Daytime Population Tracking for Planning and Pollution Exposure Assessment

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1 Introduction

The motivation for this paper is a realization by the transportation profession that to tackle many of the contemporary problems we face, we need to know where people are with increasingly fine temporal and spatial resolution (Roddis and Richardson, 1998). In our case, the original rationale was how to assess aircraft noise externalities in a way that accounts for the inter- and intra-day variability not just in flight movements, but where people are in relation to these movements (Greaves, Collins and Bhatia, 2006). The census is one potentially appealing option for such a problem (Fulton, 1984). However, this only captures journeys to work for a particular day, with the consequence that most travel in actuality goes unaccounted for.

A logical response to this problem is to take advantage of household travel survey data, which through some manipulation can provide a picture of how the population fluctuates across space and time (Roddis and Richardson, 1998). This approach is appealing because such surveys capture a range of trip purposes and in the case of Sydney, which has an ongoing continuous survey, can provide a relatively large sample if one is prepared to pool the data across years. In this paper, we provide a detailed account of how dynamic population levels were estimated for Sydney, using the Sydney Household Travel Survey. We focus on decisions that need to be made when replicating this methodology, as well as caveats that need to be considered when applying this to a variety of applications that are of some interest to the transport researcher. In addition to the aforementioned aircraft noise externalities, we examine methodological considerations for measuring the dynamic population exposure to air pollution (which in part stems from vehicle use). Also, we consider the implications of a dynamic population for disaster management and evacuation planning.

2 Method

In section 2.1, we outline some existing methodologies for measuring dynamic population. In section 2.2, we outline the steps performed to obtain dynamic population counts for Sydney. We also issue some caveats that need to be considered when replicating this methodology. In section 2.3, we consider the motivations for and risks associated with data segmentation.

2.1 Existing methodologies for measuring dynamic population

Fulton (1984) used census data to estimate daytime population for a census tract in Atlanta, Georgia. His methodology is limited to estimating maximum daytime population, and only counts non-working residential population and at-work population. He provides an extensive list of other trip attractions, but his methodology will not consider such trips.

Journey to work surveys, such as the Sydney Journey to Work Survey (TPDC, 1998), detail not just the location, but also the time of work. Consequently, they can be used to provide population estimates throughout the day, rather than just a maximum daytime population. However, they also fail to account for non-work activity patterns.

Roddis and Richardson (1998) aim to address these problems with a methodology that tracks population movement using a travel and activity survey. All survey participant records can be queried to see if the participant is located in an area of interest, at a specified time. If so, their population weight is added to a running total. The authors used the 1994 dataset of the Victorian Activity and Travel Survey (VATS), which sampled approximately 7200 valid households. Since the survey contained exact trip start and end times, it was possible to obtain unique population counts for any time of the day, a significant improvement on maximum daytime population. The survey was not restricted to home and work population, and so captured population movement regardless of the journey purpose. This dynamic population technique provides a holistic approach to measuring population. One of its key strengths is its ability to identify and quantify dynamic population levels that result from non-work travel.

Marquez, Smith, Trinidad and Guo (2001) adopt the Roddis and Richardson method, and also use the VATS dataset. Their use of dynamic population in estimating air pollution exposure in Melbourne is covered in more detail in section 3.3.1, along with several other existing methods for obtaining dynamic population for use with air pollution exposure studies.

2.2 Dynamic population from the Sydney Household Travel Survey

In this paper, we adopt the Roddis and Richardson method, making use of the Sydney Household Travel Survey (SHTS), a one-day continuous travel diary survey of residents in the Sydney Greater Metropolitan Area. We used a five year pooled data set (1998 – 2002), which included 42,790 people who made a total of 179,887 trips across all seven days of the week. Each sample member has a weighting, called a person expansion factor, which is the number of people the sample member represents in the population. This factor is determined by considering age, gender, and home location.

Choosing the size of the zones in which to allocate the population is a difficult task. Smaller sample zones will contain fewer sample members at any point in time, and consequently the dynamic population counts extracted from the sample are more prone to sudden fluctuations that do not reflect true population movement. Larger sample zones will have smoother population variations, but this may come at the cost of capturing true population changes in subsets of the larger zone. Holding the size of the zone constant, smoother and more accurate estimates of population will be obtained at times of significant population inflow, as the sample size for the zone increases at this time. Consequently, dynamic population estimates will be more accurate for zones with high levels of population inflow, such as central business district (CBD) regions. Dynamic population estimates for small areas with significant net loss of population through the day may be unstable and inaccurate, and dynamic population estimates should be treated with caution at these times. A statistical analysis of this problem might involve producing sampling errors and confidence intervals. However, it remains an area of future research.

The SHTS location data is coded to both the statistical local area (SLA), and the smaller travel zone (TZ) area. We obtained population counts for TZs, of which there are 1110 in the Sydney Greater Metropolitan Area. The TZs have an average of 39 sampled residents, from an average residential population of 4653. Each TZ has an average of 159 trip starts spread across the day. All of these averages have significant variation. Given this, use of TZ populations must be treated with caution. However, for the applications in this paper, the use of TZs was deemed adequate. In Sydney, areas impacted by aircraft noise usually have good sampling rates. We examined the Sydney CBD in the context of emergency evacuation, and the dynamic population estimates of this region are strengthened by a large inflow of sample members. For other applications in Sydney, it may be necessary to aggregate TZ populations to the SLA level. Still, it is better to sample to a fine resolution, and aggregate up if necessary.

When developing the algorithm to extract the dynamic population levels, we first needed to decide on the best way to iterate over the data. One alternative was to iterate over the zones of interest (Roddis and Richardson, 1998). However, we found that the clearest and most efficient way to extract population for the *entire* study area was to iterate over every person in the dataset, querying their trips in turn. This structure can be observed in the algorithm found in Figure 1. The algorithm also needed to consider several special cases. Some trip records flowed over into the day after the survey day. All times were checked, and times outside the survey day were ignored. Some people made no trips during the day; these people were assigned to their home TZ for the entire day. We did not record people's location for any time spent outside of the study area. The SHTS data contains no information on the route the participants took during travel. A comprehensive approach would consider location while traveling, perhaps linking origin and destination using a direct line (Roddis, Richardson and McPherson, 1998), or a shortest path. For this study, we simply excluded traveling people from the dynamic population counts. Total travel mode usage of the population by time was recorded, but the results will not be reported here.

The SHTS data was originally stored in an SPSS file format. We transferred the relevant tables and fields to the Microsoft Access relational database. By so doing, we were able to easily query the data from a Visual Basic for Applications script. The script contained the data extraction logic. The results were tabulated in a Microsoft Excel spreadsheet.

Listed below is the small subset of available SHTS tables and fields that were used in this study.

Person table

- Household identifier
- Person identifier
- Day of week of survey
- Person expansion factor
- Day adjustment factor

Trip table

- Person identifier
- Stop identifier (trip number)
- Origin travel zone
- Destination travel zone
- Departure time
- Arrival time
- Travel mode (vehicle driver, vehicle passenger, train, bus, ferry, taxi, walking, bicycle, other)

```
Method Assign All People
For each person:
      exp_factor = person expansion factor
      If (no trips):
            Call Assign (start of day time, end of day time, home location,
            exp_factor)
      Else:
            visit_start_time = beginning of day
            For each trip:
                  visit_location = trip origin travel zone
                  visit_end_time = trip departure time
                  If (visit_location falls in study area)
                        Call    Assign    (visit_start_time,    visit_end_time,
                        visit_location, exp_factor)
                  visit_start_time = trip arrival time
                  visit_location = trip destination travel zone
            If (visit_start_time < end of day time)
                  Call Assign (visit_start_time, end of day time, visit_location,
                  exp_factor)

Method Assign (start_time, end_time, location, expansion_factor)
      For each time point t to sample between start_time and end_time:
            If (t falls in the time bounds of the day)
                  Add expansion_factor to the count for time t and location
```

Figure 1 Simplified algorithm for extracting dynamic population

The following is a description of the algorithm used, and compliments Figure 1. Every person identifier is considered in turn. A query is run on the database to extract all trips made by the current person. If no trips were made, then the person's expansion factor is allocated for the entire day. Otherwise, information on the first trip is extracted from the database. The origin of the first trip is used to find the person's location at the start of the survey day, which is not necessarily at home. The complete expansion factor is then assigned to this location, for the time period spanning the start of the survey day and the start of the first trip. The next trip is extracted, and the time between the trips is assigned to the appropriate TZ (the destination of the previous trip, which equals the origin of the current trip). If a person travels outside the study area at any point, no allocation is made for the location to which they travel. This process is continued for all remaining trips. If the final trip ended after the end of the study day, the assignment is only made up until the end of the day. Alternatively, the complete expansion factor is assigned to the final trip destination TZ, for the time spanning from the end of this last trip until the end of the study day.

2.3 Issues of segmentation and filtering

We anticipated that population movement would be significantly different for weekdays and weekends. To test this, we reran the procedure twice, first selecting only those survey respondents who completed the survey on a weekday, and then selecting respondents who completed the survey on a weekend day. The population weight for each respondent had to account for the increased contribution of the respondent to the overall population. So the expansion factor of a weekend participant was multiplied by 7/2, and that of a weekday participant by 7/5. This segmentation of the data on a weekday/weekend divide confirmed that there are significant differences in population levels between the two periods. Weekdays are dominated by conventional business hour work patterns. Weekends see less drastic differences between static and dynamic population levels. These differences have important ramifications for any application that uses the data. Failure to use the correct segment will create misleading population levels.

The problem with segmentation was the effect it had on sample size. Since weekends only used two sevenths of the complete data, with approximately 12200 people and 51400 trips in the SHTS, the changes in population level were much coarser, and there was more error in the estimates. Great care must be taken when using weekend population estimates. Use of more than 5 years of survey data, as it becomes available, would increase the sample size of weekends and help alleviate this problem. However, it is debatable whether survey results can be pooled over a much longer time period, as travel behavior may change over this time. A costly alternative would be to sample disproportionately on weekends. For an example of segmenting the data by season, see Marquez et al (2001).

Similar to segmentation of the data is filtering of the results. Whereas segmentation only considers a subset of survey participants, filtering considers all respondents, but for every time and place, generates more than one population count based on some criteria. For example, Roddis and Richardson (1998) filter their results by trip purpose, such as work, education and shopping. Their approach is aided by their use of large aggregation zones. Our attempt to draw a distinction between residents and visitors had limited success due to our use of relatively small TZs. The most stable estimates were for those times and places that experience significant daytime population growth, such as business hours in the CBD.

3 Results

3.1 Differences between dynamic and static population

Figures 2, 3 and 4 compare the dynamic and static population of Sydney at three key times of the weekday. Maximum work participation occurs at 11am. 4pm lies outside of school hours. 8pm sees an extensive population return to residential locations, but also captures such behavior as long work hours and evening recreational trips. The maps show what we refer to as percentage shift. This figure is calculated by dividing the dynamic population by the static population, and expressing the result as a percentage. Hence a percentage shift of 50 indicates that the dynamic population is half the static population; 100 indicates that the two are equal; and 200 indicates that the dynamic population is twice the static population. This measure is a useful way of quickly grasping whether an area's dynamic population is less or greater than the static population, and the magnitude of this difference.

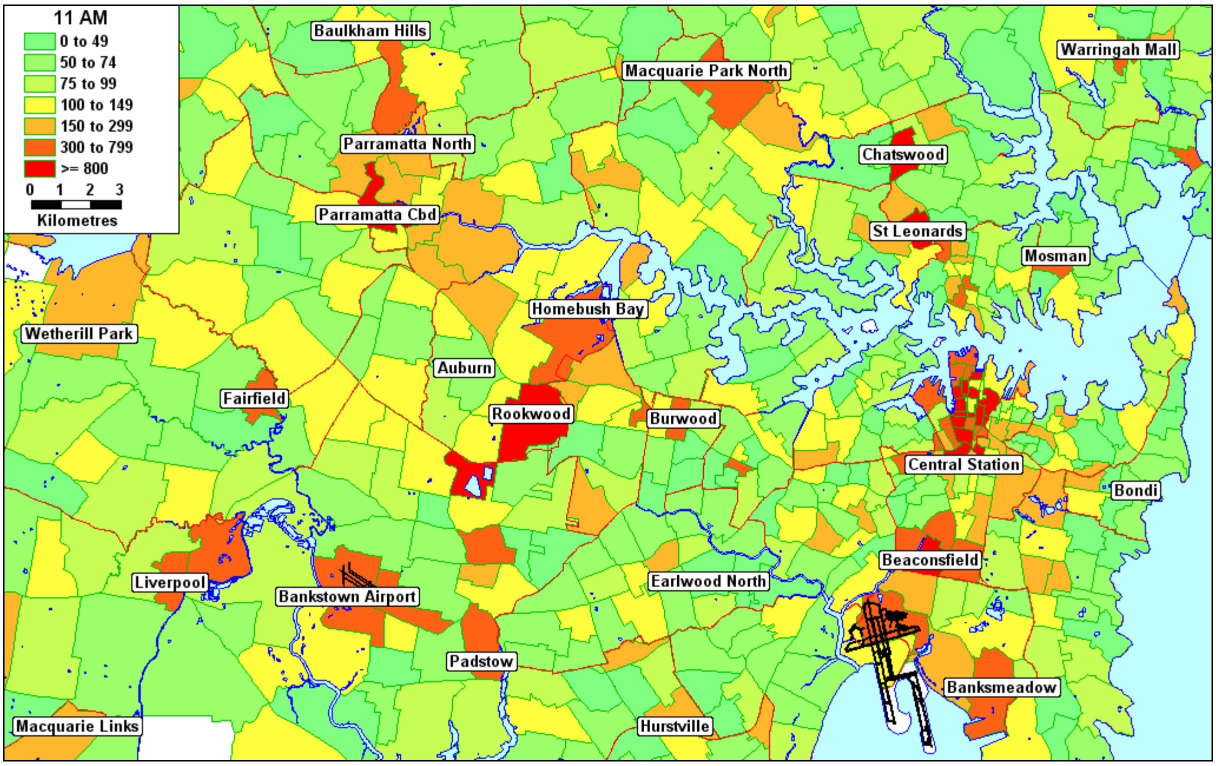

Figure 2 Sydney weekday, 11am. Dynamic population as a percentage of static population

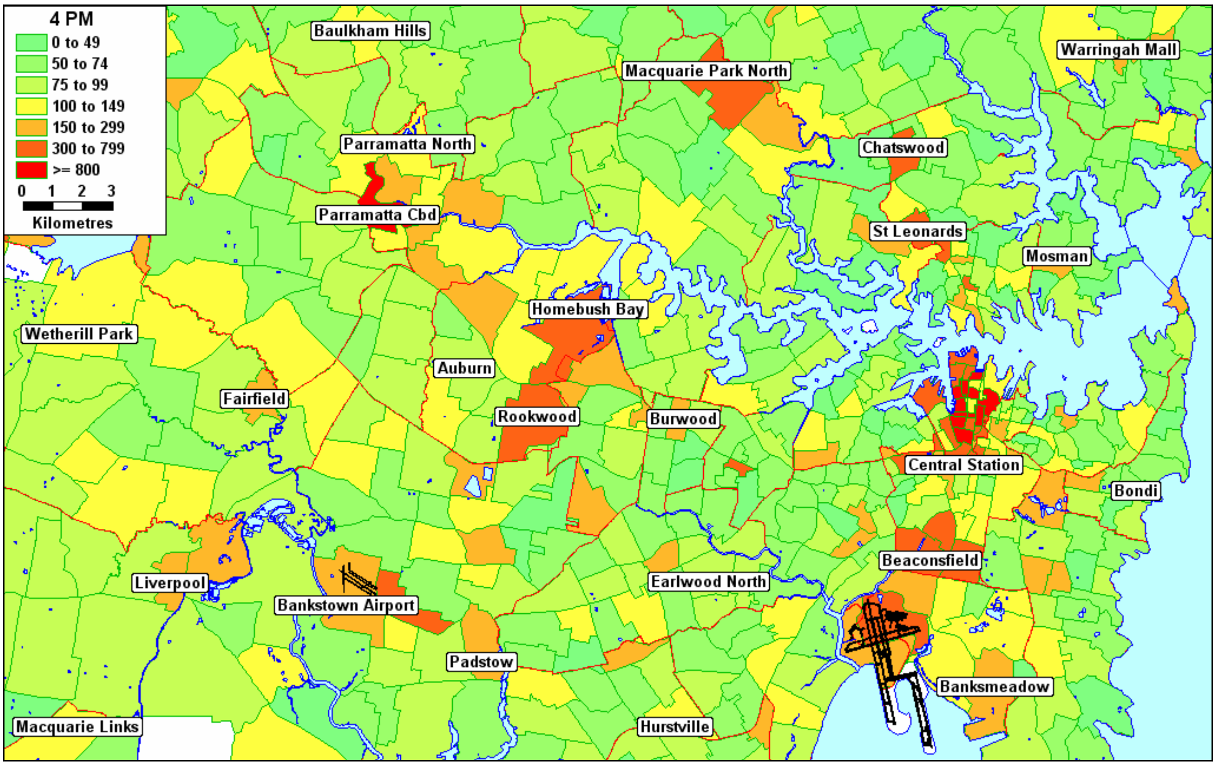

Figure 3 Sydney weekday, 4pm. Dynamic population as a percentage of static population

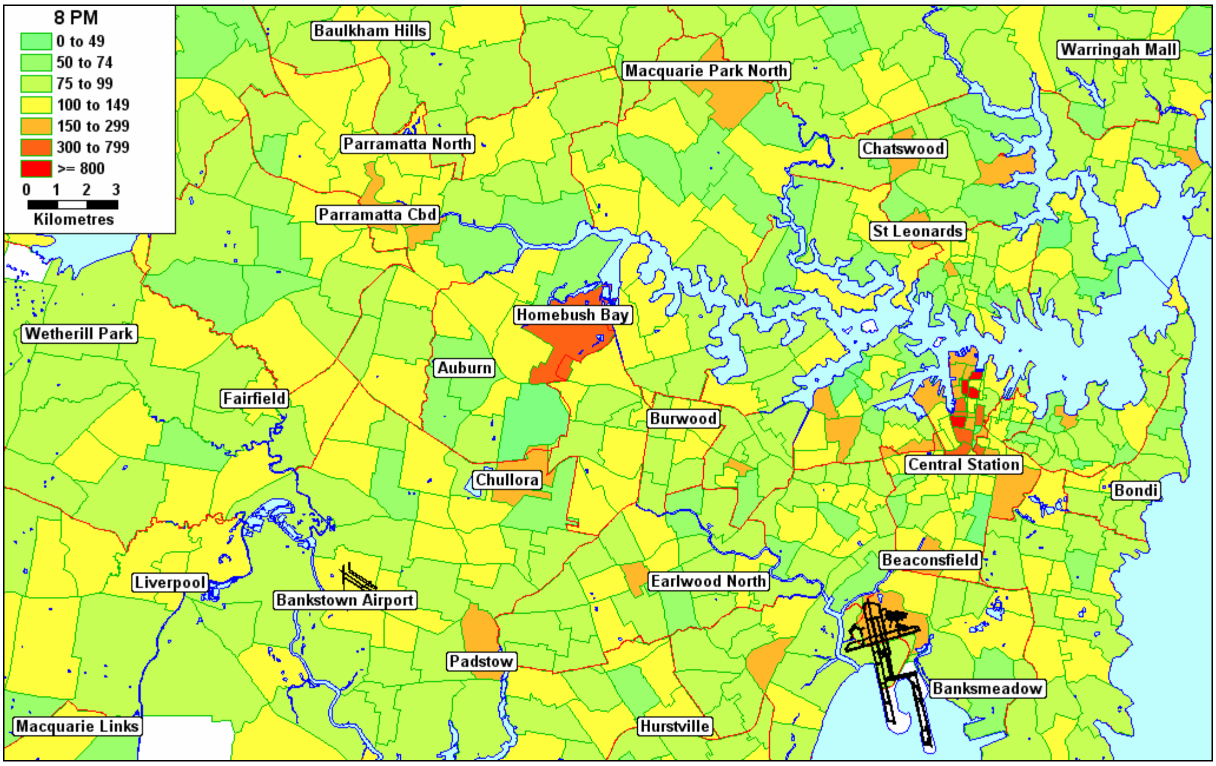

Figure 4 **Sydney weekday, 8pm. Dynamic population as a percentage of static population**

An obvious pattern is a dramatic daytime increase in population in the CBD (north of central station) and regional business districts, such as Parramatta and Chatswood. These increases are partially maintained in the evening. Other regional centres, such as Liverpool and Fairfield, have significant daytime increases that do not extend into the evening. Overall, Sydney contains a number of regions that experience significant population growth in the daytime, while vast regions in between experience a net loss of population at this time.

Figure 5 identifies the distribution of percentage shifts at 11am, 4pm and 8pm, across the 1110 travels zones in the Sydney region. At 11am, 47% of these zones have a dynamic population that is less than 75% of the static population. These zones see significant net population loss, as people move elsewhere for work. 17% of zones have a dynamic population that is at least one and a half times the static population. At 8pm, by which time many people have returned home, far fewer zones see such extreme differences between dynamic and static population. Only 15% of zones have a percentage shift of less than 75%, down from 47%. Further, only 6.5% of zones have a percentage shift of 150% or more, down from 17%.

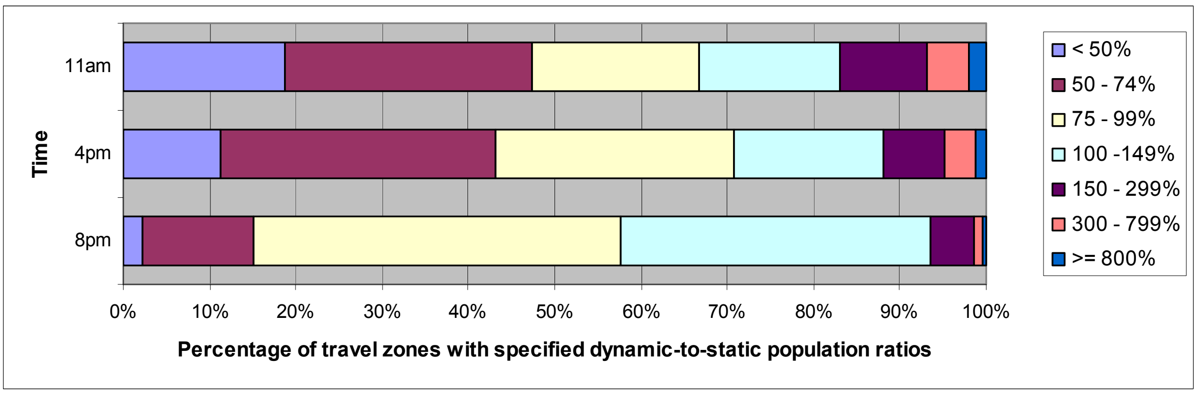

Figure 5 Shares of dynamic to static population ratios

3.2 Disaster management and evacuation planning

Dynamic population counts are useful for disaster management and evacuation planning. Large scale terrorist attacks on highly populated areas have become a great concern in recent years, although natural disasters such as hurricanes and flooding are still the most common triggers for large scale evacuation. Simulation methods have been developed to assess various evacuation plans. For a good overview of the various methods, see Pidd, de Silva and Eglese (1996). Crucial inputs into the simulations include the capacity of the evacuation routes, behavioural decisions such as when to evacuate, and the location and counts of the population that need to evacuate. Pidd, de Silva, and Eglese (1996) have developed a spatial decision support system for emergency situations. They specifically require a "distribution of the population *at the time of the incident*" (p.415, our italics). The simulation outputs are highly dependent on quality inputs. If a static, residential population is used for the simulation, then the results will only be applicable if the disaster occurs late at night. Dynamic population counts and numerous simulation runs are required to obtain results that can be applied at all times of the day.

A city's central business district (CBD) is a unique disaster risk area that requires careful consideration. Large numbers of people move into the area for work and recreation, making residential population figures particularly unsuitable for planning or as simulation inputs. The high concentration of people makes the CBD an ideal terrorist target area, as witnessed by the attacks on the World Trade Center in New York in 2001. Further, CBD area transport systems typically struggle to cope with peak demand that spans many hours, as witnessed by heavy traffic congestion and at-capacity peak hour public transport services. Church and Cova (2000) propose a useful methodology for identifying the level of evacuation risk for a given area. In high risk areas, demand significantly exceeds capacity. However, their approach uses residential population. Use of dynamic population levels would make their methodology more accurate in areas such as central business districts, and hence more generalisable.

Approximately three kilometers by one kilometer in size, the Sydney CBD area is dominated by many high rise buildings, and sees a significant inflow of visitors during the day. Figure 6 shows the weekday population of several travel zones representative of all those in the Sydney CBD area. The Martin Place travel zone contains many office buildings, and so its population grows significantly, peaking by late morning. Noteworthy is a population growth that starts slightly earlier than other zones, possibly reflective of typical corporate working hours. The World Square travel zone has a similar pattern, except with a larger residential population. The small Queen Victoria Building (QVB) travel zone is filled mostly with shops. This appears to be consistent with the data, with high population levels confined largely to the nine to five shopping hours. A population peak in lunch hours, instead of late morning, suggests that people are shopping in their lunch break. The China Town zone has a similar daytime population profile to the QVB zone, likely reflecting its retail composition. However, China Town retains much of its population levels into the evening, perhaps due to its entertainment and dining options.

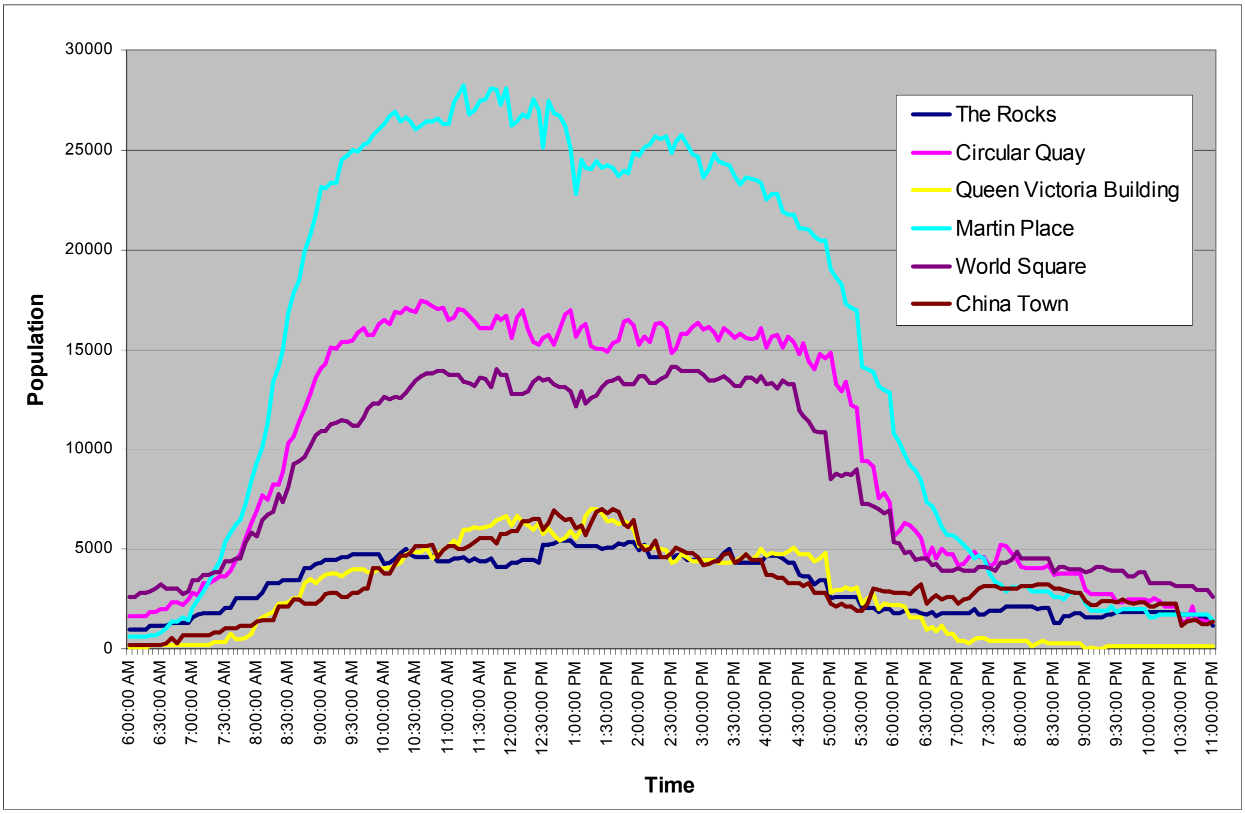

Figure 6 Selected Sydney central business district weekday populations

So, instead of running a single evacuation simulation, planners could run numerous simulations using dynamic population figures from several times in the day. Given the population patterns described above, three likely weekday scenarios would be the overnight population (4am), the highest daytime population (11am), and an evening population dominated by residents and those pursuing recreation (8pm). Weekend populations are likely to be very different again.

The NSW government has produced a simple evacuation map for the Sydney CBD (emergencyNSW, 2006). Producing different maps for different times of day is likely to only confuse potential evacuees. However, knowledge of varying population compositions, and consequent simulation outcomes, might arm emergency personnel with information that would facilitate a better evacuation. People could be directed by marshals along routes that differ according to population levels at the time of the emergency. A shortest path route adequate for nighttime populations might not be optimal for peak, weekday populations. The actual simulation of evacuations using dynamic populations is an area for future research. This paper merely offers motivation and outlines methodology for obtaining better simulation inputs.

3.3 Pollution exposure

A powerful application of the dynamic population methodology is the estimation of population exposure to various pollutants. The basic approach entails measuring or modeling the pollutant level for a defined time period across a wide area, usually on a grid. We shall refer to these levels as the pollution dataset. A population dataset is also required. The population and pollutant levels for each grid point are multiplied, and these products are summed to obtain a total, area wide exposure for the defined period. These results can be run repeatedly over a longer time span, such as a day, and again summed to obtain a total exposure for the time span. Traditional approaches have relied on largely static populations.

More recently, increasing recognition has been given to the importance of using dynamic population figures (Kousa, Kukkonen, Karppinen, Aarnio, and Koskentalo, 2002; Marquez et al., 2001; Freijer, Bloemen, de Loos, Marra, Rombout, Steentjes and van Veen, 1998; Jensen, 1998).

This section reviews several air pollution exposure studies that use some form of dynamic population, paying particular attention to some methodological considerations that are relevant to all types of exposure studies. It then reviews these considerations in the context of aircraft noise, outlines a methodology that we have developed and presents some brief results.

3.3.1 Air pollution

Most exposure studies that have used dynamic population consider exposure to various air pollutants. Kousa et al. (2002) note that air pollution levels can change by orders of magnitude over distances from tens to hundreds of meters. This variability in pollution levels raises some important considerations for all forms of pollution exposure. These considerations are broadly concerned with the spatial and temporal resolution of both the population and pollution datasets. Spatial resolution is the physical distance between spatially adjacent data points, which usually form a grid. Temporal resolution is the amount of time between consecutive time points in a time series dataset.

For each dataset:

1. Does the dataset have sufficient resolution to adequately reflect real life? Or alternatively, is important variation being lost or averaged between the adjacent data points?
2. Can the desired resolution be calculated with the data and models available?

Then, when combining the population and pollution datasets:

3. To what extent do differences in the resolution of the two datasets, if any, introduce errors into the exposure calculation?

These issues of dataset resolution are resolved variously across several air pollution exposure studies. For example, Jensen (1998) utilizes a street canyon dispersion model. This highly detailed model requires data such as building height, making it ill suited to studies over a wide area. Kousa et al. (2002) use variable grid intervals ranging from 50 to 500 meters when computing pollution levels. By increasing the resolution only near significant pollution emitters, they are able to model the entire Helsinki metropolitan area.

Kousa et al. (2002) model population exposure to nitrogen dioxide exposure, and provide an alternative approach to counting dynamic population. They obtain residential and workplace coordinates, along with the number of people living and working at these locations. Using survey results, they obtain locations of recreational and other activities, and the numbers of people potentially involved. Another survey was used to determine, for all times of the day, the percentages of the population engaged in work, travel, other activites, or located at home. These percentages were then used to weight maximum work, home, and other activity populations for each time point across the day. Their use of precise work and home locations generates a population dataset with high resolution. However, their use of aggregate level time use data can not account for many complex behavioral patterns and trip chains. Further, their approach requires many separate datasets.

Marquez et al. (2001) measure population exposure to nitrous dioxide and ozone in Melbourne. They obtain population levels using the technique established by Roddis and Richardson (1998), as we have done in this paper. Marquez et al. used the larger local government area to produce population distributions that change more smoothly over time.

Noting the differences in pollution model outputs between seasons, they segregated the population data by season, and matched the datasets accordingly.

Locating the population in broad areas only partly determines the level of exposure they might experience. The exact environment in which people are located, known as the microenvironment, will also influence the level of exposure. People spend most of their time indoors, where the pollution may be less. A common approach is to multiply the exposure levels by indoor-outdoor ratios (Marquez et al., 2001; Freijer et al., 1998; Jensen, 1998). Two parameters are required: the likelihood of being indoors, and the percentage of the outdoor pollution level that is experienced indoors.

3.3.2 Aircraft noise pollution

While researchers have begun to measure dynamic population exposure to air pollution, aircraft noise exposure studies have continued to use static population values (Franssen, Staatsen, and Lebret, 2002; Moreno-Jimenez and Hodgart, 2003). The authors of this paper have used the dynamic populations calculated here to generate more realistic exposure levels. For full results, the reader is referred to Greaves, Collins and Bhatia (2006). What follows is an overview of the methodology, and a focus on the issues of dataset resolution and microenvironments.

Unlike air pollution, which is measured as concentrations of a noxious gases or particulates that vary continuously over time, aircraft noise pollution is episodic in nature. The most meaningful way of reporting and measuring aircraft noise is to count the number of noise events that exceed a particular threshold. A commonly chosen threshold is 70 db(A), as this equates to 60 db(A) inside a house with open windows, which is the sound at which noise will interfere with conversations and watching television. An aircraft noise event that exceeds 70 db(A) is often referred to as an N70 event. The Transparent Noise Information Package (TNIP) is a powerful software package developed by the Department of Transport and Regional Services in Australia. Using outputs from an airport-specific configuration of the Integrated Noise Model (INM), and a flight arrival and departure database, TNIP can estimate the number of N70 events in each hour of a *real* day, for all affected areas around the airport.

We selected a number of real days of flight movements at Sydney's Kingsford Smith International Airport, and generated a grid of N70 values for each hour outside of the curfew period. Average dynamic populations were calculated for each hour, and transformed from an area layer to the same grid points for which we obtained the N70 values. As discussed in section 2.3, significant differences were found between weekday and weekend travel patterns. Thus, we established two separate population datasets, and used the correct one depending on the day in question. The population and N70 values were multiplied for each grid point, and summed across each grid point and hour of the day. The number thus generated represents the total citywide noise impact of that day. Each unit value represents a single N70 event affecting a single person, and so the index is called a person-event index, or PEI (DOTARS, 2000). The PEI could be restricted to movements at certain times of the day (temporally), or in specific locations (spatially). It was found that use of a static population frequently underestimated the true impact of aircraft noise on a dynamic population. Many areas affected by aircraft noise also have high daytime populations.

Modeled air pollution levels change relatively slowly and smoothly over time, and so air pollution datasets do not need high temporal resolution. The episodic nature of aircraft movements and the ability to rapidly change flight paths mean that flight operations and noise footprints could change dramatically from one hour to the next. Consequently, aircraft noise datasets need high temporal resolution to accurately model real life. That is, the datasets must contain exposure levels for many time points throughout the day. They are best coupled with a population dataset that similarly has many sample points throughout the day, such as ours, which can produce unique populations every five minutes. Our approach did not have an exact temporal match of the datasets. We could obtain N70 counts no more frequently than every hour. This was due to a limitation in an algorithm in TNIP. Further work here could see a move to the generation of N70 grids for every flight. Every flight's noise footprint could then be matched with an exact population at the time of the flight, instead of an average hourly population.

It is worth noting that the noise footprint from a single aircraft movement is much more predictable than air pollution impacts. Air pollution has many sources, is impacted significantly by weather conditions, and different pollutants might interact with each other to alter pollution levels. However, for aircraft noise pollution, usually only one aircraft's noise dispersion needs to be considered, for a fixed time and place. Figure 7 shows the noise footprint from a typical flight. It demonstrates how aircraft noise is localized within a corridor, and rapidly and predictably deteriorates with increased perpendicular distance from the flight path. Referring to the points listed earlier about dataset resolution, this predictability of noise dispersion means that in our noise dataset, we are not missing important variation between our data points. Further, the model allows us to calculate down to a relatively fine resolution, about 370 meters, which could be reduced if we were willing to increase the model run time.

A consequence of the highly localized nature of aircraft noise is that, for each single noise episode, there is significant exposure variation within each area for which we have a unique dynamic population. That is, one travel zone area has a single population, and yet various members of this population will receive quite different noise exposures. For this study, we have assumed that the population is spread evenly across the travel zone. Obviously this is a simplification of real life; a compromise due to data limitations. If there was no significant variation in pollution levels across a travel zone, then the assumption of even population distribution would have minimal impact on the exposure calculation. Conversely, significant intra travel zone pollution level variation coupled with a uniform population distribution could lead to inaccurate exposure calculations. The aircraft noise footprint could fall on near empty parkland and have minimum impact, or pass over medium density housing and have a large impact. The challenge then is to find a way to improve the spatial resolution of the population dataset.

Travel zones were the smallest area that the survey sample permitted. A larger sample might facilitate smaller areas, yet an order of magnitude improvement in spatial accuracy is unlikely. An alternative is to use land use data to weight the allocations of travel zone population to the grid points within the zone. Precise building locations allow building density to be calculated. Population could be assigned to grid points within the travel zone according to the building density in the area that the grid point covers.

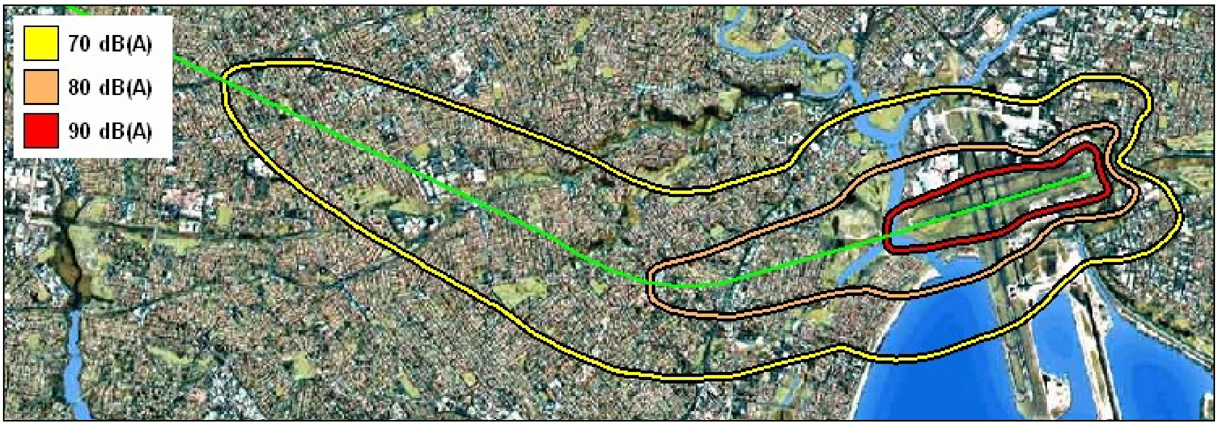

Figure 7 Noise footprint of a departing 767-300

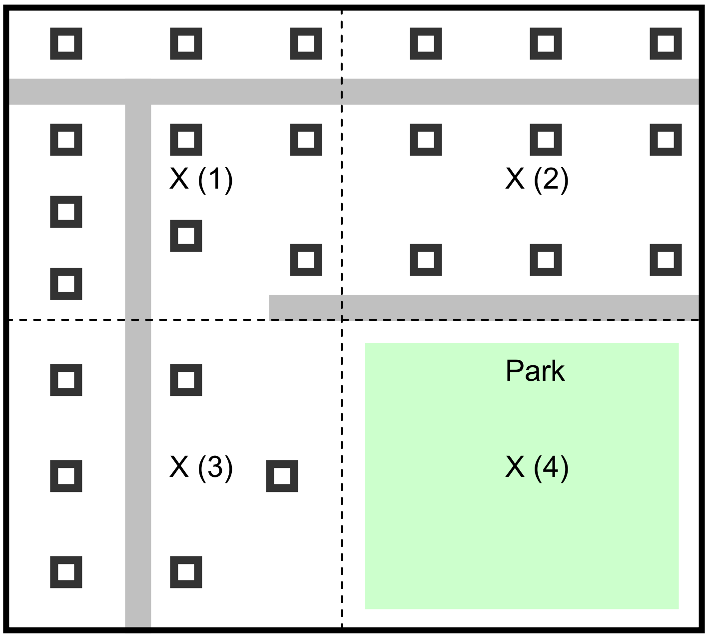

Figure 8 Example travel zone, with building locations used for weighting

Table 1 Unweighted and weighted population of an example travel zone

Travel zone population = 100			
Grid ID	**Unweighted population**	**# dwellings**	**Weighted population**
1	25	10	40
2	25	9	36
3	25	6	24
4	25	0	0
	100	25	100

Figure 8 demonstrates a simple example. It represents a small, hypothetical travel zone of population 100. Each of the four grid points, marked with an X, would receive an unweighted population of 25. Buildings are represented by a hollow square. Table 1 counts the number of dwellings in each area covered by a population grid point. It is assumed that each dwelling will contain the same number of people. The weighted population for each grid point is then simply the number of (dynamically allocated) people per dwelling multiplied by the number of dwellings.

More complex approaches might vary the weights based on trip purpose or time of day. However, this is an area for future research.

As with air pollution exposure, microenvironments will have an impact on aircraft noise pollution exposure. The N70 measure accounts for indoor exposure insofar as it equates to 60 db(A) inside a house with open windows, which is the level at which noise will interfere with conversations. This is only one possible microenvironment. Even in areas with high levels of aircraft noise, buildings and cars will often absorb enough energy to reduce the noise to an acceptable level.

Our methodology does not model the impact of microenvironments; this is an area for future research. We anticipate that a variety of indoor-outdoor ratios would be applied to the population figures. These would almost certainly consider activity type, such as work, home, travel by car (indoors) and travel by walking (outdoors). Time and season of the noise event would plausibly affect the indoor-outdoor ratio. For example, people are more likely to be spending recreation time outdoors during a summer day than a winter night. Land use is also important. For example, skyscrapers are likely to shield the majority of occupants from even very loud noise events. A greater focus on microenvironments requires more emphasis to be placed on the people who are tracked, rather than just the locations at which the exposure takes place. Instead of calculating population exposure over a period of time at a specific location, each sample individual's total daily exposure should be calculated, taking into account exposure within their various microenvironments. A distribution of personal exposures can then be reported for the entire population.

4 Conclusion

Using the Sydney Household Travel Survey as an example, this paper has outlined in detail how an activity and travel survey can be used to obtain dynamic population counts.
It also catalogs a number of important considerations, and some caveats. Chief among these is the importance of careful consideration of the size of population aggregation zones, and the amount of sample available. A full statistical analysis of this problem remains an important area of future research. Weekend and weekday segmentation is important in most scenarios.

Sydney's population levels are highly dynamic throughout the day. Even bordering zones can exhibit markedly different population dynamics. This could play an important role in evacuation planning, with dynamic population levels providing inputs to a series of evacuation simulations, possibly creating a range of evacuation management plans. Running such a simulation remains an area for future research.

Measuring dynamic population exposure to pollution is an important application of dynamic population data. We have outlined several air pollution studies, and detailed our methodology for aircraft noise pollution. Any pollution exposure studies require careful consideration of the spatial and temporal resolutions of both the population and pollution datasets. Differences in resolution between the two are not desirable, but need to be explicitly considered. For example, the spatial resolution of our dynamic population counts did not exactly match that of our noise modeling outputs. We accept that this will introduce some error, and see the weighting of intra travel zone population using land use data as a possible solution, and area of future research. A further area for future research is incorporating the role of microenvironments into the noise exposure modeling procedure.

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