Energy Policy 118 (2018) 474–481

Contents lists available at ScienceDirect

Energy Policy

journal homepage: www.elsevier.com/locate/enpol

Mitigating the impact of personal vehicle electrification: A power generation perspective

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ARTICLE INFO

Keywords:
Electric vehicles
Charging
Power grid protection

ABSTRACT

The number of electric vehicles on the road in the UK is expected to rise quickly in the coming years, and this is likely to have an impact on the operation of the power grid. This paper first quantifies the consequences of allowing a completely electric fleet to charge freely, then considers whether there is a practical way in which the impacts can be mitigated. We predict that, with an entirely electric fleet, the UK power generation capacity would need to increase by 1/3. We show that it is possible to completely mitigate this with controlled charging, although substantial infrastructure would be required. However, we propose a simple scheme which could largely avoid the negative effect and does not require the creation of new infrastructure. We show that this reduces the projected increase in peak electricity demand by 80–99%.

1. Introduction

This paper considers whether there is a practical way in which we can prevent the increase in peak power demand resulting from a large fleet of electric vehicles (EVs).

Electric vehicles (EVs) have the potential to drastically reduce the national carbon footprint; as well as having zero tail-pipe emissions, the electricity required to power them can be produced through renewable sources. Van Vliet et al. (2011) confirm that regardless of the source of the electricity, EVs produce fewer CO_2 emissions than both conventional and hybrid vehicles. It is the general consensus that EVs could also increase the amount of renewable energy that is brought online without negatively impacting the grid (Richardson, 2013). This is particularly true with relation to solar (Birnie, 2009) and wind (Short and Denholm, 2006).

The 2008 Climate Change Act commits the UK to a reduction target of 80% by 2050, and this has led the government to introduce grants to encourage people to purchase EVs. Coupled with the decreasing price of lithium ion batteries this has lead to a rapid increase in the adoption of EVs in the UK, as shown in Fig. 1. More recently, a ban on the production of diesel and petrol vehicles after 2040 was announced (Asthana and Taylor, 2017) so the move to all-electric now seems extremely likely.

However, a large-scale adoption of EVs will present significant challenges to the power grid. Electric vehicle chargers draw a large amount of power relative to standard household appliances (see Table 1). Unlike other high-power appliances vehicle chargers will be on for several hours, meaning that there is a much larger chance that many in the same area will be on at the same time. This stands to increase the current peak power demanded from the grid. As well as the peak power, the amount of electricity required in a day by households will be larger; (National Grid, 2017b) predicted a maximum increase of 11% in household electricity demand due to charging by 2050, while (Andrews, 2016) estimated that the UK electricity needs would grow by 36% if all vehicles were electric. Both of these studies were simplistic, and their disparity highlights the sensitivity of predictions to the underlying assumptions in such models. The latter assumes that electrification will not change the number of vehicles on the road, while the former uses sales and scrappage projections to arrive at an updated number.

In the UK, power generation is limited to 78 GW (Department for Business, Energy and Industrial Strategy, 2016), meaning if all power generators operate at full capacity this power is produced. In practice this is not possible as 9 GW of this is from wind and solar power which are variable, and tend to be negatively correlated with each other (Widen, 2011).

If the peak demand regularly exceeds the available supply, more generation will need to be built. For exampled, the Hinkley Point C nuclear power plant currently under construction will add a capacity of 3.2 GW at a cost of up to$21 billion (UK Government, 2016).

The high cost of building additional generation places a large value on shifting demand to off peak times. While the amount of electricity required is not changed, by spreading it throughout the day the demand can be met though increased operation of existing power stations.

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https://doi.org/10.1016/j.enpol.2018.03.056
Received 11 October 2017; Received in revised form 25 February 2018; Accepted 25 March 2018
Available online 24 April 2018
0301-4215/

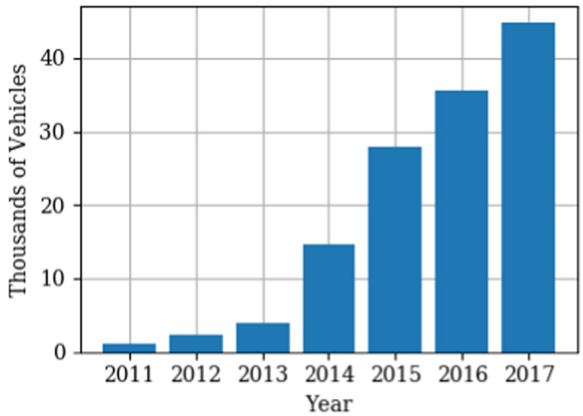

Fig. 1. The number of vehicles eligible for the plug in electric grant on the road in the UK.

Table 1
Power consumption of various household appliances.

Appliance	Power consumption (W)
Washing machine	700
Kettle	1800
Refrigerator	35
LCD TV	115
EV slow charger	3500

Smart charging refers to charging EVs in a controlled way so as to reduce the impact on the system. This is possible because vehicle charging represents an elastic demand; people don't mind whether their vehicle is on charge or not provided it has charged by the time they next need it. By contrast, normal household demand can be considered inelastic - appliances such as lights and microwaves require power at the instant they are turned on. While some trials are on-going, smart charging is not yet widely implemented in any country.

Here we focus on the case of the UK; although the methods could be used to repeat the research for a different area, the conclusions may not be the same. Only domestic vehicle use is considered, electrification of other transport (e.g. taxis and buses) would further increase electricity requirements. This paper focuses specifically on the national energy balancing problem, ignoring limits imposed at the local level by distribution system infrastructure.

Only currently available technology is included, meaning autonomous vehicles are not considered and neither are vehicle-to-grid schemes - where a vehicle can both give and receive power to and from the grid.

To consider a practical way of smart charging, this paper first (in Section 2) considers the charging infrastructure already available and outlines schemes previously proposed. Before assessing the success of smart charging the impact of a large electric fleet needs to be quantified; in Section 3 the methodology for doing this is presented, along with both an optimal and an approximate charging scheme. The proposed techniques are tested using data from the UK in Section 4, and the implications of the results are considered in Section 5.

2. Background

This section first considers the way in which people currently charge their vehicles, as a practical smart charging regime should not propose great deviation for standard practice and comfort of EV owners. Then an overview of the previously proposed schemes is given, and the reasons they are not practically implementable are explained.

Table 2
The types of vehicle chargers currently available to consumers, according to the terminology defined by Zap-Map (2017).

Charger type	Power (kW)	Charging time
Slow	3.5	6–8hrs
Fast	7	3–4hrs
Rapid	50	80% in 30–60 mins

2.1. Charging Infrastructure

Currently EV owners can choose to charge their vehicles from one of three types of charging points, summarised in Table 2. Given that their cars are parked there overnight, many customers have domestic chargers installed at their homes. These are predominantly slow chargers, but consumers can pay more to have a fast charger instead.

Once plugged in, EV batteries are charged under the *constant current, constant voltage* (CC-CV) scheme; chargers operate under a constant current until the battery is about 80% charged, when it switches to a constant voltage (decreasing current) until the battery is full. In power terms this means the charger runs at full power until 80% and then decreases exponentially to zero.

This charging profile is recommended by manufacturers in order to maximize battery lifespan, as empirical studies have observed lower levels of degradation compared to other methods (Zhang, 2006). A smart charging strategy would likely alter this profile, and the effect on the lifetime of car batteries would need be considered. However, this is beyond the scope of this paper.

The majority of drivers still see lack of public charging facilities as a reason not to purchase an EV (Office for National Statistics, 2016). This has led scientists to focus on ways to make charging more convenient, rather than minimising the charging impact; research into a cost-effective rapid charging network in the UK is already underway (Serradilla et al., 2017), despite this level of charging being the most potentially damaging to the grid.

2.2. Previously proposed strategies

An extensive array of smart charging strategies have already been proposed, and these can be broken down into three categories: time-of-use (TOU), centralised and decentralised schemes.

In TOU strategies a variable electricity price is introduced in order to incentivise charging at off-peak times. Charging is still under a CC-CV profile, and consumers have complete control over when they decide to charge. Lyon et al. (2012) conclude that TOU is the most cost effective way to shift charging, due largely to the low required infrastructure cost.

Cao et al. (2012) show that if every consumer acts to minimize the cost of charging their vehicle then valley-filling can be effectively achieved by appropriately setting the price. However, consumers are unlikely to work out their individually optimal charging strategy. In Langbroeka et al. (2017) a survey is conducted which attempts to gauge how consumers might change their charging habits in response to different pricing structure. However Hobman et al. (2016) note that historically the responses of consumers to cost-reflective pricing have not met expectation, and attribute this to psychological influences. Therefore, designing a tariff system which successfully shifts EV charging demand may be more complicated than it appears.

Another concern with TOU is that setting deterministic pricing bands may encourage all EVs to do the same thing, removing the natural diversity which the grid relies on. A possible extension to TOU which resolves this is to move to real-time pricing, where the price of electricity depends on the number of vehicles currently charging. However, Lyon et al. (2012) estimates that installing the infrastructure required to do this would be more expensive than increasing the available generation capacity to allow uncontrolled charging.

Unlike TOU, centralised and decentralised schemes directly control vehicle charging. This means that the success of the scheme is not dependant on consumer behaviour, provided they participate in the scheme.

In the centralised case, there is a single controller with access to all vehicle's individual requirements, who dictates how they will charge. An existing example of such a scheme is storage heaters in homes with Economy 7 (a differential tariff provided by UK suppliers which offers cheap off-peak electricity). In this case a radio teleswitch is used to switch on/off the heater when the cheap period begins/ends. This means that the consumer has no ability to turn the heater on, only to set the desired temperature setting. In this example the control variables are binary - the heaters are on or off, but for centralised smart charging the speed as well as the timing of charging can be determined. The charging profile is no longer CC-CV, but decided entirely by the controller. Consumers can only choose when they plug in their vehicle, and a deadline by which they need it charged. In this case optimality can be guaranteed, and the problem can often be solved using existing, well-known formulations (e.g. (Sortomme et al., 2011)).

One drawback is that these schemes do not scale very well, with a large number of vehicles it becomes difficult first to gather all of the information then to calculate the optimal profiles. The complexity can be limited by instead grouping vehicles (e.g. by location) and locally optimising their charging. In this case the agent in charge of the group of vehicles is referred to as an aggregator. Another problem is that these schemes rely on reliable communication infrastructure between each vehicle and the controller, which from a policy perspective makes them more difficult to implement.

Decentralised schemes are applied by the individual vehicles rather than a controller, which limits the size of the individual problems being carried out. Again the shape of charging profiles is variable, and the user can only decide the amount of time their vehicle is plugged in. Data security issues are avoided, as consumers preference information does not need to be transmitted.

In general a price signal is broadcast to vehicles, which then propose a charging schedule on the basis of which the price is updated. This process is repeated until the profiles converge to an optimum, an example formulation is found in Gan et al. (2013). The main problem is that this process requires an even more extensive communication network, and controllers to be installed into every vehicle or charging station.

3. Methodology

There are several steps involved in predicting the impact of a large fleet of EVs in the UK. First the level of vehicle use must be predicted, which requires analysis of data on how people currently travel. Implicitly this assumes that electrification will not affect the way people use vehicles. Once the journeys carried out has been predicted, the energy which the vehicles will use completing them must be estimated. For this a model is required which describes the way EVs use electricity. Finally we need to consider when people are likely to charge in order to calculate the demand profile. This requires formulating a set of assumptions about the way people will charge their vehicles.

Once all of this has been done, consideration into how the charging profile can be altered without inconveniencing consumers can begin.

3.1. Travel data

The National Travel Survey is a piece of research conducted annually by the Department for Transport which aims to understand how people in the UK travel (Lepanjuuri et al., 2016). Households are selected at random and asked to document all of their journeys for the week, recording (among other things) their day, time, distance, length, purpose and mode of transport. Regional and demographic data for the participating households is also collected. Diaries from 91, 755 households owning at least one vehicle are available, comprising a total of 1, 862, 168 trips. Using the *vehicleID* variable it is possible to extract week long journey profiles of the vehicles in the data set.

Here we created a journey set representative of the UK fleet by filtering the data set for relevant journeys (carried out by car and on the chosen day of the week). The number of people represented by the remaining data is then calculated and their percentage of the UK population is determined. This number dictates the required scale factor - or the number of predicted journeys each journey in the data set represents. It was decided to scale by population rather than number of vehicles because it is the journeys completed, rather than the number of vehicles carrying them out, which determines energy consumption.

3.2. Electricity use prediction

Some studies have been done, investigating the use and electricity consumption of EV users (e.g. (Davis, 2016)) however, the small scale of these studies makes it unwise to extrapolate the behaviour to a fleet the size of the UK. Instead, a vehicle model was formulated to convert the length, number of passengers and rural-urban classification of a journey into an energy consumption.

The model uses a standard drive cycle representative of European driving behaviour (proposed by (Andrè, 2004)) and calculates the force required to move the vehicle at every time-step. Coast-down coefficients are used to estimate the resistive force (White and Korst, 1972), which is the force the vehicle is required to overcome. The total force required is then the sum of the resistive force and the force needed to accelerate the vehicle. This is calculated at each time-step and converted into a power demand, full details of the model are given in Crozier et al. (2017).

3.3. Charging Demand Prediction

In order to convert the energy demands of vehicles in the test data into a grid electricity demand assumptions about charging need to be made. The first decision to be made was the power at which vehicles would charge. Slow charging would have the smallest impact on the grid, but would require vehicles to be available for large periods of time. If most charging is done at public charging points, faster charging will be required.

To determine the most reasonable assumptions the location of the vehicles throughout the day, which can be inferred from the recorded purpose of journeys, was examined. Fig. 2 shows the percentage of the fleet parked at each of the most common three locations throughout the day. The x-axis is offset so that the day begins at 8 a.m., this is because we assume that all vehicles need to be charged by the next morning, and so at the *start* of the day all vehicles are assumed fully charged and must be again before the *end* of the day. This day set up is assumed for the rest of this paper.

The most common location for vehicles is at their home - with at least half the fleet being there at any one time. This suggests that the most convenient scenario would be for every one to charge at home, using domestic slow chargers. This agrees with existing research; (Morrissey et al., 2016) state that EV users prefer to charge at home in the evening, and Farhar et al. (2016) claim that in order to be successful, charging systems must be unobtrusive and require little of consumers. Also, an initial study of EV users reported that over 71% of vehicles charged exactly once each day (Quiros-Tortos et al., 2015).

At home slow charging is therefore assumed for the rest of this study. This is not without complications; (National Grid, 2017a) estimates that 43% of vehicles do not have access to off street parking, so installing private chargers may be challenging.

Given this location constraint, the times when a vehicle will charge can be predicted. To quantify the impact of uncontrolled charging it is assumed that if a vehicle has used less than its battery in the day:

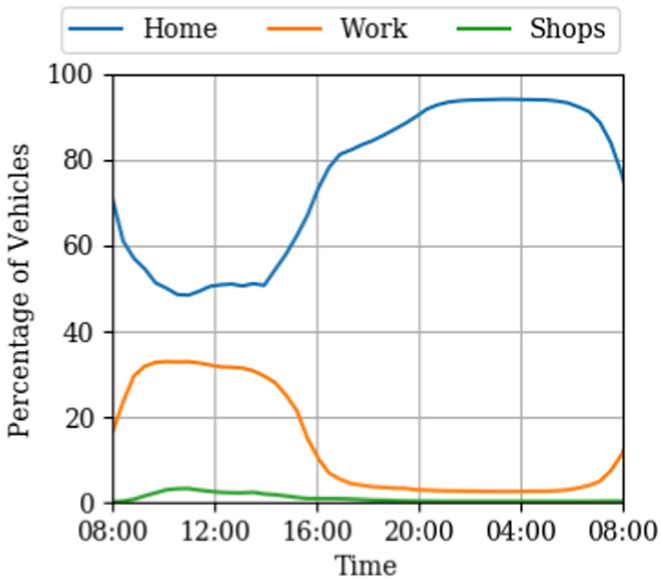

Fig. 2. The percentage of the UK fleet parked at home, work and the shops throughout the day (on a weekday).

- It will plug in when it arrives home after its final journey of the day
- It will charge until either full or it is first needed the next day,

and if not:

- It will charge whenever it is at home
- If this is still not sufficient to be fully charged at the end of the simulation it will 'rapid charge' whenever parked for more than 30 mins.

This latter step is important because if not all of the vehicles in the simulation receive sufficient charge, then the simulation will underestimate power required.

3.4. Optimal smart charging

It is important to quantify the potential of smart charging, to find out what the best we can do is under the chosen assumptions. For this reason an optimization problem was set up which takes into account the availability of the vehicles in the test set.

As previously stated, our goal is to avoid increases in national peak power demand. When optimising charging profiles, the amount of energy being demanded from the grid is constant, so the peak power is minimised when the overall demand profile is as flat as possible. This leads to the popular *valley-filling* schemes (e.g. (Chen et al., 2014)), which aim to charge vehicles in the troughs of the base demand profile.

An optimization program was formulated, which calculates the optimal charge profiles for each individual vehicle in the data set such that the aggregated demand profile is as flat as possible. It was assumed that each vehicle would be available to charge any time from the end of its last journey until the start of its first the next morning. Charge profiles were discretised into hour windows, meaning that a vehicle could only change its charging power once an hour. This had to be done in order to keep down the computational complexity of the problem. The resulting problem is formulated as a Quadratic Programming problem (e.g. (Gill and Wong, 2015)), and can therefore be solved using standard solver packages.

3.5. Approximate smart charging

There are many reasons why the optimal profiles described in the previous section could not be implemented in practice. Along side the typical problems with centralised control schemes, the controller requires future knowledge of all vehicles plans - even before they arrive at the charging point. Perfect knowledge of the electricity base load is also required, although this is already forecasted extensively with good accuracy (Taylor et al., 2006).

Here we propose a simple algorithm which could be applied individually by vehicles in order to achieve approximate valley-filling at the national level, and is readily applicable. As the constraints of the majority of vehicles will be similar (arriving home in the evening, needed by the next morning) many of the optimal charging profiles are likely to be roughly the same. Given this, it follows that a reasonable approximation can be made to the optimal solution by defining a standard shape of charging profile which vehicles can implement. The proposed algorithm is described below:

1. Predict the National base load
2. Invert prediction by subtracting each time step from the maximum value
3. Isolate the period during which the vehicle is available to charge and calculate the energy (area under curve) of the resulting signal
4. Scale the signal to the required energy

In the first stage the shape of the National demand profile for the next day without EV charging is estimated. Variation in the signal is largely dependant on time of year, and whether or not it is a weekend - neither of which need predicting. Therefore, a small number of fixed profiles could be stored from which the controller can select the most relevant.

Next the inverse of this signal is calculated, this represents the shape which aggregated vehicle charging should fill in order to achieve a completely flat demand profile. The vehicle is unlikely to be able to charge for the entire range so the signal is cut down to the times the vehicle is available. Finally the profile is scaled so that the right amount of energy will be received, meaning the EV will finish charging just as it is next needed. These stages are demonstrated in Fig. 3.

It is impossible for this algorithm to achieve optimality as all EVs would need to be plugged in for 24 h a day, meaning they couldn't actually consume energy. However, by taking a simple additional step we can ensure that this cannot be worse than the uncontrolled case. A limit on the individual power that a vehicle can charge at is set at the rate of slow charging (3 kW). This means that if a user plugs in their vehicle saying they need it again in an hour it will not fully charge, but charge at 3 kW for the duration of time it is plugged in. This is the same as the uncontrolled charging situation so in the (extremely unlikely) case that all users plugged in their vehicles will short deadlines the algorithm would have no effect.

4. Results and discussion

This section first discusses the results of the simulation of uncontrolled and optimally controlled charging for a single simulation. Then the approximate scheme is tested and sample individual vehicle profiles are examined to highlight the differences. Finally the variation of the simulation with time of year is explored.

Initially the simulation was run for a Wednesday in January. The day was chosen so that the simulation would represent the average weekday and the month because it is the one which typically experiences the largest peak power demand, and is therefore likely to represent the worst-case. All of the journeys carried out on a Wednesday in January were extracted from the travel survey, and their energy requirement predicted using the method outlined in Section 3.2. These were then scaled to represent a population the size of the UK and the uncontrolled and optimal charging profiles were calculated according to Sections 3.3 and 3.4 respectively.

Fig. 4 shows the predicted National demand profile with

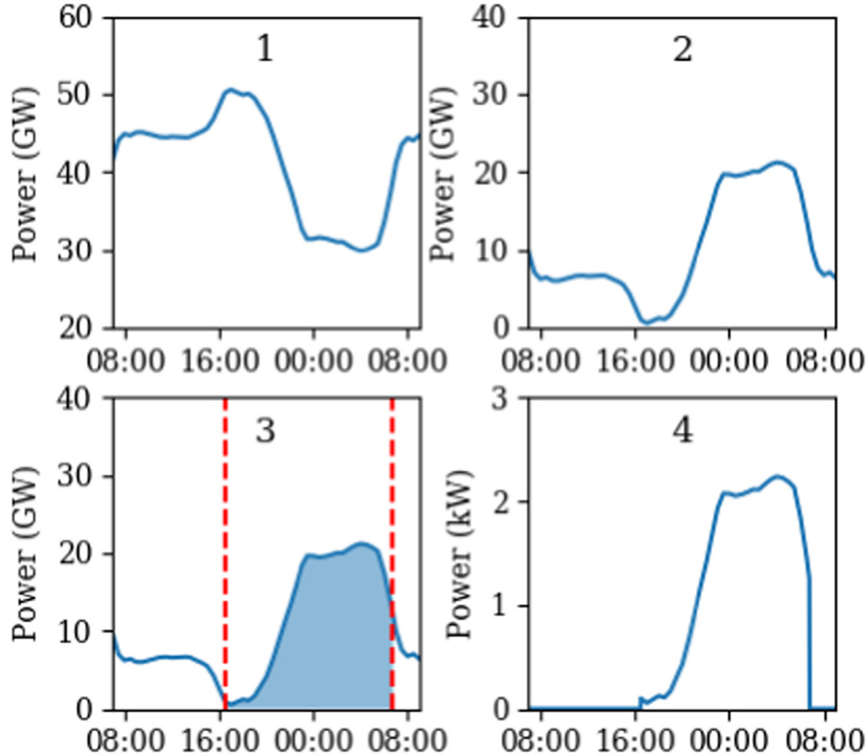

Fig. 3. Demonstration of example curves obtained from each stage in the process described in Section 3.4.

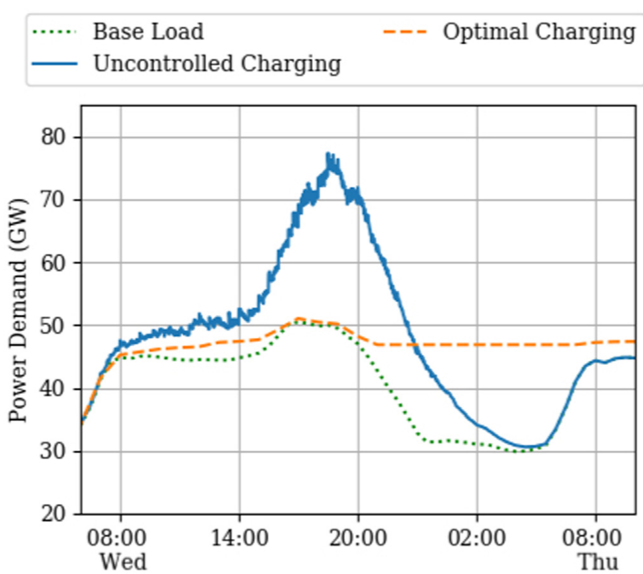

Fig. 4. Predicted effect of a 100% electric fleet on the UK energy profile in both the uncontrolled and optimally controlled cases.

uncontrolled and optimal charging of an 100% electric fleet, compared with the current profile. This suggests that uncontrolled charging could require an extra 20 GW of power generation capacity to be installed, which represents an increase of about 1/3. This is largely due to the coincidence of the evening domestic electricity peak and the vehicles plugging in, which makes sense as they are both caused by people arriving home in the evening. The assumptions that people charge every day and only once they have finished using their car for the day may exaggerate this peak, but there is currently nothing to suggest these assumptions are unreasonable.

In contrast, the optimal case shows no increase in the peak demand. While the same amount of additional electricity will need to be generated, distributing in out in time means that no additional generators will be required - the existing ones will just have to operate more throughout the day.

Next the approximate algorithm proposed in Section 3.4 was compared to the optimal solution, the results are shown in Fig. 5. While there is clearly some difference between the profiles the approximate does not result in an increase in the peak load, which is the most important point. The differences between the profiles are easy to understand; in the optimization problem when vehicles plugged in earlier in the day the controller knew that there were very few vehicles available at that time so they were charged quickly, however in the approximate when a vehicle arrives home early it has no way of knowing the number

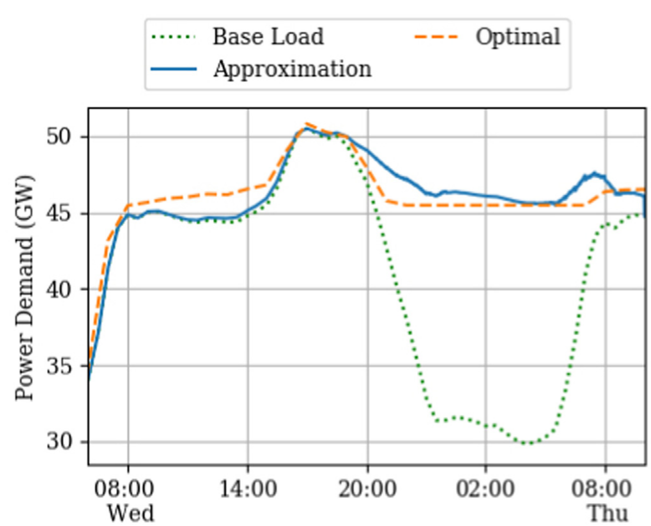

Fig. 5. The difference in performance between the optimal and the approximately optimal charging schemes.

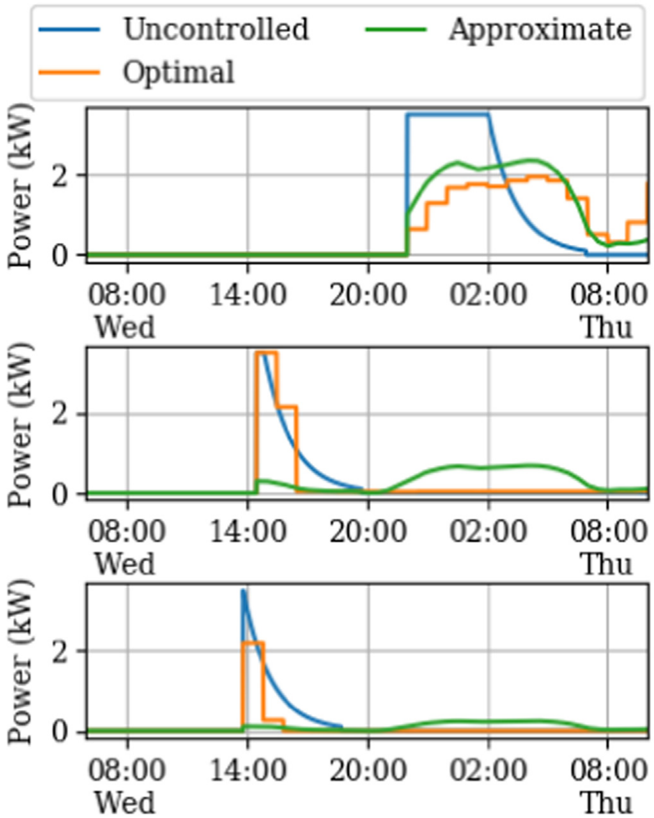

Fig. 6. Examples of the individual profiles predicted under all three charging schemes.

Table 3
The percentage increase in electricity demand due to vehicle charging throughout the year.

Month	Fleet energy requirements (GWh)	Difference from existing demand
January	202.32	+ 20.76%
April	192.53	+ 24.05%
July	171.00	+ 24.41%
October	183.12	+ 21.97%

of other vehicles available to charge.

Further insight can be gained by looking at examples of the individual profiles which are shown in Fig. 6. In the uncontrolled case vehicles charge at full power until they reach 80% capacity when the power level begins exponentially decreasing, while in both the optimal and approximate case charging is slower and predominantly overnight. Perhaps the most obvious difference between the optimal and approximate profiles is the resolution (as the optimal profiles are limited to hourly changes), but the more important difference is demonstrated in the bottom two examples. Here the vehicle arrives home before the evening peak in electricity. While the approximation holds off on charging until the evening trough, the optimal profile charges quickly for the first hour as it knows it is one of the only vehicles available to charge at that time.

Thus far all of the simulation results have been for a January, but it is important to also consider how the results of these methods change throughout the year. The base demand profile changes significantly throughout the year, increasing in the colder months due to heating requirements. This will change the shape of the charging profiles as the overnight trough in the demand profile contains a smaller amount of energy. The results of the uncontrolled, optimal and approximate charging regimes for different times of year are displayed in Fig. 7.

This shows that when the base demand for electricity is relatively

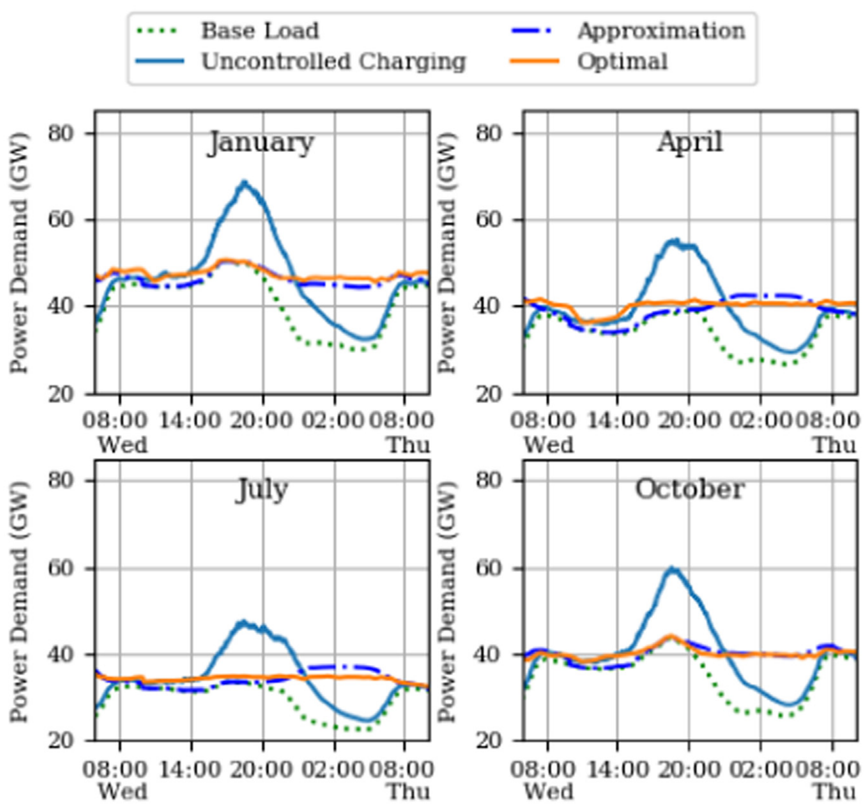

Fig. 7. The seasonal variation in the charging demand of a 100% electric fleet, under uncontrolled optimal and approximate charging schemes.

Table 4
The peak load under all three charging schemes throughout the year.

Month	Current peak demand (GW)	Uncontrolled charging peak increase	Optimal charging peak increase	Approximate charging peak increase	Approximation error
January	50.516	+ 53.04%	+ 0.01%	+ 0.67%	1.25%
April	39.170	+ 65.70%	+ 2.68%	+ 14.57%	18.9%
July	33.518	+ 75.84%	+ 2.96%	+ 17.15%	19.5%
October	43.544	+ 61.30%	+ 0.01%	+ 0.49%	0.78%

high, and the overnight trough deep, the approximation performs well. However, in the summer months the error between the approximate and optimal solutions increases noticeably. This is because in the winter months optimal charging occurs almost entirely within the valley, while in summer months the valley doesn't contain enough energy for this. In the optimal cases vehicles arriving early are charged quickly whereas in the approximation they are not. It is possible that incorporating a weighting into the algorithm which priorities charging at unpopular times could improve performance. However, it then becomes harder to prove that the algorithm will always be an improvement and the importance of getting such a weighting right is high.

The energy required by the fleet in each simulation is expressed in Table 3, where both the actual energy and the percentage increase that it represents are shown. This shows the largest predicted energy requirement in the winter, largely due to heater use. However, as the electricity demand is already highest at this time of year the biggest percentage rise occurs in the summer, where almost a quarter more energy will be required. These predictions sit somewhere between those made by National Grid (2017b) and Andrews (2016).

The predicted peak demand under all three schemes for each simulation is displayed in Table 4. This shows that the approximate algorithm achieves a very low error in the winter months, but around an almost 20% error in the summer months.

The case could be made that it is the performance in the winter months which is more important, as this is when the UK is operating close to its capacity limit; in all simulations the peak of the approximate algorithm is below the current National generation limit. Whereas, in the uncontrolled case all months show an peak increase of at least 20 GW.

5. Conclusion and policy implications

As the number of EVs on the road increase, the risk of allowing the uncontrolled charging of vehicles grows. If the UK fleet goes all electric then around an extra 20 GW of power generation capacity would be required. Additionally, the increased load will require network refurbishments and the volatility of the vehicle charging could create supply/demand balancing problems.

Here we have shown that by controlling charging the increase in power demand can be avoided, and have proposed an approximately optimal charging scheme which achieves between a 80 and 99% reduction in the projected increase of the peak. In the winter months, when the UK is closest its capacity limits, the performance is strongest.

There are several policy implications suggested from the findings in this paper. Firstly, on the implications of not controlling charging. If the UK fleet becomes entirely electric, driving behaviour doesn't change and people charge as they do now, the simulation suggests an extra 20 GW of generation capacity will be required. This would require substantial investment and would likely result in a rise in the price of electricity.

Secondly, optimal control of charging profiles can completely mitigate this impact, by completing the charging in the existing trough in electricity demand. However this would be very difficult to achieve in practice, as it would require precise prediction of all vehicle's future charging requirements, and the problem is computationally difficult.

Thirdly, there is an approximately optimal method which appears to mostly mitigate the increase in peak demand in the higher use months, and is implementable using existing infrastructure. Customers need only enter the time they need their vehicle by, and the controller would implement a scaled version of one of a handful of profiles.

Finally, this method can be achieved without impacting consumers use at all; charging occurs when the vehicle is parked at home and is finished by the time the vehicle is next needed. It could be argued that, since the consumer suffers no inconvenience, participation in such a scheme could be enforced by policy. In such a scenario, users would set a charging deadline when plugging in their vehicle and have no further control over their vehicle charging. A default deadline (e.g. 6 a.m.) could be used in the case one is not given. Consumers already have little control over their vehicle's charging profile, chargers follow a CC-CV profile which slows charging once 80% SOC is achieved.

Users setting unnecessarily early deadlines would reduce the effectiveness of the system, but there would be a reduction in the peak demand approximately proportional to the number of smart charging vehicles. For example, if 50% of vehicles adopted this strategy then the increase in peak demand will be only half what it would have been. If instead the system is opt-in then vehicles must be rewarded according to the amount of flexibility they provide, i.e. there must be an incentive to put as late a deadline as possible. In this case, the pricing and advertising of the strategy would be paramount to its success.

Acknowledgement

This work was supported by Jaguar Land Rover

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