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Controlled Charging of Electric Vehicles to Minimize Energy Losses in Distribution Systems

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Abstract: Controlled electric vehicle (EV) charging scenarios are proposed, each characterized with an algorithm and associated computational and communication requirements, to be adopted by an EV aggregator or system operator. The proposed scenarios include uniform, random, conditional-random, and valley-filling charging scenarios. Different from previous studies, this paper focuses on easy-to-implement charging scenarios. Further, a modeling framework is presented to investigate the impact of the proposed charging scenarios on energy losses in distribution systems, as compared to an uncontrolled charging scenario and a reference scenario with no EVs. The modeling framework considers uncertainties involved in the behavior of low voltage customers and EV charging loads. It is applied to a distribution system for various case studies, including different penetrations and combinations of EVs with various characteristics. As seen by the results, although the valley-filling charging algorithm represents the optimal solution from the perspective of energy losses, the uniform charging scenario emerges as a quasi-optimal solution, having lower computational and communication requirements, which makes it easier to be adopted by EV aggregators or system operators. Further, with appropriately selected coefficients, the conditional-random charging algorithm can also exhibit a performance comparable to that of the uniform charging algorithm.

Keywords: Distribution System, Electric Vehicle, Controlled Charging, Power System Operation, Smart Grids

1. INTRODUCTION

Electric vehicle (EV) technology is seen as a key component to reduce carbon emissions within the transport sector. As a result, many automotive manufacturers have begun to place an increased emphasis on the development of EVs, including pure battery electric vehicles (BEVs), and plug-in hybrid electric vehicles (PHEVs). The batteries of both technologies can be charged from domestic electrical sockets (Richardson *et al.* 2012), demanding a significant amount of electrical energy, which may adversely impact power distribution systems (Clement *et al.* 2010). Investigation into these impacts is one of the main priorities for system operators to develop controlled charging algorithms that minimize system operational costs in the presence of high penetrations of EVs.

Much effort has been devoted in the literature to investigating the adverse impacts of EVs on power systems. While some studies, such as those presented in Denholm and Short (2006) and Ramos *et al.* (2008) assessed the effects of EVs on the generation and transmission sectors, most works have focused on distribution systems. In Richardson *et al.* (2010), an analysis is performed on the voltage profiles and loading levels of distribution system components in the presence of EVs. It was shown that even for modest numbers of EVs, both factors may exceed safe operating limits. The impact of charging EVs on distribution transformers was also examined in Shao *et al.* (2009), where it was shown that in the presence of EVs, new load peaks were created that might exceed the available transformer capacity. Several charging profiles were analysed to prevent EVs from causing harmful new daily peaks. A large-scale distribution planning model was developed in Fernandez *et al.* (2011) to evaluate the impact of various penetration levels of EVs on system investments. These studies suggested that distribution systems can accommodate higher penetrations of EVs, if the EVs are intelligently charged during off-peak hours. This result was further analysed in a number of studies that aimed at proposing methodologies for controlled charging of EVs to optimize utility-side objectives, e.g. minimizing load variance (Gan *et al.* 2013; Karfopoulos *et al.* 2015; Tang *et al.* 2014), energy losses (Sortomme *et al.* 2011), and voltage deviations (Wu *et al.* 2011), EV aggregator and EV owner objectives, e.g. maximizing aggregator profit (Geng *et al.* 2013; Jin *et al.* 2013; Momber *et al.* 2015), and minimizing EV charging cost (He *et al.* 2013), respectively. A general conclusion from the reviewed studies is that from the perspectives of the utility, the aggregator, and EV owner, the optimal charge scheduling algorithm minimizes the load variance, tracks the required electricity profile in the day-ahead market, and charges the vehicle at times with the lowest electricity price, respectively.

Despite the high level of attention that has focused on identifying and minimizing the adverse impacts of charging EVs, the authors believe substantial study is still needed to

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compare easy-to-implement controlled charging algorithms, and to investigate the impacts that such algorithms may have on distribution system operation, especially from the perspective of reducing energy losses. In this context, this paper brings two main contributions to the literature. First, a modeling approach is proposed to investigate the impact of charging EVs on energy losses. The proposed approach considers the uncertainty in the characteristics of EV models based on data from their manufacturers. It simulates EV charging using the characteristics of battery packages used in the vehicles. Further, regardless of the previously used assumption of fully discharged EVs at plug-in time, EV decharging is modelled based on daily travelled distance for the vehicles. Secondly, this paper proposes and compares several charging scenarios, including uniform, random, conditional-random and valley-filling scenarios, each characterized with an algorithm and its associated computational and communication requirements to be adopted by an EV aggregator or system operator. The results are analysed and compared with those from uncontrolled charging and a reference scenario with no EVs. The remainder of this paper is organized as follows: Section 2 presents our modeling approach. Section 3 discusses the proposed charging algorithms and associated methods to calculate energy losses in the presence of EVs. Simulation results are presented in Section 4, and conclusions are given in Section 5.

2. EV CHARGING AND CUSTOMER LOAD MODELING

A distribution system with *N* customers is considered. The electrical load of the customers was modelled based on typical load data containing 15-min time-series electricity demand for high, medium and low use customers over various seasons across a one year period (Real Market Design Service 2015). Different demand profiles were randomly assigned to each of the customers of the distribution system based on the method presented in Richardson *et al.* (2010).

Assuming a maximum of one EV per house, each customer may have an EV or not. EV penetration is defined as the number of customers with an EV relative to the total number of customers. Thus, the maximum number of EVs, corresponding to 100% EV penetration, is equal to *N*. However, in real cases, the EV penetration may be anywhere from 0 to 100%. For any given EV penetration, the EV owners were assigned by a random sequence of *k* integers, representing the customer number with an EV. The EV characteristics were considered based on four EV models, including two BEVs: Mitsubishi i-MiEV (Hosokawa *et al.*, 2008) (BEV1) and Nissan Leaf (Yoshioka, 2011) (BEV2), as well as two PHEVs: Toyota Prius (Yoda, 2010) (PHEV1) and Chevrolet Volt (Chevrolet Volt Battery, 2015) (PHEV2). Table 1 shows the characteristics of the vehicles. In this table, V_{Nom} and C_{Nom} are the nominal voltage and capacity of the battery, respectively, and α is a sensitivity parameter between the state of charge and open circuit voltage of the battery.

It was assumed that the EVs are charged during the night-time charging period, e.g. from 22:00 to 06:00, and this is regardless of the EV arrival time. This assumption requires that an adjustable start delay should be applied for EVs that arrive before the charging period starts. The EVs were assumed to be charged from their arrival state of charge, SOC_a, towards the departure state of charge, SOC_d, under level 2 of the SAE J1772 standard with a maximum rate of 6.6 kW during consecutive 15-min intervals, based on the proposed charging algorithms. The energy required for charging an EV is calculated by Eq. (1) [see Ota *et al.* (2012) for details].

Table 1. Characteristics of Battery Models

Model/ Characteristics	BEV1	BEV2	PHEV1	PHEV2
Voltage (V_{Nom}) [V]	325.6	364.8	345.6	334.7
Capacity (C_{Nom}) [Ah]	50	66.2	15	47.8
Energy Capacity [kWh]	16.28	24.15	5.2	16
Sensitivity Parameter (α)	15	15	15	15
Electrical Range (km)	130	160	23	64

$$\begin{aligned} E_{Charge} = & V_{nom}(SOC_d - SOC_a) \\ & + \alpha C_{Nom} ln\left(\frac{C_{Nom} - SOC_d}{C_{Nom} - SOC_a}\right) \\ & + \alpha SOC_d ln\left(\frac{SOC_d}{C_{Nom} - SOC_d}\right) \\ & - \alpha SOC_a ln\left(\frac{SOC_a}{C_{Nom} - SOC_a}\right) \end{aligned} \quad (1)$$

where, α, V_{nom} and C_{Nom} are the characteristics of each EV, as defined in Table 1. It is also assumed that the EVs are to be fully charged when the charging period ends. The arrival state of charge is obtained for each EV using Eq. (2).

$$SOC_a = SOC_d - \frac{DTD}{ER} \times C_{Nom} \quad (2)$$

where, ER and DTD are the electrical range and daily travel distance of the EV, respectively. While the electrical range is considered based on Table 1, the daily travel distance is modelled based on data provided in Table 2, which is an extract of historical data from Commuting in Ireland (2015). Although the data from Table 2 is valid for vehicles with internal combustion engines, the driving habits of the EV owners are assumed to be similar.

Table 2. Statistics of Daily Travel Distance

Distance	Probability
< 5 km	0.10
5 – 10 km	0.19
10 – 20 km	0.19
20 – 30 km	0.14
30 – 50 km	0.17
50 – 70 km	0.06
70 –100 km	0.08
> 100 km	0.07

Three cases were studied, each representing a certain share of BEVs and PHEVs among the EV fleet. The first case considers 50% share for both BEVs and PHEVs, while the other cases assume only the presence of BEVs or PHEVs. In each case, the battery characteristic and the daily travel