TRACKING AND MANAGING REAL WORLD ELECTRIC VEHICLE POWER USAGE AND SUPPLY

G. A. Hill*, P. T. Blythe† and V. Suresh#

** Transport Operations Research Group, Newcastle University, UK. g.a.hill@ncl.ac.uk*
† Transport Operations Research Group, Newcastle University, UK. p.t.blythe@ncl.ac.uk
 # Department of Computer Science, Newcastle University, UK. visalakshmi.suresh@ncl.ac.uk

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Abstract

In this paper the tracking and analytical infrastructure necessary to adequately manage the power demands of a fleet of electric vehicles is considered. The data from a 230 day trial of 15 vehicles has been used to simulate a single day with over 3000 vehicles on the road within the North East of England. Current analytical approaches are considered and possible future avenues are addressed. A general model for predicting the probability of vehicle charging is proposed. The comparative charging rates between morning and evening and the spatial distribution of the charging are all considered. It is found that although the evening charging has the greater number of charging events across the region it is the morning charges which pose the most risk for local power management as the morning charges tend to be concentrated within a smaller spatial extent. In more general terms the use of individual vehicle tracking systems is found to be an ideal system for determining the current and future state of power consumption for electric vehicles.

1 Introduction

For the UK to achieve the target of an 80% reduction of carbon emissions by 2050 it will be necessary to make radical changes to the certain aspects of the countries behaviour. [1] As well as the decarbonisation of the power generation infrastructure, improvements in heating and general building efficiency it will be necessary to reduce the carbon footprint of the UK's transport system. Currently small personal and commercial vehicles represent 13% of the total carbon emissions in the UK. By improving the carbon efficiency it will possible to move some way towards meeting these targets.

One possibility is the partial (or full) electrification of the vehicle fleet. Electric Vehicles (EV), in general, show an improvement in carbon efficiency over Internal Combustion (IC) engine vehicles. Typically an EV will have a well to wheel emission (normally measured in gCO^2/km) which is approximately 50% that of an IC vehicle. [6] An easy solution for the reduction in the average carbon emission of the road network is a large scale switch to EVs.

However, switching to EVs is not without possible drawbacks. For the moment there are a limited number of electric vehicles operating "in the wild" but as the uptake increases then the density of electric vehicles will increase. Whilst this does not have a negative "on road" impact, indeed there is a positive direct impact from the removal of polluting vehicles from congested areas, it does have the possibility of affecting either the local power distribution system or the availability of charging points if there is an insufficient number to meet the variation in demand. [5]

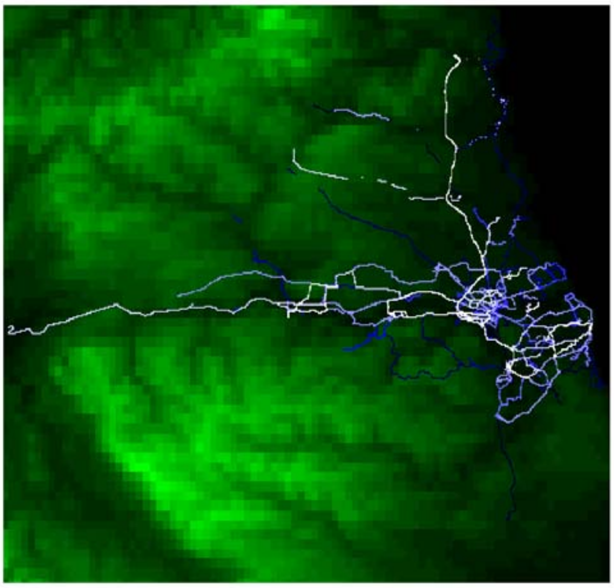

Figure 1: The figure here shows the distribution and comparative frequency by intensity of electric vehicle journeys over a topographic map of the north of England.

The local transmission network is the system responsible for converting and distributing the electricity from the high voltage national transmission network to the low/medium voltage local distribution network. Unfortunately the current system, at a domestic level, will have been created to serve the needs of the houses which it is supplying. The peak power usage of a single house will not typically exceed 10KW, and even then only for a short period of time. In contrast a fast charger can reach a power demand of 50KW, and may maintain this power for an extended (20min+) period of time. If multiple vehicles start recharging using a fast charge system then the total power demand can increase massively and well beyond the ability of the local distribution substations to cope.

Although there are possible problems in supplying the local energy surge necessary for the simultaneous charging of multiple electric vehicles, this problem becomes less pronounced as the demand is moved up the power distribution chain and closer to the power stations. Switching to a substantial number of electric vehicles will cause a rise in the total predicted electricity consumption but this is a manageable rise as in general there is the spare capacity across the entirety of the network. Unfortunately the local distribution network may not have the spare capacity necessary to handle all possible variations in charging and as such it is the local increase in power which is the concern. [2]

Local distribution substations and transformers vary in their capability but in general it may be expected that a low voltage UK distribution substation will have a rating of approximately 400kVA. This is the equivalent of 8 fast chargers operating concurrently. Whilst the possibility of this happening on a single day is remote, the possibility of it occurring over the course of a year, or longer, can become substantial. The probability of this occurring can become even greater if there is any non-stochastic factor driving the charging times of vehicles. For example if there has been a local power cut over the course of a day then it would be expected that people would aim to recharge their electric vehicles as soon as possible, which would be at the point when the network is still the most fragile.

In the North East of England [4] the availability of charging points is currently the densest in the UK with over 300 public charging posts (including 8 fast charger posts) to support a regional EV fleet of around 200 vehicles. However, as the number of electric vehicles increases it may become impossible to retain this ratio of points to vehicles which could lead to condensed areas of charging.

To alleviate this problem it will be necessary to manage the charging infrastructure in such a way to minimise the spikes in power usage from vehicle charging. Doing this will require information about all the vehicle's current battery data and also a scenario for what each vehicle is likely to do and how they are likely to behave. It is possible to create models for electric vehicles will behave in general and as a cohort using such techniques as Markov Chains. [3] Such information is useful for designing a power distribution system equipped to handle the normal demands of an EV fleet. Unfortunately creating a power system which can handle all possible fluctuations in power from EV will be prohibitively expensive. Electric vehicles can impose a much greater variation in the local power consumption than might otherwise be expected.

To counter this it is necessary to create a system which will track each electric vehicle and provide a more accurate indication of the future and current charging events. If there is accurate data on what electric vehicles are going to be doing then it will be possible to either manage the power distribution network itself or, more likely, manage the charging of the electric vehicles to cause the least amount of disruption to the network.

Collecting all this information requires that each electric vehicle has some sort of logging mechanism and can report the data back to a central server. This technique was used in SWITCH-EV to deliver data for a group of 40+ EV in the north east of England. In the Switch-EV trial a large number of EVs were placed with both company and personal users and were used in a normal manner over the course of several months. The technical details behind the data capture are discussed in the methodology section.

Within this paper the use of this existing vehicle tracking infrastructure is examined to see how it may aid in managing the power demands of a large scale EV fleet. In particular looking at the recharging information which is currently and using this information to identify the local power fluctuations and identify possible problems. The paper will concentrate on extracting useful data from the existing infrastructure in place rather than a more detailed examination of either the problems facing predicting vehicle movements or in accurately predicting the exact level of recharge and charge.

Initially a brief description of the vehicles used in this trial will be given including the infrastructure necessary for data collection. In addition the data used within the trial as well as the algorithm to generate the vehicle charging predictions is described. Finally the results demonstrating the temporal and spatial patterns of charging are shown.

2 Method

In the Switch-EV trial 44 EV (Avid CUE-V, Liberty E-Range, Nissan Leaf, Peugeot iOn and Smith Edison) were leased to private individuals, businesses and local government where they were used as either a pool or personal car. [7] Each vehicle was equipped with a logger which directly interfaced with the vehicle's CAN bus and reported data on the vehicle back to a server. [8] Measurements across the vehicles varied but each vehicle reported back position (GPS coordinates) battery voltage, battery current, date, time and temperature. Using the suite of measurements a detailed trip log for each vehicle and for each user is built up. By using this log it is possible to derive statistics about the vehicles including average journey distance, average power usage etc.

Managing the power supply to the electric vehicles requires knowledge of three main items of information.

1) Where the vehicle is charging. This is derived from the GPS coordinates supplied by the loggers installed in the vehicle. Knowing where the vehicles are is vital in understanding when vehicles are drawing power from the same local substation
2) When the vehicle is charging. Balancing may not be necessary if the vehicles are charging at different times.

3) How much power is needed. It may make sense to prioritise the charging of the vehicles with the lowest state of charge to maximise the overall utility for all.

The first two pieces of information could also be derived from any charge point which has the capability of uploading its current charge status.

Predicting the level of charging at any future point is accomplished using the following basic method.

1) List the vehicles currently charging and predict when the charge will end from the state of charge in the vehicle.
2) Predict the end location of each vehicle currently driving and the probability of each vehicle charging at its destination
3) Assume any parked vehicles will either move or not charge during the next interval

The probability of a vehicle undergoing a charge event is calculated by deriving the proportion of the total number of charge events at each starting State of Charge (SoC) as a function of all charging events.

The probable chance of a vehicle undergoing a charge event is given by the following formula:

$$P_{charge}(x) = \frac{\sum_{i=0}^{i=N} Charge\_events_{soc=x}}{\sum_{i=0}^{i=N} Drive\_events_{soc=x}} \quad (1)$$

where x is the current state of charge, $Charge\_events_{soc}$ is the number of charging events when at a state of charge *SoC* and $Drive\_events_{soc}$ is the number of driving events at *SoC.*

For this data set it is assumed that there is no difference in charging probabilities between vehicles or at different times. In general it is not expected that this would be the case.

One assumption made in this calculation is that the only thing affecting the probability of a charge event is the current state of charge in the vehicle.

In general predicting the end location of currently moving vehicle is not particularly accurate but it is possible to derive a stochastic estimate for a vehicle's end location from examining its previous journeys. For example, a vehicle leaving a place of work at 5pm will probably arrive at the home address for that vehicle as the next location. This information and predictive capability could be further improved by using a more sophisticated algorithm for the vehicles.

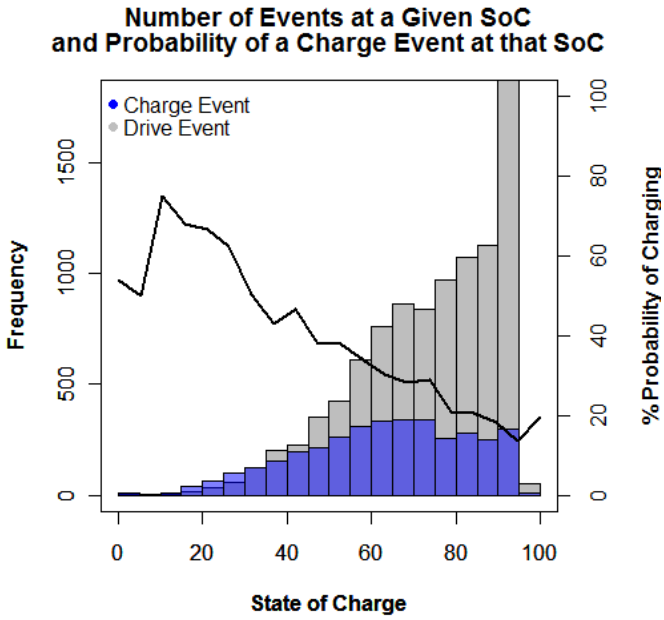

Figure 2: The image above shows the typical starting State of Charge for a charge event. The bold line represents the probability of a vehicle undergoing a charge event at SoC

In this work it is simply assumed that the end location of the journey is a known factor. Whilst this is certainly not a 100% accurate assumption, it is not unreasonable as many journeys today are undertaken with an electronic record of the intended end point of the journey. An example of this would be any GPS routing system found in many vehicles on the road today.

It may also be the case that for a vehicle to book a "charge" slot then the final destination and intended arrival time would be known to the energy planning system. For the truly efficient management of energy and the creation of a smart grid, the creation and handling of this knowledge will be a necessity.

For the particular cases used here the journey is known because the data is derived from historical data so for each vehicle there is a known start and end point.

Due to the relative lack of electric vehicles of the same type (15) it was decided to split each different date into a different vehicle. In effect this has lead to a single day trial of 3500 vehicles rather than a 230 day trial of 15 vehicles. This means that care must be taken when interpreting the results with regards to the real life statistics. In particular this approach will lead to a much greater spatial clustering of charging events than would be observed in a real 3500+ vehicle data set. Despite the limitations of the data set it is still possible to use this as a test bed for a proof of concept for future work.

3 Results

The initial results from the temporal charging pattern show that there are three main features of the graph.

Firstly there is a peak in charging between 8am and 10am. It is assumed that this is due to the increase in work place charging at this time. Secondly there is a peak between 5pm and 8pm. This is assumed to be a consequence of charging after returning from a place of work. Finally there is a pronounced dip in charging levels during the night time to early morning.

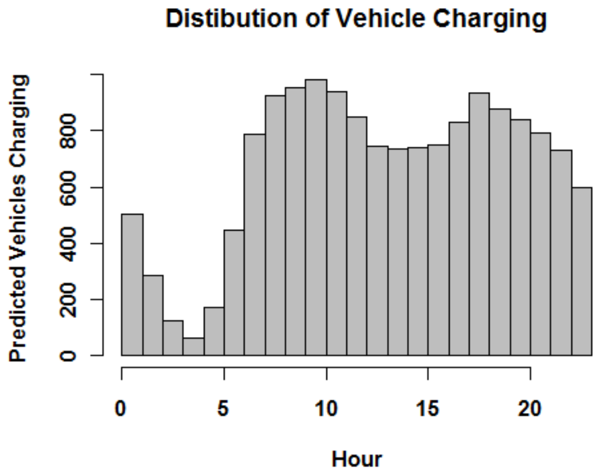

Figure 3: Two peaks in charging along with the substantial dip in night time charging are clearly shown here

From this initial result it follows that the two most likely times for an overload of a local substation are in the mid morning and the early evening.

Figure 4 shows that results of using current vehicles driving and predicting the number of charge events from this. The probability of a vehicle undergoing a charge event was derived using equation (1). It can be seen that when there is a large number of vehicles on the road that the total number of charge events can increase drastically beyond those vehicles already charging.

As expected from this basic model the time in which additional charging events are expected to occur is limited to no more than eight hours(10-13 amp, based on currently deployed public infrastructure and vehicle capability). This is the (approximate) time to charge to full capacity from a standard charge point.

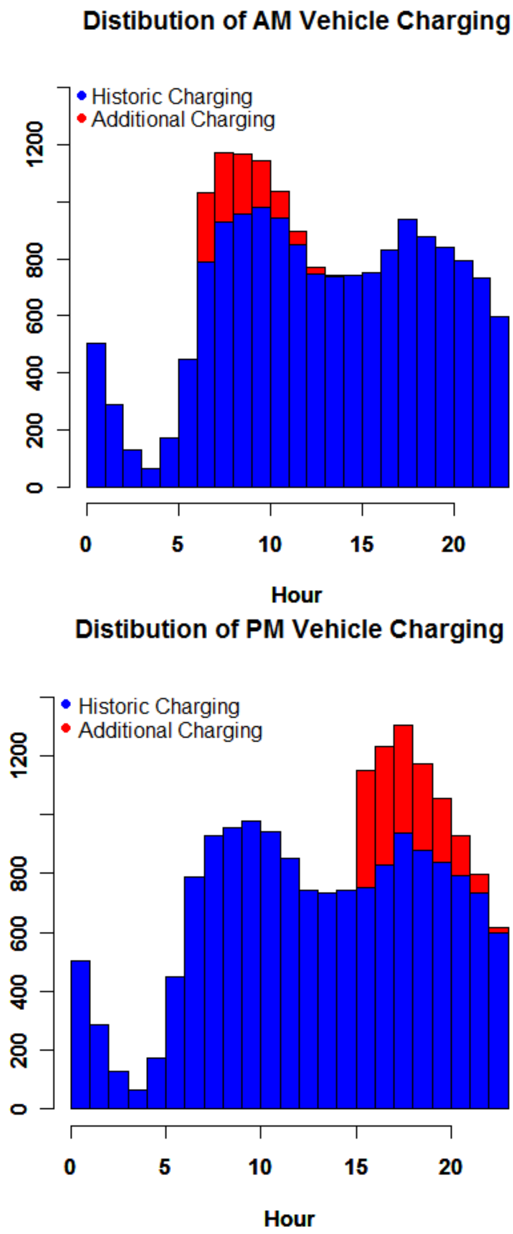

Figure 4: The two graphs show the effect of predicting the charging patterns from vehicles currently driving as well as those which are currently charging.

The location of the charging events is as important as the time of the charging as charge events must either be evenly distributed spatially or temporally to avoid placing an unnecessary strain on local power distribution networks.

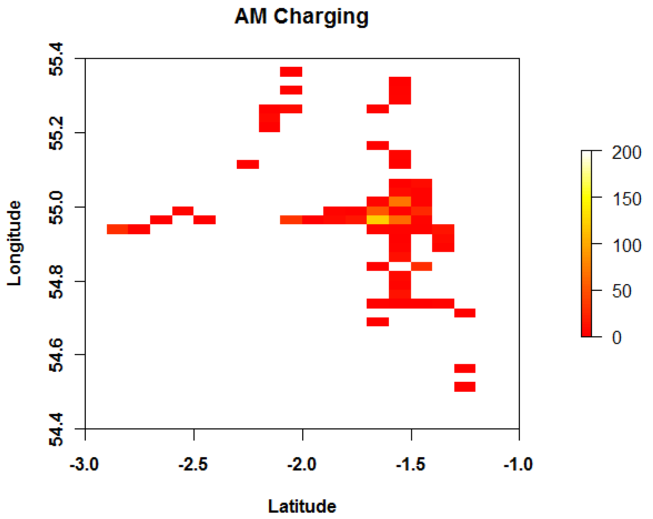

Figure 5: Here the spatial distribution of charging during the morning period is shown.

Figure 5 shows spatial spread of charging events during the morning charge period. The spatial extent of the data covers a section of the North East of England centring on Tyne and Wear. Specific geographical features have been removed to preserve the anonymity of the participants. One interesting feature is that a large number of the events are concentrated in one similar area. For this particular tranche of vehicle triallists, large proportions were part of the same company and hence their work place charges were all taking place in roughly the same area. It is not expected that this will be the case in future trials or in the general deployment of EVs. It is possible that with a bulk fleet purchase of electric vehicles there could be concentrated areas of charging, but not to the extent displayed here.

It is also useful to compare the data shown here with the data shown in figure 6. Figure 6 shows the evening charging positions and there is a much greater spatial variation than in figure 5. This is perhaps to be expected as users home addresses will be typically spread out over a larger area than their place of business, especially if there is a relatively small group of large employers within the area.

For home charging there does exist the possibility that certain housing estates could, either through chance or societal pressures, start to exhibit an increased number of electric vehicles beyond that which would be expected.

Figure 6 shows the spatial difference from including predicted charging events from currently moving vehicles to the charge map. Although the spatial map appears broadly similar there are a number of differences. Mainly this is in the greater spatial variation of drive events. There is also a more intense peak in the number of charge events in a single location. This is the data which is most important as it is the peak of charge events in a single location which will most strongly affect the ability of the local distribution network to cope with increases in power.

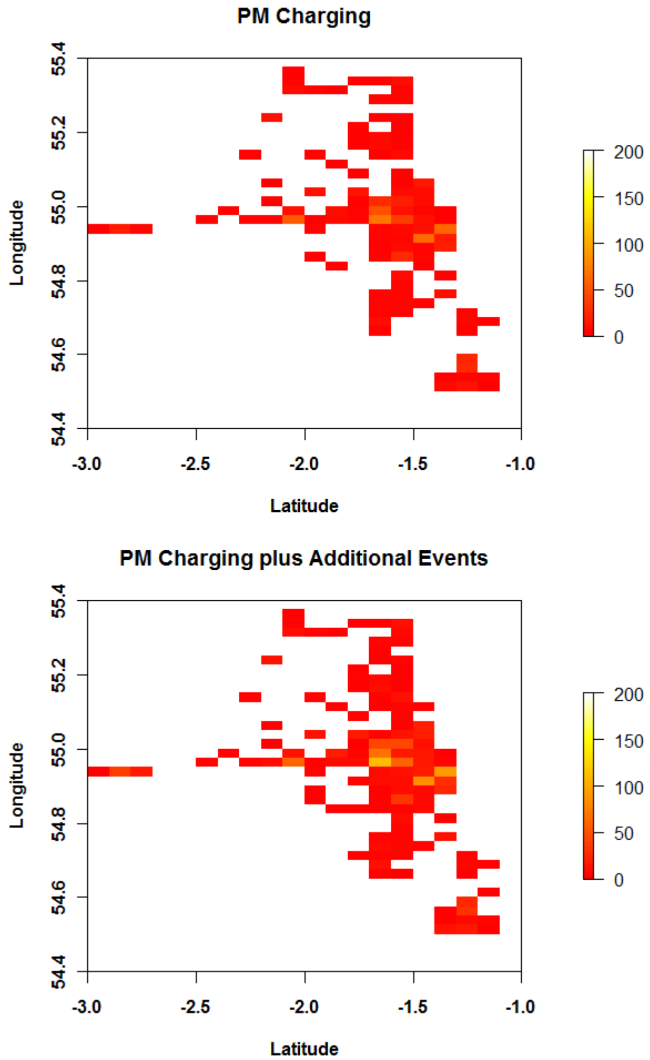

Figure 6: The difference between the data from the current charging and predicted charging is shown here

4 Conclusion

Within this paper it has been demonstrated that it is possible to use the data from multiple instrumented vehicles to derive the general state of the charging network at any given point in time.

Furthermore it is possible to use the predicted locations and a stochastic methodology to predict the future charging behaviour of vehicles. Combining the predicted charging pattern, durations, and timings can lead to the ability to identify possible problem areas in terms of local power distribution and could, in the future, enable steps to be taken to mitigate the problem.

Currently is found that the most likely time for a problem is during the morning and evening peak time for charging. However, whilst the evening peak experiences a greater predicted charge increase it is spread out over a greater distance. The morning peak, centred on areas of work, could create more problems with the local distribution network due to its spatially condensed pattern of charging.

Future work will focus on improving the predictive algorithm for identifying both the location and time of charging and also in looking at how other data sources may be combined with the on board loggers to further improve the capabilities.

Acknowledgements

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One North East
Future Transport

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