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Abstract

This study investigates the potential role of electric vehicles in an electricity network with a high contribution from variable generation such as of wind. Electric vehicles are modelled to provide both demand management through flexible charging requirements and energy balancing within the Balancing Mechanism. Balancing applications include both demand balancing and vehicle-to-grid discharging.

The main simulation in this study is configured to represent the UK grid, where the balancing requirements are governed by weather stations on the supply side and National Grid data from on the demand side. The simulation models 1000 individual vehicle entities to represent the behaviour of larger numbers of vehicles. A stochastic trip generation profile is used to generate realistic journey characteristics derived from UK national statistics, whilst a market pricing model allows charging and balancing decisions to be based on realistic market price conditions.

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The simulation has been tested with wind generation capacities representing up to 30% of UK consumption. Results show significant improvements to load following conditions with the introduction of electric vehicles, suggesting that they could greatly enhance the uptake of intermittent renewable generation. Electric vehicle owners would benefit from flexible charging and selling tariffs, with the majority derived from vehicle-to-grid participation.

Keywords: Electric grid balancing, wind generation, electric vehicles, vehicle-to-grid

1. Introduction

Coping with variability has become one of the key challenges of delivering sustainability in electricity markets. The variable or intermittent nature of renewable sources, and especially that of wind power, has led to much concern over the stability and costs of our future electricity supply. To facilitate the introduction of higher levels of intermittent sources within the grid mix, it has become clear that increased flexibility and storage will be essential in providing the stable and uninterrupted supply of electricity that the modern world depends on.

At the same time, electric vehicles (EVs) are developing as a serious mode of transport. At first sight, the charging of these new vehicles will present an added load to the already stressed grid. However, it is the opportunity for new load management services that is of greater significance where smart grid technology will allow the charging of individual vehicles to be controlled in a manner that will benefit both the vehicle owner and the grid, including the option of return of stored electricity to the grid from the vehicle's battery,

which has become known as vehicle-to-grid (V2G).

In this manner, the aggregated charging and discharging profile of large numbers of EVs will be able to smooth the demand profile that is seen by the load following thermal generators and help balance the increased scheduling uncertainty that will accompany higher levels of wind power. For example, a study of the synergy between EVs and a high wind penetration for Danmark [1] has shown that with wind penetration beyond 20% would lead to periods of time when the wind power production would exceed the average demand without EVs. To avoid substantial curtailment of renewable electricity therefore needs substantial demand management and energy storage options, both of which can be provided by electric vehicles.

This report assesses the potential role of EV charging within a UK electricity network featuring high levels of wind power capacity. The simulation includes both, strategic pre-scheduled charging and instantaneous balancing services, via demand management and V2G, and provides predictions towards the potential costs and profitability for EV owners.

The remainder of the introduction reviews the UK context, wind power characteristics, and electric vehicles. The balancing model and the input data will be described in §2, followed by the results in §3 before a discussion and conclusions in §4.

1.1. UK context

Within the UK governments low carbon transition plan, transforming the power and transport sectors and developing a smarter grid are three of their principal objectives [2]. The rate of wind power development has accelerated hugely and has the potential to meet the majority of the countrys target

of 30% of electricity from renewables by 2020. It has been estimated that a 20% contribution to the electricity supply through wind would enable a reduction in fossil generation by 20 to 30% of the installed wind capacity with an increased cost of generation of around 10% to provide the additional balancing requirement [3].

With transport accounting for approximately 25% of the UKs carbon emissions [4], introduction of low carbon vehicles is at the heart of strategic plans to transform the UKs transport sector and the governments strategic roadmap sees electric vehicles gaining mass market status before the end of the decade [2].

Simultaneously, the UKs independent transmission system operator, the National Grid, has also been looking ahead to 2020 where the expected rise in wind power capacity will herald growth in the importance and value of demand management and grid balancing services [5]. A key expectation is more demand side participation in wholesale energy markets through progress in dynamic demand management and aggregation. Electric vehicles are identified as one of the key components to achieve this, especially as they can be deployed more rapidly than many other existing sources.

The current mainland UK grid consists of a 275kW and 400kV transmission grid and fourteen regional distribution networks. It also has a connection to the European continent through a 2GW interconnector to France and to Northern Ireland from Scotland with a 400MW capacity. In 2011, a 1GW connector to the Netherlands and a 500MW connector to the Irish Republic were added to this. All large-scale thermal and hydro generators feed directly into the transmission network while the majority of smaller wind farms are

embedded in the distribution network. However, several larger wind farms are now connected to the transmission network and the majority of future capacity is expected to follow suite. Generation is currently provided by a broad mix of different types, summarised in Table 1, with a total capacity of around 90 GW of which 8% are at the distribution network level. The energy storage capacity through pumped hydro storage with an installed capacity of 2.7 GW.

The Electricity market for England, Wales and Scotland is privatised and is operating according to the *British Electricity Trading and Transmission Arrangements* (BETTA). The basic structure of the daily delivery of electricity is separated in 48 half-hour 'Settlement Periods'. On a longer time scale, from as much as a year in advance to the day-ahead stage, suppliers enter contracts to buy electricity from generators in the 'Forwards/Futures contract market' and the vast majority of all electricity exchange is agreed in this way. The short term bilateral exchange market, or 'spot market', operates from the day-ahead stage until 'Gate Closure' at the hour-ahead stage. After gate closure , the 'Balancing Mechanism', controlled by the system operator operates up to to real time. Post-hoc settlement of payment and penalties for imbalances is operated by a balancing and settlement company.

1.2. Electric vehicles and vehicle-to-grid electricity

The carbon savings of electric vehicles (EV) are unquestionable. Comparing typical efficiencies of current internal combustion engines with total efficiency of modes fossil fuel power generation, transmission losses and charging losses, a typical EV will generate significantly reduced carbon emissions compared to the average modern car.

The principal drawbacks associated with EVs surround their batteries, which are typically large, heavy and take a long time to charge, where the range of a fully charged vehicle is still typically less than 160 km. Modern EVs now use Lithium ion batteries which permit a higher charge density, have faster charging capabilities and improved degradation characteristics over their predecessors. Batteries remain expensive, but successive generations of Lithium based batteries have been able to cut costs by reducing the quantity of Lithium required, whilst equivalent technologies using more plentiful metals are approaching commercial deployment.

The success of the Toyota Prius, the first widely sold hybrid electric vehicle, has allowed electric vehicle technology to gain valuable market exposure and has paved the way for the release of further electric vehicle technology. The all electric Nissan Leaf has a range of 160 km and a charge time of between thirty minutes and eight hours. Considering that 92% of daily car use in the UK amounts to less than 150 km of cumulative driving [6], EVs at current technology would be able to satisfy the majority of our driving needs.

Whilst it is too early for widespread adoption of EVs, innovators are beginning to adopt the technology. The immediate rewards for the innovators and early adopters are considerable as the energy costs of urban driving are approximately six times lower than those of the average gasoline vehicle. Because of this reduced cost and the favourable tax status of EVs, company car fleets that utilise high levels of short range trips could become a key player in the developing the EV market. A more practical option for the rest of the potential market are plug-in hybrid electric vehicles (PHEVs) even though

they are slightly heavier and more expensive than purely electrically-driven vehicles.

It is likely that future generations of grid charging vehicles will be equipped with an onboard charge management system that is able to communicate wirelessly to the electricity supplier. This onboard system could learn the users driving habits in order to define its charging constraints complemented by driver input for special trips or to specify immediate charging. Vehicle charging would be coordinated by an aggregator utility that would utilise network forecasting to control the charging of these vehicles. Because vehicle charging is essentially flexible within the charging period specified by the onboard system, the aggregator utility would be able to adjust charging as a means to provide balancing services to the grid.

So far, linking EVs into the grid is only an added load on the grid, albeit a flexible load with opportunity for load balancing, but there is also the opportunity for a two-way flow of electricity and using the EV batteries as energy storage which can be accessed to feed electricity back into the grid if required by the grid and permitted by the onboard charging system. Since the beginning of exploring this approach, known as *vehicle-to-grid* (V2G) [7], the main obstacle has been battery degradation caused by processing the extra charge activity associated with charging and releasing energy for grid storage. However, a detailed study of battery degradation demonstrated two key characteristics of the lithium-ion batteries tested [8]. Firstly, the total quantity of processed charge was the principal factor governing battery degradation rather than the depth of a given discharge. Secondly, it was observed that the more dynamic nature of the discharge characteristics as-

sociated with driving were responsible for approximately twice the capacity fade compared to the fixed discharge rates attributed to V2G activity. The current consensus seems that V2G as energy storage would generally not prove economical in providing peak power in the near term [9] but more likely provide a financial return when employed for ancillary services such as frequency response and for balancing and reserve services [10].

While much research has explored conceptual aspects or specific technical details, e.g. [11, 12, 13], only few direct system behaviour models have been published, though a recent review has outlined the key components a system model should include and provides a good overview over typical specifications of these components [14].

Lund and Kempton [15] have based their study on the current Danish vehicle fleet electricity network but with a varying level of wind power capacity. Their model uses an electric vehicle fleet of equivalent size and behavioural characteristics to the existing Danish vehicle fleet. By employing hour by hour vehicle use profiles, the aggregated grid connection availability of the vehicles was modelled. The study presented comparisons between different connection scenarios, such as night only charging, intelligent charging and V2G enabled charging, with the outcomes suggesting that intelligent and V2G enabled charging would greatly support the operation of large wind power capacities by providing large-scale energy storage. It has recently become apparent that the overall system can really only benefit significantly from the energy use and storage provided by EVs when the electricity flow is controlled by some form advanced or intelligent control to [1].

However, the models by [15, 1] simulate all vehicle charging and V2G

discharging as the action of a single large battery representing the complete aggregated vehicle resource. Whilst the behaviour of many EVs would indeed provide a large aggregated output, it is the independent actions and requirements of many small entities that make grid vehicle charging and discharging so different to existing large scale storage systems such as pumped hydro storage. Furthermore, although incentives are repeatedly referred to, the study does not quantify or model the financial aspects of EV participation. Given the nature of modern liberalised electricity markets, an available storage resource will only be used if it provides a cost competitive option to the market.

The market value of EVs to provide energy storage of power quality was demonstrated for the Swedish and German electricity markets [16] but without modelling the time resolved operations. They observed that the structure of the electricity market has a strong effect on the potential economic benefit to EV owners. Based on their analysis, they suggested an ideal market structure in which payments would be made for both, energy sold as well as capacity provided, with a short contract time in which many small bidders can contribute.

There is clearly a need for a study that simulates vehicle behaviour on an individual basis, whilst using real market data to assess the reasonable potential roles of electric vehicles in the future electricity grid.

1.3. Aims and Objectives

The aims of this study were to investigate the role a fleet of electric vehicles would contribute to the load and energy storage potential for a national electricity network given technical and economic balancing constraints

of measured demand, intermittent (wind) generation, as well as charging and vehicle-to-grid costs.

To address these aims, the first objective was to develop a dynamic model of the electricity network with enough detail to resolve intermittent generation (initially from wind data alone), end user demand data, conventional generation, EV charging needs and V2G availability. The second objective was to configure this model to the current UK situation where one of the main variable control parameters is the amount of wind generation. The final objective was then to apply the model to a range of scenarios of EV development alone or of EV and V2G development within a network of wind penetration increasing from 2010 levels of 3.7% to an optimistic 30% - going beyond the level previously investigated by Gross et al. [3].

2. The balancing model

The structure of the balancing model is illustrated in Figure 1. The conventional grid, which is captured by the upper half of the diagram, is primarily fed by wind power and thermal generation against a consumer load (the central column), where the balancing options are constraint by market prices. On this conventional grid is added the EV fleet (the lower part of the diagram) through a charging link which can either be as a load only, as for current EVs, or as a bi-directional link to include V2G energy storage. The various generation and load types are interlinked by generation, demand, and EV charge forecasts as illustrated by the links on the left-hand side of the diagram.

The primary configuration variables are the installed scheduled (conventional) and variable (wind) capacity, the number of EVs and a weekly vehicle

trip density profile. The dynamic, time-varying, input variables are the wind power, the electricity demand, the market prices, and the electric vehicle trips all of which were in this set-up calculated on a 15-minute basis.

Given the time resolution of data available, and the main aims of this study, namely to investigate the mutual technical and economic benefit to EV users and renewable generation, the focus is on the use of EVs for energy storage rather than as an aid to improve the power quality. However, it should be noted that it has been found that V2G technology also has a great potential for frequency regulation which in turn also has potentially a beneficial impact on electric vehicle owners[17].

2.1. EV and V2G modelling

Key parameters in defining the modelling approach and model structure was to represent the EV fleet with enough resolution to allow for individual usage variation to be felt by the system without modelling each individual vehicle. This was achieved by defining 1000 'electric vehicle entities' which were then scaled up to the specified number of electric vehicles. Each entity was assumed to consist of two daily journeys following a trip probability density function as shown in Figure 2, where the distance of each journey was randomly selected from a Weibull distribution based on the actual road transport statistics for the UK from the year 2008 with an average daily travel distance of 38 km [6]. The duration of a trip was calculated on the basis of a range of average speeds where longer distances are completed at a higher average seed. The vehicle status database and charge schedule database store for each entity details such as the time of next departure or return and the vehicles battery status, or the vehicle charge schedules for each vehicle are

11

stored together in the vehicle charge schedule database. Every time a vehicle returns from a trip and plugs in to the electricity network, the stochastic trip generation profile is used to assign a new next departure time. This is used by the vehicle charge coordination model which schedules all required charging in advance of the departure. The scheduling of charging is conducted by selecting the cheapest possible charging periods in the available timeframe.

The vehicle specifications used in this model are for simplicity the same for all entities. Assuming that electric vehicles in the near future will aim at least for the stated performance of the Nissan Leaf[18] or the BMW Mini E[19], we are using values typical for these as ~~and are~~ a range of 160 km with a battery capacity of 24 kWh and an energy consumption of 0.15 kWh/km. Charging is assumed to take place at a charging rate of 6 kW with a charging efficiency of 90% which is a compromise value between the Mini E charging station options of 7.7 kW and 11.5 kW and the Nissan standard charge rate of 3.3 kW, rather than the Nissan 'quick charger' with a quoted rate of 35 kW.

To allow for typical driver behaviour and charging opportunities, the current model assumes that all trips which end after 10pm and 6am terminate at the owner's home and allow immediate charging, whereas other trips add a random delay after the end of a day-time trip for trips which end at a location without charging opportunity. Furthermore, an entity which begins its first daily trip between 6am and 9am and its second between 4pm and 7pm is modelled as a commuter for that day, and these vehicles are not recharged during the day if they have enough battery capacity to comfortably complete their next journey. This is the only circumstance in which the current model uses knowledge of a vehicles next trip distance within the

simulation. Approximately 20% of modelled daily trips are commutes which is consistent with 18% as suggested by the Department for Transport [6].

2.2. Market pricing

Decision making within the model is principally informed by market prices. The pricing model supplies three prices, namely the mean index price (MIP) which is the mean of the price for a half-hour period of spot market electricity transactions made during that half hour, and two imbalance prices. Imbalance prices are used during the post-hoc settlement period, the system buy price (SBP) for a shortfall of energy and the system sell price (SSP) for over-generation or under-consumption. The SBP is the mean price during a settlement period of the marginal 500 MWh of offers that are accepted by National Grid to correct a short system. It is used to charge parties responsible for negative imbalance during the settlement. *Vice versa*, the SSP is used to pay parties which are responsible for positive imbalance during a settlement period when the system is long.

The mean index price, MIP, is used to select the cheapest periods in which to charge, and to calculate the total costs of charging. The imbalance prices, SBP and SSP, are used by the V2G vehicle balancing model to decide if it is cost effective to partake in balancing. The profit calculated from each balancing action contributes towards determining the annual profitability for vehicle owners.

Nine years worth of mean index prices and imbalance prices were used to generate the pricing profiles, after a growth curve was removed from the historic prices to account for inflation. Because imbalance prices are derived from the marginal cost of balancing actions, they represent the higher end

of offer prices and the lower end of bid prices that are accepted. It is likely that an operator with low costs would aim to undercut these prices to ensure that their bids and offers were accepted as often as possible. However, good knowledge of the market would also allow operators to submit bid/offer prices that are close to the marginal level. For simplicity, the historical imbalance prices have been used directly to generate the pricing profiles that provide the vehicle balancing model with bid and offer prices.

System prices depend on a huge number of factors that could not have possibly been modelled. However, they are largely a function of plant availability and of demand. For this reason, the pricing was based on an empirical function of the adjusted MIP, SSP and SBP values against the demand as shown in Figure 3. The analysis of the fluctuations of the prices around their mean value at the given demand showed that the SSP obeyed a normal distribution while the SBP and MIP were distributed according to a log-normal distribution. To reflect the daily variation of the prices according to their distributions while at the same time respecting the fact that the three prices all depend on the same current market situation and are therefore closely related, the system prices were modelled on the basis of a common random number generated on a daily basis, the demand, and the knowledge of three mean system prices and their distributions. The random factor represented the daily market fluctuations but, as this situation affects all three prices, this random number was used as the common cumulative density factor for all three distributions. Once the demand, and with it the mean system price was known, the distribution for MIP, SBP and SSP, respectively could be determined, and the prices chosen as the actual prices were those at which

14

the respective cumulative distributions had the value of the random number.

~~To reflect the close relationship between the three prices, the actual modelling of the pricing uses a common randomly-generated cumulative density value to generate a price from each of the three distributions. This cumulative density value is regenerated on a daily basis in order to introduce the necessary statistical variation into the model.~~

As the pricing market will be sensitive to the degree of wind generation, the price profiles shown in Figure 3 have to be adjusted. This adjustment was carried out through rescaling the demand by the amount of conventional generation displaced by installed wind capacity using a capacity credit of 25%, that is 4 GW of installed wind allow the thermal generation capacity to be reduced by 1 GW [3].

2.3. Demand

A 15-minute demand dataset was generated from the half-hourly data available from the National Grid[20]. The fifteen-minute detail was added through a random perturbation with a standard deviation of 235 MW on the linear interpolation, where this standard deviation was calculated from a weeks worth of five minute demand data[21].

2.4. Variable power generation

Wind power generation was modelled through wind speed measurements from the UK Meteorological Office through their MIDAS dataset [22] of hourly wind measurements, with the speed rounded to the nearest *knot* (= 0.514m/s) and the direction to within $\pm 10°$. A total of 35 stations were chosen in locations of current or consented wind farms and areas with good

15

wind power potential. While it was not possible to obtain suitable data from the actual offshore regions themselves, coastal recording sites were chosen that are as close as possible to the offshore development regions. Even though the resulting geographical coverage is not ideal for representing the planned development areas, the resulting capacity factor calculated from the chosen set is, with 34% from 2000 to the end of 2009, entirely consistent with other studies that typically use a capacity factor of 35% to represent a large future UK wind power sector comprised of both onshore and offshore projects.

The hourly wind speed readings were interpolated to the 15-minutes time step of the model using a normally distributed random number with a standard deviation of 1.8 m/s as computed from a four-year long 20-second interval reading at the Armagh Observatory[23] superimposed on a linear interpolation between the adjacent measurements. These 15-minute wind speeds were then extrapolated from the anemometer height of 10 m to a typical hub height of 100 m using the power-law

$$u_z = u_0 \left(\frac{z}{z_0} \right)^b \tag{1}$$

with an exponent of $b = 0.14$ and then converted from wind speed to power output using the power curve for a Nordex N90 as a typical representative of large wind turbines. This interpolation of the height-adjusted wind speeds and subsequent conversion to power output through the performance curve of the Nordex N90 is illustrated in Figure 4 where, in a) the hourly wind speed data for a 10-hour record are shown as the open circles, and the interpolations with random perturbations as the blue crosses. These wind speed data were then fed through the performance curve (in b) to calculate the power output

16

The scenarios investigated here include current, planned and target scenarios for 2020 as listed in Table 2.

2.5. Scheduled power generation

There is a large range of thermal plant types amongst the UK grid mix, and within any fuel type bracket there is considerable variability in the performance and operating strategies of individual plants. To develop a systems overview, generalisation amongst plant by fuel type – nuclear, gas and coal – was required. Nuclear was found to provide an almost constant output at 5.3 to 5.8 GW, gas generation was between 10 and 20 GW and coal between 4 GW and 16 GW during day time as shown in Figure 5. The remaining demand was largely met by the interconnectors (on average 1.3 GW), followed by wind (on average 0.44 GW) and pumped storage hydro (on average 0.38 GW) and all others on average 0.2 GW. Whilst gas generation occupies a larger share of the load at all time periods, the load profile of coal generation exhibits a higher amplitude variation, including higher frequency load following than gas generation. Other generation sources such as interconnectors and pumped hydro are small and have currently been left out of the scheduled generation model for simplicity.

Thermal generation is scheduled at gate closure, one hour ahead of real time. It is this scheduled generation which is later balanced against the real time net demand. To forecast the required thermal generation one hour ahead, it is necessary to forecast both the wind power generation and the demand. Demand forecasting is relatively straightforward as the typical de-

mand profile for time of day and weekday is well documented from the real data. To include a realistic forecast error of 1.3%, the forecast based on the available data is multiplied with a random number of standard deviation 1.3%..

Wind forecasting has a much larger uncertainty, and the UK has until recently assumed persistence for the hour ahead. This leads to a mean wind power forecasting error of 6% for the forecast one hour ahead and around 10% for forecasting a day ahead.

2.6. Vehicle and grid balancing

Two balancing modes involving the electric vehicles were implemented in the model alongside conventional grid balancing through load following generation and pumped storage hydro. The first only uses EVs battery charging flexibility to manage the demand on the grid while the second also includes the V2G option of using EV batteries as source of electricity.

2.6.1. Demand Management balancing through EVs

In the demand management model in which EVs act as a load on the system to recharge EV batteries within the time available between reconnection to the grid and the next journey. If that time is longer than the minimum time required for recharging, this introduces the flexibility to shift the loads within that period to reduce peak demand and fill periods of lower demand, thereby reducing the need for balancing from coal or pumped storage hydro. If the system is short of generation, scheduled charging can be rescheduled to a future time period for a lower cost than the immediate system price. Conversely, if the system has excess generation, charging scheduled for a future time can be brought forward if the immediate system sell price is lower than

18

the future price. This balancing is carried out by inspecting at each time step the EV status and charging schedule and bringing forward or delaying the charging schedule according to the pricing and the need to charge the vehicles within the available time.

2.6.2. V2G balancing

The second vehicle balancing mode includes the V2G option. The associated battery degradation, taken to be £25.60/MWh for V2G delivery [9], and conversion losses of V2G make the costs considerably higher than with demand management balancing. This makes V2G balancing likely to be profitable only when the System Buy Price is highest and leads to a condition which must be met before V2G discharging occurs as:

$$
\begin{aligned}
\textit{Imbalance Price (SBP)} \quad > \quad & \textit{Re-scheduled charging cost} \\
+ \quad & \textit{Battery degradation cost} \\
+ \quad & \textit{Charging conversion losses} \\
+ \quad & \textit{Discharging conversion losses.}
\end{aligned}
$$

When the system is short, the balancing model first applies demand management balancing. If the imbalance has not been fully met when all permissible DM balancing has been allocated, the V2G balancing model is invoked. The algorithm only begins if the V2G condition above can be satisfied by at least one potential reschedule period within the upcoming 24 hours. If this condition is met, the algorithm moves through the vehicle records of vehicles that are not charging within the present time period. For each vehicle record, discharging is assigned when the re-schedule charging cost at time periods in the window before the vehicles next trip allows the V2G condition to be met. Again, the constraints of the battery capacity and maximum charge rates apply. As with demand management balancing, the algorithm contin-

ues to move through vehicle records until the imbalance is met or the records are exhausted.

2.6.3. Load following generation

For the conventional balancing actions, nuclear generation is only involved in adjusting output at a small ramp rate during the scheduling while pumped hydro storage (PHS) and coal take the majority of high frequency load following balancing with gas taking more of the low frequency load following. For simplicity, PHS is modelled as a single unit of with a return efficiency of 70%, split evenly into pumping efficiency of 84% and generating efficiency of 84%. The PHS system only buys energy if the SSP is less than difference between the average sell price and the efficiency costs, and it only sells energy if the SBP price is higher than the sum of the average buy price and efficiency costs.

3. Results

3.1. Base scenario

Figure 6 provides a base scenario against which to compare EV deployment. It shows a comparison of the thermal load profiles in networks featuring 4.6 GW to 37 GW of wind power. Within the featured week, the wind power capacity factor varies from less than 15% to above 90%, which constitutes a change in wind power output of almost 19GW for the 25GW scenario. This sequence is not a particularly extreme event and is typical of the increased variability that can be expected to accompany larger penetrations of wind power.

3.2. Using EV for demand management

With the introduction of electric vehicle charging, alterations to the load profile begin to become appreciable at EV levels exceeding 100,000 vehicles. Figure 7 demonstrates how the example load profile in Figure 6 for an installed wind capacity of 14 GW is altered as the number of vehicles is increased gradually up to a level of 10 million vehicles, or about 30% of all vehicles. During day-time demand, the electric vehicles tend to have a very small influence, though they add to the overall demand, but the ~~It can be seen that~~ troughs in the profile fill at all times of day, with the largest amount of charging assigned to the off-peak night-time troughs. While the degree of filling the troughs increases on average with the number of vehicles, the individual variation which is captured here int he stochastic modelling allows for significant variation across the different realisations of the model superimposed in Figure 6. The overall net effect is both, a considerable degree of smoothing and a reduction in the total load daily variation between off-peak and peak periods. The same effect is also seen for higher installed wind capacities.

In Figure 8, the mean 15-minute load fluctuation versus the level of electric vehicle ownership for different possible future wind power capacities demonstrate that load fluctuations steeply drop off with the initial hundreds of thousands of EV uptake, but the trend begins to lessen as low amplitude short term fluctuations are increasingly smoothed over. It can be seen that 3 million electric vehicles representing 10% of UK car ownership would reduce the mean load fluctuation by approximately a third, whilst 10 million vehicles would almost halve the level of fluctuations.

21

The average distribution[1] of a vehicles charging over the course of a day is compared to the average daily load profile in Figure 9. It can be seen that the majority of all charging is conducted over the off-peak night-time period, with a far smaller secondary charging peak coinciding with the dip in daily demand that occurs during mid afternoon. The scenario shown features present day wind power capacities. As wind power capacity increases, the visible charging trends become less distinct with daily charging deployment becoming less regular due to the growing variation amongst daily load profiles.

3.3. V2G

Including the V2G option allows for grid balancing as well as demand management. The effectiveness of using EVs through V2G for balancing is illustrated in Figure 10 for a fleet of 1 million vehicles in a network with increasing wind penetration, up to 40 GW. Not surprisingly, the mean imbalance increases with increased variable generation, roughly linearly with $I \sim 262\text{MW} + 19.4\frac{\text{MW}}{\text{GW}_\text{w}}G$. Much of this is compensated by EV charging and V2G supply. After using the EVs for grid balancing, the remaining imbalance is roughly $I \sim 59\text{MW} + 14.5\frac{\text{MW}}{\text{GW}_\text{w}}G$. Since the slope of the post-balancing imbalance is less than that of the initial suggests that even the moderate EV fleet of 1 million retains its effectiveness even for a very high wind penetration. Almost all of the remainder is then borne by pumped storage hydro.

Figure 11 provides the measured relationship between the percentage of

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[1]Is that a single, randomly chosen vehicle unit averaged over a year? or is it the average across all vehicle units for a chosen day (and then divided to make it 'per car'), or is it averaged over all units and over a year?

imbalance met and the number of vehicles providing balancing services. The results are shown for the 14 GW and 25 GW installed wind capacity scenarios. The trends demonstrate that as greater numbers of EVs join the network, the degree of extra balancing that can be met initially increases rapidly but then flattens off. For the 14GW wind power scenario, two million EVs would be able to provide almost 50% of balancing requirements while doubling the EVs to 4 million increases the fraction met to only 60%. At this moderate installed capacity, the added benefit of V2G in terms of balancing potential is very small but at the higher capacity of 25 GW, the benefit of V2G is clearly seen. Without V2G, the same number of EVs struggles to meet the same proportion of demand as at the lower wind penetration but the introduction of V2G increases the percentage of balancing that can be met by a further 10%.

The levelling off of the trends in Figure 11 suggest that it does not prove economical for EVs to partake in balancing under certain recurring circumstances. Figure 12 provides a comparison between the mean daily load profile and the mean daily balancing profiles for a single EV. The system imbalance itself does not show a significant trend according to time of day, with only a very slight reduction coinciding with the daily minimum in demand. Figure 12 shows the periods of the day during which an average EV provides balancing services with V2G enabled. The V2G balancing profile follows roughly the same form as the load profile. Its output is highest during the periods of highest demand, when the system-buy-prices are highest. The positive DM balancing output, which represents the sale of scheduled energy consumption in the Balancing Mechanism, unsurprisingly coincides with the

23

form of charging profile that was provided in Figure 9. When scheduled charging is low, positive DM balancing output also becomes low. Vehicles avoid charging during this period due to the high electricity prices. On the other hand, V2G discharging is able to cover balancing requirements in this period, precisely because of the high prices that occur.

It can be seen that the lowest positive DM balancing output occurs well after the daily peak at around 2200 hours. The reason for this is because the only vehicles that charge during this period require the charging for an imminent journey, and are hence unable to be flexible enough to allow rescheduling. The majority of vehicles do not have an imminent trip during this period, and hence are able to delay their charging until the daily minimum in prices which occurs afterwards during the night. These factors result in the very low positive DM balancing that is achieved during this period.

Negative DM balancing which represents EVs buying extra unscheduled charging within the Balancing Mechanism has a more consistent daily distribution. However, a significant reduction occurs between 0400 and 0900 hours, with next to zero balancing possible at 0700. This occurs simply because the majority of vehicles have fully charged their batteries during the night-time off peak period in expectation of both the approaching higher prices and the daily driving requirements, and are thus unable to take on the extra load.

3.4. Economics of EV participation

The results that are presented in the previous sections represent the outcomes from charging and balancing decisions that have been made on the basis of market prices that are generated within the model. This section

24

provides the results from the assessment of the economic rewards that are attributable to individual vehicles from provision of both demand management and grid balancing.

Demand management is provided by the charging flexibility of individual EVs, which allows them to charge during the lowest demand periods within the charging window that is provided by the vehicle owners. Because low demand coincides with low prices, the reward for such flexibility is cheaper charging for the vehicle owner. DM Balancing services generate revenue by allowing vehicles to either purchase electricity for cheaper than was anticipated thus saving money, or by allowing vehicles to sell the right to consume electricity thus earning money. V2G balancing services generate revenue by selling electricity that is returned to the grid directly from the vehicles batteries.

It is evident therefore, that the revenue generated on behalf of an individual vehicle is a mixture of money saved and money earned. There are no physical costs associated with DM balancing, but the organisation coordinating the service would inevitably require a small payment. V2G balancing does involve both physical costs and energy costs and the model directly calculates the profit that would be gained by each V2G transaction and hence all V2G results that are presented in this section refer directly to money earned. Charging costs presented are derived from model runs with EV balancing disabled to prevent double counting of the savings made.

Figure 13 compares the results of annual profitability per vehicle versus the number of vehicles providing balancing services. The scenario featured shows 25GW of wind power with vehicles providing both DM and V2G bal-

ancing. The two upper lines in Figure 13 present the average annual costs of charging an EV where the higher of the two indicates the standard costs which would be experienced by an EV owner in the present day without the ability to receive or respond to demand-dependent tariffs. The lower line represents the modelled situation whereby vehicles are able to provide demand management by automatically tailoring their charging to varying tariffs. It can be seen from Figure 13 that providing demand management in the manner modelled by the simulation would reduce the charging costs by 1/3 in comparison to any-time charging with a standard fixed electricity tariff. Two curves for the V2G balancing are shown where the lower curve represents the results from the standard participation model and the upper curve presents results for a scenario with high participation vehicles. This represents a minority of 5% of vehicles which follow different behavioural patterns of owners who possess both the means and inclination to ensure that their vehicles are always plugged into the network when they are not being driven. For early adopters of EV technology who exhibit standard behavioural patterns, the annual revenue derived from providing balancing services would exceed £150. This leaves the net cost of using a vehicle for a year at less than £50. For early adopters who exhibit high participation behaviour, the annual balancing revenue could be as much as £400. In this case, the annual charging cost would be exceeded, with a net annual profit of £200. The revenue drops off as further vehicles begin to participate in the balancing market and saturation starts to be seen. With two million vehicles supplying balancing services, revenue drops to 1/3 of the level that was originally available to the early adopters.

26

The manner in which charging costs and balancing rewards change with growing wind power capacity is shown in Figure 14 with a fixed number of 1 million EVs. The figure demonstrates how annual average charging costs fall as the need for using EVs for Demand Management increases. With a fixed number of EVs providing balancing services, balancing revenue is seen to rise, although not as considerably as the rate of growth of energy imbalance that was demonstrated in Figure 10. There is a more appreciable variance between the trend and the data points, which occurs as a result of the combination of the many stochastic features of the simulation. Most significantly, this is due to the growing significance of wind forecasting uncertainty in the simulation. The variance is larger for the for the high participation results, because the results are derived from a far smaller collection of EVs.

4. Discussion and Conclusions

This study has simultaneously assessed the demand side management and the grid balancing potential of EVs in a single simulation. This has enabled the benefits of EV resources to be quantified within the context of growing network intermittency. By simulating one thousand separate vehicle entities, each with individual behavioural and technical constraints, a considerably larger degree of realism has been achieved in comparison to existing studies that have restricted themselves to modelling EV resources as a single entity. Additionally, by also modelling the economic dimensions of EV involvement, the restrictions of real life market behaviour have now been accounted for. Therefore, we can begin to anticipate with greater confidence that the benefits that have long been associated with the introduction of electric vehicles will indeed emerge.

27

The simulation has demonstrated that growing capacities of wind power will increase the variability of the remaining electricity demand profile that must be met by conventional thermal load following generation. This includes both an increase in short term load fluctuations and an increase in the mean daily variation between minimum and maximum load. Additionally, the energy imbalances that must be matched by real-time load corrections will also increase with growing wind power capacity.

By developing a vehicle behaviour model that generates realistic vehicle usage characteristics for individually modelled EV entities, the charging requirements and grid availability characteristics of EV resources have been simulated. An EV charging model that allows individual vehicles to obtain the cheapest electricity within the vehicles available charging window was developed. This has enabled the aggregated effects of large numbers of grid charging vehicles to be assessed.

The model has clearly demonstrated the effectiveness of electric vehicle charging in providing demand management in the UK electricity network and reducing the variability in the national load profile on time scales from fifteen minutes to one day. Even though the simulation was limited to a fifteen minute resolution, there is no reason why the smoothing trend should not continue all the way to the smallest appreciable timescales. It was shown that the introduction of 3 million EVs would reduce the load fluctuation by about a third at all levels of installed wind capacity. One key point is that with a national wind capacity of 37 GW, representing the government's 2020 goal for 30% of electricity from renewables, the daily load variation could be reduced to below 2010 levels with the introduction of 10 million grid charging

EVs as well as stabilising a substantial amount of demand as base load. These two factors suggest that a high level adoption of electric vehicles would allow greater capacities of wind power and nuclear generation to co-exist in our future electricity network, thus facilitating the further decarbonisation of our energy supply.

The grid balancing results have clearly demonstrated the significant potential of EV resources for providing grid balancing services. A clear added to benefit of V2G over DM alone was in the ability to contribute to peak demand whereas DM is only able to effectively smooth fluctuations and utilise low-demand periods effectively. As such, V2G is complementary to DM, rather than simply being a more costly method of achieving the same outcomes. Without V2G capabilities, the effectiveness of EV resources to balance the system is reduced by approximately 10%, which directly reflects the inability to provide balancing during peak periods. However, this relatively small reduction constitutes a balancing revenue loss of approximately 400%. Given that DM balancing would be achievable without the threat of damaging vehicle battery technology, the development of the organisation and technical infrastructure to provide DM balancing capabilities would provide a direct stepping stone for the deployment of V2G in the subsequent future.

The value of the results are reinforced by the fact that all decisions have been based on realistic market conditions as well as the availability, driving requirements and the technical constraints of individual vehicles. As in the case of demand management, all grid balancing actions have been achieved without restricting the residual driving requirements of vehicle owners. It is the combined simulation of driver behaviour, market prices and national

demand that has enabled this conclusion, which would not necessarily have emerged in a more basic model. Individual EV owners using the grid to their own benefit alone will nevertheless provide a service of great value to the electricity network, as individual EVs seeking the cheapest available charging will aggregate to greatly improve grid conditions. However, the provision of good information is the key to the realisation of this modelled outcome. In the present retail market, customers are not supplied with instantaneous tariffs, and therefore do not have the means or the motivation to become involved in such demand-side market participation. In fact, it is not only good information flow about the market side which is important for best use of electric vehicles but also for the actual power quality in the grid. Khayyam et al. [24], for example, found that a smart grid improved voltage stability significantly over standard charging control of plug-in vehicles.

The overall outcomes of the project agree with the majority of existing studies that have settled on positive conclusions regarding the benefits of EV adoption towards both grid conditions and the facilitation of increased intermittent generation. Despite only representing 10% of all balancing actions, V2G is found to constitute 67% of the revenue that has been predicted for vehicle owners from the provision of energy balancing services. The predicted balancing services profitability is relatively modest, with levels for early adopters at £150/year for standard participation and up to £400/year for EV owners who enable especially high grid connectivity. These figures drop to just £40 and £55 respectively with the removal of V2G capabilities. From an economic perspective, there are no existing UK market studies with which to draw comparisons, but the outcomes from US based studies show a

degree of partial agreement. A study by Kempton[10] assessed the potential profitability of EV grid services in the Californian market, estimating that spinning reserve profitability would be between $300 and $720. This is in rough agreement with the £160 to £400 balancing profitability calculated in the model, despite significant differences between the two markets.

The potential rewards themselves do not appear large enough to encourage growth in EV ownership, as other studies have suggested, e.g. [25]. While our study will have underestimated the full benefits of EV grid services, the scale of the benefits is far below what could encourage vehicle adoption from an investment perspective, especially when considering the cost of a new vehicle. What ought to encourage EV adoption, is the low energy costs, which would be even lower with the emergence of instantaneous tariffs, smart charging and larger wind power capacity.

Acknowledgments

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List of Tables

List of Figures

Table 1: Electricity generation capacity for the UK in 2010 (source: [4]). 'Steam' refers to conventional coal fired, oil fired or mixed/dual fuel fired steam station, Gas/CCGT also includes a small contribution from oil engines. Hydro is natural flow hydropower only and PHS shows the pumped hydro storage separately.

Type	Total	Steam	Gas/CCGT	Nuclear	Hydro	Wind	other RE	PHS
at Transmission level								
MW	83,197	32,439	33,769	10,865	1,391	1,776	213	2,744
%	92	36	37	12	1.5	2.0	0.24	3.0
at Distribution level								
MW	7,011	2,757	1,890		133	484	1,747	
%	8	3.1	2.1		0.15	0.54	1.9	

Table 2: Four wind power penetration scenarios investigated. The contribution to electricity generation assumes a capacity factor of 35%.

Installed Capacity (GW)	Contribution	Scenario
4.6	3.7%	Existing installed wind capacity in 2010
14	11%	Near-term prospect with consented capacity
25	20%	Likely 2020 scenario
37	30%	High 2020 scenario
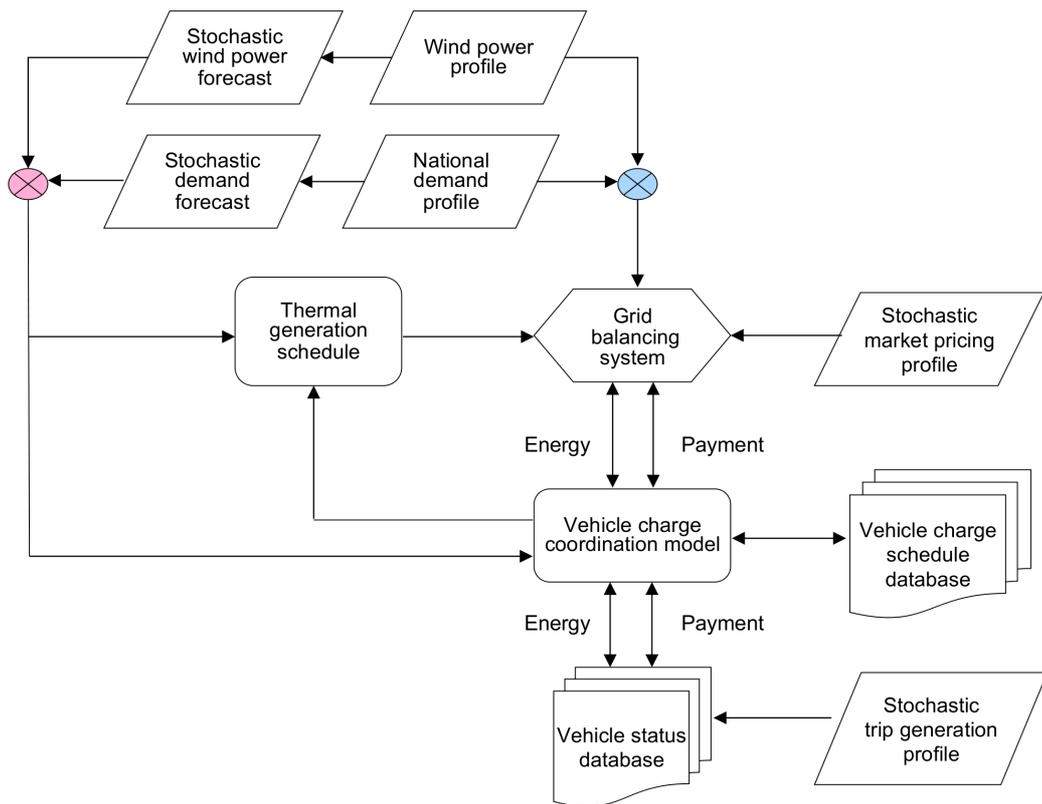
Figure 1: Flow Diagram of the balancing model.
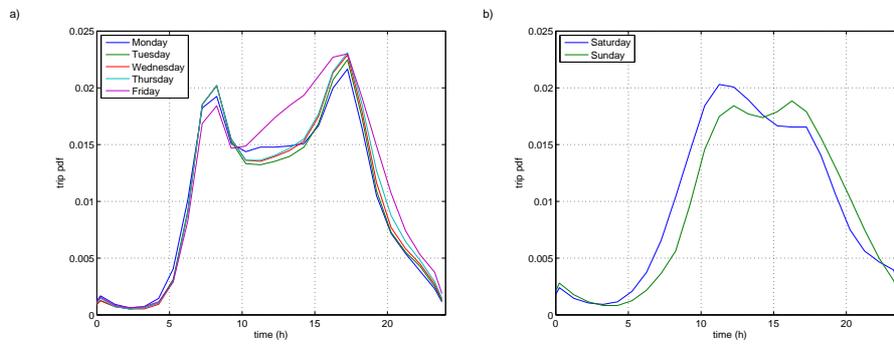
Figure 2: Trip density profiles used to generate the vehicle trips, separated into a) weekdays and b) the weekend.
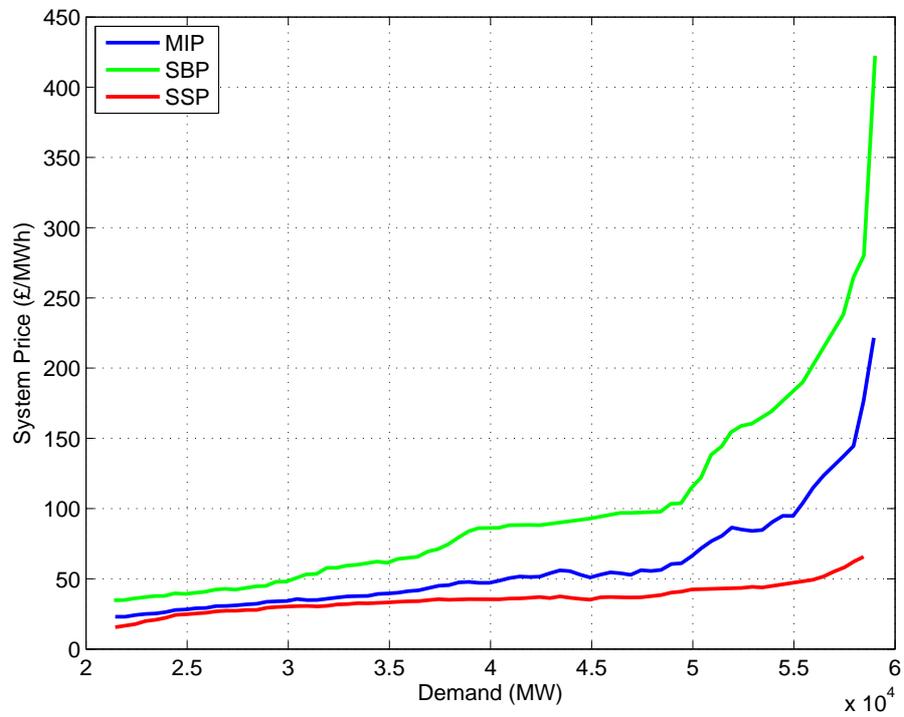
Figure 3: The mean system price profiles of Mean Index Price (MIP), System Buy Price (SBP) and System Sell Price (SSP) versus demand.
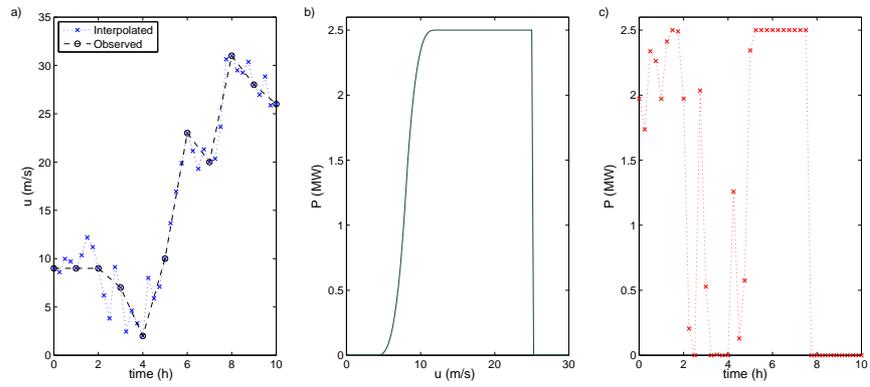
Figure 4: Illustration of calculating wind power generation from hourly wind measurements for a 10-hour section: a) hourly readings, adjusted from 10 m to 100 m as black circles; interpolated values with random perturbations as blue crosses. b) The Nordex N90 performance curve as power output against wind speed. c) The calculated power output at the interpolated times given the interpolated wind speeds and the performance curve.
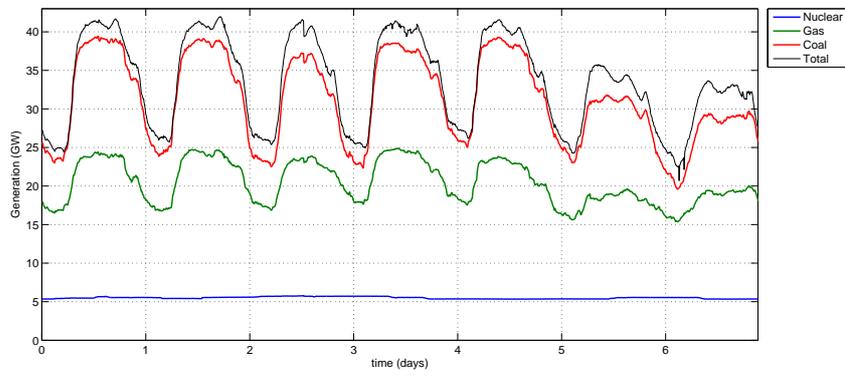
Figure 5: Generation from conventional plant as a stacked plot for nuclear, gas, coal and total generation for a 7-day period in July 2010.
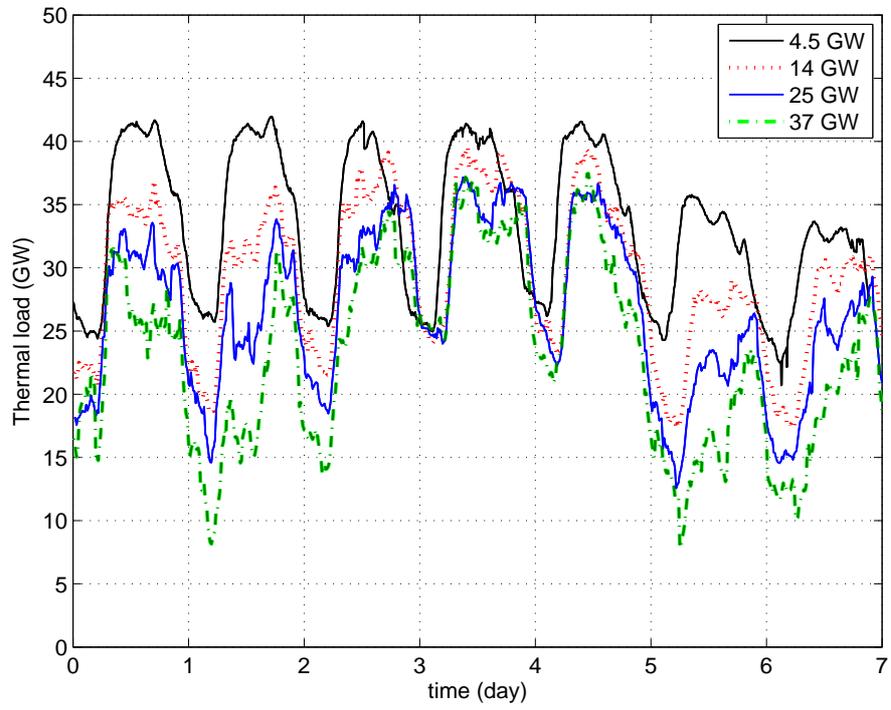
Figure 6: Thermal load without EV deployment for the four different wind generation scenarios.
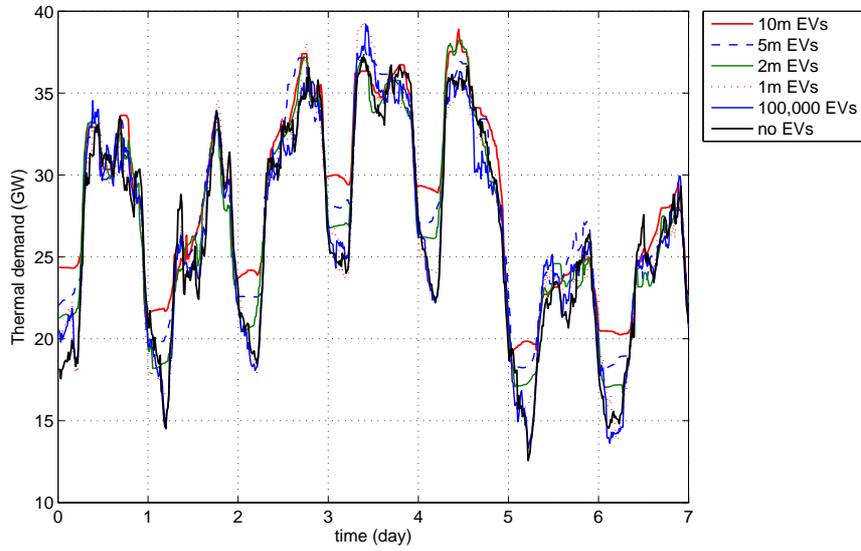
Figure 7: Comparison of load profiles with increasing number of electric vehicles step wise up to 10 million vehicles charging in the network with 14 GW of wind power capacity.
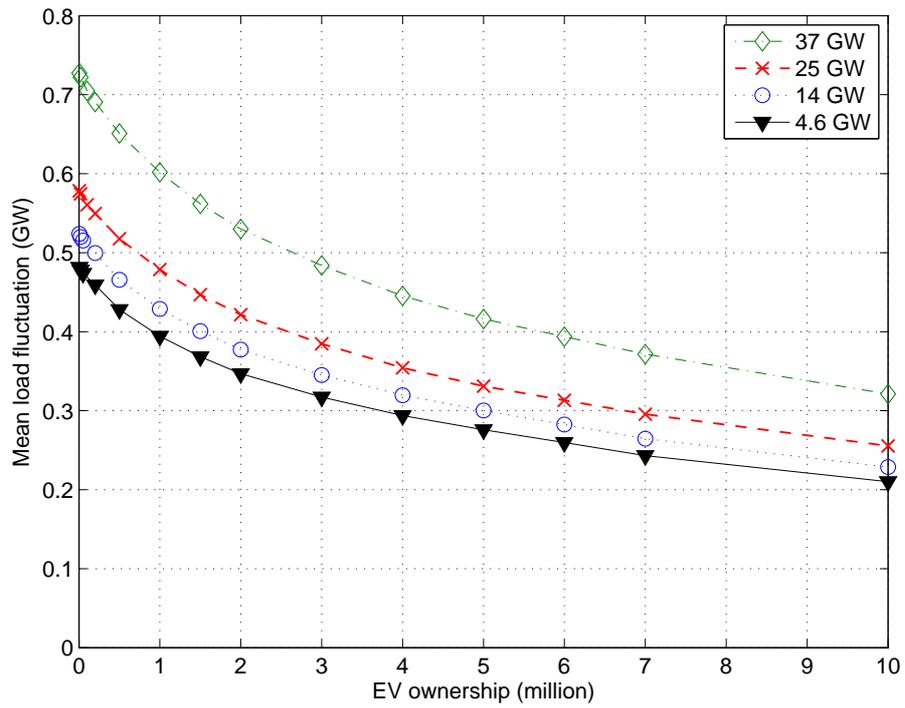
Figure 8: The mean 15 minute load fluctuation versus electric vehicle ownership for different UK wind power capacities.
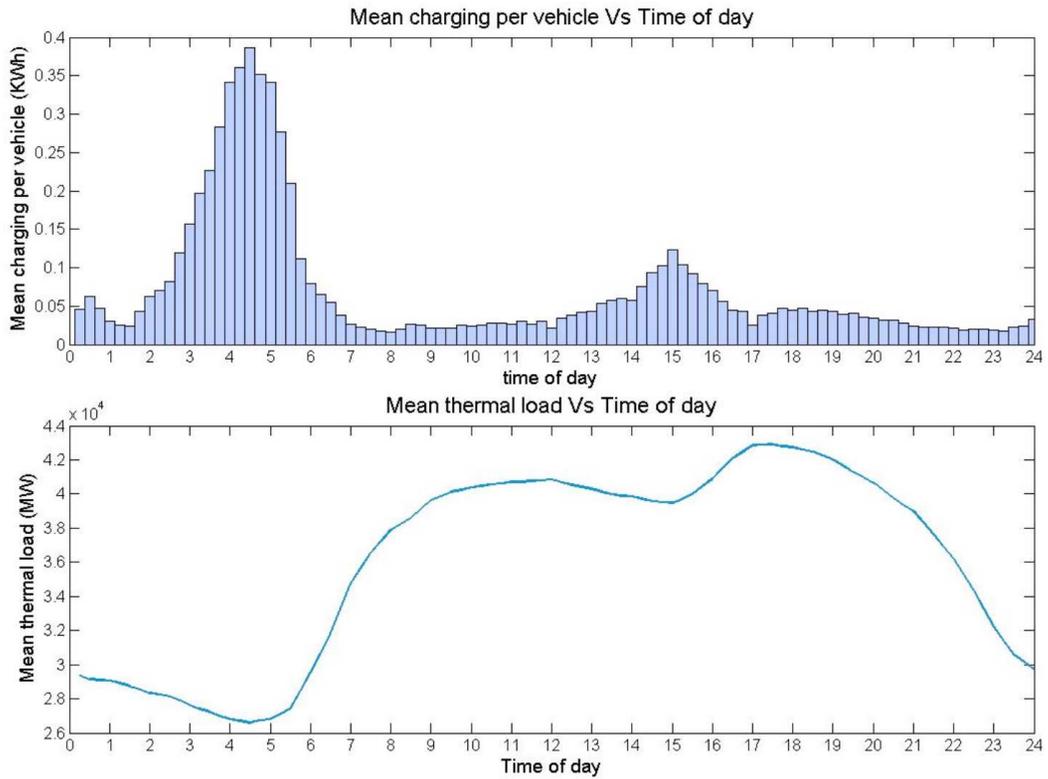
Figure 9: Comparison of the average daily charging distribution for a single vehicle (in 15 minute time bars) versus the average daily load profile with 4.6 GW of network wind power capacity.
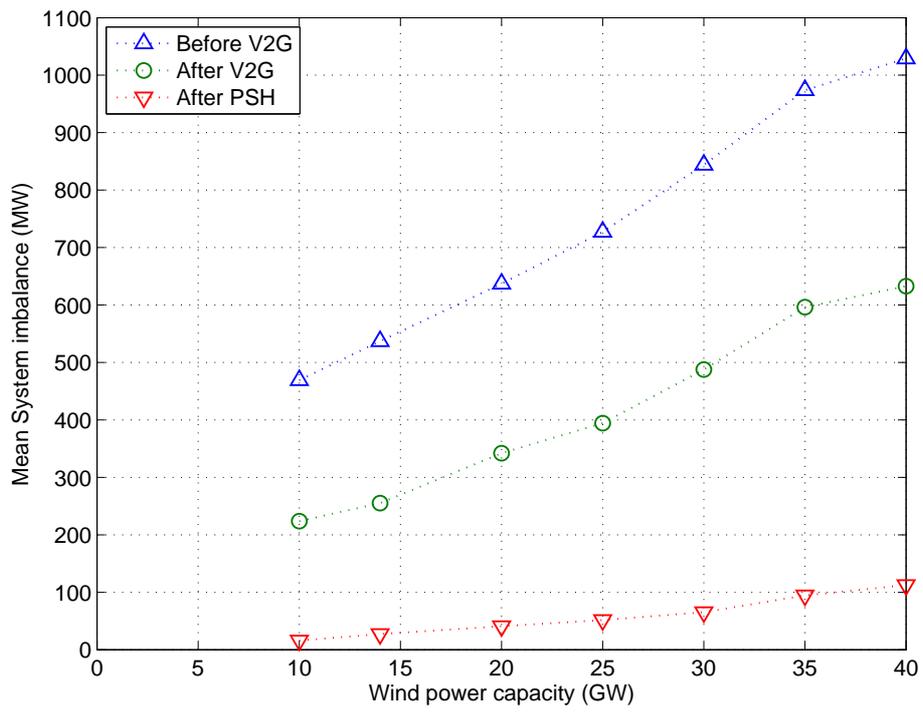
Figure 10: Average system imbalance against installed wind power capacity, before and after vehicle charging and V2G balancing, and the final imbalance after pumped storage hydro.
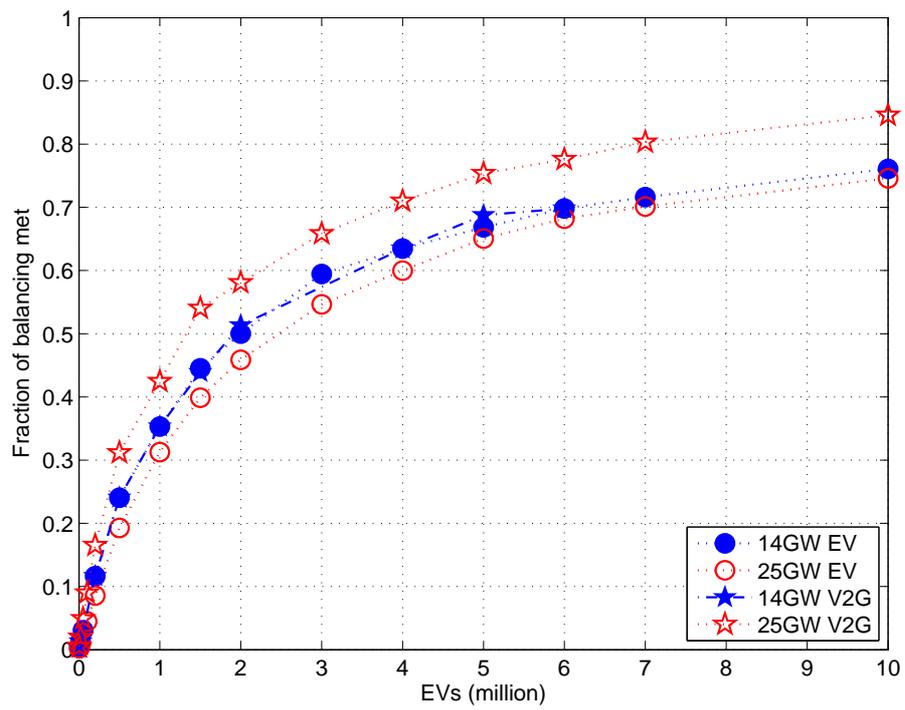
Figure 11: Comparison of the fraction of balancing met versus the number of EVs providing balancing services with V2G disabled or enable for installed wind capacities of 14 GW and 25 GW, respectively.
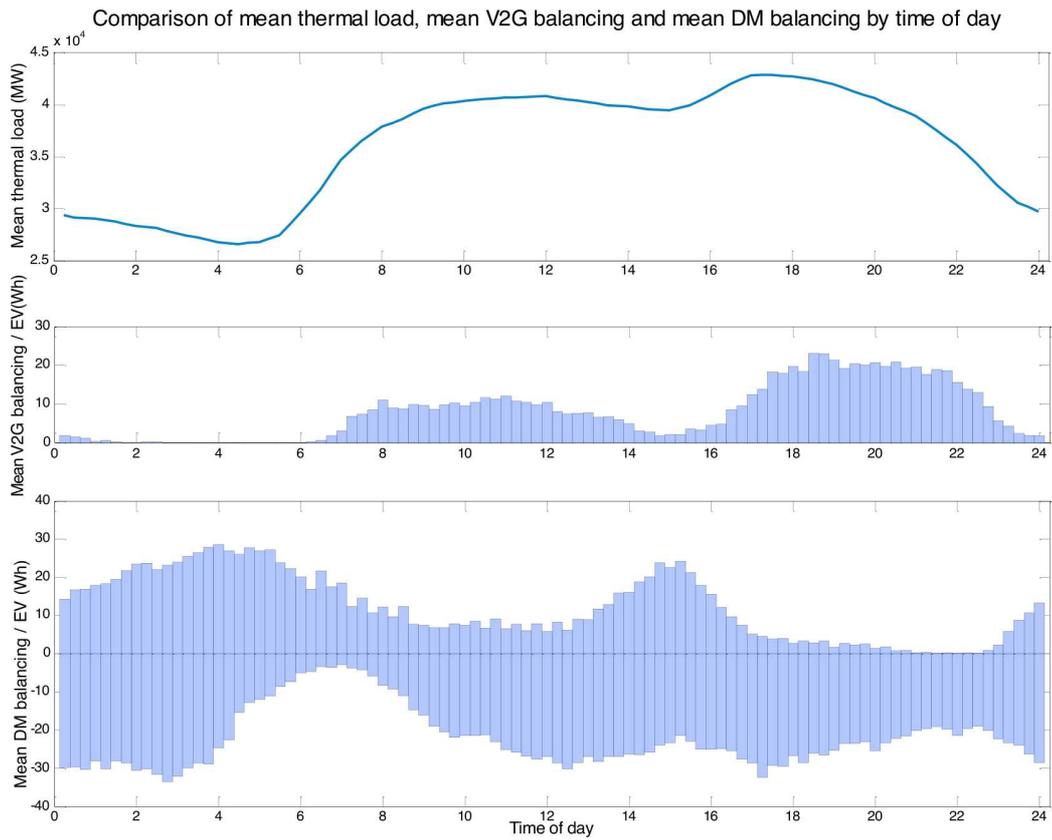
Figure 12: Comparison of the fraction of balancing met versus the number of EVs providing balancing services with V2G disabled or enable for installed wind capacities of 14 GW and 25 GW, respectively.
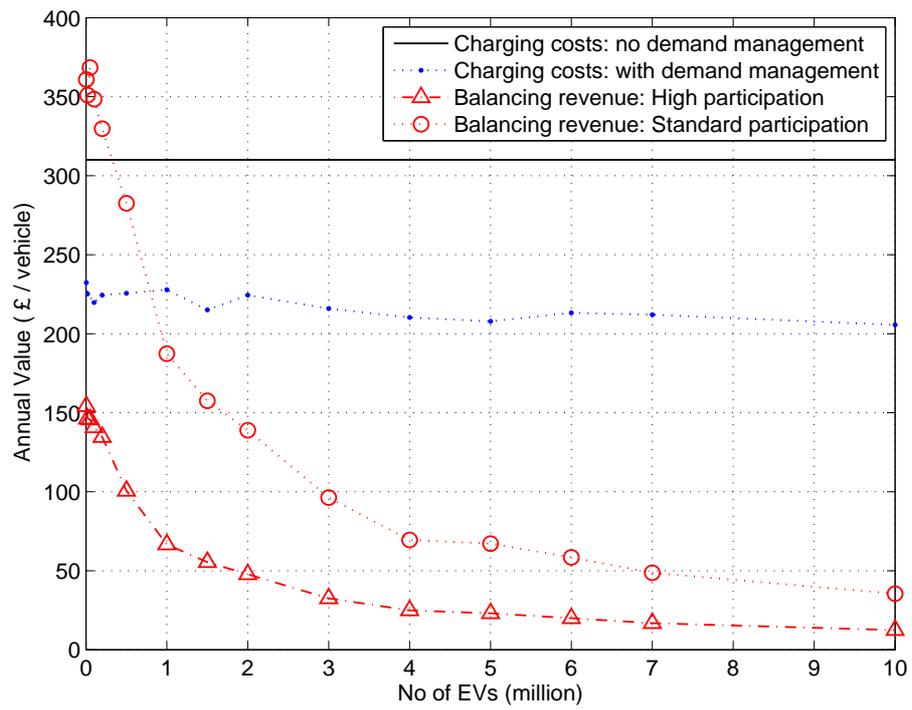
Figure 13: Comparison of the annual revenue generated through balancing and the average annual charging costs for a vehicle versus the number of EVs providing balancing services. Results from the 25GW wind power scenario.
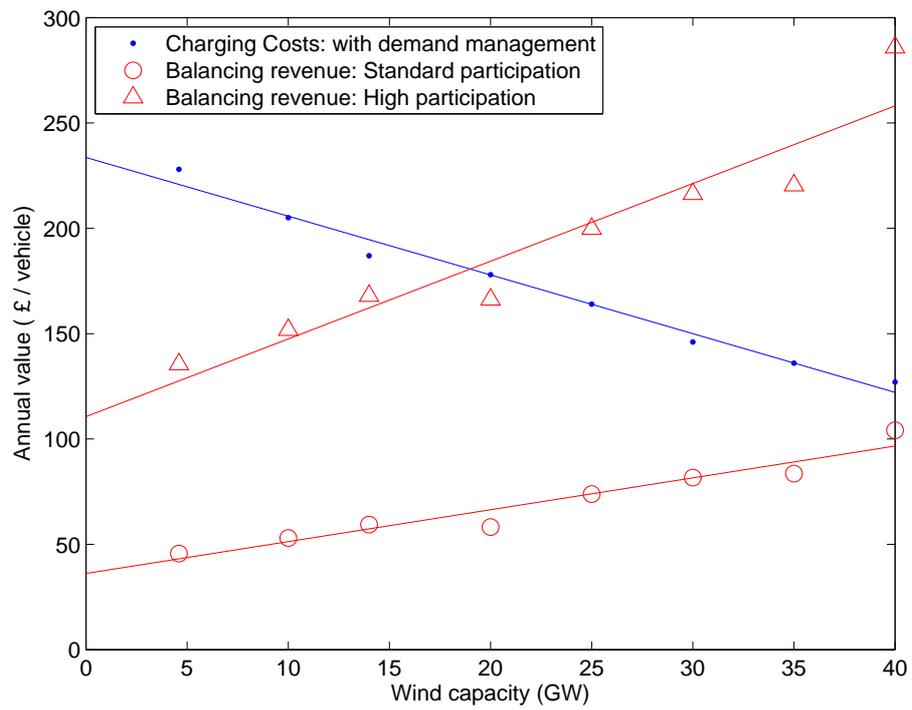
Figure 14: Comparison of the annual revenue generated through balancing and the average annual charging costs for a vehicle versus system wind power capacities between 4.6GW and 40GW. Linear fits are applied. Results are for a fixed participation of 1,000,000 vehicles with V2G enabled.