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Plug-in Electric Vehicles as Demand Response to Absorb Local Wind Generation in Power Distribution Network

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Abstract

It has been forecast that by 2020, the penetration of renewable generation in the UK energy mix will reach approximately 15%, predominantly from wind generation, and that the number of electric vehicles (EVs) deployed is also expected to exceed 1 million. Over the same period it is also forecast that the security of supply of the UK power system will be affected due to the increasing imbalance due to increased demand (from EVs) and uncontrolled supply (i.e. from wind). This paper studies the use of applying smart EV charging strategies to help the power system cope with high penetrations of local renewable generation. Key to this work is the recognition that domestic vehicles are parked for typically 95% of the time, hence these EVs can be utilised as a ready form of responsive demand.

Keywords: load management, smart grid, state of charge

1 Introduction

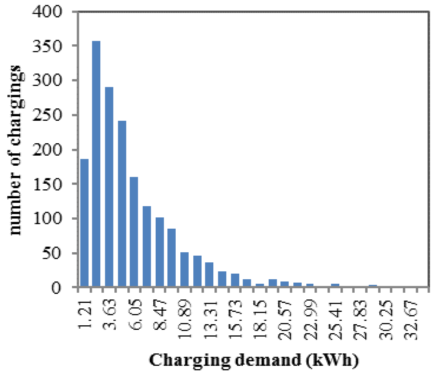
By the year 2020 the Department of Energy and Climate Change (DECC) has forecast that smart meters will be installed in every house in the UK enabled by a £500 million incentive plan created by Ofgem, the UK electricity and gas market regulator, to support smart grid trials carried out by Distribution Network Operators (DNOs), [1]. Mass rollout of smart meters will be the foundation of future smart grid networks and the anticipated outcomes are benefits for both energy consumers as well as DNOs. In this paper smart charging strategies are presented that have been developed based on Monte Carlo modelling of domestic EV use, itself based on extensive data describing UK domestic driving patterns. A specific aim of these strategies is to shift the timing of EV charging in order to absorb the excessive wind generation in the power system. The penetration level of wind generation has been assumed at 15 per cent of the typical day of month for illustration purposes.

2 Whole System Framework Development

Several studies have been undertaken that apply smart charging strategies to enable EVs to support renewable generation in the power system. In [2], Bashash et al discuss how a sliding mode control strategy for grid-connected vehicles was designed to be robust to uncertainties in renewable energy generation. Vlachogiannis presented a new formulation and solution of probabilistic constrained load flow problems, which includes renewable generation, in [3]. Results of the load flow calculation established the first benchmark for the optimal integration of wind power generation with EV integration into the power systems, which is considered within this paper. In the following section, EV charging and wind power profiles are presented and a proposed smart charging strategy for these EVs is illustrated.

2.1 Electric Vehicle Charging Profiles

The electric vehicle charging profiles have been generated by a Monte Carlo model based on data from the Time of Use UK Survey 2000 (TUS) data, [4]. It creates synthesised household vehicle movement based on the statistical distributions of vehicle arrival and distance driven. Charging rates were assumed to be constant powers of 2.88kW or 7.44kW depending on which of two types of common single phase (230V, 50Hz) EV charger is used, either 13A or 32A rated. Figure 1 shows the vehicle charging profiles 100% EV deployment in the system (ie all domestic vehicles are plug-in EVs). For these results, it is further assumed that the charging starts when the EV arrives home; sometimes referred to as ‘dumb’ charging.



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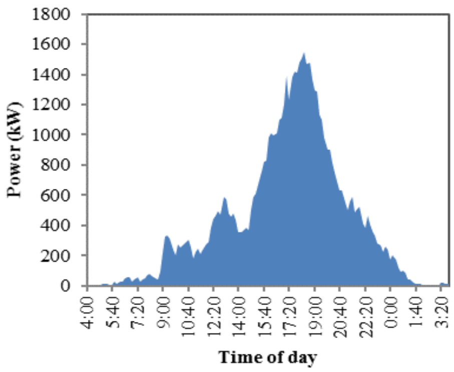

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Figure 1. Electric vehicle charging profiles for 1,262 EVs over 24 hours for 7.44kW charging only. (a) frequency distribution of charging demand, (b) time-series EV charging demand profile assuming charging on return home.

2.2 State-of-Charge of EVs

The state of charge (SOC) is one of the critical parameters to evaluate the battery health status and also the key factor improving the performance of electric vehicle. Knowing the amount of energy left in the battery compared with the energy it had when it was full gives the user an indication of how much longer a battery will continue to perform before it needs recharging. In some cases, the state of charge information can also be obtained by derived from electric vehicles driving distances with known driving patterns. Qian and his colleges have developed a simple yet effective method to derive the SOC information from the driving miles, [5-7]. The simplified state-of-charge (SOC) model consists of two sub element for discharging and charging the battery. The type of battery modelled is lithium-ion battery and its characteristics can be found in [8]. The SOC value can be determined by the formula below:

$$SOC(t_2) = \left(\frac{SOC(t_1)}{100} - \frac{D}{D_{range}}\right) \times 100\%$$

where t_1, t_2 denote the starting time and ending time of a trip, respectively. D is the distance been driven, D_{range} is the range limit of the specific type of electric vehicle, [8]. The state-of-charge simulation results, shown in Figure 2, provide the information of available amount of EV charging load to be shifted and has been calculated assuming vehicles start charging immediately on return to the home (sometimes called dumb charging). The red lines indicate the battery is at its full capacity, and the blue lines imply unknown value for state-of-charge. This is due to the

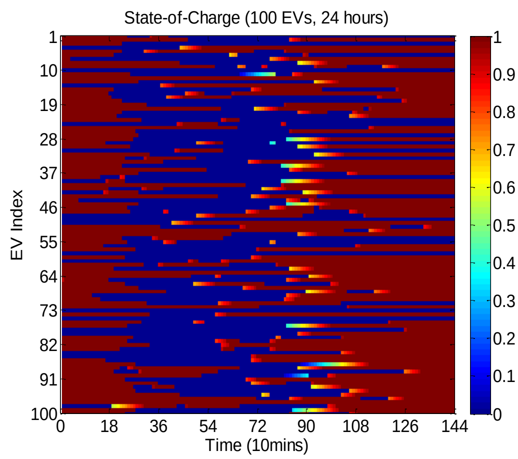
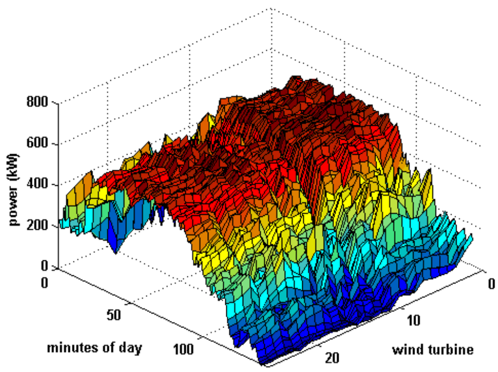


Figure 2. Simulation results of state-of-charge for 100 EVs throughout 24 hours assuming charging on return home.

approach of Monte Carlo modelling, which simulates the vehicle daily driving patterns. The model can calculate the total amount of driving time when the vehicle returns home. As illustrated in the figure, the amount of time required to charge a vehicle battery is significantly shorter than the total vehicle parking period.

2.3 Wind Farm Data

The wind farm data used within this paper has been taken from an operational Scottish Power owned site consisting of 26 Bonus 600kW stall regulated turbines producing a total installed (rated) capacity of approximately 15MW [9]. The instantaneous penetration of the wind generation in the system has been scaled down to represent approximately 2.3MW of locally installed wind capacity. Figure 3 shows the wind generation profiles obtained from April 2005. Most of the turbines produced electricity in one day of April during daytime and the total energy produced is 33.92MWh.



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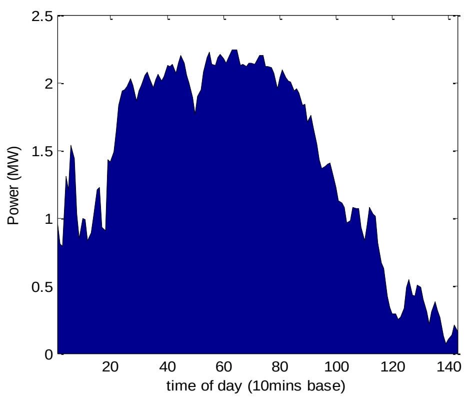

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Figure 3. Wind farm turbines output power for one day in April. (a) Individual wind turbine power generation from the wind farm, (b) Local wind power output through the day.

3 Charging Strategy to Respond to Wind Generation

In this analysis we will assume that there is significant local wind penetration (2.3 MW), so that not all this power is absorbed locally by load, or can be exported due to network constraints. Thus at times of high surplus the local electricity cost will be driven towards zero. It is assumed that a local electricity price signal is available to EV owners and that they individually seek to minimise the their EV charging costs consistent with their daily EV use pattern, and in particular the time parked at home when charging can take place. The wind power surplus has been calculated by deducting the local (non-EV) domestic load for 1,262 households. The aggregate behaviour of the EV owners will thus be as far as possible to absorb wind surplus as shown in Figure 3 for a particular example of wind power availability during the day examined. The patterns of EV use have been generated house by house using an established Monte Carlo model, [10], described in more detail below. The objective of the system as a whole is to enable, as far as possible, for the aggregated electric vehicle charging demand to track the desired wind power surplus trajectory, in this case the measured wind power generation.

3.1 Constructing EV Load profiles

Before, constructing EV load to absorb the surplus wind power, some constraints must be considered which limit the clustering and shifting the EV loads. The charging time $T_{charging}$ of an EV cannot be longer than its parking period $T_{parking}$. A simple linear electricity price function is assumed that gives the cost of vehicle charging as a function of

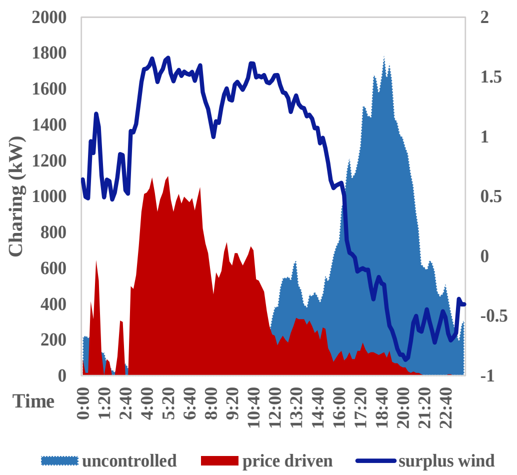

Figure 3. Applied strategy for electric vehicle charging as leveraged by surplus-wind price.

the surplus wind power in the local power system.

$$C(P_{wind}) = \begin{cases} 0 & P_{wind} > 1 \\ -13.84 * P_{wind} + 13.84 & 0 < P_{wind} < 1 \\ 13.84 & P_{wind} < 0 \end{cases}$$

where P_{wind} is the surplus wind in the system. Where the wind surplus exceeds 1 MW, the cost of local electricity is assumed to be zero reflecting power export constraints. In these cases vehicle users can charge their EVs at no cost; however, when there is no surplus wind locally, the electricity price is fixed at the standard charge rate for domestic consumers. The charging cost varies for users only when there is less than 1 MW surplus wind in the system.

Depending on the duration of vehicle charging, a previous continuous charging event will now potentially be broken down into several small charging events in order to achieve the most cost effective way to charging the vehicle as well as to satisfy vehicle user's next journey requirement. As results of the cost model used for the example considered, the cost of charging is free as long as the surplus wind power is greater than 1 MW. After each individual vehicle charging calculation, the absorbed surplus wind and electricity price is recalculated. Results indicate that for the example day, vehicle charging absorbed 42% of surplus wind and the average charging cost per house per day reduces from 13.84 pence per units down to 2.08 pence per units.

4 Conclusions

This paper presents the capability of utilising electric vehicle charging to regulate surplus wind power by implementing an electricity price function. Synthesised electric vehicle charging profiles are generated by the Monte Carlo model and state-of-charge (SOC) information is derived from these charging profiles. Real-world wind farm power output monitoring data are used to create a realistic example daily electricity cost function. For users charging their electric vehicles at minimum cost, the cost function shifts charging to the cheapest electricity time consistent with the EV being parked at home, and thus absorbs as much surplus wind as possible. This enables the power distribution network operators to benefit from the reduced curtailment of wind and for the users, identifies the cheapest way to charge vehicle batteries. In this example day, the cost savings to the consumer associated with EV charging is considerable.

Acknowledgments

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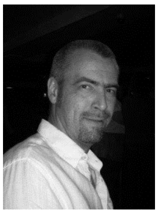
Andrew Cruden is Professor of Energy Technology within the Faculty of Engineering and Environment at the University of Southampton. Previously he was a Reader within the Renewable Technology Group at Strathclyde. His current research interests are: vehicle-to-grid energy storage of aggregated electric vehicles; wind turbine condition monitoring; continuously variable transmissions for electric vehicles using magnetic gears.


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David Densley is the Head of Sustainable Transport at SSE plc. David studied electrical engineering at Cambridge University and his current role involves understanding the impact of electric vehicles on the electricity network and the provision and standardisation of EV charging infrastructure.