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I'm coming home (to charge): The relation between commuting practices and peak energy demand in the United Kingdom

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ABSTRACT

Decarbonisation plans largely rely on the electrification of energy-intensive sectors such as transport, which has raised both concerns and hopes about the implications for (peak) electricity demand. Particularly so when it comes to the potential impact that private EV charging might have on residential demand patterns. On the one hand, the more pessimistic view suggests that this could substantially increase the demand experienced during peak periods, exacerbating the problems associated with such peaks. On the other hand, the more optimistic view suggests that mass uptake of EVs could offer the opportunity to integrate them as distributed storage units. There is evidence of the fact that synchronisation of practices associated with the use of energy-intensive devices is largely to blame for the occurrence of large peaks in demand; the question of whether this is likely to be the case for EV charging as well remains. This paper adds to the literature on the analysis of the synchronisation of energy-related practices with an in-depth analysis commuting behaviour, using driver commuters as a case study. Cluster analysis is used to identify those commuters with distinctive commuting schedules, and socio-demographic profiling of clusters is carried out with a view to identifying any meaningful correlations that could help target policy interventions. Three characteristic commuting patterns were identified, with clearly distinguishable features in terms of the timing of commuting trips. The analysis of the energy-relevant activities shows that arrival times have a noticeable impact on the scheduling and distribution of periods of engagement in such activities.

1. Introduction

The temporal organisation of daily practices is determined to a large extent by the institutionalised rhythms that rule everyday life. Perhaps the most prominent example of such rhythms is the one imposed by the typical working schedules.

In recent years – prior to the COVID-19 pandemic – we had started to see an increasingly stronger push for the flexibilisation, or reduction in the rigidity of institutionally timed work-related events [1–3]; the onset of the COVID-19 pandemic has only accelerated this. Despite all this, we are yet to see a significant impact on the temporalities of working arrangements, as typical working schedules are still collectively maintained by the vast majority of the workforce [4,5], with significant implications in terms of both time and energy use [6].

Over the last 30 years, approximately 85% of UK workers have been employed on typical full-time contracts [7], which normally entail fixed contracted hours, and are commonly referred to as '9-to-5 jobs' in some western countries. The inherent regularity of such contractual arrangements has clearly had significant bearing on the observed patterns of commuting and the peaks in traffic congestion. While these institutionally imposed working - and commuting - rhythms are also bound to have an impact on the timing of everyday domestic energy consumption [8], the less obvious implications of commuting patterns for the timing of practices in the home and energy consumption have been largely overlooked to date. However, in the context of the ongoing energy transition, this is becoming increasingly hard to ignore, particularly in the case of those workers who typically drive to work.

Like in most countries in the Global North, driving to work is the preferred mode of commuting in the UK; for over 50% of those UK workers on typical full-time contracts, the car is the default choice (Fig. 1). While the private vehicle fleet is currently dominated by internal combustion engine-powered units, these are being gradually

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replaced by electric vehicles (EVs). As the share of EVs increases, the usage patterns of private vehicles are expected to have a growing impact on the power consumption patterns of residential users. As of yet, however, there is no consensus as to what extent and how will EV charging affect residential demand, and peak load in particular. The mass uptake of EVs has raised both concerns and hopes about the potential implications for peak demand load [9]. On the one hand, the more pessimistic view suggests that EVs pose a severe threat to the grid, and according to recent estimates, it is expected that they could increase peak demand load in the UK by as much as 30 GW by 2050 [10]. On the other hand, the more optimistic view suggests that EVs offer an unprecedented opportunity to enhance the grid's capabilities by integrating EVs as distributed energy storage units – an approach commonly referred to as V2G (vehicle-to-grid) – which would allow for a more effective use of renewable energy sources during daytime and peak shaving during evening periods [11].

Peak demand mitigation has become a priority on the decarbonisation agenda due to the costly implications, both in economic and environmental terms, of catering for 'peaky' energy consumption patterns. On the one hand, the occurrence of peaks typically results in congested low-voltage distribution networks, which would have to be substantially reinforced in order to address infrastructure constraints. On the other hand, in countries where dispatchable clean power generation assets (such as hydro) are scarce or non-available, peak demand is commonly met by carbon-intensive peaker plants. Concerns around the carbon implications of peak demand have recently been compounded by the potential effects of EV charging as people return home by car after work in the evening time (e.g. [10,12–16]). An in-depth, joint analysis of the relation between commuting and other activity patterns could shed light on how social rhythms affect the fundamental temporal characteristics of the observed patterns.

This paper adds to the small but growing literature on the relation between the synchronisation of practices and peak demand [17]. The purpose of this study is to investigate the varying nature of these periods of high societal synchronisation, often referred to as 'hotspots' [18], with a view to further unpack the temporal dynamics within those periods with the highest density of practices. Previous studies have indicated that the temporal location of such hotspots of social practice are determined by a combination of institutionalised rhythms and people's own routines [19], which implies that a closer inspection of the disaggregated activity patterns should reveal measurable differences across certain groups of people with shared preferences. And the differences in the temporalities of such patterns should, in turn, be reflected on the observed in-home energy consumption patterns, as these are strongly correlated [6,20]. These issues, however, have not been studied in detail in the past. Thus, in order to start shedding some light on these issues, this paper focuses on a particular case study, namely the analysis of the effects of commuting patterns of full-time workers who typically use their car for commuting to work.

The choice of car commuters in full-time employment as a case study is due to the following reasons: 1) workers on full-time contracts are, at least in principle, more tightly constrained by institutionalised rhythms of typical working schedules [18]; and 2) the car use patterns of those who typically drive to work are more likely to have a direct impact on the potential charging patterns for EVs [21]. On this basis, the research questions guiding our analysis are as follows:

- To what extent do different preferences in commuting patterns affect the temporalities of other in-home energy-related activities during peak demand periods?
- Are the identified differences likely to have an impact in terms of the timing of energy use associated with such energy-related activities?
- Are there any meaningful correlations between the identified commuting patterns and socio-demographic factors that could be used to target policy interventions?
- Given the predominance of car commuters, how are these differences likely to affect EV charging patterns?

To address these questions, our analysis looks at the overall levels of engagement in different activities throughout the day, as well as the distributions of the start time, duration, and end time of the periods of activity, which allows for a more direct comparison of the temporal characteristics of the observed activity patterns. The daily activity patterns of car commuters are then grouped based on an agglomerative clustering approach, with a view to identifying any substantial differences in commuting patterns across the groups of car commuters that could lead to differences in the levels of in-home energy-related activities during peak energy demand periods.

In the next section, we offer a brief overview of a set of concepts arising from the social practice theory literature that underpin the rationale for the analysis that this paper reports on. We then introduce the data and analysis approach in the following section. We then present the results of the implementation of optimal-matching clustering (a sequence analysis technique) on the dataset, and profile the resulting clusters. We conclude by discussing the findings and the potential implications for energy and transport demand management.

2. Temporalities of everyday life: conceptualising evening peaks and practice hotspots

Collectively maintained social rhythms underlie the fundamental temporal characteristics of social practices relating to duration and sequence [18,23]. It is the existence of such rhythms what gives rise to the perceived rigidity of the daily temporal structures and the time dependence of the ordering of social practices [17].

The need for allocating and scheduling practices within designated

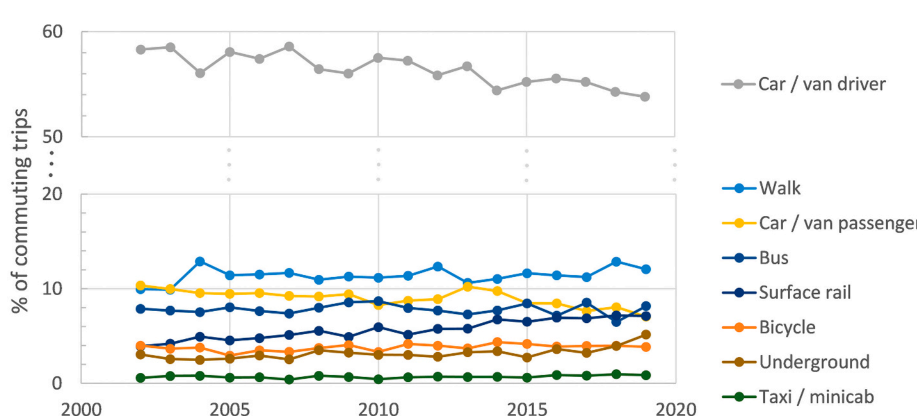

Fig. 1. Commuting modal split in the UK as a percentage of Trips per person per year.
Source: Table NTS0409 [22].

time frames creates temporal 'hotspots' [18]. These manifest themselves in the form of peaks in demand that accommodate such practices.

Time is often conceptualised as a finite resource that is consumed by the practices that encompass everyday life. Hotspots are thus characterised by the compression of certain tasks into the perceived time frames so that time can be 'saved' for other practices. In a way, hotspots are a response to the perceived 'time squeeze' which results from the 'felt need' to follow institutional and social rhythms [28].

Full-time workers are arguably one of the most susceptible groups to this compliance pressure. Typical working arrangements, such as the concept of the '9-to5 job', impose a certain temporal structure to the daily rhythms of full-time workers. The occurrence of hotspots, however, is not solely determined by the institutional rhythms that rule everyday life. Personal routines co-exist and are interdependent with social rhythms [19]. Therefore, even if hotspots are located within predictable parts of the day and/or week, their duration and frequency vary. Consequently, the 'time squeeze' features varying intensity.

In principle, hotspots are powerful explanations of peak periods. The synchronicity and sequencing of practices underpins peaks in energy demand [13,14,24]. There is also some evidence that the 'time squeeze' tends to encourage time-saving practices that tend to be energy-intensive [15–17]. In practice, studies on peak energy demand typically consider what happens in the home in isolation from patterns of travel, car use and commuting, reflecting a broader disconnect between energy and transport studies, where only a couple of studies have drawn attention to this issue [18,19]. For instance, time use studies attempt to understand what constitutes peak demand by connecting residential electricity demand with energy-related activities carried out while at home [25,30–32]. In parallel, transport research has examined evening commutes in relation to the timing of work [33].

The starting point of this paper is that the (evening) peaks in residential energy-related activity and return journeys from work cannot be treated in isolation. We propose methods and data sources which enable a cross-sectoral analysis of the dynamics of energy-related activity, and therefore, the associated demand. Understanding what gives rise to the observed energy demand loads calls for a comprehensive analysis of the reality of the unfolding of in-home energy-related activity patterns which, we contend, entails a combined analysis of (car) commuting patterns and energy-related activities in the home. In line with other empirical papers [8,34–36], we operationalise practices' enactment in terms of activities. This is not only consistent with the methodological time use approach described in the following section, but also with a key aspect of practice hotspots, which is the fact that they are better understood as groups of people performing activities synchronously. Others have pointed to the importance of focusing on clustering and grouping as part of research on congestion and peaks [37]. And based on the same reasons, we mobilise clustering techniques and socio-demographic profiling of clusters as ways to interpret how hotspots materialise.

3. Data and methods

In order to quantitatively analyse the relationship between commuting activity and in-home activity, we make use of temporally resolved daily activity sequences such as the time diaries collected as part of time-use surveys.

This paper reports on the analysis of the UK Time-Use Survey (TUS) data for the identification of driving commuting patterns and mapping of the effects of such patterns on the temporalities of other in-home daily activity profiles.

Characteristic commuting patterns were identified through the implementation of an optimal matching clustering algorithm on the TUS daily activity sequences.

The optimal matching of the commuting activity profiles was based on the dynamic hamming approach introduced by Lesnard [38,39]. This was previously applied to the identification of the 'collective rhythms' of social processes such as the scheduling of work [3,39] and vehicle use [40]. It is thus well-suited to the investigation of the social rhythms of commuting.

3.1. Data pre-processing and selection of analysis sample

Time-use surveys are studies that look specifically at how people spend their time. Survey recruitment is typically done at the household level, and the sample selection procedures aim at gathering the most statistically representative sample of the population of a given country. To ensure the representativeness of everyday life, respondents are asked to complete time diaries for (typically) two days – one work day and one weekend day – and different households are asked to complete diaries for different days of the week throughout the duration of the survey.

The analysis carried out in this paper is based on the UK TUS sample for 2014/2015, which is the most recent year available at the time of the analysis [41]. This particular TUS dataset contains time diaries for one weekday and one weekend day, where the activities of over 11,000 individuals were reported every 10 min.

Crucially for the analysis presented in this paper, the UK TUS data provides information not only on the start and end time of commuting trips, but also on the modes of transport used by the different survey respondents. In addition to time diaries, TUS studies also collect some basic socio-demographic information on the households taking part in the study, such as age, working status and income. Based on this information, we filter the TUS dataset to select a sub-sample of respondents that reported being full-time employees and living in households owning a car.

Preliminary processing of the TUS data [41] confirmed that a considerable proportion of those full-time workers with access to a car actually use their car(s) to commute to work. The sample selection was carried out as follows. Firstly, out of all respondents, we identified all potential car commuters; that is, respondents over the minimum legal driving age with access to a car. Secondly, we identify those respondents who reported being full-time workers. Finally, we selected the diaries corresponding to weekdays where at least one driving commuting activity episode was reported. We thus end up with a final sample size of $N = 2129$, which corresponds to 28.5% of all potential car commuters.

The analysis is restricted to weekday diaries only as we are interested in the relation between peaks in commuting activity and in-home energy-related activities, both of which occur during weekdays. While there are some instances of commuting activity reported in weekend diaries, the bulk of commuting activity undoubtedly occurs during weekdays. And while evening peaks of in-home energy-related activity also occur during weekends, they are considerably higher during weekdays [29].

Through the re-coding and processing of TUS diaries we obtain a set of daily activity profiles for a number of activities, including commuting to/from work. In the resulting dataset, each activity sequence consists of 144 intervals 10 min long, corresponding to a 24-hour period starting from 4:00 h on a given day and ending at 3:50 on the following day. While the overall daily activity profiles contain the information about all the activities, isolated activity profiles (e.g. the commuting activity profile) are extracted for the purpose of comparing them more closely, and thus highlight their differences.

3.2. Clustering of daily activity profiles

After filtering and restructuring of the TUS dataset, we implemented an optimal matching algorithm on the daily commuting activity profiles, in order to estimate the dissimilarity (or 'distance') between sequences, based on the Dynamic Hamming Distance approach developed by Lesnard [26,27]. We then used pairwise distance estimates as input for the clustering analysis, with the aim to determine whether certain characteristic commuting patterns can be distinguished among the driving commuters in our sample (for a similar approach see Mattioli et al.

[40]).

Optimal Matching (OM) is a sequence analysis technique used to assess the similarity of sequences of events. From a data analytics point of view, our dataset corresponds to a set of discrete categorical time series, and these can be compared based on metrics that assess the level of similarity of any two given sequences through elementary editing operations such as 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 the time diaries [38].

The clustering of activity patterns was based on the PAM (partitioning around medoids) algorithm, which is a variant of the *k*-means partitional algorithm better suited to the analysis of categorical time series [42]. Just as *k*-means, the PAM algorithm attempts to minimise the within-cluster variance. The criteria are similar to the Ward's minimum variance method, only that the variance is weighted by the average number of points in the clusters.

The optimal number of clusters was determined based on a cluster separation score known as the silhouette coefficient [43], which is a measure of how well matched are the analysed sequences to the clusters they have been assigned to.

3.3. Mapping the relationship between commuting and activity patterns

Each of the identified clusters groups those respondents whose activity patterns share some resemblance in terms of the overall levels of activity throughout the day; particularly when it comes to their commuting patterns. However, addressing the research questions that motivated this study requires a more detailed mapping of the potential effects of commuting patterns on other in-home activity patterns. Thus, in addition to the analysis of overall levels of activity throughout the day, we also look at the distribution of the start time, duration, and end time of the periods of activity. This allows for a more direct, quantitative comparison of the temporal features that characterise the observed activity patterns.

In order to obtain such distributions, we identify the relevant periods of activity in each of the daily activity diaries, from which their duration, start and end times can be extracted, and their corresponding distribution with respect to the time of day can be constructed. Based on these distributions, we are able to determine the times of day where most people start making their way to work or back home, and also the most likely times for this to happen on a given workday. Thus, the issue of studying the impact of commuting patterns on other in-home activities is reduced to the analysis of such distributions.

In the following section, we present the graphical representations of the daily activity profiles and distributions described in this section, and further discuss the implications of the differences observed across the identified groups of car commuters.

4. Results

4.1. Overall distribution of start times of driving commuting trips

The analysis of the distribution of start times of driving commuting trips during the typical work day highlights the level of heterogeneity in commuting patterns (Fig. 2). As expected, there are certain times of day where peaks in commuting activity occur (i.e. morning and evening rush hours). However, the shape of this distribution of start times of commuting trips also gives a clear indication of markedly different commuting patterns, particularly around the evening commuting period. Unlike the morning peak, where a gradual but steady increase followed by a sharp decrease in commuting activity is observed, the evening peak is characterised by a rather discontinuous progression towards the absolute peak, surrounded by pronounced albeit considerably smaller surges in activity levels. In practice, this is a reflection of the differences in working arrangements of individual workers, as well as the diversity of evening activity schedules.

4.2. Clustering of daily activity profiles

The clustering analysis was implemented multiple times to search for the solution with the optimal number of clusters, splitting the travel activity profiles into 2 through to 6 clusters. The three-cluster solution was found to be the optimal split, as shown by Figs. 3 and 4 below.

The qualitative comparison between the commuting activity profiles of individual clusters in Fig. 3 shows that when the number of clusters exceeds 3, the distinctive features of the different clusters begin to 'fade into the noise'. No improvement was seen when the number of clusters was further increased, and 6 clusters was chosen as arbitrary cut-off point for the purposes of illustrating this in Fig. 3.

Fig. 4, on the other hand, is the result of a quantitative comparison between the different implementations of the clustering analysis where a cluster separation score – namely, the average of the silhouette coefficients – is assigned to each clustering solution. The score is a measure of how similar a given activity sequence is to sequences in its own cluster, relative to those in other clusters. Higher values indicate a better match of the different points to their own cluster. Therefore, as Fig. 4 indicates, the three cluster solution is the optimal one.

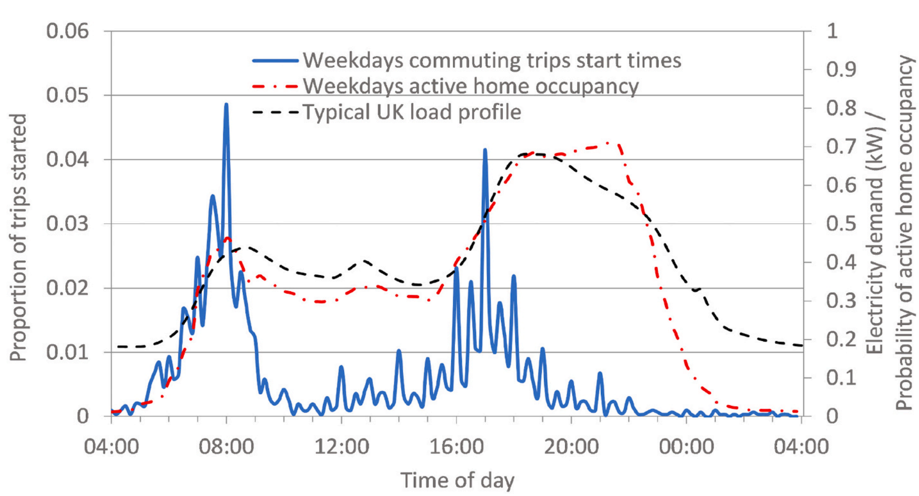

Fig. 2. Blue line: overall distribution of travel start times of driving commuting trips with respect to the time of day for a typical weekday; red line: average levels of active home occupancy during weekdays in the UK; black line: typical winter weekday electricity load profile for the average UK domestic customer – adapted from [20], based on data from ELEXON Ltd. [44].

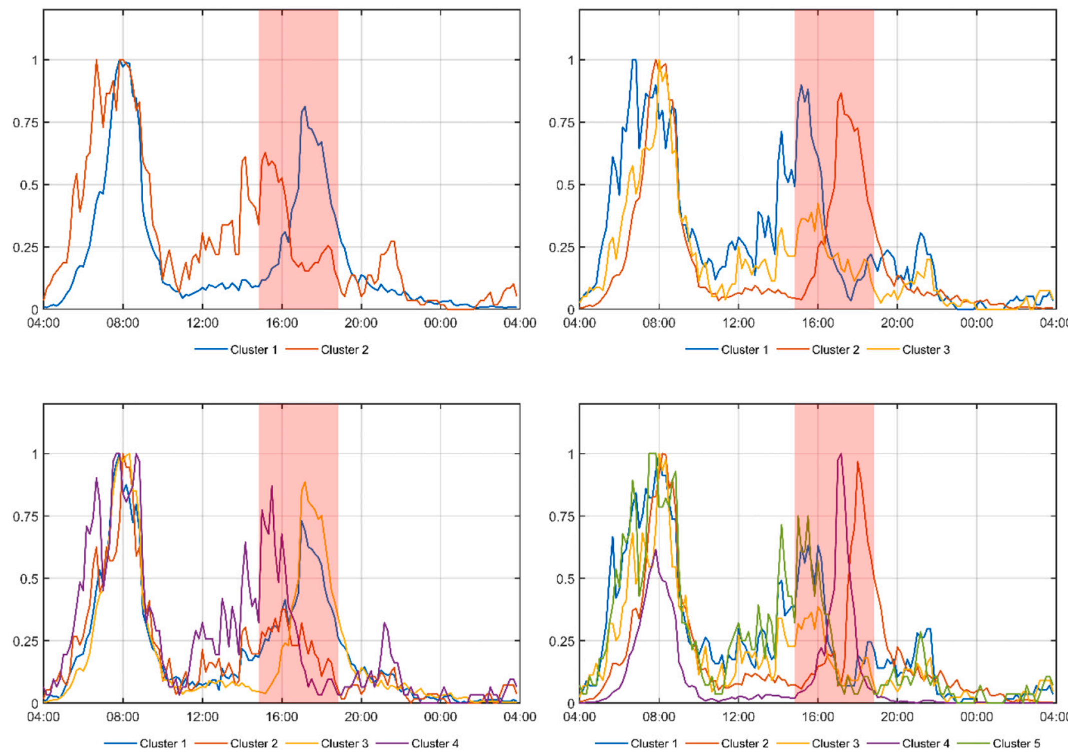

Fig. 3. Clustering of driving commuting activity profiles from TUS data; comparison between solutions with 2, 3, 4 & 5 clusters. Individual profiles correspond to the relative proportion of commuters at a given time of day. Profiles have been normalised to allow for better comparison. The shaded region indicates the period where the most critical differences are observed.

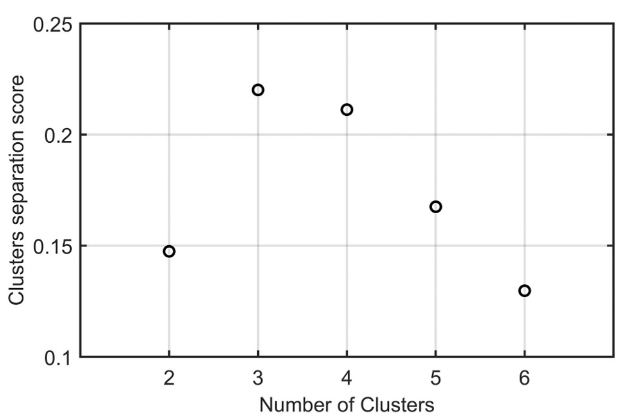

Fig. 4. Cluster separation scores for the implementation of the clustering algorithm for 2 to 6 clusters.

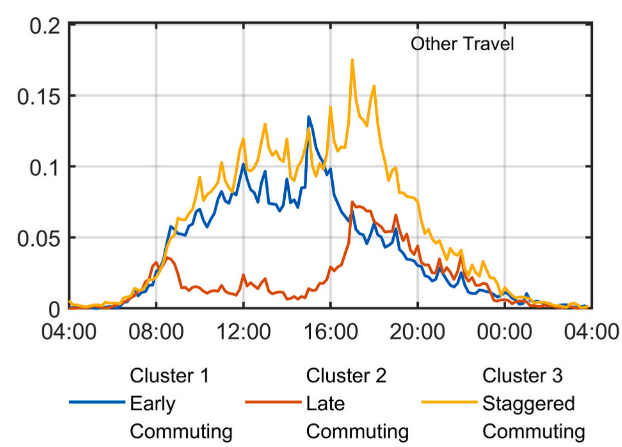

Fig. 5. Daily profiles of driving activity associated with non-commuting travel.

The three-cluster solution highlights different commuting patterns that can be summarised as follows. Cluster 1 ('Earlier commuting') accounts for 32% of the analysis sample and characterised by two rather spread-out peaks, in the morning between 6:00 and 9:00, and in the afternoon between 14:00 and 16:00. Cluster 2 ('Later commuting' - 37%) shows somewhat more pronounced peaks at around 8:00 and 18:00. The third cluster ('Staggered commuting' – 31%) is similar to Cluster 2 in terms of timing of the morning peak, but shows a less clearly defined peak in the afternoon, with higher levels of commuting activity around the overlap between the evening peaks of Clusters 1 and 2.

The choice of label for this third cluster is best understood with the help of Fig. 5, which shows the levels of travel (driving) activity associated with other purposes than just commuting to/from work. Unlike most workers in the 'Earlier' and 'Later' commuting clusters, who appear to go straight home from work, workers in cluster 3 report less commuting activity during the evening. However, as Fig. 5 shows, cluster 3 shows significantly higher levels of 'other' travel around the time where one would expect the journey home from work to take place. This kind of behaviour is consistent with people who are making stops on their way home for things like picking up kids or going to the shops, etc. – hence the 'Staggered commuting' label. Due to the way the time use diaries are structured, this tends to result in a shorter duration of 'driving home from work' episodes in the evening, even though people are effectively 'trip chaining', i.e. conducting other activities on their journey home from work.

4.3. Mapping the relationship between commuting and activity patterns

The overall levels of commuting activity provide an indication of when most people are making their way to/from work. However, in order to get a better sense of the impact of commuting patterns on the other activities that are typically carried out on a given workday, our analysis looks at the distribution of the start and end times of the periods of commuting. As Fig. 6 shows, there is nearly a 2-hour difference between the most common times at which 'early' and 'late' commuters start making their way home after work. However, it would appear that, on average, 'late commuters' have shorter commutes than 'early commuters'.

While those workers on the 'staggered commuting' cluster report less 'commuting only' episodes, when they do, they feature a similar pattern to 'early commuters' in terms of the most common start and end times of their commuting episodes. However, since their 'effective' evening commuting trips tend to be staggered, or broken down in between multiple stops along the way, their activity patterns tend to be more consistent with the behaviour of 'late commuters' as we discuss below.

The analysis of the in-home activity patterns of survey respondents in the different clusters reveals clear differences between them in terms of both the timing of activities and the rates of engagement in different activities throughout the day (Fig. 7). For example, 'early commuters' in Cluster 1 tend to start watching TV, prepare food, and wash dishes earlier than individuals in other clusters. Conversely, 'late commuters' in Cluster 2 have earlier and more concentrated 'personal care' activities in the morning, and tend to eat later in the evening. Interestingly, the three clusters show a remarkably similar distribution in terms of the time of day when people go to sleep. A total of 16 activities were analysed, including those shown in Fig. 7 and others like laundering and household upkeep. The examples in Fig. 7 were selected as they show the sharpest contrasts across all clusters.

While 'early' and 'staggered commuters' tend to start their evening commuting trips earlier (Fig. 6), Fig. 7 shows that their overall behaviour is rather similar to that of 'late commuters' when it comes to domestic activities such as 'food preparation', 'TV watching', 'eating' and 'dishwashing'.

Another interesting point of comparison when it comes to assessing the impact of the commuting patterns is the estimate of 'available time' while at home after coming back from work. A way of estimating this is through the analysis of the distribution of start (or end) times of certain activities, such as driving back home in the evening and sleeping. The purpose of this analysis is to show whether differences in the timing of home arrival determine the total amount of available time during the evening.

Fig. 8 confirms that the start times of the sleeping periods at the end of the day are quite similar across clusters of commuters. However, the distribution of home arrival times is much less regular. This suggests that 'late commuters' in Cluster 2 have on average much less time than 'early commuters' to undertake domestic activities, which might lead to a peakier distribution of their domestic energy demand associated with the concentration of energy-intensive activities around the evening activity 'hotspot'.

4.4. Socio-demographic profiling of clusters

Previous studies have highlighted the fact that differences in socio-demographic characteristics have a measurable impact on the intra-personal variability of travel behaviour (e.g. [45]), as well as in the electric load profile (e.g. [46]). In the context of policy-making, having access to this kind of information may prove particularly useful as it could help in identifying priority target groups and developing policy portfolios better suited to different segments of the population. To that end, we conducted a descriptive analysis of the three clusters of car commuters to investigate the potential differences between them. The profiling of the clusters focuses on four socio-demographic variables available from the data, namely: household composition, household income, gender and age. The focus on these particular variables is a compromise between those socio-demographic characteristics previously identified as relevant (see for instance [45]), those available from the TUS data, and those for which significant differences were identified based on the sample used in this analysis.

Eight household composition categories were used to classify TUS respondents in the original study; we have used the same categories here (see Fig. 9). In order to compare the distributions across clusters, two-sample Chi-squared tests were carried out. According to the Chi-squared cross-testing of the distributions associated with the different clusters (Table 1), the distribution of cluster members across the eight household composition categories appears to be consistent across the three clusters of commuters with a 99% confidence. Unsurprisingly,

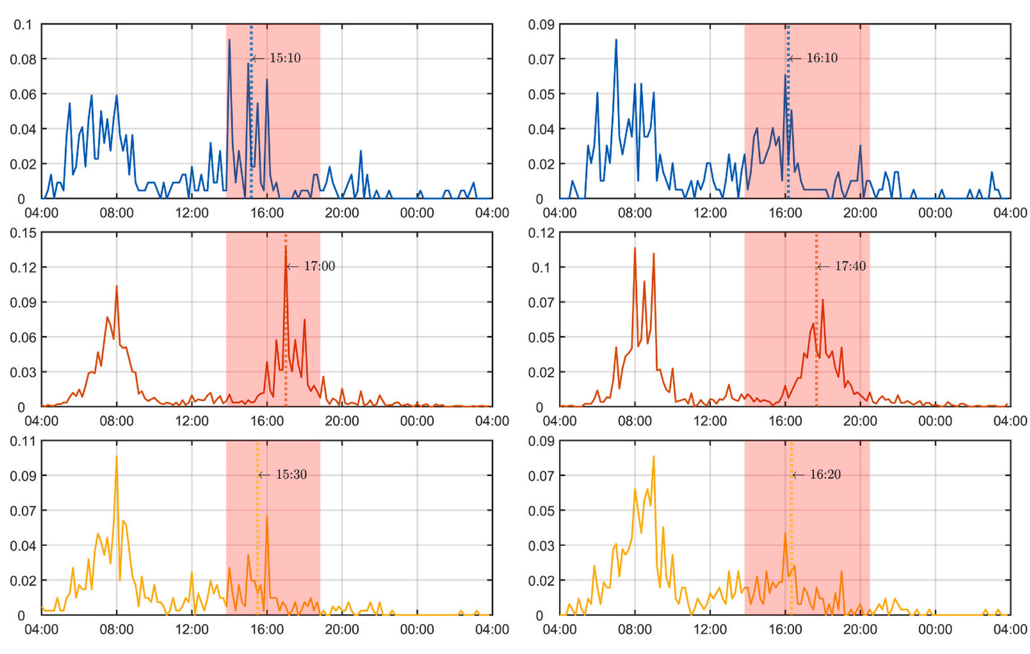

Fig. 6. Left: distribution of start times of driving commuting periods; right: distribution of home arrival times. The red bands in each plot indicate the periods over which the weighted average of start/end times was calculated.

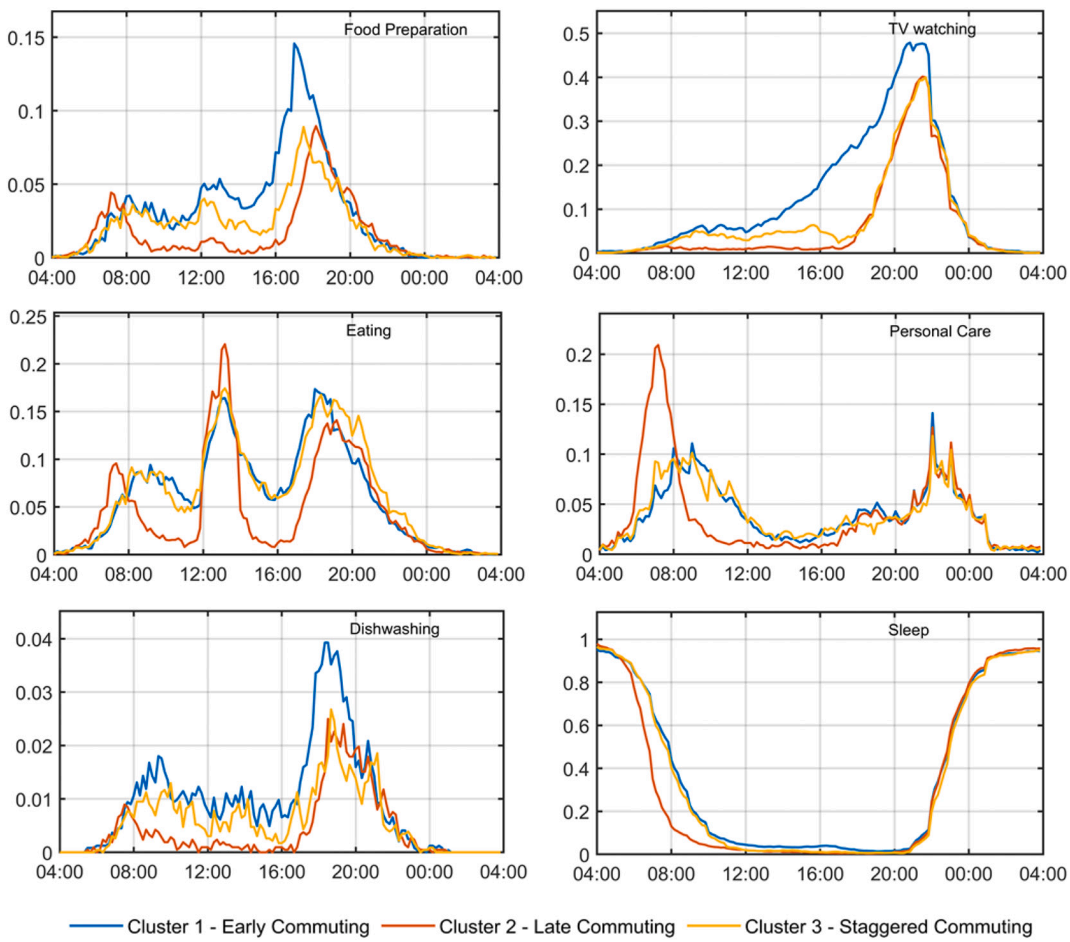

Fig. 7. Daily profiles of the rate of activity engagement (i.e. percentage of cluster members that carry out the activity) throughout the day for a set of 6 activities.

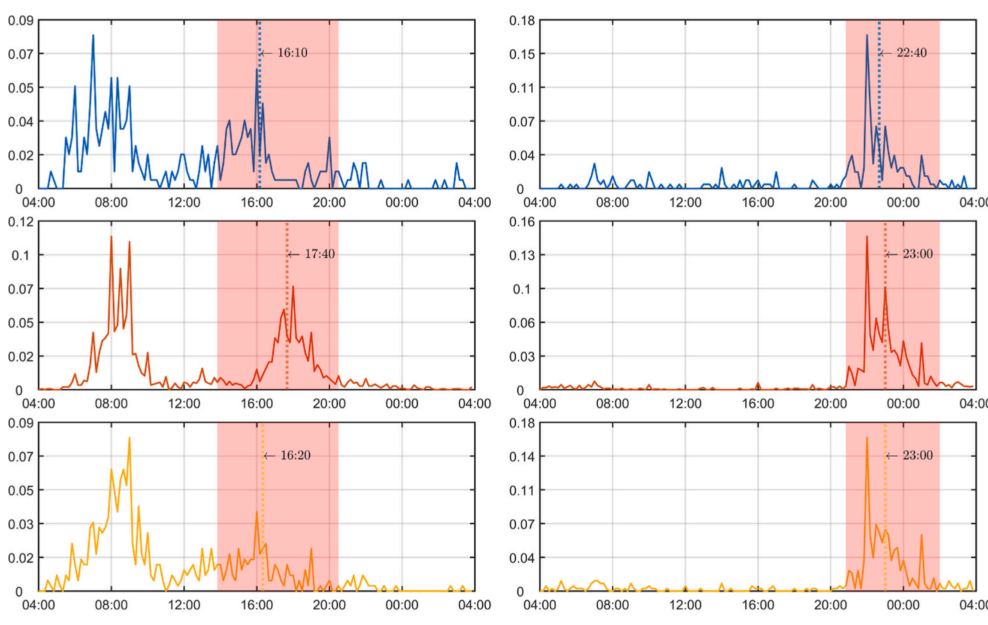

Fig. 8. Left: distribution of home arrival times; right: distribution of start times of sleeping periods. The red bands in each plot indicate the periods over which the weighted average of start/end times was calculated.

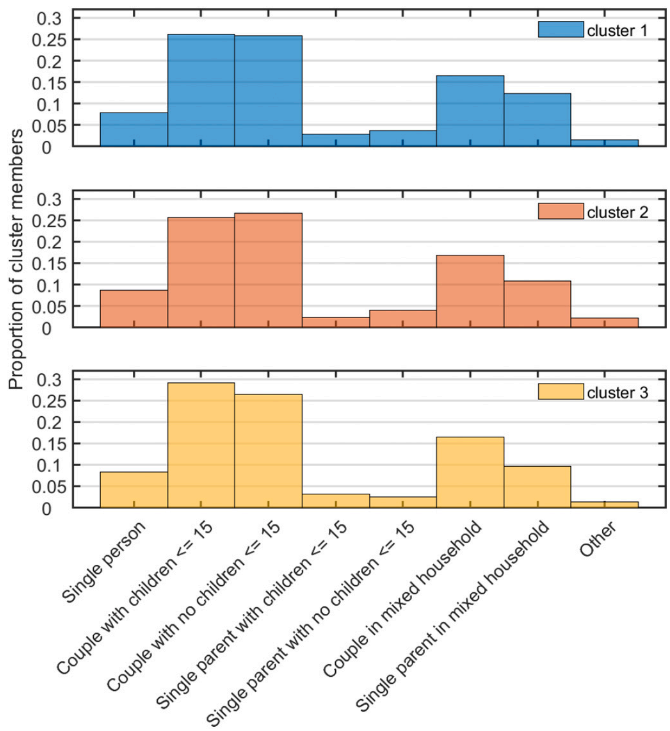

Fig. 9. Distribution of cluster members with respect to household composition.

Table 1
Chi squared cross-test matrix of household composition distributions.

p-Values	Cluster 1	Cluster 2	Cluster 3
Cluster 1	0	0.559	0.067
Cluster 2	0.559	0	0.016
Cluster 3	0.067	0.016	0

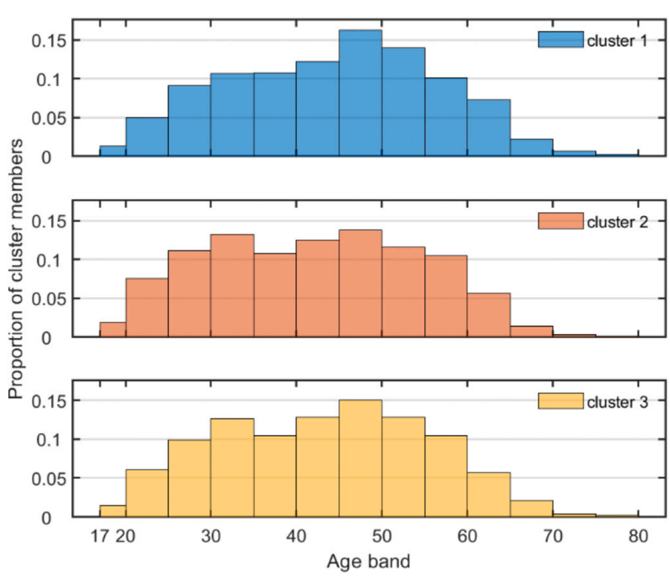

Fig. 10. Distribution of cluster members with respect to age.

couples (with or without dependent children) are the predominant group. The proportional distribution is consistent with national figures [47].

Regarding the distribution of workers with respect to their age (Fig. 10), no major differences were identified across clusters by simple inspection. The age distribution of 'early commuters' (Cluster 1) is slightly skewed towards the middle-age (45–65) band, meaning that there is a slightly lower proportion of younger (17–35) commuters compared to 'late' and 'staggered commuters' (Clusters 2 and 3, respectively). However, according to the Chi-squared cross-testing of the distributions associated with the different clusters (Table 2), the only statistically significant differences are observed between the distributions of 'early' and 'late commuters'.

The gender breakdown of individual clusters is provided in Table 3 below. As the table shows, all three clusters are rather balanced. However, the subtle differences observed in terms of gender composition, along with the activity patterns discussed above (primarily Figs. 3, 5 & 6) would appear to be consistent with the behaviours typically associated with particular genders. For example, the 'late commuters' (cluster 2) are more likely to be male than female. In contrast, women are overrepresented among 'staggered commuters' (cluster 3), which consistently show higher levels of trip chaining in the evening commute, likely due to stops along the way associated with caring responsibilities and household upkeep (e.g. shopping). The chi-squared tests for the comparison of these two clusters reveal that their differences are statistically significant.

Household income distribution is also remarkably similar across the three clusters (Fig. 11), with the majority of commuters reporting a total monthly household income in the range of £2000–£3500. Median income is also consistent with the national figures for the same year where the Time-Use Survey was carried out [48]. As the *p*-values in Table 4 suggest, there are no statistically significant differences across the different clusters.

4.5. Estimating the impact of unrestricted EV charging

Previous studies on EV charging preferences have shown that for many EV users charging immediately after arriving home has become a habit, with roughly 60% of EV users stating that their preferred charging start time lies between 5 pm and 8 pm [14]. While charging does not always take place within this (peak) period, charging events that do take place during peak times account for roughly 30% of the total [14].

As the results above show, car commuting behaviour shows significant differences, so how are these differences likely to affect the EV charging behaviour? Based on the methodology developed by Quian et al. [49], we carry out some 'back of the envelope' calculations in order to determine the potential impact of EV charging on the typical residential load profile. It should be noted, however, that this set of estimates represents a 'worst case scenario', where unrestricted private EV charging is experienced and driver commuters do indeed initiate EV charging shortly after arriving home.

In order to produce these estimates, we assume that commuters initiate EV charging 20 min after their arrival at home, where the delay accounts for any other activities taking priority over the 'pulg-in' event such as unboarding and unloading the vehicle. Obviously, not every single EV will be charged every single day, so we limit these estimates to calculating the impact of 10% and 20% of the fleet charging around the same arrival time.

As the estimates in Fig. 12 show, there are significant potential increases to the demand load during peak times, especially in the case of the 'early commuting' cluster. These are summarised in below in Table 5. Regardless of the cluster, however, we observe that this additional load results in much sharper rises towards the evening peak which

Table 2
Chi squared cross-test matrix of age distributions.

p-Values	Cluster 1	Cluster 2	Cluster 3
Cluster 1	0	0.0003	0.4527
Cluster 2	0.0003	0	0.4741
Cluster 3	0.4527	0.4741	0

Table 3
Gender breakdown of individual clusters.

	Female	Male
Cluster 1	54%	46%
Cluster 2	48%	52%
Cluster 3	55%	45%

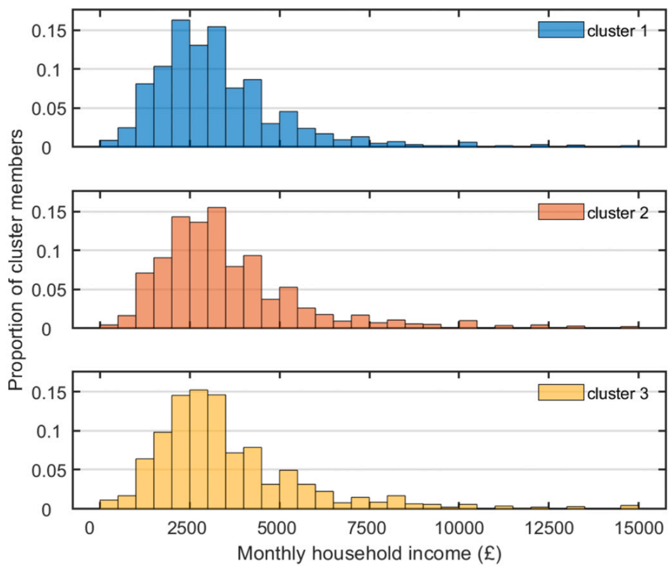

Fig. 11. Distribution of cluster members with respect to household income.

Table 4
Chi squared cross-test matrix of income distributions.

p-Values	Cluster 1	Cluster 2	Cluster 3
Cluster 1	0	0.597	0.225
Cluster 2	0.597	0	0.639
Cluster 3	0.225	0.639	0

would certainly add to the burden on the network infrastructure at an already challenging time.

It is worth noting that producing a perfectly accurate estimate of the impact of EV charging on the residential demand load profile falls beyond the scope of this paper, and indeed would merit its own, independent analysis. Therefore, the estimates provided above should be taken with a healthy dose of caution and should not serve as the basis of any definitive conclusions.

5. Discussion and conclusion

Our study builds on previous efforts to characterise separately residential peak demand and patterns of vehicle usage. Previous research has found that the employment status of car users can be used as a primary discriminator between patterns of vehicle use [40]. Our analysis reveals that there are also significant differences in the temporal characteristics of the commuting patterns of certain groups of car commuters. In particular, it has shown that both the peaks of commuting activity and the typical times of home arrival are clearly differentiated across three clusters of commuters, with e.g. a cluster of 'late commuters', accounting roughly for 37% of the full-time worker population, who arrive at home rather late. Moreover, our study shows that the temporal differences in such patterns have significant impacts on the levels of engagement in other energy-related activities in the course of the evening, with e.g. 'late commuters' more likely to eat, wash dishes and watch TV at a later hour. It should be noted that the results of this analysis have only started to uncover these issues, and are only representative of the group of commuters used as a case study, namely, car commuters in full-time employment. Therefore, the analysis can only draw conclusions about the impact of the activity patterns of this particular segment of the population. While the proportion of the population that falls into the category selected for this case study is substantial, any further generalisations need to be based on a more comprehensive analysis that extends to the remaining segments.

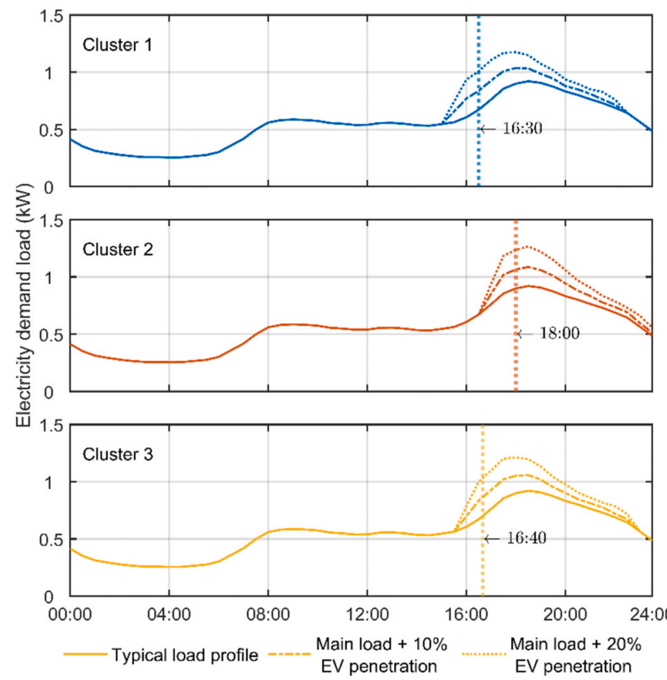

Fig. 12. Estimates of the likely impacts of EV charging on the typical load profile. Each panel corresponds to one of the commuter clusters identified in Section 4.2. In all panels the continuous line represents the Typical winter load profile for Class 1 customers [44], the dashed line represents the likely impact of 10% of the EV fleet initiating charging around the indicated time, and the dotted line represents the likely impact of 20% of the EV fleet initiating charging around the indicated time. The vertical line indicates the centre of the distribution of charging start times.

Table 5
Percentage increase in peak demand load resulting from 10% and 20% EV charging.

	Cluster 1	Cluster 2	Cluster 3
10% EV penetration	12.57%	17.98%	14.85%
25% EV penetration	27.62%	37.52%	31.73%

The importance of the potential impact of the EV charging patterns of this segment of the population, however, remains high. While the total share of vehicles with commuting-dominated usage patterns in the UK is just under 50% [40], these commuting patterns may have significant implications for domestic energy consumption patterns as the share of EVs continues to increase. Previous studies on the quantification of the recharging behaviour of EVs have found that, overall, there is currently minimal recharging during off-peak hours. More importantly, private users' peak demand is consistently registered during the evening peak at home recharging points [15,21,50]. Based on the assumption that unrestricted EV charging occurs immediately after commuters arrive home, our estimates show that with as little as 20% of the EV fleet initiating charging, peak demand load could increase by nearly 40%. The potential percentage increase on peak demand is highest for those commuters in the 'late commuting' cluster, which would appear to be the dominant car commuting group. It is therefore clear that without timely and well-designed policy interventions, these patterns will continue to put pressure on existing generation resources and may eventually push local power grids beyond capacity [15,51,52].

From a policy perspective, a number of previous studies have arrived at the conclusion that encouraging a shift to overnight charging may be the only sensible way of managing peak demand as the share of EVs grows [12–15]. While overnight charging could indeed result in better levels of capacity utilisation in the grid [53], it could also result in a new set of complications [40]. For example, as we move towards higher levels of transport electrification, other segments of the vehicle fleet, such as vans and buses, will arguably have a greater need to use capacity at this time of day. Based on the commuting activity profiles identified in our analysis, which could very well serve as a proxy for (the most part of) vehicle usage patterns, it is clear that providing better and more abundant opportunities for EV charging while at work, or more generally during the day, needs to be a key priority for policy. This would allow for a more effective use of grid capacity at times where usage is low, relative to the evening peak, and a more effective usage of any surplus output from renewable power sources.

An in-depth study of the synchronicity (both in time and space) of the periods of car use (and non-use) is key to assessing the potential for a flexible management of the demand loads associated with EV charging. Our study has focused on the temporal aspects of this problem, and 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 users than are typically the subject of current research and policy discourses. Future developments of charging infrastructure will undoubtedly have a strong influence on the opportunities for managing the demand loads associated with EVs. Perhaps in an ideal scenario, an EV charged at work could be driven home where it could then help meet the demands during peak periods (V2G). However, if the opportunities for EV charging at work are not there and charging during peak times prevails, this post-work charging could amount to about 30% of the peak load in the UK in the future [10].

Our analysis of the socio-demographic composition of the three identified clusters shows that there are no significant differences between the different types of commuters in terms of income and household composition. However, statistically significant differences were found when it comes to the distribution of commuters with respect to age and gender, with the 'early commuters' (cluster 1) slightly dominated by middle-aged workers, and the 'staggered commuters' (cluster 3) slightly dominated by female workers. In terms of the socio-demographic profiling of the identified groups of commuters, there is a key limitation worth discussing. Although the TUS data stems from a representative sample of UK households, sub-samples may suffer from under- or over-representation of certain groups. Consequently, the strength of the correlations with particular characteristics may be affected, which in turn might explain the fact that some of the differences observed between clusters are rather subtle. Other recent studies on the segmentation of workers based on the overall frequency of their work-related travel activity [45] have found stronger correlations between work-related travel patterns and socio-demographic variables in significantly larger datasets. This is an indication that the presence of the groups identified in our study should be further investigated whenever the collection of additional data offers the opportunity, as this will allow to either challenge or support the findings. As previous studies have already pointed out [45,54,55], once groups are identified, it is possible to further investigate their response to certain situations and types of policy, which in turn allows better-targeted policies to emerge.

The socio-demographic profiling of clusters provides interesting results that are in line with the insights from travel behaviour research (e.g. showing an association between female gender and trip-chaining). However, it should be noted that our primary interest lies in the analysis of commuting and other activity patterns as a reflection of the energy-relevant everyday practices of the working population. The choice of clustering commuters based on the temporalities of their commuting patterns is thus an attempt to shift the focus towards the everyday practices as the main unit of analysis. This in turn, offers the possibility to establish more explicit links between the study of mobility choices and social rhythms, and explore in more depth the implications of the prevailing commuting practices on the energy consumption associated with the practices typically carried out while at home. The breakdown into socio-economic groups also prompts questions around the relationship between socio-economic categorisations and the study of social practices. The role of socio-demographic profiling in the context of social practice theory is debated and unresolved [56]. In this context, however, socio-demographic profiling is, in principle, useful as it is a way of enabling the study of the variation of commuting in relation to different work arrangements. The findings pose questions as to whether mixing practice-level investigations with socio-demographic profiling is an approach suitable enough for revealing variation in the rhythms of everyday life.

Contrary to the somewhat intuitive expectation that the relative similarities in people's needs would entail that they need to engage in the same kind of activities and spend a similar amount of time doing so - meaning that a later home arrival time would entail a later end of the day - it would appear that the time available to the different users is generally determined by their time of arrival at home (see Fig. 7). If we equate the end of the day with the start of the sleeping periods, we can see that this time remains virtually unchanged across the three clusters. This is a significant finding which could be interpreted differently depending on traditionally separate disciplinary contexts. In time-geography, the individual is seen as a unit performing activities sequentially. Individuals' sequences of activities are constrained by priorities around sleep and meals, work schedules and opening hours of service providers, other household members' needs and abilities [57]. This means that this finding can be interpreted as evidence of how dominant priorities (e.g. sleep) shape the sequence and duration of individual activities. Conversely, in social practice theory, 'time squeeze' is a term which describes a density of social practices within specific frames of time [58]. The volume of time required to complete sets of tasks regarded as 'necessary' explains the distribution of practices in time.

As discussed in Section 2, institutionalised social rhythms induce the creation of practice hotspots [18]. This study provides evidence in support of the realisation that the exact temporal location of such hotspots of social practice is determined by a combination of the institutional rhythms and people's own routines [19]. Moreover, this result in combination with the seemingly invariable time where the 'active day' comes to an end would appear to point out that the perceived 'time squeeze' might be felt more intensely for some. From an energy perspective, this 'temporal squeezing' of evening activity is arguably undesirable, as it might result in the development of 'peakier' energy consumption patterns that put more pressure on already strained energy systems and reduce the potential for harnessing demand flexibility from the residential consumer population. The findings of our study thus highlight the need for better conceptualisations of the temporal rhythms of everyday practices and activity patterns, as further neglecting this may result in rather narrow and prescriptive ways of attempting to promote the flexibilisation of electricity consumption patterns.

Declaration of competing interest

The authors of the manuscript entitled "*I'm coming home (to charge): the relation between commuting practices and peak energy demand in the UK*" declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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