KEEPING THE CAR CLEAN

ON THE ELECTRIFICATION OF PRIVATE TRANSPORT

SUMMARY BOOKLET

The electrification of private road vehicles – and the provision of a low carbon generation mix that supplies the energy for their motion – is likely to be a key contributor to meeting *net zero* targets and limiting the disastrous effects of anthropogenic climate change.

This summary booklet contains an overview of the findings from a PhD (titled as above) carried out at the EPSRC Centre for Doctoral Training in Future Power Networks and Smart Grids at the University of Strathclyde from 2016 to 2019. The full thesis, including all the supporting analysis and assumptions behind the results presented in this booklet, is available on the author's PURE webpage.

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January 2020

ANALYSIS OF UK CAR HABITS

The tendency of EV drivers to charge their vehicles can be characterised by considering i) the energy requirement of the vehicles and ii) the opportunities for charging, both given a set of required trips.

The UK National Travel Survey (NTS) is conducted annually for around 15,000 UK residents. Data for the years 2002-2016 (inclusive) are available online, containing information on 2,042,058 car-based trips between 126,186 vehicles.

PARKING

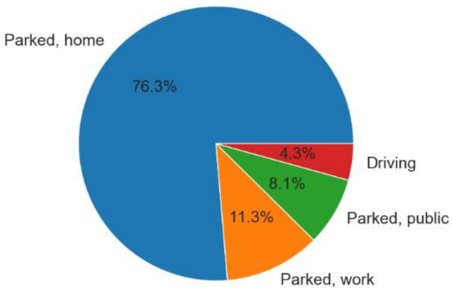

Figure 1 Parking durations by location, 2002-2016 NTS

- Cars in the UK spend on average 96% of their time parked – 76% at home, 11% at work and 8% at other public places.
- Due to the inherently low utilisation rate of private cars, their charging demand is likely to be flexible.

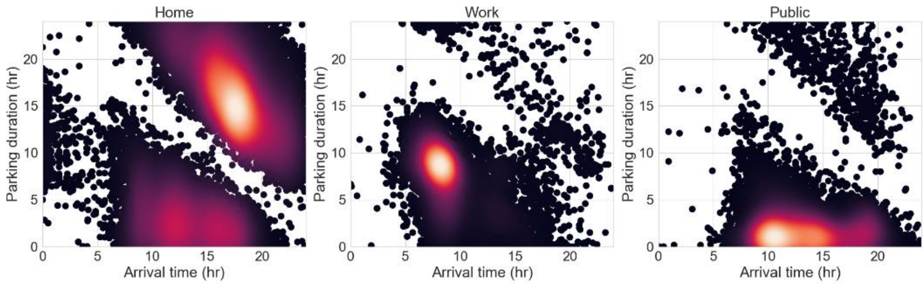

Figure 2 Arrival times and parking duration at home, work and public parking events - 2002-2016 NTS

- Arrival times at home are concentrated around 15:00-20:00 for parking durations of 10-16 hours
- Arrival times at work are concentrated around 07:00-10:00 for parking durations of 7-10 hours
- Arrival times at public places are spread throughout the middle of the day, with most parking durations under 3 hours.

DRIVING

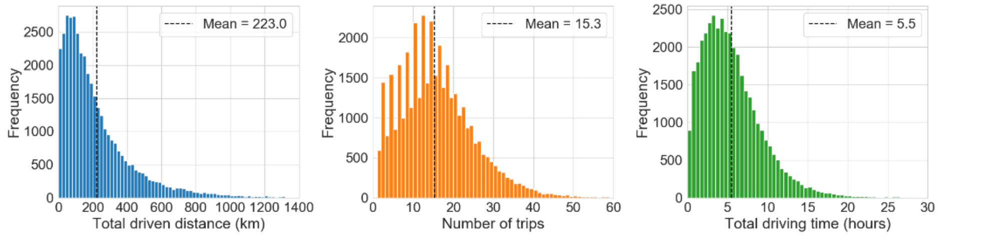

Figure 3 Total distance driven, number of trips and driving time - 2002-2016 NTS travel diaries

- On average *(mean),* drivers made 15.3 trips in the week (corresponding to 1.1 return trips per day), spending a total of 5.5 hours at the wheel and covering a distance of 223 km.
- The *modal* time and distance are significantly less: approximately 3 hours and 80 km respectively. This shows that the small number of active drivers skew the dataset for the entire population.
- These drivers could tend to be located in particular geographical locations, connected to particular electricity networks (e.g. commuter suburbs). This effect – known as 'clustering' – could lead to disproportionate stress on a subset of distribution networks.

CHARGING ARCHETYPES

On the basis of this analysis, it is hypothesised that there are four ***charging archetypes***, characterised by location, power rating and charging window (parking duration). The latter two set the *flexibility* of the charging demand.

\- *POWER* +

	Domestic	Workplace	Public	En Route
Location	At home – off-street and on-street	Workplace car parks	Supermarkets, shopping centers, on-street (public), public car parks	Motorway service stations, charging forecourts
Power rating	< 10 kW	< 10 kW	10 – 50 kW	> 50 kW
Charging window	> 9 hours	3-9 hours	20 minutes – 3 hours	< 20 minutes

\+ *FLEXIBILITY* -

Figure 4 Four charging archetypes: location, power rating & charging window

ON THE EASE OF BEING GREEN: THE INCONVENIENCE OF ELECTRIC VEHICLE CHARGING

The perception that EV charging carries some inconvenience relative to internal combustion vehicle (ICV) fuelling is a major barrier to their adoption. The aim of this work was to quantify the likeliness of ‘convenience parity’ between EVs and ICVs for different combinations of battery capacity, charger power and level of access to charging (i.e. home, work, public). Further analysis is carried out to quantify the likely delays resulting from charging during long journeys (those that exceed the vehicles’ range), given that drivers are advised to take 15 minutes’ break for every 2 hours’ driving (UK Highway Code Rule 91).

GOING ELECTRIC: BATTERIES VS INTERNAL COMBUSTION

2019 Nissan Leaf

- Battery capacity = 40 kWh
- Range ~ 240 km
- Charging power = up to 50 kW

2019 Fiat 500

- Fuel storage ~350 kWh
- Range ~ 500 km
- Refuelling rate ~ 5000 kW

- The energy storage capacity[1] and the rate at which it can be replenished[2] are far greater for the ICV than the EV.
- However, the fact that their energy storage content can be replenished while parked (during which time the driver is engaged in some other activity) could – at some level of battery capacity, charger power and level of access to charging at different locations – mean that EV drivers may achieve ‘convenience parity’ with ICV drivers.

[1] The 2019 Fiat 500 has a 40 litre fuel tank, and the US Department of Energy assumes the calorific value of petrol to be 33.7 kWh. However, due to the significantly greater losses associated with the combustion engine of an ICV than those associated with the motor and traction drive of an EV, EVs can travel around 3-4 times further on the same amount of energy storage.

[2] Petrol pumps in the UK are limited (for light cars) to around 40 litres per minute.

CHARGING SCHEDULES AND TIME PENALTIES

- Charging schedules are derived from NTS travel diaries using a heuristic approach (Figure 5).
- Time penalty of **parked** charging consists of the time taken to plug and unplug the cable (Table 1).
- Time penalty of **en route** charging is that above *plus* the time taken for the EV's battery to charge to the required state of charge (SoC)[3].

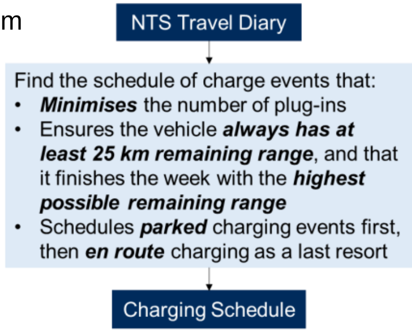

Figure 5 Derivation of charging schedules from NTS travel diaries

Table 1 Time penalties for plugging and unplugging charging cable

Fixed cable (one end in situ)	Loose cable (in boot)
17.0 s	48.9 s

- Time penalties found from experiments at DTU Powerlab[4].
- Home and en route = fixed cable; work and public = loose cable.

- Charging dictated by constant voltage constant current (CC-CV) charging curve (Figure 6); example shown for 24 kWh battery and 3.7 kW charging power (88% efficient).
- This sets the energy transferred during a parked charging event and the time taken to reach a specific SoC during an en route charging event.

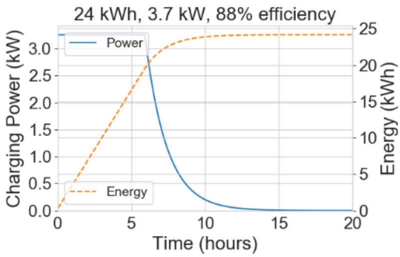

Figure 6 Example constant current-constant voltage charging curve

INTERNAL COMBUSTION VEHICLE FUELLING

- To allow fair comparison, the time taken for 50 ICVs to pass through a petrol station in Glasgow was recorded, from their arrival at the pump to their departure (neglecting any queueing time).
- Lower and upper quartiles used as best (207 seconds) and worst (294 seconds) case values for total fuelling time penalty respectively.
- These time penalties are applied to ICVs completing the same travel diaries, proportionally to how many tanks of fuel they would use.

[3] Such that it has at least 25 km remaining range at the next charging opportunity
[4] http://www.powerlab.dk/

VEHICLE PARAMETERS

- 3 battery sizes – 30 kWh, 60 kWh and 100 kWh.
- Corresponding values of energy consumption (kWh/km) taken from US Environmental Protection Agency (EPA)'s Federal Test Procedure of representative EVs: 2015 30 kWh Nissan Leaf and 2012 Tesla Model S (60 kWh and 100 kWh variants).
- 2 levels of charging power – slow (3.7 kW at home, 11 kW at work/public places and {50 kW for battery sizes less than 60 kWh; 120 kW for battery sizes 60 kWh and above} for en route); and fast (7.4 kW at home, 22 kW at work/public places and {150 kW for battery sizes less than 60 kWh; 300 kW for battery sizes 60 kWh and above} for en route).
- Level of access to charging: combinations of home, work and public denoted by H, W and P respectively. A negative (¬) sign preceding any letter indicates lack of access to charging at that location.
- Two ICV models used for comparison.

INCONVENIENCE OF EV CHARGING VS ICV FUELLING

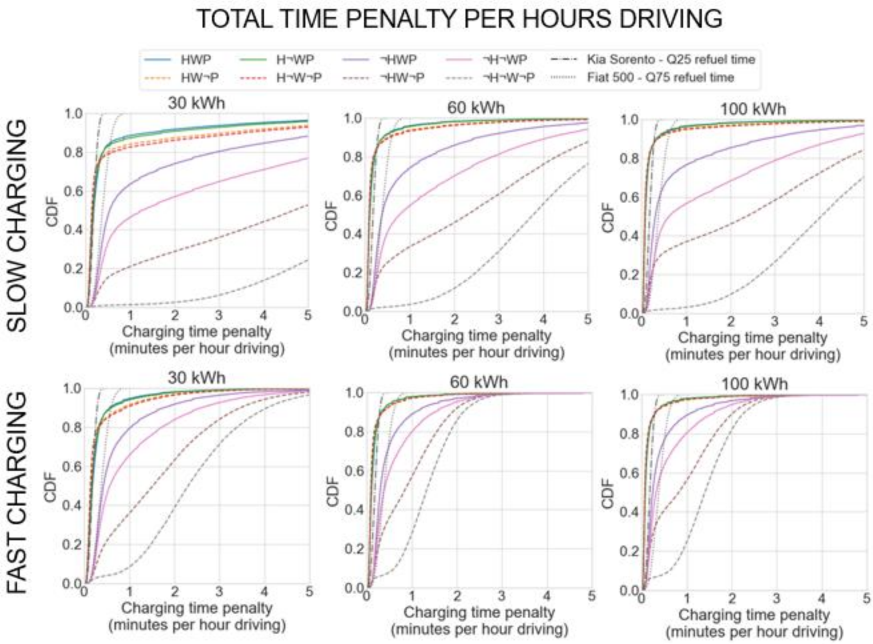

Figure 7 Cumulative distribution functions – total time penalty per hour driving

- Figure 7 shows the probability that the total time penalty experienced over the week is less than or equal to a certain value in minutes' charging per hours' driving.

IMPACT ON LONG JOURNEYS

Proportion of trips in NTS dataset greater than battery range (EPA real world range of corresponding EVs)

Drivers stop for 15 minutes' every 2 hours, and are assumed to have access to EV charging during that time (e.g. at motorway service stations)

<0.01% of journeys delayed for battery sizes of 60 kWh and above

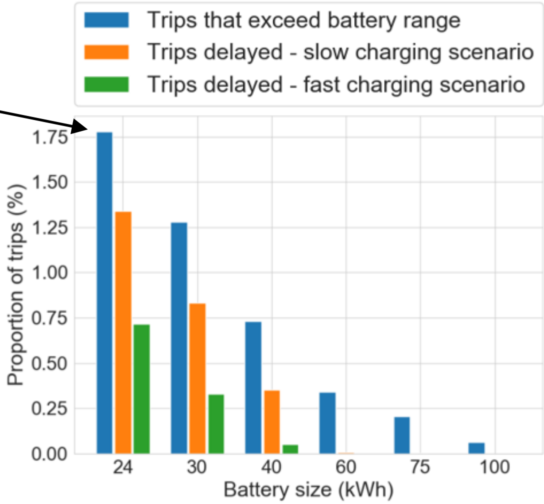

Figure 8 Proportion of trips delayed from charging

CONCLUSIONS

- Most (≥80%) of drivers can achieve 'convenience parity' even at 30 kWh with slow charging **if they can charge at home.**
- At 60 kWh, ~90% of drivers suffer *less* inconvenience in an EV than an ICV
- If they can't charge at home, convenience parity is much less likely – 95% of cases spend more than 2 minutes' charging per hour driving for 30 kWh with slow charging.
- Increasing charging power and access to charging at work and public places can help: ~70% of drivers with ¬HWP charging access, 60 kWh batteries and fast charging can achieve convenience parity.
- The resultant effect on long journeys from EV charging is small, if charging can be done when drivers take breaks: fewer than 0.01% of journeys are delayed from EV charging with batteries of 60 kWh and over.

CHARACTERISING PUBLIC CHARGING DEMAND USING SMARTPHONE GPS DATA

It was presented in the last section that widespread access to workplace and public charging is crucial in order to minimise the inconvenience on individuals who may find it difficult to charge their vehicles at home due to lack of off-street parking[5]. EV charging infrastructure is already appearing at UK supermarkets, leisure centres, shopping centres and other 'destinations' where individuals may leave their cars for periods ranging 15 minutes to 3 hours. The aim of this work was to develop a method for characterising the spatial and temporal variation of this charging demand based on the availability of large datasets of individuals' movements from their use of smartphone GPS applications.

GOOGLE MAPS POPULAR TIMES

- Google Maps Popular Times is a feature within the app that tracks the throughflow of app users (who have not actively disabled the app's location services) through a particular business, designed to allow users to see when a particular venue is likely to be busy.
- The data is shown as a percentage of the peak occupancy over the last several weeks (e.g. Figure 9).

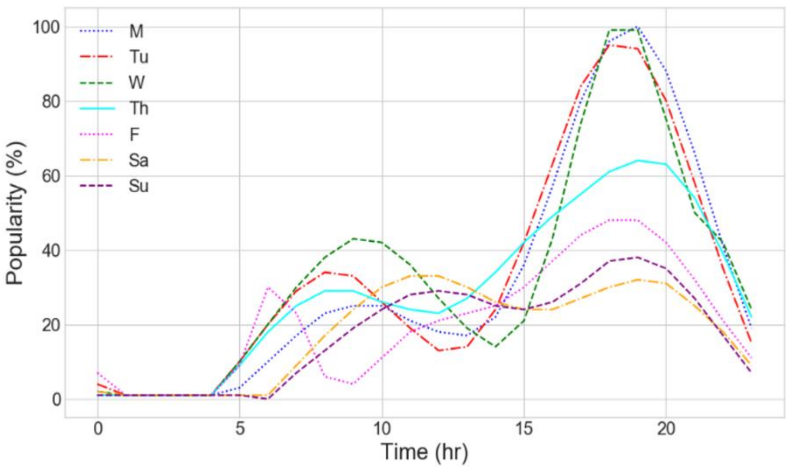

Figure 9 Example Google Maps Popular Times data for a gym in West Scotland

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[5] According to the Department for Transport (see http://bit.ly/2ROpC3F), this applies to 43% of households in the UK

QUEUE THEORY MODELLING

- Little's theorem (*eq. 1)* is used to derive a distribution of the arrival rate of vehicles μ (which is Poisson distributed about a mean of $\bar{\mu}$ *(eq. 2)*) in terms of the number of agents in the system N and the average service time T.

$$N = \mu T \qquad \textit{eq. 1}$$

$$P(\mu) = e^{\left(-\frac{N}{T}\right)} \frac{\left(\frac{N}{T}\right)^{\bar{\mu}}}{\bar{\mu}!} \qquad \textit{eq. 2}$$

- N is the number of vehicles in the car park (i.e. the percentage value in Figure 9 multiplied by an assumed peak) and T is the average duration of stay in the particular business (also available in the Popular Times data).
- The resulting *arrivals profile* is a rate of arrival of vehicles per hour with an assumed battery SoC (Figure 10), arrival minute within the hour (random) and intended stay time. The charging car park parameters (charging power, grid capacity and converter capacity are fixed (Figure 11).

INITIAL STATE OF CHARGE

- The initial state of charge for each vehicle is sampled from a Beta distribution (Figure 10), limiting possible values in the range {0,1}.
- Shape parameters α and β derived from ~2,500 real public EV charging events from the *SwitchEV* dataset.
- This gives a mean of 51%.

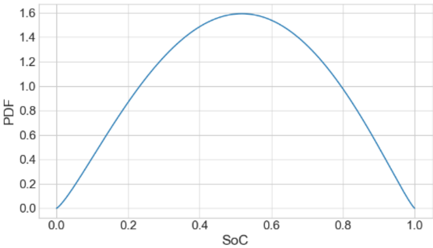

Figure 10 Beta distribution for initial SoC

EV CHARGING CAR PARK

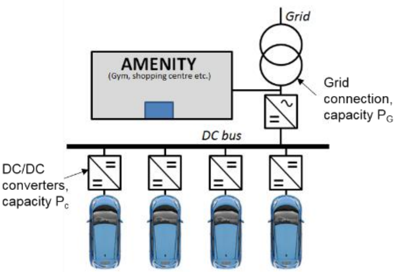

Figure 11 EV charging car park

- DC bus interfaced to grid via converter, allows controllable power flows to each vehicle via DC/DC converters at each charging station.
- Vehicles charged proportionately to their 'empty space' (the difference between their battery capacity and current energy level) as a proportion of the 'empty space' of all vehicles.

EV CHARGING AT A GENERIC GYM BASED ON 2,221 UK GYMS

- *Eq. 1* & *eq. 2* used to generate arrivals profile for a generic gym, based on a sample of Popular Times data for 2,221 gyms in the UK for a weekday (Tuesday) and weekend day (Saturday).
- Figures 12 & 13 show cumulative distribution functions for the likeliness of charging demand being less than or equal to a certain value, based on a 100-car charging car park with 2 MW grid capacity and 50 kW converter rating.
- This approach could be valuable to planners assessing the demand from the installation of charging at a new facility, and evaluating how it might interact with the existing network peak.

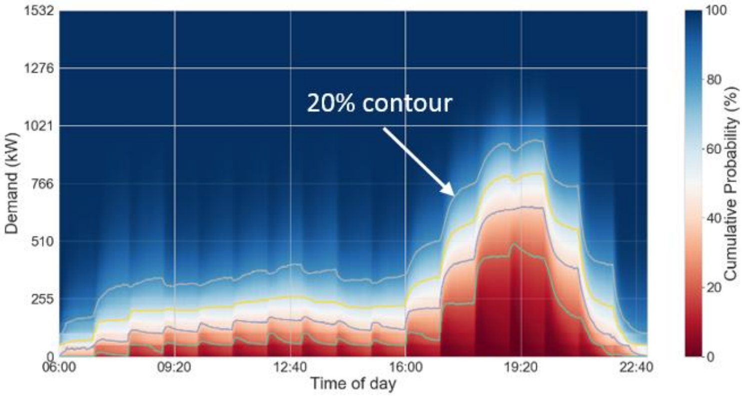

Figure 12 Cumulative distribution function of charging demand at gym, Tuesday

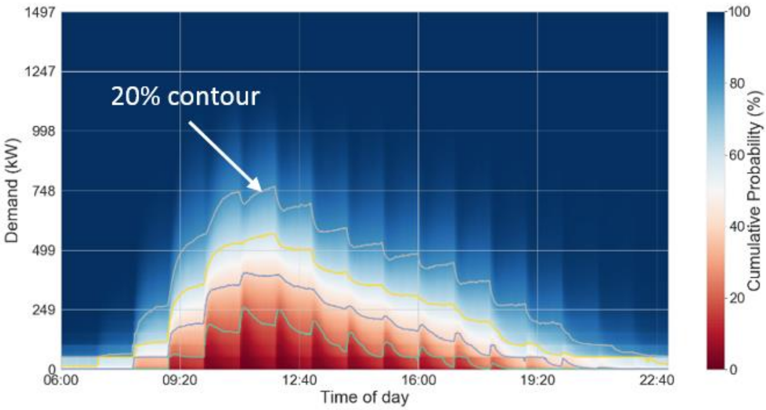

Figure 13 Cumulative distribution function of charging demand at gym, Saturday

CASE STUDY: EV CHARGING AT BRAEHEAD SHOPPING CENTRE

- Braehead shopping centre is a large leisure & shopping complex in the outskirts of Glasgow. Due to its 6,500 space car park and proximity to both the M8 motorway and electricity transmission infrastructure, it has the potential to serve as a large charging hub for visitors to charge their vehicles as they visit the centre.
- Popular Times data are used to characterise charging demand and level of service provision to EVs for various car park parameters.
- It was found that 25 MW of grid capacity is required to service the majority of EVs, and 20 kW converter capacity is sufficient.

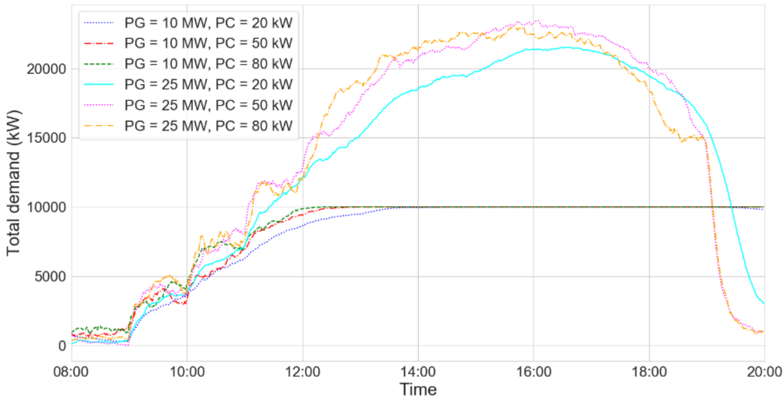

Figure 14 Demand profile of charging at Braehead for various grid and converter capacities

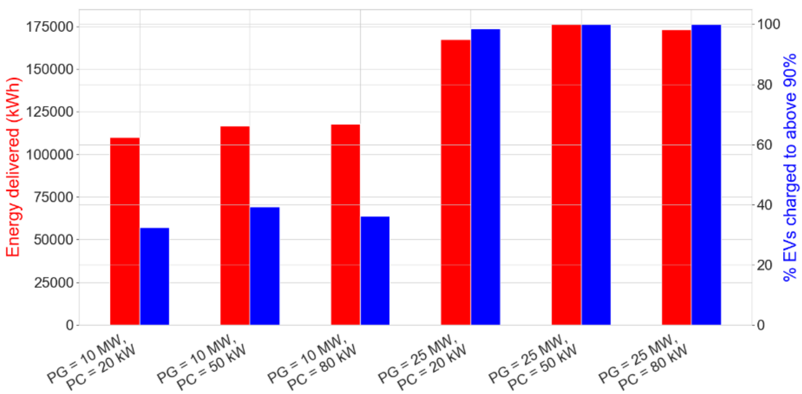

Figure 15 EV service provision at Braehead for various grid and converter capacities

HOME CHARGING AND THE RESULTING NETWORK IMPACT

In their *Road to Zero* report of 2018, the UK Department for Transport state that they expect the majority of EV charging to be carried out overnight at home. This means moving a significant proportion of the energy required to move the UK's car fleet to the end of the distribution networks, which were not designed for this level of demand. The aim of this work was to develop sociotechnical models taking into account local demographic traits of a distribution network and assign likely charging demand to electrical models generated from the same network. This is used to examine the likely differences in EV charging demand between areas of different socioeconomic traits, if drivers adopt different charging behaviours and if EV technical parameters (battery size, charger power and set of locations at which charging can be done) continue to change as rapidly as they have been doing in recent years.

GLASGOW SOUTHSIDE STUDY NETWORKS

- Geographical information systems (GIS) data of two networks covering quite different areas in Glasgow Southside: Pollokshields, a leafy suburb characterised by Victorian mansions, and Gorbals, a recently regenerated area of high-density housing in the inner city.

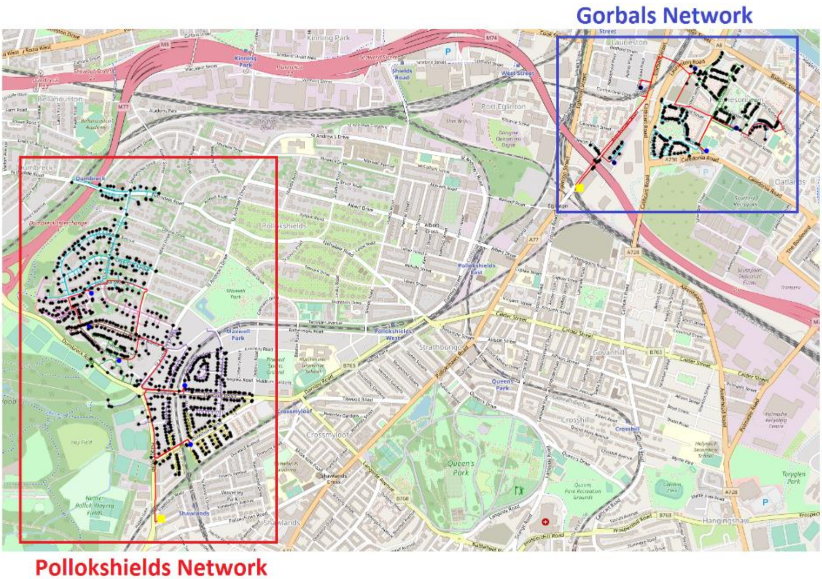

Figure 16 Pollokshields and Gorbals distribution networks, Glasgow Southside

- Network GIS data matched with 2011 UK Census Output Area (OA) data[6], Scottish Index of Multiple Deprivations (SIMD) data and an OS building dataset – such that each endpoint in the network had assigned probabilities of a given Census & SIMD outcome (e.g. number of cars at household, Figure 17) and an associated building type (e.g. terraced, detached, flat).

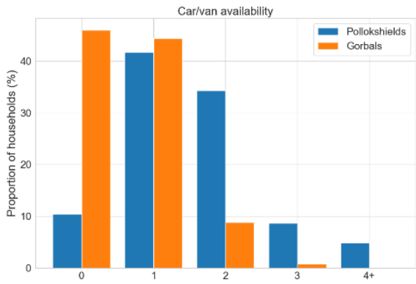

Figure 17 Number of cars at household, Pollokshields & Gorbals

- NTS travel diaries disaggregated on the basis of **economic activity** (employed, self-employed, unemployed) and **means of travel to work** (train, bus, car driver, car passenger bicycle etc.). An example of the differences between these disaggregated sets (the arrival time – and hence charge start time) is shown in Figure 18. Here, it is shown that individuals who travel to work by car are significantly more likely to arrive between 5 and 7 pm, and therefore more likely to add to the existing network peak.
- Travel diaries assigned to EVs instantiated in the network according to Monte Carlo-style simulation (sampling probability distributions for each Census/SIMD outcome and assigning travel diary from corresponding set).

Figure 18 Probability of arrival time at home by economic activity and means of travel to work

[6] Data for each OA (comprising around 50 households) in GB are available from the UK Data Service; *infuse.ukdataservice.ac.uk*. Fields used: number of cars at household, employment/means of travel to work, heating type, number of rooms, tenure and household composition.

- Established and validated Markov chain domestic demand model[7] used to generate domestic demand profiles (before the introduction of EVs) for each household in the network according to its sampled socioeconomic characteristics (Figure 20).

CHARGING BEHAVIOUR MODELLING

- Two models for deriving charging schedules from NTS travel diaries:
  - An **idealised** method finds the least time-costly set of charge events as previously presented.
  - A **routine** method is based on the same model but an EV will always plug in upon arrival at home (providing it has access to charging there).
- The latter represents a scenario where charging at home is of idealised inconvenience and drivers plug in 'routinely'; this could be due to drivers being incentivised to plug in – such as in a Vehicle 2 Grid scheme.

DIFFERENCES IN EV CHARGING BETWEEN NETWORKS

- Sociotechnical modelling approach applied to Pollokshields and Gorbals networks. Key differences in socioeconomic traits shown in Figures 19-21.

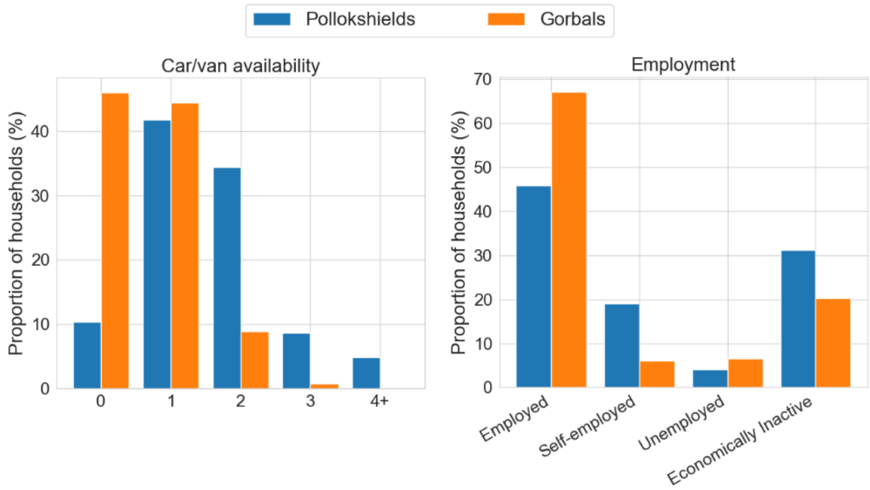

Figure 19 Car/van availability and employment, Pollokshields and Gorbals

[7]G. Flett and N. Kelly, "A disaggregated, probabilistic, high resolution method for assessment of domestic occupancy and electrical demand," *Energy Build.*, vol. 140, pp. 171–187, 2017.

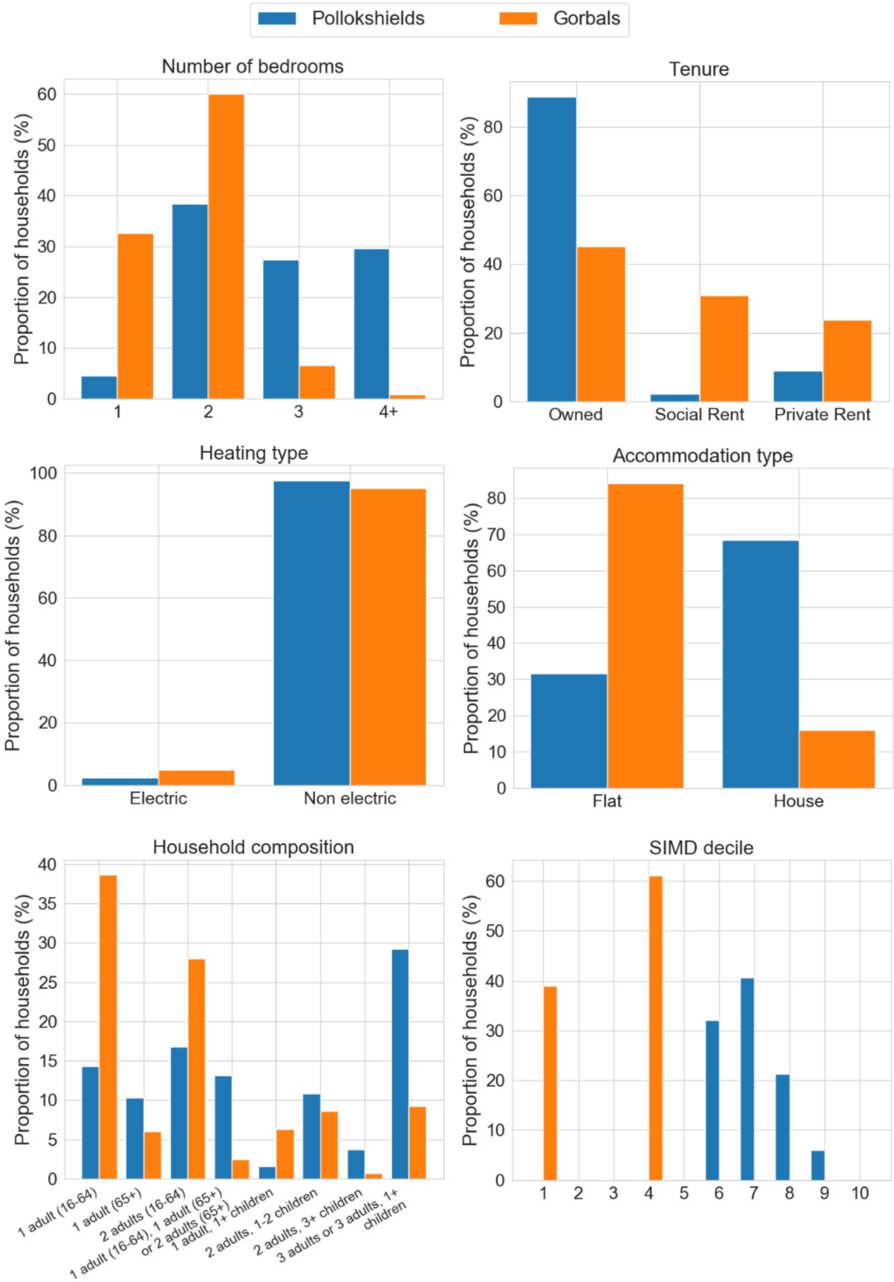

Figure 20 Factors influencing domestic demand, Pollokshields and Gorbals

- Figures 19-20 demonstrate that households in Pollokshields are more likely to have access to vehicles than those in Gorbals. Though Gorbals is shown to have a higher employment rate, Figure 21 shows that employed individuals in Pollokshields are far more likely to use their cars to travel to work.

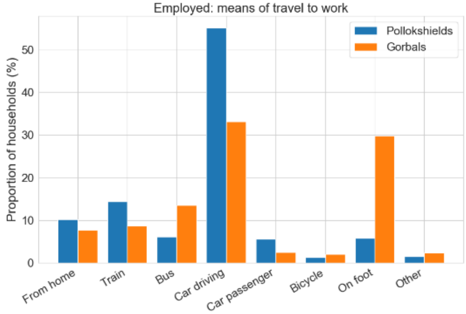

Figure 21 Employed individuals' means of travel to work, Pollokshields and Gorbals

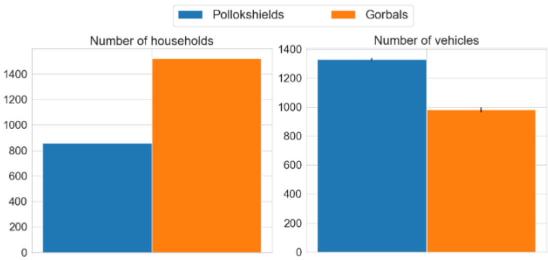

Figure 22 Number of households and number of vehicles in network, Pollokshields and Gorbals

- While there are more households served by the Pollokshields network (857 compared to 1522 in Gorbals), the likelihood of higher vehicle ownership means that the number of vehicles simulated was significantly higher in Pollokshields (Figure 22).

- Vehicles instantiated within the Pollokshields network drove, on average, 10% further over the course of the week (Figure 23**Error! Reference source not found.**).

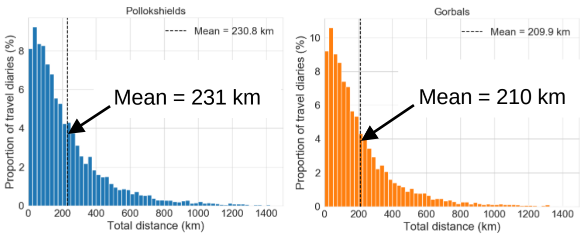

Figure 23 Travel diary distance (km), Pollokshields and Gorbals

- Vehicles in the Pollokshields network are more likely to arrive at home (and begin charge events) during peak times (Figure 24).

- Figure 25 and Figure 26 show total EV charging demand without and with domestic demand respectively for both networks.

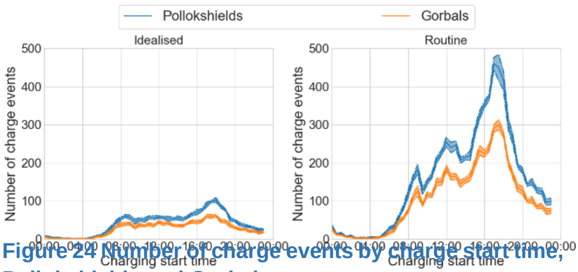

Figure 24 Number of charge events by charge start time, Pollokshields and Gorbals

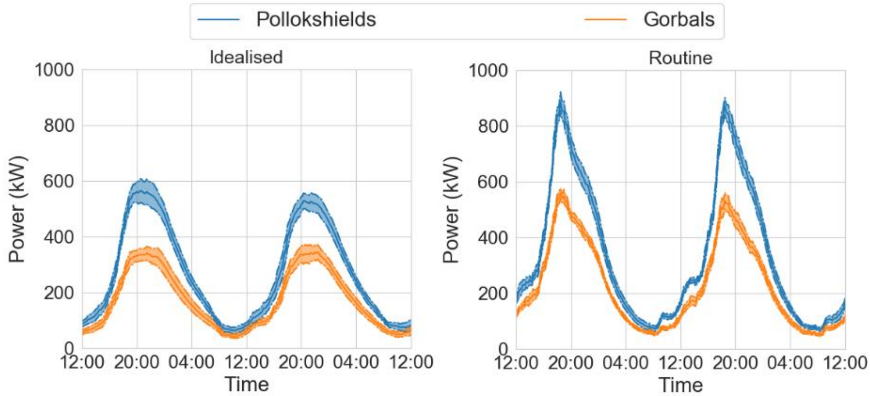

Figure 25 Total EV charging demand, Pollokshields and Gorbals – idealised and routine charging behaviour

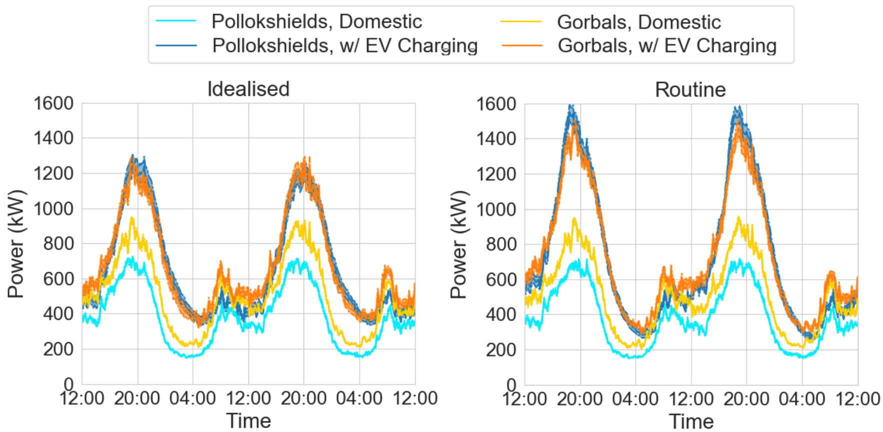

Figure 26 Total domestic demand and total domestic demand plus EV charging demand, Pollokshields and Gorbals – idealised and routine charging behaviour

- Uncontrolled EV charging is expected to increase the network peak by 35% (idealised case) – 58% (routine) in Gorbals, and by 84% (idealised) – 122% (routine) in Pollokshields.
- Though most of this difference can be accounted for by the greater number of vehicles (~40% difference), greater charging demand is accounted for by the longer distances expected to be driven) – both likely a result of a higher incidence of car-based commuters.
- The demographic make-up of the area served by the distribution network is expected to have a significant effect on the resulting EV charging impact.

DIFFERENCES IN EV CHARGING WITH EV PARAMETERS

- Differences in EV parameters (battery size, charger power and level of access to charging) is expected to affect the resulting charging demand. Figure 27 shows the total demand on the Pollokshields network for 100% penetration of EVs if all EVs had different configurations of parameters.

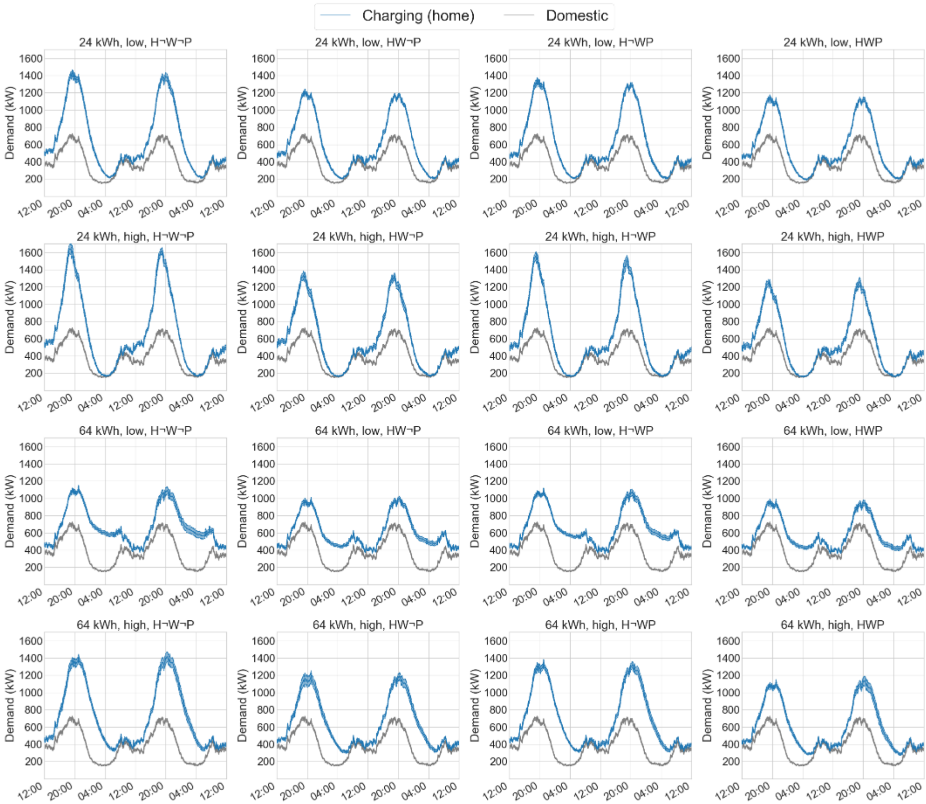

Figure 27 Total demand on Pollokshields network for different configurations of EV parameters, idealised charging behaviour

- **Increasing battery capacity is expected to *reduce* the peak and shift it later into the night**, resulting in a ‘valley filling’ effect.
- **Increasing charger power gives a sharper, sooner peak** that is the most likely to coincide with the peak in domestic demand.
- **Providing workplace and public charging reduces the burden on the residential network** – workplace charging is most effective.

OPPORTUNITIES FOR SMART CHARGING

As of July 2019, it is mandated that every EV charger eligible for government grant in the UK must be 'smart'[8]. Smart charging is often discussed as a way of limiting network stress or enabling EVs to better integrate renewable energy sources (RES) into the grid by providing demand when RES is in surplus or by providing grid services (such as frequency response) to mitigate potential stability issues resulting from large penetrations of DC-interfaced RES. The aim of this work was to use the travel data-derived charge diaries and sociotechnical modelling approach to investigate the extent to which EV charging could be managed to minimise network stress or maximise the integration of RES.

VALLEY FILLING OPTIMISATION TO MINIMISE PEAK DEMAND

- 'Valley filling' approach used to manage EVs' charging such that overall network loading is kept to a minimum subject to all EVs receiving the same amount of energy as they would have done if their charging uncontrolled.
- DC optimal power flow (OPF) formulation used with line losses; objective function seeks idealised cost of energy delivered, which leads to minimum losses (hence minimum power) solution.
- Figure 28 shows optimal scheduling of EV charging demand in the Pollokshields network for 100% penetration of EVs for both the idealised and routine cases.

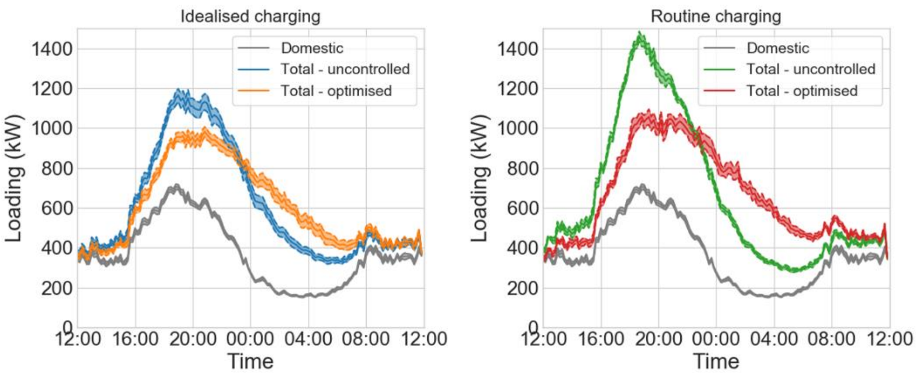

Figure 28 Total network loading for Pollokshields network, uncontrolled and valley filling optimised schedule: idealised (left) and routine charging (right)

[8] Defined as having the 'capability to receive, interpret and react to a signal' (http://bit.ly/2Z3vX1Z)

- Shifting charging demand later into the night can significantly reduce the peak demand by 16%-28% (idealised and routine cases respectively).
- The resultant peak (after optimisation) is remarkably similar between the two cases – though more cars are plugging in under the routine scenario, their energy requirement tends to be lower (as they will tend to have charged more recently) and therefore their charging is more flexible.
- Figure 29 shows the impact of EV charging on the *minimum* endpoint voltage in the Pollokshields network, for uncontrolled charging of 100% penetration of EVs and optimised scheduling using the valley filling approach for both the idealised and routine charging cases.

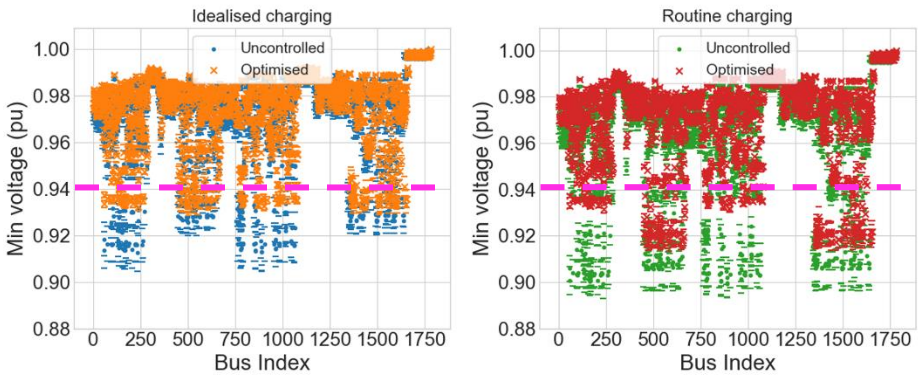

Figure 29 Minimum endpoint voltage in Pollokshields network - uncontrolled and valley filling optimised schedule: idealised (left) and routine charging (right)

- The pink dashed lines on Figure 29 represent the minimum allowable endpoint voltage in the GB system. While the management of EV charging increases the minimum voltage for both cases and the severity of the breaches (Table 2), it is an important result that even under the ‘best case’, 100% EV penetration cannot be accommodated in the Pollokshields network within statutory voltage limits.

Table 2 Summary metrics for violation of voltage limits in Pollokshields network for uncontrolled and optimised charging; idealised and routine charging cases

	IDEALISED		**ROUTINE**	
Proportion of time voltages in violation (%)	20.3	17.8	25.3	25.2
Min voltage (pu)	0.910	0.929	0.893	0.915
Av breach magnitude (pu)	0.0069	0.0023	0.0114	0.0049

HEURISTIC-BASED APPROACHES

- The results shown in the preceding section represent a case whereby the charging controller has access to the future arrival times, leave times and energy requirements of all charging EVs – in short, the ability to tell the future. While the future of EV smart charging could be based on accurate forecasts of said information based on historical data, a smart EV charger must be able to control the demand with the information that would be available to it: the SoC of every vehicle plugged in as it arrives.
- Three heuristic-based methods are detailed in Figure 30.

SIMPLE DELAY

- All charge events 16:00-00:00 delayed to midnight
- All charge events now come online at the same time

FIRST COME FIRST SERVED (FCFS)

- All charge events 16:00-18:00 delayed to at least 18:00
- Charge events brought online in the order they originally plugged in, separated by a time interval proportional to the number of plug-ins

LOWEST RANGE FIRT SERVED (LRFS)

- All charge events 16:00-18:00 delayed to at least 18:00
- Charge events brought online in the order of lowest-highest remaining range, separated by a time interval proportional to the number of plug-ins

Figure 30 Heuristic-based approaches for managing EV charging demand

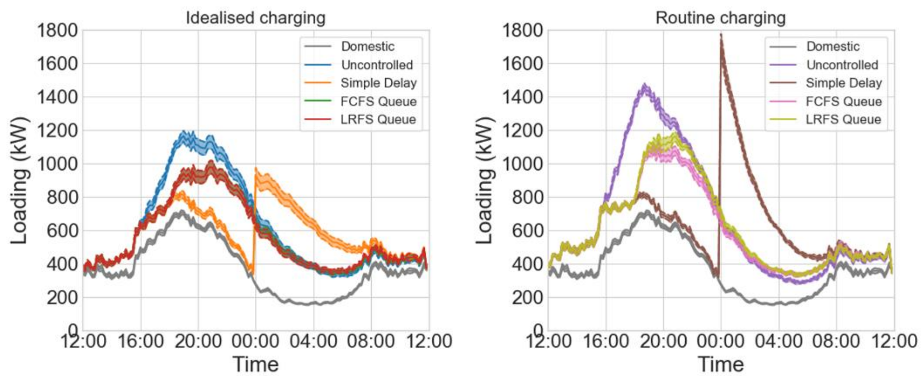

Figure 31 Total network loading, Pollokshields network - heuristic based charging control, idealised and routine cases

- The simple delay heuristic results in a loss of diversity and an increase in charging demand when all the delayed events come online at the same time – for the routine case, this means that (even though it's been shifted late into the night) the new network peak is higher than it was before.
- The FCFS and LRFS methods are shown to improve the network loading similarly to the 'best case' optimisation using DC OPF; however, whereas the latter guaranteed that all EVs would receive the same amount of energy as they would have done without smart charging, these heuristic methods do not. Figure 32 shows the impact of these methods on drivers' travel habits by further analysing the travel diaries of each charging vehicle to find out if a driver is rendered unable to reach their next charging opportunity (without stopping to charge en route) as a result of the heuristic methods.

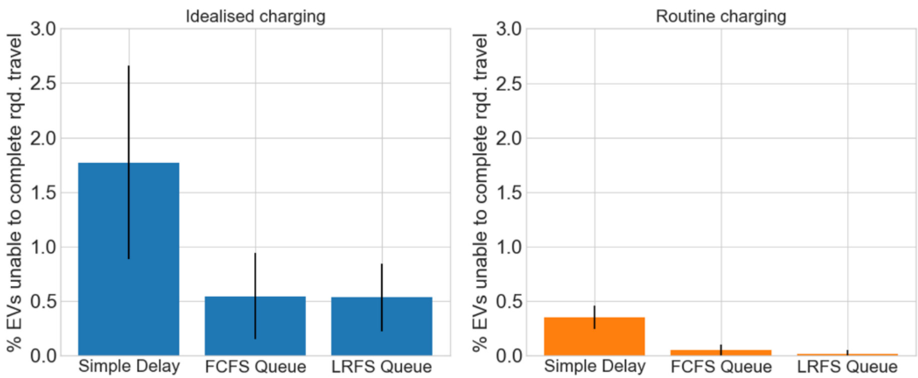

Figure 32 Bar chart showing proportion of EVs that plugged in to charge that were rendered unable to reach their next charging opportunity following a heuristic charging method being applied – idealised (left) and routine charging (right)

- If vehicles charge routinely, a diminishingly small proportion of vehicles have their travel plans affected by these charging strategies, likely because the SoC on plugin tends to be higher for these vehicles, as the distance travelled since their last charging event tends to be lower. While an average of 0.35% of vehicles that plugged in had to charge before their next charging opportunity under the simple delay heuristic, this was reduced to 0.054% and 0.017% for the FCFS and LRFS queue heuristics respectively.
- A shortfall of this analysis is that it does not consider the 'knock-on effect' of these charging management strategies; i.e. if a driver is faced with having their charging managed for subsequent nights while parked, the probability of them having to stop to charge en route may increase.

- The aim of this work was to examine how EV charging could be managed to take place at times when CO_2 intensity was at a minimum – and make use of surplus renewable energy that would otherwise be wasted.

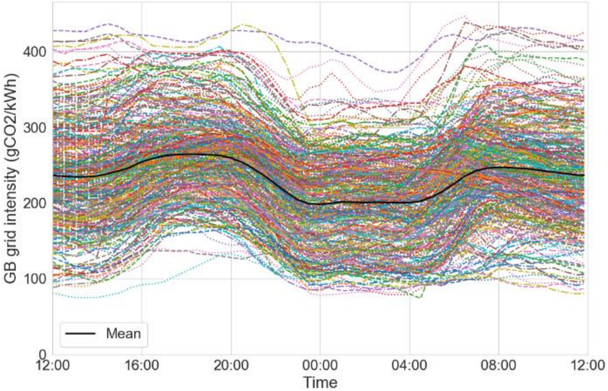

Figure 33 GB grid carbon intensity, 1 June 2018 - 31 May 2019

- CO_2 intensity of the GB grid varies significantly – and is forecasted by National Grid.
- The carbon intensity (grams of carbon dioxide per kilowatt-hour of energy) of EV charging sets a large part of EVs' environmental impact.

- Whitelee wind farm, around 15 km to the south of Glasgow, has 215 turbines with a total capacity of 539 MW.
- The wind farm is curtailed when generation exceeds local demand and transmission system capacity.
- Curtailment in period 1 June 2018 – 31 May 2019 occurred on 112 out of 365 days; the total was 227,841 MWh.
- The wind farm is paid to curtail this generation at an average of £70/MWh – bringing the total yearly sum to over ***£15.9m***.

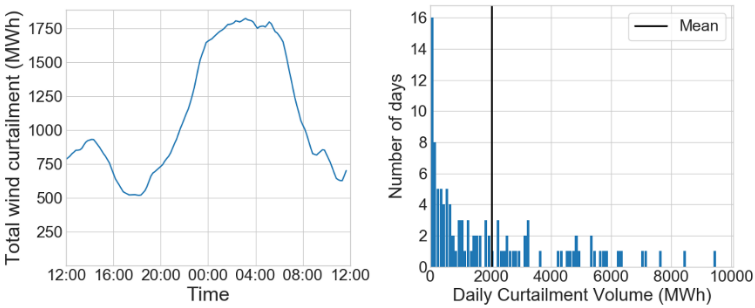

Figure 34 Total curtailment at Whitelee wind farm, 1 June 2018 - 31 May 2019

- Whitelee curtailment data was used to assess the feasibility of a large fleet of EVs in Scotland’s Central Belt ‘soaking up’ excess wind generation, that tends to be highest overnight (when EVs are most likely to be charging).
- During periods with curtailment, it is assumed that EVs can charge with an intensity of 0 gCO_2/kWh up to the volume of curtailment in that period.
- 10,000 individual NTS travel diaries used to simulate large sets of EV charging schedules – which are scaled up to represent large fleets of EVs.
- Effectively, this represents a single bus model (Figure 35).

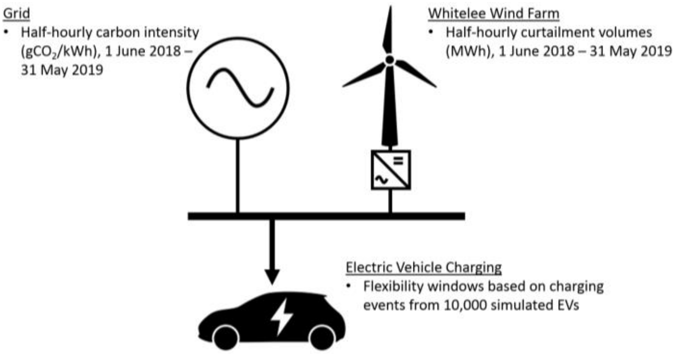

Figure 35 Single bus model used for analysis of EVs supporting renewables

- Figure 36 shows the resulting CO_2 intensity for charging.

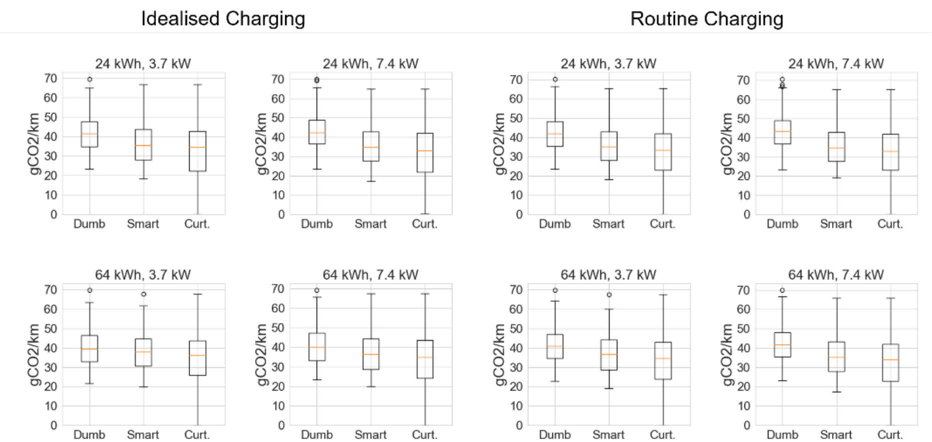

Figure 36 Carbon intensity of charging for different battery sizes & charger power, idealised and routine charging

- Figure 36 shows CO_2 emissions per km driven[9], to allow comparison with other road vehicles. The potential of smart charging to reduce CO_2 intensity is affected by the flexibility of the charging events, in turn affected by battery size and charger power, and drivers' charging behaviour.
- If 'dumb' charged from the current GB grid, *average* EVs' emissions from their charging is **35-56 gCO_2/km**.
- This can be reduced **to 27-39 gCO_2/km** by smart charging and taking advantage of excess renewables – around **20-30% of the average new car sold in Europe[10]**.
- Figure 37 shows the variation in ***total*** reduction in curtailment at Whitelees, following the introduction of various EV fleet sizes if their charging could be controlled to seek minimum carbon intensity.

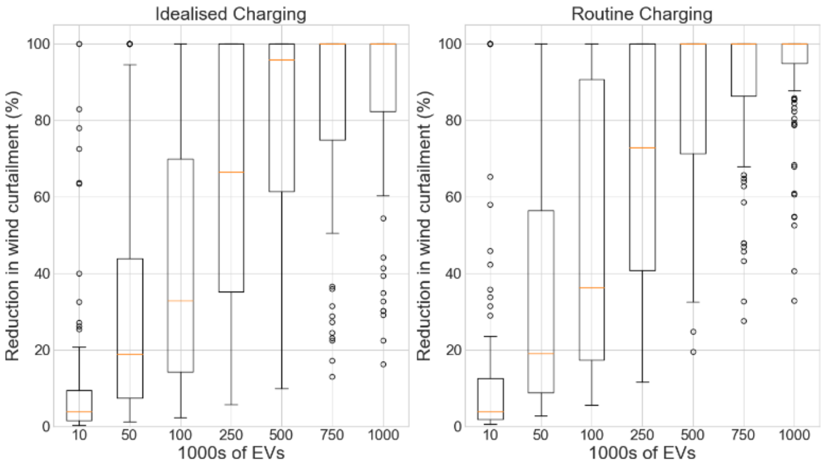

Figure 37 Total reduction in curtailment at Whitelees by number of EVs, idealised and routine charging

- 500,000 EVs (20% of Scotland's current car fleet[11] could absorb around three quarters of curtailment at GB's largest onshore wind farm.
- The rate of increase is shown to be diminishing – this is likely due to the small proportion of curtailment that happens in the middle of the day when EVs are unlikely to be plugged in (Figure 34).

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[9] These were converted from CO_2/kWh using a typical spread of EV driving 'efficiencies' of 0.15-0.19 kWh/km from the US EPA's test data
[10] 121.5 gCO_2/km (petrol) and 123.4 gCO_2/km (diesel), bit.ly/2mo8iXu
[11] Transport Scotland, "Scottish Transport Statistics", bit.ly/33kFi3o

FURTHER READING

The summary results presented in this booklet are excerpts from the thesis, with much of the detailed methods, literature reviews and extensive analysis omitted. The full thesis is available on the author's PURE webpage[12], as are a list of publications that have resulted from this work.

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[12] https://pureportal.strath.ac.uk/en/persons/james-dixon