Electric Vehicle Charging: Transformer Impacts and Smart, Decentralized Solutions

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Abstract—This paper compares distribution transformer aging impacts resulting from plug-in electric vehicles charging under AC Level 1 versus AC Level 2 charging conditions. Additionally, we propose an algorithm for PEV smart charging and evaluate its effectiveness on transformer aging. We use a Monte Carlo simulation of a 25kVA distribution transformer, with ambient temperature data from Burlington, VT and Phoenix, AZ, to calculate transformer aging under both uncoordinated and smart charging conditions. The results indicate more substantial aging as a result of AC Level 2 charging compared to AC Level 1. Smart charging can significantly mitigate these effects. We also present a more decentralized approach to smart charging and compare two distributed automaton-based charge management strategies, which both prevent the transformer from becoming overloaded. These methods give vehicle owners the ability to select among charging priorities in an environment in which the vehicles manage their charging autonomously.

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

I. INTRODUCTION

With several mass-market plug-in hybrid and battery electric vehicles (collectively plug-in electric vehicles, PEVs) currently for sale or scheduled to go on sale in the 2012 and 2013 model years, there is a growing need to assess the impact that PEV charging load will have on electricity distribution infrastructure. Substantial research exists regarding regional and national impact of PEVs on gasoline consumption [1], [2], [3], power-plant emissions [1], [2], [4], [5], electricity costs [6], [7], [8], transmission adequacy [9], and generating supply adequacy [8], [10]. One area of particular interest is quantifying the impact of PEVs on the medium and low voltage distribution infrastructure; PEV charging loads will likely impact local distribution infrastructure well before the impacts on transmission or generation infrastructure is significant. If these impacts are severe, as is suggested in [11] and [12], distribution utilities may need to make significant infrastructure investments in high-adoption locations. Accurate information describing PEV impacts is essential to ensure that these investments are made in an effective manner.

Previous studies show evidence of PEV impact on the residential distribution infrastructure. For example, reference [11] uses a time-series model of transformer aging and argues that PEV charging could decrease transformer life by 93%. Another study [13] suggests that a PEV penetration level as small as 10% could induce additional distribution transformer overloading beyond planned overloading as defined in [14]. Reference [15] estimates that distribution infrastructure costs could increase by 19% and energy losses could increase by 40% with substantial (60%) PEV deployment.

Recent publications suggest methods for coordinating PEV smart charging for distribution system efficiency improvement. For instance, the results of [9] and [16] suggest that the impacts of PEV charging on components of residential feeders could be minimal if intelligent charging schemes are used. Reference [17] and [18] solve an optimization problem considering all electric vehicles serviced by the grid to minimize power losses. However, these solutions require individual PEV battery charge status data and driver departure time data to be sent to a central location. This approach may not be feasible, as it increases existing concerns regarding data privacy in a Smart Grid environment. Also, as PEV adoption increases, the problem may not be solvable in real time. Two strategies are proposed in [13] to reduce the peak power of the grid. The first strategy limits the transformer load by a pre-defined value; the second, a household load control strategy, causes non-critical loads to shed when the PEV is charging. The decentralized demand side management problem is solved in [19], and two solutions are proposed for charge coordination. Our previous publication shows the potential benefits of smart charging in dramatically reducing accelerated transformer aging and in reducing transformer aging uncertainty caused by unique PEV charging profiles derived from diverse PEV driver travel behavior [20].

Estimating the impact of PEV charging, as well as evaluating the utility of smart charging strategies, on components of the distribution infrastructure requires not only good physical models of circuit components but also good estimates of the electric power demand due to PEV charging. Early PEV research assumed very simple methods used to model vehicle behavior and associated charging profiles [2], [21], [8], [22]. Recent work, including that by the authors, has proposed more empirical approaches [23], [24], [25], [26], [20], [27].

One objective of this paper, which is an extension of [27], [20], is to compare distribution transformer impacts of slow (AC Level 1) versus fast (AC Level 2) PEV charging under both uncoordinated and smart charging conditions (Section II). Having further explored the utility of smart charging, we then discuss decentralized methods for coordinated PEV charging strategies (Section III). Two automaton-based strategies are proposed to coordinate PEV charging, both of them limiting the power of the transformer to avoid power peaks. The first

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strategy (Method 1) uses a “first-come, first serve” approach, and the second (Method 2) uses a probabilistic approach. The probabilistic method (Method 2), which extends the approach used in [28], is a result of the analogy between power distribution system and shared channel access in wireless communication systems, including limited communication bandwidth, for which random characteristics of demand exist. This charge coordination strategy is a modified version of a technique proposed for random access communication channels in [29]. Section IV details our conclusions.

II. IMPACT OF CHARGING ON TRANSFORMER AGING

This section describes our method for estimating the impact of PEV charging on distribution transformers (Sub-Sections II-A & II-B) followed by a description of our smart charging algorithm (Sub-Section II-C). We then present the results of a full year model which investigates impacts on distribution transformers from slow (AC Level 1) and fast (AC Level 2) PEV charging using both uncoordinated charging and the smart charging algorithm (Sub-Section II-D). Finally, we conclude Section II with a discussion of results (Sub-Section II-E).

A. Modeling transformer loads given demand for PEV charging

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 variations in vehicle charging patterns, we assume that each home connected to a distribution transformer has identical, deterministic baseline load. However, in order to study travel pattern variation, we sample from empirical travel data [30] to develop a Monte-Carlo model of the PEV portion of the residential load profile.

As in our past work, we use the baseline load profile in [31] for \(L_h\), which is shown for a 25kVA transformer servicing 12 homes in Fig. 1.

We use data from the 2009 National Household Travel Survey (NHTS) database [30] to build a stochastic model of PEV charging loads \(L_v\). The goal of the PEV charging model is 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 select \(n_v\) vehicles from among the vehicles in the Vermont subset of the NHTS data that both start and end the day at home [30]. Each vehicle is assumed to have the charging and efficiency characteristics of the Chevrolet Volt [32], a series hybrid vehicle which operates in straight charge depleting mode until the limit of its all-electric range (AER) and then switches to charge sustaining mode. Additionally, we assume that all PEVs charge exclusively from a home charging station. Without a smart charging system, we assume 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 examine two PEV charging levels, as established in [33]: 1) AC Level 1 (1.4 kW); and 2) AC Level 2 (7 kW). We assume 85% charge efficiency as reported in [34]. Our model simulates a 10kWh usable battery capacity and 3.8 mi/kWh electric drive efficiency, to match that of the Chevrolet Volt [32].

We organize the NHTS travel data into two dependent sub-profiles, which we term the demand profile \(D\) and the charging availability profile \(A\). For time period \(t\) the charging availability of vehicle \(v\) is a binary value \(A_v(t)\) indicating whether vehicle \(v\) is parked at its home charging station. The demand profile for vehicle \(v\) at time \(t\) \(D_v(t)\) indicates the amount of energy required to fill vehicle \(v\)'s battery at a particular point in time. The time required to fully charge the battery at charge rate \(P_v\) is:

\[
T_v(t) = \frac{D_v(t)}{P_v} \tag{1}
\]

If the time step size is \(\Delta t\) (in hours) the load (in kW) from vehicle \(v\) during time interval \([t, t+\Delta t]\) is:

\[
L_v(t, \Delta t) = \begin{cases} 
A_v(t) P_v & \text{if } T_v(t) \geq \Delta t \\
A_v(t) \frac{D_v(t)}{\Delta t} & \text{if } 0 < T_v(t) < \Delta t \\
0, & \text{if } T_v(t) \leq 0 
\end{cases} \tag{2}
\]

For the purposes of this model, we randomly select a weekday and a weekend driving profile for each \(v\), and reproduce the two \(L_v\) trajectories that form a one-year charging pattern for each vehicle.

The total load on the transformer is the combination of the \(n_h\) residential loads where \(h\) indicates the quantity of homes and loading from \(n_v\) randomly selected PEVs:

\[
L(t) = n_h L_h(t) + \sum_{v=1}^{n_v} L_v(t) \tag{3}
\]

Figure 1 illustrates the function of the model by showing the additional load due to 6 PEVs added to the load for 12 homes. PEV load is shown at AC Level 1 and AC Level 2 charging rates.

![Figure 1](image-url)  
**Figure 1.** 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.
B. Modeling Distribution Transformer Aging

The 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 serving a set of $n_h$ homes and $n_v$ electric vehicles. The ratio of PEVs per home ($n_v/n_h$) can be chosen to reflect likely PEV adoption rates in particular neighborhoods. The output of the model is an estimate of the accelerated aging of the transformer insulation material, which results from the thermal properties of the transformer, the time-varying transformer load ($L(t)$) and ambient temperatures.

The primary input variable for the model is $L(t)$ from (3). The second input variable, $T_A(t)$, corresponds to the geographic location to be modeled and can span any desired time period. We produced one-minute resolution temperature data using a cubic spline from 15 minute temperature data from the National Climatic Data Center\(^1\). Finally, the third input defines the rated specifications and parameters of the transformer to be modeled, which can be obtained from the transformer manufacturer. With these inputs, the transformer thermal model estimates transformer temperatures, most notably the transformer hottest spot temperature, $T_{HS}(t)$. Our transformer thermal model estimates $T_{HS}(t)$ using the Annex G method of IEEE C57.91-1995 [14]. Our previous work [20] shows details of our implementation of the Annex G method.

Excessively high hottest spot temperatures damage a transformer’s insulation through the destructive process of pyrolysis [35]. Therefore, the calculated $T_{HS}(t)$ are fed into a damage function [14] 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, $F_{EQA}$ (4):

$$F_{EQA}(t) = \frac{1}{T} \int_{t-T}^{t} e^{\left(\frac{15,000}{T_{HS}(t)+273} - \frac{15,000}{T_{EQA}(t)+273}\right)} dt$$  \hspace{1cm} (4)

where $T$ is the length of time over which the average is taken, $F_{AA}$ and $F_{EQA}$ are the primary outputs of the model for estimating distribution transformer aging and are also the required inputs for the smart charging algorithm described in Section II-C.

C. Smart Charging Algorithm for Transformer Aging

If a distribution transformer is overloaded due to PEV charging, it can either be replaced with a larger unit, or the PEV charging can be managed to forestall the need for a transformer upgrade. In [20] we proposed a smart charging algorithm which successfully demonstrated mitigation of transformer accelerated aging and a dramatic reduction in uncertainty associated with diverse PEV charging profiles derived from unique PEV driver travel behavior. In our previous work, we only considered AC Level 1 charging. This section provides summary of our previously proposed smart charging algorithm.

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. Our algorithm seeks to mitigate the accelerated aging of a distribution transformer. The smart charging algorithm proposed here continuously (or discretely at time specific check points) determines the number of PEVs connected to a specific overhead distribution transformer that may charge at a given time without pushing the distribution transformer into sustained, rapid accelerated aging. We assume that smart meters (AMI - Advanced Metering Infrastructure) are installed at each home, which would allow a charge management device at the transformer to monitor instantaneous loads and send a signal to vehicles connected to the transformer to forgo charging for a specified time period.

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 II-B, 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 $q(t)$, $q_r(t)$ and the aging factors. 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 not requiring the exchange of information pertaining to battery level and 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 (Section II-B), which yields $F_{AA}(t)$ and $F_{EQA}(t)$ averaged over a period of time. Numerical experimentation with our model indicates that an $F_{EQA}$ averaged over the previous 12 hours produces good results.

After calculating $F_{AA}(t)$ and $F_{EQA}(t)$, the algorithm compares the modeled transformer aging status against four aging thresholds ($H_{EQA}, H_{min}, H_{med},$ and $H_{max}$) to determine whether $q(t)$ should be increased, decreased, or held constant in the next time period. Equation (6) is used to choose the change in $q(t)$ from the previous time period:

$$q(t) = q(t-\Delta t) + \Delta q(t)$$  \hspace{1cm} (5)

$$\Delta q(t) = \begin{cases} +1, & \text{if } (F_{AA} < H_{min}) \text{ or } (F_{AA} > H_{med} \text{ and } F_{EQA} < H_{EQA}) \\ -1, & \text{if } (F_{AA} < H_{med}) \\ -2, & \text{if } (F_{AA} > H_{max}) \\ 0, & \text{otherwise} \end{cases}$$  \hspace{1cm} (6)

Table 1 provides suggested aging threshold values, as determined from our extensive numerical experimentation. Unless $q(t)$ is greater than $q_r(t)$, in which case all requesting PEVs

\begin{table}[h]
\centering
\begin{tabular}{|c|c|c|c|}
\hline
$H_{EQA}$ & $H_{min}$ & $H_{med}$ & $H_{max}$ \\
\hline
2.5 & 3.5 & 4 & 4.75 \\
\hline
\end{tabular}
\caption{Aging thresholds used for smart charging algorithm comparison and decision process}
\end{table}

\(^{1}\)http://www.ncdc.noaa.gov
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.

Figure 2 highlights the differences between AC Level 1 uncontrolled and smart charging using a transformer operating during a high-temperature, 48 hour period for Phoenix, AZ and serving six PEVs. The smart charging algorithm delays charging for several vehicles, away from the hottest hours or heaviest load periods of the day.

Figure 2. Comparison of uncontrolled PEV charging vs. PEV charging with smart charging algorithm. Data corresponds to a 25 kVA transformer serving 12 homes and 6 PEVs during a 48 hour period in Phoenix, AZ in June 2010.

D. Full Year Model Results

As concluded in our previous work [27], the annual ambient temperature of the overhead distribution transformer contributes significantly to the PEV charging impacts. Therefore in this study we examine PEV charging impacts in two climatically distinct U.S. cities: Burlington, VT and Phoenix, AZ. Our previous work [20] introduced and demonstrated our initial smart charging algorithm but only considered AC Level 1 PEV charging. In this study, we extend the previous work to include a comparison of AC Level 1 and AC Level 2 PEV charging under both uncoordinated and smart charging conditions. For baseline purposes, we compare these results to a case with no PEV load.

We use a Monte Carlo simulation to aggregate annual transformer loss-of-life data for 500 distinct sets of travel patterns, under the following five test conditions for each geographic location: 1) no PEV charging; 2) AC Level 1, uncoordinated PEV charging; 3) AC Level 1, smart PEV charging; 4) AC Level 2, uncoordinated PEV charging; and 5) AC Level 2, Smart PEV charging. We use the factor of equivalent aging calculated over the course of one calendar year as the metric for comparison. When serving 12 homes, the baseline load, prior to PEV charging, approaches a daily average load of approximately 25kVA, or near rated capacity. We model a transformer serving \(n_v = 6\) PEVs, each with unique travel patterns resulting in a unique load profile for each model run.

Figure 3 shows the simulation results for each of the 5 cases and for each geographic location. For cases of uncoordinated charging, there is a noticeable difference between AC Level 1 and AC Level 2 charging. The aggregate \(F_{\text{EQA}}\) for Burlington increases from 0.39 to 1.08 with the introduction of AC Level 2 charging; Phoenix increases from 3.24 to 8.15. This result demonstrates the increased impact from AC Level 2 charging compared against AC Level 1 charging.

With the introduction of smart charging, the Burlington \(F_{\text{EQA}}\) reduces to 0.34 for AC Level 1 and to 0.55 for AC Level 2 charging. The aggregate \(F_{\text{EQA}}\) for Burlington increases from 0.39 to 1.08 with the introduction of AC Level 2 charging; Phoenix increases from 3.24 to 8.15. This result demonstrates the increased impact from AC Level 2 charging compared against AC Level 1 charging.

With the introduction of smart charging, the Burlington \(F_{\text{EQA}}\) reduces to 0.34 for AC Level 1 and to 0.55 for AC Level 2; The Phoenix \(F_{\text{EQA}}\) reduces to 1.64 for AC Level 1 and to 2.056 for AC Level 2. For all cases, a two-sample Kolmogorov-Smirnov test shows statistical significance of the reduction in aging from smart charging (\(p < 10^{-3}\) for all cases). This result demonstrates the utility of smart charging, especially in the warmer climate and in situations were AC Level 2 is used.

Examination of the uncoordinated charging 10th and 90th percentiles in Fig. 3 shows substantial variance in transformer aging among the model runs. Specifically, uncoordinated charging in Burlington possesses variances of 0.04 and 2.02 for AC Levels 1 and 2 respectively; in Phoenix the variances were 2.5 and 93.23 for AC Levels 1 and 2 respectively. This
result highlights the system stress that may be caused by AC Level 2 charging as well as the combination of high temperatures (in the Phoenix case) and highly unpredictable PEV driver travel behavior. With the introduction of smart charging, the Burlington variance decrease to 0.013 and 0.041 for AC Levels 1 and 2 respectively, and in Phoenix the variances decreased to 0.043 and 0.066 for AC Levels 1 and 2 respectively. Decreases are more dramatic in AC Level 2 cases and especially in the warmer Phoenix climate. As evident in Fig. 3, smart charging reduces the $F_{EQA}$ variance, demonstrating the utility of smart charging for reducing uncertainty in transformer life expectancy.

It is also important to note that an algorithm that reduces aging but does not provide adequate charging to the PEV is not desirable. To ensure that our simulated smart charging resulted in adequate PEV charging, we measured the number of cases in which vehicles fully charged before beginning their next outing, after having been parked at home for an extended period of time. Specifically, we define a “successful charge” to be a period in which the PEV was charged to at least 95% of capacity after being located at home long enough to have received a full charge with no charge management. In evaluating the success of the smart charging algorithm, we found that in the case of AC Level 1 charging that 99.1% and 98.7% of extended home stays in Burlington and Phoenix, respectively, resulted in successful charges, using this definition; the numbers were reasonable for AC Level 2 charging (98.7% in Burlington and 95.7% in Phoenix). These figures indicate that the proposed smart charging algorithm would have almost no noticeable effect on most vehicle owners.

E. Discussion of full year model results

We find that for both cases, AC Levels 1 and 2, the warmer climate of Phoenix, AZ results in notably more transformer aging from PEV charging, relative to the cooler climate of Burlington, VT. Introduction of AC Level 2 drastically increases aging compared to AC Level 1 for both locations; the results indicate that a moderate amount of PEV charging may not substantially decrease the life of transformers located in cooler climates until AC Level 2 charging is introduced. For the Phoenix, AZ cases, the average transformer aging approximately triples against the test case with no PEV charging at AC Level 1 and is nearly eight times greater at AC Level 2. These results highlight the need to use location-specific ambient temperature data when evaluating the impact of PEV charging on transformers. Additionally, because of the variability in driver behavior, PEV charging introduces enormous variance in transformer aging, particularly for the hot climate.

Smart charging has a greater effect on the hot climate and in both climates when AC Level 2 is used. In addition to this average reduction in aging effect, the introduction of charge management removes much of the variability in aging. This reduction comes at the cost of leaving vehicles with less than 95% of a full charge in only about 1% of cases except the Phoenix AC Level 2 case, in which the percentage is closer to 4%. Thus, smart charging not only decreases transformer aging, but also reduces uncertainty in transformer life, in the face of uncertain PEV travel behavior.

III. DECENTRALIZED SMART CHARGING ALGORITHM

In Section II-C, the smart charging algorithm determines the maximum number of possible PEVs that may be charged simultaneously during each discrete time period, and then randomly allocates which PEVs receive charge. This section describes two alternative approaches, which are distinct from the method presented in Section II-C in that they use discrete allocations of PEV charging and allow for decentralized implementation.

Method 1 uses first-come, first served (FCFS) PEV charge allocation. We assume that each PEV contains a charge-management automaton which sends charge requests to the transformer at discrete time intervals. If there is sufficient capacity to support charging, the PEV will charge during that epoch (discrete interval of time) on a first-come, first served basis. Otherwise, the request will be denied.

Method 2 also assumes a network of simple charge-management automaton, one per PEV. However, in this method each PEV sends a charge request with a certain probability, which is determined autonomously. Method 2 shows advantage over Method 1 by considering owner determined urgency in PEV charging, which assumes a pricing structure with increased cost for urgent charging. Section III-A explains these algorithms further and simulation results are shown in Section III-B.

A. Algorithm description

Methods 1 and 2 assume PEV charging conducted over many discrete time intervals (e.g. 5 minutes). The charge given during each interval is referred to as a charge packet in deference to communication systems data packets [29], upon which this random access technique finds inspiration. In Method 1, charge packets are given based on a first-come, first-served (FCFS) approach. All requests are treated equally and the PEVs regularly compete for charging capacity. Additionally, all PEV automatons send requests at every epoch and the requests are accepted until the overload limit of the transformer is reached.

Figure 4 shows a simple probabilistic 2-state automaton state diagram to illustrate Method 2. The PEVs adjust their state autonomously using this method based only on the feedback provided by the charge manager. This approach enables PEV owner’s to indicate charge requirement urgency. It is assumed that the PEV owner may choose to receive more charge priority if the need is immediate. Pricing structure policy may establish that the PEV owner must pay a higher price rate for increased charge priority during the peak load duration. The cost allocation is not considered in this work.

When the PEV arrives at the home charging station, the automaton sends charge requests in every epoch (for example, 5 minutes in the case of this study). If any request is denied by the transformer, as a result of overloading (congestion = 1), and the PEV owner requested normal charging by a 2-state
knob (urgency = 0), the automaton moves to the lower state, $P_2$, which is set to a lower value than $P_1$.

If a PEV owner requires charge immediately, the urgent option is selected (urgency = 1), wherein the automaton remains in state $P_1$ and sends charge requests in every epoch, repeatedly. In this way, PEVs requiring immediate charge will receive more charge, on average, during the peak load period.

B. Simulation Results

To illustrate both Method 1 and Method 2, we present three case studies. In Cases 1 and 2, the low voltage (LV) transformer is assumed to be the charge manager, and a 25 kVA transformer is considered to serve 7 customers with a daily load curve used in Section II-A. We assume 4 PEVs require charge, and one PEV requests urgent charging. AC Level 1 and AC Level 2 charging is assumed for Cases 1 and 2 respectively. In Case 3, all the charge requests are sent to a 500 kVA high voltage (HV) transformer, which is assumed to serve 100 PEVs submitting charge requests.

1) Case 1: LV transformer is the charge manager, Level 1 charging: Case 1 assumes that the requests are sent to the LV transformer, which is the first transformer upstream from the end-users. In this example, the battery capacity is selected randomly from two available PEVs which are available as of the 2011 market year. The Chevrolet Volt has a 16 kWh battery of which 10.4 kWh is available, and the Nissan Leaf has a 24 kWh battery capacity. The required charge for each PEV is assumed to be normally distributed between 70% and 90% of battery capacity. AC Level 1 charging is assumed to be available for all the PEVs, and the charge efficiency is assumed to be 90%. In our simulations, we assume that the plug-in time of the PEVs are normally distributed between 1700 and 1900 hrs. Also, the plug-out times are normally distributed between 0600 and 0800 hours of the next day. Additionally, one PEV is selected randomly to require urgent charge; its plug-out time is normally distributed between 2000 and 2200 hrs of the same day of arrival. Later, this PEV will again be plugged into the grid after a normally distributed random time between 1 and 3 hours. Fig. 5 shows the result of one sample simulation. In this example, $P_2$ is set to be 0.4.

Figure 5 shows that uncoordinated PEV charging can cause the 25 kVA transformer to be overloaded for approximately three hours. If the transformer load is limited to 25 kW, the overload problem is solved by both strategies. Moreover, a large number of simulations (500 iterations) show that when probabilistic charging (Method 2) is used, the PEV requiring immediate charge obtains 83% of the total charge received from uncoordinated charging, whereas Method 1 results in only 69% of the total charge from uncoordinated charging. Additional observations show that all PEVs receive full charge by the next morning in 97% of instances using both Methods 1 and 2.

2) Case 2: LV transformer is the charge manager, Level 2 charging: This simulation uses the same criteria used in Case 1; however, PEVs charge at AC Level 2 (3.3 kW). Figure 6 shows the results of this example, which indicates that Level 2 charging imposes a higher peak load and the transformer is overloaded for a longer period. Also, Method 2 observations indicate that the PEV with urgent need of charge will receive more of the total possible charge during the plugged-in period, as compared to Method 1.

3) Case 3: HV transformer is the charge manager, Level 1 charging: A final example shows the robustness of Method
2. The requests are sent to a 500 kVA HV transformer that is located at the beginning of the primary distribution system feeder. Overloading this transformer is riskier and must be avoided. We assume that 100 PEVs are charging on the feeder and 20 of these choose urgent charging. \( P_2 \) is assumed to be 0.2 here. Figure 7 shows the results of the third example. For best visualization, it is assumed that the last 20 PEVs of the total 100 set urgency = 1 and will depart from the home charging station later in the evening. As in Case 1 and 2, these PEVs are plugged into the grid later at night, and are fully charged at the next morning.

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**IV. Conclusions**

This paper describes a method for estimating the impact of PEV charging on overhead distribution transformers by combining a transformer thermal aging model with empirical travel behavior. We use Monte Carlo simulation to estimate the aging in overhead distribution transformers with ambient temperature data from Phoenix, AZ and Burlington, VT. We investigate and compare cases with AC Levels 1 and 2 charging. When AC level 1 charging is replaced with AC level 2 charging for the uncoordinated charging case, transformer average annual factor of equivalent aging could increase from 0.39 to 1.08 in the colder climate (VT) and from 3.24 to 8.15 in the warmer climate (AZ). This increase indicates a greater impact from AC Level 2 charging on the warmer climate. We also evaluate our initial smart charging algorithm designed to mitigate the impacts of PEV charging on overhead distribution transformers. For AC Level 1 charging, the reduction in aging for smart charging compared to uncoordinated charging is 12.8% and 49.4% for VT and AZ respectively. The reduction in aging as a result of smart charging is more dramatic for AC Level 2 cases; aging decreases by 48.9% and 74.8% for VT and AZ respectively. The introduction of smart charging also reduces uncertainty in transformer aging at both climatic regions and for both AC Levels 1 and 2 charging.

Additionally, we introduce two decentralized automaton-based strategies for charge management coordination, which limit the transformer power to its nominal value (or other acceptable limit). We have combined the independent charge management strategy with a pricing structure that allows user choice of charge urgency requirement by using the probabilistic charge request submission method (Method 2). The results indicate that if the user requires charging more urgently, there will be a greater probability of receiving charge compared against a PEV with less immediate need. If charge urgency is to be considered, Method 2 shows superiority over Method 1 and the algorithm in Section II-C. In future work we will improve upon and apply the empirically derived vehicle demand and availability profiles of Section II and the impacts of ambient temperature to simulations of the decentralized charging strategies in Section III.

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