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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

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

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 distance of each EV are randomly selected respectively from Tables 1 and 2. The daily travel distance is multiplied by 1.2 in winter to account for the air conditioning load. The arrival state of charge and the charging energy required by each EV is calculated by Eqs. (1) and (2). Next, the required charging energy is allocated to each EV for particular 15-min intervals based on the proposed charging scenarios of Section 3. Load flow is carried out in DIgSILENT Power Factory and the EV charging load (if any) is added to each customer load during 15-min intervals, if all the voltage and line limits are respected. The voltage limits ensure that the bus voltages are within the normal operating range of 0.95 to 1.05 p.u. and the line limits prevent overloading line sections and transformers. Finally, the energy loss is calculated by writing a script in DIgSILENT Power Factory to sum up the power losses of all line sections over the entire 15-min intervals of the examined day.

3. ENERGY LOSSES IN THE PRESENCE OF PROPOSED EV CHARGING SCENARIOS

Five scenarios are studied, each characterized with a charging algorithm, along with a reference scenario with no EVs. The proposed scenarios consider a centralized charging structure and are based on uncontrolled, random, conditional random, uniform and valley-filling charging algorithms. Of these, the uncontrolled scenario corresponds to a situation where there are no smart meters available to control EV charging, while the other scenarios are based on the assumption that each household is equipped with a smart meter with load control capability, utilized remotely by an EV aggregator, or system operator, to control EV charging over 15-min intervals. Scenarios 1 and 2 have no communication burden, while scenarios 3-6 require a communication link between the EVs and an aggregator or system operator. The scenarios are summarised as follows.

Scenario 1- Reference scenario

For each 15-min interval of a typical day, customer loads are obtained from the database, a load flow calculation is performed, and the energy losses are calculated. No network violations are considered.

Scenario 2- Uncontrolled charging scenario

Uncontrolled charging of EVs is applied during the charging period. It is assumed that EVs are charged at their maximum charging rate starting at 10 p.m. until they are fully charged. No voltage and line limits are considered. The energy loss is calculated based on the following procedure.

Step 1) For each charging interval k, retrieve customer loads across the typical days.

Step 2) Obtain arrival state of charge, SOC_a, for each EV, and calculate the required energy, $E_{Required}$, to charge each EV.

Step 3) Calculate the charging time, $t_{Required} = E_{Required}/CR_{Max}$, where CR_{Max} is the maximum charging rate;

Step 4) Allocate charging energy $E_{Charging} = 0.25 \times CR_{Max}$ to the EV during each 15-min interval k, if $k \le 4 \times t_{Required}$;

Step 5) Repeat steps 2-4 for all EVs to obtain the charging loads;

Step 6) For each charging interval k, perform load flow calculation, and obtain the energy loss.

Scenario 3- Random charging scenario

EVs are charged at their maximum charging rate across random 15-min charging intervals selected by a central controller. The logic behind the random selection of the charging intervals is to reduce computational burden when the algorithm is adopted by an EV aggregator or system operator in real time. Steps 1-2 and 5-6 remain unchanged with respect to the uncontrolled charging scenario. Steps 3 and 4 are modified as follows.

Step 3) Initialise the charged energy, $E_{Charged} = 0$ for each EV.

Step 4) While ($E_{Charged} < E_{Required}$), generate an integer k, $k \in \{1, \ldots, N_{ITV}\}$; to represent the interval when the EV is charged. N_{ITV} is the total number of 15-min intervals of the charging period. Allocate charging energy $0.25 \times CR_{Max}$ to the EV during interval k. Perform load flow calculation. Update $E_{Charged}$ if the voltage and line limits are respected, otherwise, remove interval k from the list of possible charging intervals and repeat this step.

Scenario 4- Conditional random charging scenario

The random charging algorithm may charge EVs during peak hours, resulting in an increase in energy losses, if no voltage and line limits are violated. This is avoided by modifying Step 4 of the random charging scenario as follows.

Step 3) While ($E_{Charged} < E_{Required}$), generate an integer k, $k \in \{1, \ldots, N_{ITV}\}$. Allocate charging energy $0.25 \times CR_{Max}$ to the EV during interval k, if k is within the peak load period and $E_{Charged} < a_1 \times E_{Required}$, or if k is within the medium load period and $E_{Charged} < a_2 \times E_{Required}$, or if k is within the valley load period. Perform load flow calculation. Update $E_{Charged}$ if the voltage and line limits are respected, otherwise, repeat this step.

a_1 and a_2 are predefined coefficients in the interval [0, 1], and are initially set to 0.33 and 0.67, respectively. The logic behind these values is to divide the required energy of each EV into three equal portions, to charge the EV with different priorities when the charged energy, $E_{Charged}$, is within each portion. The peak, medium and valley load periods are also defined based on the system operator's experience from the load shape on the distribution system.

Scenario 5- Uniform charging scenario

In order to reduce the computational burden again, it is assumed that the charging rate can be adjusted from zero to a maximum, and that each EV is charged constantly at an adjusted rate during the entire charging period. The step-by-step procedure is the same as for the random charging algorithm, with the following modification to Step 4.

Step 4) Allocate charging energy $E_{Charging} = E_{Required}/N_{ITV}$ to the EV during each interval k, $k \in \{1, \ldots, N_{ITV}\}$. Perform load flow calculation. If any voltage or line limits are violated, remove interval k from the set of 15-min charging intervals, and repeat this step. Otherwise, add the EV charging load to the customer loads in each interval k.

Scenario 6- Valley-filling charging scenario

In order to minimize the incremental energy losses in the presence of EVs, this algorithm first finds the predicted valley periods in the daily load profile, and then charges EVs in the valley times. This scenario has the highest computational burden among the examined charging scenarios. Again, the procedure is the same as the random charging algorithm with Step 4 modified as follows.

Step 4) While ($E_{Charged} < E_{Required}$), allocate charging energy $0.25 \times CR_{Max}$ to the EV during each interval k, $k \in \{1, \dots, N_{ITV}\}$. Perform load flow calculation based on the present load profile and calculate the corresponding energy losses for all charge allocations. Find the allocation with minimum energy losses, and name it as k'. The 15-min interval k' can be regarded as the valley time of the load profile. Allocate the charging energy to the EV during charging interval k', and modify the load profile during interval k'.

4. SIMULATION RESULTS

The proposed algorithms of Section 3 are applied to a LV residential distribution system in a suburban area in Dublin, Ireland (McKenna and Keane, 2015). The system, as shown in Fig. 1, includes a 10/0.4 kV transformer supplying 134 residential customers through 1.2 km of three-phase mains cables and 980 m of single-phase service cables. The technical specifications for the system components were supplied by Electricity Supply Board (ESB) Networks, who are the distribution system operator in the Republic of Ireland.

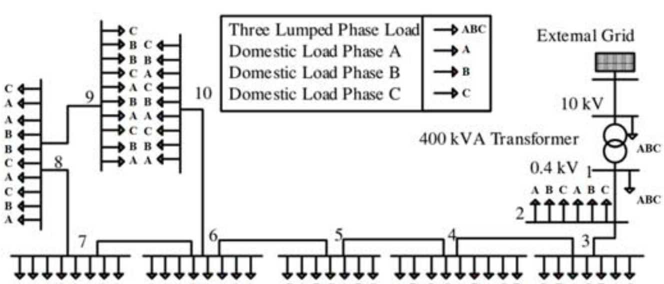

Fig. 1. Residential suburban distribution system

First, an analysis is performed to assess the impact of charging EVs on energy losses under the analysed scenarios. The EV penetration is assumed to be 50%, which means that half of the customers own an EV. The EV population is considered to consist equally of BEVs and PHEVs, with the characteristics shown in Table 1. In order to compare the proposed scenarios under different loading profiles, a Monte Carlo simulation is performed for typical days, corresponding to different seasons of the year, and the daily energy losses are calculated for each simulation. The arrival SOC of each EV battery is calculated randomly as explained in Section 2. The departure SOC is obtained based on the scenarios of Section 3. Table 3 shows the results averaged for summer weekdays and weekends (Sum-WD and Sum-WE), winter weekdays and weekends (Win-WD and Win-WE).

In Table 3, the first result that claims attention is that due to the higher customer loads, driven by heating loads in winter, the seasonal energy losses in winter tend to exceed the annual averages regardless of the charging scenario. Further, due to lower home/work activities of customers, the energy losses tend to be marginally lower at weekends than weekdays under the studied scenarios. Further, as can be seen, the energy losses increase under the proposed EV charging scenarios, as compared to the reference scenario with no EVs. Such an increase may exceed 60% of the reference value, and tends to be higher under uncontrolled charging than any other scenario. This is due to the lack of coordinated control, where EVs are independently charged during the first few hours of the charging period, which tends to coincide with the higher system load. On the contrary, adopting a valley-filling charging algorithm, which tends to charge EVs in the early morning, may limit the incremental energy losses to 21% of the reference values, even at 50% EV penetration.

Considering the other scenarios, uniform charging seems more effective than random charging in reducing the energy loss in the presence of EVs. This is due to the quadratic relationship between the energy loss and the supplied load. In fact, the uniform scenario, although not optimal, is not far away from the optimal result, and accordingly, a uniform charging can be regarded as a quasi-optimal charging solution, which has lower computational and communication requirements, and therefore is easier to implement by the system operator or EV aggregators. Further, it can be seen that including the conditional statements in the random charging introduces a slight improvement ($\approx$3%) in the results. This is because the load demand usually drops after midnight, and a conditional random scenario charges EVs at a higher rate after midnight.

Table 3. Daily Energy Loss

Scenario	Sum-WD (kWh)	Sum-WE (kWh)	Win-WD (kWh)	Win-WE (kWh)	Annual Ave. (kWh)
Reference	*153*	*117*	*350*	*319*	*267*
Uncontrolled	**240**	**188**	**588**	**523**	**443**
Random	213	165	493	450	375
Conditional Random	206	162	477	441	363
Uniform	193	148	450	408	342
Valley-filling	181	142	428	386	324

When analyzing the results of the conditional random scenario, care should be paid to selection of the coefficients a_1 and a_2. For more investigation, they are changed as denoted in Table 4, and the results are monitored.

Table 4. Coefficients of Conditional Random Charging

Cases	a_1	a_2
Case 1	0.33	0.67
Case 2	0.50	0.75
Case 3	0.25	0.50

As indicated by the results (not shown here), when the coefficients are changed from case 1 to case 2, the annual energy loss decreases from 1.36 p.u. to 1.32 p.u. (considering the daily energy loss of the reference scenario as the base quantity), whereas in case 3, it increases to 1.39 p.u. This means that decreasing the coefficients results in the conditional random scenario shifting towards that of the random scenario (1.40 p.u.), because with low coefficient values, EV charging may occur at peak load hours as likely as the valley load periods. On the contrary, by increasing the coefficients, most EVs are charged during the valley load hours, and therefore, the annual energy loss is shifted towards the valley-filling scenario (1.21 p.u.). It is noted that based on the typical shape of the aggregated load at distribution substations, the peak load period is from 16:00 to 20:00, and the valley load period is from 02:00 to 07:00.

In order to investigate the impact of EV characteristics on the results, two additional cases are studied, first when the EV population is only composed of BEVs, and then, when it only contains PHEVs. Table 5 shows the results of these extreme cases. By comparing Tables 3 and 5, it can be seen that the energy losses represent their maximum and minimum values under the BEV and PHEV cases, respectively, which correspond to 1.058 p.u. and 0.971 p.u. (on average), considering the daily energy loss of the BEV+PHEV case as the base quantity. This can be explained by the characteristics of BEVs, especially their higher electrical range and energy capacity over PHEVs, resulting in a higher charging demand upon their arrival to make the vehicles ready for next day use.

Table 5. Daily Energy Loss for EV Technologies

Scenario/EV Mix	BEV+PHEV	BEV	PHEV
Uncontrolled	**443 kWh**	**470 kWh**	**432 kWh**
Random	375 kWh	392 kWh	358 kWh
Conditional Random	363 kWh	383 kWh	349 kWh
Uniform	342 kWh	361 kWh	336 kWh
Valley-filling	*324 kWh*	*349 kWh*	*318 kWh*

In order to investigate the impact of EV penetration on the results, the penetration level is first decreased to 30%, and then increased to 80%. Table 6 shows the energy losses calculated under the BEV+PHEV case.

From Table 6, it can be observed that, as expected, the energy losses increase as the EV penetration rises. However, such an increase caused by going from 30% to 80% EV penetration under the uncontrolled charging scenario may exceed 100% of the preliminary daily energy loss (267 kWh), while the increased energy losses remain below 40% for valley-filling and uniform charging, and below 55% for the conditional random charging scenario. Thus, it can be concluded that the valley-filling, uniform and conditional-random algorithms are the most efficient algorithms among the studied scenarios to make distribution systems capable of accommodating a wide range of EV penetrations.

The results of Tables 5 and 6 are based on the definition of the charging period, which begins at 10 p.m., and ends at 6 a.m. on the next day. In order to investigate the impact of the start/end time of the charging period on the results, sensitivity analyses are carried out under the three best performing charging algorithms from the perspective of reducing energy losses. Figs. 2 and 3 show the results under the BEV+PHEV case for different start times (8 p.m., 10 p.m., 12 midnight), and end times (4 a.m., 6 a.m., 8 a.m.), respectively, in per unit of the annual energy loss against the reference scenario.

Table 6. Daily Energy Loss for EV Penetrations

Scenario/Penetration	30%	50%	80%
Uncontrolled	**337 kWh**	**443 kWh**	**675 kWh**
Random	326 kWh	375 kWh	511 kWh
Conditional Random	316 kWh	363 kWh	458 kWh
Uniform	307 kWh	342 kWh	412 kWh
Valley-filling	*293 kWh*	*324 kWh*	*394 kWh*

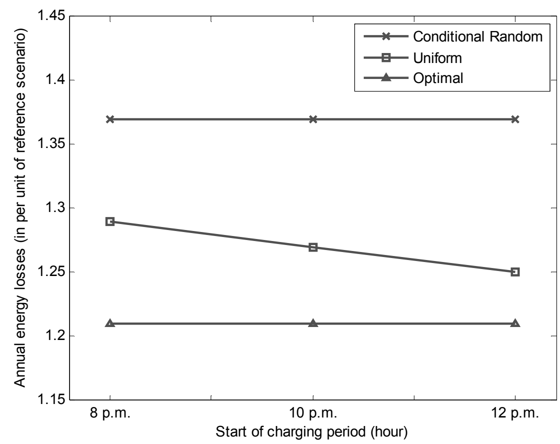

Fig. 2. Variation of the per unit energy loss as a function of the start time of the charging period

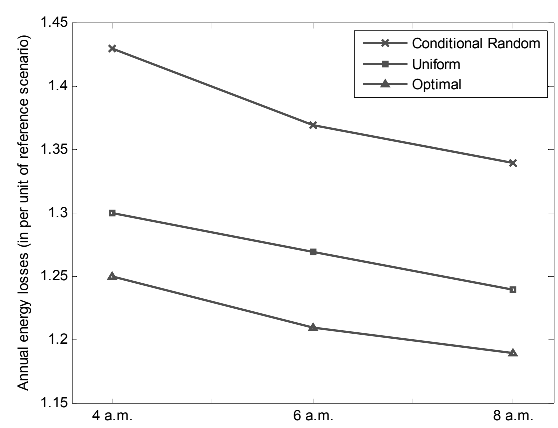

Fig. 3. Variation of the per unit energy loss as a function of the end time of the charging period

From Fig. 2, it can be seen that the efficiency of the uniform charging algorithm improves with a later start of the charging period. This is because the algorithm distributes EV charging loads more evenly across the charging period, and a later start time imposes the charging loads after the peak load hours. However, the annual loss remains almost the same under both the conditional random and valley-filling (optimal) charging scenarios, because the adopted algorithms of these scenarios inherently charge most EVs during off-peak hours in the early morning. Contrary to these results, as can be seen from Fig. 3, the annual energy loss tends to decrease with a later end charging period, regardless to the adopted charging algorithm. This is due to the low customer loads in the early morning and charging more EVs in this period may decrease the energy loss. Although Figs. 2 and 3 depict the results of the charging algorithms for various definitions of the charging period, more realistic results can be obtained by considering stochastic plug-in and departure times of the EVs and dynamic electricity tariffs, which are the subject of our future work.

6. CONCLUSIONS

A modeling framework has been presented to analyse the impact of various proposed charging scenarios, characterized by uniform, random, conditional-random, and valley-filling charging algorithms, on energy loss in the presence of EVs in distribution systems. The modeling framework and the proposed algorithms have been applied to a distribution system. As revealed by the results, the proposed valley-filling algorithm emerged as the best solution for controlled charging of EVs from the perspective of reducing the energy loss, but it has the cost of computation. Further, the uniform and conditional-random algorithms can be regarded as quasi-optimal solutions with easier application and less computational requirements. Further, high EV penetrations might increase energy losses, especially with uncontrolled and random algorithms. The sensitivity of the results has been studied against the definition of the charging period. Based on the results obtained from the test network, later start and later end to the charging period tends to improve the performance of the charging algorithms, as customer loads are lower during morning hours compared to the evening.

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