Article:

McKinney, T.R. orcid.org/0000-0001-7982-2274, Ballantyne, E.E.F. orcid.org/0000-0003-4665-0941 and Stone, D.A. orcid.org/0000-0002-5770-3917 (2023) A data-driven travel demand model to predict electric vehicle energy consumption: focusing on the rural demographic in the UK. Transportation Planning and Technology, 46 (8). pp. 951-975. ISSN 0308-1060

https://doi.org/10.1080/03081060.2023.2248195

Routledge
Taylor & Francis Group

Transportation Planning and Technology

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/gtpt20

A data-driven travel demand model to predict electric vehicle energy consumption: focusing on the rural demographic in the UK

Thomas R. McKinney, Erica E. F. Ballantyne & David A. Stone

To cite this article: Thomas R. McKinney, Erica E. F. Ballantyne & David A. Stone (2023): A data-driven travel demand model to predict electric vehicle energy consumption: focusing on the rural demographic in the UK, Transportation Planning and Technology, DOI: 10.1080/03081060.2023.2248195

To link to this article: https://doi.org/10.1080/03081060.2023.2248195

Published online: 28 Aug 2023.

TRANSPORTATION PLANNING AND TECHNOLOGY
https://doi.org/10.1080/03081060.2023.2248195

A data-driven travel demand model to predict electric vehicle energy consumption: focusing on the rural demographic in the UK

Thomas R. McKinney [a], Erica E. F. Ballantyne [a] and David A. Stone [b]

[a]Sheffield University Management School, The University of Sheffield, Sheffield, UK; [b]Department of Electronic and Electrical Engineering, The University of Sheffield, Sheffield, UK

ABSTRACT
This paper presents a 7-day Travel Demand Model (TDM) for UK rural areas to aid the Electric Vehicle (EV) transition in these regions. Utilising data from both the UK Census Survey and UK National Travel Survey (NTS), private passenger vehicle travel patterns for a rural village in the Peak District National Park (UK), were modelled. This model is adaptable to any rural community within the UK, requiring only publicly available information on households and vehicles for that community. Using a novel approach through the development of lifestyle scenarios to understand the required household activities, the TDM incorporates five different trip purposes as the building blocks for a vehicle's activity. Over a period of one week, 13,520 miles were driven by 84 vehicles across 49 households, that shows an EV fleet serving this community would consume 3562 kWh energy per week.

ARTICLE HISTORY
Received 14 November 2022
Accepted 8 August 2023

KEYWORDS
Travel demand model; rural; activity based models; passenger vehicle usage; simulation; electric vehicles

1. Introduction

The increased use of Electric Vehicles (EVs) has been recognised as a positive contributor to a wide range of transport policy goals (Hill et al. 2019; Hirst 2020), including the improvement of air quality through the reduction of greenhouse gas emissions. Most recently, the UK Governments ten point plan details the ending of sales of new conventionally fuelled cars (petrol and diesel) by 2030 (GOV.UK 2020a). This and previous examples including the Air Quality Plan for Nitrogen Dioxide (NO_2) (DEFRA & DfT 2017) and the 'Road to Zero' Strategy (DfT 2018) illustrate the pressure the UK Government is putting on the passenger vehicle industry to reduce its carbon footprint through the transition to EVs.

As stated in the 'Road to Zero' strategy, this transition is expected "to be industry and consumer led" (DfT 2018). This approach gives raise to concern, as it will only work for locations where there is a strong business case (Cooper 2018). It is also unlikely that market forces alone will lead to the installation of EV charge points in rural areas,

CONTACT Erica E. F. Ballantyne e.e.ballantyne@sheffield.ac.uk Sheffield University Management School, The University of Sheffield, Conduit Road, Sheffield S10 1FL, UK

where the customer base is significantly smaller than urban areas, and the cost of grid connections can be very high (House of Commons 2018). Morton et al. (2018) studied the variation of early adopters of EV technology through EV registrations across the UK and found the emergence of lead and laggard markets. For example, much of central and northern Wales, areas of the North of England, and the Humber region to the mid-east of the UK were shown to have low-levels of EV registrations, whereas central London had relatively high-levels of EV registrations. Population density was found to be one of the influencing characteristics for this geographical variance in EV adoption, as well as availability of charge point infrastructure, which is already unevenly distributed geographically in favour of urbanised areas (DfT 2020a).

Large socio-techno transitions have previously resulted in rural communities being left behind due to similar barriers the current EV transition is already exposing. Past examples include the internet and mobile connectivity (Williams et al. 2016). At some point in the future, all be required to transition from the current mainstream Internal Combustion Engine (ICE) regime to EVs due to legislation, as seen above. Hybrid vehicles will have an important role in this transition, particularly for rural areas where the major barrier to EV uptake is range anxiety. However, as hybrids are also set for an eventual phase out from 2035 (GOV.UK 2020a), the focus of this paper will solely be on future scenarios with 100% EV adoption. The large scale concern for the UK is this neglect will only lead to increased disparity between rural and urban areas, exacerbating such issues as social inequality, economics, and development (Kester et al. 2020; Nutley 2005).

This paper is structured as follows: The underlying research approach will be discussed in Section 2. Section 3 will present the model development/methodology and the chosen case study location. This will be followed by the results in Section 4 and the comparative EV energy required in Section 5. Section 6 concludes the paper.

2. Research approach

A crucial factor in the EV transition is understanding EV recharging, which is dependent on temporal and spatial patterns of vehicle use (Weiss et al. 2017). Due to currently low adoption levels, there is minimal, real world, empirical data on EV use and by extension their impact on the grid. There are two main approaches for studying this, public trial methods, which are expensive and time consuming; and simulations (Pareschi et al. 2020). Focusing on simulation, this consists firstly of a travel demand model (TDM), most commonly based on recorded car usage patterns. This is then coupled with scenario modelling for the EV charging behaviour (Pareschi et al. 2020). Therefore, this paper focuses on the development of a suitable TDM specifically targeting smaller, often remote, rural communities which may be the more difficult scenarios to prepare for the EV transition. This is followed by a demonstration of the TDM to predict rural EV energy consumptions.

2.1. Travel demand modelling

Travel demand survey studies originated in the 1950s in the USA (Apronti and Ksaibati 2018), from which transportation forecasts were traditionally developed following the sequential four-step model (McNally 2007) process which is still used today. Apronti and Ksaibati (2018) developed a four-step TDM for estimating traffic volume for low-volume roads in Wyoming. A key modification was the exclusion of all other travel modes except private passenger cars during the mode choice step. This same modification will be incorporated in the TDM presented in this paper to retain focus on the private passenger vehicle users only. However, Apronti and Ksaibati (2018) only considered three trip categories: Home-Base Work (HBW), Home-Base Other (HBO), and Non-Home Base (NHB) trips. This may be sufficient for an investigation into traffic volumes, for energy usage calculations for EVs more detail is required, for instance trip distances. Additionally, Apronti and Ksaibati's (2018) model requires low-level detailed geocoded input data for households and vehicles in the area of study, which makes it more difficult to generalise the results for different areas. Although the four step model is still used today, as shown by Apronti and Ksaibati (2018), it is now considered an oversimplified representation of daily travel patterns, and an overly statistical/ad-hoc approach to modelling (i.e. not behaviourally oriented) (Goulias 2021). These days multiple approaches to Travel Demand Modelling (see Table 1) have ensued (Daina, Sivakumar, and Polack 2017). Five approaches have been identified by Daina, Sivakumar, and Polack (2017):

(1) Vehicle Ownership and Annual Mileage Models (VOAMM): A high-level model with low temporal resolutions (i.e. when yearly time scales are of interest) (Brownstone, Bunch, and Golob 1994). Individual vehicles can be modelled allowing for easy aggregation, however large datasets required. Brownstone, Bunch, and Golob (1994) built an annual vehicle demand forecasting system for new and used vehicle demand by type of vehicle (Fuel Type).
(2) Summary Travel Statistic Models (STSM): This approach is based on information regarding conventional ICE vehicles (i.e. not electric) which has been extracted from national, regional, or metropolitan travel surveys. Travel pattern summary statistics obtained from travel surveys are used in combination with charging scenarios to generate charging profiles. Again this approach models individual vehicles but has not been known to consistently create representable car usage profiles (Daina, Sivakumar, and Polack 2017). Wang et al. (2011) used Summary Statistics from the US National Household Travel Survey to determine suitable home-arrival times of vehicles at the end of the last trip of the day for a modelled Plug-in Hybrid EV population for Illinois.
(3) Direct Use of Observed Activity Travel Schedules (DUOATS): Uses patterns of usage for ICE vehicles to simulate that of EVs. Can be achieved using travel diaries, surveys, or GPS data. This approach consistently creates representable car usage profiles. Axsen and Kurani (2010) conducted their own survey to elicit driving patterns and potential recharging opportunities.
(4) Activity Based Models (ABM): Similar to the STSM modelling approach and building on the traditional 'four step model', these models are based entirely on simulation. Individual cars are modelled as 'agents' providing a high-level of detail and representation of patterns (Delhoum et al. 2020).
(5) Markov Chain Models (MCM): A Markov Chain is a stochastic model which describes a sequence of events based on the probability of each event occurring at each time interval. This modelling approach has potential to provide great detail but can lack behavioural realism and requires large computational resources.

Soares et al. (2011) determined the movement of EVs across a one year period using a discrete-state, discrete-time Markov chain at 30 min intervals.

Whilst EV transport research has mainly focused on modelling EV adoption and annual usages, a much finer time resolution (typically an hour or fraction of an hour) is required for analysis into power systems, energy, and environmental implications (Daina, Sivakumar, and Polack 2017). Given this TDM is aimed at facilitating the transition to EVs and assessing their impact on rural grid infrastructures, a 30-minute time resolution was chosen. This high temporal resolution allows for cross-analysis with electricity tariffs, in particular business meters, that are monitored at a temporal resolution of 30 min (British Business Energy 2021). Given the need for a high temporal and spatial resolution model, as well as time and financial constraints for data collection, the VOAMM, STSM and DUOATS modelling approaches was discounted. Whilst both the ABM and MCM approaches provide adequate levels of detail and temporal resolutions for the TDM, the ABM approach has a lower computational complexity than the MCM approach, and hence was selected.

2.2. Activity based modelling

The ABM approach was identified as being capable of producing a high temporal resolution at a suitable level of detail (i.e. car movements every 30 min to align with electricity tariff monitoring) for time of day analysis of travel demand (Daina, Sivakumar, and Polack 2017). At the heart of the development of activity based models there is the representation of the individual process as disaggregate (Daina, Sivakumar, and Polack 2017). They are micro-simulators (or microscopic models), whereby the behaviour for each individual is simulated to mimic that of each inhabitant within the studied area (Ridder et al. 2013; Weiss et al. 2017), allowing flexible aggregation.

Mattioli, Anable, and Goodwin (2019) used the 2016 UK National Travel Survey (NTS) to classify cars based on their patterns of use over a week. This required manipulating the NTS to create a 'vehicle travel diary' dataset, to which sequence and cluster analysis of individual vehicle use were applied. Mattioli, Anable, and Goodwin (2019) extracted six types of 'car day', with less than half exhibiting the stereotypical, and largely assumed, travel pattern determined by 9 am to 5 pm working hours, as well as showing that travel habits differ significantly by day of the week. These extracted car days could be used to inform the travel demand if they were associated with group defining characteristics (i.e. working hours, number of children, etc.). Thus, this paper proposes the use of scenarios attributed to a range of generic lifestyle scenarios, and their corresponding travel patterns in rural areas. Another example of a data led TDM was developed by Kang and Recker (2009) who analysed trip diaries and evaluated the effects of changing vehicle types to various PHEV's while maintaining the vehicle trip activity recorded in the 2000–2001 California State-wide Household Travel Survey. From this, they were able to construct 1-day trip/activity chains for over 15,823 vehicles across 11,385 households.

One major challenge in TDM development is adapting methodologies that have been predominantly designed for urban and suburban areas, where roads witness higher traffic volumes compared to the countryside (Apronti and Ksaibati 2018). Highlighting that urban based research for EV viability cannot be directly translated to rural areas, and instead requires rural specific investigation. This paper attempts to address this gap through incorporating rural specific data as the input to the TDM.

2.3. Spatial microsimulation

Multi-agent simulation refers to microscopic simulation models which model the behaviours of individual agents (e.g. a vehicle) (Raney et al. 2003), as opposed to previous methods which aggregated behaviour together. This enables researchers to overcome the limitations imposed by the lack of available geocoded micro-data in relation to travel research (Lovelace, Ballas, and Watson 2014). The initial step for spatial microsimulation approaches are population generations (Raney et al. 2003), which aim to disaggregate demographic data to obtain individual households and their members. Typically, this step is achieved through census data. For example, a passenger transport CO_2 emission model for urban Guangzhou was developed using the 2010 sixth population census of Guangzhou (Ma et al. 2018). Cullinan, Hynes, and O'Donoghue (2011) used the Simulation Model of the Irish Local Economy (SMILE) to produce a synthetic population for investigating visitor numbers to outdoor recreation sites in Ireland; and Ma et al. (2014) used the 2000 population census data at a sub-district level to create a synthetic sub-district population for understanding transport CO_2 from urban travel in Beijing. This paper employs spatial microsimulation methodology through the use of census survey data, but in combination with lifestyle scenarios to represent UK household compositions. Together this enables the development of the necessary synthetic rural population and its agents of simulation for a TDM.

2.4. Rural focused research

As of May 2021 the UK Government had only just begun considering a Rural Transport Strategy, two years after publishing its Urban Strategy, again highlighting rural areas being 'left-behind' (Rural Net Zero 2021). Rural areas are often heavily reliant on cars for transport and undertake larger distance travels for services (shops, schools, health care etc.), because of this they generate more than twice the CO_2 emissions per person than the most urban areas (Rural Net Zero 2021). This also results in the most common concern regarding EVs – driving range. However, rural households hold a potential solution, due to lower population densities, most rural homes have the ability for home charger installations, but it is also imperative that private, community and public investment into rural EV charging infrastructure is considered (Rural Net Zero 2021). McKinney, Ballantyne, and Stone (2023) focused on all charging taking place at residents homes via 7 kW Pod Point home charge points and looked towards the impact of various charging behaviours and household electricity tariff distributions. In all cases, charging scenarios successfully recharged all vehicles simulated, allowing them and their owners to conduct their pre-existing travel patterns with ease.

Multiple concerns for the transition from ICE vehicles to EVs have been studied, most prominently, the impact on the electrical grid (Ridder et al. 2013), from both a generation and demand perspective. However, these studies predominantly focus on urbanised areas

(Galus et al. 2011; Munkhammar et al. 2015), where EV charging is expected to increase peak demand, system losses and voltage violations (Crozier, Morstyn, and McCulloch 2021). Similar affects are predicted in rural areas too, for example in rural Vermont, USA, where EVs would be viable for rural mobility but it was found special consideration for power supply and vehicle-charging infrastructure would be needed (Aultman-Hall et al. 2012).

There are few examples of rural focused TDMs for developed countries (Zhong and Hanson 2009) with the predominant focus being on rural travel for developing nations. However, travel patterns for developing nations are dominated by trips required to access basic needs and services (Oyeleye, Toyobo, and Adetunji 2013) which is not translatable to rural scenarios for developed countries. In developed countries, trip purposes and travel patterns are similar in both rural and urban environments, but the journey distances and durations are typically extended (GOV.UK 2020b). Furthermore, many existing TDMs are large scale (Xiong and Lei 2013) that incorporate multiple transport modes (i.e. walking, driving, public transport etc.) (Hasnine and Habib 2021). In this paper however, the model is limited to solely private passenger vehicles as it is the main mode for transportation in rural areas.

Whilst large-scale TDMs, such as state-wide models found in the US (Xiong and Lei 2013), that encompass both urban and rural areas; their high-level focus is reflected in their applications. For example, they have been used for inter-state ‘corridor-level’ transportation planning, freight analysis, congestion management, tolling scenarios, and high speed rail (HSR) development (Xiong and Lei 2013); but neglecting to address needs of local rural consumers and how this will translate to EVs. In the UK, Jahanshahi and Jin (2016) used NTS data to investigate travel behaviour’s relationship with the local built environment typologies, however, their work remained focused on “urban design measures”.

2.5. Research contribution

This paper develops a suitable TDM which reflects the nuances of the travel activity seen in UK rural areas and by extension aid research into the EV transition for these areas. It aims to contribute to academic discourse through:

- The development of a high tempo-spatial TDM applicable to UK rural areas
- Use of household lifestyle and travel scenarios to generate an Activity Based TDM
- Investigate energy requirements of EVs in rural areas

3. Travel demand model

3.1. Case study location

In order to acquire real life vehicle and household statistics to input into the TDM a case study location was identified. A rural village of Bradbourne, on the edge of the Peak District National Park in the UK (Figure 1) was chosen. The village was selected due to its small population size, and by extension a lower computational requirement. Additionally, Bradbourne has readily available public data (including, population and dwelling statistics); key inputs for the model.

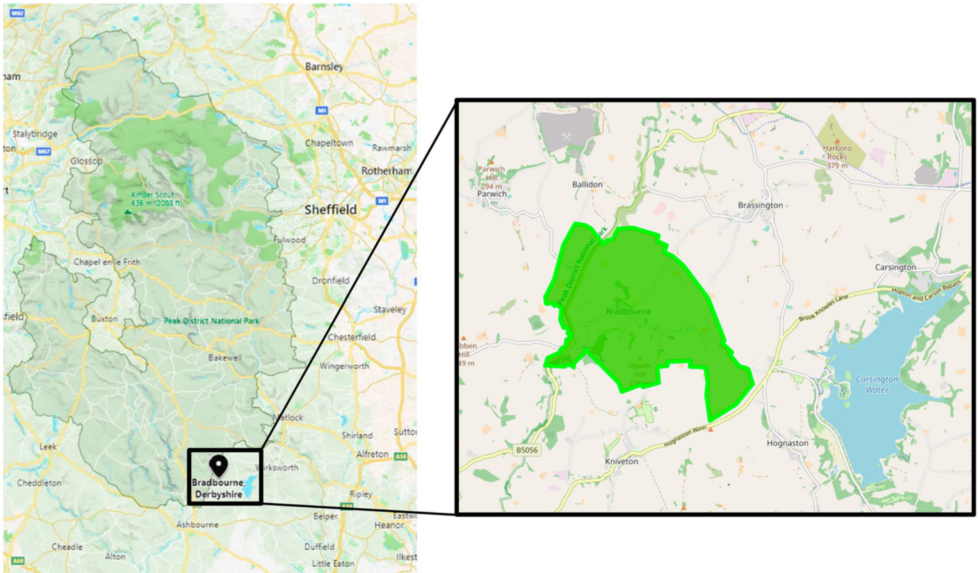

Figure 1. Bradbourne, England, UK. Source: (Left) Bing (2021), (Right) City Population (2021).

3.2. Household and car distribution

The model requires an understanding of the household and vehicle distribution across the location simulated (i.e. number of vehicles per household). The number of households (including occupancy levels) and car ownership data for Bradbourne was obtained from the 2011 UK Census Survey (Table QS406EW (Nomis 2013a) and QS416EW (Nomis 2013b), respectively). To approximate the number of cars per household, these datasets were combined on the premise that 'the larger the household, the higher the number of cars will be available'. Each house was given an ID number ranging from 1 to 49, which resulted in 49 household compositions (Table 1).

3.3. Lifestyle scenarios

Based upon the composition of each household (Table 1), coupled with consideration of how those factors reflect potential occupant(s) ages, and their employment or education status, numerous lifestyle scenarios were developed (Table 2).

To differentiate between households that would likely have children in education or not, and if the child themselves is capable of driving, households with children have been divided into three categories based on occupants age(s): '<5 yrs', '5–18 yrs', and '17–18 yrs'. A random number generator was used to determine which individual household would be assigned each lifestyle scenario within its category (Table 3).

3.4. Model inputs

From these lifestyle scenarios, a combination of trip purposes that each household might reasonably undertake in order to fulfil its lifestyle requirements (i.e. full time work – commuting trip purpose), was determined. This has the added benefit of indirectly

Table 1. Households of Bradbourne composition.

Household occupancy	House ID	No. of cars	Household occupancy	House ID	No. of cars
One Person	1	0	Three Person	30	2
	2	0		31	2
	3	0		32	2
	4	0		33	2
	5	1		34	2
	6	1		35	2
	7	1		36	2
	8	1		37	2
	9	1		38	2
	10	1		39	2
	11	1		40	3
	12	1		41	3
	13	1		42	3
	14	1	Four Person	43	3
	15	1		44	3
Two Person	16	1		45	3
	17	1	Five Person	46	3
	18	1		47	3
	19	1	Six Person	48	3
	20	1	Seven Person	49	4
	21	1			
	22	2			
	23	2			
	24	2			
	25	2			
	26	2			
	27	2			
	28	2			
	29	2			

Table 2. Lifestyle scenarios.

Household composition	Description	Lifestyle scenario
One Person & No Car	One Adult – N/A to this study	1
One Person & One Car	One Adult – Retired Individual	2
	One Adult – Working Full Time	3
Two Person & One Car	Two Adults – Retired	4
	Two Adults – One Works Full Time, One Does Not	5
	Two Adults – Both Work Full Time (Car Share)	6
	One Adult, One Children (<5 yrs) – One Works Full Time	7
	Two Adults – One Works Part Time, One Doesn't	8
Two Person &Two Car	Two Adults – Both Work Full Time	9
	Two Adults – One Works Full Time, One Works Part Time	10
	Two Adults – One Works Full Time, One 'Other'	11
	Two Adults – Both Retired	12
Three Person &Two Car	Two Adults & One Children (<5 yrs) – One Works Full Time, One 'Other'	13
	Two Adults & One Children (5–18 yrs) – One Works Full Time, One School + Other	14
	Two Adults & One Children (5–18 yrs) – One Works Full Time, One School + Part Time Work	15
	Two Adults & One Children (5–18 yrs) – Two Work Full Time	16
Three Person & Three Car	Two Adults & One Children (17–18 yrs) – Two Work Full Time, One School	17
	Three Adults – Three Work Full Time	18
	Three Adults – Two Work Full Time, One Car sits idle	19
Four Person & Three Car	Two Adults & Two Children (5–18 yrs) – Two Work Full Time, One School	20
	Two Adults & Two Children (5–18 yrs) – Two Work Full Time, One Car sits idle	21
Five Person & Three Car	Two Adults & Three Children (5–18 yrs) – One Works Full Time, One 'Other', One School	22
	Three Adults & Two Children (5–18 yrs) – Two Work Full Time, One Works Part Time	23
Six Person & Three Car	Three Adults & Three Children (5–18 yrs) – Three Work Full Time	24
	Four Adults & Two Children (5–18 yrs) – Two Work Full Time, Two Don't	25
Seven Person & Four Car	Three Adults & Four Children (5–18 yrs) – Two Work Full Time, One Doesn't, One School	26
	Four Adults & Three Children (5–18 yrs & <5 yrs) – Two Work Full Time, One Doesn't	27

Table 3. Household compositions.

House ID	Lifestyle scenario	No. of occupants	No. of vehicles	House ID	Lifestyle scenario	No. of occupants	No. of vehicles
House 1	1	1	0	House 26	12	2	2
House 2	1	1	0	House 27	10	2	2
House 3	1	1	0	House 28	10	2	2
House 4	1	1	0	House 29	9	2	2
House 5	2	1	1	House 30	13	3	2
House 6	3	1	1	House 31	16	3	2
House 7	3	1	1	House 32	13	3	2
House 8	2	1	1	House 33	14	3	2
House 9	3	1	1	House 34	13	3	2
House 10	2	1	1	House 35	14	3	2
House 11	3	1	1	House 36	13	3	2
House 12	2	1	1	House 37	16	3	2
House 13	3	1	1	House 38	13	3	2
House 14	3	1	1	House 39	15	3	2
House 15	3	1	1	House 40	18	3	3
House 16	4	2	1	House 41	19	3	3
House 17	6	2	1	House 42	17	3	3
House 18	5	2	1	House 43	20	4	3
House 19	7	2	1	House 44	21	4	3
House 20	8	2	1	House 45	21	4	3
House 21	4	2	1	House 46	22	5	3
House 22	11	2	2	House 47	23	5	3
House 23	9	2	2	House 48	24	6	3
House 24	11	2	2	House 49	26	7	4
House 25	9	2	2				

incorporating household drivers serving other household members, such as school drop-offs and car sharing to work. As the model is built from the perspective of the vehicles themselves as the agents of simulation (Raney et al. 2003), the complexities of household member task allocation and interactions are reduced.

The trip purposes were derived from the UK 2019 NTS (DfT 2020b; GOV.UK 2020b) dataset where only rural participant households were extracted (Table 4a). The NTS records 14 various trip purposes and their durations/distances (Table 4a). For simplicity, the number of trip purpose categories used for this model was reduced from 14 to 5 categories through either combination or discarded. The resulting categories and their associated duration and distances are shown in Table 4b.

The temporal resolution of the model output was set to 30 min, to align with electricity meter readings, and a blanket duration of 30 min for all trip purposes was applied, as opposed to the averaged values presented in Table 4b. Since, no trip purpose presented in Table 4b averaged over 30 min duration, this blanket approach allowed for easier computation as each trip generated occupies a single 30 min slot in the final output.

To produce a 7-day travel profile, four key factors are required:

(1) The time the activity occurs
(2) The day the activity occurs
(3) The duration of the activity
(4) The number of times this activity occurs (across the 7 day period)

The NTS dataset has been used to derive probabilities for the trip start times for the various trip purposes occurring throughout the day, and the probability of

Table 4. (a) NTS trip categories, (b) Derived trip purposes for TDM.

National travel survey categories		
Trip purpose	Trip duration	Trip distance
(a)		
Commuting	27	11.8
Business	*38*	*20.7*
Education	17	5.6
Escort Education	*14*	*4.6*
Shopping	19	7.4
Other Escort	*19*	*8.2*
Personal Business	20	8.6
Visiting friends at private home	29	15.1
Visiting friends elsewhere	20	8.3
Entertainment / Public Activity	23	9.8
Sport: participate	22	10.0
Holiday: base	*97*	*59.7*
Day Trip	28	13.2
Other including just walk	*39*	*17.3*
(b)		

Derived categories for TDM		
Trip purpose	Trip duration	Trip distance
Commuting	27	11.8
Discarded		
Education	17	5.6
Discarded		
Shopping	19	7.4
Discarded		
Other	23	10.4
Discarded		
Day Trip	28	13.2
Discarded		

which days each type of trip is most likely to occur on across the week (key factors 1 and 2). However, due to the large pre-processing requirements, the duration and number of trip occurrences (key factors 3 and 4), reasonable assumptions have been made. The individual trip purposes and their input details will now be described in detail.

3.4.1. Commuting

The model considers full time and part time employment. Full time occurs five days a week, Monday to Friday with a duration of 8 h; part-time has two options; (1) works five days a week, 4 h per day, or (2) works three days a week (randomly selected) for 8 h. A random number generator was used to determine which part time work option and for which days of the week. The model's determination of trip start time for commuting to work is based on the probability distribution shown in Figure 2.

3.4.2. Education

Education trips are modelled in a similar way to Commuting; the occurrence is restricted to Monday to Friday and only for households with an occupant of school age. An important consideration for Education trips is if the vehicle being used remains at school for the duration of the school day or is only used for 'drop-offs/ pick-ups', hence the 17–18 yr old child category previously mentioned. The trip

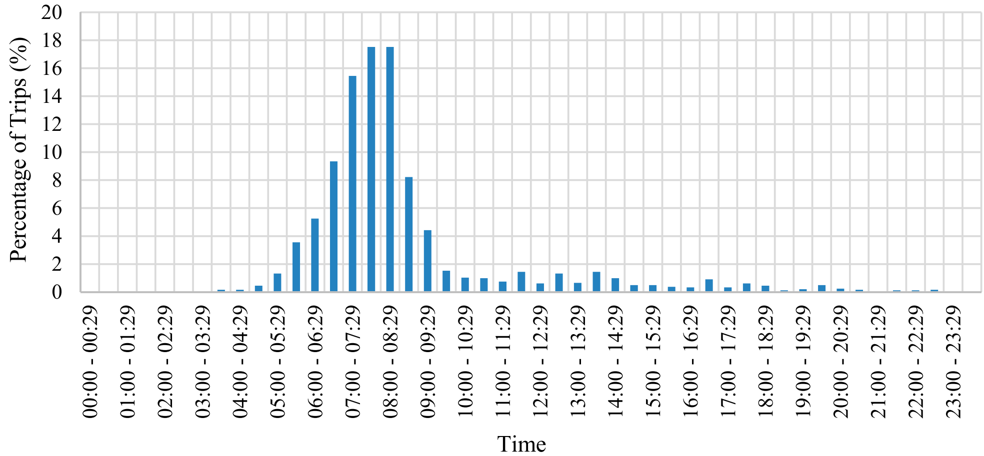

Figure 2. Trip start time probability distribution for 'Commuting'.

start time for education trips is determined by the probability distribution shown in Figure 3, and the School day is assumed to end at 15:30, thus any return or 'pick-up' trips will occur at this time.

3.4.3. Day trip

Day Trips have a set duration of 4 h, which can be initiated at any start time as per the probability distribution (Figure 4).

With regards to the occurrence of Day trips, this depends on the employment status of the household. For retired households, 2 day trips are assigned per week, one on a weekday, one on the weekend. For employed households, only one trip per week is undertaken on either a Saturday or Sunday. The determination of which day/s that a day trip is scheduled is controlled by the probability distribution for days of the week, shown in Figure 5.

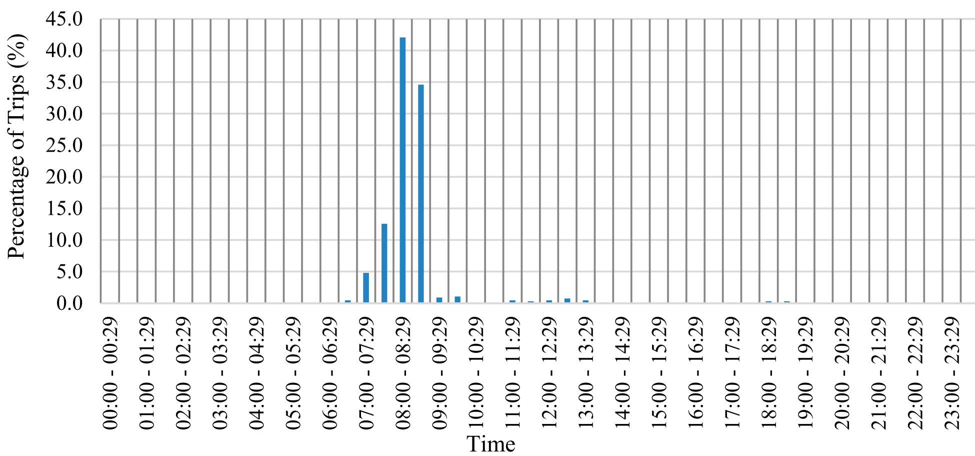

Figure 3. Trip start time probability distribution for 'Education'.

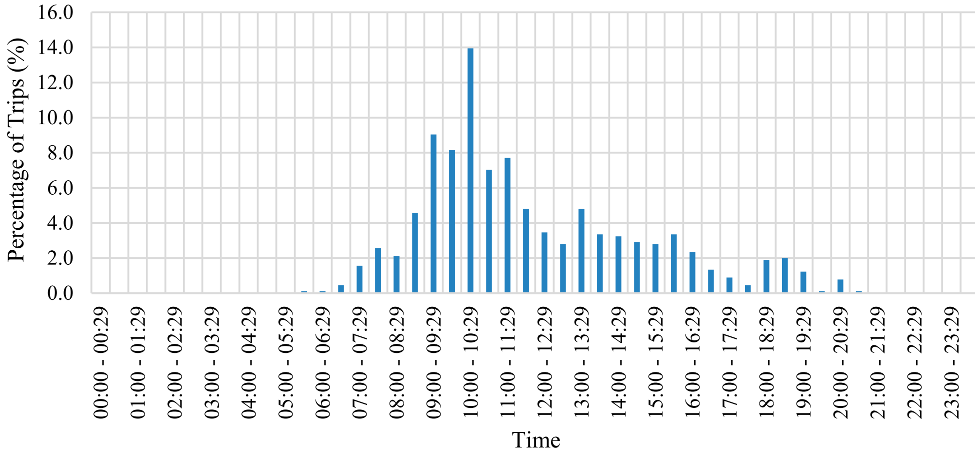

Figure 4. Trip start time probability distribution for 'Day Trip'.

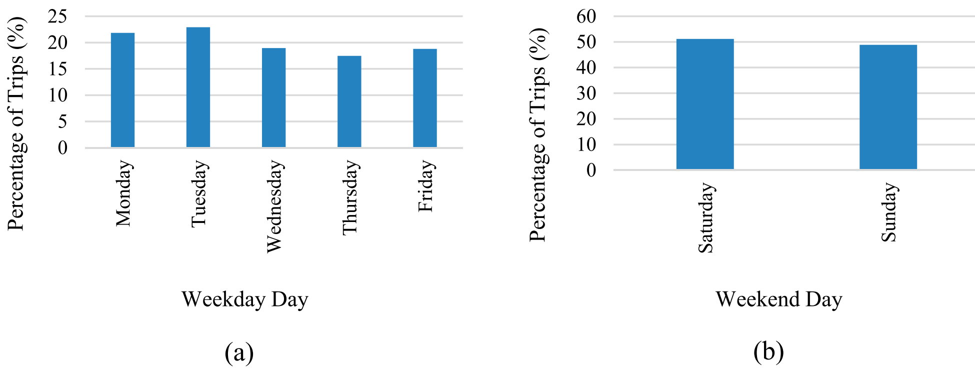

Figure 5. Day of week probability distribution for 'Day Trip'. (a) Weekday and (b) Weekend.

3.4.4. Shopping

The process of trip generation for 'Shopping' for each household depends on multiple variables. Firstly, according to the NTS, only 88% of Bradbourne's 49 households conduct shopping trips across the week. Therefore, a random number generator determined which households would conduct shopping trips across the simulated period. Secondly, the number of shopping trips across the 7-day period was required. The NTS dataset provided information regarding how often participants travel to the shops with 25% of the households shopping '3 or more times a week', it was decided to model 50% of households shopping three times, and 50% shopping four times per week. 68% of households will shop 'Once or twice a week', and so it was chosen that 50% of households will conduct one shopping trip, and the other 50% will shop twice. The remaining 7% of participants, which equates to just over 3 households in Bradbourne, shop less than once per week. This was incorporated with one household, randomly selected, to conduct just a single shopping trip during the simulation period.

The start time probability distribution for shopping trips is shown in Figure 6. The duration of a shopping trip was set to 2 h and the determination of which day of the week it would occur for an individual household was controlled by the probability distribution (Figure 7).

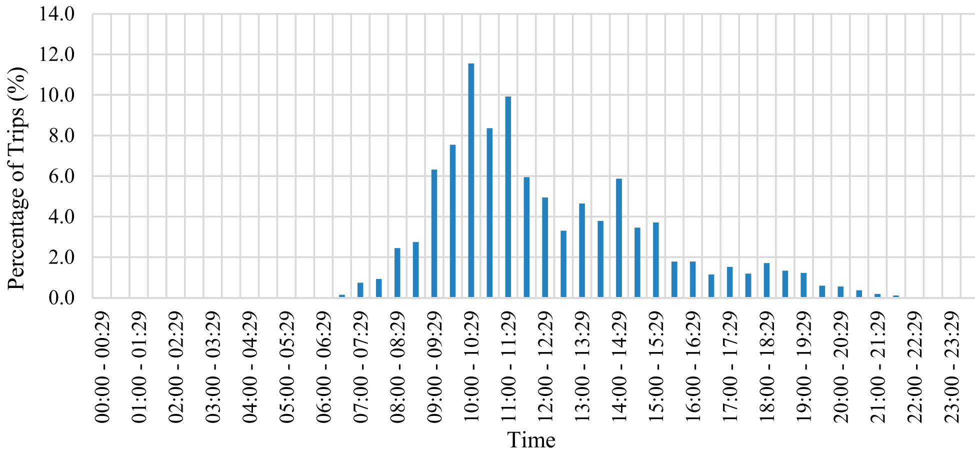

Figure 6. Trip start time probability distribution for 'Shopping'.

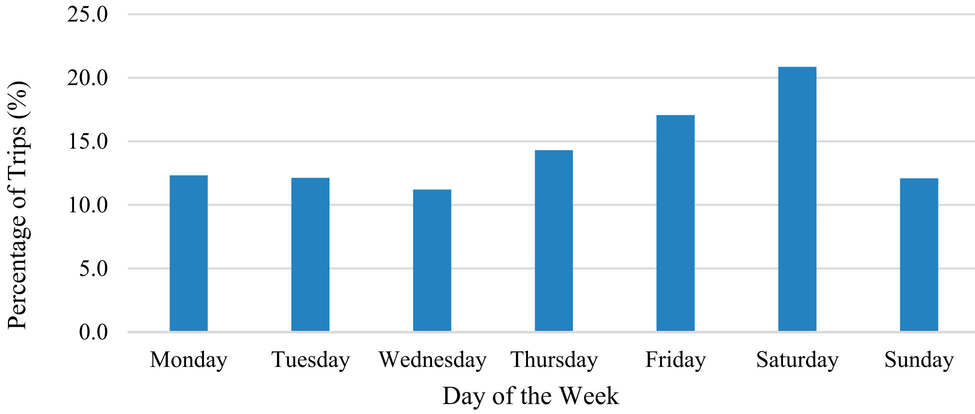

Figure 7. Probability distribution for 'Shopping' by day of the week.

3.4.5. Other

The final category, 'Other', has an activity duration of 2 h, with a start time controlled by the probability distribution shown in Figure 8.

The NTS dataset, provided the probability distribution used to choose days of the week for 'Other' trips to occur (Figure 9). Unlike the previous trip purposes, multiple 'Other' trips can be scheduled for the same day.

The number of times this activity occurs during a simulated week was determined by the number of vehicles available to the household (Table 1). The resulting number of 'Other' trips for each household composition can be seen in Table 5.

3.5. Model methodology

The model presented utilises a logic flowchart, set by rules and decisions for generating and scheduling the various trips (as detailed in Section 3.4), required by each household. The overall model process is presented in Figure 10. Additional parameters such as trip hierarchy and trip chaining will also be described.

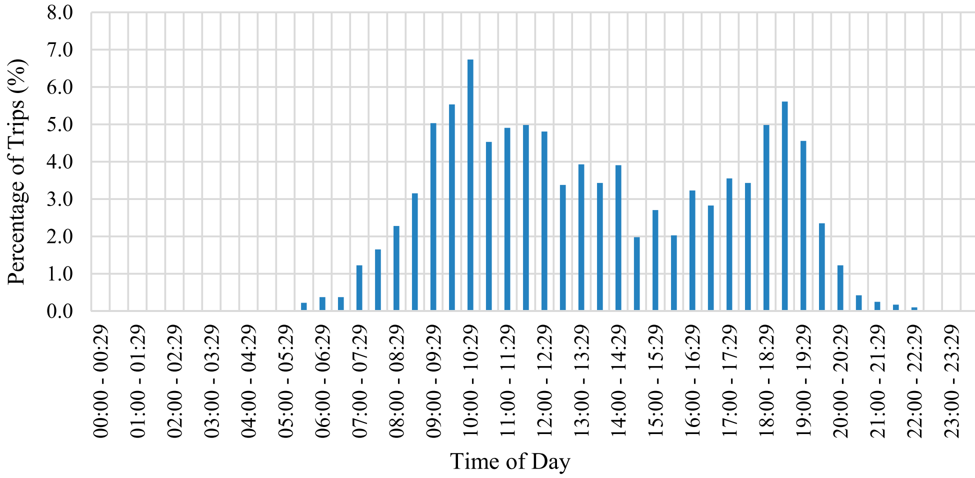

Figure 8. Trip start time probability distribution for 'Other'.

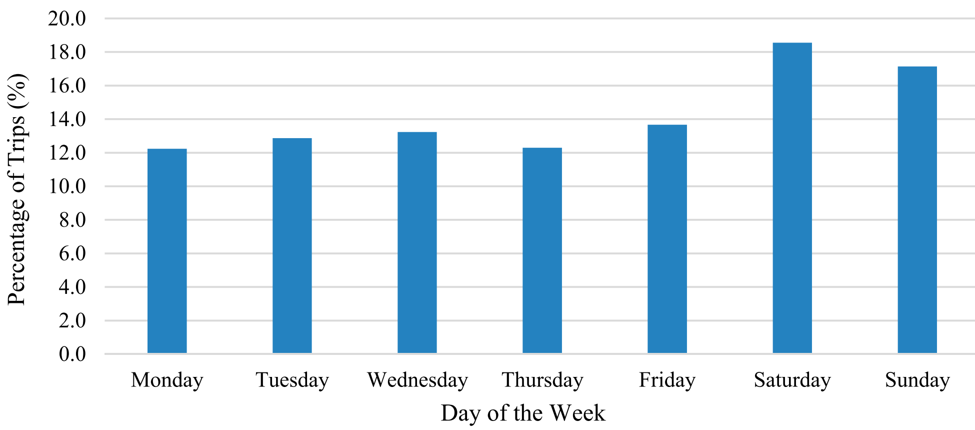

Figure 9. Probability distribution for 'Other' activities by day of the week.

Table 5. Number of 'Other' trips for households based on their composition.

Household composition	No. of other trips
1 Person/1 Car	2
2 Person/1 Car	3
2 Person/2 Cars	4
3 Person/2 Cars	4
3 Person/3 Cars	6
4 Person/3 Cars	6
5 Person/3 Cars	6
6 Person/3 Cars	6
7 Person/4 Cars	8

3.5.1. Trip priority

To overcome a common scheduling error occurring within the model, where two trips could be scheduled to coincide, a priority for the trip purposes was devised (Figure 11).

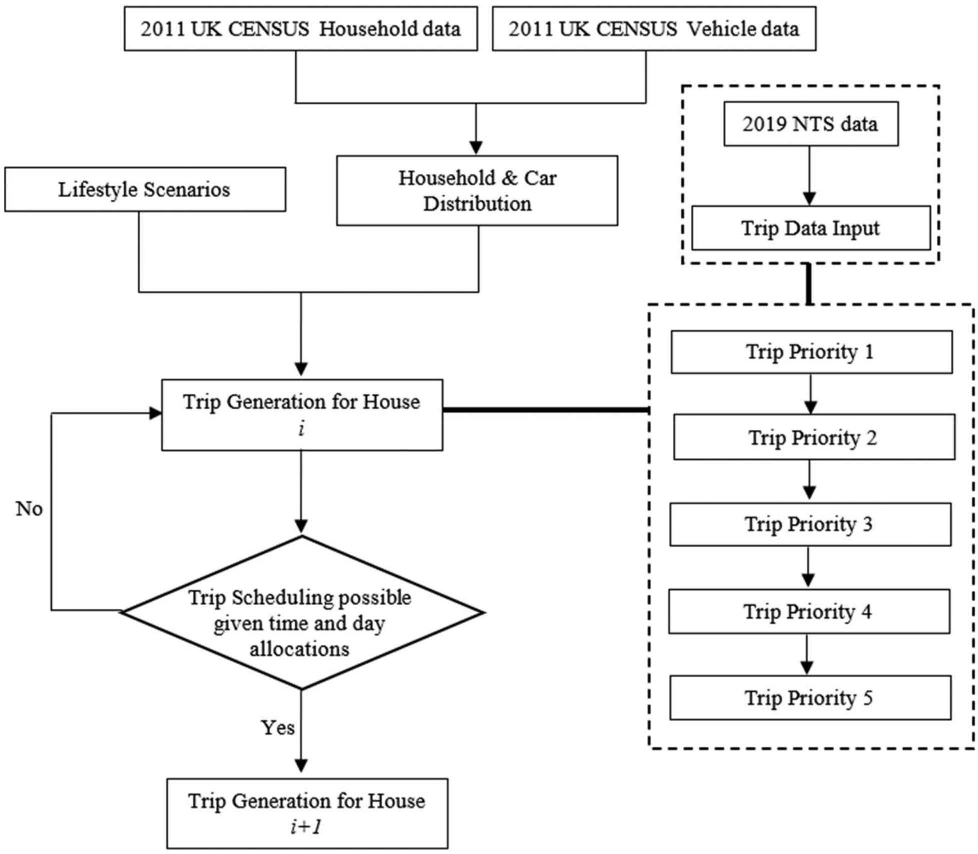

Figure 10. TDM flowchart.

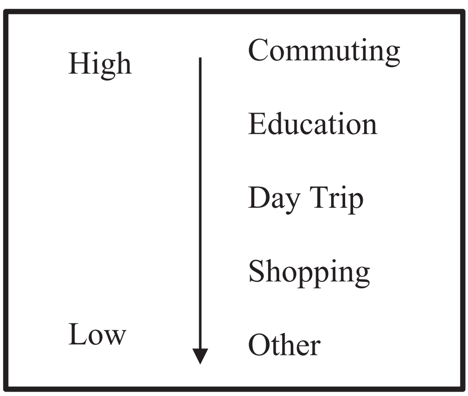

Figure 11. Trip purpose priority.

This hierarchy, or priority system was devised to determine which activity takes precedent during the scheduling and generating stage of the model. It is based upon reasonable assumptions and the idea of 'pre-planned' activities compared to more spontaneous activities. Work, School, and Day Trips have been viewed as trip purposes whose scheduling would be known by individuals prior to the start of the week (the simulation period). Whereas Shopping and Other trips are regarded as flexible or more random in occurrence, and thus adjustable in their start times. Should another trip purpose lower on the priority scale be scheduled to coincide, or during a time when the car is unavailable due to a higher priority activity, the lower priority activities start time would be recalculated until a viable solution is found.

3.5.2. Trip chaining

Trip chaining has implications for trip mileage and duration, as the vehicle is no longer used to or from 'home', but rather directly from one activity to another. Should the trip generation process schedule 0.5 h or less between two activities, these two trips will be chained together (Islam and Habib 2012). Since the mileage and durations presented in Table 4b in Section 3.4 are derived values for every trip recorded (not just trips oriented around 'home') for that purpose the values in Table 4b have been used.

3.5.3. Multiple vehicles

For households with multiple vehicles, attempts were made to reasonably distribute the trips between the vehicles available. Given the aim of this model to investigate EVs, the mileage attributed to individual vehicles becomes paramount in determining the amount of energy that vehicle uses. The constraints devised for trip distribution to individual vehicles were based on the different trip purposes.

(1) Commuting – Each employed occupant of a household conduct their commuting trips in separate vehicles (unless car-sharing). Starting with employed individual 1's commuting trips assigned to Car 1, then employed individual 2's commuting trips assigned to Car 2 and so forth.
(2) Education – Education trips are assigned to the next available vehicle not being used for commuting. If all cars are used for commuting, the last car to be assigned to an employed individual is assigned the Education trips.
(3) Day Trip – Car 1 conducts all 'day trip' trips scheduled.
(4) Shopping – Car 2 conducts all shopping trips regardless of number of vehicles required for commuting or education trips.
(5) Other – The total number of 'Other' trips for the household (Table 5), are split equally between the total number of vehicles available to that household.

4. Results and discussion

In total, 1288 trips were modelled, averaging just under 29 trips per household per week; and a total of 13,520 miles were simulated over a week, across Bradbourne's 84 vehicles. An example of the model's output for 7 days vehicle usage for House 11 is shown in Table 6.

House 11 is a 'One person & One car' household with one adult working full time. Thus the vehicle at this household was assigned 'Commuting' journeys Monday to Friday; one 'Day Trip' occurring over the weekend; four 'Shopping' trips through the week; and two 'Other' trips during the seven day simulation period.

Table 6. Simulation results for House 11.

		Monday		Tuesday		Wednesday		Thursday		Friday		Saturday		Sunday	
		Location	Miles	Location	Miles	Location	Miles	Location	Miles	Location	Miles	Location	Miles	Location	Miles
Time	00:00	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0
	00:30	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0
	01:00	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0
	01:30	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0
	02:00	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0
	02:30	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0
	03:00	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0
	03:30	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0
	04:00	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0
	04:30	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0
	05:00	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0
	05:30	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0
	06:00	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0
	06:30	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0
	07:00	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0
	07:30	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0	Home	0
	08:00	Travel	0	Travel	0	Travel	0	Travel	0	Travel	0	Home	0	Travel	0
	08:30	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Home	0	Other	10.4
	09:00	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Travel	0	Other	10.4
	09:30	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Day Trip	13.2	Other	10.4
	10:00	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Day Trip	13.2	Other	10.4
	10:30	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Day Trip	13.2	Travel	10.4
	11:00	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Day Trip	13.2	Home	20.8
	11:30	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Day Trip	13.2	Home	20.8
	12:00	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Day Trip	13.2	Home	20.8
	12:30	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Day Trip	13.2	Home	20.8
	13:00	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Day Trip	13.2	Home	20.8
	13:30	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Travel	13.2	Home	20.8
	14:00	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Shopping	20.6	Home	20.8
	14:30	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Shopping	20.6	Home	20.8
	15:00	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Shopping	20.6	Travel	20.8
	15:30	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Shopping	20.6	Shopping	28.2
	16:00	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Work	11.8	Travel	20.6	Shopping	28.2
	16:30	Travel	11.8	Travel	11.8	Travel	11.8	Travel	11.8	Travel	11.8	Home	28	Shopping	28.2
	17:00	Home	23.6	Home	23.6	Home	23.6	Other	22.2	Home	23.6	Home	28	Shopping	28.2

(*Continued*)

Table 6. Continued.

	Monday		Tuesday		Wednesday		Thursday		Friday		Saturday		Sunday	
	Location	Miles	Location	Miles	Location	Miles	Location	Miles	Location	Miles	Location	Miles	Location	Miles
17:30	Home	23.6	Home	23.6	Home	23.6	Other	22.2	Home	23.6	Home	28	Travel	28.2
18:00	Home	23.6	Home	23.6	Home	23.6	Other	22.2	Travel	23.6	Home	28	Home	35.6
18:30	Home	23.6	Home	23.6	Home	23.6	Other	22.2	Shopping	31	Home	28	Home	35.6
19:00	Home	23.6	Home	23.6	Home	23.6	Travel	22.2	Shopping	31	Home	28	Home	35.6
19:30	Home	23.6	Travel	23.6	Home	23.6	Home	32.6	Shopping	31	Home	28	Home	35.6
20:00	Home	23.6	Shopping	31	Home	23.6	Home	32.6	Shopping	31	Home	28	Home	35.6
20:30	Home	23.6	Shopping	31	Home	23.6	Home	32.6	Travel	31	Home	28	Home	35.6
21:00	Home	23.6	Shopping	31	Home	23.6	Home	32.6	Home	38.4	Home	28	Home	35.6
21:30	Home	23.6	Shopping	31	Home	23.6	Home	32.6	Home	38.4	Home	28	Home	35.6
22:00	Home	23.6	Travel	31	Home	23.6	Home	32.6	Home	38.4	Home	28	Home	35.6
22:30	Home	23.6	Home	38.4	Home	23.6	Home	32.6	Home	38.4	Home	28	Home	35.6
23:00	Home	23.6	Home	38.4	Home	23.6	Home	32.6	Home	38.4	Home	28	Home	35.6
23:30	Home	23.6	Home	38.4	Home	23.6	Home	32.6	Home	38.4	Home	28	Home	35.6

The probability distributions presented in Section 3.4 resulted in large variations of travel patterns predicted for each vehicle. Vehicles ranged from conducting 2 trips per week to over 10, and a range of weekly miles driven from 41.6 miles to 324.8 miles. The vehicles over the seven day period that drove the minimum and maximum number of miles are shown in Figures 12 and 13 respectively. House 45 – Car 3, travelled the least miles, driving a total of 41.6 miles over the simulated week, as it was assigned to only complete two 'Other' trips on the Thursday and Sunday. In contrast, House 17 has two adults both working full time and one car. The vehicle is car shared by both members of the household for commuting and completes a number of 'Other' trips and one 'Day Trip' over the weekend.

The average vehicle travelled just under 161 miles per week, scaling up to a year, on the basis of 52 weeks, combines to a total of 8369 miles per vehicle. Table 7 below shows the yearly mileage by person from the 2019 NTS dataset for comparison with the model presented in this paper.

As per Table 7, individuals within rural areas travel on average 8596 to 9756 miles per year. Comparing to the 8369 miles as forecasted by our model, this represents only a 2.7%

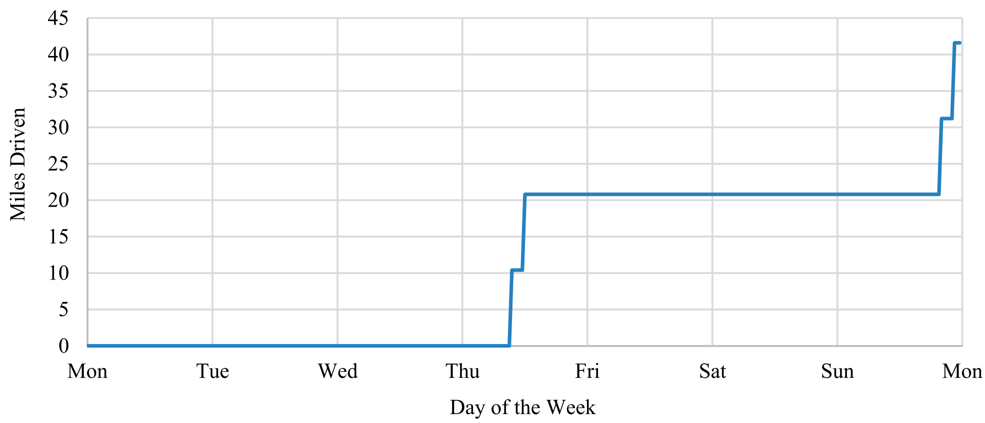

Figure 12. Vehicle with minimum cumulative mileage driven over the week (House 45 – Car 3).

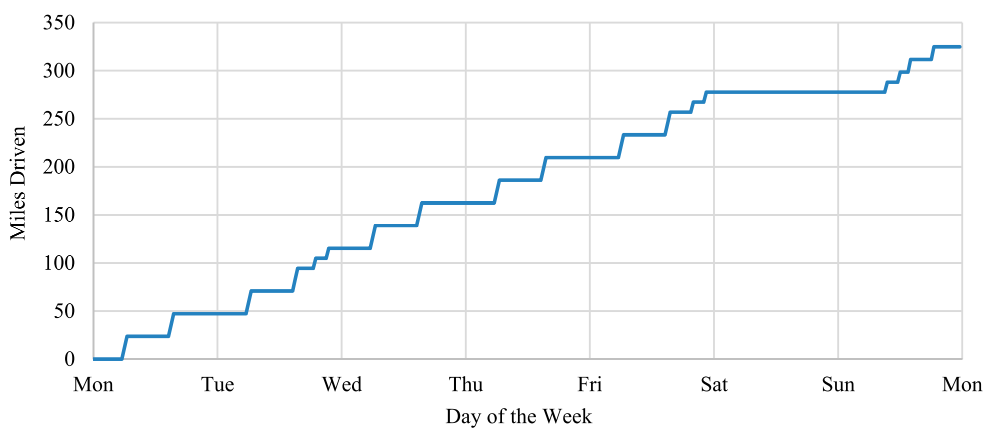

Figure 13. Vehicle with maximum cumulative mileage driven over the week (House 17 – Car 1).

Table 7. Miles per person per year from the 2019 NTS dataset categorised by rural-urban classification (NTS9907) (GOV.UK, 2020b).

Rural-urban classification	2019 NTS
Urban Conurbation	5037
Urban City and Town	6772
Rural Town and Fringe	8596
Rural Village, Hamlet, and Isolated Dwelling	9756
All Areas	6515

difference to the lower end value. This could be explained by the discrepancy between what the two values being compared are defined as. The NTS values presented in Table 7 are 'Miles per person per year', whereas the mileages forecasted by the model developed in this paper relate to the miles per vehicle per year. Due to the nature of the NTS, whereby individuals complete their travel diaries from their own point of view (POV), this can lead to higher mileages due to situations whereby two individuals are in the same vehicle conducting the same journey. For example, if an adult was taking their child to school, from the perspective of this papers model, a single car is used, and the mileage associated with that journey is recorded. However, for the NTS recording this would constitute two person trips, essentially doubling the mileage.

5. Implications for EV energy consumption

The TDM presented does not include a car type parameter, unlike some other models (Mocanu 2018). However, as the main focus of this model is to inform the equivalent energy EVs will require to conduct predicted travel patterns, incorporating car types (specifically ICE vehicles) was deemed outside the scope of the models' requirements. With the output of the TDM providing the miles driven by each car during a week, the energy consumed per mile by an EV can be calculated. For simplicity a 100% homogeneous EV population was chosen, all 84 vehicles would be assumed to be a 40 kWh Nissan Leaf. A constant consumption rate for each Nissan Leaf was taken, 26.5 kWh/100miles (Electric Vehicle Database 2018). Figure 14 shows the total energy consumed by all 84 EVs over the 7-day simulation period.

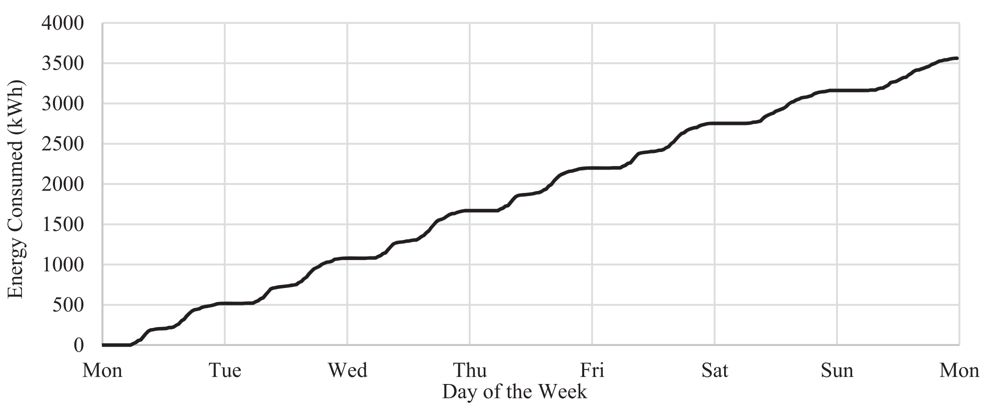

Figure 14. Total energy consumed over the 7-day simulation period (cumulative).

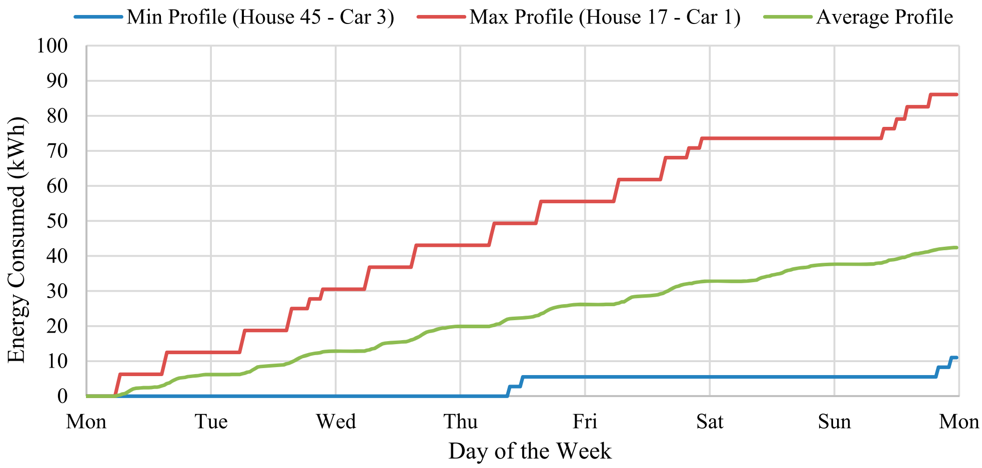

Figure 15. Minimum, maximum and average EV energy profiles (cumulative).

Over the course of the week, a total of 3562 kWh were consumed by the synthetic 84 Nissan Leaf population of Bradbourne. To put this into perspective, the average electricity consumption for a UK household is 3100 kWh/year (BEIS 2021). The energy profiles for the lowest and highest mileage vehicles, House 45 – Car 3 and House 17 – Car 1, are presented (Figure 15), alongside the average EVs energy profile.

With an understanding of the energy consumption for a fleet of 100% electric vehicles in Bradbourne over the course of a week; attention can now be focused on the recharging patterns to ensure this energy is replaced. A full in-depth analysis of charging requirements was deemed outside the scope of this paper; however this work was done in McKinney, Ballantyne, and Stone (2023).

6. Conclusion

This paper has presented the development of a 7 – day TDM built upon rural specific data which adopts a new approach incorporating lifestyle scenarios. The rural Peak District village of Bradbourne, UK, was used as a real-world application of this model. Using the UK Census for statistical data relating to the village itself, the private passenger vehicle travelling habits of a community of 49 households and 84 vehicles was simulated for a week. With a high temporal resolution of 30 min for all activities of each vehicle, a detailed picture of Bradbourne's car usage has been achieved. The level of detail provided by this TDM enables its usability for determining energy requirements for EVs in rural areas. Using a synthetic EV population, these 84 vehicles were shown to consume more energy in one week than an average UK household consumes within a year. Building upon this work, EV charging scenarios can be incorporated to determine the impact EVs will have on local rural grid infrastructure.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

This work was supported by the University of Sheffield Energy Institute.

ORCID

Thomas R. McKinney http://orcid.org/0000-0001-7982-2274
Erica E. F. Ballantyne http://orcid.org/0000-0003-4665-0941
David A. Stone http://orcid.org/0000-0002-5770-3917

References

Apronti, D. T., and K. Ksaibati. 2018. "Four-Step Travel Demand Model Implementation for Estimating Traffic Volumes on Rural Low-Volume Roads in Wyoming." *Transportation Planning and Technology* 41 (5): 557–571. https://doi.org/10.1080/03081060.2018.1469288.

Aultman-Hall, L., J. Sears, J. Dowds, and P. Hines. 2012. "Travel Demand and Charging Capacity for Electric Vehicles in Rural States." *Transportation Research Record* 2287 (1): 27–36. https://doi.org/10.3141/2287-04.

Axsen, J., and K. S. Kurani. 2010. "Anticipating Plug-in Hybrid Vehicle Energy Impacts in California: Constructing Consumer-Informed Recharge Profiles." *Transportation Research. Part D, Transport and Environment* 15 (4): 212–219. https://doi.org/10.1016/j.trd.2010.02.004.

Bing Maps. 2021. "Bradbourne, England." *Microsoft Bing*. Accessed 13 October 2021. https://www.bing.com/maps.

British Business Energy. 2021. "Half Hourly Electricity Metering & HH (00) Meters Explained." *British Business Energy*. Accessed 14 March 2021. https://britishbusinessenergy.co.uk/half-hourly/#:~:text=Half%20Hourly%20(HH)%20electricity%20metering,your%20supplier%20every%2030%20mins.

Brownstone, D., D. S. Bunch, T. F. Golob. 1994. *A Demand Forecasting System for Clean-Fuel Vehicles*. Berkeley: The University of California Transportation Center, UCTC No. 221.

City Population. 2021. "Bradbourne: Parish in East Midlands." *City Population*. https://citypopulation.de/en/uk/eastmidlands/admin/derbyshire_dales/E04002729__bradbourne/.

Cooper, G. 2018. "Welsh Parliament. Economy, Infrastructure and Skills Committee meeting minutes." Graeme Cooper – 10:50:57. https://record.assembly.wales/Committee/5150.

Crozier, C., T. Morstyn, and M. McCulloch. 2021. "Capturing Diversity in Electric Vehicle Charging Behaviour for Network Capacity Estimation." *Transportation Research Part D, Transport and Environment* 93: 102762. https://doi.org/10.1016/j.trd.2021.102762.

Cullinan, J., S. Hynes, and C. O'Donoghue. 2011. "Using Spatial Microsimulation to Account for Demographic and Spatial Factors in Environmental Benefit Transfer." *Ecological Economics* 70 (4): 813–824. https://doi.org/10.1016/j.ecolecon.2010.12.003.

Daina, N., A. Sivakumar, and J. Polack. 2017. "Modelling Electric Vehicle use: A Survey on the Methods." *Renewable and Sustainable Energy Reviews* 68: 447–460. https://doi.org/10.1016/j.rser.2016.10.005.

Delhoum, Y., R. Belaroussi, F. Dupin, and M. Zaragayouna. 2020. "Activity-Based Demand Modeling for a Future Urban District." *Sustainability (Basel, Switzerland)* 12 (14): 5821. https://doi.org/10.3390/su12145821.

Department for Business, Energy & Industrial Strategy. 2021. "Energy Follow Up Survey: Household Energy Consumption & Affordability. Final Report." Accessed 17 August 2022. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/1018725/efus-Household-Energy-Consumption-Affordability.pdf.

Department for Environment, Food and Rural Affairs, and Department for Transport. 2017. "UK plan for tackling roadside nitrogen dioxide concentrations." Accessed 30 April 2021. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/633269/air-quality-plan-overview.pdf.

Department for Transport. 2020a. "Electric Vehicle Charging Device Statistics July 2020." Accessed 29 July 2021. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/907742/electric-vehicle-charging-device-statistics-july-2020.pdf.

Department for Transport. 2020b. "National Travel Survey, 2002–2019: UK Data Service, 14th Edition." SN: 5340. Accessed 5 July 2021. https://doi.org/10.5255/UKDA-SN-5340-10.

Department of Transport. 2018. "The Road to Zero." *GOV.UK*. Accessed 20 June 2020. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/739460/road-to-zero.pdf

Electric Vehicle Database. 2018. "Nissan Leaf: EV Database." Accessed 1 February 2021. https://ev-database.uk/car/1106/Nissan-Leaf#:~:text=The%20combined%20(motorway%20and%20city,in%20a%20traditional%20petrol%20car.

Galus, M. D., C. Dobler, R. A. Waraich, G. Andersson. 2011. "Predictive, Distributed, Hierarchical Charging Control of PHEVs in the Distribution System of a Large Urban Area Incorporating a Multi Agent Transportation Simulation." *17th Power Systems Computation Conference, Stockholm, 2011*. Arbeitsberichte Verkehrs- und Raumplanung, 753. https://doi.org/10.3929/ethz-a-006999071.

Goulias, K. G. 2021. "Activity-Based Models for Travel Demand Forecasting [PowerPoint Presentation]." *MaaSLab Guest Lecture: Activity-based Models for Travel Demand Forecasting*. Accessed 04 May 2021. https://drive.google.com/file/d/16WyiPQ-tunECH9Ak20iziuwjIFp6hcGE/view?usp=sharing.

GOV.UK. 2020a. "PM Outlines His Ten Point Plan for a Green Industrial Revolution for 250,000 Jobs." *GOV.UK*. https://www.gov.uk/government/news/pm-outlines-his-ten-point-plan-for-a-green-industrial-revolution-for-250000-jobs.

GOV.UK. 2020b. "National Travel Survey: 2019." *GOV.UK*. Accessed 20 March 2021. https://www.gov.uk/government/statistics/national-travel-survey-2019.

Hasnine, M. S., and K. N. Habib. 2021. "Tour-Based Mode Choice Modelling as the Core of an Activity-Based Travel Demand Modelling Framework: A Review of State-of-the-Art." *Transport Reviews* 41 (1): 5–26. https://doi.org/10.1080/01441647.2020.1780648.

Hill, G., O. Heidrich, F. Creutzig, and P. Blythe. 2019. "The Role of Electric Vehicles in Near-Term Mitigation Pathways and Achieving the UK's Carbon Budget." *Applied Energy* 251: 113111. https://doi.org/10.1016/j.apenergy.2019.04.107.

Hirst, D. 2020. "Electric Vehicles and Infrastructure: House of Commons Briefing Paper." Number 7480. Accessed 20 May 2021. https://commonslibrary.parliament.uk/research-briefings/cbp-7480/.

House of Commons. 2018. *Electric Vehicles: Driving the Transition*. London: House of Commons. Accessed 18 January 2022. https://publications.parliament.uk/pa/cm201719/cmselect/cmbeis/383/383.pdf.

Islam, T., and K. M. N. Habib. 2012. "Unraveling the Relationship Between Trip Chaining and Mode Choice: Evidence from a Multi-Week Travel Diary." *Transportation Planning and Technology* 35 (4): 409–426. https://doi.org/10.1080/03081060.2012.680812.

Jahanshahi, K., and Y. Jin. 2016. "The Built Environment Typologies in the UK and Their Influences on Travel Behaviour: New Evidence Through Latent Categorisation in Structural Equation Modelling." *Transportation Planning and Technology* 39 (1): 59–77. https://doi.org/10.1080/03081060.2015.1108083.

Kang, J. E., and W. W. Recker. 2009. "An Activity-Based Assessment of the Potential Impacts of Plug-in Hybrid Electric Vehicles on Energy and Emissions Using 1-Day Travel Data." *Transportation Research Part D: Transport and Environment* 14 (8): 541–556. https://doi.org/10.1016/j.trd.2009.07.012.

Kester, J., B. K. Sovacool, L. Noel, and G. Zarazua de Rubens. 2020. "Rethinking the Spatiality of Nordic Electric Vehicles and Their Popularity in Urban Environments: Moving Beyond the City?" *Journal of Transport Geography* 82: 102557. https://doi.org/10.1016/j.jtrangeo.2019.102557.

Lovelace, R., D. Ballas, and M. Watson. 2014. "A Spatial Microsimulation Approach for the Analysis of Commuter Patterns: From Individual to Regional Levels." *Journal of Transport Geography* 34: 282–296. https://doi.org/10.1016/j.jtrangeo.2013.07.008.

Ma, J., A. Heppenstall, K. Harland, and G. Mitchell. 2014. "Synthesising Carbon Emission for Mega-Cities: A Static Spatial Microsimulation of Transport CO_2 from Urban Travel in Beijing." *Computers, Environment and Urban Systems* 45: 78–88. https://doi.org/10.1016/j.compenvurbsys.2014.02.006.

Ma, J., S. Zhou, G. Mitchell, and J. Zhang. 2018. "CO_2 Emission from Passenger Travel in Guangzhou, China: A Small Area Simulation." *Applied Geography* 98: 121–132. https://doi.org/10.1016/j.apgeog.2018.07.015.

Mattioli, G., J. Anable, and P. Goodwin. 2019. "A Week in the Life of a Car: A Nuanced View of Possible EV Charging Regimes." *European Council for an Energy Efficient Economy (ECEEE)* Summer Study 2019 Proceedings: ECEEE 2019 Summer Study, 3–7 Jun 2019, Hyères France, 1105–1116.

McKinney, T. R., E. E. F. Ballantyne, and D. A. Stone. 2023. "Rural EV Charging: The Effects of Charging Behaviour and Electricity Tariffs." *Energy Reports* 9: 2321–2334. https://doi.org/10.1016/j.egyr.2023.01.056.

McNally, M. G. 2007. *The Four-Step Model. Handbook of Transport Modelling*, Vol. 1, 35–53. Edited by D. A. Hensher and K. J. Button. Bingley: Emerald Group Publishing Limited. https://doi.org/10.1108/9780857245670-003

Mocanu, T. 2018. "What Types of Cars Will We Be Driving? Methods of Forecasting Car Travel Demand by Vehicle Type." *Transportation Research Record* 2672 (49): 125–134. https://doi.org/10.1177/0361198118797457.

Morton, C., J. Anable, G. Yeboah, and C. Cottrill. 2018. "The Spatial Pattern of Demand in the Early Market for Electric Vehicles: Evidence from the United Kingdom." *Journal of Transport Geography* 72: 119–130. https://doi.org/10.1016/j.jtrangeo.2018.08.020.

Munkhammar, J., J. D. K. Bishop, J. J. Sarralde, W. Tian, and R. Choudhary. 2015. "Household Electricity Use, Electric Vehicle Home-Charging and Distributed Photovoltaic Power Production in the City of Westminster." *Energy and Buildings* 86: 439–448. https://doi.org/10.1016/j.enbuild.2014.10.006.

Nomis. 2013a. "Household Size QS406EW." *NOMIS Official Labour Market Statistics*. Accessed 20 April 2021. https://www.nomisweb.co.uk/census/2011/qs406ew.

Nomis. 2013b. "Car or Van Availability QS416EW." *NOMIS Official Labour Market Statistics*. Accessed 20 April 2021. https://www.nomisweb.co.uk/census/2011/qs416ew.

Nutley, S. 2005. "Monitoring Rural Travel Behaviour: A Longitudinal Study in Northern Ireland 1979–2001." *Journal of Transport Geography* 13 (3): 247–263. https://doi.org/10.1016/j.jtrangeo.2004.07.002.

Oyeleye, O. I., A. E. Toyobo, and M. A. Adetunji. 2013. "Travel Behaviour of Rural People in Developing Countries." *The International Institute for Science, Technology and Education (IISTE), Civil and Environmental* 3 (8), Accessed 2 February 2022. https://www.iiste.org/Journals/index.php/CER/article/view/6579.

Pareschi, G., L. Küng, G. Georges, and K. Boulouchos. 2020. "Are Travel Surveys a Good Basis for EV Models? Validation of Simulated Charging Profiles Against Empirical Data." *Applied Energy* 275, https://doi.org/10.1016/j.apenergy.2020.115318.

Raney, B., N. Cetin, A. Völlmy, M. Vrtic, K. Axhausen, and K. Nagel. 2003. "An Agent-Based Microsimulation Model of Swiss Travel: First Results." *Networks and Spatial Economics* 3 (1): 23–41. https://doi.org/10.1023/A:1022096916806.

Ridder, F. D., R. D'Hulst, L. Knapen, and D. Janssens. 2013. "Applying an Activity Based Model to Explore the Potential of Electric Vehicles in the Smart Grid." *Procedia Computer Science* 19: 847–853. Accessed 6 June 2020. https://doi.org/10.1016/j.procs.2013.06.113.

Rural Net Zero. 2021. "The role of Rural Local Authorities in reaching Net Zero." *UK100' Countryside Climate Network*. Accessed 30 November 2021. https://www.uk100.org/publications/rural-net-zero.

Soares, F. J., J. A. P. Lopes, P. M. R. Almedia, C. L. Moreira, and L. Seca. 2011. "A Stochastic Model to Simulate Electric Vehicles Motion and Quantify the Energy Required from the Grid." *Conference Paper: Power Systems Computation Conference (PSCC)*. Accessed 29 November 2021. https://www.researchgate.net/publication/235721649_A_stochastic_model_to_simulate_electric_vehicles_motion_and_quantify_the_energy_required_from_the_grid/link/00b7d52fa1433d373d000000/download

Wang, J., C. Liu, D. Ton, Y. Zhou, J. Kim, and A. Vyas. 2011. "Impact of Plug-in Hybrid Electric Vehicles on Power Systems with Demand Response and Wind Power." *Energy Policy* 39 (7): 4016–4021. https://doi.org/10.1016/j.enpol.2011.01.042.

Weiss, C., M. Heilig, N. Mallig, B. Chlond, T. Franke, T. Schneidereit, and P. Vortisch. 2017. "Assessing the Effects of a Growing Electric Vehicle Fleet Using a Microscopic Travel Demand Model." *European Journal of Transport and Infrastructure Research* 17 (3): 33–-345. https://doi.org/10.18757/ejtir.2017.17.3.3200

Williams, F., L. Philip, J. Farrington, and G. Fairhurst. 2016. "'Digital by Default' and the 'Hard to Reach': Exploring Solutions to Digital Exclusion in Remote Areas." *Local Economy* 31 (7): 757–777. https://doi.org/10.1177/0269094216670938.

Xiong, C., and Z. Lei. 2013. "Deciding Whether and how to Improve Statewide Travel Demand Models Based on Transportation Planning Application Needs." *Transportation Planning and Technology* 36 (3): 244–266. https://doi.org/10.1080/03081060.2013.779473.

Zhong, M., and B. L. Hanson. 2009. "GIS-based Travel Demand Modeling for Estimating Traffic on low-Class Roads." *Transportation Planning and Technology* 32 (5): 423–439. https://doi.org/10.1080/03081060903257053.