Probabilistic Assessment of Electric Vehicle Charging Demand Impact on Residential Distribution Transformer Aging

Carolina M. Affonso
Faculty of Electrical Engineering
Federal University of Para
Belem, Brazil
carolina@ufpa.br

Mladen Kezunovic
Department of Electrical and Computer Engineering
Texas A&M University
College Station, U.S.A.
kezunovic@ece.tamu.edu

***Abstract*—This paper proposes a probabilistic approach to quantify the impacts imposed on transformer hottest-spot temperature and loss-of-life by plug-in electric vehicles (PEV) charging demand. A residential complex with 8 households connected to a 20kVA distribution transformer is considered. Monte Carlo simulation method is applied to take into account the stochastic behavior of PEVs, residential demand, photovoltaic generation and ambient temperature. Based on historical data, different aspects such as the impact of different PEV penetration levels, PEV charging power, and the potential benefits the connection of photovoltaic generation in the area can bring are considered. The obtained results provide a better understanding of the effects produced by PEV demand on transformer aging, and can be used to decide under what scenarios there may be risk of accelerated transformer loss-of-life.**

***Keywords*—plug-in electric vehicles, Monte Carlo, photovoltaic generation, probabilistic analysis, transformer loss-of-life.**

I. INTRODUCTION

Plug-in Electric vehicles (PEV) have emerged as a promising solution to help environment conservation by avoiding the consumption of fossil fuel and hence reducing emissions of greenhouse gases and other pollutants in the atmosphere. The expectation is that PEVs global fleet will continue to grow in the near future with government incentives schemes, more affordable prices and the expansion of public charging facilities. However, the increasing number of PEVs also brings challenges to power system, since it also increases demand for electricity.

The increasing demand of residential PEV charging may cause several technical problems in the distribution system, such as under-voltage conditions, power quality issues, increased system losses, and transformer aging [1,2,3]. When operating in overloaded condition, the transformer can experience accelerated aging and loss-of-life (LOL) due to insulation degradation, requiring early replacement. This problem becomes more critical in cities with hot weather, where transformers can be exposed to high ambient temperatures varying up to 35-45ºC. Some studies proposed to investigate this problem as discussed next.

Reference [4] presents a case study analyzing the impact of electric vehicle demand on distribution transformer overloading in a residential neighborhood of Toronto, Canada. The results shows that transformer overloading is expected under certain scenarios due to EV charging. In [5], the impact of plug-in hybrid electric vehicles on distribution transformers is investigated considering a typical residential system. Reference [6] proposes a model to optimize PEVs charging/discharging and investigates its effect on transformer loss-of-life. An analysis of the impact of the connection of photovoltaic generation and electric vehicles on transformer operating conditions in a district with commercial and residential consumers is studied in [7]. In [8], the impact of electric vehicles charging on distribution transformer loss-of-life is evaluated based on probabilistic analysis, considering the presence of photovoltaic generation.

This paper proposes not only to analyze but also quantify the possible effects that electric vehicles charging can produce on transformer loss-of-life, considering a residential complex with 8 households served by a 20kVA transformer. A detailed analysis is developed, quantifying the impact of different PEV penetration levels, PEV charging power, and the potential benefits that can be introduced by the connection of photovoltaic generation (PV) in the residential area under different power factors for summer and winter seasons. The Monte Carlo simulation method is applied to probabilistically estimate distribution transformer hottest-spot temperature and LOL, considering uncertainties due to residential and PEVs demand, ambient temperature, and photovoltaic generation. In order to get more realistic results, simulations were based on historical data available in different websites. Our findings show that the PEV penetration level, PEV charging power and availability of PV power have to be optimized to reduce the LOL impact on transformers.

The remainder of this paper is organized as follows. Section II shows how the uncertainties in system parameters were considered. Section III presents transformer aging model. In Section IV, Monte Carlo simulation methodology is illustrated. Section V discusses simulation results and Section VI address the main conclusions achieved.

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II. STOCHASTIC SYSTEM MODELING

The system under study is a residential complex consisting of 8 houses connected to the grid through a 20kVA distribution transformer as shown in Fig. 1. It is assumed that each household has 2 vehicles, which can be conventional gasoline or PEV, and each household may have a rooftop PV installation. Simulations are performed using historical data of demand, solar irradiance and ambient temperature considering a location in Texas, USA.

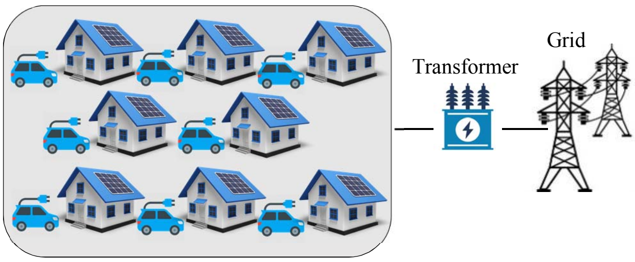

Fig. 1. Schematic diagram of the system under study.

In order to access transformer loss-of-life, its demand should be evaluated as shown in (1) taking into account: the aggregated residential demand P_{res}, the charging power consumed by all plug-in electrical vehicles P_{PEV}, and the power generated by all rooftop PV systems in the residential area P_{PV} at time t.

$$P_{Transf}(t) = P_{res}(t) + P_{PEV}(t) - P_{PV}(t), \forall t = 1 \ldots N \quad (1)$$

PEVs demand highly depends on travel patterns and drivers behavior, which varies from day to day. Also, PV generation varies with weather conditions, and the residential demand is constantly changing due to variations caused by customer behavior. Because of that, it is important to address all these uncertainties estimating transformer load and loss-of-life with probabilistically models, which is described next.

A. Residential Load

The residential load is the electric power consumed by the households with lighting, air conditioning, cooking appliances, refrigerator and others, excluding PEV demand. The houses are occupied by families that work during typical weekday hours. The load profiles adopted in this study were obtained from ERCOT website considering a residential customer in South Central Texas, and the corresponding power factor is assumed to be 0.95 [9]. Fig. 2 shows the aggregated load profile adopted for the residential complex during summer and winter, with a 30 minutes sample interval.

Based on the load profile, a Gaussian distribution is used to incorporate the corresponding uncertainties, performing random sampling to each day interval. This distribution is the most commonly used technique for electricity load modeling, with mean μ_L and standard deviation σ_L as shown in (2) [10].

$$Load = Gauss\,(\mu_L, \sigma_L^2) \quad (2)$$

B. Ambient Tempertature

The ambient temperature profiles used in this study were obtained from Weather Underground website for a typical summer and winter day in Austin, Texas [11]. Fig. 3 shows the ambient temperature profile adopted for summer (July, 2017) and winter (January, 2018) with a 30 minutes sample interval. The ambient temperature at any given day and time can also be described by a Gaussian distribution from the available historical or forecasted data, with mean μ_{Ta} and standard deviation σ_{Ta} as shows (3).

$$Ta = Gauss\,(\mu_{Ta}, \sigma_{Ta}^2) \quad (3)$$

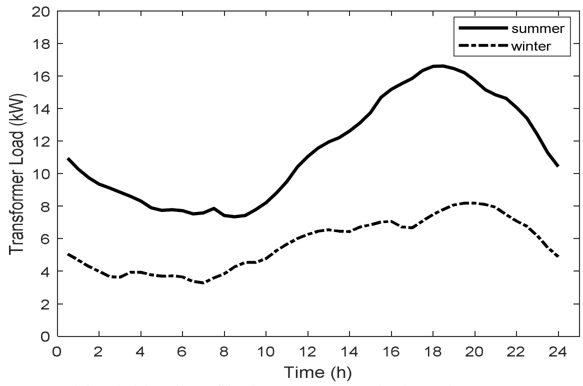

Fig. 2. Residential load profile for summer and winter in Texas.

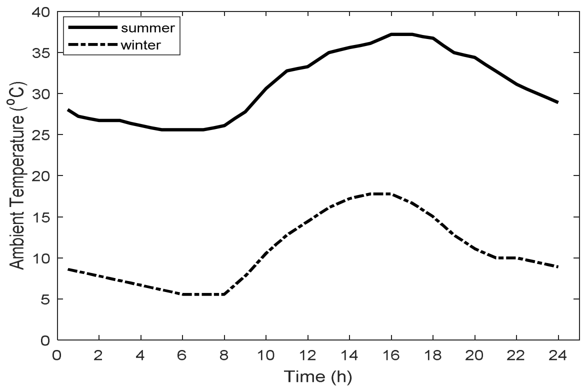

Fig. 3. Ambient temperature profile during summer and winter in Texas.

C. PV Generation

Photovoltaic generation is an intermittent energy source and depends on solar irradiance availability. Since solar irradiance is time and weather dependent, different day hours will have different probability distribution function. In order to represent this behavior, historical irradiance data was collected for Austin, Texas, using PVWatts calculator developed by the National Renewable Energy Laboratory (NREL) [12]. The mean and standard deviation values were calculated to each half-hour of the day, and a Beta probability density function is generated for each time interval. As a result, the PV output power can be obtained for a 24 hour period with 30 minutes sampling. The Beta probability density function (β-pdf) can be expressed as shown in (4) [13].

$$f_\beta(s) = \begin{cases} \dfrac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} s^{(\alpha-1)}(1-s)^{(\beta-1)}, 0 \le s \le 1, \alpha, \beta \ge 0 \\ 0, \quad otherwise \end{cases} \quad (4)$$

where Γ is the gamma function, s is the random variable of solar irradiance in kW/m^2, $f_\beta(s)$ is the Beta probability density function of s, α and β are the parameters of Beta distribution function. The values of α and β depends on the mean μ and standard deviation σ of s, as shows (5).

$$\beta = (1-\mu)\left[\frac{\mu(1-\mu)}{\sigma^2} - 1\right], \qquad \alpha = \frac{\mu\beta}{1-\mu} \tag{5}$$

Fig. 4 shows the histogram obtained for the expected PV output for different day hours. At the beginning of the day, at 8:00 a.m., there is a high probability of having low power production due to low irradiance levels. However, at 11:00 a.m., high irradiance levels increases the chance of having high power production.

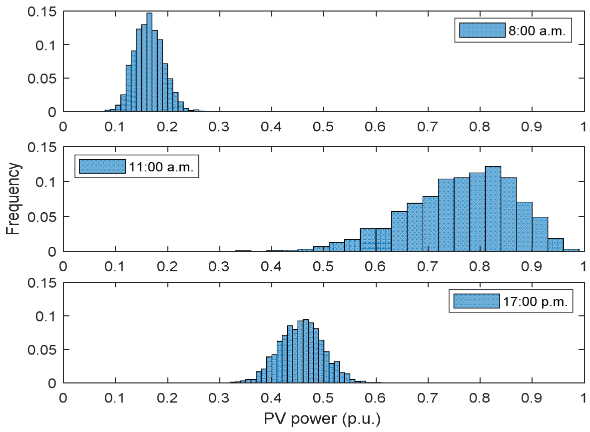

Fig. 4. Histogram of expected PV output for different hours during a day.

D. Plug-in Electric Vehicles Demand

During charging periods, PEVs represent an extra demand to the system. The PEV load profile can be estimated based on the start charging time, charging duration and other important variables as shown the flowchart in Fig. 5.

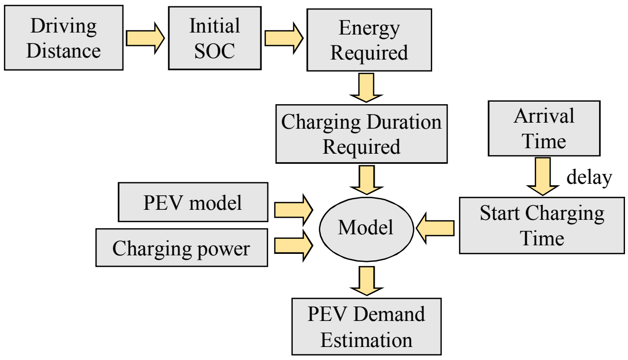

Fig. 5. Flowchart of PEV demand estimation process.

According to [14,15,16], most people drive a distance in the range of 20–25 miles per day, and 55% of people drive less than 30 miles/day. The daily miles driven may be represented by a log-normal distribution as in (6), with mean μ_d = 3.37 and standard deviation σ_d = 0.5, which is presented in Fig. 6.

$$d = Ln(\mu_d, \sigma_d^2) \tag{6}$$

Based on the driving distance, PEV state-of-charge when arriving home (SOC^{ini}) can be obtained as shows (7) [17].

$$SOC_{\%}^{ini} = \left(1 - \frac{E_{cons}\,d}{C_b}\right) \times 100 \tag{7}$$

where C_b is PEV battery capacity in kWh, E_{cons} is electricity consumption in kWh/miles, and d is daily miles driven.

The energy needed to charge the PEV until it reaches the state-of-charge required by the user SOC^{req} (assumed to be 95%) can be evaluated with (8), where η is charging efficiency assumed in this case to be 0.95.

$$E_{req} = \left(SOC_{\%}^{req} - SOC_{\%}^{ini}\right) \times C_b / (\eta \times 100) \tag{8}$$

Considering that PEVs are charged with a constant power P at unity power factor, the required time to charge the vehicle Ch_{time} is obtained by (9). The PEV model considered in this study is Nissan Leaf, a purely electricity popular car with 24kWh battery capacity and 0.34kWh/miles consumption.

$$Ch_{time} = E_{req} / P \tag{9}$$

Another important variable in PEV demand estimation process is the starting charging time. Most PEVs owner leave their houses for work in the early morning and arrive home in the evening. We assume that they start charging their vehicles when they return home, at the end of the day, considering a delay of 30 minutes between arriving and charging. According to [18], during weekdays most people arrive home between 16:00 and 21:00 after their work hours. Then, PEV home arrival time t_a follows a normal distribution with mean μ_{ta} = 17:00 and standard deviation σ_{ta} = 2.28 as shows (10). The arrival time distribution is presented on Fig. 7.

$$t_a = Gauss(\mu_{t_a}, \sigma_{t_a}^2) \tag{10}$$

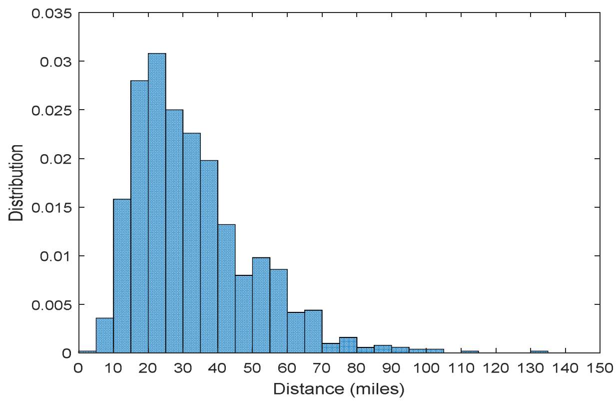

Fig. 6. Driving distance distribution.

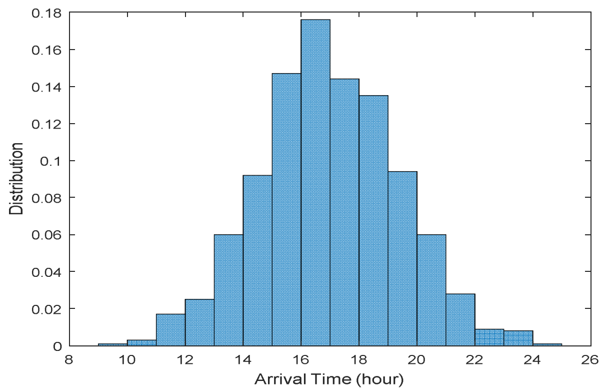

Fig. 7. Arrival time distribution.

III. TRANSFORMER AGING MODEL

Transformer aging and insulation degradation is mainly affected by its internal temperature. Since the temperature distribution is irregular, the aging effect is evaluated considering the hottest-spot temperature, which is the point where the greatest degradation occurs. According to IEEE standard C57.91 [19], the accelerated aging factor F_{AA} at a given hottest-spot temperature is evaluated using (11) at each time of the day, and the equivalent aging F_{EQA} is obtained by (12), averaging F_{AA} over the time N the transformer is under analysis. Assuming that normal aging occurs at 110ºC, for transformer operation above the reference hottest-spot temperature, F_{AA} will be bigger than one indicating an accelerated aging. On the contrary, F_{AA} will be lower than one. As an example, for a load cycle of 24 hours, F_{EQA}=1.084 is equivalent to aging of 1.084 days per one day, or 26 hours of accelerated aging in 24 hours.

$$F_{AA}(t) = exp\left(\frac{15000}{110+273} - \frac{15000}{\theta_H(t)+273}\right) \quad (11)$$

$$F_{EQA} = \frac{\sum_{t=1}^{N} F_{AA}(t)\times\Delta t}{\sum_{t=1}^{N}\Delta t} \quad (12)$$

Based on equivalent aging, the transformer loss-of-life can be obtained as shows (13), where t is the time period under analysis in hours. Considering normal insulation life as 180,000 hours (20.5 years) and that transformer operates under reference temperature, the normal daily LOL will be 0.1333%.

$$LOL(\%) = \frac{F_{EQA}\times t\times 100}{Normal\ Insulation\ Life} \quad (13)$$

The hottest-spot temperature θ_H can be evaluated by (14):

$$\theta_H = \theta_a + \Delta\theta_{to} + \Delta\theta_h \quad (14)$$

where θ_a is the ambient temperature, $\Delta\theta_{to}$ is the top-oil temperature rise over the ambient, and $\Delta\theta_h$ is the winding hottest-spot temperature rise over the top-oil, all in degree Celsius.

The changes in temperature $\Delta\theta_h$ and $\Delta\theta_{to}$ are calculated as:

$$\Delta\theta_h = \left(\Delta\theta_{h,u} - \Delta\theta_{h,i}\right)\left(1 - e^{-\frac{t}{\tau_w}}\right) + \Delta\theta_{h,i} \quad (15)$$

$$\Delta\theta_{to} = \left(\Delta\theta_{to,u} - \Delta\theta_{to,i}\right)\left(1 - e^{-\frac{t}{\tau_{to}}}\right) + \Delta\theta_{to,i} \quad (16)$$

where $\Delta\theta_{to,i}$ is the initial top-oil rise temperature over the ambient, $\Delta\theta_{h,i}$ is the initial winding hottest-spot temperature rise over the top-oil, $\Delta\theta_{to,u}$ is the ultimate top-oil rise temperature over the ambient, $\Delta\theta_{h,u}$ is the ultimate winding hottest-spot temperature rise over the top-oil, τ_{to} and τ_w are the oil and winding time constant respectively, and t is the sampling period in hours.

The ultimate change in temperature $\Delta\theta_{h,u}$ and $\Delta\theta_{to,u}$ are:

$$\Delta\theta_{h,u} = \Delta\theta_{h,r}K_u^{2m}, \quad \Delta\theta_{to,u} = \Delta\theta_{to,r}\left[\frac{K_uR+1}{R+1}\right]^n \quad (17)$$

where $\Delta\theta_{h,r}$ is the winding hottest-spot temperature rise over top-oil at rated load, $\Delta\theta_{to,r}$ is the top-oil temperature rise over the ambient at rated load, K_u is the ratio of ultimate load to rated load, R is the ratio between loss at rated load and no load loss, m and n are associated with the cooling mode.

IV. PROBABILISTIC SIMULATION METHODOLOGY

Monte Carlo simulation is a widely used method to perform probabilistic analysis [20]. It repeatedly generates random sampling of system inputs according to its probability distribution, in order to obtain a large dataset of the desired system output. After that, a statistical analysis can be performed on the model output, estimating its behavior and probability of occurrence.

In this paper, the statistical variables considered in Monte Carlo simulations are the residential and PEV demand, PV generation profile, and ambient temperature. Considering the 24-hour transformer load cycle, the hottest-spot temperature and loss-of-life can be evaluated. A large number of Monte Carlo simulations were considered to obtain an accurate estimation model (MC^{max}=3000). The following steps defines methodology adopted in this study.

- Step 1: Generate random variables sampling of residential and PEV demand, photovoltaic generation, and ambient temperature for summer and winter scenarios;
- Step 2: Evaluate transformer load to each interval of the day;
- Step 3: Compute transformer hottest-spot temperature and loss-of-life for each half-hour of a day;
- Step 4: Save simulation results and repeat steps 1, 2 and 3 until the total number of simulations is reached;
- Step 5: Perform statistical analysis.

V. SIMULATION RESULTS

This paper analyzes the impact of PEVs demand on distribution transformer aging in the residential complex presented in Fig. 1. The impact of different factors such as PEV penetration level, PEV charging power and PV generation availability in the residential complex are analyzed.

A. PEV Penetration Level Impact

The PEV penetration level (PL_{PEV}) is defined as the percentage ratio of the PEVs number to the total number of vehicles in the residential complex, considering two vehicles per household and a total of 8 households in the studied area. The penetration levels considered in this study varies from 25% (scenario with low penetration level) to 100% (scenario with high penetration level), and vehicle charging power is assumed to be 1.44 kW (Level 1). In these simulations we assume that all houses do not have photovoltaic generation.

Table I shows the probability of having an equivalent aging factor greater than one according to different PEV penetration levels, considering a typical summer and winter weekday. During summer, transformer aging increases as PEVs penetration level increases. For a penetration level of 50%, the probability of transformer aging is 57.42%, which is a significant percentage. This probability increases considerably when the penetration level is 56%, indicating that transformer life will likely be deteriorated. However, during the winter, the probability of transformer aging is 0% for most penetration levels. This is due to the fact that for the location analyzed, the load consumed in winter is usually lower than that in summer. Also, ambient temperature is much lower in winter. Fig. 8 shows the histogram of transformer LOL for 50% PEV penetration level.

As an example, Fig. 9 shows transformer load and hottest-spot temperature for one of the possible scenarios in summer with a penetration level of 43.7%. The results show that the transformer operates above its rated capacity between the hours of 16:00 and 21:00 due to PEV charging. As a consequence, its hottest-spot temperature becomes higher than the reference temperature of 110ºC, and the equivalent aging factor is 1.1045 for this day, indicating accelerated aging of 26.5 hours in 24 hours.

TABLE I. PEVS PENETRATION LEVEL IMPACT ON PROBABILITY OF AGING

Number of PEVs	PL_{PEV}	*Prob* ($F_{EQA} > 1$) in Summer	*Prob* ($F_{EQA} > 1$) in Winter
4	25.0 %	0 %	0 %
5	31.2 %	0 %	0 %
6	37.5 %	0.03 %	0 %
7	43.7 %	15.31 %	0 %
8	**50.0 %**	**57.42 %**	**0 %**
9	**56.25 %**	**83.90 %**	**0 %**
10	62.5 %	95.56 %	0 %
11	68.7 %	98.90 %	0 %
12	75.0 %	99.63 %	0 %
13	81.2 %	99.83 %	0 %
14	87.5 %	99.93 %	0 %
15	93.7 %	99.96 %	0 %
16	100.0 %	100.0 %	0.066 %

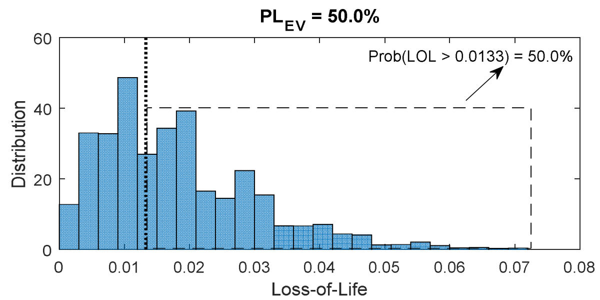

Fig. 8. Histogram of transformer loss-of-life in summer and 50% of PEV.

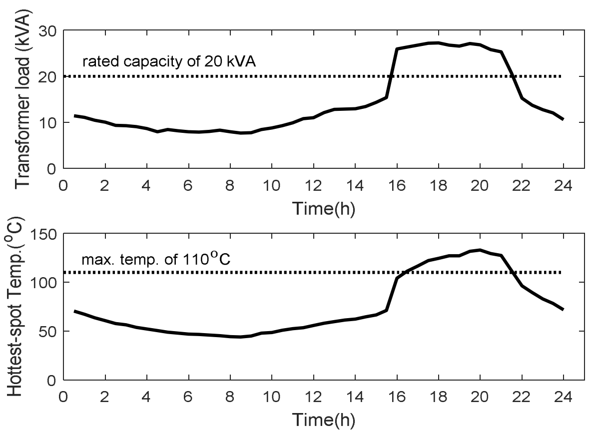

Fig. 9. Transformer demand and hottest-spot temperature for a scenario during summer with PEV penetration level of 43.7%.

B. PEV Charging Power Impact

In this section, the impact of the PEV charging power on transformer aging is analyzed. Two different charging levels were considered for both summer and winter season: Level 1 (1.44kW) and Level 2 (3.3kW). In these simulations we assume that all houses do not have photovoltaic generation. Table II shows the probability of having an equivalent aging factor greater than one for different charging power and PEV penetration levels. As the charging power increases, the probability of transformer being subject to accelerated aging also increases. During the summer, up to a penetration level of 31.2%, there is no probability of transformer aging when vehicles charge at Level 1. However, when vehicles charge at Level 2, the probability of aging is quite significant, around 85.4%. During the winter, the probability of transformer aging is 0% for all penetration levels when vehicles charge at Level 1. However, when vehicles are charged under Level 2, the addition of 10 vehicles' demand is enough to cause transformer more likely to suffer accelerated aging.

Level 2 requires more power to charge the vehicle during a shorter duration time than Level 1. It means the impact on demand is more significant in Level 2, leading to higher peaks in the load curve as shown the example in Fig. 10. It is interesting to note that although transformer operates above its rated capacity during 4 hours when charging at Level 1, the exceeded demand (maximum of 15.13%) is not enough to affect the hottest-spot temperature, which remains under the 110ºC reference and does not affect transformer life.

TABLE II. PROBABILITY OF AGING FOR DIFFERENT PEVS PENETRATION LEVEL AND CHARGING POWER

Number of PEVs	PL_{PEV}	*Prob* ($F_{EQA} > 1$) (Level 1)	*Prob* ($F_{EQA} > 1$) (Level 2)
Summer			
3	18.75 %	0 %	0 %
4	25.0 %	0 %	34.23 %
5	**31.2 %**	**0 %**	**85.40 %**
6	37.5 %	0.03 %	98.13 %
7	43.7 %	15.31 %	99.80 %
8	50.0 %	57.42 %	99.96 %
Winter			
7	43.7 %	0 %	0 %
8	50.0 %	0 %	2.33%
9	56.25 %	0 %	38.06%
10	62.5 %	0 %	84.10%
11	68.7 %	0 %	97.30%
12	75.0 %	0 %	99.83%
13	81.2 %	0 %	99.9%
14	87.5 %	0 %	99.93%
15	93.7 %	0 %	99.96%
16	100.0 %	0 %	100%

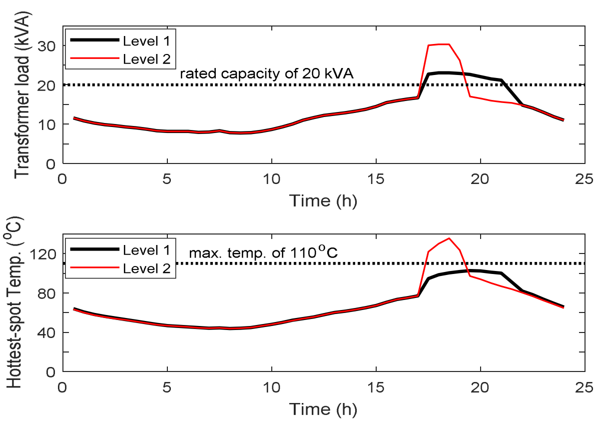

Fig. 10. Transformer demand and hottest-spot temperature for a scenario during summer with PEV penetration level of 25%.

C. PV Generation Impact

Another analysis performed in this paper is how the connection of PV generation in the residential complex can help mitigate the effects of PEVs on transformer life. In this case, charging Level 1 and summer season are considered, and two different PEV penetration levels are analyzed: 43.7% and 50%. Different scenarios are adopted according to the number of houses with photovoltaic generation in the residential complex, ranging from the case where no house has solar PV (0%), until the case where every house has solar PV (100%). The results are presented on Fig. 11. If half of the households install solar generation, the probability of transformer aging will reduce from 15.31% to 5.23% under a PEV penetration level of 43.7%. However, with a bigger PEV penetration level (50%), even if all households install solar generation, the probability of transformer aging will still be high, of 33.2%.

Presently, PV inverters do not inject reactive power into the grid. However, new grid codes may allow them to inject or absorb reactive power to support the grid. Simulations were performed assuming that PV generation can provide or absorb reactive power with 0.9 power factor in summer. The results on Table III show that when PV operates absorbing MVar, it requires more reactive power from the main grid, increasing transformer apparent power and as a consequence, its hottest-spot temperature. This negative impact is more evident under high PV penetration level.

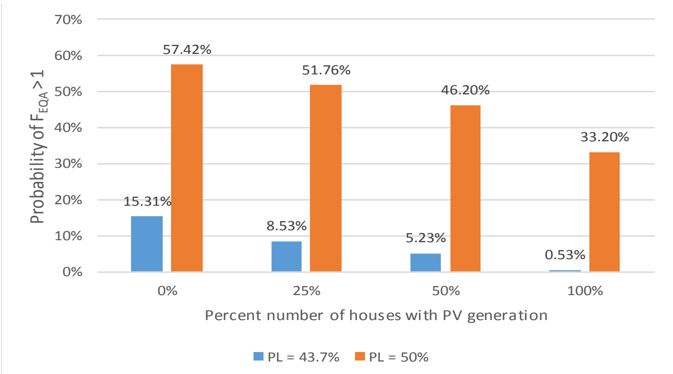

Fig. 11. PV generation impact on transformer aging at Level 1 during summer

TABLE III. POWER FACTOR IMPACT ON PROBAB. OF AGING (PL_{PEV} = 50%).

	Prob (F_{EQA} > 1)		
% houses with PV	**PV injects MVar (pf = 0.9)**	**MVar=0 (pf = 1)**	**PV consumes MVar (pf = 0.9)**
25%	51.03%	51.76%	52.50%
50%	44.43%	46.20%	48.50%
100%	**29.30%**	**33.20%**	**37.53%**

VI. CONCLUSIONS

This paper analyzes the effect of PEV demand on distribution transformer lifetime serving a residential complex with 8 houses. The Monte Carlo simulation method is used to consider all uncertainties related with residential and PEV demand, ambient temperature and PV generation. Summer and winter season are considered, and different aspects are analyzed. The results show that:

- The inclusion of 9 PEVs, a little bit more than one PEV per household, will considerably increase transformer aging factor, reducing its expected lifetime;
- When the vehicles are charging at Level 2, the inclusion of 5 PEVs in the residential area will likely deteriorate transformer life (probability of 85.4%);
- During the winter, transformer is not exposed to accelerated aging when charging at Level 1, regardless PEV penetration level. However, when Level 2 is adopted, even during the winter, transformer may experience aging depending on PEV penetration level;
- The connection of rooftop PV can avoid transformer overloading and help to prevent its life deterioration, depending on the number of PEV and operating mode.

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