-Harriman	Waterbury	THEES	PTEAM	Phillips *et al.* ETS studies	Janssen *et al.*	ULTRA	Toronto, Indianapolis manganese	*EXPOLIS*	RIOPA
Timeframe in relation to *EXPOLIS*	Earlier	Earlier	Earlier	Earlier	Earlier	Earlier	Parallel	Parallel	-	Later
Cities/areas	Kingston and Harriman (TN)	Waterbury (VT)	Phillisburg (NJ)	Riverside (CA)	8 European cities	Amsterdam, Wageningen	Amsterdam, Helsinki	Toronto (ON) Indianapolis (IN)	7 European cities	Houston (TX) Los Angeles (CA) Elizabeth (NJ)
Survey year(s)	1981	1982	1988	1990	1992-95	1994-95	1996-1999	1995-96	1996-2000	1999-2000
Compound(s) [1]	RSP	RSP	PM_{10} bentso(a)-pyrene	PM_{10}, $PM_{2.5}$ (RI+RO)	ETS, RSP	PM_{10}	ultrafines (<0.1µm), $PM_{2.5}$	PM_{10} $PM_{2.5}$ manganese	$PM_{2.5}$ + elements + BS 30 VOCs NO_2, CO	$PM_{2.5}$ VOC carbonyls
Population, age range	random, non-smoking adults	voluntary, nonsmoking	voluntary, 28-, nonsmoking	random	random, non-smoking adults	children, elderly volunteers	elderly cardiac patients	random, 16-	random, 25-55	adults & children
Nr of subjects	97	48	14	178	188-255 per city	37 adults, 45 children	82	732 Toronto 240 Indianapolis	501	212 homes
Seasonal time frame	spring	winter-spring	winter	fall	various seasons	various seasons	various seasons	one year (ON) summer (IN)	one year	one year
Air sampling time	24 hours	24 hours	24 hours	2x12 hours	24 hours	24 hours	24 hours	3 days	48 hours	48 hours
Longitudinal sampling	3 non-consequtive days	every other day for two weeks	14 consequtive days	consequtive day+night	none	4-8 measure-ments	upto 13 measurements	repetition with random lag for a subsample of 190 in Toronto	2 consequtive days for CO	repetition after 3 month lag for a subsample
Air sampling micro-environments [2]	RI, P	RI, RO, P	RI, RO, P	RI, RO, P	P	RI, P, A class rooms	RI, P, A	RI, RO, A, P	RI, RO, W, P	RI, RO, P
Reference(s)	Spengler et al. 1985	Sexton et al. 1984	Lioy et al. 1990	Clayton et al. 1993	Phillips et al. 1994-1999	Janssen et al. 1997-1999	Pekkanen et al. 2002	Pellizzari et al. 1999	I	Weisel et al. 2005

[1] See Abbreviations for symbol definitions

[2] RI = Residential indoor, RO = Residential outdoor, P = Personal, A = Ambient, W = Workplace indoor

Perhaps the best-known exposure research program in the 1980's was the Total Exposure Assessment Methodology (TEAM) focusing on multi-route exposures. Inhalation exposure compounds like carbon monoxide (CO), nitrogen dioxide (NO_2), total suspended particles (TSP), respirable (PM_{10}) and fine particles ($PM_{2.5}$), acid aerosols, environmental tobacco smoke (ETS), and ozone were included, but in a minor role in these studies and benefited mainly from the methodological developments in population exposure assessment. The other exposure routes, dietary and skin exposures, however, have a profound role for many other substances including VOC's (e.g. benzene, toluene, limonene, styrene, chlorinated hydrocarbons, different forms of xylene), pentachlorophenol (PCP), lead, cadmium, polycyclic aromatic hydrocarbons (PAH), and pesticides. Population samples in the TEAM studies varied from small and non-representative to quite large random or stratified random samples. Inhalation exposures were measured typically for one day, but some designs allowed also for longitudinal exposure analyses (Hartwell et al., 1987;Spengler et al., 1985;Sexton et al., 1984).

Concerning PM exposures, the most important study before *EXPOLIS* was initiated by the series of earlier TEAM studies and was called Particle TEAM (PTEAM, Table 1). This study was conducted in 1990 in Riverside (CA) using a random population sample of 178 subjects. Residential indoor and outdoor PM_{10} levels were monitored for two consecutive 12-hour periods (day and night) together with corresponding personal exposures. Residential indoor and outdoor $PM_{2.5}$ concentrations were also measured, allowing for modelling of $PM_{2.5}$ exposures and assessment of the ratio of PM_{10} and $PM_{2.5}$ exposures. Elemental compositions were also determined and used for infiltration modelling and analysis of the decay and penetration terms required by the mass-balance model (Özkaynak et al., 1996;Clayton et al., 1993;Thomas et al., 1993;Clayton et al., 1991). Similar analysis was developed further using the *EXPOLIS* data in **IV**.

Parallel to the current work was conducted the Ethyl Corporation funded study by Research Triangle Institute (NC) for $PM_{2.5}$ and manganese exposures in Toronto (Ontario, Canada; Table 1). This is the largest population based PM study so far with it's 732 measured subjects. Manganese used as a gasoline additive in Canada was suspected to have public health effects. A sub sample of 190 subjects was measured again within the one-year study period with a random lag. Besides personal levels also residential concentrations were measured indoors and outdoors. Each person was monitored for 3-day period. Supplementary data on traffic, meteorology, occupation, and time activity of subjects were also collected. Databases were developed to store the data and to support the data analysis. (Pellizzari et al., 1999;Clayton et al., 1999a)

A parallel manganese study was conducted in Indianapolis (IN; Table 1) to get comparable exposure levels from a city where the same gasoline additive was not used (Pellizzari et al., 2001a). In general the Indianapolis PM levels were somewhat higher than the corresponding levels in Toronto. The Mn levels, as expected, were lower in Indianapolis, especially when excluding occupational exposures. All PM_{10} levels in Toronto and microenvironment PM_{10} levels in Indianapolis were clearly lower than the PM_{10} levels in PTEAM study, Riverside (Pellizzari et al., 2001a).

Another significant U.S. program in population based exposure research in general, but having only a minor contribution to PM research, is the National Human Exposure Assessment Survey (NHEXAS) that followed the TEAM studies in assessing multi-route multi-media exposures. NHEXAS targeted the whole population of the U.S. and to this end developed geographical, urban-rural and sociodemographic stratification levels for population sampling. In respect to pollutants studied, NHEXAS was more focused than the TEAM-studies; there was a clear view that the compounds selected for such a large study should be documented or suspected human health hazards and there should be a need for exposure information for them. Pollutants of especial interest according to these criteria included benzene, pentachlorophenol, formaldehyde, mercury, and lead (Lioy and Pellizzari, 1995). Besides these, dozens of heavy metals, VOCs and pesticides were considered (Callahan et al., 1995;Sexton et al., 1995b). NHEXAS acknowledged the need to characterize population distributions of exposures, including information on both the base line exposures as well as the high percentiles and estimates on the highest exposed individual levels for both the general population as well as for population sub groups. The program was divided into three phases. Phase I targeted planning, designing and testing, phase II implemented the national survey and in depth special studies were allocated to phase III. After that, NHEXAS was envisioned to be a continuous research activity, to be repeated every three to six years. (Sexton et al., 1995b)

NHEXAS phase I studies were conducted in three different areas; (i) Arizona, (ii) EPA region 5, consisting of six states in the Great Lakes area, and (iii) Maryland. NHEXAS Arizona measured residential indoor, outdoor and personal concentrations of 25 metals, 4 pestisides and 25 VOCs for 175 subjects (study phase 3). The measurements were conducted during all seasons. (Gordon et al., 1999;Robertson et al., 1999;O'Rourke et al., 1999a;O'Rourke et al., 1999b). The NHEXAS EPA region 5 study panned six states, where selected metals and 4 VOCs were measured for a random sample of 250 subjects during an 18-month period in 1995-97. Six-day samples of residential indoor, outdoor and personal VOC levels were collected besides extensive set of other samples. (Clayton et al., 2002;Pellizzari et al., 2001b;Clayton et al., 1999b;Pellizzari et al., 1995). In Maryland the NHEXAS studies were more focused on selected specific issues. Buck et al. (1995) studied statistical aspects of estimating long-term exposures from short-term measurements. MacIntosh et al. (2001) and Pang et al. (2002) studied population exposures to pesticides, especially chlorpyrifos. Inhalation exposure related 24-hour measurements were conducted only in residential indoors of 80 subjects during a one-year study period. Longitudinal aspects were studied by repeating measurements on population sub samples up to six times.

The most recent PM study is the Relationships of Indoor, Outdoor, and Personal Air (RIOPA, Table 1) study in U.S. The concentrations of 18 volatile organic compounds (VOCs), 17 carbonyl compounds, and fine particulate matter mass ($PM_{2.5}$) were measured using 48-h outdoor, indoor and personal air samples collected simultaneously. PM2.5 mass, as well as several component species (elemental carbon, organic carbon, polyaromatic hydrocarbons, and elemental analysis) were also measured in 1999-2000 in Houston (TX), Los Angeles (CA) and Elizabeth (NJ) in 212 non-randomly sampled homes. Personal samples were collected from non-smoking adults and a portion of children living in the target homes. The population sample was stratified according to the residence location in relationship to major freeways, industry and other recognised emission sources. (Meng et al., 2005;Weisel et al., 2005)

Analysis results of the RIOPA data have just started to appear in the published literature. The first results include similar analysis of indoor-outdoor relationships of $PM_{2.5}$ levels that was earlier presented by Dockery and Spengler (1981) and Koutrakis et al (1992), and that was conducted also in the *EXPOLIS* study (**IV**).

Europe. One of the most significant early exposure studies in Europe were the German Environmental Surveys (GerES) that was first conducted in the former West Germany 1985-86 and then repeated in 1990-92, now including the whole united Germany. GerES studied representative population samples for exposures to dozens of metals and other toxicants.

Inhalation exposures to VOCs were measured only on a sub sample of 113 adult subjects, PM exposures not at all. (Hoffmann et al., 2000a;Seifert et al., 2000a;Hoffmann et al., 2000b;Seifert et al., 2000b)

In Finland the first exposure studies were conducted by Alm *et al*. (2001;2000;1998;1994) and Mukala *et al*. (2000;1996). They measured personal carbon monoxide and nitrogen dioxide exposures of pre school children panels in Helsinki in 1990-91. Personal NO_2 levels were found to be lower than levels at the day care centres and the fixed station levels. Personal CO levels were higher than fixed station levels, and they were affected by the presence of gas stove at home. Respiratory symptoms were also connected to NO_2 exposures. Both NO_2 and CO exposures were affected by tobacco smoking in the home. These studies had a significant contribution for the practical implementation of the *EXPOLIS* studies.

A significant number of PM exposure studies in Europe were conducted by Phillips et al. in more than a half dozen European cities in collaboration with local institutes in each city (Table 1). These studies, however, were solely focused on ETS and nicotine exposures. The population samples were fairly large and representative in all cities (188-255 subjects per study), including only non-smoking subjects. Particle concentrations were measured mostly with cyclone pre-separator with 50% removal efficiency at 3.5 µm (the earliest study used no pre-separator and very low flow rate). Besides gravimetric RSP particle measurement various analytical methods were used to measure tobacco smoke originating particle concentrations (ultraviolet, fluorescence and solanesol measurements). (Phillips et al., 1999;1998a;1998b;1997a;1997b;1996;1994)

Important early European PM exposure studies were conducted by Janssen et al in the Netherlands (Table 1). They measured the $PM_{2.5}$ and PM_{10} exposures of school children and elderly people in Wageningen and Amsterdam in 1994-95. Panels of 45 children and 37 adults were sampled during 4-8 periods for 24 hours. Besides personal and residential levels, also concentrations in the school classrooms were measured (1999a;1999b;1998a;1998b;1997a;1997b). From the point of view of the *EXPOLIS* study some experience in the development of silent microenvironment and personal monitors were acquired from the Dutch experiences. Data analysis benefited, too, from the publications that appeared in the literature during the active period of *EXPOLIS* data analysis.

The Dutch studies were followed by the Exposure and risk assessment for fine and ultrafine particles in ambient air (ULTRA, Table 1). Cohorts of elderly cardiovascular patients were followed for six months in Amsterdam and Helsinki, including biweekly health inspection and ultrafine PM and $PM_{2.5}$ exposure measurements (Vallius et al., 2003;Pekkanen et al., 2002;Ruuskanen et al., 2001;Janssen et al., 2000).

3.2. Databases Supporting Exposure Modelling

The enormous amounts of valuable data produced in the population based exposure studies could potentially be utilised very effectively in exposure analysis outside the original study scope, if only the data was properly documented and made available (Burke et al., 1992). The value of databases designed for this purpose has been recognized since early 1990's (Sexton et al., 1994;Burke et al., 1992;Graham et al., 1992;Sexton et al., 1992), when the revolution brought by the Internet-based networking really started to make a difference in the ways that exposure related data is collected and stored. Due to the technical nature of such databases, however, little has been written about them in the scientific literature.

A lot of effort was put in the current work in developing a researcher-friendly, efficient, and reliable database system for collecting, storing, and distributing the various subsets of data from the *EXPOLIS* centres. The databases described in the Material and Methods –section have been used in data analysis for dozens of scientific papers, and in preparation a dozen doctoral dissertations. Therefore a short review of the thin literature concerning such databases is appropriate here to foster the use and publication of exposure databases to maximise the usability of data collected on public funding.

The role of exposure databases in exposure analysis and exposure model development – the context for the current work – is depicted in Figure 1. The database provides data needed both for the process of constructing the model as well as data for the model runs.

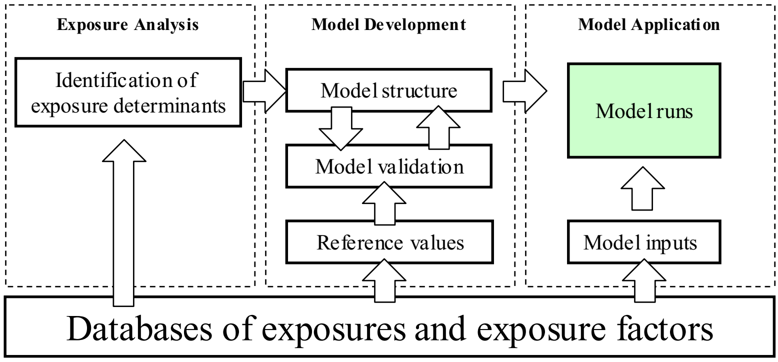

Figure 1. The triple role of exposure database s in exposure model development.

This topic was so urgent in the early 1990's that a workshop designed specifically to examine exposure-related databases was conducted in January 21-23, 1992, in Virginia Beach (VA). Participants, including scientists from federal and state agencies, the private sector and academic community, examined the utility of existing databases from different perspectives. Sexton *et al.* (1992) concluded that the existing databases of that time contained a substantial amount of relevant information, but that it was clear that the quality of the data was inconsistent and it was difficult to access the data. These statements are still valid. The studied systems demonstrated a striking absence of data on actual human exposures – a factor that has improved since. *EXPOLIS* database is one of the European milestones in this area.

Graham *et al.* (1992) recommended in the Virginia Beach workshop risk management workgroup that more human exposure measurement studies should be conducted and that new databases should be developed to meet critical data needs. The databases should emphasize quality assurance and control and they should be accessible to exposure and risk assessors. These are exactly the driving motivation for the current study: combination of conduction a population based European exposure study and development of an extensive exposure database for exposure analysis, modelling, and model validation purposes.

One of the extensive exposure databases developed based on these needs was the Total Human Exposure Database and Simulation Environment (THERdbASE) by U.S. EPA's National Exposure Research Laboratory, Las Vegas (NV) THERdbASE started as a DOS-based database system for information gathered in the TEAM studies to allow for (i) an ordered storage base for exposure-related environmental data and (ii) a convenient base for building total human exposure models (Pandian et al., 1990). In the 1990's the system evolved into a Windows based system capable of handling large databases and complex models in a networked PC-environment. Number of models and a variety of databases, including selected 1990 U.S. Census data were incorporated into one software platform. The database was peer-reviewed by a panel of national experts in December 1997. The database was downloadable from the Internet till 2004 when EPA dropped support for it, and it was adopted as a standard platform for exposure modelling across many offices within the U.S. EPA. (http://www.epa.gov/heasd/edrb/therd/therd-home.htm)

To survey the availability and quality of federally sponsored databases in the U.S. Sexton *et al.* (1994) made an inventory of databases potentially relevant for estimating human exposures to environmental agents. The inventory, reviewing and classifying 67 American databases, was compiled through a joint effort of EPA, the National Center for Health Statistics, and the Agency for Toxic Substances and Disease Registry. The inventory allowed for comparison of databases according to (i) type of exposure estimators, (ii) sample/media types, (iii) compounds, (iv) geographic scope and location coding (e.g. latitude/longitude, zip code, county) and (v) sampling frequency. The inventory showed that a significant number of the data systems contained useful information for exposure analysis, but it also was apparent that the data varied substantially according to the relevance, quality, and availability. Few databases collected representative population samples.

In the area of population time-activity the National Exposure Research Laboratory (NERL), EPA, developed the Consolidated Human Activity Database (CHAD). CHAD combined originally data from 12 U.S. studies related to human activities. CHAD, accessible in the Internet at http://www.epa.gov/chadnet1/, contains data from pre-existing human activity studies that were collected at city, state, and national levels. CHAD is intended to be an input data source for exposure/intake dose modelling and statistical analysis. CHAD is a master database providing access to other human activity databases using a consistent format. This facilitates access and retrieval of activity and questionnaire information from databases that EPA currently uses in its regulatory analyses. (McCurdy et al., 2000)

NERL produced also the Human Exposure Database System (HEDS), which is putting the NHEXAS data on-line. NHEXAS data was originally managed independently in different centres (Lebowitz et al., 1995). HEDS contains chemical composition data for air, soil drinking water, house dust, food, beverage, blood and urine (Robertson et al., 2001). The data includes pesticides, metals, VOCs and polynuclear aromatic hydrocarbons (PAHs). Questionnaire and diary responses are also included, addressing residential, life style demographic, occupational and health characteristics, time activity patterns and food consumption information (Robertson et al., 2001). HEDS is on-line at http://www.epa.gov/heds.

3.3. Theoretical Context for Exposure Modelling

Exposure models are used to estimate the concentrations of chemicals or other substances in an exposure media when in contact with the target subject. The media may be a surface becoming into contact with the skin or it may be e.g. foodstuff entering the digestive system. In the current work, focusing on inhalation exposures to fine particles, exposure is defined as airborne particle concentration in the breathing air of the subjects.

Exposure models may be developed to estimate exposures of individuals, susceptible population groups, or entire populations. They may estimate exposures as continuous variables, or integrate over time from short-term periods like minutes and hours to days, to long-term periods like years to lifetime. Modelled exposure variables may include instant values, mean exposure levels, and distribution parameters like standard deviations, quartiles, and percentiles. Consequently, exposure models range over a wide variety of complexity, approach, inputs, and outputs as discussed shortly below to put the current work into perspective with alternative methods and approaches.

3.3.1. What Are Exposure Models Needed For?

Exposure is the mediating link between man and the environment. Modelling of exposures is of interest to both exposure scientists as well as those in charge of developing environmental and public health policies. Modelling can serve three purposes:

- Understanding a phenomenon
- Estimation in lack of measurements
- Forecasting

The first category is mainly of interest to scientists, for whom sometimes merely a weak but statistically significant correlation between two variables is an interesting finding. The second one may interest both user groups equally and includes exposure modelling for epidemiology and risk assessment. The last one, forecasting, can be interpreted as a special case of the second, where the lack of measurements is due to the fact of looking into future. Forecasting may concern short (hours to days) or long-term (years to lifetime) models. Some approaches integrate modelling and measurements, e.g. data assimilation in meteorological models. Models of the third category belong to the most important tools for formulating science-based and effective public health policies (Ott, 1984).

3.3.2. Causality and Statistics

Models considered here are numerical constructs, quantifying the relationships between independent and dependent phenomena based on a theory. Independent phenomena, or events, are entered into the model as values of input variables to estimate the numerical values describing the corresponding dependent events. The dependent events that are statistically, logically, or causally related to the inputs, are then described using the output variables.

In his classical examination on exposure modelling principles, Ryan (1991) categorized exposure models into three categories: (i) *statistical*; (ii) *physical*; and (iii) *physical-stochastic*. Selection of the best approach for each modelling task is driven by the relationships of the independent and dependent variables – exposures and their determinants - in the target system. Dependency of variables can result from three alternative relationships depicted in Figure 2. The first rows represent causal relationships, where the state of the output variable is directly or indirectly caused (or more often in reality: influenced) by an input variable. In the third row the Effect 1 is irrelevant in causal sense and could be ignored, if only some alternative variable would be available to describe the underlying cause. However, in lack of such a variable the statistical relationship resulting for Effects 1 and 2 can be used for prediction of Effect 2 when observations of Effect 1 are available. A classical example of the last type of relationship is the correlation of ice cream consumption and drowning deaths –both are (causally) influenced by a warm weather, leading to an apparent relationship. In this case the true causal variable is measurable and should be used.

Relationship type	Input	Underlying	Output	Most suitable modelling
1. Direct causal	**Cause** →		**Effect**	Physical
2. Indirect causal	**Cause** →	Effect 1 →	**Effect 2**	Physical & Statistical
3. Common cause	**Effect 1** ←	Cause →	**Effect 2**	Statistical

Figure 2. Different relationships between model variables and model types suitable for them.

In reality, usually there are many independent phenomena affecting the dependent one, and in many cases feedback loops connect the output back to (some of) the inputs. The more direct and simple the causal chain is, the easier it is to model. An increasing number of intermediate variables in the causal chain shifts the relationship towards diminishing causality and weaker statistical correlation. Causal models are generally more reliable than models based on statistical associations exactly due to the increasing complexity of the chain of events in between the input and output variables. Physical modellers often take this as a disadvantage of statistical models, but as Ryan (1991) points in his Venn-diagram depicting the rather small overlapping application area of statistical and physical models, it is more reflecting the nature of the modelled phenomena for which the statistical approach becomes handy.

3.3.3. Researchers Standard Tools: Statistical Models

Statistical models are standard tools of scientists. When the actual causal mechanisms in the system under study are not yet known, they can be revealed by building hypotheses based on current theoretical understanding and testing them using statistical methods. Statistical models are typically used for description of relationships of variables when analysing a collected dataset. Sometimes the causal mechanisms are too complex, or some of the causal variables are not available, making physical modelling impossible. In such cases statistical modelling with existing empirical variables is the only option available for the modeller. More complex models also considered statistical include neural networks.

It is both strength and a weakness of empirical models that they do not require nor imply any causal relationships between the model variables. An empirical model carries on to the result all the interdependencies existing in the data, regardless of whether they are causal or introduced by chance, or considered by the modeller. Empirical models require both input and output variables to be known in the model development system. Because the outputs must be measured anyway, empirical models are not at their best in estimation of unmeasured parameters, excluding perhaps the special case of modelling missing values within a dataset or cases where time-series data is used for statistical forecasting in the same target system. In most cases their data-set dependency restricts their use for making future predictions.

Regression models. By far the most common form of statistical model is the classic regression model. In its simplest form, a regression model solves the constant β_0 and coefficients $\beta_1 \ldots \beta_n$, by minimizing the model errors (residuals) for the dependent variable. A standard equation is used to describe the relationships of the independent variables, resulting in the major benefit of statistical modelling techniques that variables having incompatible units of measure can be used together, including continuous and classification variables. Classification variables are typically transformed to binary dummies for studying the effects of a given questionnaire category on the dependent variable. Advantages of regression models include the capability of estimating the coefficient of determination (r^2) as a measure of how large a fraction of the variation of the dependent variable can be explained with the independent variables, and statistical significance (p) as a measure of the statistical probability of the model relationship being caused by mere chance.

Multiple regression exposure models can include concentrations in many microenvironments, and dummy variables for parameters such as smoking, form of commuting, type of work, gas stove, air conditioning, and other appliances. The terms of the resulting model are specific to the data set from which they have been calculated, and there are no grounds other than expert judgement to assess their applicability to some other location, time, or population. Examples of regression models used in exposure analysis include models for carbon monoxide exposures in Athens (Georgoulis et al., 2002) and Milan (Bruinen de Bruin et al., 2004a), and models for $PM_{2.5}$ and NO_2 exposures in Helsinki (Kousa et al., 2002b;Koistinen et al., 2001;Rotko et al., 2001;Kousa et al., 2001b;Rotko et al., 2000a).

Factor analysis. Another commonly applied statistical modelling technique in exposure-related studies is factor analysis. Principal component analysis (PCA), most common type of factor analysis, has been successfully applied to apportion observed air pollutant concentrations to different emission sources, or source categories, in a number of studies (e.g. Koistinen et al., 2004;Vallius et al., 2003;Edwards et al., 2001). Alternative forms of factor analysis have also been applied to environmental concentration data, including positive matrix factorization (PMF) and multilinear engine (ME) (Hopke et al., 2003;Paatero and Hopke, 2003;Basunia et al., 2003;Yli-Tuomi et al., 2003a;Yli-Tuomi et al., 2003b).

Advantages of factor analysis in source apportionment include the fact that the actual emission profiles of the different sources need not to be known. The corresponding disadvantage is that the results are largely data-set specific, and there are difficulties in comparing factors obtained from the same dataset using different methods, or factors from different studies. However, factor analysis is currently the mainstream technique to identify emission sources from concentration and exposure observations.

3.3.4. Physical Models

Capability to build reliable physical models is the best proof that all aspects of a phenomenon are well understood. Physical models, based on actual quantified physical and causal relationships between variables, are therefore, by definition, better suited for making predictions for alternative future policies than statistical models. In his overview of exposure models, Ryan (1991) divided physical models into deterministic and probabilistic ones. Short comparison of these techniques below introduces the main reasons why probabilistic modelling was selected for the current work. Deterministic techniques have their specific strengths in some exposure domains, as will be discussed in more detail later on when looking at the dimensions along which exposure data are aggregated.

Deterministic models are calculated for selected individuals using input variables describing physical processes, physicochemical characteristics, and mass-balances specific to the target individuals, locations, and points in time. Deterministic models need intensive sets of data when applied to anything more than few individuals and relatively short periods.

Dispersion models are a common exposure-related application area for deterministic techniques. Dispersion models describe emissions and atmospheric boundary layer conditions for estimating outdoor air pollutant concentrations. Such models are used for retrospective analysis of air quality and scenario analyses for policy options evaluation. Compared to air quality monitoring networks, dispersion models have tremendously better spatial resolution, and in addition support detailed analysis of concentrations caused by various emission sources. (Kousa et al., 2001a;Kukkonen et al., 2001a;Kukkonen et al., 2001b;Kukkonen et al., 2001c)

A common technique to overcome some of the limitations set by available data is to use population averages instead specific values for some variables. Typical examples of this include the use of fixed infiltration value; for O_3 in the AirPEX model in the Netherlands (Freijer et al., 1998), for $PM_{2.5}$ and NO_2 in a GIS-based population exposure model EXPAND in Helsinki (Kousa et al., 2002a) and for H^+ and sulphate in the U.S. (Suh et al., 1993). The use of population averages of input parameters instead of actual values does not pose significant problems for estimating mean exposures, but when distributions are estimated, it always reduces the modelled variance and biases individual model outputs towards the corresponding mean. It specifically leads to underestimation of the highest levels. Sometimes in cases when all causal effects cannot be included, physical models may apply physical factors estimated statistically from representative data sets (Karppinen et al., 2004b;Suh et al., 1993). Use of such factors biases results towards the mean, too.

Probabilistic models apply laws of probability to overcome the limitations of unavailable deterministic data for specific individuals, and to still capture the exposure variability in a given population. This is achieved by using the limited available data for estimating probability distributions of the values in the population in question. The population exposures are then simulated using physical equations from input values randomly sampled by the computer from them. In terms of data needs and model complexity, probabilistic modelling is the most efficient technique for estimation of population exposure distributions.

Because the input data in the probabilistic models are drawn randomly from defined statistical distributions, results of individual iterations are essentially random. Combination of a large number of them provides an estimate for population distribution. Originally probabilistic techniques were adapted to exposure analysis to model population variability. However, during the 1990’s the methods were taken into use also in analysing uncertainty (Burke et al., 2001;Cox, 1999;Hattis and Burmaster, 1994;Morgan and Henrion, 1990). The uncertainty in a model (or in an analysis) can be described using probability distributions similarly as in Bayesian techniques (Rovers et al., 2005;Wikle and Berliner, 2005;Kashiwagi, 2004;Gangnon and Clayton, 2004), and numerical computer simulation can be used to propagate them through the calculations. The resulting distributions do not represent variability in the values, but uncertainty in them. In this sense simulation of uncertainty is closely related to classic statistical methods for estimation of confidence intervals. Second-order simulations include variability and uncertainty components in the same model (Burke et al., 2001;Cullen and Frey, 1999;Frey and Rhodes, 1996).

During the last few decades several research groups have applied probabilistic modelling for population exposures. The earliest models in the 1980's targeted CO and VOC exposures, but since 1990's also particulate matter exposures have been modelled. Some of the works were mainly targeted on model validation (Law et al., 1997;Ott et al., 1988), others have been focusing on developing tools for policy evaluation (especially models by EPA, e.g. Burke et al., 2001). Yeh and Small (2002) applied probabilistic 1-microenvironment model as a research tool in their analysis of health effects associated with $PM_{2.5}$ exposures. The current work combines the aspects of model validation and development of a tool for policy evaluation. The latest $PM_{2.5}$ models developed in parallel to the current work are summarized shortly below.

U.S. EPA National Exposure Research Laboratory (NERL) developed one of the current models in parallel with the *EXPOLIS* study. The objectives set for this model, the Stochastic Human Exposure and Dose Simulation model (SHEDS) were defined as: (i) prediction of population distributions of daily PM exposures in an urban area; (ii) estimation of contribution of PM of ambient origin to total PM exposure; (iii) determination of factors influencing personal exposures to PM; and (iv) identifying factors contributing to uncertainty in the model predictions (Burke et al., 2001).

SHEDS was applied for daily $PM_{2.5}$ exposures in Philadelphia (PA, USA) by Burke *et al.* (2001). Residential indoor concentrations were modelled based on a single-compartment mass-balance equation. Residential indoor emissions were modelled for cooking, smoking, and "other sources". For the other microenvironments (vehicle, office, school, store, restaurant, bar, other indoor) the distributions of PM concentrations were determined using linear regression equations from concurrent indoor and outdoor measurement data. Target population was divided into twelve groups by age and gender. Simulation results were presented, besides for total $PM_{2.5}$ exposures (mean ± SD: 30 ± 32 μgm^{-3}), separately for partial exposures in different microenvironments, and for exposures of ambient origin. The dominating role of residential indoor environment was obvious due to the large fraction of time spent there. Burke *et al.* compared their model outputs for Philadelphia with measurement results from Toronto, Canada, (Pellizzari et al., 1999) and Basle, Switzerland, (Oglesby et al., 2000); mean population exposures were 30, 28 and 24 μgm^{-3} , respectively. Levels excluding exposures to ETS in Philadelphia and Basle were 20 and 18 μgm^{-3}.

Yeh and Small (Yeh and Small, 2002) simulated population exposures to $PM_{2.5}$ and PM_{10} as part of their work where they compared ambient monitoring epidemiology (AME) approach to individual exposure simulation (IES) model in predicting the number of annual excess deaths caused by PM exposures in Los Angeles county (CA, USA). Same toxicity was assumed for all particles. The probabilistic IES model uses microenvironment approach with two microenvironments combined with mass-balance equation estimation of indoor concentrations caused by mixing of ambient air and emissions from indoor sources (smoking, cooking, other) and additional personal cloud concentration. The mass-balance equation parameters were estimated using data from two household databases (Murray, 1997;Murray and Burmaster, 1995) and the PTEAM study in Riverside (CA, USA) (Özkaynak et al., 1996), but now only residential indoor microenvironments were modelled. Simulated personal exposures were attributed to sources, but not compared to exposure measurements. The estimated number of annual premature deaths was slightly (5 and 10% for $PM_{2.5}$ and PM_{10}, respectively) smaller for the IES model compared to the AME model.

Ott et al. (1988) and Law et al. (1997) used a large population-based CO dataset from Denver, U.S., collected in the early 1980's to simulate population exposures using SHAPE and pNEM models, respectively. These modelling exercises are examined in more detail in **III** and in the section discussing model validation later on in this chapter.

3.3.5. Exposure Dimensions: Individuals in Space and Time

Personal exposures to fine particles vary in time, sometimes even second by second. Each subject is located differently and is in motion in the environment throughout the day, week, and year. As a theoretical mind game, the complete description of population exposure for a given time period, say a year, may be defined as consisting of instantaneous exposures second by second for each individual in the population throughout the year. Such a data structure is impossible to be obtained using current exposure measurement techniques and even modelling of it meets insurmountable problems, if not computationally, then at least in obtaining the necessary data. These difficulties will hardly be overcome.

Therefore to be able to estimate exposures and to draw meaningful conclusions on them, aggregation methods must be used to reduce this imaginary data set into a meaningful one that can be collected and used in exposure analysis. Common aggregation techniques include averaging and description of variability using various kinds of distributions. In the simplest and most common form, variability can be described using mean and standard deviation or other corresponding parameters.

Aggregation of the data occurs along the dimensions of the exposure data – individuals, locations, and time. In the aggregated end of the scale is the long-term mean exposure of the whole population, a significant health measure by its own (e.g. Pope et al., 2002). Each of these dimensions and techniques for handling them in modelling are discussed below.

Individuals and populations. Epidemiological studies have shown that a remarkable number of deaths are associated with fine particle exposures. Therefore estimation of the overall population exposure is one of the main interests. On the other hand, more detailed exposure analysis requires focusing on smaller groups (e.g. exposure studies), or even on few individuals.

Exposures of large populations can be estimated by drawing representative random samples. Standard statistical laws can then be utilized to estimate the uncertainty about the underlying true population values caused by the random sampling process. This method is commonly applied in the population-based exposure studies (see references in the section about population exposure studies earlier in this chapter).

Probabilistic modelling has become a standard technique adapted for modelling of variability of personal exposures in populations (Yeh and Small, 2002;Burke et al., 2001;Lunchick, 2001;Mitchell and Campbell, 2001;Hunter Youngren et al., 2001;Hamey, 2001;Mekel and Fehr, 2001;Price et al., 2001;Cullen and Frey, 1999;Law et al., 1997;Taylor, 1993, I, II, III, V). These population distributions could in principle be estimated using deterministic models for a statistically adequate number of randomly drawn individuals. However, in the population-based exposure studies this has been rarely done (or not reported in the literature).

Depending on the modelling approach, large target populations are usually divided into groups, or cohorts, that are handled separately within the model. Examples of such groups are age cohorts, men and women, and geographic, socioeconomic, and occupational groups. Whenever the exposures of different population groups are expected to be different from each other, their exposures probably need to be modelled separately. Recent studies have reported findings of heterogeneity in the toxicity of particles from different sources and in the sensitivity of different population groups (e.g. Samoli et al., 2005). Especially the elderly, patients with some medical conditions (including respiratory diseases, cardiovascular diseases, and diabetes) and infants have been suspected for higher sensitivity. While toxicologists and epidemiologists are trying to identify the most toxic particles and the most sensitive population groups, modellers are developing methods to estimate specifically the exposures of the susceptible individuals to the most toxic particles.

On the individual side detailed deterministic models have been developed to model personal exposures of small numbers of specified subjects in a limited time frame (Gulliver and Briggs, 2004;Briggs et al., 2003). A historical solution adapted into use in occupational hygiene to account for variability of exposures among the target population included definitions of hypothetical individuals, like the theoretical maximally exposed person. The exposure of this hypothetical individual is calculated (=modelled) by setting all variables to their worst possible values. Exposure estimates calculated this way are higher than the highest exposure of any true person in the target population. Practice has shown that such approach may, indeed, produce exposure estimates that are orders of magnitude higher than any of the actual exposures. The calculation of conservative point estimates provides no information on the actual level of conservatism in the estimate; therefore the development has shifted towards probabilistic assessments in the occupational settings, too. Probabilistic assessment is used to describe the exposure variability, including the prevalence of the highest levels, as accurately as possible, including quantitative estimates for model uncertainty when needed.

Locations. Highly variable environmental pollution fields and mobility of individuals make the spatial dimension utterly important for exposure analysis. The pollutant concentrations can vary rapidly outdoors in space and time due to changes in emission sources and meteorology, but often an even more significant modifier of exposures is the fact that a majority of time in developed urban areas is spent in indoors (Wilson et al., 2000;Wallace, 1996). Outdoor particles penetrate indoors with rather high efficiency along the air intake, but the gradual air exchange makes the concentrations indoors lag behind the outdoor ones smoothing out some of the variability. Indoors the particles are removed from the air by settling on surfaces and other processes, resulting in lower levels of particles. On the other hand, other particles may be generated indoors by resuspension and emissions from especially smoking and cooking, but sometimes also other sources, and by chemical reactions (Wallace, 1996, see also IV). As an outcome the indoor environment is a significant modifier of personal exposures to particles.

Two different approaches have been developed to handle the variation of concentrations in space: spatial techniques and the microenvironment approach. Spatial techniques preserve the actual geographical locations, where the exposures occur. The common computer technique to do this is to use geographical information systems (GIS). Most air pollution dispersion models produce concentration estimates for geographical outdoor locations (Karppinen et al., 2004a;Kousa et al., 2001a;Kukkonen et al., 2001a). Detailed models of indoor air quality have also been developed, but have not been combined with larger scale models of urban air quality mainly due to the difficulties in obtaining the needed detailed data on air exchange systems in individual buildings.

Most detailed spatial modelling follows specific individuals in space and time, modelling the concentrations for the exact locations and times where the individuals are. An example of such approach is the work conducted in the Imperial College, London (Gulliver and Briggs, 2004;Briggs et al., 2003). Moving towards population level makes it impossible to follow all the individuals in space and time. Jensen *et al*. have developed techniques utilising administrative databases to model locations of population members and combine these with air pollutant concentrations from a dispersion model (Hertel et al., 2001;Jensen, 1998).

In Helsinki a statistical approach to population locations has been adapted and combined with dispersion models (Kousa et al., 2002a). Locations of residences and workplaces are retrieved from public databases and an hourly statistical population time-activity model is used to allocate the population members to the residences, workplaces (both as employees and as customers), and to traffic. Results are displayed over the whole metropolitan area using a 100 m x 100 m grid. Infiltration of pollution indoors is modelled using a population average value observed in the *EXPOLIS* study. Population members are not followed across the hours and therefore daily personal exposures cannot be estimated.

The alternative approach, commonly used in probabilistic modelling and selected for the current work, is the microenvironment approach, which classifies different locations visited by the subject into so-called microenvironments (one of the early references Fugas, 1975). The concentration field within the microenvironment is described in this approach using an average value. This is often stated in the literature as assuming the concentration field to be constant within the microenvironment, but this, of course, does not need to be true. Exposure is then calculated as the time-weighted average concentration level across the microenvironments visited (Burke et al., 2001;Freijer et al., 1998;Ryan et al., 1986;Letz et al., 1984;Dockery and Spengler, 1981, II, III, V).

The microenvironment concept has been developed for two different purposes. The first is the fact that the exposure levels of many pollutants are often more similar in e.g. two similar residences or two similar offices across the city than inside and outside of the same building. In other words, the microenvironment category may be equally or more important than the geographical location. The microenvironment concept simplifies exposure modelling dramatically when combined with probabilistic techniques by reducing the millions of actual locations into a limited number of categorised microenvironments.

The probabilistic approach assumes that the concentrations of all outdoor or indoor locations grouped together into a microenvironment can be described by the same probability distribution. The concentrations for simulated microenvironments are then sampled from the defined distributions using computer and random number generator. Exposure contributions of each microenvironment are calculated according to time activity model (e.g. original version of SHAPE, Ott et al., 1988, II, III, V) or using measured time activity patterns (SHEDS using CHAD+HAPEM, Burke et al., 2001;AirPEX, Freijer et al., 1998;pNEM/CO, Law et al., 1997).

The microenvironment approach simplifies spatial modelling substantially. Deterministic time activity model for a large target population would require the geographical locations of each subject to be recorded. Global positioning system (GPS) devices, or the even more up to date GSM based positioning techniques that function also indoors would technically allow for registering such data. The computational requirements, however, are also much reduced when geographical and indoor locations can be combined into a small number of microenvironments.

Time. Temporal scales affect exposure assessments in two ways. Any exposure data are related to some temporal time frame. Emissions, meteorology, populations, activities, and many other environmental factors all change in time, and thus any data on exposures will definitely change too. The relationship of exposure data to the time dimension is often implicit; the limitations are not clearly stated, nor are they always even known. An example of these kind of unknown limitations could be the measured personal and population exposures in the *EXPOLIS* study. The exposure measurements were carried out in 1996-2000, and probably describe the exposures in the seven European cities for some years before and after the measurements. But for how long? Limitations may be specific to a given city, or to a sub population within a specific city, and can only be judged by expert opinion. Depending on the study or model design, exposure data may be representative of a specific time of a year (e.g. summer), days of week (e.g. work days in the *EXPOLIS* study) or time of day.

Another equally important temporal aspect is the averaging time of exposures (Ryan, 1991). Biological doses are functions of uptake and removal processes and therefore the health effects depend on the temporal variation of the exposures. Same integrated personal exposure to CO that as a short-term peak would be lethal is harmless as constant annual level. Similar results have been observed for fine particles; the relative risk for additional mortality associated with daily concentration variations (i.e. short-term exposures) has been estimated to be around 1.5%, while relative risks up to and above 15% have been suggested for long-terms exposures (WHO, 2000). In the case of short-term exposures, epidemiologists find also different lags from the exposure to the health effects (Samoli et al., 2005;Katsouyanni et al., 2001;Penttinen et al., 2001;Roemer et al., 1998;Pekkanen et al., 1997).

Best compilation of current knowledge about health-relevant exposure averaging times are reflected in the definition of air quality guidelines (e.g. WHO, 2000). Several averaging times are needed to protect the public from health effects caused by some pollutants; for others a single time value - with varying averaging times - is considered to provide adequate protection. The relationship of health effects and the temporal exposure profiles is still poorly known. Short-term peak exposure values cannot be assessed from long-term average concentrations, nor can long-term averages be estimated from short samples, if the intrapersonal variation in exposure levels in not known. Therefore the selection of the relevant averaging time must be done properly when designing the model and obtaining the corresponding input data.

3.3.6. Conceptual Model and It's Implementation

The issues of aims of modelling, types of causal relationships and corresponding modelling types, discussed above, affect the development of a conceptual model, which defines the phenomena included in the model, selection of the dependent and independent events, spatial and temporal scales, and equations describing the modelled relationships (Law and Kelton, 1991). Before the model can actually be used, it has to be transformed into definitions of variables, formulas, and a logical flow of computations (Figure 3): the model has to be implemented. The conceptual model looks at the principles, but the implementation has to take care of all the details.

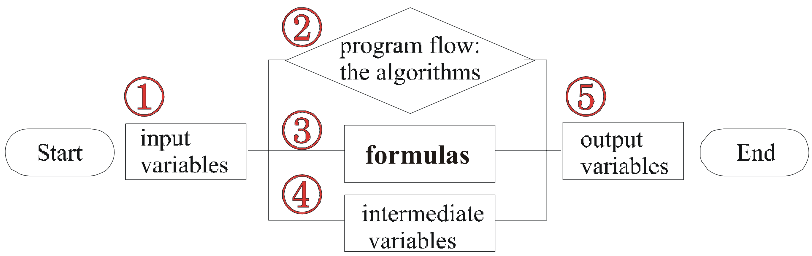

Figure 3. Five components of a computer model: 1) input variables, 2) algorithms, 3) formulas , 4) intermediate variables, and 5) output variables.

A neat conceptual model takes a lot of effort and dirty details before it has been turned into a reliable piece of computer software. The details that must be taken care include behaviour in the case of missing data and other special conditions, often created by such an unexpected source as the laws of mathematics. Besides driving the technical aspects of model reliability, implementation directly creates the user interface, consisting of methods for entering input variables, selecting model options, running the model, and retrieving the results. Model implementation has a significant effect to the required type of model documentation. In the case of a clear implementation, the model documentation needs mainly to concern about introducing the conceptual model. However, often the technical complexities in the model implementation totally drive the type of instructions required to use the model. Good model documentation should always first describe the conceptual model with its underlying assumptions and limitations clearly – good and intuitive implementation should then minimize the need for technical details.

3.3.7. Model Validation

The outset of the current work was the insight that exposure modelling is an important and necessary tool for science-based development of environmental policies. Environmental policies should pose as little limitations and costs to the society as possible while ensuring safe environment for all. But what if a model used in the development of such policies would be unreliable? All conclusions based on such a model would be dubious at best, and total garbage at worst. A model is useful only, when the limits of its applicability and its accuracy are known.

On the other hand, Oreskes *et al*. (1994) shoot calmly down any attempts to 'validate' any model that describes one part of an open system for good. Environmental exposure definitely takes place in such a system. Models work, at best, as long as the rules of the system do not change. As an example we can think of the Newton's law of gravity (Newton, 1687), thought to be the greatest of all laws in the Nature and newer to change, before Einstein was able to see beyond the its limits of applicability (Einstein, 1916;Einstein, 1905). Of course, the limits of the applicability of gravity law in an open-ended system can easily be demonstrated also in everyday surroundings by introducing e.g. resistance of air to the system under study. One law (or model) applies only until one overlooked starts influencing the system. Nevertheless, the need for model 'validation' is as clear as is the impossibility of the task. This contradiction should not lead to confusion, as discussed in more detail in **V**. There is a real need to quantify model reliability, and several techniques available, including modelling of uncertainty and analysis of model errors (**V**).

Building a valid model starts from a credible conceptual model (Law and Kelton, 1991). A model should include all phenomena that can be expected to be significant in the target system. The conceptual model should then be transformed to a mathematical form and often implemented in a computer environment without introducing errors.

Models describe how the changes in the input variables are reflected into the outputs. Model applications are linked to a larger picture, to human understanding about how the phenomena of interest affect the model inputs, and how others are affected by the model outputs (Figure 4). Models are useless in assessing events that are not related to the model inputs or outputs. Thus the model input and output variables define the main domain of the model.

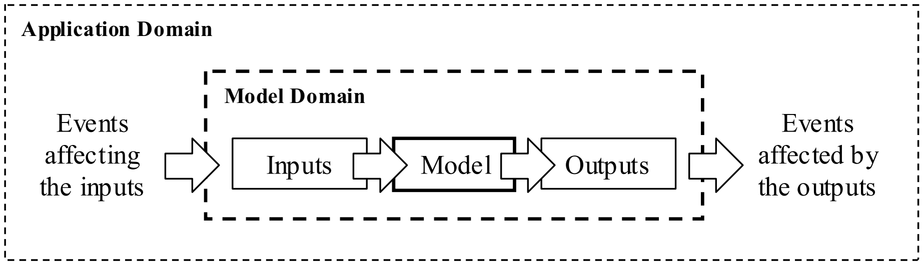

Figure 4. A model quantifies the relationships of input and output variables. Model is applied using understanding of these variables and the rest of the world that is related to them.

Law and Kelton (1991, p. 299) define model validation as determining whether the conceptual model is an accurate representation of the system under study. Model implementation transforms equations of the conceptual model into formulas that specify how the values of input variables are used to calculate intermediate and output variables. Algorithms define the computational sequences in which these calculations are performed. Comparison of the conceptual and implemented model is called by Law and Kelton 'model verification'. Implementation of even the simplest conceptual model adds another layer of complexity to the system, because valid equations produce nonsense results, if not applied in a proper sequence, or the formulas do not handle missing and out-of-range values properly.

When the model is ready, its outputs can be compared to observed values in a known system to further confirm the model (Oreskes et al., 1994). Accuracy in prediction can be tested only in a selected, existing target system. Leijnse and Hassanizaded (1994) called comparison of model predictions to observations 'strong validation'. They point out that even a conceptually bad model might by change seem to work well in a limited set of test data. Therefore, final trust or distrust on model applicability on a given problem must be based solely on our belief that our question concerns a target system similar to what the 'validated' model describes.

Two earlier works have been published on validation of probabilistic population exposure models (Law et al., 1997;Ott et al., 1988). Both of these are based on personal CO data collected in Denver, CO, in winter 1982-83. Microenvironment concentrations were estimated from the personal time-series data using time-activity diaries. The main result from both models was that the overall level of population exposures was captured well, but the variability was underestimated for reasons discussed in more detail in **III**.

4. MATERIAL AND METHODS

Model development requires both theoretical background and input data, as depicted in Figure 5. A model may be developed based on theory with literature and expert judgement for model inputs, but such an approach leaves open the uncertainties concerning the model validity and reliability. More detailed model evaluation requires data also on model output variables, exposures in the current case.

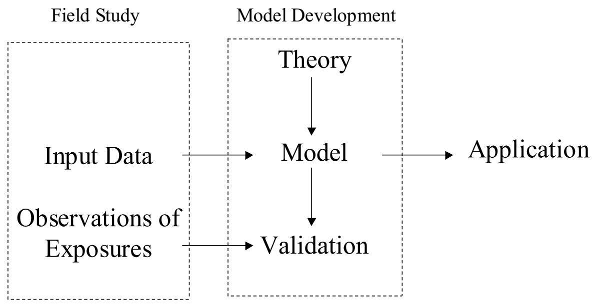

Figure 5. Relationships of the main elements of the current work.

The field data for the current work was collected in the *EXPOLIS* study (Air Pollution Exposure Distributions within Adult Urban Populations in Europe) conducted in Helsinki in 1996-97 and in six other European cities in 1997-2000. The following describes the study features relevant for the simulation of population exposures to $PM_{2.5}$ in Helsinki. The main design features of *EXPOLIS* are described in detail the original article **I** and compared to earlier and parallel PM studies in Table 1. The main study objectives were:

1 Assessment of exposures of European populations to major air pollutants
2 Analysis of personal and environmental determinants of these exposures
3 Development of a European database for simulation of air pollution exposures

The results for objective number one, the actual measured personal exposures, are used in the current work in the validation of the modelling results by comparing simulated and observed exposure distributions. Objective number two covers the measurements of microenvironment concentrations, time-activities, and personal exposure-related characteristics of the subjects that are used as model inputs. These inputs were accessed using the exposure database created according to the objective number three.

4.1. Designing the Field Study for Collecting Modelling Data (I)

The modelling approach developed as one of the main goals of the *EXPOLIS* study is not specific to $PM_{2.5}$ or Helsinki. The field study included other pollutants and cities, as shortly described below, and the modelling framework can quite well be utilized to modelling of other pollutants as well, as demonstrated by e.g. Kruize *et al*. (2003) and Bruinen de Bruin *et al*. (2004b). The current work is focused on $PM_{2.5}$ exposures in Helsinki to set a reasonable scope for a doctoral dissertation.

4.1.1. Multi-pollutant approach

While recent air pollution health studies has mainly focused on particulate matter, other pollutants have also been associated with various health effects, including mortality and morbidity, or have been shown to be irritating or carcinogenic. Many exposure-related factors correlate, causing subjects to be exposed to elevated levels of several air pollutants at the same time. Therefore it is important to be able to assess the exposures to multiple pollutants.

Exposure measurements are intruding and demanding for the subjects, including carrying the monitoring equipment with them for the study period and filling in lengthy questionnaires, taking their time and attention. In case of microenvironment measurements the subjects have to let the researcher in their homes and workplaces, installing noise-making and space-reserving monitoring devices. The subjects have to provide personal information regarding their social and occupational status, time-activities, and personal habits.

In a population-based approach a random sample of subjects must be drawn and recruited to the study. A significant load of resources are needed in the visits to the subjects' residences and workplaces, installing the monitoring equipment and instructing the subject. Several monitors can be easily installed during a single visit, and exposure related questionnaire data can be used to assess determinants of many exposures. Therefore maximal utility of the resources can be achieved by combining measuring several air pollutants together. For these reasons, the main air pollutants included in the *EXPOLIS* study were $PM_{2.5}$, a selected set of 30 VOCs, and CO. In some centres, including Helsinki, NO_2 exposures and concentrations were included with a separate funding. Additionally for a subset of the collected samples, the elemental composition of the $PM_{2.5}$ samples was analyzed separately.

4.1.2. Multi-centre study

The population-based urban, working age, multi-pollutant inhalation exposure research effort that became the *EXPOLIS* study, was originally designed as a national project for the Helsinki Metropolitan area in 1994. As such, the study was to be expensive due to the labour intensive nature of exposure measurements and other tasks, including the development of the measurement methods and quality assurance procedures, training of the research personnel, recruiting procedures for the population samples, and the computer software and databases to store and manage the collected data. Therefore the Academy of Finland redirected us to international sources. At that time Finland was just about to be a new member of the European Union, and two years after the study planning had started, the EU Directorate General (DG) for Research granted the funding for the study as part of the fourth framework program for European research. Before that, the research plan was transformed to a multi-centre approach and reviewed by European and American scientists including M. Lebowitz, B. Seifert, W. Ott, D. Mage, W. Wilson, J. Spengler, B. Leaderer, and D. Moschandreas.

Personal exposure and microenvironment monitoring techniques were not in wide use in Europe in the mid 1990's. Reliable simultaneous measurement of multiple pollutant concentrations in varying field conditions, including indoor and outdoor locations and private and semi-public places like workplaces and offices set high demands on the reliability, robustness, repeatability and user friendliness of the measurement methods. Moreover, handling of diverse sets of personal population based questionnaire data and data from physical measurements involving airflows, sample weights, temperatures, air pressures, and sample and equipment identification codes, required extensive data management procedures to maintain integrity and reliability of the collected data. Besides the development of study protocols, a written documentation and a training program for the personnel were needed to optimize data quality. All these tasks take the same effort whether done for only a single centre or for many. Air quality in Finland is known to be clean in comparison to many central European locations. All these points made it reasonable to extend the study from Helsinki to several other cities within Europe.

The multi-centre approach made the training events international and required a careful cross-translation program for the questionnaires and support materials that needed to be in the national language in each centre. The researcher-training program was conducted by having international workshops in Prague (April, 1996), Helsinki (September, 1996), Grenoble

(March, 1997), Bilthoven (February, 1998), Paris (May, 1999), and Bern (November, 1999). The study materials were developed in English, which was not the national language for any of the original partners.

4.1.3. Expedition for Exposure Determinants

The field study was designed to produce a large database on exposures and exposure related characteristics – potential exposure determinants. Detailed analysis of the potential exposure determinants was conducted. Many statistically significant determinants were found, but only factors with significant influence on exposures needed to enter the exposure model. Therefore from the point of view of the current work, the exposure determinant analyses of the collected data (Koistinen et al., 2004;Götschi et al., 2002;Kousa et al., 2002b;Koistinen et al., 2001;Rotko et al., 2000a) formed the basis for the exposure model structure, including the selection of microenvironments and population groups.

Targeting many air pollutants with different – but unknown – determinants, and multiple centres had many implications on development of the questionnaires. A good example is the use of double gazing in apartments: in Helsinki double glazing is the minimum requirement and is giving room for triple glazing, while on the other hand in Athens it stands for advanced insulation. This kind of research setup is different from the traditional experimental research, where a hypothesis is created before designing the experiment for testing the hypothesis. Therefore this type of exposure studies can be called “fishing expeditions” – large sets of presumably related data are collected with stated ideas about the needs and future use, but without definition of specific hypotheses to be tested. The actual statistical methods and variables used in the analysis of the data were to be selected later. Therefore the focus in the study design is in selection of a wide range of variables that are both (i) measurable and (ii) have causal or interesting statistical connections with the exposures. Such variables include naturally time-activities and microenvironment concentrations, but also variables related to personal, residential and occupational characteristics, including socio-economic status, smoking habits, exposure to ETS, etc.

4.1.4. Population sampling in Helsinki

Random population sample is not an absolute requirement for a model development study. The model could be developed using data from a selected group of volunteers. However, using a random population sample makes the results on model inputs and outputs representative of the general population from which the sample was drawn. Therefore the random population sample approach significantly increases the generalisability of the results.

In Helsinki the *EXPOLIS* sample was drawn by the Finnish Population Register Centre and consisted of 2523 Finnish speaking citizens of the Helsinki metropolitan area (including cities of Helsinki, Espoo, Kauniainen, and Vantaa) born in 1940-1970, inclusive (Table 2).The Helsinki population sample data was first received from the Civil Register on May 14th, 1996, with a correction file on May 21st, 1996.

Table 2. The random sample of the Helsinki working age population.

City	Male	Female	Total	%
Espoo	264	270	534	21.2
Helsinki	683	781	1464	58.0
Kauniainen	13	11	24	1.0
Vantaa	231	270	501	19.9
Total	1191	1332	2523	100.0
	47.2 %	52.8 %	100.0 %	

A mailed questionnaire was sent to this random population sample. After a mailed remainder a final attempt to reach the non-respondents was done using a telephone interview, resulting a final response rate of 74 % (Table 3).

Table 3. Response rate to the mailed questionnaire and telephone interview.

Questionnaire response rate		%
Questionnaires sent	2523	100 %
No response	650	26 %
Response, total	1873	74 %

One of the questions regarded the subject's willingness to participate in the whole study, including exposure and microenvironment measurements, or questionnaires only (Table 4).

Table 4. Responses to the willingness to participate in the study.

Willingness to participate the study		%
Respondents	1873	100.0
No answer to this question	32	1.7
Yes	1368	73.0
Yes, questionnaires only	56	3.0
No, travelling	376	20.1
No	41	2.2

Two sub-samples were randomly drawn from the respondents willing to participate in the exposure measurements or the questionnaires-only study. A running selection code was allocated to these subjects randomly to ensure random sampling over the one-year study period, integrating over seasonal variations. Computer forms supporting telephone contacts to the subjects during the study field phase were created into the local *EXPOLIS* Access Database (EADB) used in each of the study centres.

At a later stage, eleven participants of the simultaneous ULTRA-study (Vallius et al., 2003;Pekkanen et al., 2002;Ruuskanen et al., 2001) were recruited for the *EXPOLIS* exposure measurements. These subjects, being patients with cardiovascular diseases, lived in the Vallila-Kallio –area (zip codes 00500, 00510, 00520, 00530, 00550 and 00610) a few kilometres from the Helsinki downtown. Table 5 lists the relative effect of these additional subjects on the collected data used in the analyses.

Table 5. Sizes of the Exposure and Diary sub samples.

Data set	Random sample	%	Ultra subjects	%[2]	Total[1] subjects
Civil register data	2523	100.0	-	-	-
Short questionnaire	1871	74.2	11	0.6	1882
Questionnaires and diaries	423	16.8	11	2.5	434
Exposure measurements	190	7.5	11	5.5	201

[1] Data from these subjects have been used in the analysis. [2] Percentage from the total subjects

EXPOLIS subjects were aged 25-55 years at the time of sample formation. This population group forms a significant fraction of the total population, is legally and physically capable of participating in this kind of study. The selected age category includes working and non-working subjects with a large variety of leisure time activities and thus their time-activity is variable. Therefore, in terms of exposure characterization, this group is more heterogeneous than the susceptible sub populations like infants and elderly, which spend more of their time in and around their residences. Especially time spent in traffic, one of the most important exposure modifiers of the active population, has presumably much smaller effect on the exposures of the susceptible groups.

In Finland only Finnish speaking population was included in the sampling to avoid error prone and time-consuming translations of the questionnaires and other written support materials. The biggest non-Finnish speaking minority in the Helsinki metropolitan area consists of Swedish speaking Finnish citizens (9.3%, 6.5% and 3.5% in Espoo, Helsinki and Vantaa, respectively, in 2000-2002[1]). The fraction of other language minorities has been increasing constantly, being approximately 5% in Espoo and Vantaa, and almost 6% in Helsinki at the same time. Therefore the total percentage of minorities excluded from the study by the language limitation is approximately 11-12 %. Although there is no specific reason to assume that the time-activities, living or working areas, or other exposure modifiers of the language minority groups would be significantly different from the Finnish speaking majority, this limitation should be kept in mind when interpreting the results.

The population sampling and sample quality are described in detail in Rotko *et al.* (2000b). Rotko *et al*. found that the biggest loss of representativity occurred in the first contact phase, answering the short questionnaire. In general, women and individuals with higher education were overrepresented in the exposure and diary samples, and men, younger subjects (defined as 25-34 years) and unmarried individuals were somewhat underrepresented. In comparison to the other *EXPOLIS* cities the Helsinki response rates were good. From the model development point of view the population sampling can be considered successful and the results from the modelling representative of the general working age population in Helsinki metropolitan area.

[1] Tilastokatsaus 2003:5. Vantaan kaupunki, B6, ISSN 0786-7832. (In Finnish)

4.2. Time-Activity Measurements

One of the main exposure modifiers is the mobility of subjects. People spend their time in various types of environments in different locations within the metropolitan area. Time-activity measurements were conducted using a structured 15-minute resolution diary with eleven microenvironments and three activities. The microenvironments were grouped into transportation (five categories) and stationary microenvironments (residence, workplace and other, each subdivided into indoors and outdoors). The subjects classified their locations into these categories for approximately 48 hours, the same period when their microenvironment concentrations and personal exposures were monitored.

The diaries were entered into EADB and transformed into fractions of time using the duration of the subject's diary. Time fractions for the elementary diary microenvironments were further combined to create aggregate microenvironments for the simulation models (Table 6).

Table 6. Microenvironment categories used in the simulations.

	Number of microenvironments in the model			
μE	2	3	4	5
1	Residence	Residence	Residence	Residence
2	Workplace	Workplace	Workplace	Workplace
3		Other	Traffic	Traffic
4			Other	Other indoors
5				Other outdoors

The three activities were smoking, exposure to ETS, and cooking. The two tobacco activities were combined to ETS-exposure yes/no indicator also for active smokers, because only exposure to ETS was sampled. Cooking was recorded without more detailed specification of the type of cooking (e.g. boiling water versus frying or toasting). Moreover, the effects of cooking were diluted into the 48-hour sampling period and therefore cooking was found not to have a notable effect on concentrations and was not included in the exposure models.

4.3. $PM_{2.5}$ Measurements

In Helsinki a full set of personal workday and leisure time exposures, and residential indoor, outdoor and workplace concentrations were successfully obtained from 194 subjects (total number of exposure measurement participants was 201 with 7 subjects with various failures). The number of non-ETS exposed subjects was 126. The $PM_{2.5}$ measurement techniques and quality assurance results are described in Koistinen *et al.* (1999)and Hänninen *et al.* (2002b) and primary analysis of the data in (Koistinen et al., 2004;Götschi et al., 2002;Kousa et al., 2002b;Koistinen et al., 2001;Rotko et al., 2000a).

The measurements were carried out in a random sequence during an approximately 12-month field survey period (three final subjects were measured after a 2-month pause at 14 months from the beginning of the field phase). Each subject was measured for two consecutive working days, from Monday to Wednesday or from Wednesday to Friday. National holidays were excluded and during the holiday seasons only subjects not on vacation were measured.

Residential indoor and outdoor air was sampled from evening to morning, approximately at times when the study subject was expected to be at home according to the subject interview. The workplace air was sampled during the normal working hours. Personal samples were taken on two filters; one was taken into use in the morning, just before the subject left home or started the daily activities at home. Second filter was changed to when the subject returned home in the afternoon. Thus filter one corresponds to the daytime exposures, including workday and commuting, and filter two to leisure time (including night) exposures. The elemental composition of the filters of 98 subjects was analyzed using Energy Dispersive X-ray Fluorescence technique (ED-XRF) in the University of Basle (Mathys et al., 2001). Sulphur data was used in the current work to apportion indoor concentrations into ambient and indoor generated fractions (**IV, V, VI**).

4.4. Data Management

Data management for this work was integrated with the data management of the whole *EXPOLIS* study. This included managing data for over 300 measured compounds (i.e. selected target VOC compounds (30) and other compounds observed (290), and elemental composition of the PM samples (37 elements)), questionnaires, and time-activity diaries. Only $PM_{2.5}$ and sulphur data, time-activity diaries, and some questionnaire variables were used in the current work (**II** – **VI**), but the database was designed to support corresponding simulation of exposures to any of the measured pollutants (e.g. Bruinen de Bruin et al., 2004b).

The original objectives underestimated the role of the exposure database by putting it into being merely an aid for the simulation. As later summarised in the article **VII**, the combined international database (CIDB) turned out to be a major outcome of the project by itself. The database has been used for data analyses producing over thirty original articles with only few relevant ones for exposure simulation, and besides the current work, over ten doctoral dissertations in seven countries, involving nine universities and four other research institutions have been based on the data.

EXPOLIS data management goals were specified as: (i) all data items affecting the final calculated results are stored, (ii) data from all centres are stored, (iii) data storage structure is flexible, allowing later any analyses necessary, (iv) correctness of the data is maximized, (v) data entry tools and procedures are provided, and (vi) privacy of study subjects is protected. The data management procedures were developed as the second phase of the current work in integration and partly overlapping with the first one, the field phase.

Database design. A project database (*EXPOLIS* Access Database, EADB) was developed using Microsoft (Seattle, WA) Access 7.0 (a.k.a. version 95). Relational database model was selected to allow maximum flexibility. Microsoft Access with a powerful, visual, and user-friendly environment, low software cost, and easy availability as part of the most abundant office software package was selected as the platform. The database used in the European CESAR project served as a model in designing the *EXPOLIS* approach (Fletcher et al., 1999)

A local database was created for each centre. The local database consisted of several Access database files, containing data from local Civil Register and other national registers, *EXPOLIS* time activity diaries, questionnaires, monitors, laboratory analyses, calibration procedures and environmental conditions as well as urban air quality network and meteorological data covering the field study periods. All data was stored in its primary form and calculations were performed using the primary data dynamically.

The local data was grouped to be stored in separate database files. Population sample management, questionnaire data, and concentration sampling were stored into the local main database. Time-activity diaries were stored in a 15-minute resolution time series database, CO data in 1-minute resolution time series database, meteorological data in 3-hour resolution time series database, and ambient air quality fixed station data in one-hour database. Averages of environmental variables from the meteorological and fixed station databases were calculated into the *Fixedruns* database for the microenvironment and personal sampling periods.

Table 7. Local database files in Helsinki. Corresponding files were used in all centres.

Data files	Tool file	Description
`HELSINKI.MDB`	`EADBTOOL.MDB`	Main local database: Questionnaires, exposures, concentrations etc.
`TMAD15min.MDB`	`TMAD15minTOOL.MDB`	Time-activity diaries (15-min resolution), 15-min avg. personal CO data
`CO1min.MDB`	`CO1minTOOL.MDB`	1-min CO exposures and TMAD data
`FIXED.MDB`	`AmbientTOOL.MDB`	Hourly ambient air quality data
`MET.MDB`		3-hourly meteorological data
`FIXEDRUNS.MDB`		sampling period averages of ambient and met data; all stations

The local database files were split into two functional groups. (i) Data files contain all data tables; (ii) the data processing tool elements, queries, forms and Visual basic modules, were stored in tool files (Table 7). The tool databases were then linked to the data files using Access Linked Table Manager, allowing for development and upgrading of the tools without changes to the data files in continuous use. Finally after the field phase and local data cleaning were completed in each centre, the local database files were collected and combined into the Combined International *EXPOLIS* Database (CIDB). The database structures are described in detail elsewhere (Hänninen et al., 2002a).

A data integrity protocol was established according to the data security requirements of EU Directive on Protection of Individuals with Regard to Processing Personal Data (Directive 95/46/EC). Persons were labelled using codes, and personification information (names, addresses) was removed after the field phase. The database files were secured with user identification and password control and the staff working with the databases in all centres were specifically trained in several common workshops.

4.5. Simulation Framework (II)

Eighteen simulation models are presented in the original papers (**II**, **III**, **V**, **VI**). All these models were implemented using the microenvironment-based simulation framework developed originally in collaboration with **RIVM** (National Institute for Public Health and the Environment, Bilthoven, NL) as part of the *EXPOLIS* study (**II**). The development of the modelling framework was one of the main objectives of the *EXPOLIS* study to support exposure assessments for alternative policy options. The models based on the framework were to allow for assessing population exposure distributions of (i) selected sub populations and (ii) urban areas for (iii) different future scenarios (**I**).

The framework uses similar microenvironment approach like independently developed models by e.g. Burke *et al.* (2001) and Yeh and Small (2002) to calculate time weighted average exposure levels (Ryan et al., 1986;Letz et al., 1984). The framework allows for definition of sub populations, macro- and microenvironments, indoor sources and time activities. Population time is allocated to macro- and microenvironments selected by the user and modelled as fractions of time using 2-parameter beta-distributions (**II**, **III**, **V**, **VI**).

Microenvironment concentrations can be modelled in *direct* or *nested* mode. In the *direct mode* the concentration distribution is assumed lognormal and the probability distribution parameters are directly entered as inputs (**II**, **III, V**). In the *nested mode* the concentration of ambient origin is modelled from an ambient concentration distribution using an infiltration factor distribution (**V**, **VI**). In both modes indoor sources can be defined for a given fraction of each microenvironment type. The additional indoor source concentrations are defined as 2-parameter lognormal distributions. (**II**, **V**, **VI**). The framework was implemented as Microsoft (Seattle, WA) Excel workbook using the @Risk add-on software (Palisade, Newfield, NY).

The population exposure distribution is then simulated by applying probabilistic sampling to each of the input distributions. The partial exposure in each microenvironment is calculated by multiplying the microenvironment concentration (C) by the fraction of time spent in that microenvironment (f). The exposure level $\overline{E}$ of each iterated population member is calculated as the sum of the partial exposures over all microenvironments in the model (**II**).

The use of fractions of time to describe population time-activities implies that the microenvironment model in this equation must be complete for the equation to produce average exposure level, i.e. that $\sum f_i = 1$. When this condition is met (or the result is scaled to unity time fraction by dividing it by $\sum f_i$), the equation is applicable for any averaging time and any number of microenvironments and can in principle be used for any air pollutant. Repeating the calculation for a large number of hypothetical population members estimates the exposure distribution for the target population. The number of iterations in simulation runs ranges typically from hundreds to thousands.

The development of the framework was described and models based on it were demonstrated in **II** using two examples. The first example used *direct* mode models to simulate the annual distribution of 48-hour $PM_{2.5}$ exposures in Athens, Basle, Helsinki, and Prague. ETS and other indoor source exposures were not separately modelled, but were included in the microenvironment concentration distributions as observed in the *EXPOLIS* study. The second example demonstrated the *nested* mode to model the distribution of daily PM_{10} exposures in the general Dutch population, including all age groups and both rural and urban areas, for current situation and an alternative scenario, where ETS exposures were set to zero.

A more detailed evaluation of the *direct* mode was conducted for $PM_{2.5}$ exposures in Helsinki in **III**. The required number of microenvironments was studied by starting with the simplest possible models that take into account the mobility of the population, i.e. models with two and three microenvironments. Because in this stage (and in **II**) it turned out, that ETS exposures are a significant modifier of the exposures, the more detailed models in **III** were run excluding these to see how well the non-ETS exposures can be captured by the model. Population time-activity was modelled separately for the working and non-working adults.

Analysis of residential infiltration factors and indoor source strengths was conducted in **IV**. These data were used as inputs in the main paper of the current work (**V**), where validation of the *nested* modelling approach was completed. This paper elaborated on the theoretical aspects of terminology in model validation and uncertainty analysis, and quantified model errors for $PM_{2.5}$ models in Helsinki. The model was enhanced by handling exposures in traffic as a separate fourth microenvironment; the exposure levels while in traffic were estimated using separate traffic measurements conducted during the *EXPOLIS* field phase.

Finally, the use of the developed and evaluated modelling tool was demonstrated in **VI** by estimating the risk reduction potential achievable by using modern ventilation systems. The current situation was described using the *EXPOLIS* measurement data and a subset of the data was utilized in creating the future scenario. Occupational buildings built in and after 1990 all use a mechanical ventilation system with fine particle filtration according to the Finnish Building Code. The infiltration factors analysed for these buildings were used in the alternative scenario for all buildings, assuming that the whole Helsinki building stock would have been renewed to the condition currently required for new buildings.

5. MODEL AND EVALUATION RESULTS

Model development and model evaluation were conducted in two major steps. In the first phase a *direct* microenvironment-approach was used, where the parameters of concentration distributions in all microenvironments are entered directly into the model as inputs. These concentration distributions represent the total measurable $PM_{2.5}$ concentration in the microenvironments, making no difference on origin of the particles. In the second phase another layer of modelling was added to allow for *nested* modelling of concentrations in indoor microenvironments by using ambient concentrations, infiltration factors and indoor sources as inputs. This approach required analysis of the infiltration factors and contributions of indoor generated particles to the indoor concentrations from observed total concentrations and corresponding elemental compositions.

The *direct*-mode results from the first phase proved that the microenvironment-based modelling approach and the simulation technique can be applied to 48-hour $PM_{2.5}$ exposures without any significant problems (**III**). Starting with the simplest approach with only two microenvironments and no sub population divisions, and working towards more detailed models when a need was indicated by the previous step, ETS exposures were identified as the most significant modifier of personal exposures. Further division of the target population into two groups according to the working status improved the time-activity modelling, but still turned out not to be a very significant modifier for $PM_{2.5}$ exposure modelling.

Infiltration factors and indoor source strengths were analysed for Helsinki and three other *EXPOLIS* cities (**IV**). Buildings in Helsinki were better sealed than in the other cities, leading to slightly lower infiltration factors. Concentrations caused by non-ETS indoor sources were comparable in all cities. Similar finding was made in U.S. using a statistical estimation technique for PM_{10} (Ott et al., 2000). The *nested* model, based on ambient concentrations, infiltration, and indoor sources, produced equal results to the *direct* model, indicating that the additional layer of modelling did not significantly deteriorate the modelling results. From the model applicability point of view, however, the ability to use ambient levels instead of microenvironment measurements is a significant advantage.

After model validation, the model was applied to a hypothetical, but data based exposure reduction scenario (**VI**). The buildings sampled in the *EXPOLIS* study were classified into two categories according to the construction year, dividing line drawn to 1990. Mechanical ventilation is more common in the newer buildings, and in the occupational buildings built after 1990 mechanical ventilation system with efficient fine particle filtration is standard. Therefore the infiltration factors estimated for these buildings were used to define the hypothetical scenario representing a future building stock where all buildings utilize controlled ventilation and fine particle filters. The validated simulation model is used to estimate the exposure reduction potential for such a scenario that will, in fact, become reality, as the required standards have already been mandated in the National Building Code of Finland (section D2, 2003).

The main findings are summarized in the sub sections below. The reader is directed to the original articles for more detailed presentation.

5.1. Direct Microenvironment Model (III)

The simulation framework was applied on $PM_{2.5}$ exposures in Helsinki in the *direct* mode in **III**. The simulated exposure distributions matched the observed ones well, especially when the ETS exposures were excluded from the model.

Four simulation models were built; the first two crude models targeted the whole *EXPOLIS* population without using any sub groups. The refined models 3 and 4 excluded ETS-exposed subjects (Another option would have been to model the ETS-exposures as separate indoor sources, but this was done later as a part of the *nested* model in **V**). In the models 3 and 4 the time-activity of the working and non-working subjects were also modelled separately.

The distribution assumptions of lognormality of concentration distributions and beta-distribution for the time fractions were tested statistically and graphically. The concentrations followed lognormal distributions quite well. The goodness-of-fit of the beta distribution for the time fractions was worse.

5.1.1. Simulation of Population Time-Activity

Simulated three-microenvironment fractions of population time were compared to corresponding observed distributions in **III**, Figure 2. First, the whole *EXPOLIS* population was grouped together in the left column of charts labelled “whole population”. Simulated distributions are shown as lines and observed ones as histograms. X-axis represents the fraction of time spent in each microenvironment; y-axis shows a measure of the relative frequency of each value in the distribution (defined so that the area under each distribution is unity).

For the home microenvironment (topmost chart) the Figure 2 in **III** displays a clear underestimation of the relative frequency of the mode and other central percentiles. This underestimation is compensated in the tails of the distribution around time fractions 0.25 – 0.45 and 0.60 – 0.85 where the modelled frequencies are to high. The mode of the fraction of time distribution is somewhat shifted to the right (i.e. overestimated) by the model. Simulated frequencies for those that spent their time almost completely at home are underestimated.

For the workplace the most obvious discrepancy between the simulated and observed distribution in **III**, Figure 2 is the significant probability mass at zero, representing the subjects that did not spend any time at work. This might include some occupied subjects that happened to be off-duty for the measurement period and is called the “non-working” subpopulation for simplicity’s sake. The simulated beta distribution is shifted to left and the observed mode around fraction of time 0.35 is underestimated to be around 0.20. The main cause of this problem, the probability mass at zero, cannot be handled by the beta distribution.

The fitted beta distribution has a closest resemblance to the observed one for the “Other” microenvironment class (the bottom chart in **III**, Figure 2). The mode height is still somewhat underestimated. Kolmogorov-Smirnov test for the above comparison shows clearly that the fitted beta distributions are not statistically representative of the histograms.

In the second step the *EXPOLIS* population was divided into two main categories according to the major modifier of their time-activity: the working status. In the centre and right column of charts in **III**, Figure 2 (labelled “working” and “non working sub population”) the fitted beta distributions have much better resemblance with the observed ones. Still, for the working sub population the mode frequencies are underestimated for all three microenvironments.

Kolmogorov-Smirnov test still indicates statistically significant differences for all cases of the working subpopulation (p-values below 2%), but the two non-working population distributions are acceptable even in terms of statistical significance (p-values >0.25).

5.1.2. Microenvironment Concentration Distributions

Simulated and observed microenvironment concentration distributions for the homes and workplaces were compared visually in **III**, Figure 3. Visually all the five fits seem to capture the overall shape of the observed data. The main determinant of the microenvironment concentrations was clearly shown to be exposure to tobacco smoke. Both of the distributions on the left column of charts labelled “whole population” show slight indications of two modes, the higher mode being attributable to smoking. Because smoking in residences in Finland is becoming rare, the second mode in the home distribution is clearly weaker than the first one, attributable to other $PM_{2.5}$ sources than smoking. In the workplace case the smoking mode is more profound.

Shapiro-Wilk’s test indicated statistically significant deviations from the lognormal distribution fitted using method of matching moments (Small, 1990) (p-values < 0.00). Same result applied to the distribution of ambient 1-hour concentrations from Vallila monitoring station. In the Vallila case the cause for the statistical deviation from log-normality were negative measurement results close to zero that were coded as zeros for the analysis.

When the ETS-exposed microenvironments are excluded from the data, the lognormal fits become statistically acceptable (p-values 0.2 and 0.6 for homes and workplaces, respectively).

5.2. Nested Model: the Infiltration Approach (IV, V)

The next step, after the functionality of the *direct* simulation was affirmed, was to add the *nested* layer of modelling indoor concentrations using outdoor concentrations, infiltration factors, and indoor sources as inputs. The basic time-activity model remained the same, but the number of microenvironments was increased from 2-3 to 4 by splitting the aggregate group “Other” into “Traffic” and “Other-non-traffic”.

5.2.1. Infiltration Factors (IV, V)

Infiltration factors and fractional concentrations from indoor and outdoor sources cannot be directly measured in practical situations, where both indoor and outdoor sources are present. Therefore these terms have to be analysed from the observed total concentrations. In the current work sulphur was used as a particle bound marker element that seemed to have no indoor sources in Helsinki or the other cities included in the analysis.

Residential indoor $PM_{2.5}$ concentrations regressed well against corresponding outdoor concentrations in Helsinki (slope 0.64, p-value <0.000). Corresponding slope for sulphur were 0.76 (p-value <0.000), showing that the particles with high sulphur content, infiltrate indoors with a slightly higher rate. This was expected, because sulphur is mostly of secondary origin in air and is mostly present in submicron accumulation mode particles. A significant fraction of the mass-based $PM_{2.5}$ concentration, on the other hand, is in the largest particles. The larger particles have higher settling velocities and therefore are removed from the indoor air more rapidly, leading to a lower infiltration rate even in case when the penetration rate of both particles would be identical. However, in cases of tightly sealed buildings with coarse filtering in the air exchange system, the larger $PM_{2.5}$ particles are also removed more efficiently at entry. For these reasons, when using sulphur as a marker for particles of ambient origin, the sulphur infiltration rate should be corrected for these differences caused by the different size distributions. The ratio of the regression slopes (0.84) was used to scale sulphur infiltration factors for $PM_{2.5}$ in individual residences.

Concurrent outdoor measurements were not available for the workplace locations. Therefore the infiltration factor analysis for the workplaces was conducted using the residential nighttime outdoor sulphur concentrations, daytime workplace indoor sulphur concentrations, and daytime $PM_{2.5}$ concentrations from the Vallila fixed monitoring station. PM-bound sulphur, being a long-range transported pollutant, does not have a diurnal pattern or any significant spatial variation in the Helsinki metropolitan area. Consequently this replacement of missing observations should not introduce significant bias (i.e. systematic error) to the results. Naturally in individual cases the uncertainty of the infiltration rates is higher.

The resulting mean infiltration factor for the workplaces was significantly lower (mean 0.47) than that for residences (0.64). This could be expected and is presumably mainly due to the higher percentage of mechanical ventilation systems with PM filtering in office and other occupational buildings than in residential buildings.

5.2.2. Indoor sources (IV, V)

Estimation of the infiltration rates for individual indoor environments allowed, together with the observed outdoor concentrations, for calculation of the level of outdoor generated particles indoors. This, subtracted from the observed indoor concentration, is then an estimate for the indoor generated $PM_{2.5}$ level. Assuming a constant decay rate for $PM_{2.5}$ particles based on the PTEAM study in Riverside, U.S., also the ventilation rates (h^{-1}) and consequently the source strengths could be estimated for residences. Indoor source generated concentrations were 2.5 and 4.2 µg m^{-3} in non-ETS exposed residences and workplaces, respectively. In the residences ventilation rate was 0.8 h^{-1} and mean indoor $PM_{2.5}$ source strength was 0.6 mg h^{-1}. Relative variability of the indoor generated particle levels was much higher than that of the infiltration factors.

The simulation of the indoor concentrations in the next step will show that the presented estimates for the infiltration factors and indoor source strengths produce reasonable total concentration distributions when compared to corresponding observations.

5.2.3. Simulation of Indoor Concentrations (V)

For simulation model component evaluation, the simulated indoor concentrations were compared against corresponding observed distributions (**V**). The comparison included both a *direct* model, where the indoor concentration model consisted of a lognormal distribution fitted to the observations, and a *nested* model where the distributions of infiltration factors and indoor source generated concentrations were used as inputs in the simulation model together with a distribution of ambient concentrations. Numerical results for the latter approach are shown for residences in Table 8

In the residences (**V**, Figure 7, left chart) the performance of both approaches was almost identical and matched the observations very well. In the case of workplaces (right chart in the same figure) both modelling approaches had a lower correspondence to the observed distribution. The *direct* model predicted the upper half of the distribution quite well with rather clear overestimation of the highest five percentiles, but somewhat underestimated the lower percentiles. In absolute terms the underestimation, however, was small (<1 μg m^{-3}). The *nested* model matched the lower tail quite well, but underestimated the percentiles between the 70^{th} and the 95^{th}. In relative terms the biggest underestimation for the 95^{th} percentile was almost 30%.

Table 8. Comparison of simulated and observed residential indoor concentration distributions.

		First Moments		Percentiles						
	n	**mean**	**sd**	5 %	10 %	25 %	50 %	75 %	90 %	95 %
		[μg m-3]	[μg m-3]	[μg m-3]	[μg m-3]	[μg m-3]	[μg m-3]	[μg m-3]	[μg m-3]	[μg m-3]
Simulated	2000	8.80	5.82	2.8	3.4	5.0	7.4	10.9	15.6	19.5
Observed	153	8.76	5.66	2.7	3.4	4.7	7.1	11.0	18.1	21.2
Difference:										
Sim - Obs		+0.0	+0.2	+0.1	+0.1	+0.2	+0.3	-0.0	-2.5	-1.7
Relative to Obs		**+0.5%**	**+2.9%**	**+4.8%**	**+1.7%**	**+4.7%**	**+4.8%**	**-0.4%**	**-13.6%**	**-8.1%**

An alternative approach to the indoor concentration simulation used by many modellers would have been a mass-balance approach (Yeh and Small, 2002;Burke et al., 2001). It requires more input data, some of which are not widely available or easy to measure. The infiltration approach selected here is based on the same overall equation, but only two probability distributions are estimated (for F_{INF} and C_{ig}, see symbol definitions in **IV**) instead of five (for P, a, k, Q and V). The more detailed mass-balance approach is more flexible in modelling various technical changes affecting ventilation patterns and indoor sources, but as it is based on more numerous inputs it is potentially more prone to parameter uncertainty induced errors than the infiltration model.

5.2.4. Model Evaluation: Characterisation of Model Errors (V)

Model evaluation can be attempted using different setups, some of which are depicted in Figure 6. An exposure model is based on a conceptual model and its implementation includes the definition of input variables used in the model calculations. These input values are typically estimated using measurements from a population sample. Even a randomly drawn sample gives imperfect information on the true values of the variables of interest in the whole population due to sampling error (response bias can be added due to imperfect sampling). The extent to which the sample represents the whole population is called “representativeness” and for a good random sample it is a function of the sample size. Case 1 in Figure 6 describes the calculation of the model error, which will be pursued in more detail shortly.

Case 2 in Figure 6 describes the use of an independent data set for model validation, partly utilized e.g. in (Ott et al., 1988). While this setup makes sure that any specific relationship of the model structure and the sample 1 are not driving the model results, and the model results really can describe another population sample as well, two separate sampling errors are added to the comparison. Case 3 adds another layer of sampling errors and representativity issues to the comparison by using input values created from multiple samples of the target population.

The model evaluation in the current work was done in **V** by quantifying the model errors using setup case 1 for the non-ETS exposed Finnish speaking working age Helsinki metropolitan area inhabitants. The model errors were quantified by comparing the observed and simulated distributions, and compared to the other error terms affecting population exposure assessments: the error in the observed exposure distribution caused by measurement error and to the sampling error in the observed distribution caused by the random sampling process. The latter represents the uncertainty in the field study results in representing the true underlying target population.

Graphical comparison of the simulation results and the observed distribution is shown in **V**, Figure 5. It can be seen that the overall match is similar for both the *direct* and *nested* models. For the upper half of the distribution the *direct* model performs slightly better, and both models somewhat underestimate the observed levels. In the lower half of the distribution the models perform identically. The same comparison is presented numerically in **V**, Table 3. The *direct* model overestimates population mean exposure by 1%, the *nested* model underestimates it by 5%. Both results can be considered at least satisfactory. The model errors are bigger for the standard deviation, which is underestimated by both models, by –9 and –23% by *direct* and *nested* models, respectively. In the 25th and 50th percentiles the relative error approaches 10%, but is well below 1 µg m^{-3} in absolute terms. Such an error is comparable to the measurement error in a single measurement. Highest model error occurs for the 99th percentile in the *nested* model – this level is underestimated by –18%. The corresponding absolute error is –6 µg m^{-3}.

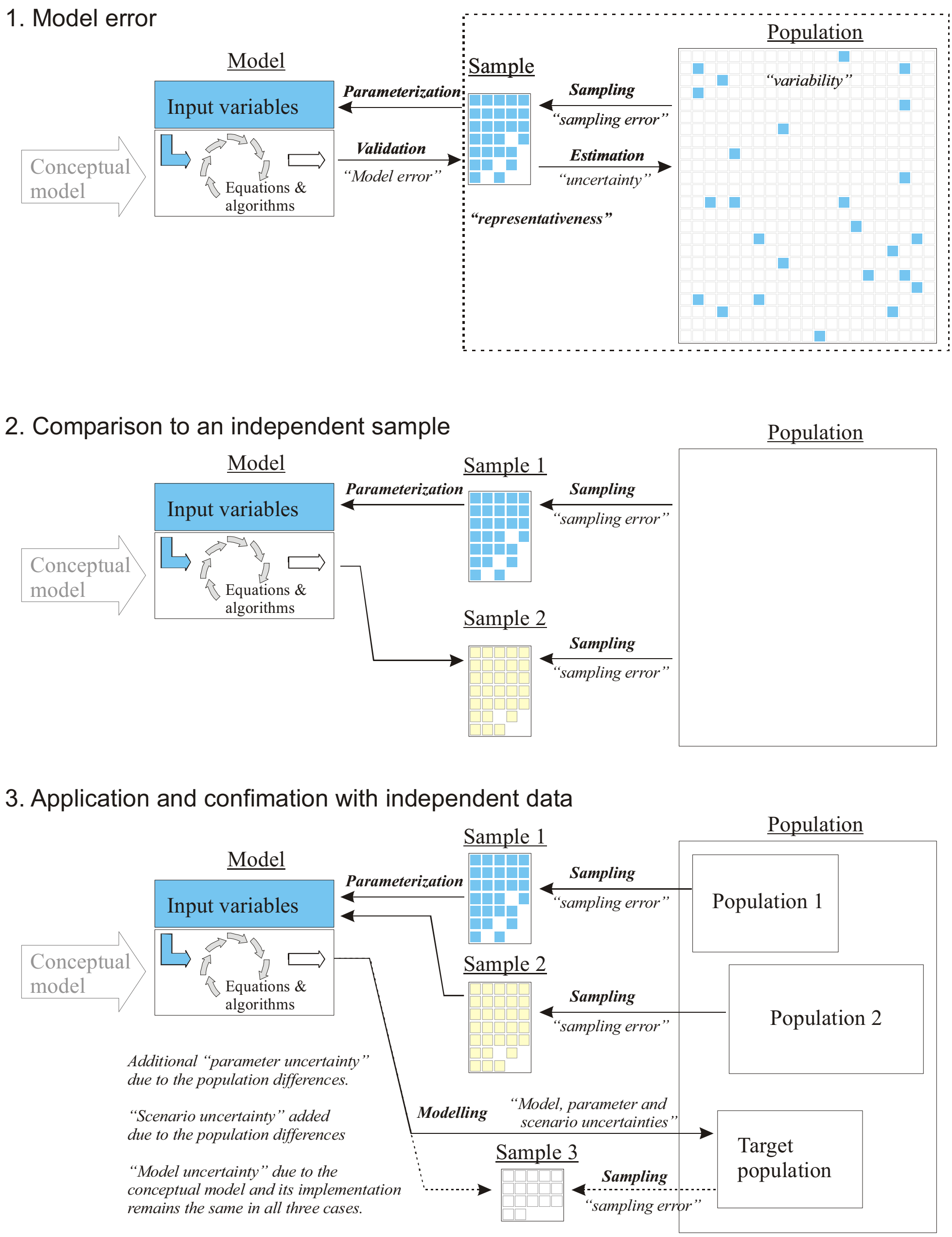

Figure 6. Different possible setups for model evaluation. Setup 1 allows for estimation of model error by excluding probabilistic sampling errors.

The different error terms affecting population exposure assessments are compared in **V**, Figure 6. The top chart displays the uncertainty caused by population sampling. The current study with its 201 exposure measurement subjects can be considered a medium-to-large sized exposure study, and yet the uncertainty in the exposure percentiles is notably large. In the percentiles above 90^{th} the uncertainty increases above ±10 μg m^{-3}.

The middle chart displays the effect of measurement errors. The light grey area displays the measurement error in single personal exposure measurements. The dotted line displays the corresponding bias in the observed distribution. The dark grey area displays an estimate for the uncertainty in this bias by assuming 0.5 (the edge of the dark grey area that is closer to zero) and 2 x (the other edge) measurement error. It can be seen, that the measurement error biases the lower tail low and upper tail high, meaning that the ob served distribution is, in fact wider than the true underlying distribution. Because the measurement error adds a random variation component to the observations, this is natural.

The bottom chart in the **V**, Figure 6, displays the measurement error bias corrected model errors for the *direct* and *nested* models. These are comparable, the *direct* model being slightly more accurate. The model errors are somewhat smaller than – but comparable to – the uncertainty about the true population exposure distribution caused by the random sampling error. It should be noted that as this analysis of sampling error accounts only for the effect of random sampling; it does not include any effects of potential participation bias or subject modification of behaviour. Therefore the random sampling error represents a minimum estimate for the sampling error component.

5.3. Application: Risk Reduction Potential of Good Ventilation (VI)

$PM_{2.5}$ infiltration factor distribution for all residential buildings was 0.64±0.20 and 0.47±0.24 for occupational buildings. In the occupational buildings mechanical ventilation systems with at least coarse particle filters are more common than in residential buildings. However, in the newer buildings, which in the current study are represented by buildings built in or after 1990, the corresponding mean values are 0.58 and 0.35, respectively, indicating a clear lowering tendency. The difference is especially significant in relative terms for occupational buildings.

The simulation model developed and validated in the earlier part of the work was now applied for the estimation of the exposure reduction potential in a future scenario, where the infiltration efficiency of all buildings would follow the distribution of infiltration factors in the post 1990 occupational buildings in the *EXPOLIS* sample. It was assumed that all the other model parameters would be unchanged.

Because the infiltration efficiency affects mainly particles of ambient origin, the model was run without indoor sources. The health effects connected with the ambient PM levels in the epidemiological studies must be caused by ambient particles, because the indoor generated particle levels do not correlate with the ambient levels. Therefore, if the indoor generated particles have similar health effects than the ambient particles, they are additional to those observed in the epidemiological studies. Therefore the exposure reduction potential for the demonstration case was calculated mainly for the ambient particles.

The results (**VI**, Table 3) indicated that a 27% reduction could be achieved by the changes in the ventilation systems. Because the needed requirements have already been implemented in the Building Codes, it can be assumed that this reduction will be achieved along the natural renewal of the building stock in every case. When new understanding is generated on the risks caused by particles to susceptible population groups, special actions regarding building characteristics can be taken to target exposure reductions to those that will benefit most.

6. DISCUSSION

Comparison of deterministic and probabilistic approaches. In the strictest sense of the phrase, deterministic models are based on physical equations describing causal relationships and target identifiable individuals and events. A single outcome of such a model could at least in principle be validated by comparing the model estimate to a corresponding observation. Deterministic models are, of course, not limited to modelling ‘specific individuals or events’. Large populations may be modelled by including all population members individually into the model. A common objection to deterministic models is that the collection of the input data needed for such an attempt would be impossible. But there is no need to include every member of the target population in a deterministic model, similarly as no one would suggest this for a personal exposure monitoring study. A statistical sampling scheme can be employed to create a random sample of the target population, to collect the required input data for this more limited number of subjects, and to run the model for them.

Strengths of deterministic exposure models include presentation of exposures in geographical scales (using GIS), short-term forecasting, and modelling of alternative future scenarios. Practical challenges of the deterministic modeller may be solved using probabilistic approaches. It is obvious that in fact we do not need exposure data for specific individuals to manage exposures in a city or for a specific sub population. Relevant are the general exposure characteristics of the target population, including estimates for the mean exposure, exposure variability, and perhaps some idea of the levels of the highest exposures. For a model to be useful, it should help answering questions like “How could we best reduce these exposures?” and “How much would the exposures be reduced if we implemented these management options?” Of course, a model can replace neither the exposure analyst nor the decision maker in this process, but the model should be usable as a tool for comparing alternative options and scenarios for them.

Because it is very difficult or practically impossible to collect individual data for anything more than small samples of selected populations, the deterministic modeller is drifted towards estimating input variables with point values more or less representative for the target population. Such point values are in the best case not biased, but they always lead to ignoring some of the variability of the values within the target population. Therefore such model can in the best case estimate the population mean exposures well, but the estimates of variability will be compromised. This is exactly the main issue that a probabilistic modeller tries to solve. Probabilistic input variables are described as distributions that intend to capture the true variability of the input values.

Another point related more to risk than exposure modelling, is the use of conservative point estimates in the models to create a safety margin. In such a context, instead of using conservative point estimates in a deterministic model, the probabilistic modeller tries to capture the true variability (and sometimes also separately the uncertainty) in the input variables, and to create a best estimate for the whole range of variability of the exposure in the target population. Then, it is on the responsibility of the risk manager to apply a required margin of safety on top of the exposure assessment representing our best knowledge (with explicitly expressed uncertainty) on the true exposures.

Model development and data acquisition. In the current work a population exposure model was developed in the context of a large European multi-centre study with extensive fieldwork in seven metropolitan areas. This directed resources towards the data collection, including personal exposure and microenvironment concentration measurements with the accompanying work related to development of measurement methods, quality assurance, multi-centre collaboration, data management, and data analysis, and it is difficult to avoid the question whether such a large field study gives the best environment for model development. The current work would have benefited more from an environment focusing on model development with support for theoretical aspects, computer based modelling, and statistical and mathematical expertise.

On the other hand, a major limitation in many deterministic and probabilistic modelling attempts is the implicit uncertainty in the model inputs and outputs. When model inputs are estimated from various sources, including literature and pilot studies to mention few examples, the only way to assess the applicability and representability of the data for the purpose at hand is expert judgement. Here, at best, science enters to the round table of experts, where the peer review of the presented models and results judges the validity of selections and assumptions made by the model authors.

On the other hand, when the model input data are collected using population-based random sampling, it is ensured that the data entering to the model are representative of the underlying population. Traditional statistical techniques can then be used to assess the uncertainty about the underlying population caused by the random sampling process. Collecting observations of the model output variables at the same time and from the same subjects makes it possible to compare the observed and predicted values to calculate the model errors as the difference of these two.

Estimation of model parameters from observations. In an ideal world a good model would use easily observable variables as inputs and calculate the desired outputs from those using physical equations completely capturing causal relationships between the inputs and outputs.

Unfortunately we do not live in an ideal world. Taking ventilation as an example, it is operated by individuals, affected by e.g. ambient temperature and stochastic events like burning a toast, with a great personal variability, suitable for probabilistic characterization at best. A modeller could attempt to use questionnaire data specific to the day and apartment in case, or a typical value (perhaps classified more specifically to the type of day and apartment and other factors perhaps affecting the outcome). The first option becomes soon too detailed and demanding when the target population size increases. The second option in the simplest case uses population average as a point value for a specific individual, or uses statistical modelling to estimate it from other variables. This is not far from full-fledged probabilistic modelling, where uncertain statistical determinants can be left out of the model and replaced by a description of the variability of each variable.

Attempts to model validation. As Oreskes *et al*. (1994) point out in their rather philosophical study, it is it is always impossible to 'validate' a model in an open system in a pre-emptive way. This is similar to ideas presented much earlier by Karl Popper (Popper, 1935) about falsification of a scientific theory: even what we considered the laws of nature are subject to falsification they are applied in a new environment, where new forces became effective. Any success in model evaluations may only increase gradually on our trust on the model. When the model fails in a new setting, limits of the model applicability become clearer. A classic example from physics were the measurements of the speed of light in late nineteenth century that led to the birth of the theory of relativity few years later and changed our understanding on the nature of gravity. In exposure modelling similar limits of model applicability may be associated with interactions of relatively simple phenomena like air exchange of an unoccupied room interacting with its complete environment including human behaviour in the rest of the building, ambient wind, temperature, radiation balance, etc.

Popper and Oreskes *et al*. are, of course, right in principle. On the other hand also the need for different kind of models and the evaluation of their accuracy are very real. Therefore Oreskes et al.'s point should not be taken as discouragement for evaluation of model accuracy. Decision makers, for example, need to be aware of the uncertainties in the model predictions that they rely on when making expensive or restrictive decisions to protect the safety of the public. This very well illustrated by the benzene exposure reduction case in California (Jantunen, 1998;Ott, 1995) where expensive requirements were set on industry to reduce their benzene emissions. Later it turned out that a simple evaluation of population exposures to benzene would have saved all the trouble, as the controlled industrial emissions had only marginal impact on population exposures, which were driven by tobacco smoke and traffic. The underlying model that the population risk is a straightforward function of emission tons was false and the decision makers should not have counted on it in the first place.

Ott *et al*. (1988) and others have argued that the model validation data set has to be independent of the one used for the model development. Ott *et al*. used the personal CO monitoring data from Denver, Colorado, to develop the SHAPE (Simulation of Human Air Pollution Exposures) model. In the monitoring study the exposures were logged with 1-minute resolution for two days per subject. Ott *et al*. used the first day data to create concentration distributions for the 22 microenvironments included in the model. Then they combined these distributions with the time-activity diaries for the day 2 and compared the model outputs with the observed day 2 exposures, claiming that now the model development data (day 1) and the model validation data (day 2) were independent. However, this approach can be expected to work only if the true day 2 concentration distributions were similar to the day 1 ones. If, e.g. different mixing conditions, or ambient temperature that would affect the use of indoor heaters and ventilation patterns, would be different for the second day, there would be no reason to expect the day 1 distributions to represent the day 2 ones.

The above example demonstrates that the requirement for independent data for model validation is problematic; the input data used in validation must be representative of the target system from where the corresponding observations are collected. If this is not the case, then similarities or differences in the input values may drive our comparison and conclusions, and this of course makes no sense. Therefore in the current study the model input values and the personal exposures used in the model validation were specifically collected from the same population sample.

Underestimation of variance. In the two validation studies for probabilistic population exposure models one common finding has been the underestimation of exposure variability (Law et al., 1997;Ott et al., 1988). One factor not mentioned by the authors is the use of 1-minute concentration data in combination with time-activity diaries. Individual entries in time activity diaries may have significant timing errors due to watches, recall errors, errors in filling the diary, and errors in the data entry into the database. These dilute the estimated concentrations in all microenvironments towards the overall average concentration, i.e. the concentration variation is underestimated. Moreover, in those microenvironments, where the concentrations are especially high, like in the case under study focusing on CO exposures, parking garages, highways, street traffic, tunnels, gasoline stations etc., the time spent is very short. Even a minor error of few minutes in the timing of the visit to such a microenvironment will have a significant effect on the observed average concentration for the visit. Minor timing errors do not have remarkable effects on microenvironments where the time spent is hours.

Time-activity modelling. The most common approach to time activity modelling is to use a database of actual time-activity diaries. Such a database is sampled in the simulation; individuals with the correct gender, age, and ethnic, socioeconomic, and other characteristics for the current simulated population group are randomly selected and used in the simulation (AirPex, SHAPE, pNEM etc.). The main strength of this approach is that the actual sequential dependences between visits to various microenvironments are completely maintained. The actual diaries are also very suitable for tying the visits to specific times of the day.

On the other hand, if the model is used for future scenarios, it must either be assumed that the time-activity of the population does not change, setting a limit to the scenarios that can be studied, or the change in time activity must be implemented on each of the used diaries in the database. Both alternatives are limiting from the point of view of model application. Therefore a different approach was selected in the current work. The time of day and sequential nature of visits to microenvironments are merely ignored, and the total daily fraction of time used in each microenvironment is used instead. This way the time-activity inputs are very easily documented and hypothetical changes can be easily applied to them.

Correlations. One new feature that seems to have been added to probabilistic exposure models in the current work is the statistical modelling of correlations of values sampled from various input distributions. The sampling used in basic probabilistic model simulations assumes independent input distributions. In such a model the dependencies between model variables should be causally modelled as far as possible, but those phenomena for which no causal relationships are specified, are assumed independent. This is not true in the real world. A good example is exposure to tobacco smoke. Smoking subjects are more likely to be exposed to ETS in all of the microenvironments they visit, and subjects sensitive to tobacco smoke will try to avoid all contact with it.

Correlations of microenvironment concentrations can be partly traced back to correlations of ambient concentrations. Ott *et al*. (1988) used this in their SHAPE model, where the microenvironment concentrations were split into an ambient background component and microenvironment specific component. On the other hand, also other factors may affect the correlations of microenvironment concentrations. For example a smoking subject is likely to be exposed to higher levels at both home and workplace – and even the restaurants he or she visits. Also, daily ambient temperatures and the season affect the ventilation patterns and thus modify the infiltration rates in a way that will increase the correlation between the different microenvironments. As a conclusion, the factors leading to correlations can partly be traced back to causal issues (e.g. the general ambient background level), but partly are merely statistical phenomena. In this sense it can be said that ultimately it might be impossible to capture the full range of variability of exposures using purely deterministic models.

Simulation of exposures to other air pollutants. The original goals set for the simulation model development presented in this thesis were not limited to $PM_{2.5}$. In principal the simulation framework, and the conceptual exposure model behind it, are generic and can be applied to different pollutants, as demonstrated e.g. by the simulations run for PM_{10} (**II**) and CO (Bruinen de Bruin et al., 2004b). In models for other pollutants than $PM_{2.5}$, the role of different microenvironments and population groups must be considered separately. Exposures to benzene are driven by different microenvironments than exposures to particles, and even when looking at different size fractions of particles, or particles from specific sources, the microenvironments to be included in the model must be carefully considered.

Exposure-response relationships. During the past decade of intensive research on health effects of particulate matter it has become evident that not all particles are equally toxic, nor are all people equally sensitive to the toxicity of the particles. It is clear that there are many toxic components in particulate matter and that the toxicity is mediated via numerous mechanisms. As the epidemiological and toxicological studies bring more light to the subject, the question about environmental health protection and particles becomes increasingly complex. For each mechanism affecting health there are susceptible population groups, and particles from different sources affect different health mechanisms differently. Therefore the answer to the question: “How can we reduce these health effects most effectively?” requires population group level assessment of exposures to a multitude of PM fractions.

The development of the current modelling approach towards this direction has already begun. In the national HEAT study we have specifically modelled exposures to traffic generated combustion particles (a.k.a. tailpipe particles) (Tainio et al., 2005). In the EU-funded FUMAPEX study we have looked at $PM_{2.5}$ exposures of the most important general population groups that are considered susceptible to particles: elderly and infants (unpublished work). Much remains, however, to be done in this area.

Exposure Modelling and Air Pollution Risk Management. Risk management policies cost money and restrict the alternatives available for individuals and institutions. The justification for such policies is the reduced mortality and disease burden. Therefore the public health achievements of the implemented policies should be evaluated against the set risk reduction objectives. The achieved mortality and morbidity reductions due to implementation of an air pollution policy, however, are in most cases practically impossible to measure. Implementation takes years, and other simultaneous changes in diseases, treatments, demography, and other environmental parameters will inevitably, and in many unknown ways, change the population mortality and morbidity – with all likelihood more than air pollution reduction. Options as dramatic, instantaneous, and effective, as the banning of coal sale for domestic use in Dublin in 1990, are rarely identified and even more rarely successfully implemented (Clancy et al., 2002). While the ultimate goal of urban air pollution abatement policy is to reduce the avoidable disease burden, the targets must be set on intermediate goal, reduction of air pollution exposures, because this can be planned, modelled, managed, measured, and verified independently from other developments in the society. When alternative future policies are being compared, exposure modelling is the only means to perform this important comparison.

Exposure to some pollutants may concern only a small minority of the public. This may be the case, if this minority has much higher exposures than the rest (occupational or vicinity to a source), or if the minority is exceptionally sensitive to this pollutant (e.g. allergic). In these cases, the target population must, of course, be selected accordingly.

7. Conclusions

The developed probabilistic modelling techniques can be successfully used for modelling of population exposures to $PM_{2.5}$, capturing the population variability of exposures (**II, III, V**). The model is suitable for comparison of alternative future scenarios (**VI**). Such analysis should be conducted regularly for optimization of environmental policies (**VII**). The following paragraphs list the main conclusions associated with the detailed study aims.

7.1. Study design (I, II, III, V, VII)

◆ Integrated population-based measurement of exposures and affecting factors (i.e. microenvironment concentrations, time-activity, etc.) allows for detailed analysis of exposure determinants and development of exposure models with detailed evaluation.

◆ Population-based sampling of subjects ensures that the observations, and thus exposure analysis and modelling based on them, are representative for the general population from which the random sample was drawn.

7.2. Simulation Framework (II, III, V)

◆ Implementation of the modelling system using a pre-structured framework makes model development faster, easier and more reliable.

◆ Inclusion of correlation structures is much easier using a pre-structured approach.

7.3. Model input estimation methods (III, IV, V, VI)

◆ Some model parameters (best examples being infiltration factors and indoor source strengths) are not directly measurable, but can be estimated from observed variables using state of art numerical analysis techniques.

◆ Correlations are population level features that can be estimated from population sampled data. The causal dependencies between model variables should be modelled as such as far as possible; however, in some cases this may not be possible. Probabilistic model with the rank correlation feature is one solution to the modelling of these features that are not easily included in physical models.

◆ In model application many parameters must be estimated based on assumptions on local conditions etc., or values measured elsewhere must be used in lack of local data; heterogeneity of correlation structures, infiltration factors and other input values remains an interesting and potentially important research area relevant to future applications.

◆ Goodness-of-fit evaluation methods for probabilistic exposure modelling are not very well established. Some methods based on p-values indicate statistically highly significant differences for distributions that are for all practical purposes identical. On the other hand in some cases (especially time-activity modelling) even visually obvious discrepancies have only minor effects in simulation results. Evaluation of GOF should not be excluded in data-based modelling studies, but care should be taken in interpretation of the results.

7.4. Model Accuracy (II, III, V, VI)

◆ Model errors were found to be relatively small; comparative or smaller than population sampling uncertainties.

◆ Measurement error is typically smaller in microenvironment monitoring than in personal exposure measurement (in case of $PM_{2.5}$ due to the larger flow rates and consequent sample sizes) and therefore modelling based on the microenvironment monitoring can produce more accurate results than personal exposure monitoring.

◆ Simulation models can be used to estimate population variances (unlike deterministic models without proper population sampling schemes), but as found also in previous studies, tend to underestimate exposure variances. With inclusion of correlations and by taking into account the measurement error bias in the observed exposure distribution the underestimation can be alleviated but not completely removed.

◆ Model predicts $PM_{2.5}$ exposure percentiles from 5th to 95th very well; in the tails the model errors become relatively (lower tail) or absolutely (upper tail) larger. Only the upper tail underestimation has practical significance for exposure management.

7.5. Model error, uncertainty and need for independent data (V)

◆ Uncertainty concerns probabilistic evaluation of possible errors in model estimates; more precise and not probabilistic model error may be estimated using a observations of the model output variables together with carefully designed setup that removes other error terms.

◆ Quantification of model error must be based on model inputs and comparison data from the same population sample and times, because otherwise sampling errors obscure them.

◆ Requirement of independent data for model evaluation applies for evaluating model equations and algorithms in alternative setups. In such tests the input data used must describe the alternative target system.

7.6. Model application for a policy-relevant scenario (VI)

◆ Successful model application demonstrated that the developed modelling environment can be used to estimate reductions in exposures for given exposure scenarios.

◆ Population-based exposure studies allow for data based development of exposure scenarios.

◆ The model itself can be applied for hypothetical scenarios (with increased uncertainty).

7.7. Development of efficient environmental policies (II, V, VI, VII)

◆ Policy decisions must be based on reliable quantitative estimates of the expected benefits.

◆ The model was validated for the current exposure scenario and applied successfully for a data based future scenario.

◆ Preliminary scenarios may be created using theoretical assumptions about model inputs, but a data based approach, as demonstrated, ties the scenarios more tightly to reality.

◆ Limitations in obtaining model parameters concern alternative modelling approaches, too.

◆ Exposure assessment using this kind of models allows for realistic and quantitative risk assessment and management.

8. Impacts on Environmental Policy and Public Health (VII)

Exposure analysis is a crucial part of effective management of public health risks caused by pollutants and chemicals in our environment. Development of science-based policies for promotion of public health requires careful analysis of exposures within the population, including identification of emission sources, exposure routes, behavioural determinants, and population groups at risk. Comparison of alternative future policies in terms of environmental health is possible only by using exposure models. One such model was developed and evaluated in the current work with encouraging results.

Exposures to specific pollutants vary from subpopulation to another, and various policy options affect these exposures with largely different efficacies. Therefore future exposure and risk analyses should be carried out in population group level. Optimal benefits can be achieved by reducing exposures specifically in those subpopulations where the burden of adverse health effects is the highest.

In the case of particulate matter, the pollutant itself consists of different fractions, with presumably different toxicities, and thus in this case the dose–response factors should be determined for each of these fractions. If analysis of population exposures is based on only centrally monitored ambient air quality data and dose-response factors obtained for the general population, non-optimal policies may be selected.

EC pursues to develop guidelines for new pollutants, including $PM_{2.5}$, and methodologies to control exposures to pollutants and chemicals with significant indoor sources. The collected exposure data in the *EXPOLIS* database and the models developed as part of the current work should, can and will be used to support these processes among other available tools and exposure analysis techniques.

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