Risk Assessment of Transformer Loss-of-Life due to PEV Charging in a Parking Garage with PV Generation

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***Abstract*—This paper presents a probabilistic risk assessment methodology to evaluate distribution transformer loss-of-life in a commercial building parking garage, in the presence of plug-in electric vehicle (PEV) charging stations and local photovoltaic generation. The Monte Carlo method is applied to address the uncertainties resulting from PEV charging, photovoltaic generation and garage load. A risk matrix combining the severity measures and associated probability distribution function is used to quantify the risk of transformer loss-of-life. The results show a significant reduction in transformer loss-of-life risk when connecting photovoltaic generation, resulting in saving avoiding transformer aging and early replacement. Based on the findings, the proposed method can be a helpful tool in the decision making process that needs to balance the risk and investment costs.**

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

I. Introduction

Plug-in electric vehicles (PEVs) are gaining much popularity nowadays due to environmental issues and the necessity to reduce greenhouse gas emission. A variety of PEV models from different companies is available in the market, and the penetration level of these vehicles will continue to grow in the coming years bringing new challenges for their proper integration into grid. PEVs charging represents an additional demand to the existing distribution transformer, especially under high penetration level. These transformers usually do not have monitoring capability, and when operated in a continuous overload condition its temperature increases exponentially, which may shorten transformer service life, representing extra costs due to the necessity of early replacement [1].

Some papers have already addressed the issues regarding PEVs charging demand and transformer loss-of-life (LOL). Reference [2] analyzes the impact of PEV charging on distribution transformers loss-of-life at residential level. Reference [3] proposes a smart charging algorithm based on estimated transformer temperatures, considering that all PEVs charge exclusively from a home charging station. Reference [4] proposes a strategy to charge and discharge PEV in a residential neighborhood, in order minimize the total cost of operation, and uses transformer temperature as a constraint in the problem formulation to avoid transformer LOL. In [5], the impact of PEVs' demand on distribution transformer overload and LOL in the presence of rooftop solar photovoltaic (PV) is probabilistically quantified. In this paper, most PEVs charge at the end of the day when arriving home from work. Reference [6] presents a study to evaluate the impact of PEV charging on distribution transformer life in the presence PV units. The system considered comprises residential customers and assumes the PEVs charge at home. In [7], a methodology to determine the proper transformer capacity in a PEV charging station in order to minimize transformer LOL is proposed.

Most of the previous work has focused on proposing smart charging algorithm or developing probabilistic techniques to model PEV demand and analyze its impact on transformer LOL. However, none of them has introduced a risk analysis of transformer LOL, which considers the severity and probability of occurrence of the resulting conditions, especially in the presence of PEV charging and PV generation. Most of the studies consider residential consumer, which exhibit a different demand and charging profile as compared with commercial consumers. This is more relevant nowadays with the significant increase of new PEV charging station in workplace, malls, business parks and other common-use facilities.

Our paper proposes a risk assessment methodology to quantify the risk of distribution transformer LOL due to PEV charging demand in a commercial building parking garage in the presence of PV generation. The novelty is the use of Monte Carlo (MC) method to consider a wide variety of uncertainties due to PEVs charging, PV generation and commercial building load forecasts. We developed a risk matrix to assess the risk of transformer LOL, considering the severity of transformer aging using the probabilistic means. The impact of the local PV generation on the risk of transformer LOL is assessed.

The remainder of the paper is organized as follows. Section II describes system modeling under uncertainties due to PEV charging demand, PV generation and load. Section III presents transformer LOL evaluation. The proposed risk assessment methodology is developed in Section IV, followed by Section V where an analysis of the results is presented. The conclusions of the paper are addressed in Section VI.

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II. Modeling System Uncertainties

The system under study is a commercial building connected to the distribution network through a 150 kVA transformer as shown in Fig. 1. The building is integrated with PV generation and PEVs charging stations in a parking garage. The PV system may be installed on the roof of the building or parking lot, and can supply power to the charging station at the parking garage. Since PEVs charging increases the transformer demand, the use of local PV generation has a significant role in decreasing the transformer load, and as a consequence, transformer loss-of-life. Due to many uncertainties involved in modelling the transformer load profile, a probabilistic analysis is more suitable instead of a traditional deterministic approach. The uncertainties considered in this study are correlated with the building load, PV generation, and PEVs charging demand.

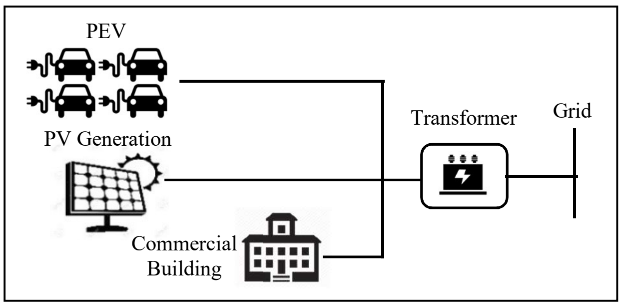

Figure 1. Commercial building configuration.

A. Building load

The building load is equivalent to the electric load excluding PEV charging demand, and the corresponding power factor is assumed to be 0.9. The forecasted load is assumed to follow a typical weekday curve for a small commercial customer, as shown in Fig. 2 (a). The building load profiles to be used in the probabilistic analysis can be generated with a normal distribution, which is the most common technique to model electricity loads [8]. The mean μ is assumed to be equal to the forecasted load, and the standard deviation σ is taken as 3% of the mean.

B. PV generation

The solar generation profile used in this paper is obtained from PVWatts Calculator tool from NREL [9], selecting a location in Texas during July (summer) as shown in Fig. 2 (b). The solar generator parameters include system location information such as latitude and longitude, and solar generation specification such as the PV rating, efficiency, and tracking. The solar generation profiles to be used in the probabilistic analysis are generated with a normal distribution, with μ equal to the forecasted load, and the standard deviation σ is taken as 5% of the mean [10].

C. PEV charging demand

There are many variables regarding PEV charging demand, and the random variables considered to capture these uncertainties are the driving distance, initial state of charge of the battery and arrival time.

1) Driving distance:

According to [11], the average yearly total miles driven in the USA is 12,000 miles, with 50% of drivers driving 25 miles/day or less, and 80% of drivers driving 40 miles/day or less. Based on [12], a log-normal distribution is used to generate random values for the daily miles driven, with mean μ = 3.37 and standard deviation σ = 0.5, which closely approximates the driving performance from [11]. The distribution is as shows Fig. 3.

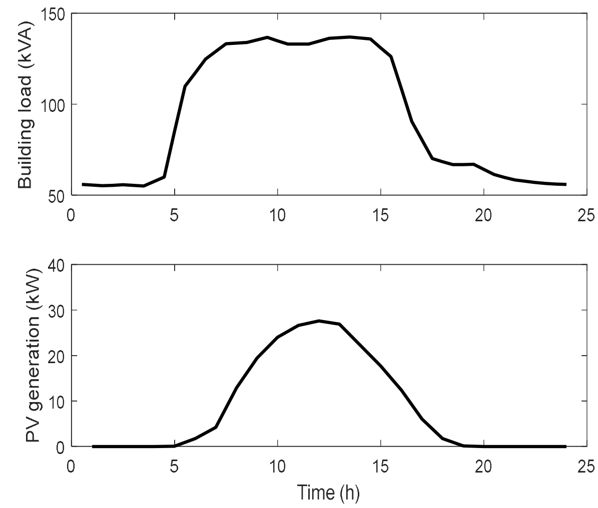

Figure 2. Generation and load profile: (a) building load, (b) PV generation.

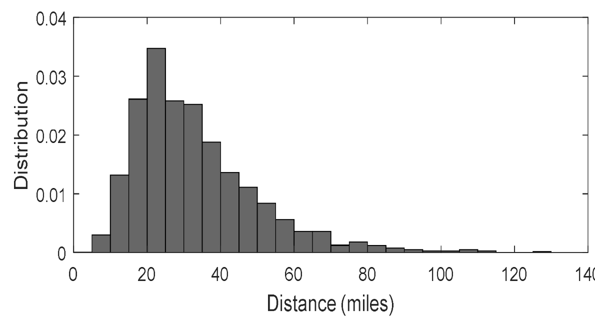

Figure 3. Distribution of daily miles driven.

2) Initial State of Charge:

Another important parameter to know is the initial state of charge (SOC) of PEV batteries when they arrive in the parking garage. The SOC is a measure in percentage of the amount of energy remaining in the vehicle, and the initial SOC depends on energy consumed in the previous trip. Knowing the previous distance traveled by vehicles, it is possible to estimate their initial state of charge ($SOC_{\%}^{ini}$) as shows (1) and (2).

$$E_{cons} = (\varepsilon \times d)/E_b \tag{1}$$

$$SOC_{\%}^{ini} = max\{(SOC_{\%}^{max} - E_{cons} \times 100), SOC_{\%}^{min}\} \tag{2}$$

where E_{cons} is the energy consumed, ε is PEV electricity consumption in kWh/100 miles, E_b is PEV battery capacity in kWh, d is daily miles driven, and SOC^{min} and SOC^{max} indicate the SOC safe operation window due to batteries life cycle considerations, which in this example is assumed to be 20% and 90% respectively. It is assumed that all vehicles are fully charged before departing home each morning.

3) Arrival time:

The last important parameter is vehicle's arrival time distribution, which will define the start of PEV charging time. According to [13,14], the best fitted distribution for arrival time to parking lots during weekdays is the Weibull distribution. Then, random values are generated following a Weibull distribution with mean $\mu = 9.2$ and standard deviation $\sigma = 13$, and the probability distribution function of the start of PEV charging time can be obtained, as shown in Fig. 4. The peak arrival time at work occurs around 9 a.m.

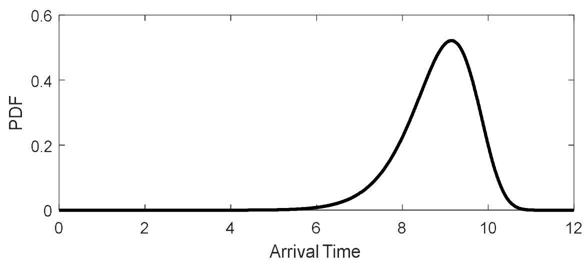

Figure 4. Vehicles arrival time during weekday.

4) Required Energy:

Knowing PEV's initial state of charge and battery capacity in kWh, it is possible to compute the required energy to charge vehicles battery until the required state-of-charge ($SOC_{\%}^{req}$) is reached, given by (3).

$$E_{req} = \left(SOC_{\%}^{req} - SOC_{\%}^{ini}\right) \times E_b/100 \qquad (3)$$

Assuming that PEV owners start to charge their vehicles immediately after arriving at the building and park their cars (plug and charge), and supposing electric vehicles are charged with a constant power P, the charging duration time Ch_{time} in minutes can be obtained by [15]:

$$Ch_{time} = (E_{req} \times 60)/P \qquad (4)$$

After determining the charging duration and using the start charging time of each vehicle in the fleet according to its arrival time, the charging profile is constructed during the study period. Battery specifications of Nissan Leaf are used to perform calculations, which is a purely battery electric vehicle and one of the top selling PEV in the United States, with battery capacity of 24 kWh and fuel efficiency of 34 kWh/100miles. PEV loads are modeled as constant power load, and level 2 charging station was considered for being more appropriate for workplace garages, with a charging power rating of 3.3kW.

III. Transformer Loss-of-Life

The continuous operation of transformers in overloaded condition may cause its temperature to rise. As a consequence, the insulation of distribution transformers can deteriorate and fail prematurely, resulting in accelerated transformer loss-of-life [1]. The IEEE standard C57.91 proposes a model for estimating transformer hottest-spot temperatures and its loss-of-life [16]. The transformer hottest-spot temperature θ_H is evaluated as in (5):

$$\theta_H = \theta_A + \Delta\theta_{TO} + \Delta\theta_H \qquad (5)$$

where θ_A is ambient temperature, $\Delta\theta_{TO}$ is the top-oil rise over ambient temperature, and $\Delta\theta_H$ is the winding hottest-spot rise over top-oil temperature.

The temperature rise $\Delta\theta_H$ and $\Delta\theta_{TO}$ are calculated as:

$$\Delta\theta_H = \left(\Delta\theta_{H,U} - \Delta\theta_{H,i}\right)\left(1 - e^{-\frac{t}{\tau_w}}\right) + \Delta\theta_{H,i} \qquad (6)$$

$$\Delta\theta_{TO} = \left(\Delta\theta_{TO,U} - \Delta\theta_{TO,i}\right)\left(1 - e^{-\frac{t}{\tau_{TO}}}\right) + \Delta\theta_{TO,i} \qquad (7)$$

where, $\Delta\theta_{H,U}$ is the ultimate winding hottest-spot rise over top oil temperature, $\Delta\theta_{TO,U}$ is the ultimate top-oil rise over ambient temperature, $\Delta\theta_{H,i}$ is the initial temperature rise, $\Delta\theta_{TO,i}$ is the initial top-oil rise over ambient temperature, τ_w is the winding time-constant, τ_{TO} is the oil time-constant, and t is the duration of time interval in hours.

The ultimate temperature rises $\Delta\theta_{H,U}$ and $\Delta\theta_{TO,U}$ are evaluated by:

$$\Delta\theta_{H,U} = \Delta\theta_{H,R} K_U^{2m} \qquad (8)$$

$$\Delta\theta_{TO,U} = \Delta\theta_{TO,R}\left[\frac{K_U R+1}{R+1}\right]^n \qquad (9)$$

where $\Delta\theta_{H,R}$ is the winding hottest-spot temperature rise over oil, $\Delta\theta_{TO,R}$ is the top oil temperature rise over ambient at rated load, K_U is the ratio of ultimate load to rated load, R is the ratio between no load loss and loss at rated load, m and n are empirically derived exponents which value depends on transformer type.

The accelerated aging factor at a given hottest-spot temperature can be evaluated using (10), assuming that normal aging occurs at 110ºC. If the hottest-spot temperature is bigger than 110ºC, F_{AA} will be bigger than one. On the contrary, F_{AA} will be lower than one for hottest-spot temperature lower than 110ºC. The equivalent aging of a transformer F_{EQA} can be obtained by averaging F_{AA} over the period of time N that transformer is under the study, as shows (11).

$$F_{AA}(t) = exp\left(\frac{15000}{110+273} - \frac{15000}{\theta_H(t)+273}\right) \qquad (10)$$

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

Using the equivalent aging, the transformer loss-of-life (LOL) in normal insulation can be obtained as shows (12):

$$LOL(\%) = \frac{F_{EQA} \times t \times 100}{Normal\ Insulation\ Life} \qquad (12)$$

where t is the time period of the analysis in hours, and a typical transformer must have a minimum normal insulation life of 180,000 hours (20.5 years) according to IEEE standard [16].

IV. Proposed Risk Methodology

A. Risk matrix

This paper adopts risk matrix to estimate risk of transformer loss-of-life. Risk matrix is a common method of qualitative risk analysis, and describes risk using defined descriptive terms such as “low”, “medium” and “high”, evaluated according to a qualitative criteria [17]. Non-numerical labels are given for input parameters, which often represent a numerical range. The qualitative analysis has the benefit of the simplicity and linguistic interpretability, with an easily understandable descriptive nature.

Risk is a function of the probability *Prob(e)* of an event *e* occurring, and the subsequent impact and severity *Sev(e)* of the event as shows (13). Probability is the likelihood of the event occurring, and severity is the amount of damage and negative consequences that would result with the event. This study adopts the transformer aging factor (F_{EQA}) as a measure to quantify the severity. The probability and severity are ranked in four classes, and a numerical range is associated to each class as shown in Table I.

$$Risk = Prob(e) \times Sev(e) \tag{13}$$

Considering a 24-hour load cycle, F_{EQA} will have a value of 1.0 for continuous operation at rated winding hottest-spot temperature. Then, the normal rate of loss-of-life is one day loss per 24hs. If F_{EQA} is bigger than one, the equivalent aging is more than one day, which means transformer will experience loss-of-life. The transformer life estimation is based on an idealized accelerated reaction condition, and is subject to certain limitations that bring uncertainties in LOL estimation. The equivalent aging factor is obtained by averaging F_{AA} during the period of analysis, so it is possible to have short periods with hottest-spot temperature slightly above 110°C with daily equivalent aging factor lower than one. As a safety margin, a ‘moderate’ severity class is adopted for F_{EQA} values in the range of 0.95 and 1.0.

Table II shows the adopted risk matrix conveying that based on the likelihood and severity the risk can be: low, medium, high and very high. The risk increases if either likelihood or severity increases, and if risk is not sufficiently low, appropriate mitigation actions should be applied.

TABLE I
PROBABILITY AND SEVERITY DEFINITION

Probability		Severity	
Condition	**Range**	**Condition**	**Range**
Unlikely	$P(e) < 10\%$	Insignificant	$F_{EQA} < 0.95$
Possible	$10\% \leq P(e) < 50\%$	Moderate	$0.95 \leq F_{EQA} < 1.0$
Occasional	$50\% \leq P(e) < 90\%$	Critical	$1.0 \leq F_{EQA} < 1.2$
Frequent	$P(e) \geq 90\%$	Severe	$F_{EQA} \geq 1.2$

TABLE II
RISK MATRIX FOR TRANSFORMER LOSS-OF-LIFE

Severity	Probability			
	Unlikely	Possible	Occasional	Frequent
Insignificant	low	low	low	low
Moderate	low	low	medium	medium
Critical	medium	medium	high	high
Severe	high	high	very high	very high

B. Monte Carlo Simulation

This paper adopted Monte Carlo (MC) method to evaluate the risk of transformer loss-of-life. The MC simulation is well-suited to solve problems with significant uncertainties in inputs, which makes it difficult or even impossible to compute a deterministic solution. It consists of repeating a system process with random inputs in order to obtain statistical data for the expected outputs. For each trial of the simulation, the output of the system is stored, and the statistical behavior of this stored data is constructed. The best and worst scenarios among the MC iterations can be captured, and a risk analysis can be performed. The steps of implementing the proposed risk assessment methodology are presented below:

1. Generate pseudo-random numbers to represent the building load, PV generation, and PEV demand;
2. Process the evaluation of transformer daily demand with all the random variables;
3. Store results and repeat steps 1 and 2 until the total number of simulations is reached;
4. Evaluate transformer hottest-spot temperature, aging factor and loss-of-life for all MC scenarios;
5. Perform statistical analysis and risk assessment of transformer loss-of-life using the proposed risk matrix.

V. SIMULATION RESULTS

In this paper, 2,000 consecutive Monte Carlo simulations were performed to evaluate the impact of PV generation on transformer loss-of-life risk. This number of trials was adopted since it was noticed that increased number of simulations does not affect the results significantly. Each trial simulates a whole day (24 hours) with a 30-minute sampling interval. The transformer parameters were obtained from [16], and since ambient temperature has a considerable impact on transformer life, this paper considered an hourly-based curve with historical data of ambient temperatures for a hot summer day in Houston, Texas, from July 2017 [18].

Fig. 5 presents the cumulative distribution function before and after the integration of the PV generation. Considering a 24-hour cycle, the results show that without the PV generation, there is a small probability of only 4.15% of transformer operating with F_{EQA} <1, which is the recommended criteria to avoid LOL. However, after the PV generation is connected to the building, even with uncertainties related to solar radiation, the probability of transformer operating with F_{EQA} <1 increases to 100%.

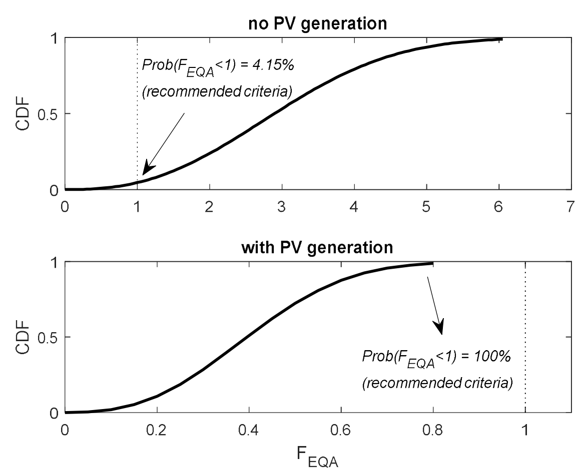

Figure 5. F_{EQA} cumulative distribution function.

Fig. 6 shows the histogram of transformer aging factor after the PV generation is integrated to the system. It is possible to see that, in this case, transformer equivalent aging factor is lower than one to all scenarios. Then, the PV generation has a positive impact on transformer aging. The probability of occurrence of each risk class is presented in Fig. 7 for both cases with and without PV generation. It is possible to see the positive effect of PV generation, making most risk scenarios shift from the very high to the medium level.

Fig. 8 shows the risk matrix and the points located in green, yellow, orange and red areas means risk levels equivalent to low, medium, high and very high respectively. When PV generation is connected, most scenarios (99.45%) have medium risk level ($0.95 \leq F_{EQA} < 1.0$). Although these cases have F_{EQA} lower than one, they are categorized as medium risk because they have a high probability of occurrence. Also, these scenarios represent the possibility of transformer operating with hottest-spot temperature above 110°C during some time, which is not desirable, but does not represent high risk, hence being acceptable.

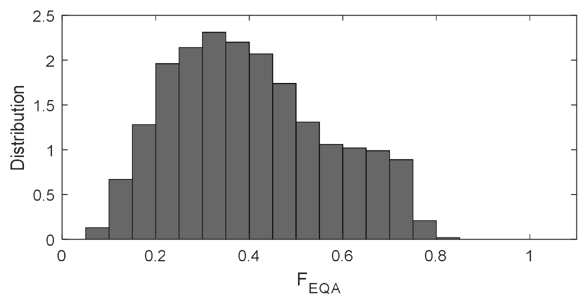

Figure 6. PDF for transformer aging factor with PV generation.

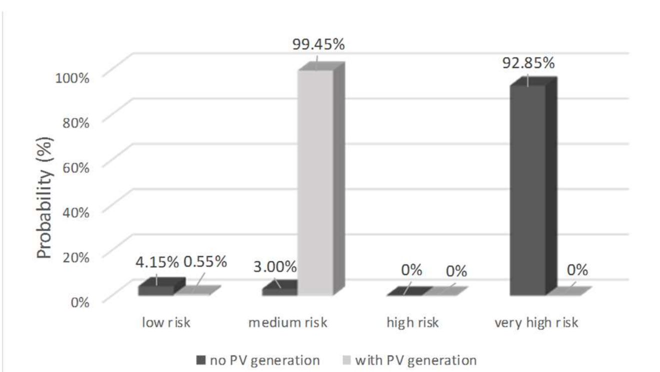

Figure 7. Risk of LOL with and without PV generation.

No PV generation			
4.15%			
3.00%			
			92.85%

with PV generation			
0.55%			
			99.45%

Figure 8. Risk matrix with and without PV generation.

VI. Conclusion

This paper presented a probabilistic methodology to assess the risk of transformer loss-of-life in a commercial building parking garage, integrated with photovoltaic generation and plug-in electric vehicles charging stations. The following conclusions can be drawn from the results:

- The integration of PV generation in a parking garage with PEVs charging stations has a positive impact on transformer aging, reducing the risk of LOL. The energy produced from PVs reduces the transformer loading, resulting in lower transformer hottest-spot temperatures.
- The proposed method provides a decision-making tool for optimizing the risk between the excessive transformer LOL and financial costs due to the installation and connection of the PV system.
- The approach also provides a way to assess the risk from operating transformer in an overloaded condition.

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