Spatially disaggregated domestic road transport energy demand in Great Britain

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Word Count: 4756 + 2000 (3 tables and 5 figures)
ABSTRACT

Reducing energy consumption is an important objective of policy makers. Road transport accounts for a significant portion of energy consumption in the UK and worldwide. This paper presents a method of highly spatial disaggregation of domestic road transport energy demand in Great Britain using a “home-based” modelling approach. Specifically, a household-based car ownership model was developed using the Living Costs and Food Survey (LCF) data. Car ownership and regional effects are controlled for in this model. The modelling results are combined with census data so as to predict transport energy demand by small census tract (i.e. output area, OA) in Great Britain. The spatial distribution of road transport energy demand is also mapped at the resolution of 1km square grid.

It is anticipated that the home-based transport energy demand model developed in this paper is useful and informative for policy makers and planners, for instance plan of electricity supply and energy crops as electric and biofuel cars are increasingly becoming popular.

INTRODUCTION

It is now well established that climate change is occurring as a consequence of the release of greenhouse gases produced by burning fossil fuels (1). International action to reduce emissions was agreed under the Kyoto Protocol, and agreement on a new international process is currently sought.

The UK responded with a legally binding commitment to reduce emissions by 80% by 2050 based on 1990 levels (2). The Low Carbon Transition Plan (3) set out a national strategy for meeting the 5-yearly carbon budgets included in the Act. The recently-announced fourth budget (4) proposes a reduction by 50% in Britain’s emissions for the period 2023 to 2027.

The transport sector is responsible for nearly a quarter of total UK emissions (4). Emissions from the sector are expected to be reduced by between 17% and 28% based on 2009 levels by the end of 2027 (4) and “radically reduced” (3) by 2050. Within the transport sector, vans and private cars represent the majority of transport emissions in the UK at nearly 70% of the total (5). This sector clearly has an important part to play in future emissions reductions and therefore forms the focus of the present paper.

The UK’s Department for Energy and Climate Change (DECC) produces statistics on the fuel consumption by different types of road transport broken down by region and local authority (6). They were derived by AEA using the NAEI Road Transport Inventory methodology (7). The process makes use of data on traffic activity produced by the national traffic census and fleet composition based on data from the Department for Transport and the Transport Research Laboratory. The resulting estimates are based on where the fuel was consumed, so they are “road-based” in the terminology of this paper, described later. The data are described in more detail in the data section.

The DECC data are provided at local authority (LA) level. There are just over 400 LAs in Britain so some degree of detail is available. But a higher resolution would provide the opportunity for a more detailed understanding of how transport energy consumption varies spatially, and the generation of such higher-resolution data is the subject of the present paper. As part of the process, the data were expressed in terms of energy demand for energy demand and non-heating electricity demand (9). The increased resolution was achieved by use of a model based on census data and described in Section 2. A natural consequence was that the data were assigned to the homes of the drivers of the cars and vans rather than the stretch of road where the emissions were produced. This generation of “home-based”, as
opposed to “road-based”, results was seen as a valuable outcome because it assigns transport energy demand to the user and allows its inclusion in household energy budgets.

A further advantage of the home-based approach becomes clear when a future shift to electric cars is considered. The most ambitious scenario in the 2050 Pathways Analysis includes 80% of passenger car distance powered by electricity by 2050 (10). Home-based charging points are likely to form part of the infrastructure supporting mass electric car use. This means that the charging of electric cars will in many cases be from the home electricity supply, with significant impacts for local electricity distribution networks. The maps produced by the present work provide useful information about the placement and level of such new loads.

More generally, the results of the present work could be of value for studying the supply of transport fuels, such as biofuel which plays a significant role in some of the UKERC 2050 scenarios (11). Spatial factors were found to be important in the viability of bioenergy by Booth et al. (12), Cavalett and Ortega (13) and Wang et al. (14).

The process of generating data of higher spatial resolution is known as spatial disaggregation. Many quantities of interest, in energy studies and elsewhere, are obtained by summing individual values at some lower level of spatial organisation, e.g. local authority, to give a total for a higher level like a region. Spatial disaggregation is the opposite process: the derivation of local from global values, with the aim of revealing spatial variations hidden by the summation process. In the present work, the process of spatial disaggregation made use of existing statistics of the Living Costs and Food Survey (LCF) and census data.

Recent research on spatial disaggregation of energy demand includes the study by Druckman and Jackson (15) who developed a highly disaggregated household energy consumption model in the UK. Similarly, Cheng and Steemers (16) developed a tool for modelling domestic energy consumption at district scale in the UK. These studies mainly focus domestic building energy demand. There however seems a dearth of research in spatial disaggregation of domestic transport energy demand. One related study was conducted by Shu and Lam (17) who disaggregated the carbon dioxide emissions from road traffic in the State of Louisiana, US. One feature of their study is that a regression model was employed to obtain the expected carbon dioxide emissions.

The aim of this paper is to develop a method for estimating domestic road transport energy demand at a highly disaggregated spatial level. It is expected that the results of this paper will be of value and informative for the policy makers and planners. The following section will describe the modelling methodology and data used in this paper, which is followed by the presentation of the results and relevant discussion. The summary and conclusion of the paper is provided at the end of the paper.

MODELLING METHODOLOGY

In this paper, a household-based car ownership model is developed with the aim of spatially disaggregating the domestic road transport energy consumption. The Living Costs and Food Survey (LCF) is a UK government national survey of households which provides data on a series of key variables on weekly household expenditure, including petrol and diesel, as well as household characteristics such as number of cars/vans owned. From this it is possible to define a number of Household Categories (HoC) based on their car ownership. With fuel price data, average fuel consumption (in litre per week) for each HoC can then be obtained.

While one can simply use this average fuel consumption data for each HoC directly from the raw data, a model based method seems more appealing as it can take into account uncertainty and heterogeneity. In a model based method, actual fuel consumption per household (as recorded in LCF) was modelled against car ownership as an explanatory
variable. This calibrated model was then used to obtain the “expected” fuel consumption for each HoC. This data, when combined with Census 2001 datasets, can be used to generate spatially disaggregated area-wide ‘home-based’ transport energy demand. The process of this method is illustrated in Figure 1.

Figure 1 A disaggregate area-wide fuel consumption model

While developing the model, car ownership is one obvious variable that can explain a household’s expenditure and consumption on petrol or diesel, other factors may also have an impact, such as regional differences, household income, and age, sex and economic position of the household reference person (HRP). Since the purpose of this study is to develop an area-wide transport energy consumption map where census data (at OA level – an OA is the smallest Census area for which 2001 data is available for) will be used, data that are not available from the census are not used. Although census data contains rich socio-economic variables at OA level, these variables are not fully cross-referenced, so HoC at higher resolution (i.e. HoC with more detailed characteristics) cannot be determined. For example, while it is known that how many households in an OA having one car/van, it is not known that among these households how many of them are economic active. Therefore the model mainly uses car ownership information as a predictor. Another possible method that has the potential use more predictors could be estimating a model at household level using the LCF data; and then directly applying this model to OA level census data. There are however two
problems: first, while it is convenient to calculate corresponding OA level values for non-categorical variables (e.g. average age/car ownership in an OA), it is not so straightforward for categorical variables. For example it is difficult to define an “average gender” at OA level. Thus a household-level model may not be directly applicable at OA level. Second and the most important, such method (applying one model at one spatial level to another spatial level) may be subject to ecological fallacy or modifiable areal unit problem (MAUP, 18). It is unknown that whether parameters estimated at household level would remain the same at the OA level. Both the signs and absolute values of the coefficients can be different at different spatial levels (i.e. household and OA levels). Ignoring the ecological fallacy or MAUP could lead to biased and misleading results. As such, this paper will use the household category method (described in Figure 1) in which car ownership was mainly used as a predictor. In addition to car ownership though, regional differences have been considered and controlled for using a series of dummy variables representing different regions.

The fuel consumption model takes the following form:

$$E(y_i) = \exp(\beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \varepsilon_i)$$

where $y_i$ is the dependent variable, and in the case of this paper, is the volume of petrol or diesel (in litres) household $i$ consumed per week; $\beta_0$ is the intercept; $\beta_1, \beta_2 \ldots$ are coefficients; $x_{1i}, x_{2i} \ldots$ are series of explanatory variables, and in this case, are number of cars or vans household $i$ owns and dummy variables representing regional effects; $\varepsilon_i$ are errors.

This model differs from a simple linear regression that the right hand side of the equation is in an exponential form, which reflects the fact that fuel consumption ($y$) is non-negative. This model can be estimated under the generalised linear model (GLM) framework using the Huber/White/Sandwich estimator so robust standard errors can be obtained (19).

The calibrated model can then be used to estimate the expected annual fuel consumption for each HoC. In the next stage, proportion of each HoC in each OA can be obtained from the census data, and with the fuel consumption for each HoC predicted from the model, the weighted average fuel consumption for a ‘typical’ household in each OA can be determined. At this stage, petrol and diesel demand (in litres) can be converted to kilowatt hour (kWh), and vehicle engine efficiency rate and number of households in an OA can then be applied to calculate the total ‘real’ energy demand for domestic road transport (in kWh).

DATA DESCRIPTION

As stated in the methodology section, there are primarily two data sources in this study: Living Cost and Food Survey (LCF) and UK Census. LCF provides weekly household expenditure on many items including petrol and diesel. The data used in this study is LCF 2010 which contains a sample of 5,263 households in different regions in the UK. These households were sampled evenly in the four quarters in the year, so the best estimate of average weekly expenditure can be achieved. In order to convert the expenditure on fuel to volumes (litres), average quarterly fuel price data in 2010 was required and obtained from the UK Department of Energy & Climate Change (DECC). The fuel prices range from £1.13 to 1.20 per litre for petrol; and £1.14 to 1.23 per litre for diesel, depending on the quarter of the year. The summary statistics for the data used in the fuel consumption model are presented in Table 1:

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1 More details of the LCF can be found on [http://www.esds.ac.uk](http://www.esds.ac.uk).
Table 1 Summary statistics for the data to be used in the fuel consumption model (data source: LCF)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs</th>
<th>Mean</th>
<th>Standard deviation</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Petrol (in litre)*</td>
<td>5116</td>
<td>13.366</td>
<td>18.514</td>
<td>0</td>
<td>174.119</td>
</tr>
<tr>
<td>Diesel (in litre)*</td>
<td>5116</td>
<td>4.912</td>
<td>12.785</td>
<td>0</td>
<td>178.957</td>
</tr>
<tr>
<td>Number of cars/vans in a household</td>
<td>5124</td>
<td>1.138</td>
<td>0.829</td>
<td>0</td>
<td>3</td>
</tr>
<tr>
<td>Regions (dummy variables. 1 means in the region; 0 means otherwise)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>North East</td>
<td>1 (count=258); 0 (count=4858)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>North West &amp; Merseyside</td>
<td>1 (count=596); 0 (count=4520)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yorkshire and the Humber</td>
<td>1 (count=485); 0 (count=4631)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>East Midlands</td>
<td>1 (count=413); 0 (count=4703)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>West Midlands</td>
<td>1 (count=470); 0 (count=4646)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Eastern</td>
<td>1 (count=515); 0 (count=4601)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>London</td>
<td>1 (count=476); 0 (count=4640)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>South East</td>
<td>1 (count=679); 0 (count=4437)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>South West</td>
<td>1 (count=495); 0 (count=4621)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wales</td>
<td>1 (count=261); 0 (count=4855)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scotland</td>
<td>1 (count=468); 0 (count=4648)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* Weekly fuel usage per household

As can be seen in Table 1, the number of cars/vans in a household ranges from 0 to 3 according to the LCF. Therefore four HoCs were created corresponding to each case of car ownership, i.e. HoC 1 is household with 0 car; HoC 2 is household with 1 car; HoC 3 is household with 2 cars; and HoC 4 is household with 3 cars. Additional attention was paid to the regional differences which will be controlled for in the model.

Another source of data, UK Census 2001, provides information on many socio-economic factors, including car ownership – i.e. number of households with 0, 1, 2, 3, and ‘4 or more’ cars/vans respectively (in total 5 cases) in an OA. To be consistent with the LCF data, 3 and ‘4 or more’ were combined to be one category which corresponds to the households with 3 cars/vans in the LCF data. This practice should have marginal effects on the results as households with ‘4 or more’ cars/vans only represent an average proportion of 1.31% of all households in an OA. The summary statistics of total number of households and the proportions of all the four HoCs computed from the census at the OA level in Great Britain are presented in Table 2:

Table 2 Number of households and proportions of HoCs (data source: Census 2001)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs</th>
<th>Mean</th>
<th>Standard deviation</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of households</td>
<td>218038</td>
<td>109.401</td>
<td>32.898</td>
<td>20</td>
<td>616</td>
</tr>
<tr>
<td>Prop. of HoC 1</td>
<td>218038</td>
<td>0.280</td>
<td>0.196</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Prop. of HoC 2</td>
<td>218038</td>
<td>0.437</td>
<td>0.100</td>
<td>0</td>
<td>0.886</td>
</tr>
<tr>
<td>Prop. of HoC 3</td>
<td>218038</td>
<td>0.228</td>
<td>0.141</td>
<td>0</td>
<td>0.889</td>
</tr>
<tr>
<td>Prop. of HoC 4</td>
<td>218038</td>
<td>0.056</td>
<td>0.053</td>
<td>0</td>
<td>0.5</td>
</tr>
</tbody>
</table>

As Table 2 indicates, the category of HoC 2 – i.e. households with one car represent the most common scenario in Britain, with the average proportion of 0.437 in an OA.

RESULTS

Two fuel consumption models were developed for both petrol and diesel household weekly usage. As stated above, number of cars/vans in a household is the main predictor explaining
the fuel usage. Regional effects were also controlled for by testing a series of regional
dummy variables. After the extensive tests, no significant regional effects were found for
petrol usage; whereas, households in London were found to have used less diesel compared
to other regions while there is no significant difference among regions outside London.
Therefore only the dummy variable for London was included in the diesel model. A series of
interaction terms with London dummy and number of cars/vans in a household (as both
categorical and continuous) are also tested and they are all statistically insignificant at 95%
confidence level, so they are not included in the models either. The modelling results for both
petrol and diesel usage are presented in Table 3:

Table 3 Modelling results for petrol and diesel consumption

<table>
<thead>
<tr>
<th>Model</th>
<th>Petrol</th>
<th>Diesel</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coef. t-statistic</td>
<td>Coef. t-statistic</td>
</tr>
<tr>
<td>Number of cars/vans in a household</td>
<td>0.717** 38.17</td>
<td>0.801** 22.29</td>
</tr>
<tr>
<td>London</td>
<td>-</td>
<td>-0.618** -2.74</td>
</tr>
<tr>
<td>Intercept</td>
<td>1.591** 46.93</td>
<td>0.485** 7.02</td>
</tr>
<tr>
<td>N</td>
<td>5116</td>
<td>5116</td>
</tr>
<tr>
<td>Log likelihood</td>
<td>-52531.8</td>
<td>-42588.6</td>
</tr>
<tr>
<td>Likelihood-ratio index</td>
<td>0.199</td>
<td>0.131</td>
</tr>
</tbody>
</table>

** p<0.05

As Table 3 shows, number of cars/vans in a household is positive and statistically
significant in both petrol and diesel models at 95% confidence level. This indicates that a
household with more cars/vans would consume more fuel, which is expected. London on the
other hand, is negative and statistically significant at 95% confidence level, suggesting that
households in London use less diesel, given other factors (i.e. number of cars/vans) remain
the same. The petrol model achieves better goodness-of-fit given the higher likelihood-ratio
index, although it uses fewer parameters than the diesel model.

Since there is a log-linear relationship between fuel consumption and explanatory
variables, the following formula can be employed to determine the percentage change in fuel
consumption for a $\delta$ unit change in an independent variable $x_k$, holding all other variables
constant (Long and Freese, 2006):

$$100 \times \{\exp(\beta_k \delta) - 1\}$$

in which $\beta_k$ is the estimated coefficient (as shown in Table 3) associated with the household
attribute $x_k$. Therefore, the modelling results above suggest that if a household owns one
more car/van, their fuel consumption will increase by 104.83% for petrol, or 122.78% for
diesel. Households in London would use 46.10% less diesel compared to regions outside
London given the same number of cars/vans owned.

The next step is to use the calibrated models to predict the expected fuel consumption
for each HoC (for diesel the results for HoCs both in and outside London were obtained). The
census data was then used to calculate the proportions of different HoCs in each OA (based
on car ownership), and with the expected annual fuel consumption estimated from the model,
it is straightforward to compute the weighted average annual fuel usage per household in an
OA. This was then multiplied by the total number of households in an OA (also from census
data) so the total fuel usage in each OA in Great Britain can be determined. In order to obtain
the ‘true’ energy demand, the fuel usage (in litre) is converted to kWh and it is then
multiplied by the car engine efficiency rate. This way, the energy demand estimated is
independent from types of cars or energy sources used. The conversion factor used in this
paper is 9.42 (kWh/litre) for petrol, and 10.89 (kWh/litre) for diesel (20). The average car engine efficiency is assumed to be 25% (21).

The total domestic energy demand estimated by OA ranges from 18,451.42 to 1,199,993 kWh. The histogram graph below (Figure 2) shows the distribution of the energy demand. It is clear from the figure that the majority of OA level energy demand falls below $5\times10^5$ kWh where the energy demand generally follows a normal distribution.

![Histogram graph of domestic transport energy demand (kWh) by OA](image)

The regional differences in OA level energy demand are presented in Figure 3 which shows the box plot of energy demand by regions. It can be seen from the plot that Scotland clearly has lower transport energy demand compared to other regions in GB, which may reflect the low number of households per OA in that region (Scotland has a median of 50 households per OA while the figure for other regions is 124 or 125). South East on the other hand, has the highest energy demand. London, not surprisingly, has lower transport energy demand per OA compared to other regions in England. This is because households in London on average have fewer cars/vans and people in London may tend to use more public transport. The household density in London is higher than other regions in GB according to the census, which makes the provision of public transport more appealing. Also according to the modelling results above, people in London tend to use less diesel given other factors (e.g. car ownership) constant. This further reduces the household transport energy demand in London.
The predicted energy demand can also be compared with other data sources for the purpose of model validation. The following figure compares the total regional energy demand estimated from the ‘home-based’ method with data from DECC\(^2\). The DECC data showed in the figure include the fuel consumption by petrol and diesel cars in 2010. Similar to the method employed in this study, the ‘true’ energy demand was calculated by applying the 25% car engine efficiency rate.

The DECC data for road transport fuels is based on the emissions from the National Atmospheric Emissions Inventory (NAEI) and traffic flow data from the Department for Transport (DfT). Namely the DECC used a “road-based” approach. As can be seen from Figure 4, the DECC data clearly has higher estimation than the “home-based” method employed in this paper with the only exception of London. This is expected as the DECC data counts all petrol and diesel cars on road, while the “home-based” approach only considers cars used by households (i.e. domestic). Therefore it is not surprising that the DECC data has slightly higher estimation of energy demand than the “home-based” method.

The DECC data however does not differentiate road energy demand by households or industry therefore further comparison cannot be conducted. Overall the prediction using the “home-based” method in this paper is satisfactory.

In order to accurately represent the spatial distribution of energy demand, the OA level data is converted into 1km² grids using a ‘proportion sum’ method – i.e. the value for a grid square is the weighted total of all intersecting/overlapping OAs where the weights are the proportions of an OA within a grid square. The spatial distribution of the energy demand by both OAs and 1km² grids are presented in Figure 5 for comparison.
Figure 5(a) Spatial distribution of energy demand by OA in Great Britain
As can be seen, the map at 1km² resolution (Figure 5b) is clearly much smoother than the map by OA (Figure 5a). It is interesting to note that, London has relatively lower energy demand compared to other areas in England as shown in Figure 5(a), which is in-line with Figure 3 as they both present OA level demand. However, London is demonstrated to have relatively higher energy demand in Figure 5(b). Similarly there is difference in terms of presentation of energy demand for Wales. As explained earlier, this may be due to the MAUP. In this case, this problem occurs because the physical sizes of OAs in London are relatively smaller than other regions (an OA contains roughly the same number of households in England and Wales). Therefore when the OA-level data is weighted to be converted into the
same sizes (i.e. 1km square in this case), data in London turns out to be more aggregated (i.e. 1km square contains more OAs) than other areas. This outcome is expected as London is more densely populated. Similarly, it can be observed in Figure 5(b) that energy demand is usually high in dense populated urban areas. When MAUP occurs, uniform grid cells are generally preferred (18), so the map presented in Figure 5(b) should be used for any interpretation and planning.

**DISCUSSION AND CONCLUSION**

The UK government has set an ambitious objective to reduce energy consumption in the following decades. To achieve this goal, careful planning is required. Road transport represents a significant portion of energy consumption in the UK. The future development and adoption of electric cars and biofuels may play an important role in reducing domestic road transport energy consumption.

This study contributes to the ongoing research efforts in energy by spatially disaggregating the domestic road transport energy demand in Great Britain. Specifically, a method for estimating “home-based” transport energy was developed. A household based car ownership model was firstly calibrated using the LCF data. The modelling results found that, as expected, increased car ownership would increase the consumption of both petrol and diesel by a household. The model also found there is some regional difference in terms of diesel consumption – namely London was found to use less diesel compared to other regions. The modelling results, combined with census data, are then used to predict OA level energy demand which has also been compared/validated with other data sources such as DECC. OA level data was also converted to 1km squares for the purpose of mapping.

The methods and results developed from this paper can be useful in many ways. For example, the increase in the adoption of electric cars will have an impact on the electricity supply and distribution. Thus it is useful to know where there is high road transport energy demand. In addition, since it is likely that electric cars will be charged at home, this home-based method employed in this study may provide more accurate distribution of energy demand.

Similarly, this study may also be informative for the supply of biofuels. Policy planners could use the method described in this study to determine where to plant energy crops (e.g. near where there is high energy demand).

It is noted that this study only looks at energy demand by private cars/vans. Energy demand for public transport is not included. Generally public transport such as bus is more energy efficient than private cars/vans. Policy makers and planners could use the result from this study to investigate areas where there is high energy demand for private cars/vans, and devise a plan to encourage using more public transport. For instance, some innovative form of public transport such as demand responsive transport (22) could be introduced in some selected areas.

It is believed that this paper presents an important tool for energy policy makers and planners. For future research, more efforts could be devoted to refining the car ownership model. Currently only car ownership and regional effects were included in the model, which is the main weakness of this paper. Future studies can employ more explanatory variables and as a consequence more HoCs, so as to more accurately predict the household and area level energy demand, subject to data availability.
ACKNOWLEDGEMENTS

Thanks are due to the UK Energy Research Centre for their funding of the project Disaggregated Scenarios for Demand Studies (see www.ds4ds.org).

REFERENCES


