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Creating virtual energy storage systems from aggregated smart charging electric vehicles

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Abstract: Electric vehicles (EVs) have been proposed previously to be a form of flexible electrical load (including potentially vehicle to grid generation) that could be controlled to help support distribution networks. Considering each vehicle individually poses many challenges including significant smart grid control system computational effort and uncertainty. This study proposes an aggregation and control methodology for the grid to consider a number of EVs in a similar way to more established energy storage systems (ESS) allowing existing ESS control algorithms to be utilised. Central to the methodology is the knowledge that flexibility will only be realised if drivers are willing to use utility controlled charging posts and as such the drivers' requirements are prioritised; a minimum amount of energy is guaranteed to be within each vehicle at the time of departure.

1 Introduction

The UK has a target of reducing carbon emissions to 80% of 1990 levels by 2050 [1]. Small personal and commercial vehicles currently represent 13% of the total carbon emissions in the UK and an EV typically has a well-to-wheel emissions ~50% of an internal combustion vehicle [2]. EVs in 2013 had a UK new-car market share of 0.34% [3] and will only reduce carbon emissions with consumer adoption which relies on sufficient charging infrastructure and managing its impact on the electrical distribution network. If EVs are considered as inflexible loads, then the network impacts as EV popularity grows have been studied by [4]. However, EVs are stationary for around 95% of the time [5] and as such there is potential for flexibility. The majority of the literature considering EV flexibility does so considering just EVs; however, establishing how to utilise flexible loads, of all types, in Smart Grids is a subject of intense research [6]. Therefore, this paper takes the approach of establishing the flexibility that can be reliably called upon from EVs in aggregate, to form a virtual energy storage system (VESS), as an input to wider microgrid control systems.

2 Flexible EV charging

It has been suggested that vehicle to grid (V2G) technology is best suited to high-value and time critical services [7] as opposed to generating value from energy trading [8] where algorithms designed to extend battery life generate twice as much value [9]. The battery degradation has an impact on V2G viability [10] and should be considered in any algorithm development. Offering capacity as a back-up yet rarely utilising it also presents opportunities for EVs to earn additional revenue [11].

The benefits of utility controlled charging (UCC) can only be realised if EV owners are willing to plug their vehicles into such charging posts, which was considered by [12]; 53% of respondents were open to enrolling without any benefit (financial or increased renewable penetrations) provided 100% state of charge (SOC) was ensured by morning. As the guaranteed SOC by morning

decreases, the acceptance of users also decreases as shown in the reproduced graph in Fig. 1. Reducing the cost of the energy by 20% increased adoption by 18 percentage points. There is clearly potential for significant numbers of prosumers to partake in flexible charging.

An optimal power flow was used in [13] to solve network congestion considering each EV and its location individually. In [14], a central price signal was used, both system wide and nodal, to decide locally whether a vehicle should charge or not. A more centralised aggregated approach was also taken by Vaya [14] that returned a greater economic value than the price signal method. The full potential of the flexibility was not utilised by only allowing charging (and not V2G) whereby the energy was allocated to each EV based on its priority; a function of its SOC compared with that required on leaving and the time until departure. It was noted that the internal EV fleet energy management could result in the calculated aggregate power and energy not being realisable. In contrast, Lamedica [15] calculated a desired average SOC across the whole EV fleet, those with a higher SOC discharged while those with a lower SOC charged. The method results in better internal energy management of the EV fleet in terms of ensuring that the maximum aggregate power can be delivered; however, this also results in some EVs having a net energy loss over their time plugged in, conflicting with the needs of the users. A fuzzy logic scheme considering present SOC, SOC required on leaving, time remaining and the cost of energy was proposed by Ma [16], allowing the vehicles to charge with the lowest energy cost, resulting in valley filling and peak shaving. Work in this area to date has mainly been theoretical. UCC was implemented, however, in the 'My Electric Avenue' trial [17], where a binary on-off decision is taken to ensure that voltage and thermal limits are not exceeded on the feeders studied.

3 Aggregate power and energy flexibility

Provided the energy management within the EV fleet ensures no vehicle reaches a SOC limit before any other vehicle, the

Fig. 1 Respondent acceptance of guaranteed minimum charge assuming a pure EV with 240 km range. Early mainstream consumers only, $n = 530$ [12]

aggregate maximum and minimum power and energy demands can be defined as follows:

- The maximum potential power demand is the sum of all the charge point ratings where vehicles are plugged in.
- The minimum potential power demand (or maximum V2G supply) is the sum of all the charge point V2G ratings.
- The maximum potential energy demand is 100% minus the present SOC, multiplied by the battery capacity.
- The maximum potential energy supply is the present SOC, multiplied by the battery capacity.

Since the arrival time, arrival SOC and departure time are all stochastic [18] for which the aggregate power and energy are dependent; the aggregate power and energy flexibility is also stochastic.

4 EV fleet energy management

The algorithm used to control the internal energy management of the EV fleet to form a VESS is shown in Fig. 2 and described next.

In any EV flexible charging algorithm, it must be ensured that all vehicles have sufficient energy at departure; otherwise consumers will not charge their EVs using the algorithm. How the EVs get to that minimum SOC at the time of departure is irrelevant (if neglecting battery degradation issues). Therefore, if a vehicle requires its charge point's fully rated demand to achieve the minimum SOC in the time remaining before departure, this is allocated to those vehicles. The remaining power requirement to meet that requested of the VESS must then be shared between all other vehicles.

In being sympathetic to battery degradation, the remaining power required should be shared between as many vehicles as possible. In that way both C-rates and V2G-induced additional cycles' depths of discharge are kept to a minimum. The downside to this simple concept is that those vehicles that have an initially high SOC can easily reach 100% SOC resulting in them losing the ability to demand power. To reduce the occurrence of this situation, when the remaining required aggregate power is charging power, it is averaged between only the EVs that are presently below the SOC required at departure. Those vehicles with a SOC above the

Fig. 2 Algorithm deciding individual EV power exchange

minimum at departure only demand power if additional aggregated power is required to meet the grid request. When V2G power is required, the power is shared between all vehicles that do not require fully rated demand to meet the minimum SOC at departure, regardless of their SOC.

5 Case study: work-based car park

Consider an EV charging station with 50 spaces at a work-based site. The number of vehicles arriving in a day is assumed to follow a normal distribution, with a mean of 45 and standard deviation of 3. The arrival time for each vehicle is established using a normal distribution, with the average car arriving at 09:00 with a standard deviation of 1.2 h. Similarly for departure time, a normal distribution is used with the average car departing at 18:00 with a standard deviation of 1.2 h. This is consistent with the weekday modelling approach used in [16]. A more detailed statistical analysis of EV charging times was undertaken in [18].

The SOC on arrival is based on the SwitchEV project [4] and is established using a normal distribution with an average of 53% and a standard deviation of 15%. The battery capacity of all vehicles was assumed to be 24 kWh, with a requirement for 80% SOC on departure.

It was assumed that the charge rating is 7 kW and V2G rating is 3 kW. The model is calculated based on a time-step of 1 min.

Based on a Monte Carlo approach simulating 1000 days, the stochastic maximum and minimum aggregate power demand and percentiles of the parked EV fleet is shown in Figs. 3 and 4 respectively.

If the higher level controller of VESS output can handle uncertainty, such as that proposed in [19], then a greater level of flexibility can be utilised than if the VESS alone is being relied upon to ensure the robustness of the network against thermal and voltage limit violations. In such a situation where the EVs are being fully relied upon, then the VESS power should be limited to the region bounded by the minimum of Fig. 3 and the maximum

Fig. 3 Maximum aggregate power demand of the VESS on the grid

Fig. 4 Minimum aggregate power demand (or maximum power supply) percentiles of the VESS on the grid

Fig. 5 Maximum aggregate energy demand percentiles of the VESS on the grid

Fig. 6 Minimum aggregate energy demand (or maximum supply) percentiles of the VESS on the grid

of Fig. 4. This could be considered somewhat pessimistic and the 5th and 95th percentiles have been used, respectively, giving a 90% confidence.

Figs. 3 and 4 assume that no vehicles have reached their SOC limits and can contribute their fully rated power. This may not be the case depending on the internal energy management of the EV fleet, and the previously called services of the VESS by the grid controller. The percentiles of maximum and minimum aggregate energy available based on the arrival SOC as determined by the stochastic modelling and a departure SOC of exactly 80% for all vehicles is shown in Figs. 5 and 6, respectively. To achieve a 90% confidence of delivering to the grid what is requested, the energy exchange should remain within the region bounded by the 5th percentile in Fig. 5 and the 95th percentile in Fig. 6. These two lines cross shortly after 18:00, however making it impossible to achieve. This is due to the assumption that all vehicles leave with exactly 80% SOC in the figures, which may not be exactly true depending on the internal energy management of the EV fleet and the number of vehicles parked on any particular day. Instead the range should consider the potential for some vehicles to leave with more than the minimum 80% SOC and as such the 5th percentile in Fig. 5 is taken to not reduce once it reaches its maximum value and corresponds to all the vehicles having 100% SOC or less on leaving, 95% of the time, assuming the internal energy management ensures all EVs would reach 100% SOC at the same time.

6 Case study results

Using the power and energy bounds defined, two possible VESS service requests have been developed. profile A is shown in Fig. 7 and displays a low constant load while profile B shown in Fig. 8 displays higher load variability while reaching the defined power and energy bounds numerous times throughout the day.

For each VESS power profile, 1000 days of Monte Carlo simulation was undertaken using the model as described previously and the internal energy of the EV fleet managed using

Fig. 7 Grid power decision, profile A: low constant load

Fig. 8 Grid power decision, profile B: high variability load reaching both power and energy bounds

the control logic of Fig. 2. The realised power delivered to the grid is shown in Fig. 9 for profile A and in Fig. 10 for profile B. In both profiles, the grid demanded output is realised in the majority of cases, and when it is not then the value delivered is often close to that requested. Over the full day, the probability of realising profile A was 99.98% and the probability of realising profile B was 98.83%.

In Fig. 9 at around 16:20, there are some days within the Monte-Carlo analysis that the VESS was unable to deliver the service requested by the grid. It is unlikely to be as a result of vehicles leaving earlier than normal because the power demanded is significantly below the maximum power bound in Fig. 8. The energy delivered to the VESS is, however, relatively close to the maximum energy bound and as such the loss of control is due to some vehicles reaching 100% SOC and being unable to demand any further energy. Additional power is demanded on some days within the Monte-Carlo analysis at around 20:00. This is because

Fig. 9 Resulting power percentiles delivered to the grid, profile A: low constant load

Fig. 10 Resulting power percentiles delivered to the grid, profile B: high variability load reaching both power and energy bounds

Fig. 11 Uncontrolled charging demand percentiles at the end of the day resulting from no energy delivered throughout the day

the SOC of some EVs are below the minimum at departure when the desired VESS demand is zero.

In Fig. 10, the power delivered around mid-day is less than that requested of the VESS. This is likely to be due to some days within the Monte Carlo analysis having either too few EVs, or EVs reaching 100% SOC, or a combination of the two, since both desired power and energy are close to the bounds at this point in time in Fig. 8. In a similar way to that described for profile A, there is a limited loss of control at around 19:30 when the EVs start to leave, where the VESS request is close to both the power and energy bounds.

From these studies, it can be concluded that there is a high degree of controllability of the VESS for the majority of the day. When vehicle numbers reduce to very low numbers, the EV fleet becomes less reliably controllable. If the car park was located where new EVs were always arriving as suggested in [18], then this limited loss of control would be reduced. Furthermore, the closer the energy delivery is to the mid-point of the upper and lower energy bounds in Figs. 7 and 8, the less likely and severe the reduced controllable period becomes. To consider an extreme case of the reduced controllable period of the day, one further study has been conducted whereby the VESS is requested to demand no power throughout the full day. It results in the EVs all waiting until the last moment to charge, and then do so at full charge point rating. The resulting power demand percentiles of the VESS are shown in Fig. 11.

7 Battery degradation cost

By actively controlling the charging process, there will inevitably be an impact on the EV battery degradation and consequentially an economic impact on the EV owner. This cost is very difficult to quantify, and an active area of research in its own right. A qualitative assessment of the impact is given below.

Additional cycling: With the proposed control algorithm, it is expected that an individual vehicle will rarely give up energy to charge another vehicle, and in most cases will only act as V2G when the aggregate power requirement of the grid is from the

VESS and to the grid. Therefore additional charging cycles, causing additional degradation, are likely to only be created when the aggregate power required is V2G.

Charging rates: At present, vehicles charge at the rating of the charge point. In the proposed algorithm, the averaging of power across all vehicles reduces the charge rate meaning that the battery degradation through charging could be expected to reduce, relative to present charging arrangements.

State of charge: By charging at a rate lower than the charge point rating, or using V2G, the SOC will be at a lower level relative to uncontrolled charging. This results in a reduced degradation effect on the battery.

Overall impact: It is expected that charging flexibility can be realised, using the algorithm presented, with reduced degradation in the majority of situations relative to uncontrolled charging. If the VESS is supplying power to the grid then an increase in degradation could be expected.

8 Conclusions

The stochastic nature of EV charging requirements has been considered and the aggregate flexibility calculated for the grid. An internal energy management control scheme has been developed to realise the grid requested demand within the advertised flexibility, prioritising at the highest level the EVs SOC to be at a minimum level at the departure time. Monte-Carlo techniques have been used to show the resulting aggregate power exchange delivered by the VESS to the grid for two fictitious grid requested demand profiles. Over the full day, the probability of realising profile A was 99.98% and the probability of realising profile B was 98.83%.

Future work will include deriving the power and energy bounds by stochastic analysis of real charging data, rather than assumed statistical distributions. The impact on EV battery degradation will be quantified for various realistic grid requests of a VESS.

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