Urban transport: analysis of commute energy use

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Abstract

Worldwide energy consumption is generally related with fossil fuels that increase CO_2 and other greenhouse gases (GHG) emissions. The transport sector represents a significant part of energy demand. As its share comes mostly from petroleum products, known for their highly polluting effects, there is the need to quantify energy use by transport. This assessment supports the planning and implementation of energy consumption mitigation policies that reduce negative environmental outcomes of transport systems.

The research introduces an approach to estimate transport energy consumption obtained from available data and scaling factors. As the emphasis is put on urban transport, only commute road and rail transport are considered in the analysis. Data is stored and managed in a Geographical Information Systems (GIS) framework environment that also supports mapping the results. These maps allow identifying higher energy consumption areas by mode of transport and type of vehicle. Plotting the results also enables understanding the geographic distribution of energy demand from urban to rural regions, providing tools to perceive the relationship between urban form and energy consumption of the transport sector. Taking into account that the analysis is produced at a large scale, the obtained results offer support to planners and policy makers that seek solving transport-related problems, as pollution and high energy demand. Large scale analysis allows and enhances better planning, primarily when designing strategies for such detailed areas as urban spaces. Assessing and analysing energy consumption of the transport sector, enables deriving alternative energy layouts that present better energy efficiency, aiming for the final goal of mitigate the negative effects of urban transport systems.

Keywords: energy use, planning, transport, commute, GIS.

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1 Introduction

Urbanisation has promoted the increase of energy demand [1, 2]. The transport sector is a major contributor to energy consumption in urban areas and an important source of CO_2 and other greenhouse gases (GHG) emissions [3]. McKinnon [4] estimates that in 2004, freight transport represented about 6% of the United Kingdom's (UK) total CO_2 emissions, whereas Lovelace [3] calculates that commuting trips comprise about 3% of these total emissions. Given that those emissions have significant negative impacts on people, climate and environment [5, 6], proper mitigation measures have been implemented in recent years, as for example actions to reduce energy demand. Therefore, a fundamental step is obtaining an estimate of transport energy consumption. The research in this paper introduces a methodological approach to estimate that consumption from available data. The analysis only considers commuting transport, i.e. work travel flows that are part of urban transport energy use. Data is stored and managed in a Geographical Information Systems (GIS) framework environment that also supports the mapping of results. These maps allow the identification of higher energy consumption areas by mode of transport, as well the geographic distribution of energy demand.

2 Methodology

In urban spaces, the highest energy consuming sectors are buildings and transport [7, 8]. Regarding the practical difficulties in obtaining actual energy values for all elements, the common approach is to estimate energy consumption. The research in this paper considers an estimate based on statistical data published by official governing bodies in UK, focused only on the transport sector. The methodology presented here is based on our previous work [9].

A significant amount of energy use by transport is related to commuting [10]: circa 4.1% of total energy use and about 14.4% of transport energy spending in UK [3]. For this study, a commuting transport energy consumption estimate was computed at the Lower layer Super Output Area (LSOA) geographic level [11] and derived from an Origin-Destination (OD) matrix table of usual resident's commute to work published by the Office for National Statistics (ONS) and mapped by the DataShine web platform [12]. LSOA is a statistics-purpose geographical unit and refers to a large scale – between 1000 and 3000 usual residents [11], enabling the focusing of planning strategies that establish more realistic and feasible scenarios to modify energy demand. The larger scale also allows better control of the policies implemented by government authorities.

Considering that energy consumption is obtained from OD flows, an estimate is given by carbon footprint, i.e. consumed carbon calculated from the OD distance and the method of travel for each trip, using standard calculation factors for various fuels as outlined below. Thus, the energy consumption mapped by LSOA in this paper is assumed to be the computed carbon footprint for those commute flows. To obtain proper comparison of energy use by the different methods of travel, this carbon footprint uses a common and single unit of measure – $kgCO_2e$. Combining OD distances with the number of people travelling in each OD travel flow, and the table of greenhouse gas (GHG) conversion factors published by the Department of Energy & Climate Change (DECC) [13] – giving the expected $kgCO_2e$ spending per kilometre or passenger kilometre, the total commuting carbon footprint is calculated and given by the following:

$$T = D_{OD} C_f P, \tag{1}$$

where T is the transport energy consumption, D_{OD} is the distance between origin and destination travel flow, C_f is the GHG conversion factor for each method of travel and P is the number of people commuting by method of travel.

Although DataShine provides information for inbound and outbound commuting flows, only outbound trips and the following methods of travel were considered: train, bus/coach, motorbike/moped and car (driving). Thereby, the analysis is limited to road and rail transport, i.e. the transport of passengers or goods on roads and by railway whose energy consumption is primarily based on oil products and related fuels [14–16]. Commuting flows are presented by population-weighted centroids of Middle layer Super Output Areas (MSOA) [11]. Consequently, after obtaining OD distances for each trip and respective carbon footprint between each MSOA centroid of the case studies, a scaling process was applied to calculate that energy consumption by LSOA. Scaling is a common method used to overcome the problem of non-standardized data statistics [17]. For this paper, the downscaling technique [18, 19] was selected, as it enables the setting of a relation between different spatial resolutions [20, 21] (in this case, from MSOA to LSOA). The scaling procedure consists of: i) computing the number of people commuting by method of travel per LSOA using the surface area of each MSOA and LSOA as a scaling factor; ii) from the previous results, calculating carbon footprint by LSOA based on (and scaling) the respective MSOA values. Thus, energy consumption by LSOA results from distance travelled and number of people commuting by each mode of transport.

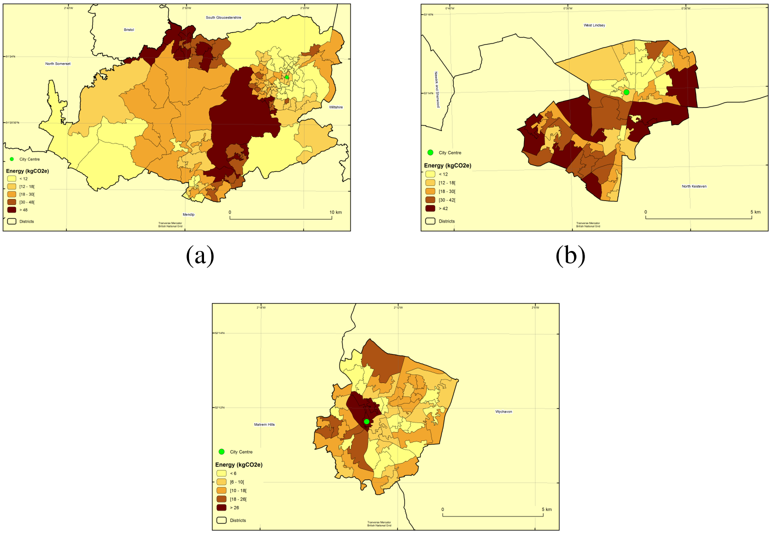
As mentioned, the carbon footprint was obtained considering the method of travel and distance for each OD flow. This distance was assumed as the space between MSOA centroids given by DataShine. For the methods of travel related with road transport, road distance (in kilometres) was calculated using online Google Maps [22] that does not consider traffic flow, congestion and timetable restrictions. As for rail transport, the distance pertains to the length between the closest train station to each centroid of every OD trip, again disregarding any restrictions.

As the methodological approach required the use of a large quantity of information, a Geographical Information Systems (GIS) framework environment was employed to store and analyse data, besides mapping the results [23, 24]. GIS favours multidisciplinary studies and the integration of differentiated data [25], demonstrating also usefulness in planning and decision-making processes, as it allows the identification of patterns and adds value to the analysed data [26].

3 Results and discussion

Analysing commute transport enables understanding household travel behaviour and habits, and its related energy consumption [27, 28]. To introduce the methodology and acknowledge its replicability, three different case studies were selected: the unitary authority of Bath and North East Somerset (commonly referred to as BANES or B&NES) and the cities of Lincoln and Worcester (both non-metropolitan districts). Despite the difference on governing responsibilities, the main centres (cities) of the three case studies have similar population: between 90,000 and 100,000. The option for these case studies refers also to their distinct status and location within England: Bath is a World Heritage Site [29] and a major tourism centre; Lincoln is a cathedral city with an important historical background; Worcester is located close to the southern suburbs of the city of Birmingham and was the place of the final battle of the English Civil War.

Supported by GIS environment, several maps were created, allowing comparison of results. For better analysis, a LSOA centroid was selected (and mapped) as the city centre of each case study. As given by Figure 1, BANES and Lincoln have higher carbon footprint values related with bus commuting. In Worcester, most people commuting to work by bus live in the city centre or the nearby LSOAs, distinct from what is observed for BANES and Lincoln: higher values are located in the outskirts of the centre (to the West for BANES and primarily to southern areas for Lincoln). While Figure 1 is related with total carbon footprint given by bus commute, one may deduce that bus services in Worcester are not very efficient and effective, compelling people living in the outlying areas to rely on car as a method to travel to work. The previous finding may also be presumed by analysing Figure 2: the highest value LSOAs are positioned in the surroundings of the city centre, implying that residents depend more on car to commute. This is observed in all case studies, though for BANES the highest value regions are located farther away from the city centre than in Lincoln and Worcester. The dependence on car to commute also raises concerns about the accessibility of places located at the outskirts, i.e. located outside the major urban spaces. As Figure 2 refers to per capita energy consumption, areas displaying higher values may indicate less availability of jobs and/or lower economic activity, compelling residents to work far off their home. In the case of Worcester, that has a major significance, as not only distant LSOAs from the city centre show higher values, but also some nearby areas. Nevertheless, the lower reliance on car observed in areas located distant from the city centre (mostly in Lincoln and Worcester), suggest the opposite conclusion from the previous finding: residents on those LSOAs are not compelled to work outside their home. Indirectly this may indicate that energy efficiency measures may have been taken successfully in those areas, reducing consumption and supporting alternative methods of travel to work (e.g. bicycle). However, that must be confirmed with additional analysis of commute flows and travel methods. Energy consumption related with train commuting presents low values of $kgCO_2e$, and it is evidently noticeable in nearby areas to train stations. As given by the maps (Figure 3), the considered case

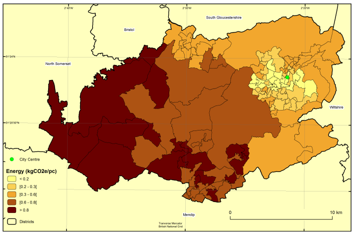


(a) (b)

(c)

Figure 1: Total bus commuting energy consumption by LSOA for (a) BANES (b) Lincoln and (c) Worcester. (Source: DataShine (data); Ordnance Survey (cartography).)

studies display dissimilar energy spending from train commute that results, for example, from the availability of railway service. In effect, BANES is served by three train stations (the major one located at the city centre), Worcester has two stations and Lincoln only benefits from one. Consequently, people living on the West region of BANES do not use train to travel to work (Figure 3(a)); the highest value LSOAs are centred on the East area (the region closer to the city centre). For Lincoln, LSOAs displaying higher carbon footprint are placed nearby the city centre, suggesting that only a small number of people use train to commute and, therefore, the remaining residents rely on other methods of travel. Worcester shows a peculiar behaviour: only a few LSOAs have zero $kgCO_2e$, and are mostly located in the outskirts of the city. From these zero carbon footprint spending areas, it is possible to identify a region positioned Northeast of the city centre: those LSOAs also present low values for bus and car commuting energy consumption (Figures 1 and 2, respectively), indicating that people may work close to their residence or use alternative methods of travel to work. Even so, highest value areas are located in the vicinity of the city centre or in the outlying regions of the district, i.e. distant from the centre. Figure 4 pertains to total commuting energy consumption, i.e. carbon footprint resulting from both road and train transport. Since the plotted values consider the distance of each LSOA centroid to the city centre (i.e. the centroid selected as city centre), describing the variance of commuting energy, the analysis provides information about the areas located in the



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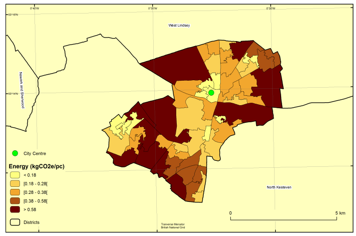

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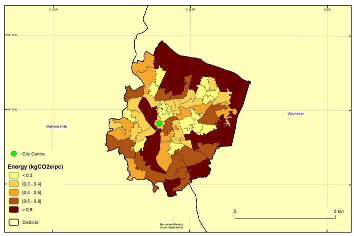
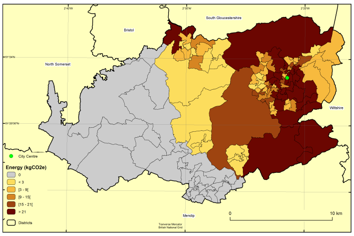


(c)

Figure 2: Total car (driving) commuting energy consumption by LSOA per capita for (a) BANES (b) Lincoln and (c) Worcester. (Source: DataShine (data); Ordnance Survey (cartography).)

outskirts and their road network accessibility. BANES shows a increasing carbon footprint trend from the city centre, especially from around 5.5 km (Figure 4(a)). Insomuch, BANES' outlying LSOAs display high reliance on transport that use much energy (as car transportation), likely in consequence of lower accessibility and/or economic activity in those areas, pressuring residents to work faraway. As regards to Worcester (Figure 4(c)), the increasing tendency is much slighter (and not very clear), but still commuting energy consumption rises from the city centre. Still, that trend is very weak and small, making possible to notice outlying LSOAs with similar carbon footprint values to the ones found close to the city centre. Lincoln (Figure 4(b)) displays an unusual behaviour: highest value LSOAs are located nearby the city centre (until around 3 km). Besides, there is not an evident trend for the commuting energy consumption from the centre, revealing some homogeneity of that expenditure. Although both Lincoln and Worcester represent cities with smaller area than BANES (circa 35 km^2 against about 350 km^2), this uniformity of carbon footprint is an important matter for further study to understand if that homogeneity is, for example, related with urban form, an important urban feature that influences transport [7, 8].

Employing a LSOA geographic level analysis, supported by GIS-mapping, enables a better understanding of commuting energy consumption. Moreover, considering that three case studies were presented, it is assured that the methodological approach introduced in this paper may be replicated for distinct



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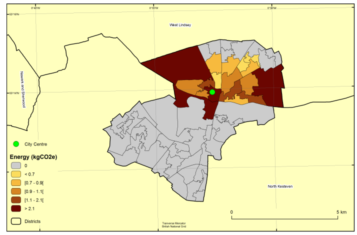

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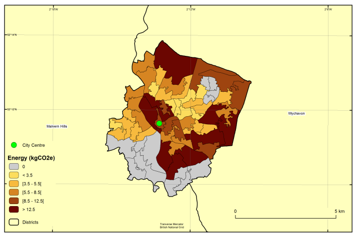
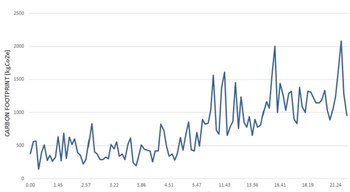


(c)

Figure 3: Total train commuting energy consumption by LSOA for (a) BANES (b) Lincoln and (c) Worcester. (Source: DataShine (data); Ordnance Survey (cartography).)



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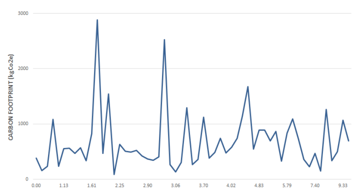

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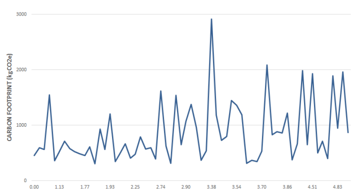

(c)

Figure 4: Total commuting energy consumption by LSOA from city centre for (a) BANES (b) Lincoln and (c) Worcester.

regions/areas. As given by the preceding figures, most carbon footprint related with commute transport pertains to road transport, i.e. bus and car. Train transport is disregarded as a method of travel to work; with a few exceptions for BANES, the vast majority of the total commuting energy consumption for the considered LSOAs comes from road transport (usually figures higher than 90%, and for both Lincoln and Worcester can even be higher than 97%). That may be explained by the inefficiency and/or lack of train services, but also by the significant reliance on other methods of travel (mainly car transport). Figure 2 gives support to this latter finding by showing that car is a central method of travel to work, especially from areas located at the outskirts of the city centres. Analysing the calculated data, most of road transport's carbon footprint from commuting trips refer to car transport (generally more than 90%). As car represents a key source of CO_2 emissions from commuting flows [30], mitigation actions must be implemented, as well strategies to shift people's travel modes in a overall policy to decrease and/or minimize energy demand and consumption by transportation.

4 Conclusions and future work

In urban spaces, transport energy consumption is one of the two major contributors to the total energy demand (the other being buildings sector) [31, 32]. From that transport sector consumption, commuting travels constitute an important sub-sector [10, 33]. Therefore, it is essential to measure and understand commuting transport energy spending to devise better planning and policies [34–36] that may be used to reduce global urban energy consumption.

The methodology introduced in this paper provides a procedure to estimate carbon footprint from commuting flows by LSOA geographic level. The approach benefits from its simple applicability, enabling it to be reproduced for different regions if using the same database resources. Mapping the results delivers valuable knowledge about the dynamics of energy consumption by, for example, identifying the most used methods of travel to commute. The results also show that areas (LSOAs) located more distant from city centre have higher carbon footprint expenditure, since they rely more on road transport. As this road transport is essentially car usage, that may denote inefficiency of bus services and the need of promoting alternative methods of travel (e.g. bicycle and walking). These alternative methods will then promote the reduction of energy use and its related consequences, as well supporting the decrease of pollution and anthropogenic global warming [5].

The presented approach has some limitations that suggest further developments. Future work may include time-series information into the analysis, allowing to perceive the variation and modification of travel modes and energy consumption from commuting. Additionally, a more detailed analysis of travel flows, i.e. understanding OD movements on a larger scale, could provide information upon human behaviour and its effect on energy consumption [37, 38] during a period of time. On top of that, as household travel behaviour is also shaped by urban form [27, 28], understanding human behaviour may enable finding causes for the geographic distribution of commute energy demand. However, the outlook of behaviour and urban form must be taken with caution, as household and work locations are largely influenced by transport accessibility [39–41]. Regardless, the focus of the results on LSOA scale and their mapping by GIS may already support the design and planning of alternative urban energy layouts that produce a long-time sustainable strategy to decrease energy use, as the previous figures allow to acknowledge the highest consuming areas.

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