Urban Structure and Transport – Melbourne case study

Marzieh Reisi¹, Lu Aye, Abbas Rajabifard, Tuan Ngo

¹ PhD student, Department of Infrastructure Engineering, University of Melbourne, Australia. Email: marziehr@student.unimelb.edu.au

Abstract

Studies about relationship between urban form and travel are generally at household level. Australian Bureau of Statistics (ABS) and Victorian Integrated Survey of Travel and Activity (VISTA) data at statistical local area (SLA) level for Melbourne, Australia were used to estimate greenhouse gas emissions from personal transport. An integrated model which consists of three sub-models (car ownership, vehicle km travel, mode share) has been proposed in this paper. The model suggests that population density, distance from central business district (CBD) and dwelling types are influencing factors for urban structure measurement and can be used for estimating energy consumption and greenhouse gas emissions. It was found that the model developed is not complex enough for considering the relationship between urban form and personal travel.

Key Words: Urban structure, Land use, Transport

1. Introduction

Interests in the effect of land use on transport energy date back to 1970s with Newman and Kenworthy as pioneer researchers in this topic from 1980s [1]. Considering the effect of land use on transport can help policy makers to identify new strategies for urban development that reduce car dependency and good accessibility to facilities [2].
There are two theories about the effect of urban form on transport. The first one is the Compact City theory which claims that compact city results in least energy-intensive pattern, low energy use for travel and proximity to workplace, public and private services and public transport services. On the other hand, the Dispersed City theory believes that density increases congestion and reduce environmental quality [3].

Population density is the most common factor of land use which is used in transport studies [4, 5]. Some researchers argue that the relationship between land use and transport is so complex that factors such as population density alone is not good enough for estimating transport volume. But on the other hand, in some other studies population or activity density is a good prime factor for showing lower automobile ownership and use [4]. Distance from CBD and dwelling types are among other land use planning factors that have significant effects on transport volume [2, 7, 8].

Although there are several studies that show the relationship between land use planning and transport, some studies reject and argue that travel preference, socioeconomic factors, engine technology, taxes on driving and fuel, road price are more influential than urban planning in energy consumption reduction [2].

The main aim of this study is developing a model which can estimate transport greenhouse gas emissions in Melbourne, Australia. The model provides good insights about influencing factors such as urban form and socio economics aspects.

2. Research Methodology

For the development of the model, VISTA 07 and ABS 2006 data at the SLA level for Melbourne (Figure 1) were used. The data sets used are population density, household’s annual income, percentage of different dwelling types and percentage of different household types. There are 76 SLAs in Melbourne metropolitan area and SLA level is selected because it has comprehensive spatial coverage across Melbourne.
Car ownership, vehicle km travel (VKT) and transport mode share are all factors that influence transport demand. They, themselves, can be affected by land use and socio economic factors. The model proposed in this paper, includes three sub-models: car ownership, VKT and transport mode share. These sub-models were integrated for estimating transport greenhouse gas emissions.

**- Car ownership model**
Vehicle ownership has been considered as an explanatory variable in travel demand systems [7, 9]. The model is shown in Equation 1.

\[
 cph = b_1 + m_1 x_1 + m_2 x_2 + m_3 x_3 + m_4 x_4 
\]

\[ b_1 = \text{constant} \]
\[ m = \text{coefficient} \]
\[ x = \text{independent variables} \]

The dependent variable in this sub-model was number of cars per household \((cph)\). Selected independent variables for this model were population density \((x_1, \text{people/ha})\), household annual income \((x_2, \$/\text{annum})\), proportion of detached house compare to other dwelling types \((x_3, -)\), proportion of couple with children compare to other household types \((x_4, -)\). Other dwelling types are semi detached house and flat. Other household
types are couple without children, single parent families, and other families. Most of available models consider the effect of population density and distance from CBD at the same time [8, 9, 10]. Because of high correlation between these two factors, one of them was used in the car ownership model and the other was used in VKT model. By this way, co linearity problem was avoided and the both factors were included in the integrated model. Multiple regression analysis was used to consider effective factors on the car ownership. The linear regression coefficients found for the car ownership model are shown in Table 1. The significant level of 0.05 means the independent variables can explain the variation in the dependant variable.

Table 1. car ownership model (All factor are significant at 0.05 level)

<table>
<thead>
<tr>
<th>Factor</th>
<th>Coefficient</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>$b_1 = 0.707$</td>
<td>0.380</td>
</tr>
<tr>
<td>Population density</td>
<td>$m_1 = -0.381$</td>
<td></td>
</tr>
<tr>
<td>Household annual income</td>
<td>$m_2 = 0.219$</td>
<td></td>
</tr>
<tr>
<td>Proportion of house compared to other dwelling types</td>
<td>$m_3 = -0.315$</td>
<td></td>
</tr>
<tr>
<td>Proportion of couple with children compared to other household types</td>
<td>$m_4 = 0.392$</td>
<td></td>
</tr>
</tbody>
</table>

- **Household VKT model**
The VKT model is shown in Equation 2.

$$\nu_k = b_2 + m_3x_3 + m_6x_6 + m_7x_7 + m_8cph$$

- $b_2 =$ constant
- $m =$ coefficient
- $x =$ independent variables

Linear regression was used for estimating daily household travel by car. The total vehicle km travel ($\nu_k$) is used as dependant and the distance from CBD ($x_5$, km), household annual income ($x_2$, $$/annum), proportion of couple with children compared to other household types ($x_4$. Couples with
children, couple without children, one parent families, other families ) and number of car per household (cph) as independent variables. The linear regression coefficients found are shown in Table 2.

Table 2. VKT model (All factors are significant at 0.05 level)

<table>
<thead>
<tr>
<th>Factor</th>
<th>Coefficient</th>
<th>R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>$b_2 = 0.938$</td>
<td>0.439</td>
</tr>
<tr>
<td>Distance from CBD(Km)</td>
<td>$m_5 = 0.344$</td>
<td></td>
</tr>
<tr>
<td>Household annual income</td>
<td>$m_6 = 0.123$</td>
<td></td>
</tr>
<tr>
<td>Proportion of couple with children compare to other household types</td>
<td>$m_7 = 0.096$</td>
<td></td>
</tr>
<tr>
<td>Number of cars per household</td>
<td>$m_8 = 0.404$</td>
<td></td>
</tr>
</tbody>
</table>

- **Travel by public transport**
  For better estimates of transport greenhouse gas emissions, the percentage of journey by public transport ($pjp$) is required. This percentage depends on the percentage of journey by car ($pjc$). Distances from CBD ($x_5$, km) and population density ($x_1$, people/ha) were used as factors for estimating this percentage mode split by car (Equation 3).

3) $pjc = 76.05 + 0.608x_5 - 0.092\ln(x_1)$ \hspace{1cm} R² = 0.469

$pjp = 100 - pjc$

The public transport travel was assumed to be a substitute for car travel. This substitution was assumed to depend on household’s access to public transport, which was estimated using distance from CBD and population density. It was assumed that total travel demand is given by the distance that a household would travel (as estimated by VKT model) if they had full car ownership. Full car ownership was assumed to be ($cph = 2$) for each
household. For car ownership below two, public transport \((pkt)\) partially substitutes for gaps between total travel demand (i.e. estimated VKT with full car ownership) and actual travel demand (i.e. estimated VKT with actual car ownership).

\[
4) pkt = \alpha \times \text{pj}(vkt_2 - vkt)
\]

\(vkt_2\) = Estimated VKT with full (2 cars) ownership
\(vkt\) = Estimated VKT by using Equation 2

Where ‘\(\alpha\)’ is a constant of proportionality calculated across all households so as to make sure that summing individual household passenger kilometres matches published aggregate figures [1].

- **Integrated model**

Using the sub-models presented (Equations 1 – 4), VKT by public and private transport in each SLA were estimated. By using Equation 5 and the emission factors (Table 4), transport greenhouse gas emissions \((E)\) shown in Figure 2 can be estimated for each SLA.

\[
5) E = vkt \times EF_c + pkt \times EF_p
\]

\(EF_c\) = Emission factor for private car \((\text{CO}_2/\text{VKT})\)
\(EF_p\) = Emission factor for public transport \((\text{CO}_2/\text{PKT})\)

<table>
<thead>
<tr>
<th>Transport type</th>
<th>Emission factor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Private car</td>
<td>260 gm CO$_2$/VKT</td>
</tr>
<tr>
<td>Public transport</td>
<td>95 gm CO$_2$/PKT</td>
</tr>
</tbody>
</table>
Figure 2. Transport greenhouse gas emissions
3. Results and Discussion

Car ownership model showed that higher income families with more children have more cars compare to other household types. While increasing population density and living in detached houses decrease car ownership. These results are consistent with some of available car ownership models [12, 13]. But there are some inconsistencies with other models. Soltani & Somenahalli (2005) considered the effect of dwelling structures on vehicle ownership in Adelaide. They concluded that living in separate house increase the probability of having more cars, it is perhaps because of more available parking in houses compare to other dwelling [8]. The results in this study showed that living in house decreases car ownership, one of the reasons may be that houses have private open space (back yards), so people’s needs for travelling to open space decrease and consequently car ownership decreases as well. Different factors used in this model compare to Soltani & Somenahalli (2005) and co linearity among factors may also be the reasons.

VKT sub model showed that the distance from CBD, high household income, high car ownership and large number of couple with children compare to other household types increase VKT. These results are also consistence with available VKT models [4, 9, 14].

Mode share is something that was ignored in the available models. Based on the proposed mode share model, distance from CBD increase car mode share while population density decrease car usage as travel mode.

All sub models confirm that land use factors (distance from CBD, population density, and dwelling type) are more influential than socio-economic factors (household type, income) on personal travel.

The results of transport greenhouse gas emissions (Figure 2) also confirms that higher density areas near CBD have low greenhouse gas emissions and outer suburbs with low density, long distance from CBD and low accessibility to public transport (high car usage) have the highest transport emissions.

4. Conclusions

This paper tries to develop a better understanding of how urban structure relates to personal travel in Melbourne. Although limited numbers of factors were used, the results give good insights which can be useful in early stage of strategic urban plans.

The results suggest that population density, distance from CBD and dwelling types are influencing factors for estimating car ownership, vehicle
km travel and mode share and their influences are more than socio economic factors. Low emissions in SLAs near CBD, supports the idea that land use factors must be considered in future planning strategies and concentrating growth in inner SLAs will bring better future in transport.

The effects of considered factors on personal travel change, as more complex measures of urban form are introduced into the model. So for better transport emissions estimation, more complex land use factors such as accessibility and land use mix should be considered.

Linear regression analysis provides a simple formulation for the relationship between travel and other factors. Although regression is used widely in transport models, it has a problem of inter correlation among independent variables and there is a need for new models that avoid co linearity problem.

5. Acknowledgement
The authors would like to thanks Dr Peter Rickwood, Institute for Sustainable Futures, University of Technology Sydney and The Statistical Consulting Centre, the University of Melbourne for their feedback and support.

6. References