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Reducing Urban Pollution Exposure from Road Transport (RUPERT)

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Abstract

This paper presents the preliminary results of a two-year study on reducing urban pollution exposure from road transport (RUPERT). The main aim of this project is to develop a new modelling framework for nitrogen dioxide, carbon monoxide and particulate matter to simulate exposures of different population groups across a city, and to assess the impact of roadside concentrations on these exposures. This will be achieved by modelling the frequency distribution of personal exposures (PEFDs) as a function of urban background and roadside concentrations, under different traffic conditions. The modelling approach combines new and existing models relating traffic and air pollution data, with particular emphasis of the impact of congestion, and the probabilistic modelling framework of personal exposure. Modelling of roadside concentrations consists of two main elements, namely the analysis of concentrations patterns at different roadside sites and of the relationship between traffic conditions and added roadside pollution. Roadside concentrations are predicted using empirically derived relationships; statistical models, novel statistics and artificial neural networks namely feed forward neural network and radial basis neural network. The exposure modelling is carried out by linking two models: the INDAIR model, which is designed to simulate probabilistically diurnal profiles of air pollutant concentrations in a range of microenvironments, and the EXPAIR model, which is designed to simulate population exposure patterns based on population time-activity patterns and a library of micro-environmental concentrations derived from the INDAIR model.

Keywords: traffic, outdoor pollution, indoor pollution, exposure, neural network.

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1 Introduction

Health effects of air pollution are related to personal exposure. However, current assessments of the health benefits of air pollution control policies rely on estimates of outdoor concentrations rather than personal exposures. The current project aims to develop an innovative modelling framework that will simulate personal exposures frequency distribution (PEFDs) as a function of urban background and roadside concentrations, under different traffic conditions. The relationships between predicted PEFDs across a city and outdoor concentrations will provide a basis from which to estimate the potential health benefits of traffic measures designed to reduce concentrations at roadside and urban background locations. Our approach links modelling of roadside concentrations with the probabilistic modelling of population exposures. The modelling of roadside concentrations consists of two main elements, namely analysis of concentrations patterns at different roadside sites and the use of neural networks to derive the relationship between traffic conditions and added roadside pollution. The exposure modelling has been carried out by linking two models: the INDAIR model, which simulates probabilistically diurnal profiles of air pollutant concentrations in a range of indoor microenvironments, and the EXPAIR model, which simulates population exposure patterns based on population time-activity patterns and a library of micro-environmental concentrations derived from the INDAIR model [1]. Each of these models has been re-designed, and in the case of INDAIR, completely re-coded, to provide a new and flexible approach to modelling population exposures across a city network with different traffic conditions. This paper elaborates on the roadside concentration models and presents the components of an integrated tool capable of estimating the impact of urban traffic on exposure.

2 Modelling of roadside concentrations

2.1 Analysis of roadside pollution concentration

A comprehensive statistical analysis of roadside pollution data has been completed. The analysis focused on air quality data from Leicester. The Leicester dataset consists of data from the AURN (Automated Urban and Rural Network) site, 13 RPMs (roadside pollution monitors) and seven air quality monitoring stations maintained by Leicester City Council (LCC). Additional data from two urban sites in London (Marylebone Road and Bloomsbury) and two rural sites in Rochester and Harwell were analysed to establish a better understanding of the temporal and spatial variability of gaseous pollutants and the size distribution of particulates. The location of the 12 RPM sites in Leicester City are shown in Figure 1. Data collected at one-minute interval was analysed for the year 2001 to give 15 minute and 5 minute averaged diurnal, weekly, seasonal and yearly profiles of CO and NO_2 concentrations. The yearly profile of CO concentrations (15-min averaged) at RPM locations is shown in Figure 2.

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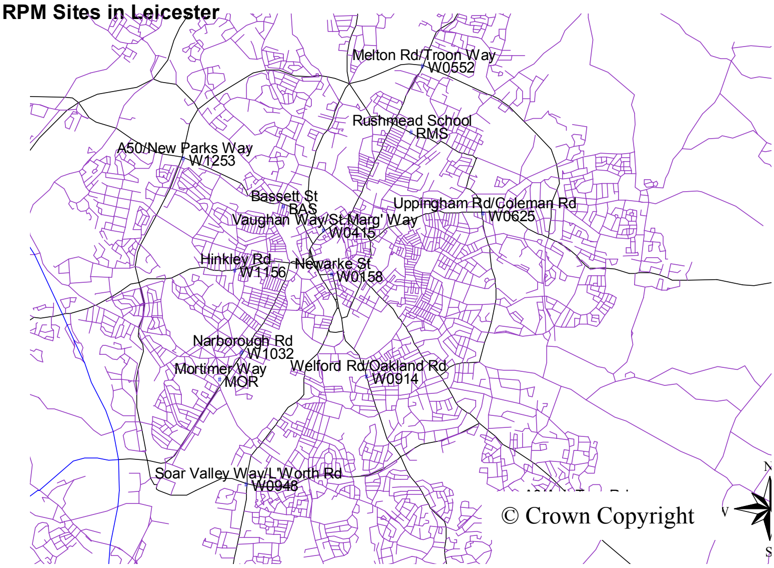

Figure 1: Location of Roadside Pollution Monitors in Leicester. Note: One RPM not shown here is at Melton Mowbray.

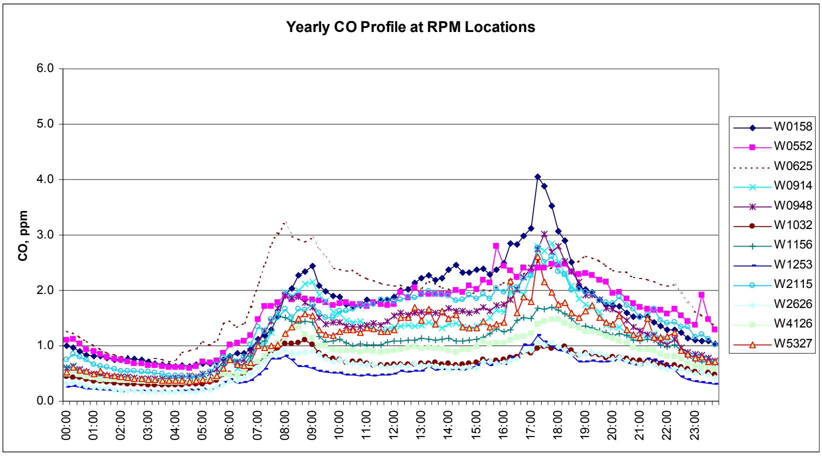

Figure 2: Profile of CO at RPM locations.

These profiles represent average pollution over the year and therefore, without the day-to-day variation, help to illustrate the underlying relationships between roadside pollution and traffic conditions. The profiles are seen to fall into different categories, those displaying a dominant morning (W0625) or evening (W0158) peak or both, with profile W5327 being more pronounced than W1032. The profiles reflect not only the volume (W0158 has higher levels throughout the day compared to W2626) but also the nature of traffic on the road. For example, a one-way street (W0158), a two-way radial with a dominant flow into (W0625) or out of city (W0948) or with busy commuter traffic at peak times in both directions (W0914).

2.2 Relationship between traffic conditions and roadside pollution

In order to develop a more fundamental understanding of the relationships between, and relative importance of traffic characteristics, e.g. flow, delay, stops, congestion on the levels of roadside pollutants to explain their variation within hours from day to day it was necessary to also consider the meteorological data and adopt a different statistical approach. This section describes the use of novel statistics and artificial neural networks, namely feed forward neural network, and radial basis neural network to estimate roadside CO and NO_2 concentrations near a road intersection making use of traffic and meteorological data available from the Instrumented City facilities. The results demonstrated that the neural networks well captured the relationship between the pollutants concentrations and the local traffic characteristics and meteorological conditions.

2.2.1 The study site and data

The selected location was a road intersection in Melton Mowbray, a town in Leicestershire UK, where SCOOT (Split Cycle Offset Optimisation Technique) detectors and a RPM monitoring system is installed. The RPM is located at traffic signals (where there are higher levels of pollution due to contributions from each approach road at the junction) and records CO and NO_2 levels on the footpath edge of the close to the road every minute. Traffic parameters (i.e. flow, delay, stops, cong) and meteorological data (i.e. temperature, wind speed and direction) were chosen to be the input variables. All the data used were regularised and synchronised into five-minute intervals. Data between 01/01/2001 and 30/09/2002 inclusive were collected and pre-processed to remove invalid values for the training and testing of neural networks. The initial data set of input variables was made by 31 parameters (four traffic parameters from each of the seven links plus 3 weather parameters) and consisted of 115,000 cleaned records (65,000 for 2001 and 50,000 for 2002). The 2001 dataset was divided into three different data subsets: the training set with 50% of the whole records, validation and test sets each with 25% of the records respectively.

2.2.2 The results and analysis

It was shown that the neural network explained about 77% and 65% of the CO and NO_2 variations respectively. It is conjectured that the remaining variations could be due to the absence of other important parameters (e.g. ozone, solar radiation etc.) in our models. Figure 3 shows a comparison between actual and predicted CO concentrations, considering a single month (April 2001) for feed forward neural network (FFNN).

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The results also showed that the meteorological data plays the most important role in the formation process of the concentrations. The congestion parameters have the least influence to the process.

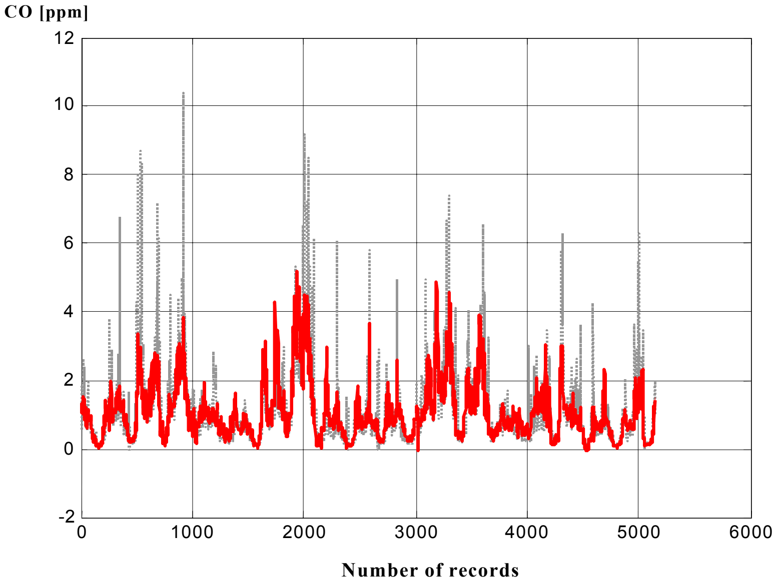

Figure 3: Comparison between actual (thin dotted line) and predicted (bold solid line) values of FFNN, considering a single month: April 2001.

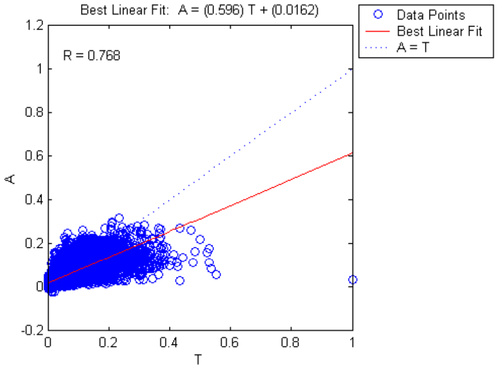

Figure 4: CO - Goodness of fit between estimated values (A) and actual values (T), 2001.

A generic approach was developed to allow the neural networks derived at the selected study site to be transferable to other sites, regardless of the topologies of intersections in urban areas. In order to achieve this, it was necessary to aggregate the flow, stops and delay for inbound and outbound links on each arm of the junction to produce 6 input variables based on the traffic data, together with three meteorological conditions. Figure 4 shows the goodness of fit of the network with the 9 input variables. The correlation coefficient between actual and estimated values is 0.7682 for CO pollutant concentration. This result was very encouraging being very similar to the performance of the neural network with 31 input variables. It is clear from the data presented in Figure 4 that the model is less effective at predicting the higher levels of pollutants.

As a result of the statistical approach described above the descriptions of pollutant concentrations at the roadside can be modelled to capture within day and yearly variations created by traffic and/or meteorological conditions on all the links in the demand responsive control regions. The following section describes how these will be used to model exposure.

3 Exposure modelling

3.1 Development of INDAIR-2 model

The original INDAIR model, in its non-probabilistic form, used a detailed physical model to simulate frequency distributions of concentrations in the three major rooms of the home (kitchen, lounge and bedroom) [2], but concentrations in four other micro-environments (MEs) in non-home locations were simulated by ME/outdoor ratios. The model parameters were defined in the INDAIR/ EXPAIR framework as probability density functions to provide frequency distributions of personal exposures in different MEs. Model parameterisation is based on data for the UK, and the results were consistent with measured micro-environmental concentrations in the UK. This version of INDAIR/EXPAIR was designed to simulate indoor concentrations and personal exposures at specific locations, using an assumed and fixed activity pattern, in terms of smoking and cooking and was unable to accommodate time varying levels in outdoor concentrations caused by changes in traffic and meteorological conditions. In the RUPERT project, a more flexible version of the model has now been designed and parameterised to address this shortfall.

The new INDAIR-2 model predicts the frequency distribution of concentrations in each microenvironment as a function of the outdoor concentration and four regression coefficients. Two of these coefficients define the relationship between indoor and outdoor concentrations in the absence of any significant indoor source, on the basis of log-transformed variables. The remaining two coefficients describe the incremental effect of differing activities, appropriate to each microenvironment, on the modelled concentrations. Each coefficient is defined as a probability density function, while the input concentrations are defined as log-normal distributions for each of four road categories. The INDAIR code allows, if appropriate, for the values of these coefficients to be varied over the course of the day, to reflect different levels of

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activity. Table 1 summarises the MEs selected for simulation, and the additional coefficient terms proposed for each ME in our model.

Table 1: Summary of model terms included in INDAIR-2.

Micro-environment	**Default parameterisation**	**Additional factor 1**	**Additional factor 2**
Home – kitchen	No source	Cooking	Smoking
Home – living room	No source	Cooking	Smoking
Home – bedroom	No source	Cooking	Smoking
Transport	Bicycle/walk/public transport	Car	Underground
School	No source	-	-
Office	Naturally ventilated	Mechanically ventilated	Multi-occupancy
Shops/large buildings	No source	-	-
Bars/restaurants	No smoking	Smoking	Cooking

Parameterisation of this model structure is being developed in two ways, as described below.

3.1.1 Parameterisation for homes

The first stage of the analysis was to define probabilistic indoor/outdoor relationships of vehicle generated pollutants for no-indoor-source situations. Initial trials with the original INDAIR model clearly showed that analysis of log-normal distributions of air pollutant concentrations is to be preferred. Back-transformed values from the log-normal hourly mean concentrations for all four pollutants show a linear relationship between outdoor and indoor levels with high values of R^2.

The second stage of the analysis was to introduce the effect of cooking and smoking, as time-dependent factors. The process for cooking is presented here by way of illustration. The concentration frequency distributions for hours with current cooking activity, and for hours with cooking one or two hours previously, were examined, and the sensitivity of these frequency distributions to time of day, season, weekend/weekday and location, were evaluated. The results showed that cooking source concentrations, expressed as the difference from the no-source simulations, are effectively independent of both time of day and outdoor concentrations. Figure 5 shows the relationship between back-transformed values of indoor and outdoor concentrations of NO_2 in the kitchen for one hour's cooking at 18.00h. Mean indoor concentrations on the hour of cooking (line C) are raised by about 200 ppb, one hour after cooking (line B) by about 50 ppb and by the second hour after cooking (line A) are almost back to background levels of the no source runs.

The next step was to combine frequency distributions of 1000 iterations for no cooking, the hour of cooking, cooking 1h previously, cooking 2h previously

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etc. in proportion to the probabilities of each event to create a new combined frequency distribution for each hour. The geometric mean and standard deviation of the fitted log-normal frequency distributions are for concentrations of each source pollutant above background (no source) concentrations. Values for cooking times of 15, 30, 45 and 60 minutes in the hour together with combinations of cooking times and the cooking hour/cooking 1h previously/2h previously etc. are then used as the input data to INDAIR-2 as a function of time of day for each room. Unlike the NO_2 concentrations shown in Figure 5, which dropped to background levels by 2 hours after cooking, modelled concentrations of particulates and CO do not drop to background levels until several hours after cooking.

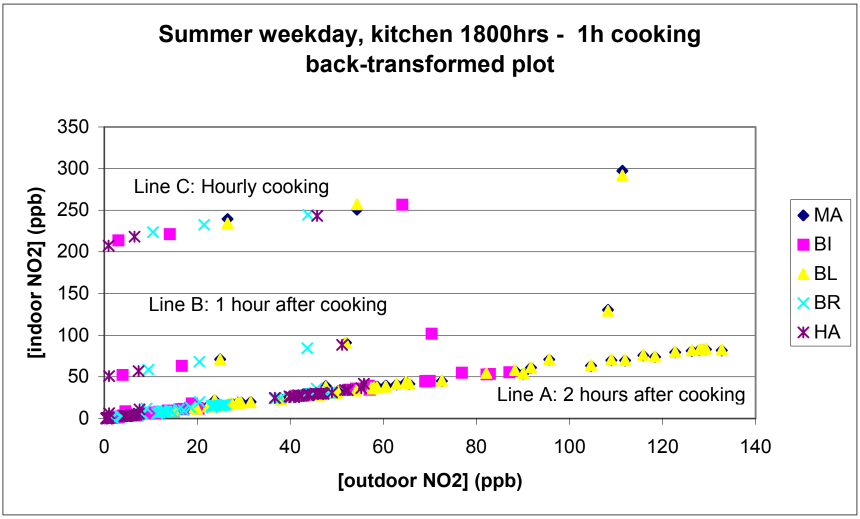

Figure 5: Relationship between indoor and outdoor NO_2 concentrations for 1 hour of cooking at 18.00h. NB: The parallel lines represent different lengths of time after cooking. The symbols represent outdoor data from different UK network sites. (MA=Marylebone Rd, BI=Birmingham, BL=Bloomsbury, BR=Bradford, HA=Harwell)

3.1.2 Parameterisation for non-home MEs

The original INDAIR model was only parameterised to allow the physical simulations to be made for MEs in the home. Therefore, the parameters for non-home were derived from an analysis of measurement data from published and unpublished sources, after appropriate quality evaluation. A detailed literature review has updated the information used to provide input frequency distributions of I/O ratios for these non-MEs in the original INDAIR model. This review identified a number of important new studies, which have been complemented by unpublished data from our own work. Data for homes, as well as non-home

MEs, has been collected, in order to provide a comparison with model predictions from the INDAIR-2 model. A statistical analysis of all the data from these studies, was conducted in order to determine the variation between replicate locations in micro-environmental concentrations; to partition this variation into that due to variation in outdoor concentrations and that due to variation in micro-environmental factors; and to establish, through regression analysis, relationships between outdoor and micro-environmental concentrations

3.2 Development of the EXPAIR model

The previous version of the EXPAIR model took outdoor concentrations from a single site typically from the AURN. The data was used to simulate population exposures from appropriate time-activity data. However, this approach assumed that all micro-environments (homes, schools, offices, etc.) have the same outdoor concentration, which is clearly inappropriate for complex urban environments. In the RUPERT project the EXPAIR model has been modified to allow simulations to be undertaken based on simultaneous outdoor concentration frequency distributions representing four types of road traffic environments instead of a single location. This demands a further input data-stream namely the proportion of the locations for each generic micro-environment which is linked to the four types of traffic environments for any particular city. For the RUPERT project the proportion of all links that belong to each of the four types of traffic environments was identified for Leicester using a K-means statistical analysis of traffic data. Two independent data sets were considered. The first was the hourly levels of traffic flow, delay, stops and congestion measured throughout the year 2001 for the 323 links across Leicester's demand responsive control system. The second set of data was the modelled flow and speed for the 4353 links available from Leicestershire County Council strategic transportation model. The two sets of four families of road/link types were then bench marked using those links in Leicester where RPM pollutant concentrations were measured (see Figure 1). Each distribution of pollutant concentration was assigned to a type of road traffic environments. Population time-activity profiles for the EXPAIR model are already available for children, home workers, office workers and elderly people, based on UK census data [3, 4, 5] and a national survey of personal activity [6].

The next step of this work is to use the enhanced INDAIR-2 and EXPAIR-2 together with the rich statistics derived from the analysis of measured pollutant concentrations and traffic data to derive the PEFDs for typical activity patterns and indoor/outdoor microenvironments.

4 Conclusions

This paper has described the methodological approach to the development of a tool that will play an important role in understanding the health impact of traffic related air pollution and identifying ways of reducing personal exposure. Fundamental to this approach was the statistical analysis of comprehensive data sets of measured roadside pollutant concentrations of CO and NO_2. This was

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available from the Instrumented City database for the city of Leicester. A conventional statistical analysis of the measured data provided the 15-minute diurnal profile averaged over the year. Using neural networks, the variation in roadside concentrations within the hour from day-to-day over the year was derived to predict pollution distributions for the links without roadside monitoring using traffic and meteorological conditions. The analysis confirmed that meteorological conditions are more significant than congestion. The INDAIR model was substantially recoded to define the relationship between indoor and outdoor concentrations in the absence of any significant indoor source; and, to model the incremental effects of differing activities appropriate to each microenvironment, on the modelled concentration. A state of art review and new measurements has allowed the INDAIR-2 to be extended further to include non-home MEs. The EXPAIR model has been enhanced to allow four types of road traffic environments to be modelled rather than a single one. This requires additional data on the proportion of all links for each of the flow types of roadside location in the modelled city. This was derived for Leicester City urban area by K-means statistical method on two independent traffic datasets.

The next step in the RUPERT project is to carry out a validation of the INDAIR-2/EXPAIR-2 modelling approach and then to assess its effectiveness as a tool to quantify the impact of traffic management on personal exposure.

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References

[1] Ashmore, M.R., Dimitroulopoulou, C., Hill, M.T.R., Byrne, M.A. & Kinnersley, R.P., *Modelling of Indoor and Personal Exposures to Air Pollution*, DETR research report EPG 1/3/110, 2000.

[2] Dimitroulopoulou, C., Ashmore, M.R. Byrne, M. and Kinnersley, R., Modelling of indoor exposure to nitrogen dioxide in the UK. *Atmospheric Environment*, **35**, pp. 269-279, 2001.

[3] Office for National Statistics, *Living in Britain: Results from the 2001 General Household Survey*, TSO: London, pp. 115-138, 2001.

[4] Foster, K., Lader, D., Cheesbrough, S., *Infant Feeding Survey 1995*, Office for National Statistics: London, 1997.

[5] Freeth, S., *Smoking–Related Behaviour and Attitudes*, *1997*, Office for National Statistics: London, 1998.

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