Activity Patterns and Pollution Exposure

A Case Study of Melbourne

Leorey Marquez, Nariida Smith, Gerardo Trinidad and Jessica Guo
CSIRO Building, Construction and Engineering
Victoria
AUSTRALIA
E-mail: leorey.marquez@dbce.csiro.au

EJTIR, **1**, no. 4 (2001), pp. 371 - 390

Received: July 2001
Accepted: October 2001

In recent times there has been increasing interest in modelling policies to limit impacts of air pollution due to motor vehicles. Impacts of air pollution on human health and comfort depend on the relationship between the distribution of pollutants and the spatial distribution of the urban population. As emissions, weather conditions and the location of the population vary with time of day, day of month and season of the year, the problem is complex.
Travel demand models with activity-based approaches and a focus on the overall structure of activity/travel relations, not only spatially, but temporally can make a valuable contribution. They are often used to estimate emissions due to the travel patterns of city populations but may equally be used to provide distributions of urban populations during the day. A case study for Melbourne, Australia demonstrates the use of activity data in the estimation of population exposure. Additionally the study shows some marked differences in activity between seasons and even greater the differences in effect of that activity on exposure to air pollution. Numbers of cities will have seasonal pollutant patterns similar to Melbourne and others will benefit from exploring such patterns.

1. Introduction

Motor vehicles contribute heavily to the urban air pollution load in developed countries. Estimates for Melbourne Australia, a city of 3.5 million people suggest that, 83% of CO, 63% of SO_2, 41% of VOC and 16% of PM_{10} emissions in 1996 were due to motor vehicles. Numbers of policies to limit emissions and guidelines for permissible emission levels have been proposed or put in place over time. For example, European air quality guidelines specified a threshold of 150 micrograms per cubic meter of NO_2 from urban traffic per day (WHO, 1987). Transport planners and modellers are increasingly called upon to assess the effectiveness of such policies. Models have been used directly to measure the implications of a variety of demand management strategies to lower emissions due to motor vehicles. Even where studies have had some other major purpose, emission implications are frequently also produced due to the degree of interest in such environmental impacts shown by both community and government. An Australian survey in 1997 showed urban air pollution as the environmental issue of greatest concern to urban citizens.

The majority of such studies consider the efficiency of policies in limiting emissions; they do not usually address effectiveness in limiting air pollution. Nor do they go on to measure the impacts of pollution. It is assumed that less emissions will mean less pollution and in turn less impacts. However these relationships are neither direct nor linear. The alternative with the lowest resulting emissions may not have the lowest impact on the population. Pollution is related to emissions via the mechanisms of the urban air shed. Concentrations vary across the city dependent upon the weather. As concern about air pollution relates to its effects on the natural, built and, in particular, the human environment, the spatial distribution of pollution is very important.

Urban air pollution can damage buildings, limit growth of city vegetation and impact on city amenity for both residents and visitors. Economic consequences range from lowering housing values to discouraging tourism (Smith, 1997). However of major concern is the impact of air pollution on the health of the population. Health effects which arise from exposure to air pollution can be classified as (1) irritation and annoyance, (2) loss of organ functions, such as reduced lung capacity, and (3) morbidity and mortality (Stanners and Bourdeau, 1995). Some of these effects can be minor and reversible, while others develop gradually into irreversible chronic conditions. The respiratory system and the eyes are the main organs affected by air pollution, while systemic effects may also result. Where interest in human health and comfort is uppermost, the spatial distribution of the urban population must be considered in conjunction with the pollutant distribution for proper assessment. As emissions, weather conditions and the location of the population vary with time of day, day of month and season of the year, the problem is complex.

While transport researchers have been developing emissions models, researchers in other disciplines have been developing various exposure models. These combine microenvironment concentrations with individual time-activity patterns and extrapolation to the entire population to give population exposure distributions (Sexton and Ryan, 1988). This paper begins by considering issues in modelling exposure with reference to such models. It then addresses modelling city-wide activity patterns with reference to the Victorian Activity and Travel Survey (VATS). VATS collects information on daily travel and out-of-home activity of household members in the Melbourne metropolitan area. It is based on a survey of 20,000 households and complements the census data collected by the Australian Bureau of Statistics (ABS). A case study for Melbourne is presented to show the advantages of jointly modelling emission rates and distribution across the city, then distribution of air pollution, via an urban airshed model, and finally population exposures based on activities.

Seasonal, as well as time of day, differences in impacts of air pollution are also considered. Most travel models whether activity-based or using traditional approaches consider time of day differences in travel and a few distinguish weekend. However there has been less attention to modelling differences across seasons of the year.

Yet in the great majority of the worlds cities, weather, and hence the airshed, differs with time of year and most also see changes in the activities of the urban population with season. More significant than the changes in activity are the differences in effect of that activity and the resulting emissions. The major pollutant hazards vary markedly between summer and winter. Thus seasonally sensitive models can be of value in alternative measures to limit pollutant impacts.

2. Estimating exposure

Exposure as a general term has been used in a variety of ways to indicate the degree of contact between a target object and a pollutant (Duan, 1991). In the context of the impacts of air pollution to humans, exposure is normally defined in terms of an individual, a population or an area.

The potential exposure concentration $E([x,y], t)$ of an individual is equal to the concentration of a specific pollutant which may vary in time t and in space $[x,y]$. The potential exposure concentration $E([x,y], t)$ is normally expressed in ppm (parts per million), ppb (parts per billion) or mg / m^3. If each person p moves through space and time such that the location of person p can be defined as a function of time t, $[x,y]_p = location_p(t)$. If this function can be specified, the actual exposure experienced by person p during a time period T can be defined as

$$E_p = \int_T E(location_p(t), t)dt \tag{1}$$

An extended way of analyzing exposure is to define a threshold concentration τ such that only levels exceeding this threshold are considered. This measure magnifies the risk associated with levels that exceed the allowable threshold. Thus, the modified equation appears as

$$E_p = \int_T iff\,(E(location_p(t), t) \geq \tau, E(location_p(t), t), 0)dt \tag{2}$$

Both the preceding equations assume that the full dosage of the pollutant enters the recipients body. If we take into account the intake rate $i_p(t)$ of person p expressed as a function of time then the actual total pollutant uptake of a person p can be expressed as

$$U_p = \int_T i_p(t) \times E(location_p(t), t)dt \tag{3}$$

If exposure of a population in a given area A is desired, then the population in A at any point in time can be expressed as $P(A, t)$. As a consequence, the measure of the impact of an air pollutant to the people in area A changes to

$$I_A \approx \int_A \int_T P(A,t) \times E(A,t)dtdA \tag{4}$$

For grid-based data sets, the equivalent formulation is

$$I_A \approx \sum_{g \in A} \sum_{t \in T} population_{g,t} \times concentration_{g,t} \tag{5}$$

For example, the total daily exposure to ozone received by the population of a city can be estimated by computing the 24-hour sum of the product of the hourly ozone concentration and hourly population distribution.
Unfortunately, the above exposure metric suffers from two practical problems:

1. The function $location_p(t)$ is difficult to specify without actually tracking the movements of a significant sample of the total city population. The habitual use of a static residential population oversimplifies the exposure value which should reflect the movement of people to and from a given area;
2. The potential exposure concentration E, the pollutant concentration in a specific microenvironment (i.e. inside a car, inside a bedroom or office, on the pedestrian strip, etc.) may be related to, but not necessarily equal the more readily available ambient air pollution concentration. Thus, most estimates of outdoor pollution exposure fail to account for the fact that up to 95% of activities are held indoors.

Models have addressed these issues in a number of ways. Jensen (1998) describes a model for estimating population exposure based on hourly time series of ambient pollution levels for three microenvironments separately: residences, workplaces, and streets. For the residential environment, differences in exposures between various population groups categorised by gender and age can also be estimated. The model adds a geographic dimension by taking advantage of GIS, digital maps, and administrative databases. A selected urban area of 1150 inhabitants and 550 addresses was used for a case study. This model addresses the second issue but requirements of ambient pollution measurements preclude application over a large city with varying pollution levels.
Freijer et. al. (1998) describes AirPEx (air pollution exposure), a mathematical model that estimates the inhalatory exposure of humans to air pollution. It is used to assist in assessing the impacts of proposed health policies. The model quantifies individual population exposures using data from air quality time series and activity pattern surveys. A sample application studied the exposure to ozone of the Dutch population in the summer of 1991. This study models area wide exposure addressing issue one but times series air quality data did not provide the detailed variations in concentration required by issue 2.
The US-EPA’s Hazardous Air Pollutant Exposure Model for Mobile Sources (HAPEM-MS) was used to show the effect that emission controls have had in reducing CO exposures in the US in recent years (EPA, 2000). The HAPEM-MS calculates exposures on a seasonal basis, for different demographic groups, for each hour of the day, for a single calendar year. The HAPEM-MS is important to the EPA's Office of Mobile Sources for evaluating human exposures to motor vehicles. Some of the results show that reductions in both ambient concentrations of CO and average personal exposure in Denver, Colorado have occurred over the last ten years. This model differs from the two mentioned above, and most exposure models, by actually linking exposure to motor vehicle use. Exposure models usually just measure exposure to pollution. However HAPEM-MS is designed to link measured broad air quality outcomes resulting from broad changes in vehicle travel. It does not directly link impacts of specific policy on travel, through to exposure.

2.1 An activity-based approach

Activity data, analysis and models should be considered for addressing the two issues identified above in relation to exposure. Additionally such models were designed to estimate travel demand. The mechanics behind the scheduling and sequencing of activities and trips have benefited from activity-based approaches and a focus on the overall structure of activity/travel relations, not only spatially, but temporally as well. Activity models are thus particularly suited to linking activities leading to emissions, such as using a car to make a morning trip, with exposure to pollution later in the day due to the sum of individual activities.

While in the context of exposure studies the term activity data is used for average time use data for population, the discussion here addresses the application of disaggregate activity data following individuals throughout the day. The Victorian Activity and Travel Survey (VATS) provides such data. Since the survey covers all 365 days of the year seasonal variations in travel and activity patterns can be observed. On average, about 5,000 households respond to the survey each year. Household details, personal details and the activities undertaken at "stops" during a day of travel are recorded. This yields a total of approximately 12,000 person records and 50,000 stop records per year (TRC, 1997).

VATS data has already been applied to modelling daytime populations, see, for example, Roddis and Richardson (1998). This has been done in response the need for a more realistic description of population distributions. Applications requiring these include: more accurate transportation planning, environmental impact analysis, disaster planning and economic development planning (Fulton, 1984). For many urban planners and transport professionals, the perception of population distribution is home-based. That is, the distribution is assumed static and is described by where people live based on the census data. While this may be adequate in some contexts it is particularly unsuitable in others. Census data gives the late night urban population: "*people staying under your roof the night of …*". This is a particularly bad time for pollution exposure estimates since late night pollution is usually low and the population is indoors. The stop records collected in the VATS can be used to provide more accurate population distribution estimates.

As depicted in Figure 1, the data gives the exact locations, as well as the times of departure and of arrival, where a respondent has, in travel terms, stopped. The information allows the estimation of a movement trajectory over time and space for each respondent. The vertical lines indicate the times during which the respondent has remained stationary, whereas the dotted lines represent the estimated routes that the respondent has taken to traverse between locations. The actual paths which the respondent takes to travel between these locations are not known, but they can be either approximated by straight lines, the shortest paths or more sophisticated network models. There are two major issues involved in estimating the population distribution from the set of sample trajectories. One is how the distribution is measured. The other is how the population is inferred from the sample.

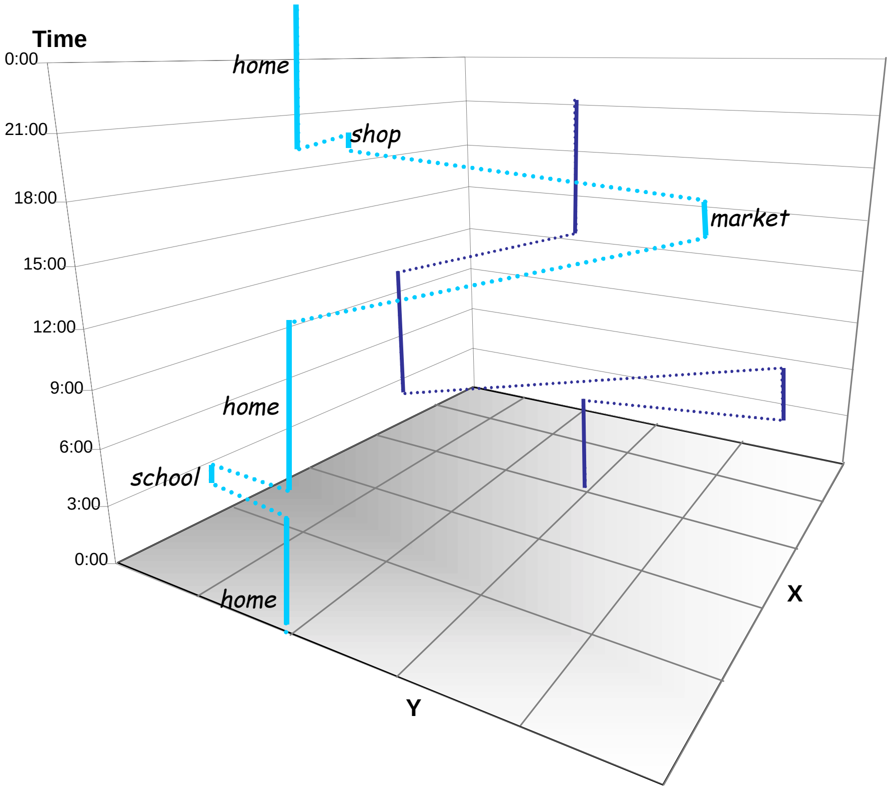

Figure 1. An Indicative Daily Movement Trajectory for two VATS respondents

Measuring the Population Distribution

For exposure estimation, the measurement of interest is the number of people in a region at a given instance in time. In the ideal situation where the actual trajectories of the entire population were available, such a measurement would be very straight foreword and involve counting the number of trajectories intersecting the plane of interest in the time-space system as shown in Figure 2. Furthermore, the measurement could be made for spatial regions of any size and delineation. However, the reality is that only the trajectories of a relatively small portion of the population are available. That number becomes still smaller when data is to be segmented by season. Any estimates drawn for the population from the sample implies inaccuracy. In addition, the uncertainty in people's travel paths also introduces errors into the result. These sources of inaccuracies need to be taken into consideration when choices are made about the level of spatial scale to measure the population distribution. A suitable level of aggregation will smooth out the variances in the distribution and thus reduce the effect of the inaccuracies inherited in the methodology.

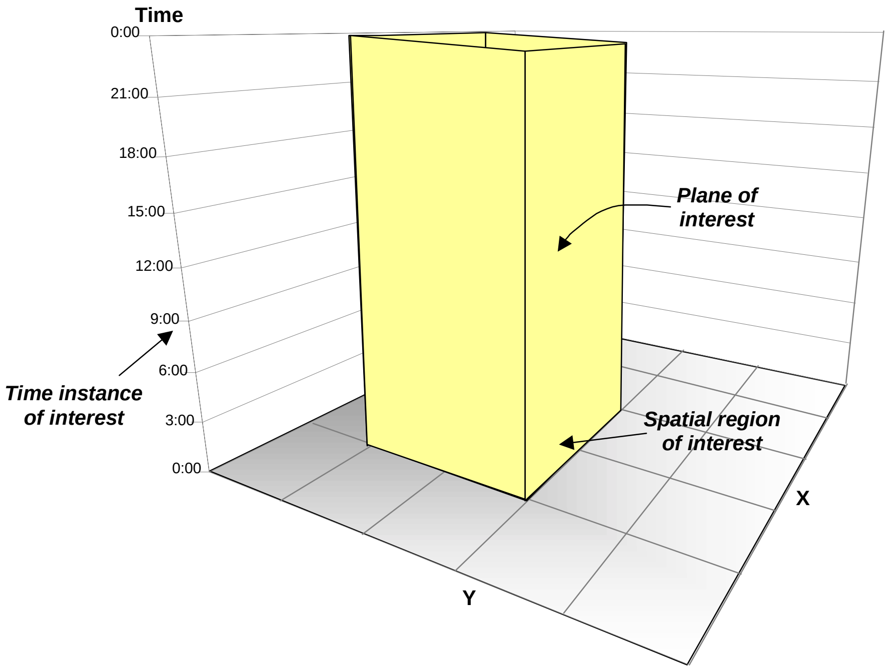

Figure 2. Plane of Interest from Time Instance of Interest and Spatial Division of Interest

Inferring from Samples

As each year the respondents in VATS represent only less than 0.5% of the population, estimating the movements of the remainder of the population becomes difficult. One way is to model and to simulate all the travels made by all individuals. The approach would require a large amount of data, which can not be provided by VATS alone, and, more importantly, established theories and models of activity patterns. However, as research in activity-based modelling has been very fragmented and a unifying framework remains missing (Ettema and Timmermans, 1997), this approach to estimating population distributions has yet to become applicable.

A much simpler approach is to expand the sample directly to the population size using weighting factors (Roddis and Richardson, 1998). The approach is equivalent to multiplying the movement trajectory of each respondent to many copies to represent the trajectories of the un-surveyed population. The sample and the multiplied trajectories together form the basis of the population measures. This approach thus assumes that each respondent represents a group of population and that the group has the same activity-making behaviour as the respondent. VATS holds weighting factors of the type typically used to expand the sample date to produce population estimates (Richardson et al., 1995). This approach was used in the case study below with a further refinement of allowing variations in choices of destinations in the multiplied trajectories.

3. A Melbourne case study

VATS data was used to create snapshots of the population count in each census collection district (CCD) in Metropolitan Melbourne. These snapshots were taken at every mid-hour of a 24-hour day. Aggregation to smooth accuracy in the distribution, as described above, resulted in initial analyses along spatial and temporal lines providing estimates of hourly population at local government areas level. Melbourne has 74 local areas. It should be noted that the results reported are early findings from a suite of models being built to link the activities of the population with urban air pollution due to emissions from mobile and stationary sources: household, industrial and biogenic. The emissions data come from a traditional land use transport model, calibrated using season emissions data rather than the planned activity model. Future analyses are expected to relate the types, duration and location of activities and the generation of travel hence emissions. Time-of-day, day-of-week and season-of-year emissions would then be available for pollution distribution estimation.

Extended activity analysis is also expected to identify the proportion of the population that are actually exposed to the different pollutants at any given time. This process may require more detailed activity data. In the meantime, bounds on the indoor-outdoor ratios based on other studies are used to adjust exposure levels. For example, smog pollution indoors is expected to be significantly lower than outdoors so numerical estimates will have to be adjusted accordingly. However, it is unclear whether relative estimates would change significantly.

To incorporate indoor-outdoor variations, two parameters can be introduced. First, let α be the probability that a person is indoors and let β be the ratio of the indoor concentration of the pollutant to its corresponding outdoor concentration. Note that the effective correction factor for exposure is simply $\alpha\beta + 1 - \alpha$.

In general, the values of α and β varies with each individual, as well as time and location. Values of observed β for ozone have shown variations between 0.1 to 0.65 (Freijer et. al., 1998; Isukapalli et. al., 1999). Jensen (1998) reports that the probability that a person is indoors is between 80% to 90%. Without additional information, there is no alternative but to apply a constant α and β for all individuals, at all times and locations. Thus two bounding conditions can be defined, (1) where $\alpha = 0.8$ and $\beta = 0.65$, and (2) where $\alpha = 0.9$ and $\beta = 0.1$. This would result in correction factors of 0.72 and 0.19, respectively. Equally important to indoor-outdoor variations are seasonal variations although there has been far less research emphasis on these.

3.1 Seasonality and weather

In the great majority of the worlds cities, weather, and hence the airshed, differs with time of year and most also see changes in the activities of the urban population with season. Even Melbourne, with a temperate climate subject to neither winter snows nor summer monsoons displays differences. Seasonality would then be an important consideration in assessing the air pollution implications of travel demand management strategies.

Two of the three major air pollution situations that occur in most European cities are:

- Winter-type smog by sulfur dioxide (SO_2) and particulate matter (PM) measured by the black smoke or by gravimetric methods, and
- Summer-type smog by ozone (O_3) resulting from emissions of VOCs and nitrogen oxides (NOX) (Stanners and Bourdeau, 1995).

Numbers of cities will have seasonal pollutant patterns similar to Melbourne and others will benefit from exploring such patterns. It is hoped that this work will stimulate discussion of this extremely complex problem among the travel modellers now charged with assessing air pollution.

Weather conditions, particularly temperature, wind speed and wind direction, influence ambient pollution levels. During summer, increased ozone concentrations are associated with warm temperatures and stable atmospheric conditions. Temperature inversions usually occur in winter and autumn and can last a few hours or a few days. These inversions can lead to episodes of high airborne particle pollution (EPAV, 1998a).

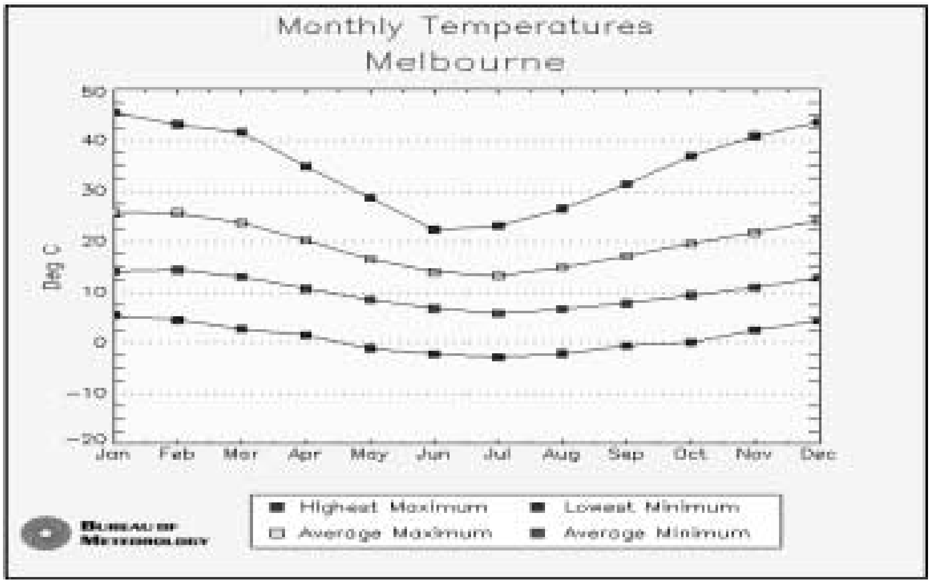

Figure 3. Monthly temperature extremes for Melbourne

Melbourne enjoys a pleasant maritime temperate climate with warm summers and chilly winters. Summers have very few hot days with respite coming from cooler evenings and 7 to 9 days of rain each month. Winter brings some frost but no snow and ice. Winter temperatures can drop 2 to 5 degrees Celsius over night. There are about 10 to 16 days of rain bringing 50–60 mm of rain each month. Figure 3 shows the average monthly temperature as recorded by the Bureau of Meteorology for 1999 (BOM, 1999a). The chart shows that the highest temperatures occur in December-January while the lowest are in June-July. Small variations in the monthly minimum temperatures and large variations in the maximum temperatures mean that summer months can still be cold while winter months are rarely very warm. This difference has special significance in the emission of carbon monoxide, volatile organic compounds and particulates and in the production of ozone and smog.

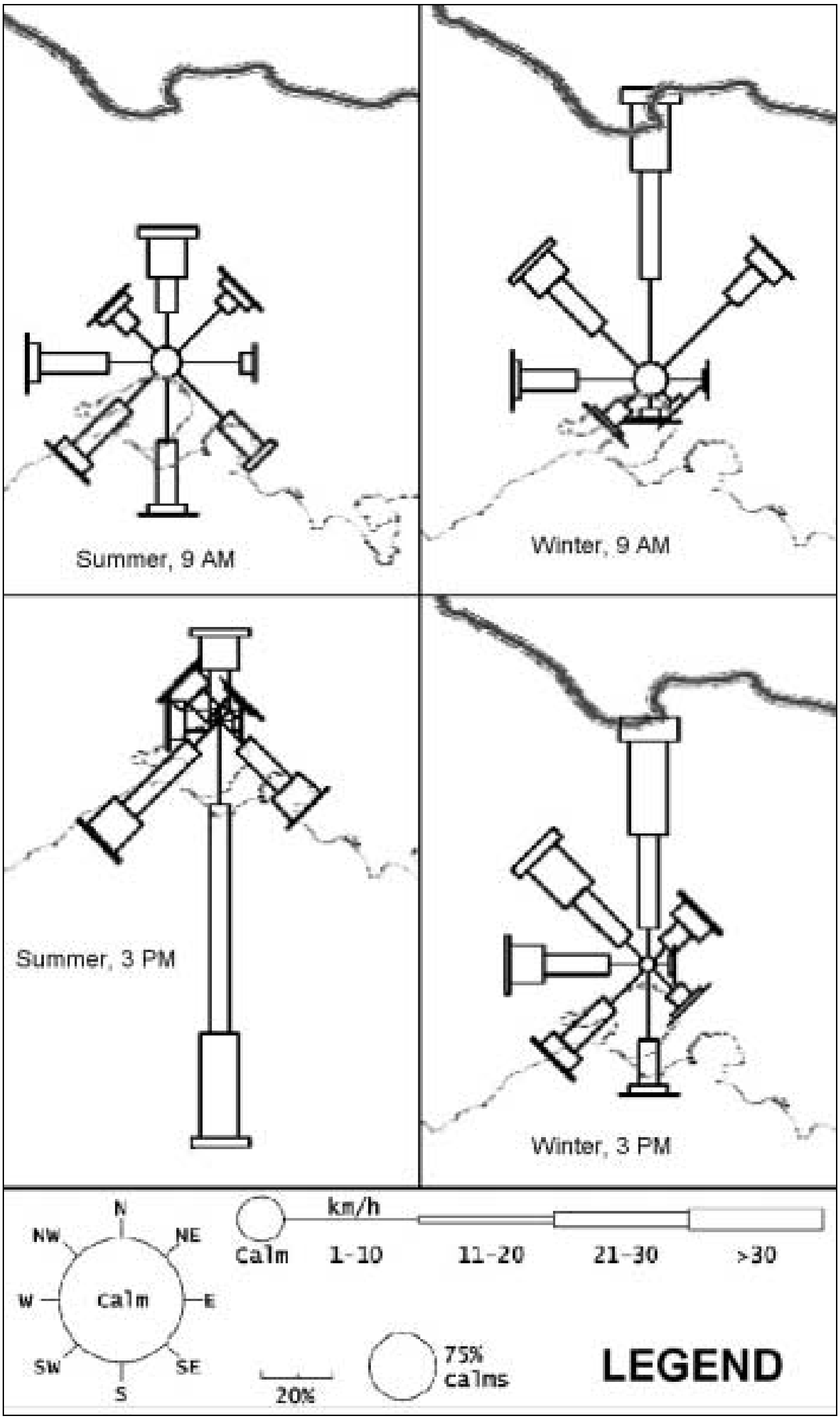

Figure 4. Summer and winter wind patterns for Melbourne

Winds are the main method of removing or dispersing air pollutants from an area. Under calm conditions, with low wind speeds, this dispersion does not occur and pollution concentration builds up. Figure 4 shows the wind roses for Melbourne at 9 am and 3 pm of a typical summer and winter day (BOM, 1999b). Wind roses summarise the occurrence of winds at a location, showing their strength, direction, and frequency. The percentage of calms is represented by the size of the centre circle. Each branch represents wind coming from that direction, with north to the top of the diagram. The branches are divided into segments of different thickness, which represent wind speed ranges from that direction. For example, the thinnest segment may represent winds between 1 and 10 km/h. The length of each branch segment is proportional to the percentage of winds in that speed range, blowing from that particular direction.

Summer mornings are usually calm with light winds expected from virtually all directions while in the afternoon, moderate to strong winds are expected from the south and southwest. During winter, days are usually calm with moderate winds expected to come from the north in the morning, and from the north and west in the afternoon. These wind patterns imply that pollution tends to remain more stationary during winter than in summer increasing the health risk for the population of Melbourne.

3.2 Seasonal pollution

The major pollutant hazards vary markedly between summer and winter. The major sources affected by seasonal variations are domestic and commercial fuel combustion, lawn mowing and barbecues (EPAV, 1998b). In summer, a major concern is volatile organic compounds (VOC) concentration. Summer smog produced in this manner presents dangers to both health and amenity. In contrast, in winter, particles in the atmosphere are the major concern. PM_{10} emission could be doubled and $PM_{2.5}$ tripled in a typical winter day compared to a typical summer day. These increase susceptibility to lung disease and cause deaths in the vulnerable sections of the population, the very old and the very young. Additionally there are significant costs in lost productivity due to illness in the working population.

Table 1. Seasonal variation in total daily emissions (tonnes per day)

Pollutant	Summer	Winter
Carbon monoxide	1689.0	2164.0
Oxides of nitrogen	227.0	246.0
Particulates (PM_{10})	216.0	266.0
Particulates ($PM_{2.5}$)	90.1	124.0
Sulfur dioxide	45.0	45.9
Volatile organic compounds	392.0	654.0

The winter months also produce significantly higher daily emissions of carbon monoxide, oxides of nitrogen, particulates (PM_{10} and $PM_{2.5}$) and volatile organic compounds (VOC) compared to summer, as shown in Table 1 (EPAV, 1998b). This is primarily due to increased wood burning for heating and cooking, lawn mowing, and other domestic activities. The seasons appear to have no significant effect on the emissions of sulfur dioxide (SO_2).

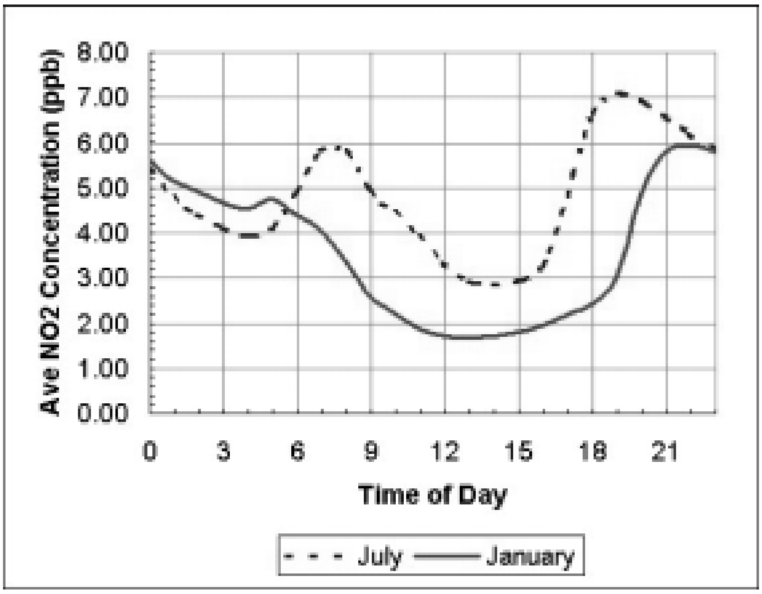

Figure 5. Seasonal comparison of hourly average NO2 concentration

Figure 5 shows the hourly average concentration of NO_2 for the months of January (summer) and July (winter). The chart shows significantly higher levels of NO_2 in July from 6 am to 9 pm. The troughs occur during the day, between 7 am to 7 pm for winter and 5 am to 9 pm in summer. Thus, between 10 pm and 3 am, summer and winter levels remain relatively the same. The lowest levels are achieved at around 1 pm while the highest levels occur at around 7 pm in winter and 9 pm in summer.

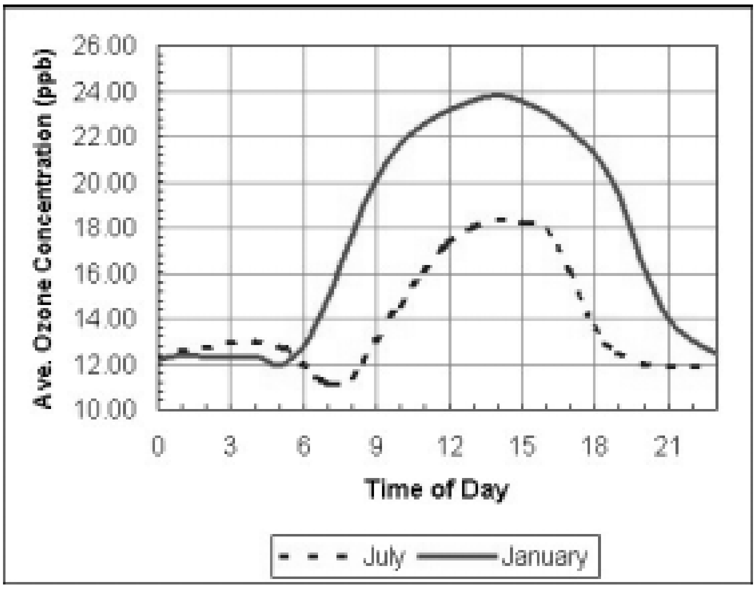

Figure 6. Seasonal comparison of hourly average ozone concentration in Melbourne

As mentioned earlier, the warm temperatures in summer correlate with increased concentrations of ozone and stable atmospheric conditions. Figure 6 shows a 24-hour comparison of the average ozone concentration again for the months of January and July. The chart shows relatively equal levels of ozone between 12 midnight and 6 am. With the warmer temperatures in January, the ozone levels reach significantly higher levels, about 30% more than their July counterparts. While NO_2 had troughs during the day, ozone had crests between 6 am and 11 pm in summer and between 8 am and 7 pm in winter. In addition, the maximum levels are again achieved around noontime.

3.3 Activity patterns

As noted Melbourne has a temperate climate. Thus activities are not unduly curtailed by extremes of weather. Car or public transport travel is not effected by weather events. Even so there are some marked differences in activities between seasons as evidenced by changes in the resulting emission levels.

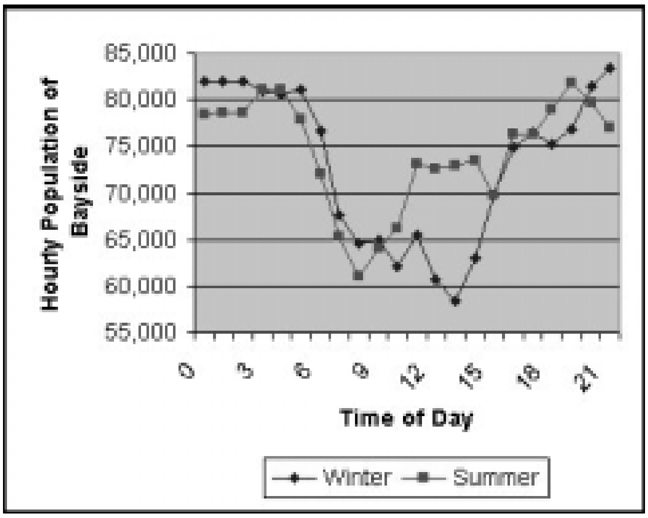

Figure 7. Seasonal variation in hourly population of Bayside

Using VATS data, a comparison can be made between the seasonal exposure levels between local government areas with different population movement patterns. Bayside is a predominantly residential area along Port Philip Bay 14 kms south of the CBD with popular areas for dining and evening social activities. Figure 7 shows the hourly distribution of population in Bayside. Dandenong, on the other hand, is also a residential area aside from being an important centre for commercial and industrial activities. It lies about 30 kms southeast of the CBD along one of the major radial arterials. Figure 8 shows the hourly distribution of population in Dandenong. Bayside has a residential population of around 80,000 while Dandenong's residents number about 126,000.

For Bayside, the significant change in the hourly population occurs at 6 am when the population starts to decrease because of residents leaving for work. In summer, this decline continues until 9 am when the population reverses direction with the arrival of vistiors to Bayside's beach facilities and parks. This increase continues until about 4 pm when the visitors start leaving Bayside. At 5 pm, the visitor departures are offset by the arrival of returning residents as well as the dining public. At around 9 pm, the population declines again with departure of evening visitors. In winter, the morning decline continues until about 2 pm with the arrival of the residents. The increase continues well into the night with more evening visitors staying longer than during summer.

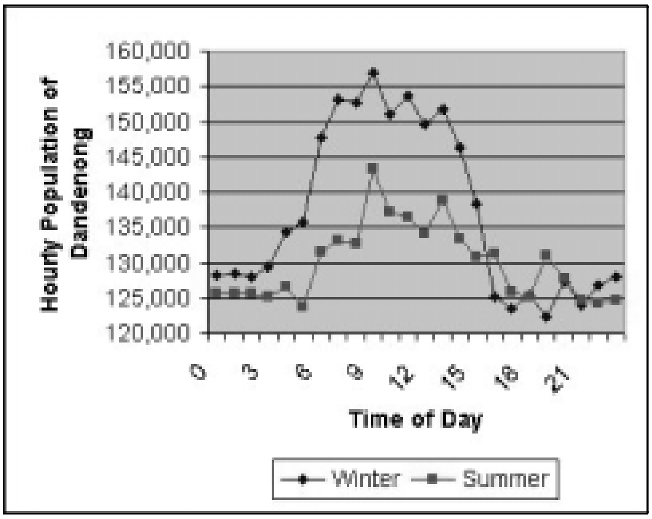

Figure 8. Seasonal variation in hourly population of Dandenong

While the hourly population of Bayside attains its peak numbers in the evening hours between 7 pm and 3 am, the city of Dandenong has its crest during the day between 4 am and 6 pm when most stores, factories and businesses are open and workers and customers flock to the city. After 7 pm, the population returns to its residential levels. The highest hourly population reaches 157000 in summer but only 144000 in winter, again in contrast with Bayside which obtains its highest population in winter.

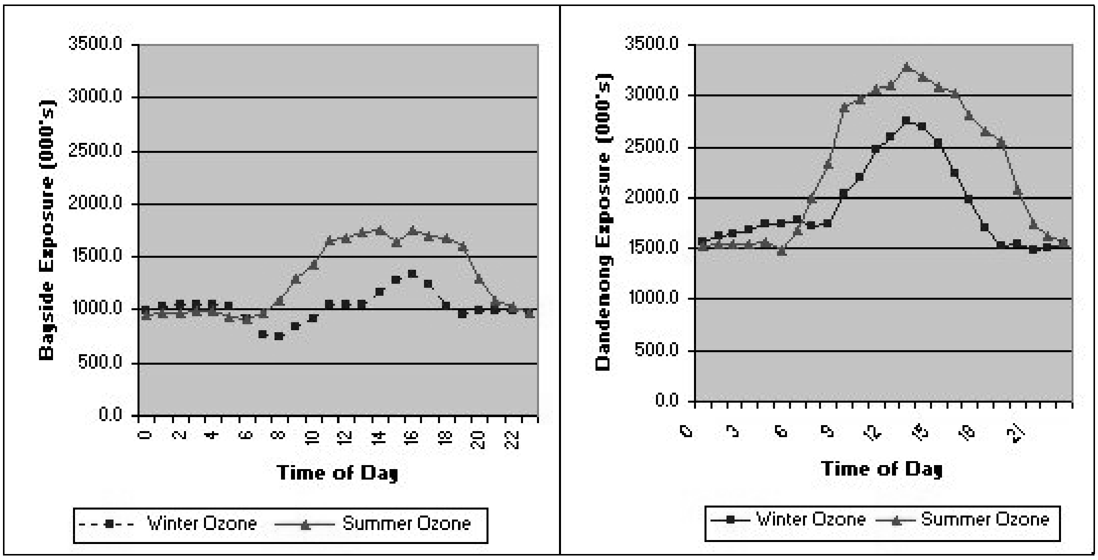

Figure 9. Seasonal ozone exposure for Bayside and Dandenong

Figure 9 gives a comparison of the seasonal exposure (in thousands of persons - parts per billion) to ozone of the hourly populations of Bayside and Dandenong. The trends are fairly similar although Dandenong exhibits significantly higher exposure levels at all times. This is due to the fact that Dandenong's period of increased population coincides with the period of highest ozone concentrations. Summer levels consistently exceed winter levels for much of the day.

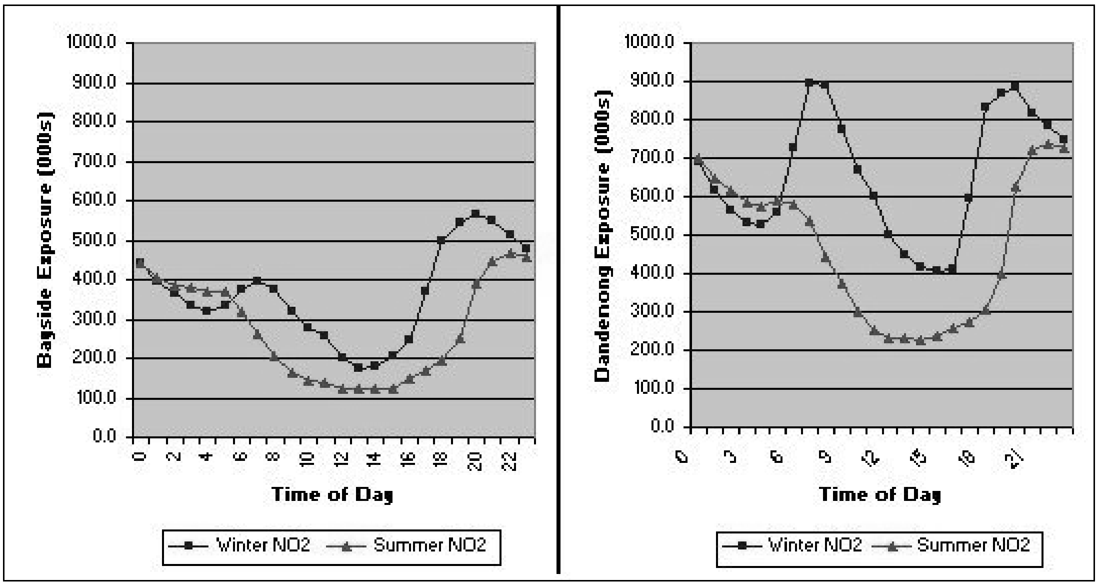

Figure 10. Seasonal NO_2 exposure for Bayside and Dandenong

In a similar fashion, Figure 10 provides a comparison of the seasonal hourly NO_2 exposure (in thousands of persons - parts per billion) in the two cities. Both cities exhibit troughs during the day following the pattern set by NO_2 in Figure 5. However, Bayside achieves its highest levels on winter evenings while Dandenong peaks on winter mornings. Bayside's minimum levels occur around noon while Dandenong bottoms out in the late afternoon. Winter values are considerably higher than their summer counterparts for much of the day.

So far, the full hourly population has been used in the computation of exposure. As noted earlier, the results overestimate the actual exposure levels since a large proportion of the population are actually indoors for most of the time. Bounds for the correct exposure levels can be obtained by using indoor/outdoor variation parameters based on recent studies. For ozone, these parameters have resulted in effective correction factors of 0.72 and 0.19. Applied to the accumulated daily exposure for Bayside of 24.5 (million persons – ppb) for winter and 31.1 for summer, the bounds are (3.3, 17.6) for winter and (4.2, 22.4) for summer. Figure 11 shows a comparison between the levels of estimated and adjusted daily exposure to ozone for the city of Bayside.

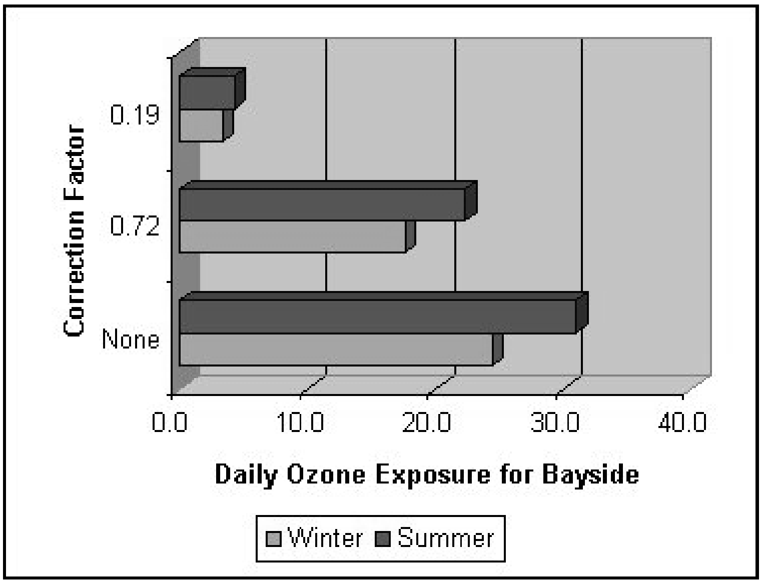

Figure 11. Adjusted ozone exposure for Bayside (millions of persons-ppb)

Figure 12 shows the daily ozone levels for Dandenong. The estimated daily exposure in winter is 46.0 (million persons – ppb) and 54.8 for summer. The correction factors produced bounds of (6.3, 33.1) for winter and (7.5, 39.5) for summer. As in the case of Bayside, the bounds produced need to be refined to be of greater use in policy assessment applications.

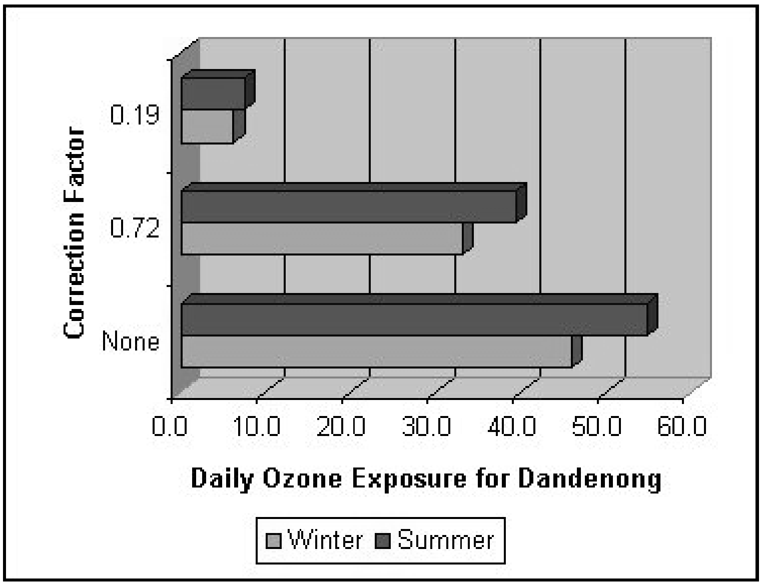

Figure 12. Adjusted ozone exposure for Dandenong (millions of persons-ppb)

4. Conclusion and future work

4.1 New findings

The results reported are early findings from a suite of models being built to link the activities of the population with urban air pollution due to emissions from mobile and stationary sources. In order to obtain accurate estimates of exposure for a dynamic population, the type, location and timing of the activities performed by the population need to be identified to determine the particular pollutants involved and the conditions of intake. A comparison of the temporal distribution of population between a residential/recreational area versus an industrial/commercial location showed that activities not only determine the generation and timing of trips but also the participants who are made most susceptible to the resulting emissions.

Seasonality then adds a new dimension by affecting the frequency and duration of activities and by changing the weather patterns which provide the mechanism for transforming the emissions into pollutants and for distributing pollution spatially and temporally. Thus, an activity-based model of travel demand supported by geographic and demographic data could provide guidance on issues such as periodic movement of population, indoor versus outdoor emissions, indoor versus outdoor exposure, and the health impacts of exposure on age, gender, and economic status.

Many of the results and techniques described in this paper require further refinement Additionally there are some fundamental research challenges in progressing the area. Recommendations for further research fall into two broad categories: extending the scope and accuracy of the work and demonstrating the value of the work.

4.2 Extending scope and accuracy

Dis-aggregation of the population data by activity by time would be needed to allow appropriate outdoor correction factors to be calibrated and applied. It will be important to also consider exposure of commuters while traveling. Variations due to seasonality could be expanded to distinguish monthly, weekday/weekend, and even daily variations in emission and exposure levels. However such extensions are challenging.

Micro-simulation techniques, which have been widely used to model traffic at the vehicle level, might be adopted to extend the estimation of exposure to individual-person level and this research could progress in that direction but all models can only be as good as the data underpinning them. There are difficulties in obtaining data at sufficient detail for this type of study from activity surveys, the usual source of activity data.

The problem of obtaining detailed information from surveys is not new but it is possible that new requirements for detailed activity over a wide area pose sampling problems that cannot be resolved. The sample size is dependent upon variation in behavior and when the range of possible activities and their location is expanded that variation calls for larger sample sizes. When the added requirements for place sensitive information, tied to days of week and months of year, is added, the sample becomes too large for practical collection of survey information, even if an unlimited budget was available. Study of sample error and sizing techniques will be helpful in better understanding the limitations of available information. At the same time new methods for obtaining activity data or augmenting survey information are needed. Tracking broad populations using information from telecommunications systems such as cell phones or payment systems has been mooted, see for instance Limoges et al. (2000), but significant difficulties in implementation, including issues of privacy, will need to be resolved. Meanwhile modeling of the type presented here could play an important role in pollution impact assessment.

4.3 Spatial and temporal modeling of exposure

Demonstrating the value of spatial and temporal modeling of population exposure is a more urgent research task than improving model accuracy. Simple results such as those derived in this study should be sufficient to show the value of measuring variability. While average exposure across the city, across the day, may be low, people in particular areas, at particular times, may be exposed to very high levels of pollution. Exposure based on place of residence underestimates impacts. Estimates using whereabouts during the day are higher because, on average, work locations are in more polluted areas.

Health threats due to pollution are known to vary with season. Health research studies incidence of illness in the population to assess pollution impacts. Measures of exposure levels may add value to these studies. Including consideration of exposure by season in epidemiological studies may help in targeting populations at risk.

Governments would like to predict the relative effectiveness of pollution amelioration measures to best target funding. Unfortunately this is much more difficult than measuring the effectiveness of greenhouse gas amelioration measures. GHG emissions have the same effect, no matter where in the city, or indeed where in the world, the source may be. In contrast pollution varies spatially as does exposure to pollution and the links of exposure to health outcomes are not yet completely understood. More accurate measures of exposure may help in establishing links.

It is hoped that this work will stimulate discussion among the travel modelers now charged with assessing the air pollution implications of travel demand management strategies.

Acknowledgements

This work has been supported by Executive Special Funding for the CSIRO Low Energy Vehicle Project and we are grateful for the support of our colleagues at CSIRO Atmospheric Research in this work. The study would not have been possible without assistance and data from the Transport Research Centre at RMIT.

References

BOM (1999a). Rainfall and Temperature Graphs. Australian Bureau of Meteorology, http://www.bom.gov.au/climate/forms/map_forms/imagemap.shtml, Accessed: 5 November 2001.

BOM (1999b). The Wind Across Australia. Australian Bureau of Meteorology, http://www.bom.gov.au/climate/averages/wind/wrselect.shtml, Accessed: 5 November 2001.

Duan, N. (1991). Stochastic microenvironment models for air pollution exposure. Journal of Exposure Analysis and Environmental Epidemiology. 1991 April, 1:235-257.

EPA (2000). Hazardous Air Pollution Human Exposure Models, US Environmental Protection Authority, http://www.epa.gov/asmdnerl/hazair.html, Accessed: 19 May 2000.

EPAV (1998a). Air Quality Management Plan. Environmental Protection Authority Victoria, Publication 608, June 1998, Melbourne, Australia, p.3.

EPAV (1998b). Air Emissions Inventory Port Phillip Region. Environmental Protection Authority Victoria, Publication 632, December 1998, Melbourne, Australia, p.38-39.

Ettema, D.F. and H.J.P. Timmermans (1997). "Theories and models of activity patterns" in Ettema and Timmermans H.J.P. (eds.), Activity-based Approaches to Travel Analysis, Oxford, Pergamon.

Freijer, J., H. Bloemen, S. de Loos, M. Marra, P. Rombout, G. Steentjes, and M. van Veen (1998). Modelling exposure of the Dutch population to air pollution. Journal of Hazardous Materials, Vol. 61, No. 1-3, Elsevier Science, pp. 107-114.

Fulton, P. (1984). "Estimating the daytime population with the urban transportation planning package". Transportation Research Record 981, TRB, National Research Council, Washington, D.C., pp. 25-27.

Isukapalli, S., V. Purushothaman and P.G. Georgopoulos (1999). Mechanistic Modeling of the Interrelationships Between Indoor/Outdoor Air Quality and Human Exposure in a GIS Framework, Proceedings of 92nd A&WMA Annual Meeting, June 20-24, 1999, St. Louis, MO, USA.

Jensen, Steen (1998). Mapping human exposure to traffic air pollution using GIS. Journal of Hazardous Materials, Vol. 61, No. 1-3, Elsevier Science, pp. 385-392.

Limoges, E., C. L. Purvis, C.L., Turner, S., M. Wigan and J. Wolf. (2000) Future of Urban Transportation Data. Millennium Papers of TRB A1D08: Committee on Urban Transportation Data and Information Systems, http://www.nationalacademies.org/trb/publications/millennium/00135.pdf. Accessed June 2000

Richardson, A.J., E.S. Ampt and A.H. Meyburg (1995). Survey Methods for Transport Planning, Melbourne, Eucalyptus Press.

Roddis, S.M. and Richardson A.J. (1998). Construction of daytime activity profiles from household travel survey data. Transportation Research Record 1625, TRB, National Research Council, Washington, D.C., pp.102-108.

Sexton, K. and P. Ryan (1988). Assessment of human exposure to air pollution: methods, measurements, and models, in A. Y. Watson, R. Bates, D. Kennedy (eds.) Air Pollution, the Automobile, and Public Health, National Academy Press, Washington, D.C., pp. 207-238.

Smith, N. (1997). Economics of Benefit and Cost, Supporting Report No. 6, Urban Air Pollution in Australia, An Inquiry by the Australian Academy of Technological Sciences and Engineering, http://www.ea.gov.au/atmosphere/airquality/urban-air/urban_air_docs.html, Accessed: 5 November 2001.

Stanners, David and P. Bourdeau (1995). Chapter 4: Air, in Europe's Environment: The Dobris Assessment, Copenhagen: European Environment Agency.

TRC (1997). The VATS Process, Transport Research Centre, RMIT University, Melbourne.

WHO (1987). Air quality guidelines for Europe, WHO Regional Publications, European Series No. 23, World Health Organization, Regional Office for Europe, Copenhagen.