

# Probabilistic Sizing of PV Generation on Commercial Parking Lot with PEVs to Avoid Transformer Aging

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**Abstract**—This paper presents an analytical method for sizing photovoltaic (PV) generation aiming at reducing transformer hottest-spot temperature and loss-of-life due to overloaded operation with the connection of plug-in electric vehicles. The study considers a commercial building with 8 electric vehicles charging stations supplied by a 75 kVA transformer. The methodology uses Monte Carlo simulation in order to consider data uncertainties, and simulations are performed based on real ambient temperature and irradiance data from Austin, Texas. The results show the connection of eight Level 2 charging stations is enough to make transformer operate overloaded for several hours and suffer premature aging in some scenarios. Also, the installation of PV generation with penetration level of 39.6% is enough to make transformer operate under the recommended temperature levels without suffering premature aging, even when operating overloaded for few hours.

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

## I. INTRODUCTION

Plug-in Electric Vehicles (PEV) fleet grew 54% worldwide in 2017 reaching about 3.1 million cars [1]. The electrification of mobility is causing an increase in total energy demand, which can significantly affect distribution system. Under uncoordinated charging, PEVs demand may exceed distribution transformer capacity during prolonged periods and may cause overheating and degradation of transformer insulation system, resulting in accelerated loss-of-life and economic losses [2].

Some possible solutions to avoid transformer premature aging are transformer upgrades, demand response methods, smart charging procedures and installation of photovoltaic generation (PV). Reference [3] develops an optimization model to charge/discharge PEVs aiming at reducing the impact on a 25 kVA transformer serving six residential consumers. Reference [4] presents an optimal scheduling method for PEVs in a Norwegian distribution grid with PV generation. The objective is to minimize the cost of electricity purchased from grid while maintaining transformer and line loads within their limits. In [5], the impact of price-incentive based demand response is investigated in a neighborhood consisting of four

houses with PVs, battery energy storage system and PEVs. The results show the integration of PEVs in a residential area may cause transformer accelerated aging, and the use of price mechanisms may create another load peak during off-peak periods. Reference [6] probabilistically evaluates the effect of electric vehicle fast chargers on transformer aging considering the presence of rooftop solar panels and community battery energy storage in a residential sector. In [7], authors evaluate the positive effect of PV generation to avoid transformer overloading and reduce accelerated loss-of-life due to PEV demand in an industrial sector in Portugal. In [8], the impact of PEVs charging demand on transformer lifespan is probabilistically evaluated in a residential area with rooftop solar PV. Twenty scenarios are considered with different penetration levels of PVs and PEVs. Reference [9] analyzes the benefits of using PV systems to charge PEVs in workplace parking areas using different vehicles typologies. Reference [10] uses Monte Carlo simulation to evaluate the impacts on transformer lifespan occasioned by PEV demand on a residential complex with eight households. Two charging levels are considered: Level 1 (1.44kW) and Level 2 (3.3kW).

The use of PV generation has been strongly encouraged in the last years since it is a clean energy source. Solar panel prices have been dropping and the payback period looks more favorable for the owners. This paper extends the work developed in our earlier studies [10] by addressing some of the shortfalls not yet investigated and presenting an analytical method for sizing PV generation aimed at reducing the impact on transformer load and hottest-spot temperature due to PEV charging. It considers a commercial building with eight PEV charging stations supplied at Level 2 (6.6 kW). The uncertainties in the model are considered by adopting a probabilistic approach based on Monte Carlo simulation using ambient temperature and irradiance data from Austin, Texas. Seasonal variation of PV generation is considered dividing data into four seasons: winter, spring, summer and autumn.

This paper is organized as follows. Section II describes the methodology adopted in this study and Section III presents the test system. Section IV shows simulation results, and the concluding remarks are summarized in Section V.

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This publication was made possible by NPRP 8-241-2-095 from the Qatar National Research Fund (a member of Qatar Foundation). The statements made herein are solely the responsibility of the authors.

## II. METHODOLOGY

### A. Monte Carlo

Monte Carlo (MC) method is used to verify the influence of input data uncertainties in output results [11]. Random numbers are generated for all input parameters following a probability distribution function (pdf) that approaches real data. The results are used to estimate transformer load and hottest-spot temperature hourly. This procedure is repeated for each sampled value for a statistically significant number of times until convergence is reached. Results are stored and analyzed using statistical tools. In this study, uncertainties are present in PEV load, building load, PV generation, and ambient temperature. The methodology applied is shown in Fig. 1, and the pdf adopted to represent each input parameter is presented next.

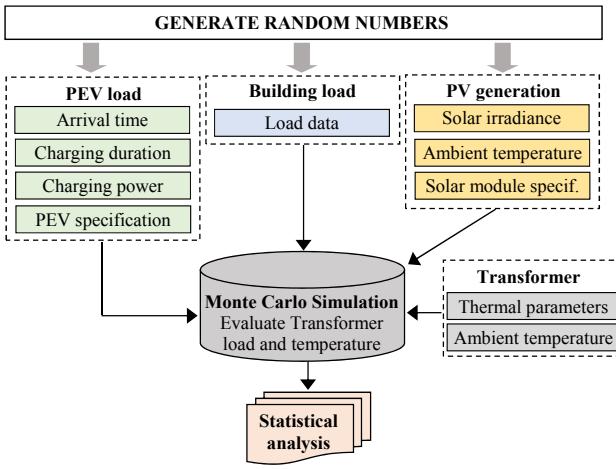


Figure 1. Methodology

### B. Photovoltaic Generation Profiles

Photovoltaic generation depends on solar irradiance, ambient temperature and solar module parameters. It is usually modeled by a Beta pdf as shown in (1).

$$f_s^t = \begin{cases} \frac{\Gamma(\alpha^t + \beta^t)}{\Gamma(\alpha^t)\Gamma(\beta^t)} (s^t)^{(\alpha^t-1)}(1-s^t)^{(\beta^t-1)}, & 0 \leq s^t \leq 1, \alpha^t, \beta^t \geq 0 \\ 0, & \text{otherwise} \end{cases}, \quad (1)$$

where  $s^t$  is solar irradiance in  $\text{W/m}^2$ ,  $\Gamma$  is Gamma function,  $\alpha^t$  and  $\beta^t$  are the shape parameters calculated based on the mean  $\mu^t$  and standard deviation  $\sigma^t$  of solar irradiance at time  $t$ , as shown in (2).

$$\beta^t = (1 - \mu^t) \left[ \frac{\mu^t(1-\mu^t)}{(\sigma^t)^2} - 1 \right] \quad \alpha^t = \frac{\mu^t\beta^t}{(1-\mu^t)} \quad (2)$$

This study used solar irradiance and ambient temperature data from Austin, Texas, available from National Renewable Energy Laboratory (NREL) website [12]. Data was collected for one year and divided into four seasons: winter, spring, summer and autumn. Irradiance mean and standard deviation values are evaluated to each day hour, and Beta pdf parameters are obtained in order to consider hourly fluctuations of solar irradiance. Then, pseudo-random numbers of irradiance are generated following the pdf to each hour of the day to each season. Based on irradiance profiles, the output power of PV module is evaluated by (3) - (4) [13]:

$$P_{PV}^t = \left( \frac{P_n s^t}{1,000} \right) \times [1 + \lambda(T_{cell}^t - 25)] \quad (3)$$

$$T_{cell}^t = T_a^t + \frac{s^t}{800} (NOCT - 20) \quad (4)$$

where  $P_n$  is module nominal power in W,  $\lambda$  is manufacturer's power temperature coefficient in  $^{\circ}\text{C}/\text{W}$ ,  $T_{cell}^t$  is cells temperature in  $^{\circ}\text{C}$ ,  $T_a^t$  is ambient temperature in  $^{\circ}\text{C}$ , and  $NOCT$  is the normal operating cell temperature in  $^{\circ}\text{C}$ .

### C. Plug-in Electric Vehicles Model

PEV charging demand is influenced by many parameters such as the number of electric vehicles, charging power, vehicle battery specification, arrival time and battery initial state-of-charge (SOC). In this study, electric vehicle arrival time is modeled according to [10], using NHTS 2017 data [14] representing initial SOC with Weibull distribution. This study considers that most cars arrive to the commercial building at noon, and the arrival time pdf follows a normal distribution as shown in Fig. 2, with  $\mu = 12$  and  $\sigma = 1.7$ . Total PEV demand for one day is obtained by aggregating individual demand of each vehicle, and vehicles are charged at Level 2 (6.6kW). The vehicle model adopted is Nissan Leaf, with battery capacity of 24kWh and 0.34kWh/miles consumption.

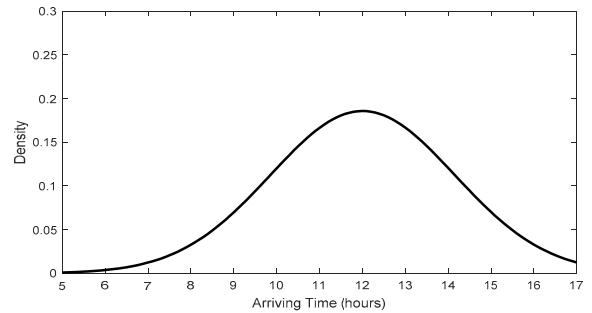


Figure 2. Vehicle arrival time pdf

### D. Local demand Profiles

Average daily demand profiles are collected from Electric Reliability Council of Texas website (ERCOT) for each season of the year to represent building local load [15]. Random samples are generated to each hour of the day according to the mean values of demand profile following a normal distribution function. A constant power factor of 0.9 is employed.

### E. Transformer Hottest-spot Temperature

Transformer life is determined by deterioration of its dielectric insulation, which is affected by temperatures above the limiting values. Since transformer temperature distribution is not uniform, transformer aging analysis considers the highest temperature, named hottest-spot temperature, which can be evaluated as shown in (5) [16]:

$$\theta_h^t = \theta_a^t + \Delta\theta_{TO}^t + \Delta\theta_H^t, \quad \forall t \in T \quad (5)$$

where  $\theta_a^t$  is ambient temperature,  $\Delta\theta_{TO}^t$  is top-oil rise over ambient temperature,  $\Delta\theta_H^t$  is winding hottest-spot rise over top-oil temperature at time  $t$  in  $^{\circ}\text{C}$ , and  $T$  is the study period.

The top-oil temperature rise and winding hottest-spot rise are evaluated to each load step by:

$$\Delta\theta_{TO}^t = (\Delta\theta_{TO,U}^t - \Delta\theta_{TO}^{t-1}) \times (1 - e^{-\Delta T/\tau_{TO}}) + \Delta\theta_{TO}^{t-1} \quad (6)$$

$$\Delta\theta_H^t = (\Delta\theta_{H,U}^t - \Delta\theta_H^{t-1}) \times (1 - e^{-\Delta T/\tau_w}) + \Delta\theta_H^{t-1} \quad (7)$$

where  $\Delta\theta_{TO,U}$  is ultimate top-oil rise over ambient temperature,  $\Delta T$  is time interval of duration of load,  $\tau_{TO}$  is transformer oil time constant and  $\tau_w$  is winding time constant in hours.

The ultimate top-oil rise and hot-spot rise are obtained by:

$$\Delta\theta_{TO,U}^t = \Delta\theta_{TO,R} \times \left[ \frac{(K_r^2 R + 1)}{(R + 1)} \right]^n, \forall t \in T \quad (8)$$

$$\Delta\theta_{H,U}^t = \Delta\theta_{H,R} \times K_r^2 m, \forall t \in T \quad (9)$$

where  $\Delta\theta_{TO,R}$  is the top-oil rise over ambient temperature at rated load,  $\Delta\theta_{H,R}$  is the winding hottest-spot rise over top-oil temperature at rated load,  $K$  is the ratio of ultimate load to rated load,  $R$  is the ratio of load loss at rated load to no-load loss,  $m$  and  $n$  values depends on cooling mode.

According to IEEE Std C57.91-2011, maximum hottest-spot winding temperature should not exceed 110°C on a continuous 24 hours basis with average ambient temperature of 30°C. Transformer aging acceleration factor  $F_{AA}$  for a varying load and temperature profile can be evaluated for each time  $t$  as a function of hottest-spot temperature as in (10). For hottest-spot temperatures greater than reference (110°C),  $F_{AA}$  becomes greater than 1, and becomes less than 1 for temperatures below reference. Transformer equivalent aging factor  $F_{EQA}$  over a 24 hours period can be evaluated as in (11).

$$F_{AA}^t = e^{\left[ \frac{15,000}{383} - \frac{15,000}{\theta_h^t + 273} \right]} \quad (10)$$

$$F_{EQA}^t = \frac{\sum_{t=1}^N (F_{AA}^t \times \Delta T^t)}{\sum_{t=1}^N \Delta T^t} \quad (11)$$

where  $N$  is the total number of intervals during the day and  $\Delta T$  is the time interval considered.

The percent loss of transformer insulation life for a given period can be evaluated as shown in (12), considering a normal insulation life of 180,000 hours (20.55 years). The daily normal transformer loss-of-life when operated at a rated hottest-spot temperature of 110 °C is 0.0133%.

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

### III. TEST SYSTEM

The system under study comprises a commercial building with intended photovoltaic generation and eight electric vehicles charging stations supplied at Level 2 (6.6 kW). The building is connected to the grid through a distribution transformer of 75 kVA as shown in Fig. 3. Transformer thermal parameters used on this study were obtained from [8] and are presented on Table I. The total number of Monte Carlo simulations considered is 20,000, which proved to be enough to obtain convergence.

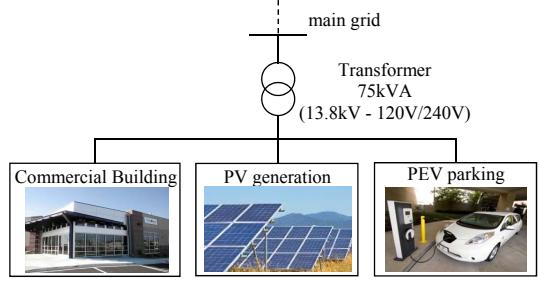


Figure 3. System under study.

TABLE I. TRANSFORMER THERMAL PARAMETERS.

Parameters	Value
Top-oil rise over ambient temp. at rated load ( $\Delta\theta_{TO,R}$ )	53°C
Winding hottest-spot rise at rated load ( $\Delta\theta_{H,R}$ )	27°C
Transformer oil time constant ( $\tau_{TO}$ )	6.86h
Winding time constant ( $\tau_w$ )	0h
Ratio of load loss at rated load to no-load loss ( $R$ )	4.87
Exponent $m$	0.8
Exponent $n$	0.8

### IV. SIMULATION RESULTS

In this study, PV penetration level (PL) is defined as the ratio of installed PV peak power to distribution transformer rated capacity as shown in (13) [17]. In order to evaluate the impact of PV generation on transformer load and hottest-spot temperature, different PV sizes are considered: 9.9kW, 19.8 kW, and 29.7 kW. The respective penetration levels analyzed are: 0%, 13.2%, 26.4%, and 39.6%.

$$PL = 100 \times \frac{PV \text{ Peak Power}}{\text{Transformer Rated Capacity}} \quad (13)$$

Two criteria are evaluated: transformer overloading, which occurs when the load exceeds 100% of rated capacity, and overheating, which is considered to occur when hottest-spot temperature exceeds reference temperature of 110°C. Results are presented using boxplot, which is a tool that summarizes statistical results information as shown in Fig. 4. The blue box comprehends 50% of data going from the first quartile to the third quartile, the median is represented by the center red line, minimum and maximum values are represented by whiskers, and outliers are individually represented by '+'. Results are presented next.

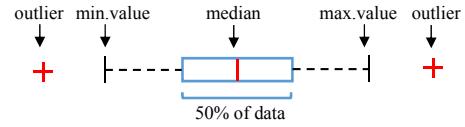


Figure 4. Boxplot attributes.

#### A. PV Penetration Level = 0 %

This case considers the installation of eight PEV charging stations without PV generation. Fig. 5 shows the boxplot of transformer load. For most scenarios, transformer load exceeds its rated capacity in all seasons. Also, transformer hottest-spot temperature exceeds the reference value of 110°C in many scenarios as shown in Fig. 6. Although transformer operates overloaded both in winter and summer season, cases with higher hottest-spot temperature occur mostly on summer due to higher ambient temperatures. Transformer operates overloaded

for several hours as shown Table II. This situation combined with high ambient temperatures makes equivalent aging factor become bigger than one in some scenarios during summer, indicating accelerated loss-of-life.

### B. PV Penetration Level = 39.6 %

This case considers the installation of eight PEV charging stations and PV with penetration level of 39.6 %. In some scenarios, transformer still operates overloaded in all seasons, although the probability of occurrence decreases, as shown in Fig. 7. With the presence of PV generation, only few scenarios present hottest-spot temperature exceeding the reference temperature, which occur mostly on summer, as shown in Fig. 8. The equivalent aging factor does not become bigger than one for any scenario, even when hottest-spot temperature is bigger than 110°C. Therefore, the probability of transformer undergoing premature aging is zero. This is because transformer operates overloaded only for few hours as shown in Table III, not being long enough to suffer premature aging.

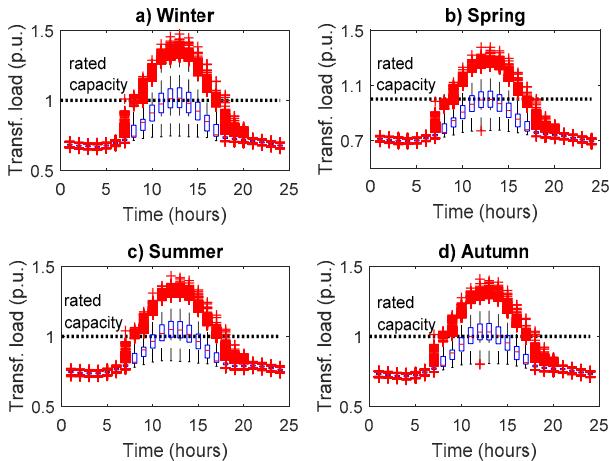


Figure 5. Boxplot of transformer load with  $PL = 0 \%$ .

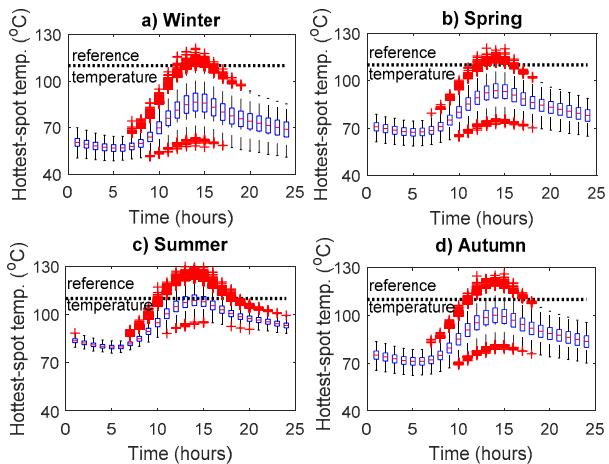


Figure 6. Boxplot of hottest-spot temperature with  $PL = 0 \%$ .

TABLE II. HOURS TRANSFORMER IS OVERLOADED DURING SUMMER.  
Number of hours transformer is overloaded

Probability (%)	1h	2h	3h	4h	5h	6h	7h	8h
6.0	17.3	<b>29</b>	27.77	15.4	4	0.5	0.03	

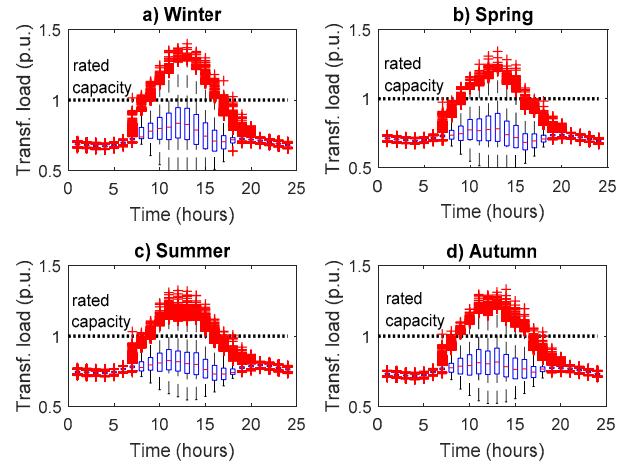


Figure 7. Boxplot of transformer load with  $PL = 39.6 \%$ .

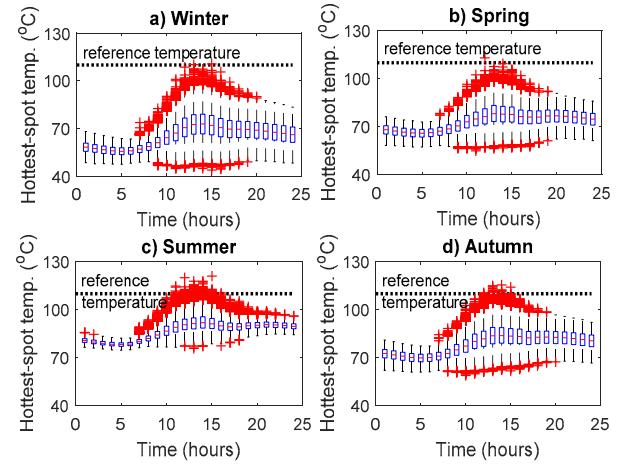


Figure 8. Boxplot of hottest-spot temperature with  $PL = 39.6 \%$ .

TABLE III. HOURS TRANSFORMER IS OVERLOADED ( $PL = 39.6 \%$ ).

Probability (%)	Number of hours transformer is overloaded						
	1 h	2 h	3 h	4 h	5 h	6 h	7 h
82.7	15.5	1.7	0.1	0	0	0	0

Fig. 9 exemplifies this presenting two scenarios. In the first scenario,  $PL=0\%$  and transformer operates overloaded with hottest-spot temperature exceeding the reference for 7 hours. Therefore,  $F_{EQ4}=1.3427$  and  $Loss\% = 0.0179\%$ , indicating accelerated aging. This corresponds to aging of 1.3427 days or 32.2 hours in a day (24 hours). In the second scenario,  $PL=39.6\%$  and transformer operates overloaded with hottest-spot temperature exceeding the reference for 3 hours. In this case  $F_{EQ4} < 1$  indicating no accelerated aging. Since thermal aging is a cumulative process, distribution transformers may be safely operated above 110°C for short periods since they are operated for much longer periods at temperatures below 110 °C, being loss-of-life adequately compensated.

Fig. 10 shows the probability of transformer overloading and overheating under several PV penetration levels during summer, which is the most critical season due to high ambient temperatures. The results show probability of overloading/overheating considerably reduces with the increase

of PV penetration level. The maximum number of hours transformer operates overloaded also reduces.

Fig. 11 shows the probability distribution function of transformer maximum load and hottest-spot temperature for different PV penetration levels during summer. The results clearly show the positive impact of PV generation, bringing transformer to the recommended operation zone regarding its loss-of-life.

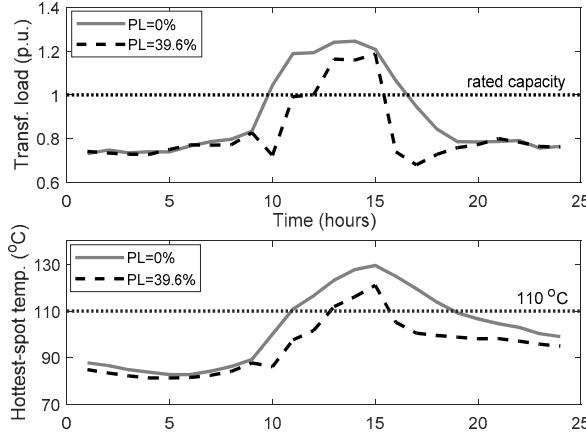


Figure 9. Comparision of two scenarios during summer.

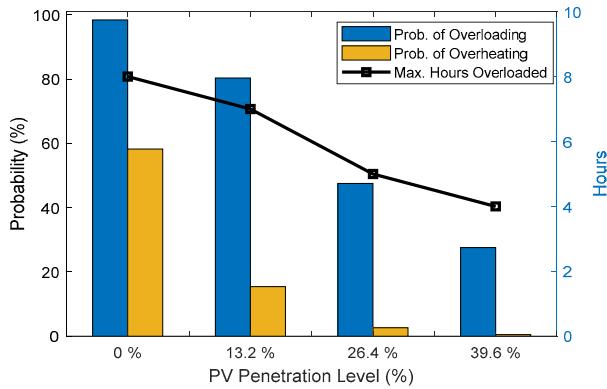


Figure 10. Probability of transformer overloading and overheating for different PV penetration levels in summer.

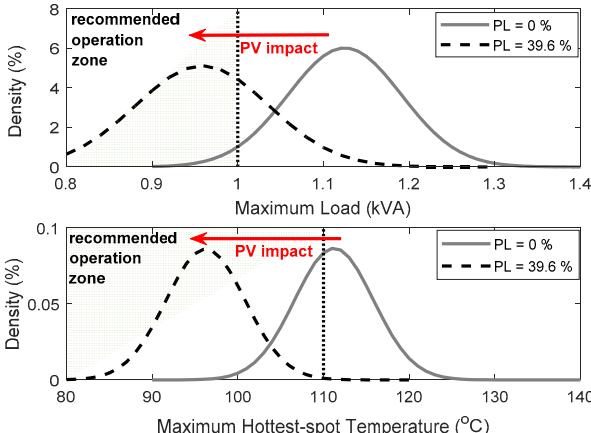


Figure 11. Impact of PV penetration level on transformer maximum load and hottest-spot temperature during summer.

## V. CONCLUSION

This paper presents an analytical method for sizing PV generation in order to reduce transformer load and hottest-spot temperature due to PEV charging. The system under study comprises a commercial building with PV generation and eight electric vehicles charging stations. Monte Carlo simulation is employed using real ambient temperature and irradiance data from Austin, Texas. The following conclusions can be drawn from obtained results:

- The connection of eight PEV Level 2 charging stations is enough to make transformer operate overloaded for several hours, and experience premature aging in some scenarios;
- Transformer experiences higher hottest-spot temperature during summer season due to higher ambient temperatures;
- PV generation can potentially reduce transformer load and hottest-spot temperature even during winter season, when PV generation levels are lower;
- The installation of PV generation with penetration level of 39.6 % is sufficient to make transformer operate under the recommended temperature levels without suffering premature aging, even when operating overloaded for few hours.

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