The Effect of Cycling on the State of Health of the Electric Vehicle Battery

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***Abstract*-This paper provides an analysis of the experimental results available for lithium ion battery degradation which has been used to create a model of the effect of the identified parameters on the ageing of an EV battery. The parameters affecting degradation are generally accepted to be; state of charge, depth of discharge, charging rate and battery temperature. Values for each of these parameters have been found for three versions of a typical daily cycling scenario; uncontrolled charging, delayed charging and V2G. A comparison is made of the expected overall degradation using four different charging rates and different charging patterns based on the model. A link is made between the charging patterns and the effect on the power flow at the transformer of a typical section of LV network using a ADMD profile.**

The analysis shows that delayed charging and V2G slow down the rate of battery degradation. However, fast charging appears to accelerate battery degradation. Delayed charging also helps avoid excessive evening loading and thus will help delay distribution network asset upgrading. Uncontrolled charging increases evening loading and V2G can reduce it. However, the EV then needs more power for charging and the charging after V2G needs to be managed if it is not to create another spike in demand at a later time.

***Index Terms*—Li ion battery, battery ageing, battery degradation, calendar life, cycle life, V2G**

I. INTRODUCTION

If the EU is to meet its carbon cutting targets, electrification of the transport system is essential. It is suggested that 95% of all vehicles will need to use electrical power as the primary method of propulsion by 2050 [1]. The take up of sales of Electric Vehicles (EVs) has been slow and for take up to rise as anticipated, changes will be needed. The main objections to buying EVs have been that they either have or are perceived to have an insufficient range ("range anxiety"), to meet drivers' needs, convenience and preferences [2] and they are too expensive [3]. Uncertainties with battery technology in terms of performance and range, but also crucially battery degradation, has been identified as one major barrier factor to wider uptake of EVs.

In a study by Egbue and Long [4], early failure of the battery was a concern for some respondents because of the high cost of replacement. The cost of the battery is the greatest single cost in the purchase of the EV and there are several strategies available from the manufacturers to spread the cost such as leasing the EV, or just leasing the battery and buying the car. Receiving payment from the Transmission Network Operator (TNO) for using the EV battery to provide balancing services to the grid (V2G) [5] could be an attractive option for an EV owner concerned about the high capital outlay.

One strategy to ameliorate range anxiety is to set up a system of fast charging points within a city and also at stopping points such as service stations where the EV can charge whilst the driver takes a break. This provision is not universally provided throughout the EU but provision is increasing. Therefore the effect of fast charging on battery health is an issue which needs addressing if fast charging is to be used routinely as a part of the charging regime of the EV battery.

Much effort has been made to survey and monitor EV users' charging behaviour in order to provide a convenient infrastructure of charging points [6]. The Switch EV trial analysed the recharging patterns of 44 different EVs over two successive six month periods. EVs were monitored using a data loggers and GPS devices. Recharging locations were identified as Home, Work, Public and Other. Less than 10% of recharging took place off peak. Work was the most popular location to recharge, and demand peaked between 8.00 a.m. and 10:00am [7]. The project recruited many businesses, and perhaps this fact reflects that the most prominent place of charging was at work; 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, between midnight and early morning [8].

The results from the first 12 month of the CABLED EV trial in the West Midlands in the UK [9] "clearly showed that EV users are not motivated to replenish their vehicle's battery by reaching a particular point of depletion; rather they are driven by convenience and the results show that charging habitually takes place upon reaching a destination.

Advice by some battery makers is that *"Li-ion batteries prefer a partial rather than a full discharge. Frequent full discharges should be avoided when possible, ideally for a li-ion battery to charge it every day a little bit as the li-ion batteries generally last longer when they are charged and discharged more shallowly, Generally speaking, batteries live* *longer if treated in a gentle manner. High charge voltages, excessive charge rate and extreme load conditions will have a negative effect and shorten the battery life."* [10]

A charger which can allow two way power flow for V2G and protect the battery from overcharging during fast charging will be needed to provide these services. In addition, smart charging can also help the distribution network operator (DNO) by keeping voltage within limits and allow greater use of renewable energy before upgrading of assets becomes necessary[11].

A literature review reveals that most of the published work on battery cycling and degradation is simulation and most of the published experimental results address only one type of battery cycling and there is very little integration or attempt to use typical EV cycling patterns for the purpose of investigating battery degradation. Fewer still attempt to verify simulation with experimental results. [12][13]

This paper identifies the charging regimes which might be used in smart charging for optimal use of the EV battery. Smart charging might involve incentivising the EV users to adopt a charge regime which optimises battery health and avoids charging during times of high grid demand whilst still allowing freedom of use for driving. It could also involve using charging points which will measure these factors and charge without needing overt control from the user. It summarises the main causes of battery aging and proposes a model for the battery degradation for different charging patterns. In this way the paper shows how the state of health (SOH) of the battery might be affected by providing smart charging with or without V2G.

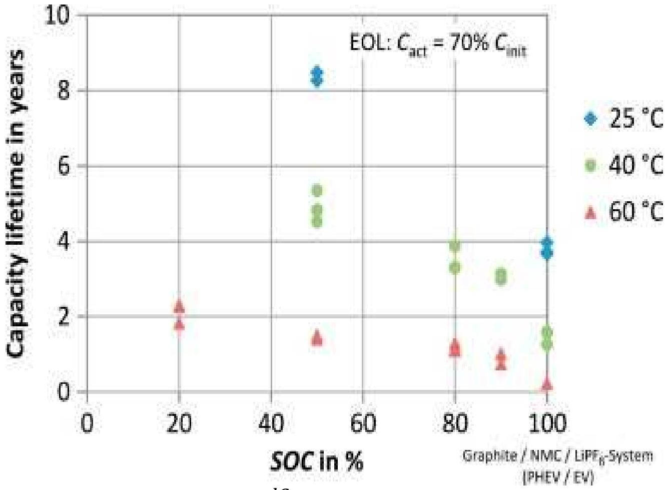
II. Factors which affect battery degradation

The literature identifies battery temperature [14], charge/ discharge (C/D) rate [15], average state of charge [12] (SOC) and change in SOC [16] or depth of discharge (DOD) [17] as the principle agents in battery degradation. Most experimental cycling has been at the same discharge rate as the charging rate, EV is charged to full and discharged to empty on every cycle, and each cycle is the same. This is not realistic so this tool has been developed to model any cycling scenario and calculate the expected degradation. Battery degradation can be modelled as a function of each of these factors, as follows.

A. Calendar life

This is defined as the battery loss in capacity due to the passage of time, whether or not the battery has been charged and discharged. Experimental data on calendar lifetime has been published [18] and these may be used for modelling of calendar ageing.

1) Temperature: Degradation due to ion loss is generally attributed to permanent chemical change and thus follows Arrhenius law [19] which is given as:



$$\frac{dC}{dt} = Ae^{kT} \tag{1}$$

Fig. 1. Capacity lifetime vs. SOC for calendar life tests at 25°C, 40°C and 60°C. These results consider lifetime to be at an end when useable capacity is 70% of new value [12]

where an increase of 10°C doubles the degradation rate.

This can be verified using experimental data [12]. Fig. 1 shows the effects of temperature and average SOC on Lithium ion cells. Using SOC of 50%, the lifetime of the battery to 70% of new capacity is shown as 8.2 years and 1.7 years at 60°C and 25°C respectively. These values are used to populate the proposed model using a 'base case' where there is no cycling of the battery.

Plotting these values on a graph of degradation rate loss –v- temperature^{-1} gives realistic values for the gradient k and the intercept A as:

$$k = 0.05$$
$$A = 3.7\text{x}10^{-11}$$

These values can be substituted into equation (1) and used to calculate the degradation rate due to temperature.

(2) *Charging current*: The magnitude affects calendar ageing insofar as it affects the battery temperature due to ohmic heating. Thus the battery temperature is the sum of the ambient temp and the heating effect of charging current.

$$Tbatt = Tamb + \frac{heat\ generated\ by\ current}{heat\ capacity}$$
$$= Tamb + \frac{I^2R}{C_H} \tag{2}$$

Nominal values of internal resistance(R) and heat capacity (C_H) are used based on known values for individual cells and the EV battery arrangement of Lithium ion cells given by the manufacturers for each vehicle modelled.[20][21][22][23]

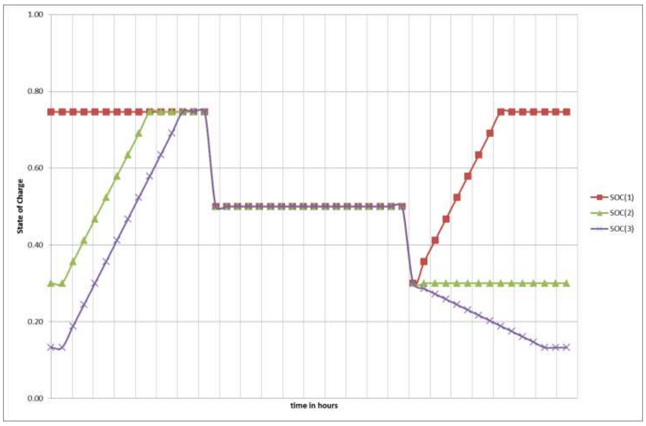


Fig 2. Charge at end of trip (SOC(1)), charge before next trip (SOC(2)), V2G (SOC(3)), maximum charge is 75% and discharged SOC is 30%

3) Average state of charge: SOC of the battery affects battery aging. It is suggested that the average SOC should be kept as low as possible and ideally around 50% [12]. The average SOC is lower if the EV is charged just before using rather than immediately at the end of a trip. The average SOC is calculated using the time of charging and the time when the car is charged ready for driving and assumes that the car is charged up ready for the next trip when it is connected, unless delayed charging or V2G is specified. The SOC whilst connected but not charging is then added to the degradation model to find an average SOC. Delayed charging is modelled by assuming the EV is at a low SOC at the end of the trip until the time for it to be charged ready for the next trip. V2G is modelled by allowing the SOC to reduce to 10% whilst providing grid support when first connected after a trip and then to remain at that minimum value until the time required to start charging for the next trip. These SOC daily patterns can be seen in Fig.2.

A correction can be made to the battery lifetime based on average SOC, as follows [14]:

$$Cs = \frac{1}{a + be^{c(100-SOC)}} \tag{3}$$

The values of the coefficients have been chosen to reflect the experimental data given in Fig.1.

B. Cycle life

Published results which contain values for degradation due to cycling from experimental work have been used to populate the model. However, these results should be treated with care as they are obtained under different conditions and control parameters. Reference [15] doesn't control temperature and assumes a C-rate of C/2; whereas ref [17] gives values for charging rate. Both lack the need for a more comprehensive relationship for degradation due to cycling.

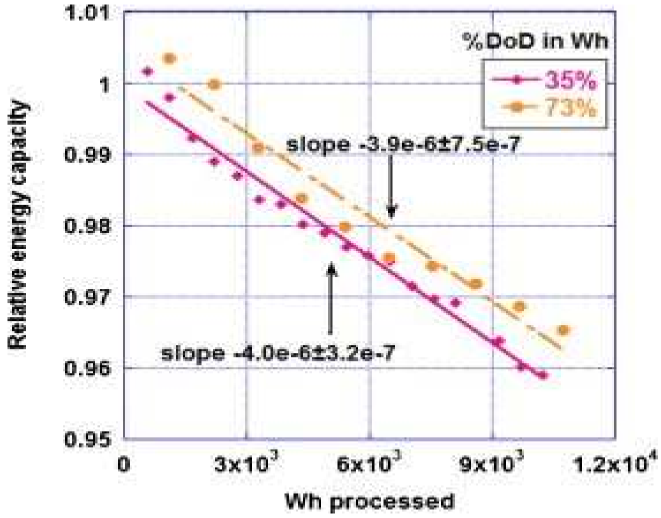


Fig 3: degradation as a function of energy processed for two cells tested with contrasting end-of-cycle depth of discharge values (35% and 73% DoD [15]

1) *Adjustment for charge transfer*: There is evidence that the cyclic aging is due to mechanical stresses due to volume change of the active material and is therefore dependent on the amount of charge transferred during charging and discharging. This can be modelled using the change in SOC, assuming a periodic charge/discharge cycle. Experimental results [15] normalised for the cell and with a low cycling rate (C/2) which is low enough to not cause a temperature rise from the stated ambient temperature of around 25°C, give the capacity loss due to energy throughput as approximately linear. The depth of discharge does not appear to be a factor with Lithium phosphate/graphite batteries which are typically used in EVs.

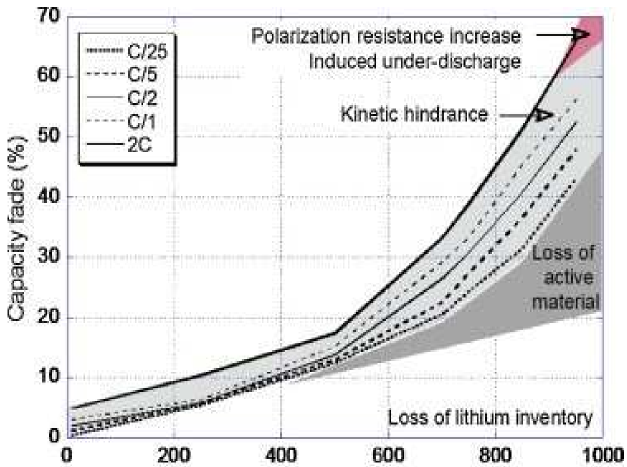


Fig. 4 The capacity fade map under 2 C cycle aging in room temperature depicting the attributes and their contributions to the total capacity fade in the cell as a function of cycle number [24]

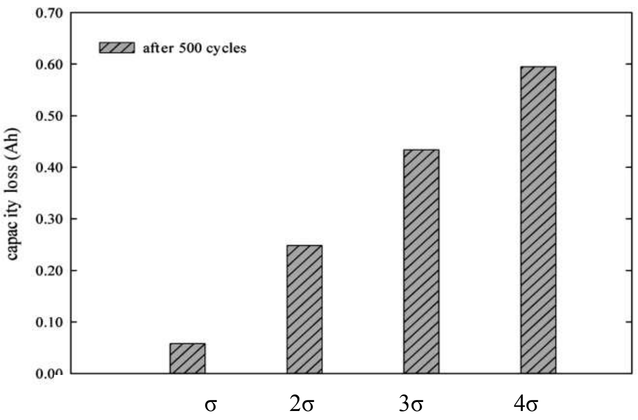


Fig 5 graph of capacity fade after 500 cycles with current density (σ) [25]

2) Adjustment for charging rate: Cyclic aging accelerates with charging current rate. Ref [24] indicates that for the first 500 cycles or so the capacity fade is linear. The graph shown in Fig. 4 is based on experimental data and modelling based on electrochemical behaviour. This is backed up by ref [25] which also shows an experimentally linear rate with current density as shown in Fig. 5.

Using the assumptions above and fitting values of charging rate to the Watt-hours processed from the graph in Fig. 3 to the reduction in capacity gives the degradation factor C_E which is the percentage change in usable capacity per unit energy transferred based on the change in SOC and the battery nominal capacity in one cycle. That is:

$$C_E = -4.0 \times 10^{-7}\%/\text{kWh} \quad (4)$$

The values are empirical but a correlation can be found using a base of 20% at 1C rate after 500 cycles; this gives a degradation rate for the 23kW of 0.0004. Scaling from Fig. 5 gives the values in table I.

The total degradation due to cycling is assumed to be the sum of the degradation due to charge throughput (C_E) and that due to charging rate (C_c).

C) Combined degradation

Loss of capacity = dC_T/dt due to temperature per day

TABLE 1: DERIVED CAPACITY LOSS DUE TO CHARGING RATE

Equivalent kW charge rate	Loss after 500 cycles	Loss per cycle	% Loss per cycle
3	0.0125	0.000025	0.0025
7	0.03	0.00006	0.006
23	0.18	0.00036	0.036
50	0.43	0.00086	0.086

$$Calendar\ loss\ in\ capacity = \frac{dC_T}{dt} \times C_S \quad (5)$$

Calendar aging is a function of temperature and SOC, so the loss in capacity is multiplied by C_s the correction factor for average SOC. Then the loss due to cycling is added; assuming one cycle per day.

$$Cyclic\ loss\ in\ capacity = C_E + C_C \quad (6)$$

The total loss allows the calculation of the state of health (SOH) of the battery after each daily cycle; the degradation after 1000 cycles and the time in years before 80% capacity is reached which is generally considered to be the end of life of the battery.

Results are presented in section IV.

IV EV USE AND BATTERY PROFILE

In this section a comparison is made between three charging profiles of an EV. These are (1) Charged on demand, (2) delayed charging to avoid the evening peak, and (3) V2G.

A) An outline scenario

An outline scenario for the EV is described here showing how the SOC varies over one day for driving, charging and resting.

The EV is assumed to charge to 80% SOC and connect after one trip at 40% SOC. The discharge rate is assumed to be steady over the discharge time and the same for each scenario. The trip or the time when the EV is not connected is from 8:00 a.m. to 6:00 p.m. The charger is assumed to be available for the rest of the 24 hour period. In this way the control variables of charge rate, discharge rate change in SOC, DOD and battery temperature are the same. The charging rate is 3 kW or 7 kW (domestic charging) and a comparison is made of each.

TABLE II.
THE DEGRADATION FACTORS ARE SHOWN FOR DIFFERENT SCENARIOS, TOGETHER WITH THE DEGRADATION AFTER 1000 CYCLES AND THE TIME IN YEARS FOR THE BATTERY TO REACH 80% OF ORIGINAL CAPACITY.

	Charge only (3 kW)	Delayed charge (3 kW)	Charge only (7 kW)	Delayed charge (7 kW)	V2G (3 kW)	V2G (7 kW)	Base case
Average SOC	56.5%	51.6%	54.2%	34.6%	32.2%	27.2%	0.0%
Change in SOC	40%	40%	40%	40%	70%	70%	0%
C/D rate (A)	7.50	7.50	17.50	17.50	7.50	17.50	0.00
Degradation 1000 cycles (%)	4.54%	4.46%	8.00%	7.71%	4.19%	7.63%	1.29%
8 years	13%	13%	23%	23%	12%	22%	4%
Lifetime (years)	12.1	12.3	6.8	7.1	13.1	7.2	42.5

1) In the first scenario, the EV is assumed to be charged up to 80% immediately upon connection at 6:00 p.m. It then remains at 80% until 8:00 a.m. the next day. This means that the EV's SOC at rest is the higher charged value of 80% and this gives an increased average SOC.
2) In the second scenario, known as delayed charging, the EV remains at 40% SOC from 6:00 p.m. until the time when it needs to charge ready for the next trip at 8:00am. This means that the EV's SOC at rest is at the lower discharged value of 40% which means the average SOC is lower, whilst the change in SOC and charging rate is the same.
3) In the V2G scenario the EV is discharged to the grid from the connection time at 6:00 p.m. until its SOC is 10%. It then remains at this minimum until it is charged ready for the next trip at 8:00 a.m. the next day. This means that the EV's rest SOC is 10%.

The charging rate is 3 kW or 7 kW converted into a current using the voltage published for the EV battery. The capacity and configuration of cells in a Nissan LEAF are used as a typical value, the change in SOC and the DOD are derived from the charged and discharged SOC.

The main parameters of average SOC, change in SOC, DOD and C/D rate are calculated from the SOC profile. Table III shows these values for each scenario and a comparison of the degradation of the battery for each scenario is made.

B) Comparison of different charging patterns

If the EV user creates a charging pattern of adding just one fast charge once a week to a weekly pattern of 6 uncontrolled slow charges at either 3 kW or 7 kW, the effect on the degradation is shown in Table III. The effect of using a fast charger once a week in addition to the overnight charging is shown to compare the effect on the degradation. Even with this relatively modest use of fast charging it appears that the battery cannot provide the required performance for the manufacturers agreed acceptable lifetime of 8 years.

TABLE III

THIS TABLE SHOWS THE EFFECT OF A WEEKLY FAST CHARGE ON THE BATTERY DEGRADATION IN COMPARISON WITH UNCONTROLLED DOMESTIC CHARGING

battery charging pattern				degradation	
home charging per week		fast charging per month		after 1000 cycles	time to 80% new capacity
3kW	7kW	23kW	50kW		
6	0	0	0	1.5%	13.77
6	0	4	0	3.3%	6.09
6	0	0	4	5.7%	3.52
0	6	0	0	2.5%	8.01
0	6	4	0	4.3%	4.62
0	6	0	4	6.7%	2.97

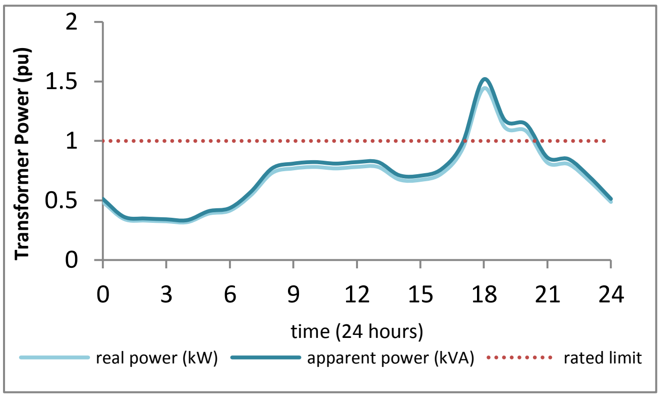


Fig. 6. If charging occurs at 6pm; the evening arrival time, there is peak power flow on the transformer which exceeds rating significantly

C) Effect of charging on typical load profile

The daily demand profile is used and EV charging is added to give a profile of the net demand on the network for each charging pattern [26].

A graph of the power flow at the 11kV/400V transformer for a typical network with 30% EVs is shown in Figs. 6 to 8 for each charging scenario. 10% of the EVs are charged at 3kW and 20% at 7 kW.

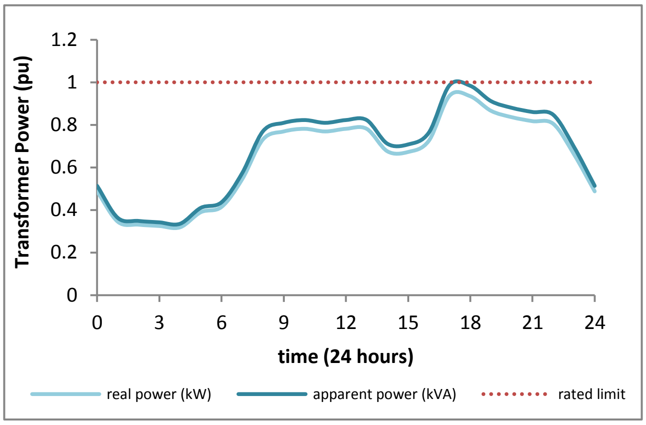


Fig 7. If charging is delayed to midnight and staggered, the rating exceedence disappears.

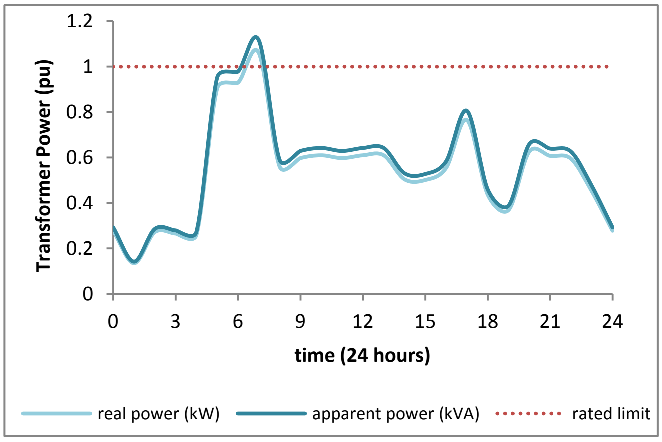


Fig 8. V2G moves the charging time to the night time which will need to be managed if a peak power demand is to be avoided

Conclusions

Three scenarios which might be used for daily charging have been described and a comparison of the effect of these charging scenarios on the LV power network has been made using a power simulation tool which models a typical LV power network profile over 24 hours and adds EV chargers to it. Delayed charging allows the network avoid overload at the evening peak, and if V2G is also used at this time, the net flow will be even lower. However, V2G will cause the batteries to require more charging before the next trip and the network could overload then if charging is not staggered throughout the night.

The literature suggests that the parameters which affect battery ageing are average SOC, change in SOC during cycling, DOD and battery temperature. The charging scenarios have been used to calculate values for the parameters so a comparison can be made of the effect of these cycling patterns on the battery. Delayed charging has the effect of reducing the average SOC of the battery which slows down battery ageing. V2G reduces SOC still further, but since it also creates a greater DOD the difference in battery health with V2G and delayed charging is very small.

Fast charging appears to have a marked effect on the degradation of the battery, even if only used on a weekly basis. Fast charging must be controlled to avoid excessive battery heating and thus accelerated degradation.

Further work to verify the model with experimental battery testing is on-going and the results will be published when some conclusions have been reached.

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