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Research paper

Rural EV charging: The effects of charging behaviour and electricity tariffs

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A B S T R A C T

As with many socio-techno transitions, rural areas often get left behind and Electric Vehicles (EVs) are no exception. This paper aims to highlight the lack of academic discourse surrounding the transition to EVs for rural areas as well as presenting the modelling and results of several potential scenarios for rural EV charging habits. Utilising 7-day travel patterns for a small rural village in the Peak District National Park, UK, this paper investigates the energy requirements and potential recharging patterns should this settlement switch all vehicles to EVs. Two key parameters have been incorporated into the EV charging model; electricity tariffs and charging behaviour based on current battery State of Charge (SoC). The model simulated a 4 week period, from which a time period, with a minimum length of one week, where energy balance could be assured for the whole system was extracted. Results show that instantaneous energy and power requirements can vary drastically depending on electricity tariffs and charging behaviours which could be a major cause for concern for rural grid infrastructure, and for the larger EV transition across the UK.

1. Introduction

Over the past 50 years, the global temperature has been increasing at an unprecedented rate (NRDC, 2016). This global temperature increase leads to the interchangeable phenomenon of Climate Change, and furthermore, can be attributed widely to the results of human activities; mostly through pollution from burning fossil fuels (Greenhouse Gases, GHG) (Syed and Khan, 2008). The UK's latest response to Climate Change is a "net-zero" target by 2050 (BEIS, 2019). This target aims for a 100% decrease in GHG emissions by 2050, relative to 1990 levels. To achieve this goal, all sectors of our society will need to reduce their carbon footprints. One of the most crucial sectors, and the larger focus of this paper, is the transport sector.

In 2019, transport in the UK was responsible for 122 $MtCO_2e$ of GHG emissions, over 55% of which can be attributed to 'Cars & Taxis' (DfT, 2021). It is worth mentioning that provisional data for 2020 has since been released (BEIS, 2021), which indicates a drastic decline of 19.6% compared to 2019 in the transport sectors GHG emissions. However, this fall is associated with the transport restrictions placed in response to the COVID 19 pandemic during 2020 and so are likely to not represent a permanent fall that will continue through to post-COVID times.

In order to achieve the 2050 target, it is therefore imperative for the transport sector to reduce its GHG emissions, in particular from the private passenger vehicle mode. Following this requirement, a large socio-techno transition is currently underway to transition from an internal combustion engine (ICE) based transport sector to an electric one. Electric Vehicles (EVs) are low emission vehicles that have been gaining popularity due to the multiple benefits they can offer society, with sales increasing 600% between 2019 and 2021 (Jolly, 2022). This transition will one day become non-optional for motorists, since the UK Government, as part of their new Ten Point Plan (Energy Saving Trust, 2021) has now agreed to ban the sale of new petrol and diesel cars and vans from 2030. The sale of hybrids will be allowed to continue until 2035, at which point all new vehicles sold in the UK will be fully electric (Energy Saving Trust, 2021). These resolute timelines are of particular concern for rural communities of the UK, where private vehicle ownership is a necessity given the lack of public transport options in these areas (Better Transport, 2018). Car ownership levels within these communities illustrate this disparity, with 93% of rural households owning a car, compared to only 66% for their urban counterparts (DfT, 2018).

Considering the UK Governments 'Road to Zero' strategy, this transition is expected "to be industry and consumer led" (DfT, 2018). As shown by previous socio-techno transitions, such as Internet connectivity (Williams et al., 2016), rural areas are often

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left behind their urban counterparts. Morton et al. (2018) already supports this with data indicating the trend towards an urban switch to EVs beginning to emerge across the number of EV registrations against location. However, as electric cars will soon become the only option, it is imperative rural areas are also ready for EVs, both in terms of the local grid infrastructure as well as ensuring confidence that the electric vehicles themselves are sufficient for rural inhabitant's travel requirements.

As of March 2020, there were 11,293 public charging points in Great Britain (Hirst, 2020), this equates to 31,504 connections, of which 24% (7630 charge points) were rapid (+25 kW). However, there is an uneven geographical distribution of this charging network (Jolly, 2022) as the majority of the infrastructure provision has been market-led (DfT, 2020). This unevenness can be attributed largely to variations in population density, and by extension, the level of urbanism or rurality of a location. There are over 100 local authorities in the UK with fewer than 10 public charging devices per 100,000 population (GOV.UK, 2019), compared to the UK average of 27, and the densest charge point location, London, with 57 public charging devices per 100,000 population (DfT, 2020).

The focus of this paper is to investigate the impact on a UK rural community, should their current vehicle population fully convert to EVs, with respect to the energy and power requirements that will be imposed on the local utility grid infrastructure. Upon understanding their impact, solutions to potential problems can be devised, so that these rural communities do not struggle with the EV transition moving forward.

The remainder of this paper is organised as follows: the research approach, including background literature and the highlighting of this paper's contribution will be discussed in Section 2. The EV Charging model and its simulation process will then be discussed in Section 3, along with the various scenarios that have been investigated. Section 4 is the presentation and discussion of the results and finally, conclusions are made in Section 5.

2. Research approach

The quantity of academic discourse surrounding the EV transition specific to rural areas is far lower than that for urban locations, however some studies have highlighted this disparity and produced work to compensate. Cowie et al. (2020) highlights not just the lack of consideration regarding EVs in rural areas, but that the current debates surrounding a wide range of technological developments which will fundamentally change society, often referred to as the 4th Industrial revolution, are centred on the urban scenario. With respect to EVs themselves, Cowie et al. (2020) points out the "lack of thinking" with using EVs as regulators for peaks and troughs in renewable energy generation, as the rural vehicle is much less likely to be spending as much time parked compared to their urban counterparts, upon which this demand side management idea is based.

There have been some trials of electric vehicles in rural areas, most notable, Jones et al. (2020) study of electric vehicles and rural businesses, who reports the promising suitability of electric vehicles in a rural setting, given the required support (infrastructure enhancement and technical developments) is provided. As adopted in the model presented in this paper, Jones et al. (2020) reported the Nissan Leaf as the most popular electric vehicle adopted by the businesses monitored in this trial. Although Jones et al. (2020) focused on rural businesses and the travelling required by such, many findings are still applicable to the private passenger scenario in rural areas.

Compared to urban areas, rural locations and their communities experience different nuances when it comes to vehicle usages and grid infrastructure. Most notably is the larger longer journey distances/times (DEFRA, 2021), see Fig. 1 below, which gives rise to a much larger cause for concern amongst rural residents over range anxiety (Jones et al., 2020). Having these different travel patterns, when conducted by an EV, will result in differing charging behaviour/profiles compared to their urban counterparts.

Additionally, rural electrical grids typically consists of less robust grid infrastructure in general (i.e. smaller substations, or transformers, attached to wooden poles) (Western Power Distribution, 2022). This has already led to the weaker business cases when it comes to EV charger point installation (Cooper, 2018) due to the higher grid connection costs (Parliament House of Commons, 2018).

It is widely understood and expected that EV uptake will lead to a greater demand for electricity. From a grid perspective, this transition will change current load profiles witnessed by the electricity grid. The most likely scenario being increased local peaks in consumption, something current grid infrastructure may struggle with Ridder et al. (2013). Therefore, understanding this relationship between the EV usage/charging and current electrical grid capabilities is imperative. Particularly in rural areas where current infrastructure may already be lacking (Western Power Distribution, 2019).

Determining EV charging profiles can be achieved in two ways, and both require the knowledge of travel patterns: (1) conducting large scale EV trials and analysing empirical data for deductions and predictions; (2) modelling EV usage and using those results, alongside potential charging scenarios and assumptions to determine power and energy demands of the EVs (Brady and O'Mahony, 2016).

From an empirical data perspective, Kim (2019) analysed empirical meter-level data to investigate the energy load profiles of residential customers under the Time-Of-Use (TOU) rate with and without EV charging. When considering the TOU tariffs, a high correlation was found between charging schedules and the electricity rate tariff structure participants were contracted to. Individuals' electricity tariffs heavily influenced the time of day that people would start charging their EV. TOU and smart charging tariffs have been recognised as a method to not only shift peak demands to off-peak times and by doing so alleviate pressures on grid infrastructure, but also lower the cost of charging an EV (Hardman et al., 2018). Given the lack of EV trial empirical data (Jones et al., 2020) for this study, the second approach will be employed.

Brady and O'Mahony (2016) used simulation to generate a schedule of daily travel, then based on the daily travel calculated the State of Charge (SOC) of the EVs through that simulation period. The energy consumption of the vehicles was set at 0.265 kWh/km. For calculating EV charging, a probabilistic charging decision model was used to determine when charging takes place. This decision was based on the State of Charge (SOC) of an EV at a destination, the duration a vehicle is parked for, and the current journey number (i.e. how many trips the car has already undertaken that day, assuming a higher probability that an individual would charge after the last journey of the day). A noteworthy consideration is Brady and O'Mahony's (2016) simulation period, two consecutive days are modelled to reduce the influence of initial assumptions. This is a common problem faced when modelling EVs over multiple days — the initialisation of the SOC on the first day of simulation. Pareschi et al. (2020) used a 'Day 0' approach, where an extra day was added to the start of the simulation time period. On Day 0, all EVs would begin with full charge, and the end SOC's used as initial SOC's on the actual first day of simulation. The Day 0 approach has been incorporated into the model presented in this paper, as well as extended periods of simulation in order to overcome the initial transient state of the simulation results.

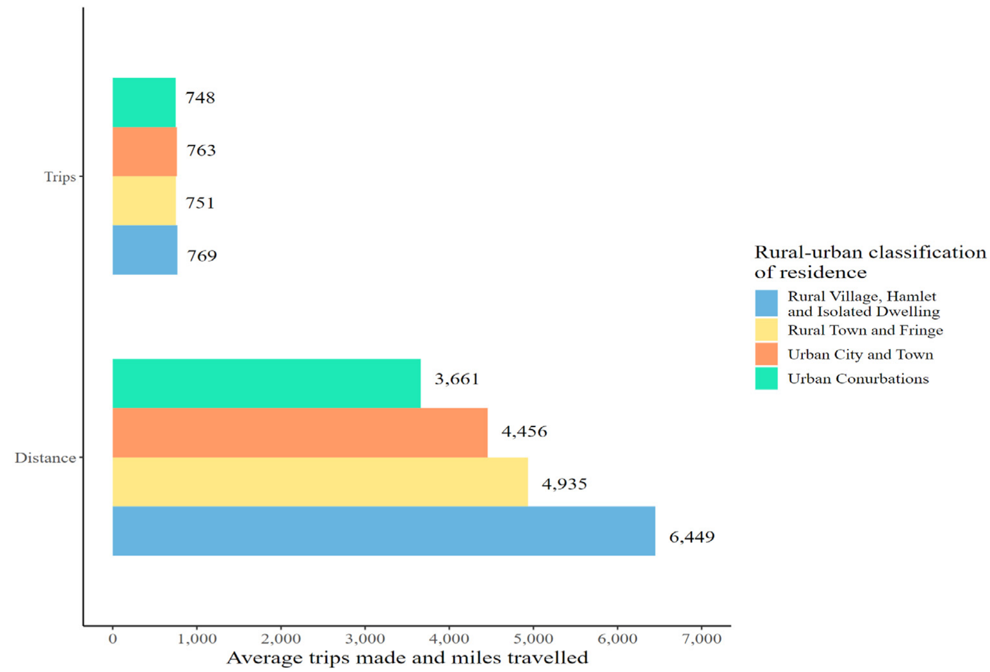

Fig. 1. Average trips made, and miles travelled per person per year by rural and urban classification of residence: England, 2021 (GOV.UK, 2022).

Brady and O'Mahony (2016) having only modelled 2 days, also fail to address effects in charging behaviour and thus the impact on the grid due to longer simulation time periods, i.e. the variance seen in activity between different days of the week. In particular, weekday to weekend activity differences, where weekend travel activity will be significantly less than weekday activity (GOV.UK, 2020).

Hardman et al. (2018) conducted a review into consumer preferences for charging infrastructure, and how they interact with this infrastructure. It was found that the most popular locations for EV charging are at home (usually overnight), followed by at work, and then public locations (i.e. supermarkets). Additionally, Hardman et al. (2018) showed that 50%–80% of all charging events occur at home which explicitly links the majority of the refuelling process of EVs to the vehicle owners' home (Ofgem, 2018), and by extension the residential energy sector. Hardman et al. (2018) also highlighted the importance of home charging, as a mitigation to issues that relate to large-scale public charge point usage (i.e. congestion) – suggesting pricing and policies implementation that limits public charging and pushes for home charging. Hardman et al. (2018) shows that a 100% home charging scenario is a meaningful basis for investigation and will be the focus of location for EV charging in this study. Rural areas are ideal for home charging due to the number of households with dedicated off-street parking space (driveway or garage), which can be difficult to find in the built up urban areas.

Crozier et al. (2021) examined various methods for modelling the variability of EV charging and categorised these methods into three groups: (1) bottom-up charging models applied to varied vehicle use, (2) stochastic bottom-up charging models applied to a fixed set of vehicle usage, and (3) top down stochastic charging models.

The first group refers to the use of a set of rules which define the conditions for charging to take place, the most common of these being for charging to begin after the final journey of the day (Pashajavid and Golkar, 2012) which is usually at the EV owners' home (Kang and Recker, 2009; Hardman et al., 2018). Expanding this, others have instigated charging whenever the vehicle is at home (Grahn et al., 2013; Wu et al., 2011). The second group of models take a given vehicle use and produce a stochastic estimate of charging. Creating these models requires large amounts of data pertaining to the usage and charging of EVs. The variability in charging can be captured through the use of Monte Carlo simulations, but this approach can overestimate the peak aggregated charging demand when considering many agents (vehicles) together (Crozier et al., 2021). The third group directly models charging, rather than the relationship between vehicle use and charging. In other words, these are top-down models for EV charging. This approach is most suited to public charging investigations, where questions of charge point numbers and availabilities are the focus (Crozier et al., 2021). The model presented in this paper adopts a bottom-up charging model approach (group one) as the basis for the EV charging, the specifics of the conditions will be discussed in Section 3.

2.1. Research contribution

This paper presents an EV charging model which has been used to investigate multiple scenarios of charging behaviour for a small rural village in the UK. This paper aims to contribute through:

- Addressing the lack of academic discourse on the EV transition for rural areas
- The development of an EV charging model, adaptable to any rural community given their travel patterns are known
- Investigating multiple charging scenarios to thoroughly capture their potential impact on rural grid infrastructure

3. Electric vehicle charging model

To ensure this work has a rural focus at its centre, the small rural village of Bradbourne, in the Peak District, UK, was chosen as the base. With this chosen area, the 2011 UK Census provides the latest figures on the number of households and vehicles via the surveys published tables, Table QS406EW (Nomis, 2013a) and Table QS416EW (Nomis, 2013b) respectively, so that this work may accurately reflect a real life scenario. Bradbourne is home to 49 households and 84 vehicles.

As highlighted before, a key factor to accurate EV charging predictions is the knowledge of the underlying travel patterns, as this will determine when cars are in use or not and thus available for charging. Travel patterns for this rural scenario were developed using data from the 2019 National Travel Survey (GOV.UK, 2020). A detailed 7-day forecast for all 84 vehicles of Bradbourne was achieved, where the location and miles driven of each vehicle at a time resolution of every 30 min resulted. The details of this process will not be discussed any further as it is outside the scope of this paper.

This section presents a model which takes these travel patterns, and calculates the energy consumed should the car population be replaced by Electric Vehicles. Further to this, potential charging scenarios are then simulated via a custom written python script. These processes are all encapsulated into a single model which will henceforth be referred to as the EV Charging Model.

3.1. EV charging model parameters

To determine the resulting charging profiles from this travel activity, certain information is required. This includes:

3.1.1. EV model and specifications

A 100% homogeneous EV car population has been assumed, composed solely of the 40 kWh Nissan Leaf. This vehicle was chosen as the authors have access to this car, thus enabling the possibility of future real-world data collection and analysis. The consumption rate of each Nissan Leaf was set at 26.5 kWh/100mile (Electric Vehicle Database, 2018).

3.1.2. Charge points

As the Nissan Leaf has been selected as the focus of this study, the Charge Points that will be modelled are Pod Point's 7 kW Chargers, a Nissan preferred brand (Nissan, 2021). The Nissan leaf has one or two on-board charge ports, an optional fast 46 kW DC port and a standard 6.6 kW AC port. Thus 7 kW Pod Point charge points will be used to support the standard 6.6 kW AC port on the Nissan Leaf. The efficiency of the charger and the battery input have been assumed to be 100%. Every vehicle will be assumed to have its own Chargepoint, i.e. the number of vehicles belonging to a household dictates the number of chargepoints at that household. For example, a 3 vehicle household will have 3 chargers.

3.1.3. Battery capacities

As stated above, the car chosen to act as the EV's conducting the predicted travel for the residents of Bradbourne is the 40kWh Nissan Leaf. For battery life improvement measures, the manufacturer limits the range a consumer has 'access' to with regards to the kWh's of their EV battery. In the case of the Nissan Leaf, this is 37 kWh (Electric Vehicle Database, 2018). In the model, it was decided this 3 kWh difference would be split between empty and fully charged. As another measure to improve the EVs battery life, the model has been set to keep the batteries state of charge between 20%–80% (from the consumers perspective, i.e. 20%–80% of 37 kWh). These various battery charge limits are illustrated in Fig. 2.

3.1.4. Electricity tariffs and charging times

The start time of a charging event, should it be triggered, is dependent on the electricity tariff serving the household to which the current electric vehicle being modelled belongs to. Details of the requirements to trigger a charging event are dependent on the type of scenario being modelled and will be discussed in further details in Section 4.4

Table 1
Electricity Tariff Distribution for 50:50 split scenarios.

House ID	Electricity Tariff
1, 2, 6, 9, 11, 14, 15, 17, 18, 19, 21, 22, 23, 24, 25, 28, 29, 30, 32, 35, 38, 39, 41, 47, 49	Standard
3, 4, 5, 7, 8, 10, 12, 13, 16, 20, 26, 27, 31, 33, 34, 36, 37, 40, 42, 43, 44, 45, 46, 48	Economy 7

The electricity tariff is a critical factor which largely influences charging behaviour, specifically the time of charging (Kim, 2019). The electricity tariff serving a household is largely dependent on the type of electricity meter installed at a given house. Whilst there are multiple types of electricity meters available in the UK, the standard and economy meters will be focused on in this study due to their commonplace in UK households.

Corresponding to these two meter types are the electricity tariffs the households will be presumed to have. Households with a standard meter will be assumed to be on a standard electricity tariff (flat rate tariff), and households with an economy meter will be assumed to be on an economy 7 tariff. At the time of writing, the average price per kWh on a standard flat rate tariff is 22.77 p/kWh (Power Compare, 2022), whereas for economy 7 tariffs the higher day unit rate of 27.55 p/kWh is compensated by the reduced night unit rate of 15.93 p/kWh (Consumer Council, 2022). For households with a standard electricity tariff, charging the EV will begin as soon as the vehicle is plugged into the charge point, as timing is no concern from a financial point of view due to the flat rate pricing nature of the tariff. For households with an Economy 7 tariff, the charging of the EV will not begin until 00:00 (midnight), when the cheaper, off-peak hours of the tariff begin. It is assumed that the off-peak hours for the Economy 7 tariff range from 00:00-07:00. Four scenarios for electricity tariff popularity have been analysed:

1. **100% Economy tariffs**
   In this scenario every household will be assumed to have Economy 7 electricity tariffs. As these tariff plans come recommended for EV charging (Hardman et al., 2018), to take advantage of cheaper night-time (off-peak) price rates for charging, they are predicted to become more common place so it is important to understand impact this could have.
2. **100% Standard tariffs**
   In this scenario every household will be assumed to have Standard Electricity tariffs. This investigation provides contrast to the solely Economy 7 scenario due to the timing of charge events not determined by time of day but when the vehicles return home.
3. **A 50:50 split of the two tariff types**
4. **37.5% Standard, 62.5% Economy split of the two tariff types** In this scenario, half of the households will be designated standard tariffs, with the remaining assigned Economy tariffs. This mixture scenario is aimed at understanding the possible demand side management solutions that tariff options could provide from a grid impact perspective. A random number generator was used for the assignment process of electricity tariffs to each household, the results of which can be seen in Table 1 below.

This scenario aims to provide the most realistic approach to the electricity tariff split in the village of Bradbourne. The 'split' was determined by postcode level electricity data released by the UK Government every year which includes the number of meters and type of meters (BEIS, 2022). Since Bradbourne is comprised of 6 postcodes (ONS, 2021), the tariffs have been split accordingly

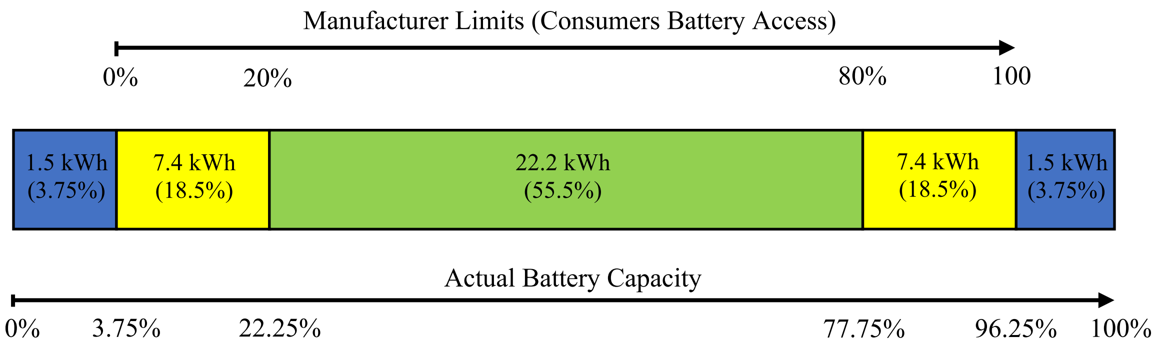

Fig. 2. Battery Capacity (*Not to Scale).

Table 2
Postcode Level Electricity Meter Data for the postcodes of Bradbourne.

Postcode	2013	2015	2016		2017		2018	
	Standard	Standard	Standard	Economy	Standard	Economy	Standard	Economy
DE6 1NP	–	–	–	–	–	–	–	–
DE6 1PA	19	19	6	10	6	10	–	10
DE6 1PB	20	15	–	14	–	13	–	13
DE6 1PD	–	–	–	–	–	–	–	–
DE6 1QY	–	–	–	–	–	–	–	–
DE6 1RG	–	–	–	–	–	–	–	–

Table 3
Electricity Tariff Split for realistic scenario.

Standard Electricity Meters	Economy 7 Meters
6 37.5%	10 62.5%

Table 4
Electricity Tariff Distribution for 37.5:62.5 split scenarios.

House ID	Electricity Tariff
2, 4, 8, 9, 13, 15, 16, 19, 20, 21, 22, 25, 26, 27, 30, 35, 37, 45,	Standard
1, 3, 5, 6, 7, 10, 11, 12, 14, 17, 18, 23, 24, 28, 29, 31, 32, 33, 34, 36, 38, 39, 40, 41, 42, 43, 44, 46, 47, 48, 49	Economy 7

across the households. The number of electric meters, and their types across Bradbourne's six postcodes are shown in Table 2.

As shown in Table 2, the published data lacks continuity across the years and due to their sampling methodology, many postcodes which serve small numbers of households (<10 – a common occurrence for rural areas) lack data. For this study, data from 2016 & 2017 (BEIS 2022) for the postcode DE6 1PA (one of the six postcodes which make up Bradbourne) was used to derive a ratio for the two types of electricity meters measured in this dataset; Standard and Economy 7. These years and this postcode show the most continuity in readings. The results are shown in Table 3, as well as the percentage split.

This percentage split was then extrapolated to all the households of Bradbourne (49), and a random number generator was used to assign each house one of the two electricity meter types. Table 4 shows the results of this process, each household, and its assigned Electricity Tariff.

3.2. The simulation process

The model presented is carried out by a custom written python script which follows a flowchart like design of rules and decisions for generating the energy consumed by each vehicle and the charging events that occur during the simulation time periods. The overall model process is presented below in Fig. 3.

As detailed by Fig. 3, the predicted 7-day travel patterns for each of the 84 vehicle belonging to Bradbourne act as the input for the EV charging model. The simulation can be set for any number of weeks to run, as the travel pattern is simply repeated as many times as required. Additionally, the first Monday's travel is replicated and added to the start to act as a 'Day 0' (Pareschi et al., 2020). On Day 0, all vehicles start with 100% battery capacity, and thus a range of State of Charges (SOC's) are generated from this Day 0 to act as the starting SOC for the first Monday of simulation. Using the Nissan Leaf's consumption rate of 26.5 kWh/100mile, and the mileages driven forecasted by the predicted travel patterns, the battery depletion through the day can be calculated. Once this has completed, should the battery capacity reach a set lower threshold (<20% taken in the illustration above) after the last journey of the day (Kang and Recker, 2009), this will initiate a charging event for that vehicle. The start time of this charging event depends upon the household the vehicle belongs to, and specifically the electricity tariff of said household. As described in Section 3.1.4, if the household is served by a standard tariff, the charging shall begin immediately upon the vehicle returning home. On the other hand, should the household be served by an Economy tariff, the vehicle will begin charging at midnight, i.e. the start of the following day to align with the cheaper electricity rates. The vehicle is then either charged back to a pre-set upper limit threshold (80% taken in the illustration above), or till the vehicle is set to leave the house the following day. This whole process then continues for each day of the week, and for the number of weeks the simulation has been set to run for. Further charging behaviour scenarios were also developed, whereby the vehicles were charged every night. This was achieved through changing the lower 20% threshold in the model (highlighted in the bold red box) to 80% (i.e. any SoC less than the 80% capacity limit would initiate a charging event). This will now be discussed in more detail in the following section.

3.3. Charging scenarios

In total 8 scenarios have been simulated using the EV Charging Model presented in this paper, these are listed below in Table 5. In principle, two different charging behaviours have been modelled

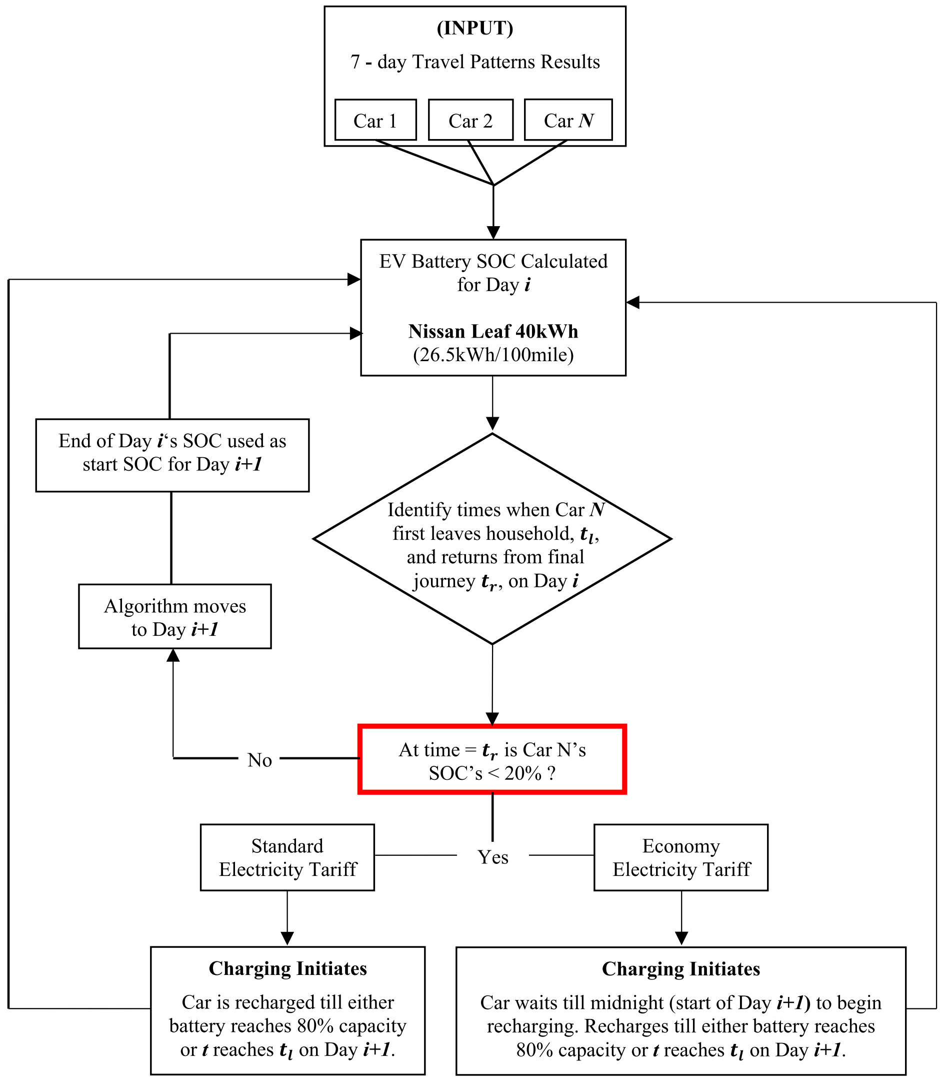

Fig. 3. Flowchart representing the Simulation Process (Charging Initiated when SoC < 20% Scenario).

across a range of electricity tariff combinations. The two charging behaviours have been chosen as they provide a contrasting insight into the effects that different EV charging behaviour will have on the energy and power demand. The first behaviour being that described previously in Fig. 3, where individuals let their vehicle discharge until 20% remains before charging. This behaviour is more in line with the refuelling process experienced in the current ICE regime (Berkeley et al., 2018). In contrast to this, the other recharging behaviour is that of plugging in the vehicle to charge every night, regardless of the amount of driving and or charge undertaken that day. This scenario has been inspired by the charging behaviour consumers hold for other electrical devices around the house, i.e. mobile phones, laptops. This is achieved by setting the lower threshold for initiating charging in the model to 80%, i.e. any use of the vehicle each day will initiate a charging event upon that vehicles return following its last journey of the day. These two charging behaviours aim to achieve the extreme opposites that is the highly variable nature of EV charging, a phenomenon due to the inherent variable nature of human behaviour (Fotouhi et al., 2019).

4. Results and discussion

Simulations ran for a time period of 4 weeks. This was to ensure no divergences in the longer term, i.e. the scenario would not end up losing all the energy within the system. From these results, to ensure an energy balance, a time period was selected from these 4 weeks. The criteria for this time period being selected was as follows:

- The start and end total battery capacity of the entire EV population (the sum of all vehicles' battery capacities at any one time) would be equal, or as close as possible given the half-hour resolution of the model. This ensures the 1st law of thermodynamics of the system is met, i.e. energy in equals energy out, and thus the system is sustainable.
- The total battery capacity values at the chosen start times were equal for the four different electricity tariff options, as well as at the end. This ensured that the electricity tariff options for each of the two behaviour scenarios could be compared.

As simulations ran for 4 weeks in total, a weekday and week number system was employed to differentiate across the weeks. For these four weeks, the days ran from 'Mon1' to 'Sun4', where the day of the week is followed by the week number.

First looking at Scenarios 1, 2, 3 and 4, the results of running the EV charging model for 4 weeks are shown below, see Fig. 4, with the selected time period superimposed.

For scenarios 1, 2, 3 and 4, the time period from 'Week 2 Tuesday' to 'Week 4 Monday' was selected, 03:30 and 10:00

Table 5
Details of the 8 charging scenarios to be investigated.

No. of Chargers	Electricity tariff	Scenario	
1 per car	0% Standard : 100% Economy	1	Charging initiates once EV falls to below 20% SoC
	37.5% Standard : 62.5% Economy	2	
	50% Standard : 50% Economy	3	
	100% Standard : 0% Economy	4	
No. of Chargers	**Electricity tariff**	**Scenario**	
1 per car	0% Standard : 100% Economy	5	Charging initiates every night
	37.5% Standard : 62.5% Economy	6	
	50% Standard : 50% Economy	7	
	100% Standard : 0% Economy	8	

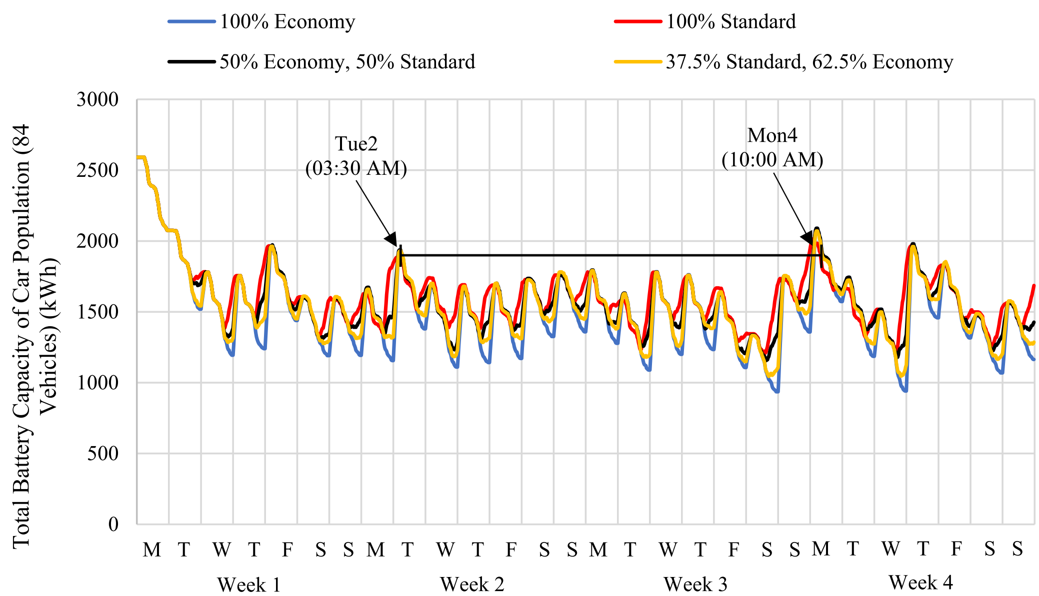

Fig. 4. Total Battery Capacity for the vehicle population of Bradbourne (Scenarios 1, 2, 3 and 4).

respectively. This 13 day period provides an energy balance to the system when the charging energy and power is investigated as well as comparable values for the four electricity tariff options. From Fig. 4, the first indication of scheduled charging events do not appear until the Tuesday of Week 1. With a population of 84 Nissan Leaf's, each with capacity of 40 kWh, of which only 37 kWh is available to the consumers, this yields a maximum of 3108 kWh to exist in the system at any one time. The simulation starts (Monday, Week 1) at roughly 2600 kWh, this is due to the implementation of the 'Day 0' SOC initialisation, i.e. the 84 vehicles do not start with the same full capacity battery, but rather a range of already depleted batteries. The start and end SOC's for each vehicle will be presented later in the paper for only the selected time period of the scenarios. To reiterate, scenarios 1, 2, 3 and 4 follow the charging behaviour of vehicles not being charged until they reach the lower threshold of 20%. With this behaviour in mind, we can see it leads to Bradbourne's EV population holding on average 1500 kWh of charge across its 84 vehicles, that equates to an average battery charge of 18 kWh (48%) at any one time. Turning the focus to the selected time period of Scenarios 5, 6, 7 and 8, the results of these simulations can be seen in Fig. 5 below.

Scenarios 5, 6, 7 and 8 focus on charging behaviour centred around charging every night and the most noticeable difference this creates compared to the opposing charging behaviour investigated is the much higher amount of stored energy in the vehicles at any one time. The average energy in the system has roughly increased to 2250 kWh due to the much higher frequency of charging events. With the higher charge threshold set at 80%, the maximum energy in the system at any one time, i.e. all 84 EVs holding 80% battery capacity, is 2486 kWh, which the population in these scenarios achieve almost every night in each of the four electricity tariff options. Additionally, compared to the other modelled charging behaviour, the charging pattern is much more predictable day-to-day, which is beneficial for grid demand management solutions. The time period selected for these scenarios is from 'Monday Week 2' to 'Friday Week 3'. Again, this time period for these scenarios meets the criteria described previously. The specifics of these selected time periods can be found in Table 6 below.

The time periods detailed in Table 6 will be the period of time for which the in-depth analysis of the EV charging model results will be focused on. These results will be presented and discussed in the following two subsections (4.1 & 4.2).

4.1. Scenarios 1, 2, 3 and 4

Fig. 6 below shows the predicted power consumption across the selected time periods for these four scenarios given the population of 84 electric vehicles in Bradbourne. The highest peak energy demands consistently belong to the 100% Economy tariff scenario, with the consumption spread out over a longer period of time with the higher the number of standard tariff households. This is expected as the charging events for standard tariff households can begin at any time and are thus dictated by the travel patterns of the individual vehicles, which vary from vehicle to vehicle and thus give rise to this spread. When considering the higher proportion of Economy tariff scenarios, the charging

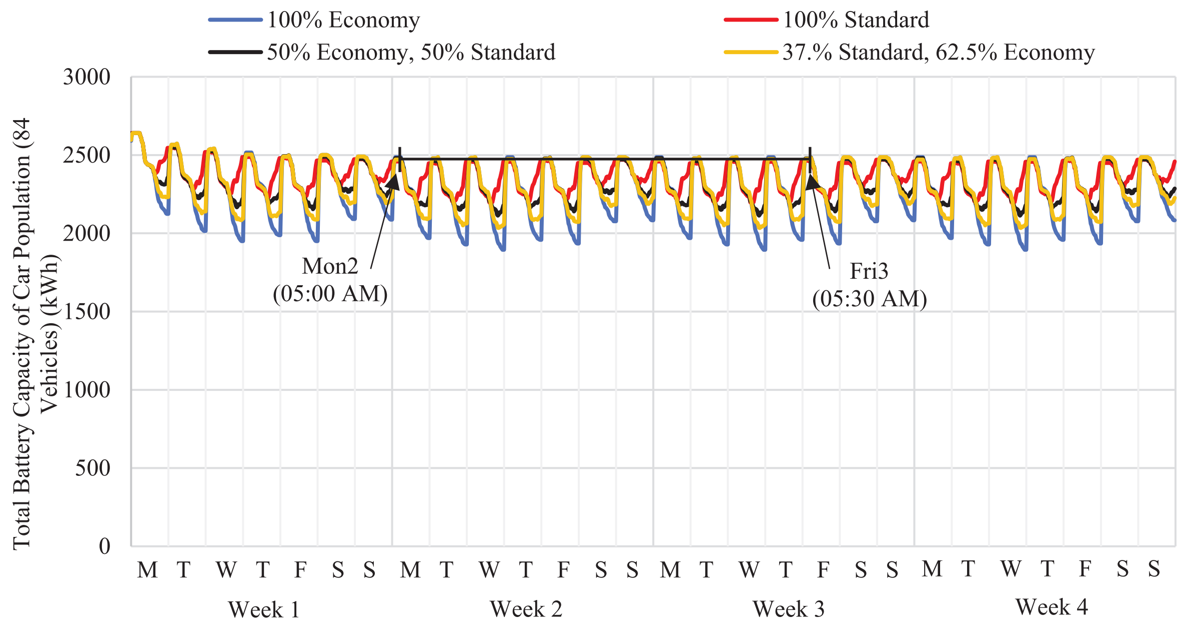

Fig. 5. Total Battery Capacity for the vehicle population of Bradbourne (Scenarios 5, 6, 7 and 8).

Table 6
Selected Time Periods for the 8 scenarios investigated.

No. of Chargers	Electricity tariff	Scenario		Time Period (Tue2 03:30–Mon4 10:00) (kWh)	Delta (kWh)
1 per car	0% Standard : 100% Economy	1	Charging initiates once EV falls to below 20% SoC	1872.16–1896.987	+24.827
	37.5% Standard : 62.5% Economy	2		1875.787–1877.915	+2.128
	50% Standard : 50% Economy	3		1898.89–1896.987	−1.903
	100% Standard : 0% Economy	4		1884.796–1790.598	−94.198
No. of Chargers	**Electricity tariff**	**Scenario**		**Time Period (Mon2 05:00–Fri3 05:30) (kWh)**	**Delta (kWh)**
1 per car	0% Standard : 100% Economy	5	Charging initiates every night	2486.4–2484.534	−1.866
	37.5% Standard : 62.5% Economy	6			
	50% Standard : 50% Economy	7			
	100% Standard : 0% Economy	8			

events are largely dominated by the midnight start time, resulting in the higher peaks at midnight. The difference between peak power demands of the opposing tariff scenarios (100% Economy vs. 100% Standard) is significant, over 200 kW compared to roughly 100 kW respectively. Indicating the types of electricity tariffs in this community can result in an 100% increase in peak energy demands.

The energy demand due to the 84 chargers follows a similar profile with only half the magnitude of the power demand. This is due to the nature of the 7 kW charger and half-hourly time resolution used by the model. Fig. 6 indicates that the '50% Economy, 50% Standard', provides the largest balance of delivering the required power and energy over the longest period of time, thus proving the least cause for concern from a grid perspective.

Looking at the State of Charge of the vehicles in the model, in particular the start and finish SOC's, Figs. 7 and 8 show that great variability in these parameters was achieved through this model. Fig. 7 presents just the 100% Economy tariff, with the start and end SOC for each vehicle, as well as the direction of the SOC change over the course of the selected time period for scenario 1 (Tue2 03:30–Mon4 10:00). Whereas, to show this same variability across the other tariff scenarios, a subplot has been created for all three, see Fig. 8.

It should be noted that in Scenario 1, 2, 3 and 4, as a consequence of the simulation methodology, multiple vehicles reached 0% capacity during usage and thus would not suffice for these required journey routes. Due to the nature of charging events only occurring once the 20% threshold has been reached, if a vehicle reaches a low state of charge, for example 22% after the last journey of the day, a charging event for this vehicle will not be triggered that night and thus this vehicle is required to complete the travel activities of the following day with only 22% capacity. Should this day's activity require more than 22% capacity of the battery, this results in the vehicle modelled to reach 0% battery capacity, being unable to continue the days travel journeys should this happen in real life. The worst case being a total of 29 vehicles experiencing an empty battery at some point during the simulation period for the 100% Economy scenario. This could be solved by adding a 'foresight' aspect to the custom written python algorithm which considers the next day's travel activity in its decision to initiate a charging event, a behaviour likely to be shown by a real-life EV consumer. This is also solved by raising the lower charging threshold, as will be shown in the following scenarios 5, 6, 7 and 8.

4.2. Scenarios 5, 6, 7 and 8

Scenarios 5, 6, 7 and 8 focused on the charging behaviour whereby each vehicle is charged every night, regardless of the days travel. This was repeated for a range of different electricity

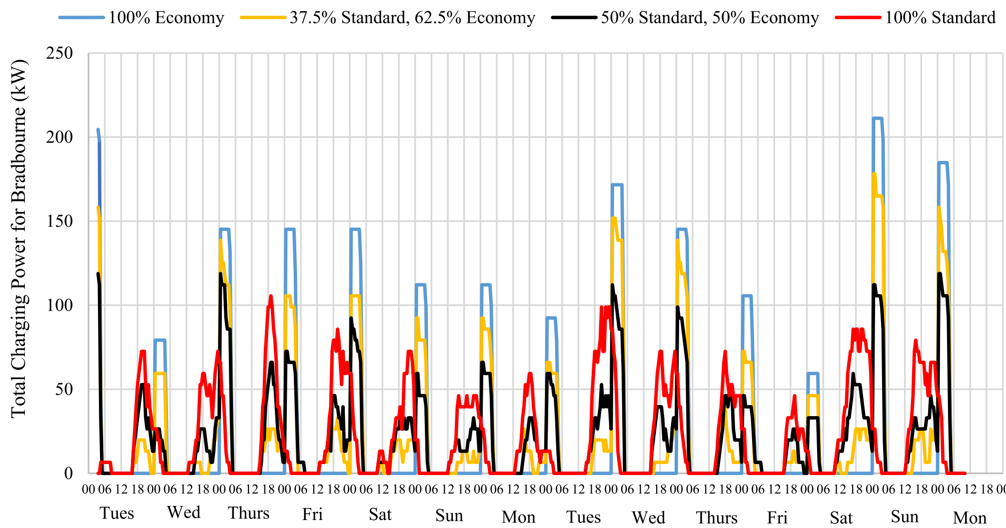

Fig. 6. Charging Power for scenarios 1, 2, 3 and 4.

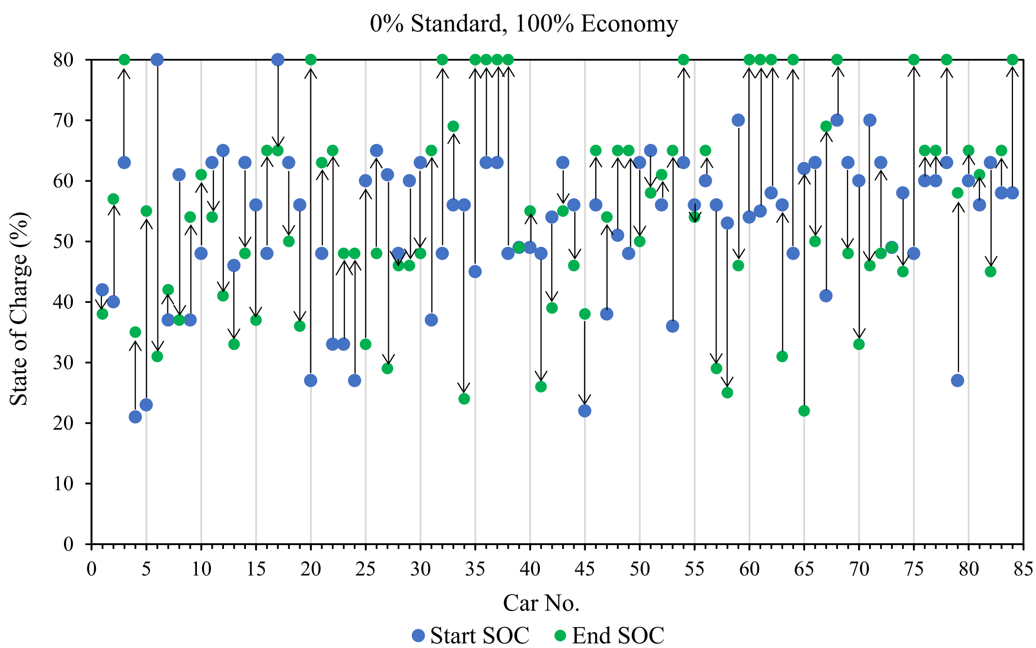

Fig. 7. Start and End SOC's for scenario 1 (100% Economy tariffs).

tariff combinations for the various households of Bradbourne to create these four scenarios. Fig. 9 below shows the power demand for each of these four scenarios over the selected time period. What becomes most apparent when comparing these four scenarios (scenarios 5, 6, 7 and 8) to the first four (scenario 1, 2, 3 and 4) is the much higher magnitude for the high Economy tariff scenarios, which has almost doubled. This is due to the number of chargers in use at any one time, due to the much higher frequency of charging events in these scenarios. Thus resulting in a higher peak demand but existing for a much shorter amount of time. Conversely, when comparing the higher standard tariff scenarios of both charging behaviours (scenarios 2 and 4 against scenarios 7 and 8), the power demand at any one time decreases for the latter charging behaviour (charging every night). This is due to the higher frequency of charging in these latest scenarios, combined with the high standard tariff distributions enabling charging events to occur over a larger period of time and thus reducing the larger instantaneous demands seen in scenarios 3 and 4.

Overall, in scenarios 5, 6, 7 and 8, the charging times have dropped compared to scenarios 1, 2, 3, and 4. These behaviours, likewise again are seen in the energy demand, which can be envisaged as the same problem but with half the magnitude. When considering the grid impact, the drastically higher power demand, not only compared to the previous four scenarios (scenarios 1, 2, 3 and 4), but especially considering the higher Economy split tariff options (scenarios 5 and 6) is cause for concern. Should the current grid load be considered, local rural grid infrastructure capabilities will need to be thoroughly assessed to withstand peak demand increases up to 0.5 MW. This paper only considers 84 vehicles (or in other words, 84 charge points), when in reality, many more would be expected to be linked to the local substation that serves not only Bradbourne but other surrounding villages.

Looking at the vehicles SOC's in scenarios 5, 6, 7 and 8. This time the 100% Standard is presented by itself, see Fig. 10 as this had the most variability in start and end SOC's compared to the other 3 tariff split options, presented in Fig. 11.

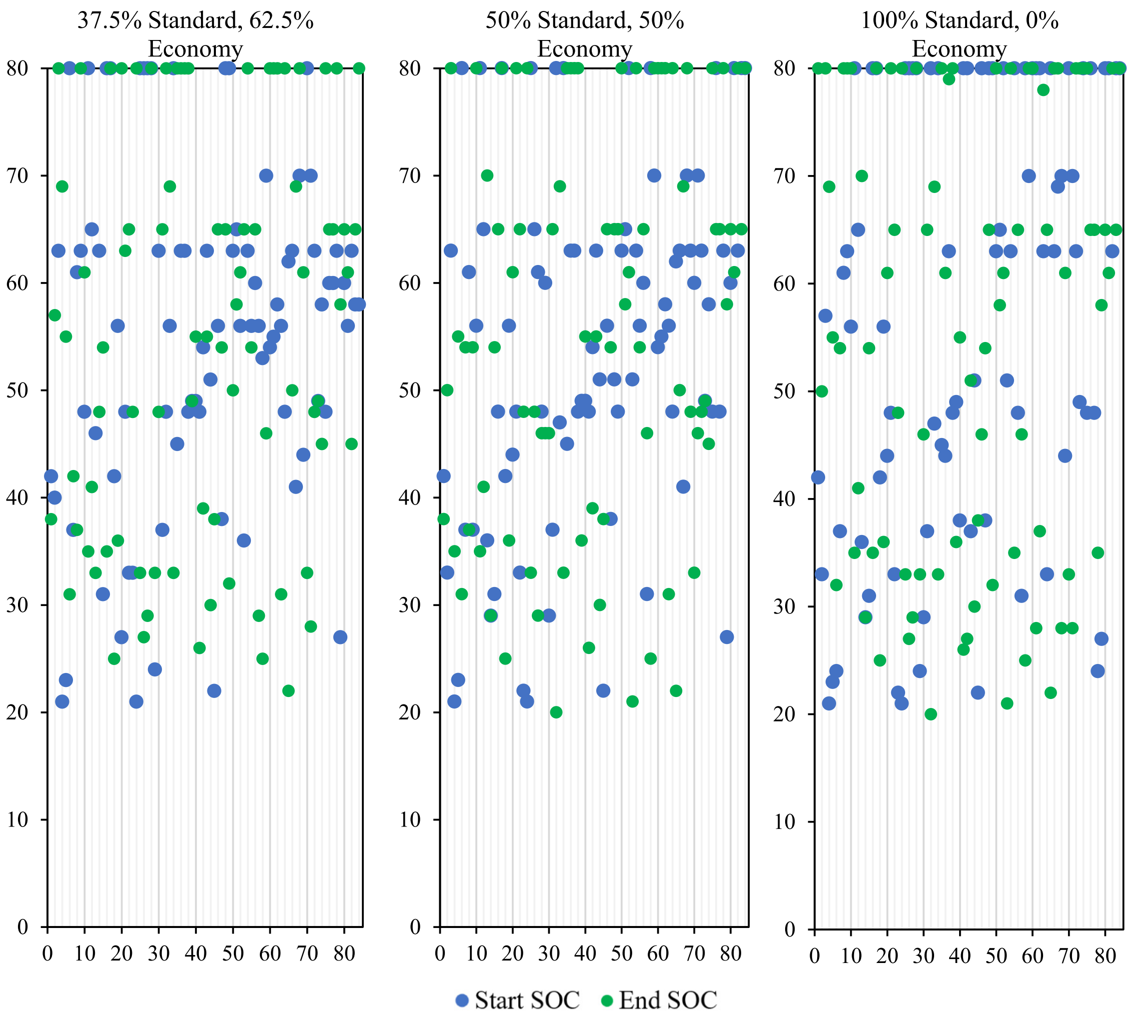

Fig. 8. Start and End SOC's for scenarios 2, 3 and 4.

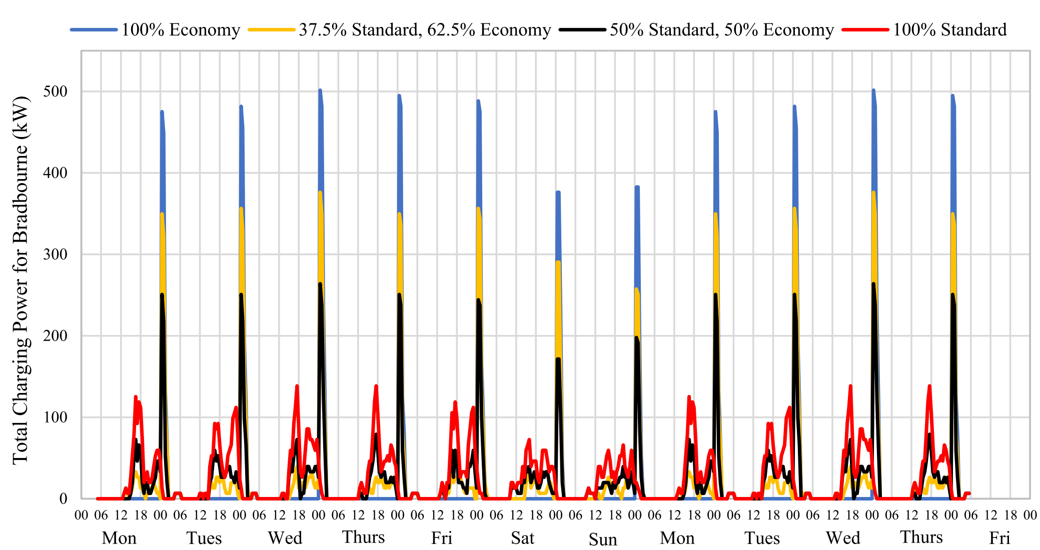

Fig. 9. Charging Power for scenarios 5, 6, 7 and 8.

As shown by Figs. 10 and 11, some vehicles end up with less than 80% SOC at the end of the selected time period. For these four scenarios where every car is recharged back to 80% every night, this would seem to highlight an error. However, some vehicle's travel patterns belong to individuals simulated to have overnight work patterns, resulting in these few vehicles either having not yet returned home to charge, or already returned but yet to complete their latest charging event.

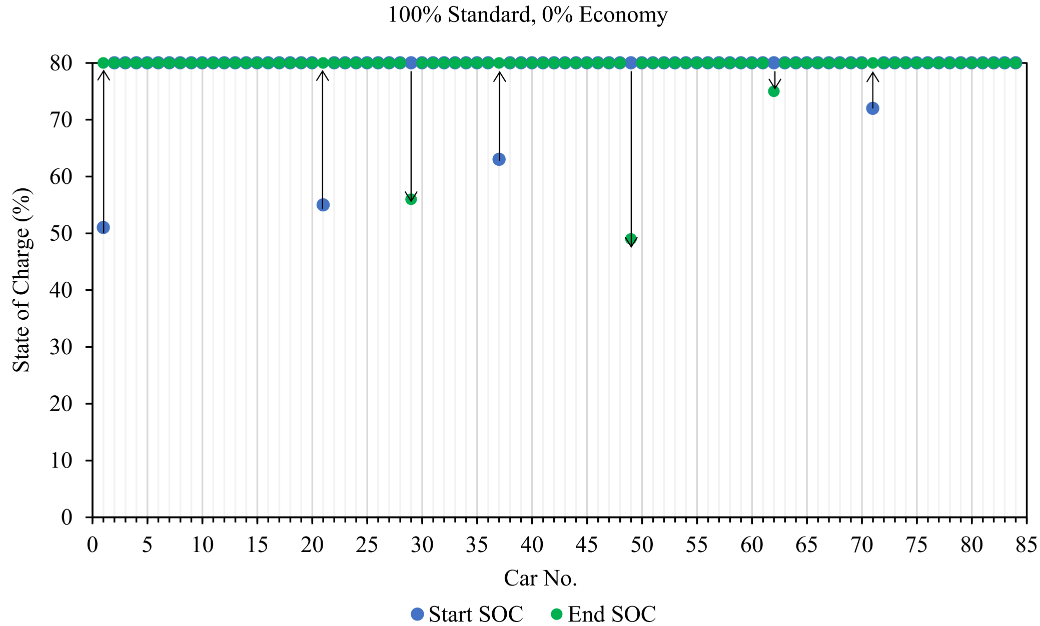

Fig. 10. Start and End SOC's for scenario 8 (100% Standard tariffs).

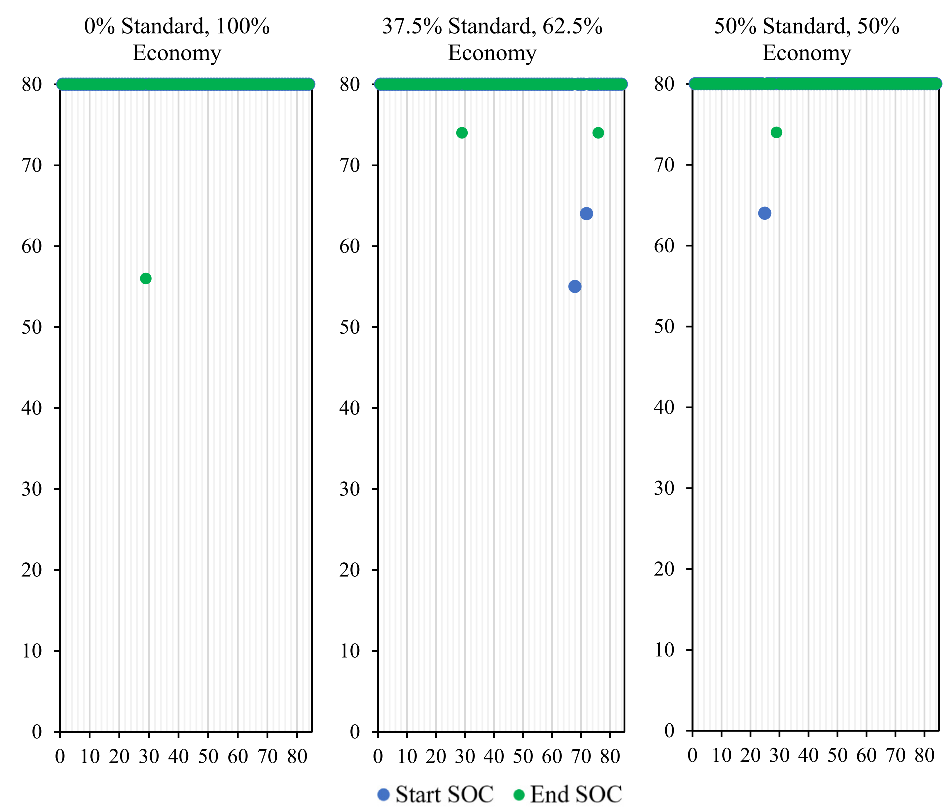

Fig. 11. Start and End SOC's for scenarios 5, 6 and 7.

When considering the EV chargers by themselves, i.e. not in relation to the grids current demand, these results indicate that a push for more standard tariffs to become the mainstream tariff option for households would be the more ideal case for demand side management. This would go against the perceived notion that EV charging should be pushed to the early hours for demand management, a fact that many energy companies are basing their EV specific tariffs on (cheaper rates overnight). However, investigations into the addition of these energy and power demands with current grid readings for energy and power will be required in order to draw a final conclusion on this matter.

A key parameter of this model which requires further attention is the allocation of one charger per vehicle. In reality this would not be practical given the fact some households own 4 vehicles, as household electrical wiring would prohibit the use of so much power being drawn at any one time. Whilst the permission of 84 charge points being used from the grid perspective still stands, scenarios considering the number of charge points per

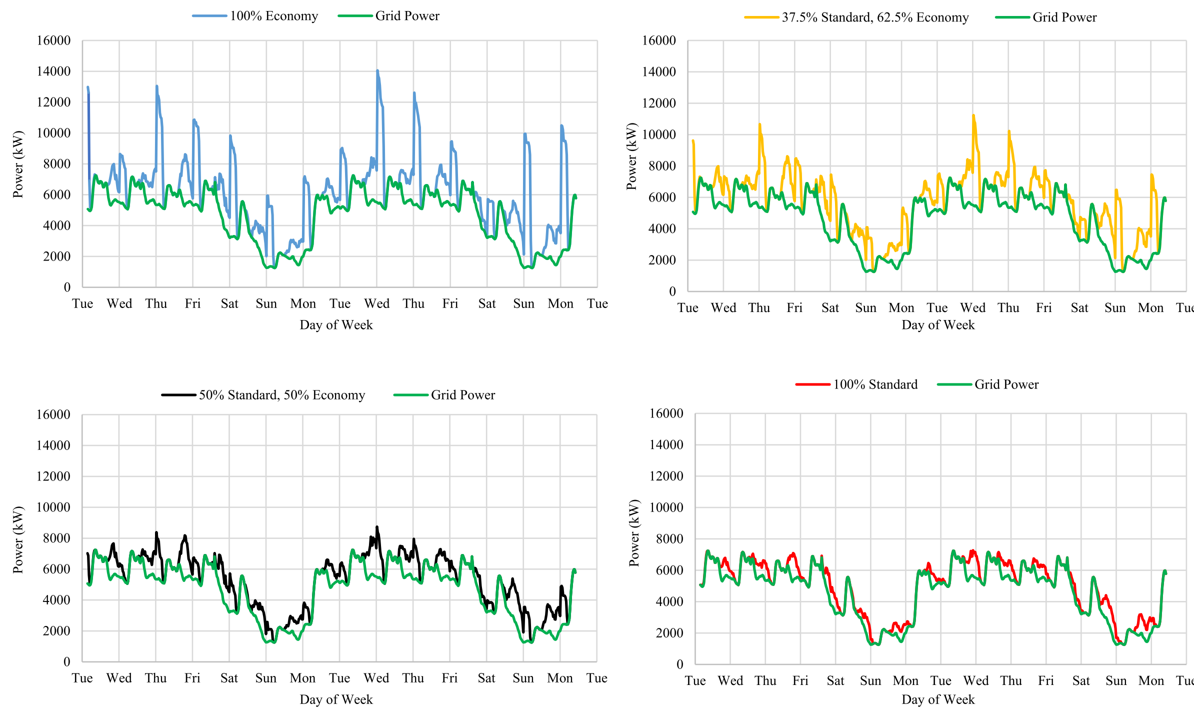

Fig. 12. Grid Impact for Scenarios 1, 2, 3 & 4.

household should be devised and investigated. Additionally, the two charging behaviours themselves investigated in this study could be improved upon. One such improvement would be the use of more sophisticated charging algorithms, whereby vehicles are charged based on their upcoming usage patterns, knowledge which would be known by drivers and thus reflect a more real life scenario. The incorporation of less restricted charging patterns, which in this model are largely dictated by the electricity tariffs pricing plans, would also reflect users who may choose to pay higher rates of electricity in order to make sure their vehicles have enough charge to complete their upcoming driving trips.

4.3. Grid impact

Using data acquired from Western Power Distribution, real world power measurements from the primary substation (Longcliffe 890067), enabled a thorough analysis into the grid impact the results of this EV Charging model would give rise to. This substation feeds an area much larger than Bradbourne alone, and thus to ensure a proper analysis the results previously discussed have been scaled by a factor of 16.43 to compensate. A total of 1380 vehicles are registered to the households within the distribution network of primary substation 890067. This scaling factor was computed from the relationship between the 84 vehicles simulated for Bradbourne and the total 1380 potential EVs that would be demanding energy and power from this transformer.

Once the scaling up process was completed, the results of all 8 scenarios were combined with the readings from Western Power. Figs. 12 and 13 present the results of scenarios 1, 2, 3 & 4 and scenarios 5, 6, 7 & 8 respectively.

Depending on the charging scenario, a 100% EV population has major implications for the grid. With the 100% Economy tariffs resulting in the most cause for concern, an increase of over 100% for the '20% charging behaviour' and over 200% for the 'charging every night' behaviour. Whereas the results for the 100% standard tariff scenarios actually place very little increases in peak demand for grid operators' perspective. Again reinforcing the position against the current push for EV only tariffs operating on an economy (TOU) type plan.

It should be noted that this 100% EV penetration scenario is far away given current market penetration figures in the UK and so there are multiple possible solutions for mitigating these increases in peak demands. One of which is Demand Side Management (DSM), which utilises pricing signals and behavioural changes (López et al., 2015) to manage fluctuating loads and reduce peak demands. An example investigated by Ciabattoni et al. (2021) limited the power availability to EV chargers, although this would increase duration of charging it reduced peak power demands.

Additionally, alongside these increases in power, the required energy generation is also cause for concern. This is exacerbated by the need for this additional energy to be produced from renewable sources so as to align with the underlying goal of this EV transition — to reduce GHG emissions. Future work is expected to look into the incorporation of wind turbines and solar panels as locally generated renewable energy combined with suitable energy storage solutions to offset the increases in demand due to EV consumption.

5. Conclusion

This paper presents the results from 8 scenarios of EV charging for the 84 vehicles belonging to the residents of a small rural village, Bradbourne, located in the Peak District, UK. The energy consumption and charging energy and power requirements have been modelled for a period of 4 weeks. From this 4 week period, a specified time period was selected to ensure all results presented are in accordance with the 1st Law of Thermodynamics. The results presented were for 4 variations of household electricity tariff options (combinations of Economy and Standard tariffs) and 2 behavioural options (charging upon the battery reaching a lower threshold and charging every night regardless) to create the 8 scenarios investigated.

It was found that for a charging behaviour whereby the batteries of EVs are depleted to a low level before recharge, the whole

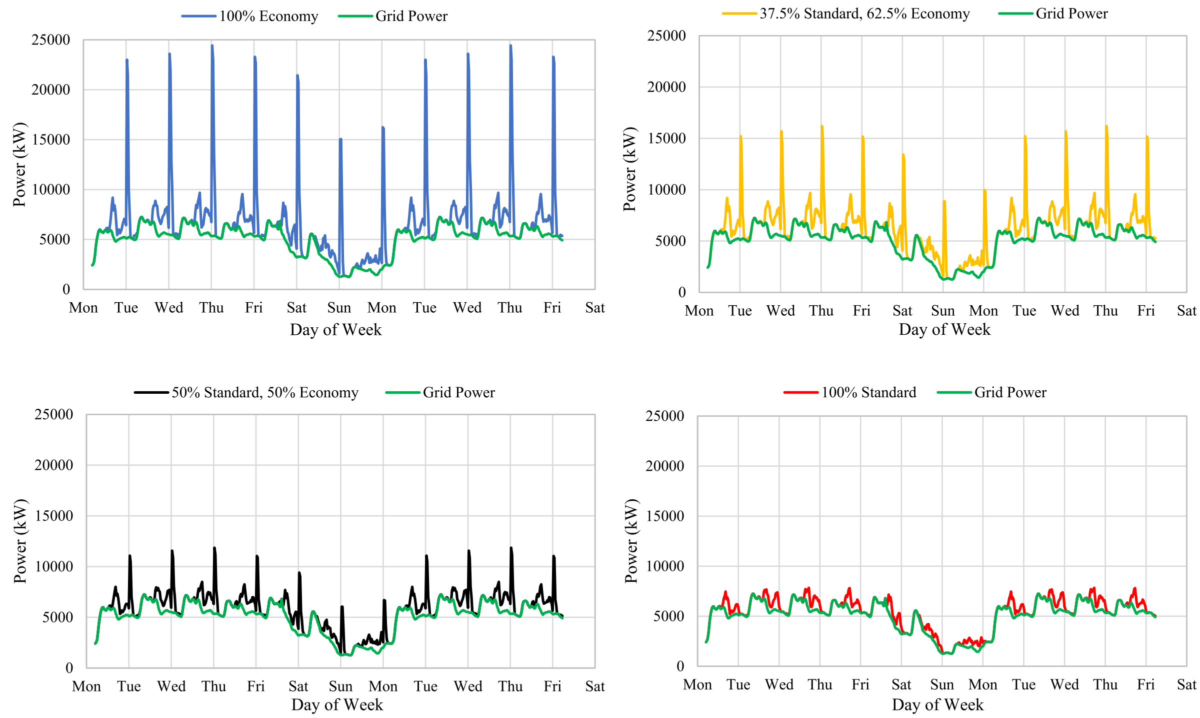

Fig. 13. Grid Impact for Scenarios 5, 6, 7 & 8.

system exists at a much lower average state of charge, compared to a charging behaviour whereby the vehicles are recharged every night regardless of their state of charge before recharging. This is influenced heavily by the varying travel patterns which result in fewer overlaps of charging events for multiple vehicles at any one time, and thus reduces the peak demand requirements. However, in general, this charging behaviour leads to longer charging times once charging events begin. When compared to the scenarios whereby the EVs are charged every night, more chargepoints are in use at any one time, especially for high economy tariff scenarios where charging start times are all similar. This results in much larger peak demands which may be a cause for concern for local rural grid infrastructure. Although, the benefits of this charging behaviour regime are much smaller charging dwell times, this means the higher energy/power requirements do not last long. The results from these various scenarios analysed with the EV Charging Model where then combined with real-life measurements from a local distribution substation serving Bradbourne to investigate their impact on local grid infrastructure. This showed the addition of EV's, and their charging profiles, can be done so in a way which leads to very little impact on grid infrastructure. For both charging behaviours, which represent the two extremes, a 100% standard tariff (flat rate regime) has minimal impact, and due to the pre-existing electricity demands, the addition of EVs is able to fit into that pre-existing profile. However, problems are envisaged for scenarios with increasing Economy tariff market shares, which although forces EVs to charge during the troughs of the pre-existing profile, the coalescences of all EVs beginning charging at the same time leads to detrimental power spikes.

The findings from this study have multiple implications for policy makers, electrical grid planners, and energy generation and storage, as well as extending the academic discourse for the EV transition in rural areas. Most critical is the determination of the timing and magnitude of the peak load, both in terms of energy and power, placed on the grid when considering a rural landscape undertaking large EV adoption.

CRediT authorship contribution statement

Thomas R. McKinney: Conceptualization, Formal analysis, Investigation, Methodology, Validation, Writing – original draft. **Erica E.F. Ballantyne:** Funding acquisition, Project administration, Resources, Supervision, Conceptualization, Writing– review & editing, Writing – original draft. **David A. Stone:** Funding acquisition, Project administration, Resources, Supervision, Data curation, Conceptualization, Writing – review & editing, Validation, Writing – original draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors are unable or have chosen not to specify which data has been used.

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