A week in the life of a car: a nuanced view of possible EV charging regimes

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Keywords
electric vehicles, flexibility, behaviour, clusters, time use

Abstract
In thinking about the charging and associated energy requirements of plug-in vehicles, spatial and temporal forecasts of electricity demand tend to rely on analysis of individual car usage. These are derived from travel diary studies or, increasingly, GPS traces to provide diurnal, weekly and seasonal patterns by different people in different places. More accurate forecasts of electricity demand require knowledge of the patterns of the individual cars themselves – where they will be, when, for how long, and with what likely level of battery charge. We present a two-stage optimal matching analysis of the 2016 UK National Travel Survey (NTS) to classify cars based on their patterns of use over a week. This required a novel reconfiguration of NTS data into a 'vehicle travel diary' dataset, to which sequence and cluster analysis of individual vehicle use sequences were applied. Firstly, each of the seven days of the travel diary was subdivided into 48 half hour time slots with cars recorded either in use or not in use at any point in each slot. From this, six types of 'car day' were identified, with less than half of those exhibiting the stereotypical pattern of 'morning-out and evening-home'. These six rhythms are exhibited by different groups of cars, and in different proportions on different days of the week. Secondly, each car was attached with their own set of 7 x daily rhythms using the car-day types and then grouped with cars with similar 'lifestyle' across the week. Here we found eight clusters of car-weeks, each with different rhythms within and across weekdays and weekends. We examine how these car 'lifestyles' are associated with household and vehicle characteristics using a broad range of variables available within the NTS. Finally, we contrast these findings to assumptions commonly being made in assessments of the impacts of electric vehicle grid integration. A key finding is that as electric vehicle use becomes more common in wider sections of the population, the present clustering of charging needs at times of relatively high electricity demand may become a more spread pattern, making power demand peaks somewhat easier to manage.

Introduction
The mass uptake of (plug-in) electric vehicles (EVs) is seen as a key ingredient of the energy transition, and of climate mitigation in the transport sector (Tran et al., 2012). In several countries, transport decarbonisation strategies rely heavily, if not exclusively, on the electrification of the vehicle fleet, with the UK expecting the majority of new cars and vans sold to be 'ultra low emission' by 2040 – up from just 1.8 % in 2017 (HMG, 2018). Despite this urgency, behavioural factors influencing the diffusion of EVs have been under researched until relatively recently (Sovacool & Hirsh, 2009; Sovacool et al., 2018; Tran et al., 2012).

One of the implications of the EV transition is to bring together two sectors, transport and electricity, which have to date been relatively separate, despite having both major relevance for energy consumption and greenhouse gas emissions. The potential impact of mass EV uptake on the decarbonisation of the electricity grid is contested (e.g. Colantuono, 2016; Huang & Infield, 2009; ITF, 2012). On one hand, it may improve 'grid flexibility', helping to smooth the inherently variable and intermittent supply of electricity from renewables. This would happen if significant numbers of vehicles connected to the grid were able to provide storage at times of day when demand is low, and potentially even feed this back at peak times as in the Vehicle-to-grid (V2G) concept (Moura et al., 2019; Sovacool et al., 2017). Conversely, if many EVs are recharged at peak load times, as empirical studies suggest (Carroll et al., 2013; Hardman et al., 2018; Langbroek et al., 2017; Robinson et al., 2013), decarbonisation could be more difficult, as further fossil fuel generation may be required. In addition, the potential convergence of significant additional electricity demand in time and space will have implications for where the local supply network may require expansion.

It appears thus that a crucial factor in the EV transition is the timing of EV recharging, which in turn is crucially dependent on temporal patterns of vehicle use. Yet as Tran et al. note, when these questions are explored, there is a tendency to overlook the potential heterogeneity of vehicle use patterns (2012, p.329–331). Notably, much extant research assumes that temporal patterns of EV use will reflect the rhythms of commuting, with e.g. a daily return trip at 'rush hour' (e.g. 9am and 5pm), and little use outside of that (e.g. Colantuono, 2016; Huang & Infield, 2009; Lund & Kempton, 2008). Yet there are reasons why such an assumption may be misplaced.

First, non-work activities account for a large and increasing share of passenger travel, and are often rather car-dependent (Anable, 2002; Mattioli et al., 2016). In the UK, commuting accounted for only little more than a fifth of all trips in 2016 (DfT, 2018). Second, vehicles may be used by more than one household member (not all of which are necessarily employed), notably in households with fewer cars than driver licences. We would expect this to result in more 'mixed' patterns of vehicle use than usually assumed, reflecting the temporalities of more than one type of activity, and use by the secondary driver will inherently tend to make use of some of the time unused by the primary driver, leaving less time available for charging. Third, research on the temporality of working patterns shows that these have become less standardised over time (e.g. Lesnard & Kan, 2011), and this is reflected in an increasing heterogeneity of commuting patterns (DfT, 2016).

If that is the case, it is essential to provide a comprehensive, accurate and nuanced picture of the temporal patterns of use of the current vehicle fleet, and to reflect on how these may affect the electricity grid, similarly to studies on domestic energy consumption (e.g. Anderson & Torriti, 2018). This could inform more accurate forecasts of electricity demand, which will require knowledge of the patterns of the individual cars themselves – where they will be, when, for how long, and with what likely level of battery charge.

In this study, we provide an initial picture of temporal patterns of vehicle use in England in 2016, based on a sequence- and cluster-analysis of travel survey data. In the next section, we introduce the dataset and analysis approach. We then present the results of the two-stage optimal matching analysis, and at both stages profile the obtained clusters based on a range of variables. We conclude by discussing the findings and contrasting them to assumptions commonly being made in assessments of the impacts of electric vehicle grid integration.

Data, methods and approach

Our analysis in this paper uses travel survey data to create a typology of vehicles based on the timing of their use over a week. We applied Optimal Matching (OM) to the National Travel Survey of Great Britain (NTS) in two stages (as proposed by Lesnard & Kay, 2011) to first discover the different types of usage patterns cars can be characterised as having over a day, and secondly how sequences of these daily patterns can be differentially adopted by individual cars over a week. The 'dynamic hamming' approach to OM adopted here is well suited to identify different 'collective rhythms' of social processes such as the scheduling of work (Lesnard, 2010; Lesnard & Kay, 2011). We conduct the analysis using the SADI command packages in Stata (Halpin, 2017). Our analysis is organized in five consecutive steps, as described below.

DATA CONFIGURATION AND SELECTION OF ANALYSIS SAMPLE

The NTS is a cross-sectional representative survey of household travel behaviour, carried out continuously since 1988 (since 2013 in England only). The analysis in this paper is based on the sample for 2016, i.e. the most recent year available at the time of the analysis. Unlike other comparable surveys, which are generally limited to one or two travel days, the NTS travel diary collects information on respondents' mobility (timing of the start and end of trips, distance, mode etc.) over seven consecutive days. To ensure representativeness, households start their travel diary week on different days, so that, approximately, one seventh of the sample starts on Monday, another seventh on Tuesday, etc.

Crucially for the analysis in this paper, the NTS collects information on all motor vehicles to which the household has access. The 'vehicle dataset' contains details about vehicle characteristics (e.g. make, model, and age) and use (e.g. self-reported annual mileage). Every vehicle in the dataset can be linked to the characteristics of the household to which it belongs, to those of its 'main driver', and to trip 'stages' reported by household members in the travel diary. NTS provides weighting factors to adjust for probability of selection, non-response, under-reporting of trips, as well as to reproduce sample population characteristics. These were applied where appropriate in our analysis.

Through manipulation of NTS data, we obtain a dataset where the unit of analysis is 'vehicle days', i.e. every record in the dataset reports information on the use of a specific household vehicle during a specific travel diary day. This is a form of 'event-based data', i.e. "data composed of sequences of ordered events (where) each event … has a start time, and a duration, and each begins when the previous ends (and) the types of event … all belong to a set of predefined event types" (Vrotsou, 2010, p. 6).

In the resulting dataset, each event-sequence consists of 48 30-minute 'time slots' (adding up to 24 hours, from 0:00 to 24:00), with just two types of event (or 'states'): 'vehicle in use' and 'not in use'. A time slot was marked as in-use if any household member reported vehicle use (as either driver or passenger) during that half-hour interval, even if for a single minute. While this leads to overestimation of vehicle use in our dataset (and hence an underestimate of the time available for charging), this is not an issue since our analysis aims to identify broad patterns of similarity in the timing of car use throughout the day, not for grossing up estimated total energy use, which can be calculated separately from the same data base[1].

The NTS 2016 sample includes information on 8,445 four-wheel cars (including Land rover and jeeps). Our analysis focuses on a subsample of vehicles of households whose travel diary started between February and June, for two reasons. First, when applying the specific sequence analysis technique and similarity measures described below on such a large sample, Stata is unable to complete the task, due to the memory requirements of computing such a large pairwise distance matrix[2]. Second, we aim to control for seasonality effects, which might confound our analysis. For example, patterns of vehicle use will be rather different during the summer school break, when a proportion of people in employment will be on annual leave, and their travel patterns influenced by the disappearance of school trips. Were we to analyse the entire twelve-month worth of data, we might end up with a classification that is overly influenced by the timing of the household interview, and we would need to provide a further distinction into months and seasons for the analysis. Therefore, we select a five-month span during school term, which is arguably relative homogenous from this point of view. This provides a more accurate picture of the part of the year which transport analyses often treat as normal, and for which much infrastructure planning is focussed, at the expense of putting aside the patterns in the other parts of the year for later analysis. We further exclude vehicles that the respondents reported not to be in regular use, those that became available to use during the travel week (e.g. newly acquired), and vehicles of households with incomplete travel diary information. This leaves us with 3,064 vehicles, which constitute our analysis sample.

CLUSTERING OF VEHICLE-DAYS

After having restructured the NTS dataset, we conduct Optimal Matching (OM) on a sample of 14,265 vehicle-days – corresponding to seven days for each of the 3,064 vehicles, minus 7,183 vehicle-days with no occurrence of car use, which are excluded from the analysis at this stage. The aim here is to discover a set of distinctly different and meaningful patterns of usage across a day that an individual car may undertake.

Optimal matching (OM) is a sequence analysis technique used to assess the similarity between sequences through elementary editing operations (insertion, deletion and substitution). The (weighted) number of operations required to transform a sequence into another provides a metric of dissimilarity, enabling the clustering of event-sequences (Halpin, 2013; Lesnard, 2006). There are various ways of measuring dissimilarity between sequences in OM, each corresponding to a different 'narrative of similarity' and thus suitable to different applications (Halpin, 2013).

In our analysis, we adopt the 'dynamic Hamming' approach to OM proposed by Lesnard (2006; 2010), which uses substitution operations only, and defines 'dynamic' substitution costs that are inversely proportional to the transition rates between states at a given time. In practice, this means that substitutions at times of high transition (e.g., in our analysis, the rush hour where lots of cars are going from being in use to not in use) are weighted less than those at times when transitions are rare (e.g. the middle of the night). In other words, in this approach the distance between two sequences depends not just on the number of substitutions, but also on their timing, making it easier to identify the 'collective rhythms' of social processes.

After having estimated pairwise distances between sequences, we conduct cluster analysis on the resulting matrix, with Ward's linkage method[3]. To determine the appropriate number of clusters, we use the cluster stopping rules proposed by Halpin (2016). We retain a five-cluster solution based on considerations of parsimony, interpretability and on the Duda-Hart Je(2)/Je(1) index, assessing how much the clusters are distinct from each other (Halpin, 2016).

PROFILING OF VEHICLE-DAY CLUSTERS

We conduct descriptive analysis (means and crosstabulations) of the five vehicle-day clusters. The profiling variables include the frequency, duration, distance and purpose of car travel on the day, as well as vehicle occupancy. We test differences between clusters with Chi-square tests at the 0.05 level (design-based F) for percentage values, and with ANOVA post hoc analysis (Scheffe test searching for differences among all combinations of groups, at the 0.05 level) for means.

CLUSTERING OF VEHICLE-WEEKS

Following Lesnard & Kay (2011) we conduct a second round of OM. At this stage, our unit of analysis is individual vehicles, or more precisely their sequences of seven vehicle-days (from Monday to Sunday). Each event (day) in the sequence can assume six different states, corresponding to the five vehicle-days clusters derived from the first-stage OM, plus an additional cluster for the 7,183 'empty' vehicle-days. So, for example vehicle X may correspond to a sequence where Monday is a vehicle-day cluster no. 1, Tuesday is a vehicle day cluster no.5, and so on. After excluding 247 vehicle-weeks with no occurrence of car use (which we retain as a separate cluster in the analysis below), we are left with a sample of 2,817 vehicle-weeks, on which we conduct OM. We retain a seven-cluster solution based on considerations of parsimony, interpretability and on the distinctiveness of clusters.

PROFILING OF VEHICLE-WEEK CLUSTERS

We conduct descriptive analysis (means and crosstabulations) of the seven vehicle-weeks clusters, and an additional cluster consisting of the 247 'empty' vehicle-weeks excluded from the previous step of the analysis, for a total of eight groups. The profiling variables include variables derived from the travel diary, as well as attributes of the vehicles, the households owning them and their main drivers. We test differences between clusters with Chi-square tests and ANOVA post hoc analysis as detailed above.

1. We tried adopting a more fine-grained definition of events (144 10-minutes slots) but we ultimately decided against it because: i) the data shows that respondents are more likely to report start and end of trips at o'clock times and half past times; ii) such level of granularity tends to make the identification of broad patterns of similarity more difficult, especially for vehicle use which is typically relatively rare event over 24 hours.

2. Brendan Halpin, personal communication, 27 June 2018.

3. While the Ward method is sometimes criticized for being biased towards producing equally-sized clusters (e.g. Lesnard, 2006, p.13), this is not the case for our results (see Results section).

Results

CLUSTERING OF VEHICLE-DAYS

Out of 14,265 vehicle-day sequences with a least one car use episode, there are 7,653 ‘unique’ observations, i.e. different types of sequences. This highlights high levels of heterogeneity in the timing of vehicle use, even when using a relatively coarse measurement approach (48 half-hour time slots), and thus indicates the need for OM to classify the patterns into a manageable number of clusters.

Through OM we identify five vehicle-day clusters (VDC in the following), which we illustrate with density plots in Figure 1. In addition to the five VDCs derived from OM, the graph depicts an additional ‘no use’ cluster for sequences that were excluded from OM (33.5 % of all sequences – henceforth referred to as VDC0).

VDC1 (accounting for 23.3 % of vehicle-day sequences) and VDC2 (7.9 %) are both characterized by a morning and an afternoon ‘peak’ of use, with some subtle differences. Vehicle use in VDC2 is more synchronized at specific times in the morning and afternoon, as shown by the more distinct bands in the indexplot and by the ‘peakier’ curve in the chronograph. Also, both morning and afternoon peak are slightly later in the day for VDC2, and further exploration shows that a minority of sequences in VDC1 do not include any vehicle use in the morning. VDC3 (14.3 %) groups sequences with vehicle use in the mid-afternoon, with a concentration around 16, although with a relatively low degree of synchronization, and relatively many car use episodes before 12 and after 18. VDC4 (7.4 %) is similar in showing a mid-late afternoon peak, but vehicle use appears much more concentrated at a specific time of day here (which is slightly later than the peak of VCD3), and most sequences include some vehicle use in the morning as well, although that is less synchronized. Finally, VDC5 (13.6 %) shows a clear concentration of use around noon (from 10 to 14). There is relatively little use outside of those hours (mostly in the afternoon, and not particularly synchronized).

PROFILING OF VEHICLE-DAY CLUSTERS

There are notable differences between the VDCs in terms of frequency, distance and duration of car travel during the day (Table 1). VDC4 (characterized by a concentration of vehicle use in the late afternoon) stands out as the type of day with the most intensive car travel patterns. Conversely VDC5 (concentration of use around noon) has the lowest values in terms of travel frequency, duration and distance. Other clusters are between these two extremes, but it is interesting to note that VDC2, while being relatively similar to VDC1 in terms of timing of vehicle use (with concentrations of use in both morning and late afternoon), has lower overall car travel distance and duration (although not frequency). Average vehicle occupancy is also lowest for VDC1 and 2, while it is highest for VDC4.

These differences may be explained by systematic differences in travel purposes between the clusters. Approximately 60 % of vehicle-days in VDC1 and 2 include at least one commuting trip – significantly higher than all other clusters. Education (and escort to education) trips are also more highly represented in VDC2. This is consistent with the dual rhythm of vehicle use in these clusters, with a morning trip and a return trip in the afternoon, and with low average vehicle occupancy for VCD1.

Conversely VDC3 (characterized by a concentration of use in the mid-afternoon), shows higher representation of all trip purposes other than commuting, business and education, with e.g. virtually 50 % of vehicle days including at least one leisure trip. Other clusters are similarly characterized by a low incidence of commuting trips but differ in the other trip purposes they are more likely to include besides leisure. VDC4 shows an overrepresentation of education and escort trips (reflected in high occupancy levels), as well as business and personal business trips. It also shows the highest diversity of trip purposes undertaken during the day among all clusters. The prevalence of escort education trips may explain the strong concentration of vehicle use at a specific time of day during the afternoon (Figure 1) possibly corresponding to the end of school hours.

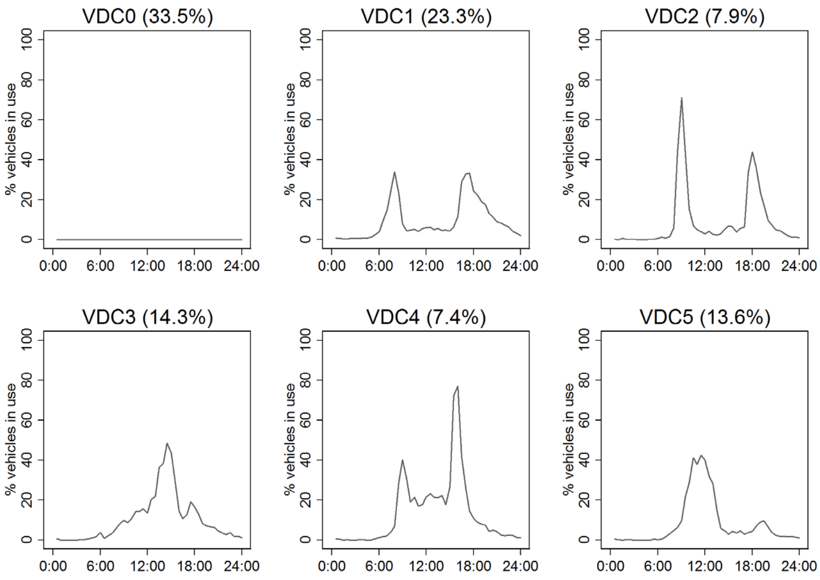

Figure 1. Density plots for the vehicle-day clusters identified.

Table 1. Profiles of vehicle-day clusters.

		VDC0	VDC1	VDC2	VDC3	VDC4	VDC5	Full sample
Mean no. of stages*		0.0	2.8^{3,4}	3.0^{3,4}	3.3^{A}	4.1^{A}	2.9^{3,4}	3.1
Mean travel time (minutes)*		0.0	64.7^{4,5}	60.8^{3,4,5}	66.5^{2,4,5}	90.7^{A}	50.1^{A}	64.5
Mean travel distance (miles)*		0.0	26.8^{2,4,5}	21.5^{1,3,4}	27.1^{2,4,5}	38.9^{A}	19.3^{1,3,4}	26.1
Days with long-distance (> 50 miles) stages (%)*		–	4.1^{2,4}	2.4^{A}	5.0^{2,4}	9.4^{A}	4.1^{2,4}	4.7
Average occupancy*		–	1.4^{3,4,5}	1.4^{3,4,5}	1.6^{A}	1.7^{A}	1.5^{A}	1.5
Whether vehicle used for trip purpose on day (%)	Commuting	–	58.5^{3,4,5}	60.2^{3,4,5}	23.5^{1,2,5}	20.3^{1,2,5}	15.7^{A}	38.8
	Business	–	9.1^{4,5}	9.8^{5}	9.0^{4,5}	12.3^{1,3,5}	6.2^{A}	8.9
	Education (including escort)	–	4.7^{2,3}	13.8^{A}	5.9^{A}	30.3^{A}	3.6^{2,3,4}	8.6
	Shopping	–	18.6^{3,4,5}	16.4^{3,4,5}	40.4^{A}	33.1^{A}	46.3^{A}	29.9
	Other escort	–	15.2^{3,4}	16.3^{3,4}	19.5^{A}	25.4^{A}	16.7^{3,4}	17.6
	Personal business	–	12.5^{A}	19.4^{1,4}	21.4^{1,4}	26.4^{A}	21.4^{1,4}	18.5
	Leisure & other	–	36.2^{A}	29.4^{A}	49.1^{1,2,5}	46.6^{1,2,5}	41.7^{A}	40.2
Mean no. of different trip purposes		–	1.45^{2,3,4}	1.54^{1,4,5}	1.59^{1,4,5}	1.79^{A}	1.41^{A}	1.52

*Items in superscript indicate which values are significantly different from each other, with 'A'/grey-shading indicating it differs from all other clusters. VWC0 was excluded from significance tests and from the values in the 'full sample' column. * Denotes that only car driver stages were considered (to avoid double-counting).*

Vehicle days in VDC5 are the most likely to include at least one shopping trip and have high levels of personal business travel as well.

To sum up, our results shows a relatively clear distinction between two 'commuting' clusters, characterized by trips at 'peak times' and accounting for roughly 30 % of days, and the other clusters, characterized by trips at noon and in the afternoon, but distinct from each other in terms of the (non-commuting) trips that they tend to include. These differences are reflected in the distribution of VDCs across days of the week (Figure 2), showing an overrepresentation of VDC1 and 2 on weekdays, and a higher share of VDC3, VDC5, and vehicle days with no use on weekends.

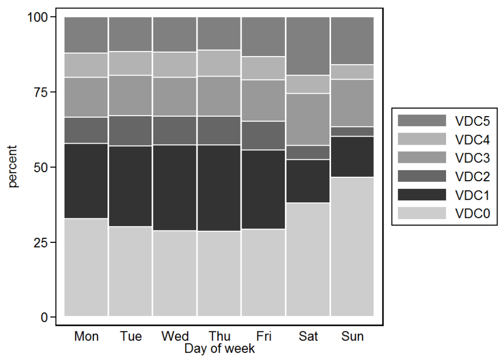

Figure 2. Distribution of vehicle-day clusters for each day of the week.

CLUSTERING OF VEHICLE-WEEKS

Out of 2,817 vehicle-week sequences with a least one day of car use, there are 2,306 'unique' observations, i.e. different types of sequences. Again, this highlights high levels of heterogeneity in the weekly patterns of vehicle use, even with the simplification afforded by considering only six different types of vehicle-days. Through OM we identify seven vehicle-week clusters (VWC in the following), which are illustrated with spineplots in Figure 3, along with an additional 'no use' cluster for the 8.1 % of sequences consisting of seven consecutive 'no use' days (VDC0), which were excluded from second-stage OM (henceforth referred to as VWC0[4]).

Besides VWC0, there is another large cluster (VWC1, 24.1 %) with low levels of vehicle use: on average, vehicles in this cluster were used for less than three days on the diary week. VWC2 (4.9%) and VWC3 (10.3 %), have a very different profile, corresponding to a stereotypical working week, with vehicles used in the morning and the afternoon from Monday to Friday, and a greater incidence of no use (VDC0), midday (VCD5) and afternoon use (VDC3) on weekends. The two clusters differ with regard to the type of commuting day that is prevalent on weekdays, with VWC2 characterised by later out and return trips (VCD2).

VWC4 (3.4 %) is the smallest cluster, and from Monday to Friday sees a prevalence of morning and mid-afternoon use patterns (VDC4), which our analysis suggests are particularly associated with the school run. The remaining three clusters are characterized by a lower prevalence of one type of day over the others, although VWC5 (13.0 %) shows an overrepresentation of afternoon use patterns (VDC3), and VWC6 (8.8 %) of midday use patterns (VDC5), particularly on the first days of the week. Both VW5 and VW6 also show little differentiation in the timing of car use between weekdays and weekends, although vehicles are somewhat less used on Saturdays and Sundays (higher prevalence of VCD0). VWC7 is the largest cluster (27.5 %) and shows an overrepresentation of morning

4. Respondents were asked about reasons for the lack of use of a vehicle during the travel diary week. For vehicles included in VWC0, 29.5 % indicated that the vehicle was not 'in everyday use', 24.2 % 'other' reasons, and 46.3 % did not provide any information.

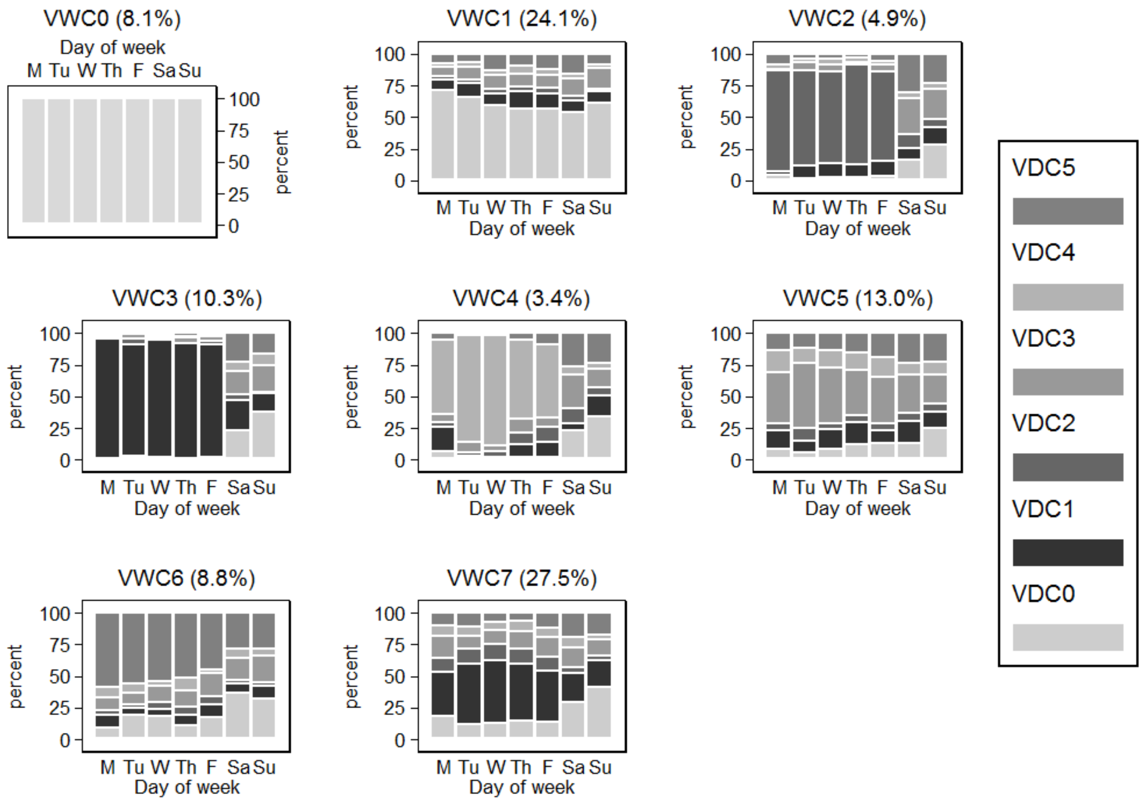

Figure 3. Distribution of vehicle-day clusters (VCD) by day of the week, for each vehicle-week cluster (VWC) identified.

Table 2. Profiles of vehicle-week clusters (usage during travel diary week).

	VWC0	VWC1	VWC2	VWC3	VWC4	VWC5	VWC6	VWC7	Full sample
Mean no. of stages*	0.0	7.2^{A}	$18.6^{1,4,5}$	$18.2^{1,4,5}$	27.5^{A}	$21.5^{1,3,4,6,7}$	$17.0^{1,4,5}$	$17.2^{1,4,5}$	15.8
Mean travel time (minutes)*	0.0	165.6^{A}	$405.2^{1,6}$	$433.1^{1,6,7}$	$474.1^{1,6,7}$	$402.4^{1,6}$	309.5^{A}	$364.8^{1,3,4,6}$	329.3
Mean travel distance (miles)*	0.0	71.2^{A}	155.7^{1}	$185.2^{1,6,7}$	164.1^{1}	$155.5^{1,6}$	$117.2^{1,3,5,6}$	$149.5^{1,3,6}$	132.9
Mean no. of different 'time slots' in which the car was in use	0.0	11.4^{A}	$28.6^{1,4,6}$	$29.0^{1,4,6,7}$	36.2^{A}	$30.7^{1,4,6,7}$	$24.1^{1,2,3,4,5}$	$26.2^{1,3,4,5}$	23.7
Mean no. of different trip purposes for which the car was used	0.0	2.2^{A}	$3.4^{1,4}$	$3.2^{1,4,5}$	4.2^{A}	$3.6^{1,3,4,6}$	$3.2^{1,4,5}$	$3.4^{1,4}$	3.1
Vehicles driven by more than one driver (%)	–	$15.0^{4,5,6,7}$	$14.0^{4,5,7}$	$15.5^{4,5,7}$	$25.2^{1,2}$	$30.1^{1,2,3,6}$	$21.0^{1,5}$	$25.2^{1,2,3}$	21.1
Longest spell of non-use (mean no. of half-hour slots)	336	177.9^{A}	$61.8^{1,6,7}$	$63.7^{1,6,7}$	$62.8^{1,6,7}$	$69.2^{1,6,7}$	$89.1^{1,2,3,4,5}$	$84.6^{1,2,3,4,5}$	101.8
Average occupancy*	–	$1.6^{2,3,4,7}$	$1.4^{1,4}$	$1.3^{1,4,5,6,7}$	1.9^{A}	$1.6^{3,4}$	$1.5^{3,4}$	$1.5^{1,3,4}$	1.5

*Items in superscript indicate which values are significantly different from each other, with 'A'/grey-shading indicating it differs from all other clusters. VWC0 was excluded from significance tests and from the values in the 'full sample' column. * Denotes that only car driver stages were considered (to avoid double-counting).*

and afternoon use patterns associated with commuting (VDC1 and 2) although, as compared to other commuting week clusters (VWC2 and 3), there is a more substantial share of other types of days (including no-use days), and a less clear distinction between weekdays and weekends.

PROFILING OF VEHICLE-WEEK CLUSTERS

In this section, we profile the vehicle weeks clusters described above against various NTS variables, starting with variables derived from the travel diary (Table 2).

Unsurprisingly, levels of car use (in terms of stages, travel time and distance) are very low for VCW1, and much higher for VWC3 and 4 – although differences are not always statistically significant perhaps due to small sample size for some clusters. VCW4 is also characterized by the highest average vehicle occupancy, which is consistent with the high share of escort trips. The total duration of vehicle use over the week is particularly low for VWC6, characterized by the prevalence of midday use patterns. VWC4 also shows the greatest diversity of vehicle use, both in terms of diversity of travel purposes and different times of day at which the vehicle was used during the week, which may be the result of greater overall usage. Interestingly, in all clusters only a minority of vehicles were driven by more than one household member over the week, and this figure appears particularly low for the typical 'commuting weeks' in VCW2 and 3. For each cluster, we estimated the average length of the longest spell of non-use during the week, which is interesting from an EV charging perspective. For all clusters, the value is over 60 half-hours, i.e. one day and six hours, and this is even longer for VCW6 and 7 as well as obviously for low-use vehicle-weeks (VCW0 and 1).

The NTS includes a wealth of vehicle-related variables on which to profile the clusters (Table 3). Overall, many differences are not statistically significant, which may be related to small sample size or the lack of any statistically significant differences found between clusters in terms of propulsion type. Whilst this suggests, somewhat surprisingly, that fuel type and temporal patterns are not linked, we did find a strong association with vehicles that were not used during the travel week (VWC0). These cars stand out from the others as they are older, more likely to be secondary cars and to be parked in a garage. They also have the lowest annual mileage, demonstrating that it would be wrong to see them as 'unused cars' – rather, they are less frequently used and thus include some travel which would be included in the analysis if the survey had been for two weeks, a month, or a whole year. The distribution of frequency of use has necessarily been truncated and the result must be that there is some loss of information about a potentially important seg-

Table 3. Profiles of vehicle-week clusters (vehicle characteristics).

		VWC0	VWC1	VWC2	VWC3	VWC4	VWC5	VWC6	VWC7	Full sample
Mean vehicle age (years)		12.6^{A}	8.4^{0}	7.3^{0}	7.2^{0}	7.6^{0}	7.0^{0}	7.6^{0}	7.3^{0}	8.0
Average engine Capacity (litres)		$1.84^{5,6,7}$	1.70	1.72	1.70	1.72	1.63^{0}	1.63^{0}	1.68^{0}	1.69
Mean annual mileage (1,000 miles)		$5.9^{2,3,4,5,7}$	$6.4^{2,3,4,5,7}$	$8.9^{0,1}$	$10.1^{0,1,5,6,7}$	$9.1^{0,1}$	$8.2^{0,1,3}$	$7.1^{3,7}$	$8.7^{0,1,3,6}$	7.9
Mean total mileage (1,000 miles)		67.0	56.90	54.80	67.50	60.2	58.1	55.4	59.9	59.6
Average CO_2 emission factor (gCO_2/km)		175.6^{A}	154.6^{0}	149.3^{0}	149.0^{0}	155.1^{0}	147.1^{0}	148.2^{0}	149.5^{0}	152.5
Mean annual CO_2 emissions (ton CO_2)		$1.51^{2,3,4,7}$	$1.55^{2,3,4,5,7}$	$2.14^{0,1}$	$2.40^{0,1,5,6,7}$	$2.25^{0,1}$	$1.93^{0,3}$	1.71^{0}	$2.02^{0,1,3}$	1.89
Type of household car (%)	Only car	$29.7^{1,4,5,6}$	$40.1^{0,6}$	34.8^{6}	$35.3^{5,6}$	$46.5^{0,7}$	$43.8^{0,3,6,7}$	$51.4^{0,1,2,3,5,7}$	$35.4^{4,5,6}$	38.7
	Primary car	$19.8^{2,3,7}$	$23.3^{2,3,7}$	$32.8^{0,1,6}$	$33.0^{0,1,3,6}$	23.5	26.4	$21.6^{2,3,7}$	$30.7^{0,1,6}$	26.9
	Secondary car	50.5^{A}	$36.6^{0,5,6}$	32.4^{0}	31.7^{0}	30.1^{0}	$29.9^{0,1}$	$27.0^{0,1,7}$	$34.0^{0,6}$	34.3
Company car (%)		2.3^{2}	$1.6^{2,3,7}$	$7.3^{\ 0,1,5,6}$	4.5^{1}	4.3	$2.4^{2,7}$	$1.6^{2,7}$	$5.0^{1,5,6}$	3.4
Propulsion type (%)	Petrol	64.0	62.3	57.6	60.9	63.6	63.2	61.8	60.4	61.6
	Diesel	34.9	36.3	41.7	38.6	34.4	35.9	37.5	38.8	37.4
	Other	1.1	1.3	0.7	0.5	2.1	0.9	0.7	0.8	1.0
Vehicle is usually parked overnight... (%)	...in garage	$21.1^{1,2,3,4,5,7}$	$14.8^{0,2,4,5,7}$	$2.9^{0,1,5,6}$	$5.3^{\ 0,1,6}$	$4.2^{0,1,6}$	$9.3^{0,1,2,6}$	$15.4^{2,3,4,5,7}$	$6.5^{0,1,6}$	10.3
	...other private	48.2^{A}	57.2^{0}	62.5^{0}	62.6^{0}	63.0^{0}	62.5^{0}	61.5^{0}	61.8^{0}	59.9
	...on street or other	30.7	28.0	34.5^{6}	32.1^{6}	32.7	28.1	$23.1^{2,3,7}$	31.8^{6}	29.9

Items in superscript indicate which values are significantly different from each other, with 'A'/grey-shading indicating it differs from all other clusters.

ment of the population of cars, and their owners. Yet low annual mileage means that VWC0 has the lowest estimated annual CO_2 emissions, despite having the highest CO_2/km emission factor. VWC1 (low use week) has a similar profile, albeit less pronounced.

VWC3 (commuting week) has sort of the opposite profile, with the highest annual mileage and associated emissions. These vehicles are also most likely to be the primary – but not the only – household vehicle. VWC2 has a similar profile to VWC3, plus an overrepresentation of company cars. The third 'commuting-heavy' cluster (VCW7) also shows high annual mileage. Finally, the highest percentage of 'vehicles in one-car households' ('only car') is found in clusters characterized by a mix of type of days (VWC5 and 6). This suggests that their fuzzier profile might be the result of the car being used for a variety of activities, reflecting the needs and preferences of several household members. These vehicles are also relatively more likely to be parked in a garage.

The vehicle-week clusters differ from each other also in terms of the characteristics of the households that own them (Table 4). The economic status of the household reference person (HRP) is one of the most discriminating variables here, with more than 95 % of HRPs employed in typical 'commuting week' clusters (VWC2 and 3) but a relatively high share of retired householders for clusters with more varied temporal patterns of vehicle use (i.e. those centered around midday and the afternoon (VWC5 and 6), or low vehicle use (VWC0 and 1)). VWC5 and 6 also have some of the lowest values for household income and household size. VWC4 is characterized by the highest percentage of HRPs in part-time employment or 'other' economic status (including people in education), although not all differences are statistically significant. This cluster, which is characterized by the importance of education and related escort trips, also shows the largest values for household size and number of children. Vehicles that were not in use during the week (VWC0) tend to belong to households with more vehicles (more than two on average), despite relatively low household size. There are no statistically significant differences in type of residential area, suggesting, perhaps surprisingly, no spatial variation in the temporal patterns of vehicle use. We also looked at type of dwelling and, once again, the differences were inconclusive.

Finally, we find the clusters differ in terms of the characteristics of their main driver (Table 5). In most clusters, males account for over 50 % of main drivers, with the significant exception of VWC4 where roughly two thirds are female. Main drivers in part-time employment or in 'other' non-employment are also overrepresented in VWC4. This is consistent with the importance of education and escort-related travel in this cluster. Part-time employment is similarly overrepresented in VWC5, which may go some way to explaining its variable pattern of vehicle use over the week. Overall, the share of self-employed and of working from home is higher for clusters that diverge from the stereotypical commuting week (although differences are mostly not statistically significant). The average age of the main driver is lowest for commuting week clusters (VWC2 and 3) and highest for vehicle weeks dominated by midday (VWC6) and afternoon (VWC5) travel patterns, as well as for vehicle weeks with little reported use (VWC1).

Discussion and conclusion

Our study provides a descriptive picture of current temporal patterns of household vehicle use in England. We contend that this analysis has the potential to introduce some new thinking to the planning and projection of infrastructure requirements to support the introduction of plug-in electric vehicles (EVs) and associated potential to 'flex' electricity demand. Studies of EVs and their charging regimes are dominated by an actual or conceptual focus on commute trip patterns (Koyangi and Urui, 1997; Smith et al., 2011), or at least on the home arrival time after the last trip of the day (Weiller, 2011). This focus comes from a tendency to supply EVs to employees in vehicle trials, or by assumptions about the prevalence of the journey to work in structuring daily car use. These studies start or end with the premise that, unless influenced by time of use charging tariffs and smart charging infrastructure, drivers are likely to charge their EVs in the evening at home thus exacerbating peak power demand events. We offer three main critiques of these simplistic representations on evening peak-time charging.

Firstly, our results suggest the focus on commuting is misplaced. It is true that our analysis finds employment status of the vehicle's main driver to be the variable that best discriminates between different patterns of vehicle use – while the clusters differ little on other dimensions that may have been considered as crucial (including various socio-demographics, type of residential area and vehicle propulsion type). However, not all vehicles conform to the rhythms of commuting, with our study revealing only roughly 15 % with a stereotypical working week profile (VWC2 and 3). Even when adding VWC7 – with a similar prevalence of commuting days but a fuzzier profile – the total share of vehicles with commuting-dominated weeks is still below 50%. Moreover, these figures are likely overestimates given our deliberate focus on a five-month period (February to June) in which holiday and active travel are known to be lower. This suggests that assessing the potential distribution of electricity demands across the day, week as well as from place to place, requires detailed understanding of heterogeneity in these patterns, most of which are not rigidly structured by the journey to work.

Secondly, our results suggest that attempts to encourage off-peak and flexible charging behaviour may benefit from focusing on a much more diverse set of times of day and types of user than are typically the subject of current research and policy discourses. It is true to say that existing studies find the majority of charging events in this early EV market occur at home in the evening or at public chargers coincident with peak commuting times (Carrol et al., 2013; Hardman et al., 2018; Langbroek et al., 2017; Robinson et al., 2013). These studies not only infer from this that it is related to commuting activity, but also deduce that the only real solution for managing peak demand as the EV market grows will be to encourage a shift to overnight charging. Whilst overnight charging could indeed bring capacity benefits to the electricity grid (Sovacool and Hirsh, 2009), it could also bring its own problems (e.g. the fact that other vehicle with considerable demands (eg vans and buses) arguably have a greater need to use capacity at this time), and suffer from behavioural resistance (Hardman et al., 2009). However, it is possible that these empirical findings are based on behaviour representative of the early adopters of EVs which are disproportionately used with commuting-based temporal

Table 4. Profiles of vehicle-week clusters (household characteristics).

		VWC0	VWC1	VWC2	VWC3	VWC4	VWC5	VWC6	VWC7	Full sample
Average no. of cars/vans		2.3^{A}	1.8^{0}	2.0^{0}	1.9^{0}	1.7^{0}	1.8^{0}	$1.6^{0,7}$	$1.9^{0,6}$	1.9
Mean income (1,000£ per year)		48,8	$47{,}5^{3}$	57,5	$57{,}1^{1}$	54,7	$43{,}7^{2,3,7}$	$38{,}4^{2,3,4,7}$	$54{,}2^{1,5,6}$	50,1
Average household size		$2.6^{2,4}$	$2.5^{2,3,4,7}$	$3.1^{0,1,6}$	$3.0^{1,4,6}$	$3.6^{0,1,3,5,6,7}$	2.7^{4}	$2.5^{2,3,4,7}$	$2.9^{1,4,6}$	2.8
Average no. of children		$0.3^{2,4}$	$0.4^{2,4}$	$0.7^{0,4}$	0.6^{4}	$1.4^{0,1,2,3,5,6,7}$	0.5^{4}	0.4^{4}	0.5^{4}	0.5
Economic status of household reference person (HRP) (%)	Employed full time	$59.9^{1,2,3,6,7}$	$49.2^{0,2,3,4,7}$	$85.1^{0,1,4,5,6,7}$	$90.3^{0,1,4,5,6,7}$	$67.2^{1,2,3,5,6}$	$53.4^{2,3,4,6,7}$	$43.1^{0,2,3,4,5,7}$	$70.1^{0,1,2,3,5,6}$	63.0
	Employed part time	9.6^{3}	$12.9^{2,3}$	$5.0^{1,4,5,7}$	$4.8^{0,1,4,5,6,7}$	$12.3^{2,3}$	$12.9^{2,3}$	10.4^{3}	$11.0^{2,3}$	10.6
	Retired	$25.9^{1,2,3,4,6,7}$	$33.6^{0,2,3,4,6,7}$	$6.3^{0,1,5,6,7}$	$3.3^{0,1,4,5,6,7}$	$9.3^{0,1,3,5,6}$	$31.9^{2,3,4,6,7}$	42.2^{A}	$16.0^{0,1,2,3,5,6}$	22.9
	Other	4.6	$4.3^{4,5}$	3.6^{4}	1.5^{4}	$11.2^{1,2,3,5,6,7}$	$1.8^{1,4}$	4.3^{4}	2.8^{4}	3.5
HRP self-employed (%)		$19.4^{2,3}$	$18.9^{2,3}$	$10.7^{0,1,4}$	$9.6^{0,1,4,5,6,7}$	$24.2^{2,3,7}$	16.8^{3}	15.3^{3}	$15.1^{3,4}$	16.0
Type of area (%)	Metropolitan area	26.1	24.4	$29.3^{5,6}$	27.1	26.5	20.4^{2}	19.7^{2}	24.1	24.2
	Large urban	19.4	17.7	12.1^{3}	20.3^{2}	15.5	16.6	17.8	15.6	17.0
	Medium urban	$21.8^{2,7}$	26.7	31.6^{0}	28.4	27.3	28.3	28.2	29.3^{0}	27.8
	Small urban	11.7	13.4	10.7	9.6^{5}	9.3	14.8^{3}	14.8	12.5	12.6
	Rural	21.0	17.8	16.3	14.6^{5}	21.4	20.0^{3}	19.6	18.6	18.4

Items in superscript indicate which values are significantly different from each other, with 'A'/grey-shading indicating it differs from all other clusters.

Table 5. Profiles of vehicle-week clusters (main driver characteristics).

		VWC0	VWC1	VWC2	VWC3	VWC4	VWC5	VWC6	VWC7	Full sample
Average age (years)		50,4^{2,3,6}	53,3^{2,3,4,7}	42,7^{0,1,5,6}	41,9^{0,1,5,6,7}	45,2^{1,6}	51,6^{2,3,6,7}	57,4^{0,2,3,4,5,7}	46,2^{1,3,5,6}	49,1
Sex: male (%)		63,7^{1,4,5,6,7}	52,9^{0,3,4}	54,4^{4}	61,9^{1,4,5,6}	33,8^{A}	50,8^{0,3,4}	50,4^{0,3,4}	56,4^{0,4}	54,7
Economic status (%)	Employed full time	54,0^{1,2,3,5,6,7}	40,7^{0,2,3,6,7}	82,8^{A}	90,6^{A}	42,8^{2,3,7}	41,9^{0,2,3,6,7}	33,1^{0,1,2,3,5,7}	61,5^{A}	55,0
	Employed part time	12,3^{3,4,5}	16,6^{2,3,4,5}	9,1^{1,4,5,6,7}	6,2^{0,1,4,5,6,7}	29,0^{0,1,2,3,6,7}	22,8^{0,1,2,3,7}	16,5^{2,3,4}	17,1^{2,3,4,5}	16,0
	Retired	28,9^{2,3,4,6,7}	33,9^{2,3,4,6,7}	5,3^{0,1,3,5,6,7}	1,1^{A}	8,8^{0,1,3,5,6}	29,3^{2,3,4,6,7}	43,0^{A}	14,3^{0,1,2,3,5,6}	22,2
	Other	4,8^{4}	8,8^{2,3,4}	2,9^{1,4,6,7}	2,1^{1,4,5,6,7}	19,4^{A}	6,1^{3,4}	7,4^{2,3,4}	7,1^{2,3,4}	6,8
Self employed (%)		24,2^{2,3,6,7}	18,6^{2,3,7}	4,6^{0,1,4,5,6,7}	10,0^{0,1,5,6}	18,5^{2,3}	18,4^{2,3,7}	15,6^{0,2,3}	13,4^{0,1,2,5}	15,6
Works from home at least once a week (%)		9,7	14,5^{2,3,7}	7,1^{1,6}	6,4^{1,3,6}	10,8	11,9^{3}	15,4^{2,3}	10,0^{1}	10,6
Education level (%)	No qualification	9,8^{3}	12,3^{2,3,7}	5,7^{1}	4,6^{0,1,5,6}	6,5	9,1^{3}	9,7^{3}	6,6^{1}	8,5
	Qualification below degree	59,7^{2}	54,9^{5,6}	45,9^{0,3,4,5,6,7}	57,4^{2,5,6}	60,8^{2}	65,8^{1,2,3,7}	66,0^{1,2,3,7}	58,6^{2,5,6}	58,6
	Degree or above	30,6^{2}	32,8^{2,5,6}	48,4^{A}	38,0^{2,5,6}	32,7^{2}	25,1^{1,2,3,7}	24,3^{1,2,3,7}	34,8^{2,5,6}	32,9

Items in superscript indicate which values are significantly different from each other, with 'A'/grey-shading indicating it differs from all other clusters.

patterns, even though, as we have shown, this is not representative of the activities being undertaken by the vehicle fleet at large. Although the sample of EVs in our study is too small to confirm that this is how they are mainly being used so far, previous research suggests that early EV adopters tend to be higher-income, middle-aged males in multi-person households, who use the vehicle for regular, well-planned journeys like commuting (Carroll et al., 2013; Jensen & Mabit, 2017; Morton et al., 2017; Plötz et al., 2014; Sovacool et al., 2018). In our findings, all these characteristics are associated with the stereotypical working week clusters (VWC2 and 3). Thus, as the EV market develops, recharging at peak load times may become (relatively) less prevalent as EV penetration reaches broader sectors of the population, i.e. the other clusters in our classification. Our findings indicate that for many vehicles – i.e. those with fuzzier profiles and frequent midday or afternoon use, or low levels of use – recharging at off-peak times might be easier than for cars constrained by the rhythms of commuting (which also tend to be those with the highest mileage). Although it could be assumed that the less routine or predictable nature of non-commute-dominated profiles might actually command *less* flexible charging regimes as cars need to be 'ready at all times' to fulfil journey needs, this patterning still allows much more distributed charging patterns through the day, much of this at home. Moreover, although our 7-day data cannot confirm this, even a more complex activity pattern can be part of a regular routine, as has been found in other studies (Axhausen et al., 2002)

Thirdly, even if initial uptake of EVs were to be dictated by household commute patterns, that does not account for the dynamic nature of behavioural adaptation by individuals and between individuals within households. Most research and policy-making has assumed that the EV transition will (have to) play out as a mere 'technological substitution', which leaves current patterns of car use unaltered (Bergman et al., 2017). Not only is this assumption theoretically flawed (Hui, 2017), the few existing studies that have examined what happens after a household adopts an EV show that it starts to be used differently to the users' initial expectations, often being 'promoted' to the primary household car and used for the majority of miles (Daramy-Williams et al., 2019). This is yet more evidence to suggest that the simplified assumptions and conceptualisations of daily activity patterns and the associated temporal rhythms of car use are in danger of leading to overly constrained and prescriptive ways of attempting to foster flexible patterns of electricity demand.

Further analysis using this data and approach will use the vehicle-week typologies to examine aspects of out-of-home charging potential in more detail. This will include the relationship between journey distances, locations and parking duration (and battery capacity) and the relevance (and scope for) sharing of vehicles across household members and primary and secondary cars. Examining the shortest and longest spells of non-use and the synchronicity of these in time and space are key to assessments of the impacts of electric vehicle grid integration. Future research on EV charging would benefit from integrating consideration of this heterogeneity and less constrained thinking about the scope for flexibility and capacity management in the future.

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Acknowledgements

Brendan Halpin kindly provided advice on aspects of the sequence data analysis. The research was funded by the UKRI Grant EP/R035288/1 (Centre for Research into Energy Demand Solutions (CREDS). The NTS 2016 special licence data set of the British Department for Transport was kindly provided by the Economic and Social Data Service (ESDS) through the UK Data Archive at the University of Essex, Colchester. The responsibility for the analysis, interpretation and all conclusions drawn from the data lies entirely with the authors.