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Modelling charging profiles of electric vehicles based on real-world electric vehicle charging data

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ABSTRACT

This paper uses a stochastic simulation methodology to generate a schedule of daily travel and charging profiles for a population of electric vehicles with GPS travel data collected during an electric vehicle demonstration trial. The dependence structure between six variables is modelled using a non-parametric copula function. Then an iterative method of conditional distributions with a Bayesian inference is used to generate travel patterns that comply with the uncertainty of the inputs. At each destination a probabilistic charging model is used to translate the travel patterns of the electric vehicles (EVs) into the respective power demand of the vehicles. These synthetic datasets capture the degree of uncertainty of the travel and charging behaviour of EVs (contrary to single realisations) and are scalable to different EV populations (allowing uncertainty reduction effects in large populations). Such charging profiles would be useful to electric vehicle grid integration studies such as aggregated power demand, power systems services and charging optimisation analyses.

1. Introduction

Electric vehicles (EVs) coupled with low carbon electricity, have the potential to contribute to climate change mitigation. The literature demonstrates that EVs have the potential to reduce greenhouse gas (GHG) emissions in several countries. Orsi, Muratori, Rocco, Colombo, and Rizzoni (2016) proposed an energy-based well-to-wheels analysis and analysed different fuel types for Brazil, China, France, Italy and the United States, finding that low-carbon electricity mix electric vehicles reach almost-zero CO_2 emissions. They produce less effective CO_2 per kilometre (i.e. including CO_2 emitted from electricity generation) travelled and produce no local pollution such as PM_{10} and NO_2. Even in dirty power systems, if a power system has enough efficient natural gas-fired generating capacity (or any other technology with low emissions rates) to serve the PHEV charging loads, PHEVs could be cost-effectively accommodated without a net increase in emissions (Sioshansi & Miller, 2011).

EVs are a sustainable alternative to internal combustion engine vehicles (ICEVs), provided that the energy used for charging is generated by renewable sources or low carbon fuels. However, electricity generation from renewable sources is dependent on weather conditions in the case of wind energy and as a consequence there is a high degree of variability in power generation. In the absence of large-scale energy storage technology, electricity must be consumed at the time of generation. In the case of wind energy, there is less flexibility to produce additional power, if weather conditions do not permit. Weldon, Morrissey, Brady, and O'Mahony (2016) and Weldon, Morrissey, and O'Mahony (2016) showed that the environmental impacts of EVs are highly influenced by the charging behaviours of individual users, and night-time charging was found to produce the largest environmental impact as a result of grid management decisions. Li et al. (2016) studied electric vehicle deployment in China and found that controlled charging results in more CO_2 emissions associated with EVs than uncontrolled charging, as it tends to feed EVs with electricity produced by cheap yet low-efficiency coal power plants located in regions where coal prices are low. In addition, in times of low demand and high availability of renewable electricity the full economic benefits of renewable energy may not be achieved. Ghasemi et al. (2016) proposes an optimised framework to use the potential of EVs and battery energy storage to manage the possible imbalance in wind farms.

System operators are responsible for managing power system services and are constantly matching supply with demand. It is generally accepted that the charging of a large population of EVs

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will have two major effects on the grid; it will increase the overall power load needed and it will increase the load on local distribution networks. For example, Morrissey et al. (2016) found that electric vehicle users prefer to charge at home in the evening at peak electricity demand times. Either of these effects could become the limiting factor but it is believed that the local load distribution problems will become prevalent sooner than the more general overall power supply issue (Clement-Nyns, Haesen, & Driesen, 2010; Denholm & Short, 2006; Duvall, Knipping, & Alexander, 2007; Liu, Dow, & Liu, 2011). However, the uncontrolled charging of a large population of EVs could increase peak demand substantially. Babrowski, Heinrichs, Jochem, and Fichtner (2016) identified a large potential for load shifting through controlled charging. Neaimeh et al. (2016) demonstrated the spatial and temporal diversity of EV charging demand to reduce the estimated impacts on the distribution networks. Peaking at certain times of the day has been observed by EV users in a number of EV trials (Robinson, Blythe, Bell, Hubner, & Hill, 2013; Weldon, Morrissey, Brady, & O'Mahony, 2016; Weldon, Morrissey, & O'Mahony, 2016). System operators must largely rely on conventional generators (fossil fuels) to meet this demand. This would reduce the potential GHG reduction benefits. Moreover, increases in the peak demand could require transmission capacity expansion. To mitigate these concerns, controlled charging of EVs may need to be implemented. Yagcitekin and Uzunoglu (2016) proposed a smart charging management algorithm strategy that successfully routes electric vehicles to the most suitable charging point, decreases the charging costs and prevents the overloading of transformers.

In order to support policy decisions, the impacts of EVs on the power system needs to be evaluated. In order to achieve this, reliable models capable of translating the travel patterns of a large population of EVs into the respective power demand are needed. The complexity and stochastic nature of travel patterns point to a stochastic model to satisfactorily model travel patterns. The effect of the large-scale integration of EVs into the power grid has been studied in several papers (Coelho et al., 2016; Dallinger, Krampe, & Wietschel, 2011; Di, Aliprantis, & Gkritza, 2011; Kristoffersen, Capion, & Meibom, 2011; Lojowska, Kurowicka, Papaefthymiou, & Van Der Sluis, 2012). Issues such as peak load, network losses and cost minimisation have been analysed, as well as the impacts on emissions (Rangaraju, De Vroey, Messagie, Mertens, & van Mierlo, 2015). However, the majority of the early studies have used a deterministic approach to model travel patterns, using collected data directly or expected values and averages (Di et al., 2011; Mullan, Harries, Bräunl, & Whitely, 2011; Weiller, 2011). This approach fails to capture the stochastic nature of travel behaviour. Observed vehicle travel patterns have been reported in many studies (Golob & Gould, 1998). Stochastic modelling of driving patterns has received more attention recently (Green, Lingfeng, & Alam, 2010). Muratori et al. (2013) proposed a large-scale stochastic model of driving patterns based on user behaviour. Their model enables evaluation of the impact of plug-in electric vehicles on the electric grid especially at the distribution level and it can be used as a tool to compare different vehicle types. Muratori and Rizzoni (2016) used the model to estimate residential demand using a novel bottom-up approach that quantifies consumer energy use behaviour, providing an accurate estimation of the actual amount of controllable resources.

Widén and Wäckelgard (2010) used a model to generate both synthetic activity sequences of individual household members, including occupancy rates, and domestic electricity demand based on these patterns. McKenna and Thomson (2016) developed a high-resolution stochastic model that can model domestic energy demands within the broader field of urban energy systems analysis. Arghira, Hawarah, Ploix, and Jacomino (2012) used a predictive model to estimate the energy consumption of appliances in homes using a full year of data for 100 households in France. Xydas et al. (2016) developed a fuzzy based model to estimate the potential relative risk level of EVs charging demand among different geographical areas independent of their actual corresponding distribution networks. Paterakis and Gibescu (2016) developed a methodology to derive power profiles for EV parking lots so that different operational strategies may be used in order to achieve operational or economic benefits from the perspective of the EV parking lot owner.

Lojowska et al. (2012) used a travel survey dataset relating to ICEs to model the power demands of EVs in the Netherlands under the scenario of uncontrolled domestic charging. The travel patterns of the EVs were modelled using three variables: the time a vehicle departs home, the time a vehicle arrives home and the overall distance travelled during the day. The dependence structure between the variables was modelled using a normal copula function. The load due to EVs was computed based on the combination of simulated commuting patterns with the charging profile of a typical EV battery. The model focused on journeys to and from the home (i.e. it excluded intermediate journeys) and assumed that the vehicles began charging immediately upon arrival home.

The work presented here builds on the work of Lojowska et al. (2012) by using data downloaded from EVs on the driving patterns of users in the model development, it includes travel throughout the entire day, in addition to only trips starting and ending at the home, and the work assesses the accuracy of the model against real world data. The novel aspects of the work presented in this paper include the use of real EV data to inform the modelling process and the focus at trip level; a level that is more useful for grid managers. An additional novel aspect to try to better replicate real world behaviour is the use of conditional probabilities of a number of variables, state of charge (SOC), parking time and trip number, to determine whether an EV will be charged after a trip or not. By its stochastic nature it offers a more realistic degree of variability that improves on average behavioural assumptions made in previous work.

2. Background

There are generally two ways in which to investigate the travel patterns and charging behaviour of a large population of EVs. One method would be to conduct a large scale EV trial and to use the results from that trial to inform and deduce charging patterns and power demand predictions. The second method would be to model a fleet of EVs and to use the results of the model as an indication of the power demands of the EVs.

For the second method, ideally a micro-simulation package combined with a charging decision algorithm would be used to achieve this. However, given the number of vehicles (e.g. 200,000) and the size of the area of interest it would be computationally intensive to model and predict charging patterns through direct simulation on an individual basis (Hill, Blythe, & Higgins, 2012). In addition, currently no charging decision algorithm exists in literature, although research is being conducted in the area (Axsen & Kurani, 2010). Another option would be to scale the data collected in a large scale trial of EVs. However, these data could only be used to model the circumstances in which the data was collected and the explanatory power of the data would be limited to the fleet composition for which the data exists.

A stochastic model would be computationally less intensive than micro-simulation and would have more predictive power than just the use of historic data. In addition, as outlined in the introduction, driving patterns are stochastic in nature and as a consequence, the power demand of EVs should inherit this randomness. Recently several studies have examined the effect of EVs on power system demand and their ability to provide power system services.