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Estimating the Impact of Electric Vehicle Smart Charging on Distribution Transformer Aging

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***Abstract*—This paper describes a method for estimating the impact of plug-in electric vehicle (PEV) charging on overhead distribution transformers, based on detailed travel demand data and under several different schemes for mitigating overloads by shifting PEV charging times (smart charging). The paper also presents a new smart charging algorithm that manages PEV charging based on estimated transformer temperatures. We simulated the varied behavior of drivers from the 2009 National Household Transportation Survey, and transformer temperatures based an IEEE standard dynamic thermal model. Results are shown for Monte Carlo simulation of a 25kVA overhead distribution transformer, with ambient temperature data from hot and cold climate locations, for uncontrolled and several smart-charging scenarios. These results illustrate the substantial impact of ambient temperatures on distribution transformer aging, and indicate that temperature-based smart charging can dramatically reduce both the mean and variance in transformer aging without substantially reducing the frequency with which PEVs obtain a full charge. Finally, the results indicate that simple smart charging schemes, such as delaying charging until after midnight can actually increase, rather than decrease, transformer aging.**

***Index Terms*—Plug-in hybrid electric vehicles, transformer aging, smart charging**

I. Introduction

With a growing number of mass-market plug-in hybrid and battery electric vehicles (collectively plug-in electric vehicles, PEVs) currently for sale or scheduled to go on sale, there is a growing need to understand the impact that PEV charging load will have on the electricity distribution infrastructure. Substantial research exists regarding the impacts of PEVs on gasoline consumption [1], [2], power-plant emissions [3], [4], electricity costs [5], [6], [7], transmission adequacy [8], and generating supply adequacy [7], [9], [10]. However, the literature on medium and low voltage distribution system impacts (see Sec. I-B) is more limited and offers less guidance to utilities looking to incorporate PEV impacts into their maintenance and investment plans.

Several factors combine to make quantifying the impact of PEVs on the medium and low voltage distribution infrastructure a particularly pressing issue. First, the social benefits offered by PEV deployment in terms of reduced oil consumption and life-cycle greenhouse gas emissions have prompted policies at the state and federal levels geared toward increasing the rate of PEV adoption [11], [12], [13]. Second, because early PEV adopters are likely motivated, at least in part, by environmental concerns, and because there is evidence from past hybrid electric vehicle sales that environmentally motivated vehicle consumers tend to be geographically clustered [14], [15], it is likely that PEV sales will be concentrated in particular areas. This clustering means that PEV charging loads will impact local distribution infrastructure well before the impacts on transmission or generation infrastructure is significant. If, as is suggested in [16], these impacts are severe distribution utilities may need to make significant infrastructure investments in high-adoption locations to facilitate this new load. Accurate information on PEV impacts is essential to ensure that these investments are made in an efficient manner. Thus the objective of this paper is to present, and illustrate the utility of, a computational method for estimating the additional transformer aging resulting from PEV charging load and to evaluate different approaches to manage the additional transformer load from PEV charging.

A. Background on modeling PEV power demand

Accurately estimating the impact of PEV charging on electric power system components requires both component models and good estimates of the magnitude and timing of demand increases due to PEV charging. Early PEV research assumed very simple charging profiles, such as assuming that vehicles will charge daily starting at 17:00, 18:00 or 19:00 hours, with batteries fully depleted at the start of each charge cycle [17], [2], [7], [18]. However actual PEV charging loads will depend highly on travel patterns, which vary tremendously from driver to driver and day to day. To better capture this variability in driving behavior, researchers have used either detailed GPS data for small groups of drivers, or survey data from larger populations. Ref. [19] used data from 9 drivers to estimate variability in daily miles driven, but with fixed evening arrival times. Another study [20] used GPS data from 76 vehicles to derive a stochastic model of miles driven and arrival/departure times. Reference [21] uses a larger set of GPS data to develop a Monte Carlo model that is similar to the one presented here, but the data are not used to model the miles driven, which is necessary to estimate the battery state-of-charge on arrival. Other researchers have also use Monte Carlo methods to study PEV charging impacts [22], [23], [24] but do not specifically consider distribution transformer aging. The authors in [22] study harmonics due to PEV fast charging; Ref.

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[23] investigates system level PEV charging impacts including bus voltages, branch currents, and energy losses; and [24] uses a Monte Carlo model to predict reliability, efficiency and profitability of Vehicle-to-Grid (V2G) technology.

While GPS data can allow one to estimate day-to-day variability in driver behavior, the small sample sizes, typical of GPS studies, may result in biased outcomes. An alternative (or perhaps supplement) is to use large-scale driver survey data, such as the US National Household Travel Survey (NHTS) [25] to estimate driver behavior. Ref. [26] used NHTS data to develop a probabilistic model for PEV loads, but focused on modeling large numbers of vehicles, such that the patterns for individual PEVs are averaged. This paper also employs the NHTS data, but with a pure sampling strategy that allows for precise tracking of vehicle departure and arrival times, and the battery state of charge.

B. Background on transformer aging models

There is conflicting evidence regarding the impact of PEVs on the residential distribution infrastructure. Ref. [16] uses a time-series model of transformer aging and argues that PEV charging could decrease transformer life by 93%. The study results, however, are based on a transformer model [27] that does not consider the impact of transient ambient temperatures. Another study [28] suggests that a PEV penetration level as small as 10% could induce additional distribution transformer overloading beyond planned overloading. Ref. [29] discusses two residential distribution circuits and estimates that distribution infrastructure costs could increase by 19% and energy losses could increase by 40% with substantial (60%) PEV deployment.

Transformers are among the most costly components in the medium and low voltage distribution infrastructure, and therefore, transformer aging is a key consideration when evaluating the impacts of PEV charging and deciding whether or not to employ smart charging. Transformer aging depends highly on the state of internal insulation material, which is impacted by internal transformer temperatures, specifically the hottest spot temperature. Accurately modeling hottest spot temperature is crucial to accurately predicting transformer aging. Pierce [30] provides a detailed thermodynamic model of transformer temperatures and fluid flow during transient temperature and loading conditions. This method became the industry standard when it was published in the 1995 revision of IEEE C57.91 [31] as Annex G. The Annex G method is not, to our knowledge, contested in the existing literature, and was thus chosen for the transformer model used in this paper.

C. Background on Smart Charging

The extent to which PEV charging will impact the distribution infrastructure will depend highly on the charging method used. For instance, the results of [8] and [32] suggest that impacts of PEV charging on components of residential feeders could be minimal given the presence of smart charging, and Ref. [33] argues that PEV deployment with smart charging could yield net benefits for the distribution system by leveling power demand and thus reducing distribution losses per unit energy. Ref. [19] used GPS travel data to obtain expected transformer insulation life in different charging scenarios, and proposed a smart-charging algorithm to reduce the loss of life in transformers. The authors in [34] used time-of-use price to find optimal charging loads, which minimize the charging cost in a regulated market. They argue that using their method reduces cost and flattens the load curve. Ref. [35] used the same GPS data as [20] to predict realistic driving habits and proposes a decision-making process for charging based on a fuzzy-logic system. The authors in [36] proposed an optimal charge management algorithm for a large number of PEVs in a parking lot and compare their optimization algorithm with more traditional methods. Ref. [37] investigated unidirectional V2G to maximize aggregator profit while satisfying system load and price constraints; different smart charging algorithms for a hypothetical group of commuter cars are simulated to obtain a continuous variable charge rate. They showed the benefits of combining regulation and reserves bids [38] and concluded that that price constrained optimal bidding outperforms other methods. Centralized charging of PEVs is studied in [39] to minimize distribution network losses using three different objective functions and using simplified travel behavior. In addition, there is substantial international research into electric vehicle smart charging (e.g., [40], [41], [42]), as well as international efforts to develop standards for PEV communications (e.g., ISO 15118 [43]).

This paper extends previous work [44] to describe both a method for estimating the impact of PEV charging on overhead distribution transformers (given a time-series transformer insulation material thermal model and PEV charging demand derived from observed light-duty vehicle travel patterns) and a method for mitigating this impact through a transformer temperature-based smart charging algorithm designed to reduce damaging transformer overloading. Furthermore, temperature-based control is compared to several other approaches to smart charging. Sec. II describes a method for modeling residential load with PEV charging. Sec. III describes the transformer thermal model, summarizing and providing a supplemental guide to the Annex G transformer thermal model. Sec. IV describes the various smart charging algorithms employed, which is followed by results (Sec. V). Finally we summarize our conclusions in Sec. VI.

II. Modeling PEV charging loads

In this paper, residential load profiles are comprised of two components: residential baseline load (L_h) and load from PEV charging (L_v). As we are primarily focused on the effect of PEV loads, we assumed that each home connected to a distribution transformer has identical, deterministic baseline load. However, in order to study travel pattern variation, we sampled from empirical travel data to develop a Monte-Carlo model of the PEV portion of the residential load profile.

A. Residential baseline load without PEV charging

The National Energy Modeling System (NEMS) reported itemized residential load profiles in [45], which are interpreted in [28] to produce a single home daily load profile. We fed

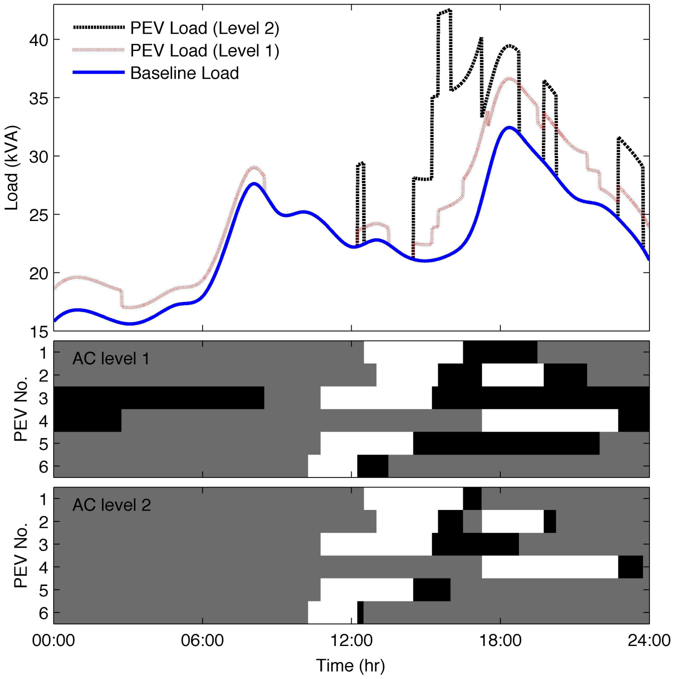

Figure 1. The top panel shows the daily baseline load profile with and without PEVs for a 25kVA overhead distribution transformer servicing 12 homes and 6 randomly selected PEVs charging at AC Level 1 and AC Level 2. Both charging levels correspond to the same sample set of PEV charging behavior. The middle and lower panels show the state of each vehicle throughout the day, which is one of: away (white), parked but not charging (gray), or charging (black).

these data into a cubic spline to produce a one home, 24-hour load profile, $L_h(t)$, with one minute time steps. Our model multiplied this daily pattern by the quantity of homes (n_h) serviced by an overhead distribution transformer to obtain the total transformer load, before adding vehicles. The power factor for the residential loads was assumed to be 0.9 lagging. The result is a baseline demand profile, which we assume to be constant from day to day over a one-year period. Fig. 1 displays the daily baseline demand profile for a 25kVA transformer servicing 12 homes and 6 PEVs, along with the travel patterns for the 6 PEVs. Baseline load values in Fig. 1 that are in excess of the 25kVA transformer rating represent periods of planned overloading, which are acceptable according to [31].

B. Additional load from PEV charging

This section describes the method used to develop a Monte Carlo model of PEV load (L_v), based on National Household Transportation Survey data [25]. The NHTS is a comprehensive survey of U.S. travel patterns conducted by the Federal Highway Administration. The survey data aim to include all trips taken by all members of the household within a 24 hour period including the length, timing, duration and mode of transportation for each trip. As the NHTS travel data do not reflect behavior of PEV-specific drivers, we assume that travel behavior of PEV and non-PEV drivers is indistinguishable.

The goal of the PEV charging model was to estimate the additional time-varying load that would result from n_v vehicles charging at a certain point in a power grid. For each one-year run of our model we randomly selected n_v vehicles

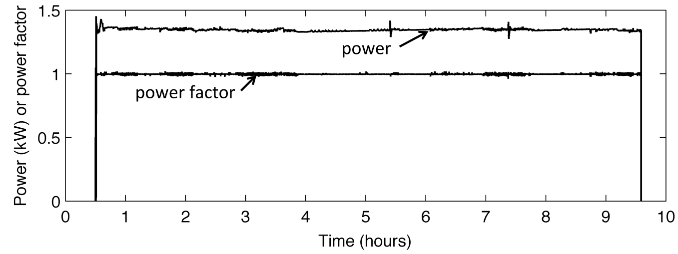

Figure 2. AC power consumption and power factor for a full (AC Level 1) charge of a GM Volt. Data courtesy of Central Vermont Public Service.

from among the vehicles in the New England subset of the NHTS data that both start and end the day at home. In our model half of the vehicles were assumed to have the charging and efficiency characteristics of the Chevrolet Volt (10.4 kWh battery and 0.26 kWh/mile), and the other half had the characteristics of the Nissan Leaf (24 kWh and 0.24 kWh/mi)[1]. Additionally, we assumed that all PEVs charge exclusively from a home charging station. Without smart charging in place, we assumed charging begins immediately upon the vehicle's arrival at home and continues until either the battery reaches full capacity or the vehicle begins a new trip. We assumed either AC Level 1 (1.4 kW) or AC Level 2 (7 kW) charging as established in [46] and 85% charge efficiency as reported in [47]. Based on data obtained from a GM Volt (Fig. 2), we assumed that the power draw was constant until the battery fully charged and that the power factor was 1.0.

The sampling method used in this paper represents the state of each vehicle v using two variables: the state-of-charge for each battery (represented by D_v, the amount of energy needed to fill the battery) and a binary variable, A_v, indicating whether the vehicle is parked at home and connected to a wall socket. Thus, the time required to fully charge the battery of vehicle v at charge rate P_v is $T_v = D_v/P_v$. If the step size for vehicle modeling is Δt (in units of hours), the load (in kW) due to vehicle v during time interval $[t, t+\Delta t)$ is:

$$L_v(t,\Delta t) = \begin{cases} A_v(t)P_v, & \text{if } T_v(t) \geq \Delta t \\ A_v(t)\frac{D_v(t)}{\Delta t} & \text{if } 0 < T_v(t) < \Delta t \\ 0, & \text{if } T_v(t) \leq 0 \end{cases} \quad (1)$$

For the purposes of this model, we randomly select a weekday and a weekend driving profile from the New England subset of the NHTS data for each v. These are reproduced to give a one-year charging pattern for each vehicle. We chose a vehicle model step size (Δt) of 0.25 hours.

The total load (in kVA) on the transformer is the combination of the n_h (complex) residential loads and loading from n_v randomly selected PEVs:

$$L(t) = \left| n_h L_h(t) + \sum_{v=1}^{n_v} L_v(t) \right| \quad (2)$$

Fig. 1 illustrates the results from the model by showing the additional load due to 6 PEVs added to the load for 12 homes, at Level 1 and Level 2 charging rates.

[1]Battery size and efficiency calculated from data provided in the vehicle owner's manuals from GM and Nissan.

It is important to note that the baseload data $L_h(t)$ (as well as the temperature data for the thermal model below), were initially available at hourly intervals. These were translated into one-minute data (the step size for the thermal model) using a cubic spline. The PEV load is also translated into one-minute data, from the 15 minute step size in the model, assuming that the PEV load does not change within each 15 minute interval.

III. Modeling Distribution Transformer Aging

Our model for estimating distribution transformer aging simulates the thermal performance of an overhead distribution transformer, installed in a location with a known trajectory of ambient temperatures $T_A(t)$ and load $L(t)$, based on IEEE C57.91-1995. One-minute ambient temperature data, $T_A(t)$, were obtained by feeding hourly temperature data from the National Climatic Data Center[2] into a cubic spline to produce one-minute data. The combined PEV/baseline data came from (2). We obtained transformer specifications from data provided by a local distribution utility.

The output of the model is an estimate of the total one-year accelerated aging of the transformer insulation material, in years. When this "Factor of Equivalent Aging" (F_{EQA}) is greater than 1.0, the transformer is aging at a rate that is greater than its designed level of 1 year per year.

A. Transformer thermal model

The transformer thermal model estimates internal transformer temperatures using the Annex G method of IEEE C57.91-1995 [31]. Annex G describes the heat transfer and fluid flow dynamics of the transformer while accounting for transient loading and ambient temperature conditions, changes in oil viscosity and winding resistance, and cooling mode. While the reader should refer to Annex G for precise details, the core of the method consists of three differential equations for internal transformer temperatures, which have the general form:

$$\frac{dT_W}{dt} = f_1\left(L^2(t), T_W(t) - T_{DAO}(t)\right) \quad (3)$$

$$\frac{dT_O}{dt} = f_2\left(L^2(t), T_A(t) - T_O(t), \ldots \right. \quad (4)$$
$$\left. T_W(t) - T_{DAO}(t)\right)$$

$$\frac{dT_{HS}}{dt} = f_3\left(L^2(t), T_W(t) - T_{HS}(t)\right) \quad (5)$$

The first equation (3) describes the average transformer winding temperature, $T_W(t)$, as a function of the square of load, $L^2(t)$, and the average temperature of fluid in the winding cooling ducts, $T_{DAO}(t)$. The second (4) models the average cooling oil temperature, $T_O(t)$, based on the difference between $T_W(t)$ and $T_{DAO}(t)$, and between $T_A(t)$ and $T_O(t)$. Equation (5) describes the transformer hottest spot temperature based on the difference of $T_W(t)$ and $T_{HS}(t)$. Calculated values for (5) are used in the transformer damage function, as described in Sec. III-C. Following the procedure in Annex G, we solved (3)-(5) using first order Euler's method, with a 1-minute time step.

[2]http://www.ncdc.noaa.gov

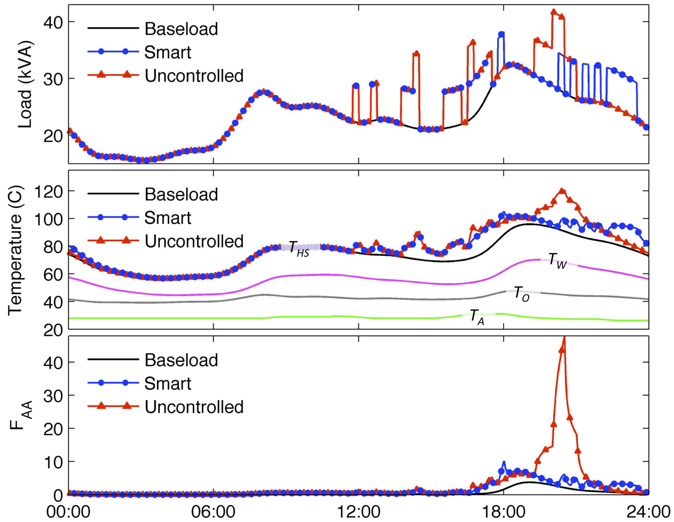

Figure 3. Illustration of model estimating distribution transformer aging over the course of one day. The transformer modeled is a 25kVA overhead distribution transformer servicing 12 homes. The temperature data come from Phoenix, Arizona, 2010. The transformer is modeled under zero PEVs, 6 PEVs with uncoordinated AC Level 2 charging and 6 PEVs with temperature-based AC Level 2 smart charging ("Smart" in the graph above). The top panel shows load as seen by the transformer. The middle panel shows ambient temperature and internal transformer temperatures; T_O and T_W are only shown for the base load case. The bottom panel shows the instantaneous factor of accelerated aging, $F_{AA}(t)$.

B. Transformer insulation loss-of-life equations

Transformer insulation typically fails prior to other components within a transformer. For this reason, the estimated life of a transformer is primarily a function of aging within the transformer insulation. Accelerated aging is a measure of how quickly the transformer insulation degrades under actual conditions, relative to degradation at rated loading and rated ambient temperature conditions. Clause 5 of IEEE Std. C57.91-1995 [31] provides a method for estimating distribution transformer aging, which we summarize here.

Excessively high hottest spot temperatures damage a transformer's insulation through the destructive process of pyrolysis [48]. To model this, the calculated $T_{HS}(t)$ are fed into a damage function [31] that estimates the instantaneous accelerated aging of the transformer ($F_{AA}(t)$), which can be integrated to compute the total transformer thermal aging over a time horizon (T) to yield the average Factor of Equivalent Aging (F_{EQA}):

$$F_{EQA}(t) = \frac{1}{T}\int_{t-T}^{t} e^{\left(\frac{15{,}000}{T_{HS,R}+273} - \frac{15{,}000}{T_{HS}(t)+273}\right)} dt, \quad (6)$$

Equation (6) was used to estimate the total distribution transformer aging over a $T = 1$ year period.

C. Distribution transformer aging model sample result

Fig. 3 illustrates the combined effect of the transformer thermal model and transformer insulation aging equations, with and without PEV-charging load ($n_v = 6$) and under smart and uncontrolled charging. For this sample result, the transformer thermal model produced transformer internal temperatures and F_{AA} values for a 25kVA distribution transformer serving 12 homes. Table I describes the transformer parameters used in

Table I
TRANSFORMER PARAMETERS USED*

Parameter	Symbol	25kVA
Rated httest spot temp.	$T_{HS,R}$	84.4 °C
Rated winding temp.	$T_{W,R}$	77.0 °C
Rated ambient temp.	$T_{A,R}$	30 °C
Volume of oil	-	41.6 L
Mass of core	M_C	79.9 kg

*Parameter values were obtained from transformer manufacturer specification sheet provided by a local utility. Parameter values not provided by the manufacturer (not shown) were chosen in accordance with Annex G recommendations.

this study. The ambient temperature in Fig. 3 represents a 2010 "hot" day in Phoenix, AZ. As shown in the lower panel of Fig. 3, the uncontrolled PEV charging case exhibits a brief period of extreme aging, approaching 50 years per year.

IV. SMART CHARGING METHODS

If a distribution transformer is overloaded due to PEV charging, it can either be replaced with a larger unit, or the PEV load can be managed with financial incentives and smart charging technology. This section describes several different approaches to smart charging, which might be employed to to extend the life of a transformer serving several electric vehicles.

A successful smart charging algorithm should ensure that all PEVs receive as close to a full charge as possible, thus minimally inconveniencing the PEV owner, while mitigating the negative impacts of high loads on the electricity infrastructure. The smart charging algorithm proposed in Sec. IV-A seeks to do this directly by determining how many PEVs may charge at a given time without pushing the distribution transformer into sustained, rapid accelerated aging. Other approaches are discussed in Sec. IV-B. In all cases, we assume that smart meters (Advanced Metering Infrastructure) are installed at each home, which allow a charge management device at the transformer to monitor instantaneous loads and send signals to vehicles connected to the transformer to forgo charging for a specified time period. Finally, we also assume that sufficient financial incentives and technology are in place to ensure participation. While this last assumption is unrealistic (some vehicle owners are unlikely to participate in smart charging programs), doing so allows us to understand the impact of different approaches.

A. Smart charging based on transformer temperature

Our smart charging algorithm requires two inputs: the transformer aging status, comprised of $F_{AA}(t)$ and $F_{EQA}(t)$, which are derived from the aging calculations in Sec. III, and the quantity of PEVs requesting charge, $q_r(t)$. The algorithm yields one output: the quantity of PEVs that may charge at time t: $q(t) \leq q_r(t)$. When implemented in a charge management device associated with a transformer, the algorithm operates in two steps. Step one determines $q(t)$. The second step dispatches a signal to smart meters, which subsequently signal each vehicle to either continue or discontinue charging. Step two is performed by random allocation, which has the advantages of 1.) not requiring the exchange of information pertaining to battery level and 2.) avoiding the need to decide which PEV "deserves" charging precedence.

To determine the modeled transformer aging status, we assume that smart meters report instantaneous household load to the transformer, as well as the number of vehicles available for charge management, $q_r(t)$. The aggregated $L(t)$ and a measured value for $T_A(t)$ are fed into the transformer thermal model (Sec. III), which yields $F_{AA}(t)$ and $F_{EQA}(t)$ averaged over a period of time. An F_{EQA} averaging period of 12 hours was chosen to ensure that brief periods of high-temperature operation did not extend to produce high average aging over longer periods. Numerical tests of the algorithm with averaging periods of 6, 12, 18, and 24 hours did not show that the averaging period had a statistically significant effect on annual transformer aging.[3]

After calculating $F_{AA}(t)$ and $F_{EQA}(t)$, the algorithm compares the modeled transformer aging status against four aging thresholds ($H_{EQA}, H_{\min}, H_{\text{med}}$, and $H_{\max}$) to determine whether $q(t)$ should be increased, decreased, or held constant in the next time period. Equation (8) is used to choose the change in $q(t)$ from the previous time period:

$$q(t) = q(t-\Delta t) + \Delta q(t) \tag{7}$$

$$\Delta q(t) = \begin{cases} +1, & \text{if}\,(F_{AA} < H_{\min})\,\text{or} \\ & (F_{AA} < H_{\text{med}} \& \, F_{EQA} < H_{EQA}) \\ -1, & \text{if}\, F_{AA} > H_{\text{med}} \\ -2, & \text{if}\, F_{AA} > H_{\max} \\ 0 & \text{otherwise.} \end{cases} \tag{8}$$

Table I provides suggested aging threshold values, as determined from numerical experimentation.

Table II
AGING THRESHOLDS USED FOR TEMPERATURE-BASED SMART CHARGING ALGORITHM

H_{EQA}	$H_{\min}$	H_{med}	$H_{\max}$
2.5	3.5	4	4.75

Unless $q(t)$ is greater than $q_r(t)$, in which case all requesting PEVs may charge, the smart charging algorithm randomly chooses $q(t)$ vehicles from the set of vehicles that are currently requesting charge, $q_r(t)$, and signals the smart meters to allow or forgo charging to their respective PEVs.

Fig. 3 highlights the differences between uncontrolled and smart charging using a transformer operating during a high-temperature, 24 hour period for Phoenix, Arizona and serving six PEVs. The smart charging algorithm delayed charging for several vehicles, away from the hottest hours or heaviest load periods of the day.

Note that the communication costs for this control algorithm are minimal. The only data exchange that is needed is for the vehicle to query a "transformer control agent" once every 15 minutes to request permission to charge. The transformer would need to assemble the requests and randomly grant a subset of these requests, according to (8). The transformer control agent does not need to gather information about the battery state of charge, the departure time of the vehicle, or

[3]In our test, mean aging ranged from 1.572 to 1.588, with a standard deviation of 0.2. The differences were not significant.

whether the PEVs will charge at other locations, which is advantageous in terms of customer privacy and simplicity. The algorithm, as implemented, is fully capable of handling the adding and removing of vehicles, assuming that the vehicles can communicate with the control agent. We assume that this communication would be encouraged through a preferential smart charging rate structure.

The algorithm could also be applied without major changes to mitigate overloads on a distribution feeder transformer, so long as there was sufficient communication bandwidth to facilitate requests between the vehicles and the transformer. Also, the algorithm assumes that PEVs can only be controlled in a binary manner, making it feasible to implement within bandwidth-limited, high latency first generation Advanced Metering Infrastructure (AMI). As AMI improves, real-time communications between grid infrastructure and smart meters will be increasingly feasible, making it feasible to adapt the temperature-based control algorithm for bi- or unidirectional and continuous charging control (V2G).

B. Other smart charging methods

To compare temperature-based smart charging to other approaches, we measured transformer aging and the frequency of charge mitigation for three existing smart charging methods:

1) *After Midnight* (AM): all charging is postponed until after 12:00 am, and before 6:00 am to avoid the peak load period;
2) *Load Cutting* (LC): charging starts immediately upon the arrival of the PEV at the home charging station but is limited based on the aggregate transformer load such that PEV charging (w/ 15 minute intervals) is randomly allocated every 15 minutes, to ensure that the transformer load remains below its load limit; in a variant of this method, the load limit is increased to 30kVA during nighttime hours (10:00 pm - 8:00 am);
3) *"Randomized Charging Strategy"*: following the method proposed in [19], a random array of charging time slots, with 15 minute intervals, is allocated between 7:00 pm or the vehicle arrival time (whichever is later), to ensure that the vehicle is charged by 6:00 am.

V. RESULTS

As concluded in previous work [44], ambient temperatures can dramatically affect the impact of PEV charging on transformers. Therefore, we examined PEV charging impacts with one year of ambient temperature data from two climatically distinct U.S. cities: Burlington, Vermont (VT) and Phoenix, Arizona (AZ), which have average July temperatures of 21.4°C and 34.8°C respectively. The main goal was to compute the annual factor of equivalent aging (F_{EQA}), which we also refer to as the transformer's aging rate. To compensate for variability in PEV driver travel behavior, we ran the transformer model for 10,000 sets of randomly generated travel patterns, under each of the following five test conditions, for both locations: 1) no PEV charging; 2) AC Level 1, uncoordinated PEV charging; 3) AC Level 1, temperature-based smart PEV charging; 4) AC Level 2, uncoordinated PEV charging; and 5) AC Level 2, temperature-based smart PEV charging. In addition, the three smart charging algorithms from Sec. IV-B were compared, for both charging levels and in both locations. As in Fig. 3, the 25 kVA transformer was assumed to serve 12 homes and 6 vehicles, each with unique weekday and weekend travel patterns for each model run. The average baseline load was 22.8 kVA, which is near the rated limit.

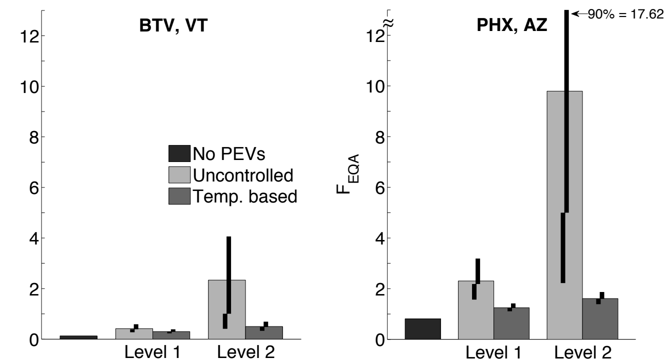

Figure 4. The annual factor of equivalent aging (F_{EQA}) for Burlington, VT & Phoenix, AZ for no PEVs, uncontrolled PEV charging, and temperature-based smart charging. The graph displays average (bars) and $10^{th} - 50^{th}$ & $50^{th} - 90^{th}$ percentile (black lines) F_{EQA} values for each location and charging rate.

Figure 4 shows the simulation results for no PEVs, uncontrolled, and temperature-based charging for each location. The uncontrolled charging results show a substantial difference between AC Level 1 and 2 charging. Level 2 charging increases aging rates by a factor of 5.6 and 4.2 above the uncontrolled level, in Vermont and Arizona respectively. Clearly, higher charging rates will result in increased aging rates for distribution infrastructure. Additionally, the results show that temperature-based smart charging can dramatically reduce transformer aging. The proposed smart charging algorithm reduced average transformer aging in Burlington by a factor of 1.4 for AC Level 1 and a factor of 4.8 for AC Level 2, relative to uncontrolled charging. In Phoenix, the differences are greater, with average F_{EQA} falling by factors of 1.8 and 6.3 for Levels 1 and 2, respectively. For all cases, a two-sample Kolmogorov-Smirnov test shows statistical significance of the reduction in aging from temperature-based smart charging ($p < 10^{-3}$ for all cases).

The results also indicate that temperature-based smart charging can dramatically reduce the uncertainty in transformer aging that results from differing travel patterns among vehicles. The 90^{th} percentile aging rates for the Level 2 cases (from Fig. 4) decrease by an order of magnitude under temperature-based smart charging in both Arizona and Vermont. This indicates that temperature-based smart charging can reduce both the average, and the variance in transformer life expectancy under high levels of PEV adoption.

It is important to emphasize that an algorithm that reduces aging but does not allow adequate charging to the PEV batteries is not desirable. To ensure that the proposed smart charging method resulted in adequate PEV charging, we measured the number of cases in which vehicles fully charged before beginning their next trip, after having been parked at

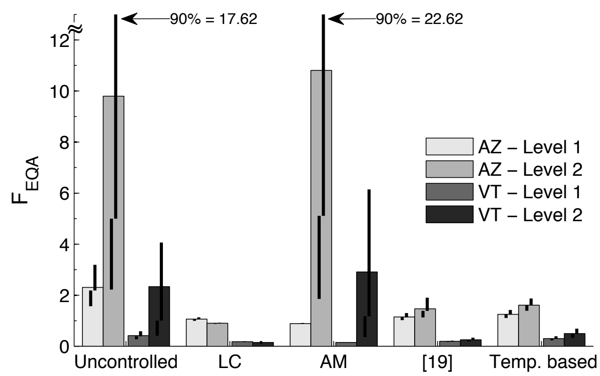

Figure 5. Transformer aging (F_{EQA}) results for uncontrolled charging, and four smart-charging methods: load cutting (LC), after midnight (AM), randomized charging [19], and our temperature-based method. The graph displays average (bars) and $10^{th} - 50^{th}$ & $50^{th} - 90^{th}$ percentile (black lines) F_{EQA} values for each location and charging rate.

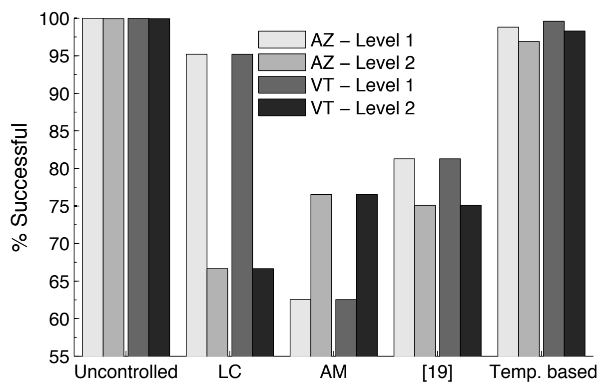

Figure 6. Average percent successful charging for uncontrolled charging and each of the smart charging methods in Fig. 5.

home for an extended period of time. Specifically, we define a "successful charge" to be a period in which the battery was charged to at least 95% of its capacity after being at home long enough to have received a full charge at the unmitigated Level 1 or 2 charging rate. We found that for both charging rates and both locations, vehicles received successful charges in greater than 98% of extended home stays. The only exception to this was AC Level 2 in Arizona which showed an average of 97% successful charge rate. Given that the algorithm achieves a very high rate of charging success for the case of a very heavily loaded transformer, we conclude that the proposed scheme would have almost no noticeable effect on most PEV owners.

For comparison purposes, the three smart charging methods described in Sec. IV-B were evaluated under the same model parameters as those for the temperature-based smart charging method (both locations and both charging rates). As before, we compared the average annual aging rate (F_{EQA}) for 10,000 iterations and the average percent of successful charges. The results of these simulations are found in Figs. 5 and 6.

All simulated cases showed that load cutting method substantially reduced distribution transformer aging. For AC Level 1, the aging rate decreased from 0.42 (for uncontrolled charging) to 0.18 in VT, and from 2.30 to 1.07 in AZ. For AC Level 2, the average aging rate decreased from 2.34 (for uncontrolled charging) to 0.15 in VT and from 9.79 to 0.90 in AZ. However, the successful charge rate for load cutting was only 66.6% for AC Level 2 and 95.2% for Level 1, which is notably lower that what was obtained from the temperature-based algorithm. This indicates that controlling transformer load based on temperature or aging, rather than merely based on load, will reduce the need to curtail PEV charging loads, likely leading to less customer aggravation. In order to further explore the load-cutting method, we attempted to improve the results by increasing the load limit by 20% (to 30 kVA) during night-time hours (10:00 pm to 8:00 am). This modification caused the percent of successful charges to increase by as much as 10% in Level 2 charging (from 67% to 77%), but did not have a significant impact on successful charges in Level 1 charging, or on the average aging rate. The reason is that in the simple load cutting method many Level 2 charging instances are cut when the transformer reaches its full load, but in Level 1 charging the lower charging power allows more PEVs to obtain nearly a full charge before departing. However, in the modified load-cutting method a greater quantity of Level 2 charging occurs during the night, without substantially increasing the aging rate. The results make the modified version more desirable than the simple load cutting method, but still less attractive than the temperature-based method.

At AC Level 1, the after-midnight method resulted in a decrease in aging from 0.42 to 0.15 (compared to uncontrolled charging) for Vermont, and from 2.30 to 0.90 Arizona. At AC Level 2, however, the after-midnight method resulted in an increase in average aging rate from 2.34 to 2.91 and from 9.79 to 10.81 for VT and AZ, respectively. Additionally, the percent of successful charges were quite low: 62.5% for Level 1 and 76.5% for Level 2. These results show that time-delayed charging may only be helpful in reducing distribution transformer aging when AC Level 1 is used, and can have a substantial negative impact on transformer life with higher charging rates. In both cases, the after-midnight method results in a low rate of successful charges, because charging is delayed until after 12:00 am.

The randomized charging strategy from [19] also produced good results in terms of mitigating distribution transformer aging. For AC Level 1, the aging rate decreased from 0.42 to 0.19 in VT and from 2.30 to 1.15 in AZ. For AC Level 2, the average aging rate decreased from 2.34 to 0.26 in VT and from 9.79 to 1.47 in AZ. However, the percent of successful charges was found to be 81.3% and 75.1% for AC Levels 1 and 2 respectively. Therefore, the randomized charging strategy, which clearly is effective in reducing distribution transformer aging, may be less desirable given the need to maintain a favorable battery state of charge.

VI. Conclusions

This paper describes a method for estimating and mitigating the impact of electric vehicle charging on overhead distribution transformers by combining a transformer thermal aging model with empirical travel behavior and a temperature-based smart charging algorithm. We use Monte Carlo simulation to estimate thermal aging in a fully loaded 25 kVA overhead distribution transformer serving 12 homes and 6 PEVs, with ambient temperature data from Phoenix, Arizona and Burlington, Vermont. We compared the thermal aging in the transformer, as well as the likelihood that vehicles would be able to successfully charge their batteries, for several smart charging algorithms, including a new temperature based control algorithm proposed in this paper.

The results suggest a number of interesting conclusions. First, we found that in all cases the warmer climate of Phoenix, AZ resulted in notably more transformer aging, relative to the cooler climate of Burlington, VT. This indicates that, in cooler climates, a moderate amount of overloading from PEV charging may not substantially decrease transformer life. The results also highlight the need to use location-specific ambient temperature data when evaluating the impact of PEV charging on thermally sensitive infrastructure. Additionally, because of the variability in driver behavior and the exponential aging function, PEV charging is likely to introduce enormous uncertainty in transformer aging, particularly for hot climates. Second, the results show that smart charging in general, and the proposed temperature-based algorithm in particular, can substantially reduce transformer aging. These reductions were substantially greater in the hot climate location, relative to the cool climate one. In addition to this average effect, we found that smart charging can also reduce uncertainty in transformer life, in the face of highly uncertain vehicle travel behavior.

These benefits came with very little cost in terms of inconvenience to PEV drivers. In the proposed temperature-based method, vehicles were able to charge their batteries to at least 95%, after having been at home for long enough to get a full charge, in more than 97% of all cases. While the model indicated that other smart charging algorithms can also reduce transformer aging, methods that were not explicitly focused on mitigating transformer damage tended to result in a greater number of unsuccessful charges. For the case of vehicles charging at AC Level 2 rates, but only being allowed to charge after midnight, smart charging actually increased, rather than decreased transformer aging over the uncontrolled case. Time-of-use pricing schemes, in which vehicles could charge at a reduced cost after a certain hour, could have a similar negative impact on the distribution infrastructure. This emphasizes the need to exercise caution when designing new incentives and technology for time-delayed charging. Unintended consequences, such as creating a sudden spike in load when lower-priced electricity becomes available, could have costly impacts on power delivery infrastructure.

While the focus of this paper is on mitigating transformer damage due to electric vehicle charging, similar methods can be used (and similar results are likely to be obtained), if the proposed temperature-based smart charging algorithm were applied to other large loads that can be time-shifted, such as air-conditioners and water heaters. Also, the relatively smart-charging algorithm proposed in this paper considers only one constraint: the thermal limit of a transformer. Future work will focus on integrated control methods that can manage smart charging to satisfy the many limits in a power system, such as bulk generation availability (and bulk prices) as well the thermal limits of power transformers and underground cables. In addition, as the communications capabilities of AMI systems improve, it will become increasingly feasible to deploy more sophisticated load management algorithms. In future work, we will also investigate the potential benefits and costs of continuous, rather than binary electric vehicle charge management methods.

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