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Technical and Economic Impact of PV-BESS Charging Station on Transformer Life: A Case Study

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***Abstract*-- The uncoordinated charging of several plug-in electric vehicles in a parking garage can potentially overload distribution transformer reducing its lifetime. Attempting to mitigate this issue, this paper proposes a smart charging method to minimize electricity consumption costs and avoid transformer overloading, considering a charging station integrated with photovoltaic (PV) generation and battery energy storage system (BESS). The optimal coordination among all these elements is investigated assessing transformer hottest-spot temperature and loss-of-life, considering a case study with time-of-use rate and meteorological data from Texas, USA. In addition, an economic analysis is developed to evaluate the viability of the project, with a sensitivity study considering different charging fees and variation in the daily number of vehicles parked in the garage. The results show the proposed approach is feasible, yields tangible financial benefits and can preserve distribution transformer life.**

***Index Terms*-- battery energy storage system, economic analysis, electric vehicles, photovoltaic generation, smart charging, transformer loss-of-life.**

I. Introduction

ELECTRIC vehicles (EVs) are quite promising transportation technology as its commercialization is growing fast as an alternative to reduce fossil fuel consumption and greenhouse gas emission. According to the International Energy Agency, new registrations of electric vehicles hit a record in 2016 with over 750 thousand sales worldwide [1]. In addition, the smart grid infrastructure with distributed photovoltaic generation and battery storage with advanced communication technology creates conducive environment to EVs effective use. Among different types of EVs, this paper focuses on plug-in electric vehicles (PEVs) as they can be charged by plugging into an outlet. These vehicles include hybrid EVs (PHEVs) and battery EVs (BEVs), and for the purpose of simplicity they will be referred as EVs.

The increasing penetration of plug-in electric vehicles brings new challenges for their proper integration into the grid, especially due to uncertainties related to the behavior of EV users [2]. If a large number of EVs start charging at the same time, a significant power consumption can be experienced resulting in distribution transformer overload. This overloading causes an increase in transformer operating temperature and may lead to its loss-of-life [3].

Some studies have been proposed in this area and they focus mainly on analyzing the impacts on transformer loss-of-life and proposing intelligent charging strategies to avoid transformer aging. Studies in [4,5] analyze the impact of uncoordinated EV demand on transformer aging in a residential area. In [6], the impact of EVs charging on distribution transformer loss-of-life is probabilistically quantified considering a residential area with photovoltaic generation (PV). Reference [7] proposes a probabilistic approach to quantify the impacts imposed on transformer loss-of-life by EV demand in a residential complex with PV generation, considering different EV penetration levels and charging power for summer and winter seasons. Reference [8] investigates the effect of PV generation on reducing distribution transformer aging caused by charging EVs in a residential area.

In [9], the authors propose a rule based algorithm which determines the minimum charging power level for EVs charged at home, and analyze their impact on transformer aging. In [10], the authors propose a model to minimize electricity costs and transformer loss-of-life in a residential area considering the presence of an aggregator, which is a management entity. Reference [11] proposes different EV charging algorithms based on time-of-use tariff and grid valley filling considering transformer maximum power as a constraint and analyzing the effects on transformer aging in a residential area. In [12], an EV charging method is proposed to prevent transformer overloading in an industrial area in Portugal, and transformer loss-of-life is evaluated considering both slow and fast charging modes. In [13], an approach to optimally design a battery energy storage system for a community with high penetration of rooftop solar photovoltaics and electric vehicles is proposed. The objective is to mitigate transformer aging while maximizing the profit.

Although these studies considered the effect of EV charging demand on transformer aging, they focus mainly on the residential sector. Few papers analyzed this problem from a perspective of a commercial building with parking garage, which presents different installation costs, EV charging and demand profile, and chronological coincidence between PV production and EV demand. Although most EV drivers currently charge their vehicles overnight at home, the number of new non-residential EV charging station facilities has been

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increasing significantly and such facilities are expected to keep growing in the future years. Then, there is a need for more studies to enhance the understanding of the impact of EV charging demand on transformer aging by considering non-residential charging such as the workplace parking garage. The integration of PV generation and battery energy storage system (BESS) in EV charging infrastructure is a possible way to minimize the negative impacts of EVs on the grid, especially in commercial building parking garage where EV charging may become significant and occur during daytime hours, when PV is available, and EVs remain parked for several hours throughout the day, offering the possibility to charge with PV generation produced locally.

This paper proposes a smart charging scheme to optimally coordinate EVs and BESS avoiding transformer overloading in a commercial building parking garage powered by PV. Practical constraints and user preferences are taken into account during the optimization, based on time-of-use rate, load and meteorological data from Texas, USA. In addition, an economic analysis is carried out to verify the viability of the project for the garage owner. A sensitivity study is performed considering different charging fees and variation in the daily number of vehicles parked in the garage.

The main contributions of this paper are as follows:

- Propose a smart charging method to coordinate EVs and BESS in the presence of PV generation in order to reduce energy consumption costs in a commercial building parking garage, considering transformer maximum capacity as a constraint;
- Analyze the impact on transformer hottest-spot temperature and loss-of-life, incorporating the effect of variations in the ambient temperature using localized meteorological data;
- Assess the economic viability of non-residential EV charging stations, and estimate the return on investment and profitability with respect to the garage owner under a variety of charging fees.

The remainder of the paper is organized as follows. System modeling and EV charging demand are presented in Section II. Section III describes the transformer thermal model. The proposed optimization method is developed in Section IV. Section V presents simulation results, and the conclusions are outlined in Section VI, followed by references.

II. System Description

The system under consideration consists of a commercial building integrated with photovoltaic generation (PV), battery energy storage system (BESS) and a garage with 39 EVs charging stations. The building is supplied by a 150 kVA transformer and is connected to the grid. The use of photovoltaic generation has been increasing significantly in recent years, not only with the conventional approach of rooftop PV systems, but also integrated into building facade and parking canopies. The BESS can be used to ensure the security of energy supply, storing PV power to use it later (when PV is not available or during high tariff periods). This concept of smart buildings integrating renewables, BESS and EVs plays an important role in the future smart grid [14]. This section presents details of the system components used based on data from Texas, USA.

A. Commercial Building Load

In this study, the load profile adopted for the commercial building is presented in Fig. 1, collected from ERCOT website for South Central Texas area [15]. The building load does not include electric vehicles charging demand, and a power factor of 0.90 was considered. During the day, the electricity consumption increases as people arrive in the building to work, and decreases in the evening when the building is not occupied.

B. PV Generation and Ambient Temperature

This paper used PVWatts software provided by National Renewable Energy Laboratory (NREL) to estimate the output power of a 50kW PV system, based on solar radiation and ambient temperature historic data from Austin, Texas [16]. The summer season was considered in this study since distribution transformer is more likely to experience accelerated aging when subjected to high ambient temperatures [7]. Fig. 2 shows PV generation and ambient temperature profiles during summer (June, July and August). Three scenarios were adopted for future analysis as shown in Fig. 3: sunny, partly cloudy and cloudy.

C. Battery Energy Storage System

This study considered a battery bank of Hoppecke 26OPzS, a lead acid battery with total capacity of 200 kWh. The battery lifetime is assumed to be 12 years considering a minimum SOC of 50% as suggested by the manufacturer (50% DoD – depth of discharge) [17].

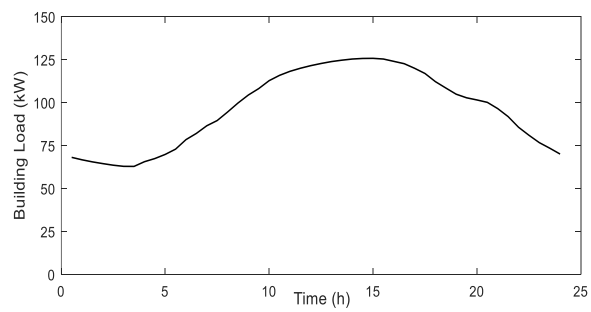

Fig. 1. Commercial building load.

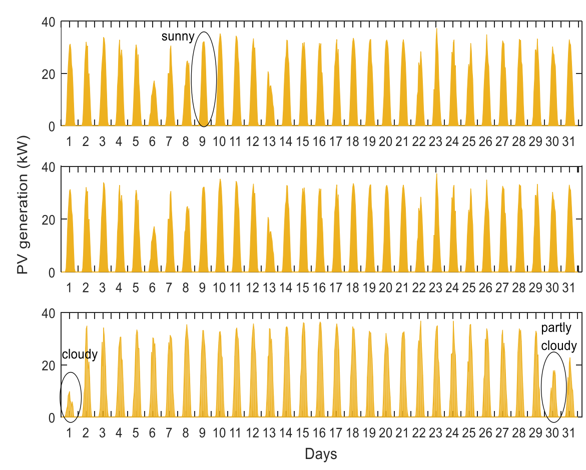

Fig. 2. PV generation during summer in Austin, Texas.

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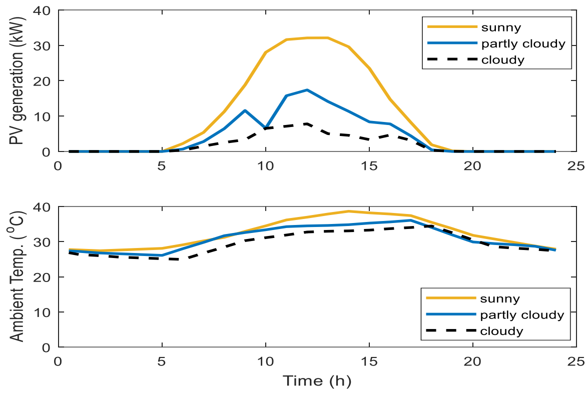

Fig. 3. Scenarios analyzed: sunny, partly cloudy and cloudy.

D. Time-of-Use Rate

With the increasing use of smart meters, many utilities are adopting time-of-use (ToU) pricing instead of conventional fixed-rate pricing models, in order to change consumer behavior and balance demand. The ToU tariff is cheaper during off-peak periods when demand is low, and higher during peak periods when demand is high. The ToU tariff considered in this paper is presented in Table I, which is adopted by a power utility from Texas during the summer and applicable to commercial users [18].

E. Electric Vehicle Consumption Profile

The EV parking garage under consideration in this paper is in a commercial building where cars are parked during the day. The EV charging demand is obtained following the flowchart presented on Fig. 4, based on mobility behavior and EV battery model data. The EV state-of-charge (SOC) measures the remaining energy capacity of the battery. The initial state of charge of the vehicles depends on its previous trip, and according to [19] vehicle travel an average of 30 miles per day. Then, the initial state of charge of each vehicle can be evaluated using (1) [20]:

$$SOC_{\%}^{ini} = max\{SOC_{\%}^{min}, 100 \times (1 - E_{cons} d / C_b)\} \quad (1)$$

where E_{cons} is EV energy consumption per mile in kWh/100miles, C_b is EV battery capacity in kWh, d is daily driven distance in miles, and SOC^{min} is the minimum SOC to avoid battery degradation, which is assumed to be 20%.

The energy needed to recharge the battery until the required state-of-charge $SOC_{\%}^{req}$ is expressed by (2), where η_{EV} is the charging efficiency assumed in this case to be 0.95.

$$E_{req} = \left(SOC_{\%}^{req} - SOC_{\%}^{ini}\right) \times C_b / (\eta_{EV} \times 100) \quad (2)$$

In this paper, two charging strategies are investigated: the uncoordinated charging and the proposed smart charging. In the uncoordinated charging scheme, EV owners start to charge their vehicles immediately after arriving at the building and parking their cars (plug and charge). In this case, electric vehicles are charged with constant power P and the charging duration Ch_{time} in minutes can be obtained by [20]:

$$Ch_{time} = (E_{req} \times 60) / P \quad (3)$$

TABLE I
COMMERCIAL TIME-OF-USE RATES

	May – October (Summer)	
	On-Peak hours (3p.m. - 8 p.m.)	**Off-Peak hours**
\$/kWh	0.163989	0.070605

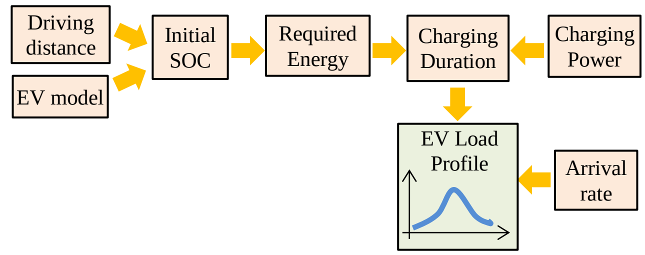

Fig. 4. Flowchart for EV load profile evaluation.

The vehicles arrival rate curve adopted in this paper is presented in Fig. 5, and based on this curve and on the charging duration time, it is possible to determine the total electric vehicle consumption profile. In the proposed smart charging scheme, the hourly EV charging power is evaluated according to the optimization model, which will be presented next. Among the electric vehicles considered, it is assumed that around 44.4% are Nissan Leaf (BEV) and 55.6% are Chevy Volt (PHEV), which are one of the most popular EV cars in the USA. The battery specifications are presented in Table II, and an average of 5 hours is adopted for the electric vehicles parking duration. EV loads are modeled as constant power load using charging station AC Level 2, which is more suitable for workplace garages [21]. The charging power is mainly limited by EV on-board charger. The different EV models may have different sizes of on-board chargers from 3.3 kW in Chevy Volt to 6.6 kW to Nissan Leaf. This study considers a maximum output power of 3.3kW for all vehicles.

III. TRANSFORMER THERMAL MODEL

Overloading transformers above their nameplate capacity may cause the temperature to rise. The insulation properties may deteriorate prematurely, resulting in transformer loss-of-life. These thermal effects are mainly affected by the loading and ambient temperature [22]. Transformer hottest-spot temperature and loss-of-life can be estimated according to the model presented in IEEE standard C57.91 [23].

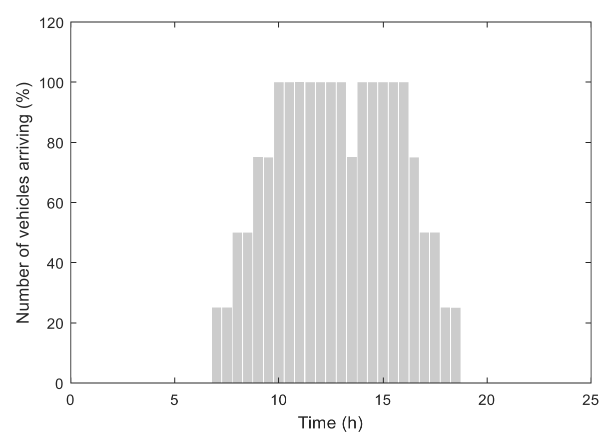

Fig. 5. Arrival rate curve.

TABLE II
ELECTRIC VEHICLES MODEL AND SPECIFICATION

	Battery Capacity (kWh)	**Electricity Consumption (kWh/100miles)**
Nissan Leaf	24	0.34
Chevy Volt	16	0.36

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The hottest-spot temperature θ_{HT} can be calculated as in (4):

$$\theta_{HT} = \theta_A + \Delta\theta_W + \Delta\theta_{To} \quad (4)$$

where θ_A is the ambient temperature, $\Delta\theta_W$ is the winding hottest-spot rise over top-oil temperature, and $\Delta\theta_{To}$ is the top-oil rise over ambient temperature, all in °C.

The temperature rise $\Delta\theta_W$ and $\Delta\theta_{To}$ are obtained as:

$$\Delta\theta_W = \left(\Delta\theta_{W,f} - \Delta\theta_{W,i}\right)\left(1 - e^{-\frac{t}{\tau_W}}\right) + \Delta\theta_{W,i} \quad (5)$$

$$\Delta\theta_{To} = \left(\Delta\theta_{To,f} - \Delta\theta_{To,i}\right)\left(1 - e^{-\frac{t}{\tau_{To}}}\right) + \Delta\theta_{To,i} \quad (6)$$

where, $\Delta\theta_{W,f}$ is the final winding hottest-spot temperature rise over the top-oil, $\Delta\theta_{W,i}$ is the initial temperature rise at the beginning of a time interval, $\Delta\theta_{To,f}$ is the final top-oil temperature rise over the ambient, $\Delta\theta_{To,i}$ is the initial top-oil temperature rise over the ambient at the beginning of a time interval, τ_W and τ_{To} are the winding and oil time constant respectively, and t is the time interval in hours.

The final temperature rise ($\Delta\theta_{W,f}$,$\Delta\theta_{To,f}$) are obtained by:

$$\Delta\theta_{W,f} = \Delta\theta_{W,r} K_f^{2m} \quad (7)$$

$$\Delta\theta_{To,f} = \Delta\theta_{To,r}\left[\frac{K_f^2 R+1}{R+1}\right]^n \quad (8)$$

where $\Delta\theta_{W,r}$ is the winding hottest-spot temperature rise over top-oil at rated load, $\Delta\theta_{To,r}$ is the top oil temperature rise over ambient at rated load, K_f is the ratio of final load to rated load, R is the ratio between loss at rated load and no load loss, m and n are empirically derived exponents and their values depend on transformer cooling mode.

The aging acceleration factor for a given load and hottest-spot temperature can be obtained using (9). According to [23], normal aging occurs at the reference hottest-spot temperature of 110°C. Then, if $F_{AA} > 1$ the transformer is experiencing accelerated aging.

$$F_{AA}^t = exp\left(\frac{15000}{110+273} - \frac{15000}{\theta_{HT}^t+273}\right) \quad (9)$$

The equivalent aging F_{EQA} over the time period the transformer is under study can be evaluated as shown in (10).

$$F_{EQA} = \frac{\sum_{t=1}^{N} F_{AA}^t \times \Delta t}{\sum_{t=1}^{N} \Delta t} \quad (10)$$

where N is the total number of time intervals.

Transformer percent loss-of-life (LOL) can be obtained by (11), where t is the time period of the analysis in hours.

$$LOL(\%) = \frac{F_{EQA} \times t \times 100}{Normal\ Insulation\ Life} \quad (11)$$

The normal insulation life is not uniquely defined and IEEE standard C57.91 provides some benchmark values. Based on this data, this study adopted a retained tensile strength (RTS) of 20% as the end of life criteria, which is equivalent to a normal insulation life of 150,000 hours (17.12 years) at the reference temperature of 110°C, and yields a normal loss-of-life of 0.0160% for a period of 24 hours. The tensile strength is a mechanical property of the insulation material that can indicate its aging process and degradation state. This property decreases with time and is accelerated under thermal stress. The RTS can be evaluated as shown in (12), and T is time in per unit life [24]. The thermal parameters used in this study to estimate transformer hottest-spot temperature and loss-of-life were obtained from [23].

$$RTS = 97.05 e^{-1.58T} \quad (12)$$

IV. Formulation of the Proposed Optimization Method

The proposed smart charging method coordinates a PV-BESS charging station in order to minimize the electricity consumption cost and analyze its impact on transformer loss-of-life. Since transformer lifetime is affected by its temperature, which in turn increases with ambient temperature and active loading, the objective is to reduce high peak demand caused by EV charging. From the perspective of the charging station owner, the main objective is to minimize the daily costs of purchasing power from the grid considering a time-of-use tariff. It is also important to consider BESS lifetime in the optimization process since battery life is significantly reduced according to its usage, and its early replacement causes extra costs. Then, a multiobjective optimization is employed with the goal of achieving minimum electricity consumption cost while at the same time extending battery lifetime, as shown in (13). In order to avoid transformer overloading, constraint (16) is added in the optimization model.

$$Min.f = \sum_{t=1}^{N} P_T^t\, \Delta t\, Tar^t + BD_{cost} \sum_{t=1}^{N} E_{BESS}^t \quad (13)$$

where P^t_T is the transformer loading at time t in kW, Tar^t is the energy tariff at time t in \$/kWh, E^t_{BESS} is BESS energy at time t in kWh, BD_{cost} is the battery degradation cost in \$/kWh, Δt is the time interval, and N is the total number of time intervals during simulation.

The battery degradation cost BD_{cost} can be defined in terms of the battery lifetime reduction due to a charge cycle, and can be evaluated by (14) [25].

$$BD_{cost} = \frac{R_{cost}}{LT \times \sqrt{\eta}} \quad (14)$$

where R_{cost} is the battery replacement cost in \$, LT is the lifetime throughput of the battery in kWh, η is the roundtrip battery efficiency in %.

The lifetime throughput (LT) is the total amount of energy that can be charged and discharged from the battery until its end-of-life is reached. There is a lifetime throughput LT_i associated to each depth of discharge i, which can be calculated by finding the product of the maximum capacity of the battery $E_{BESSmax}$, the depth of discharge DOD_i, and the associated number of cycles to failure (nc_i) as shown in (15). Then the battery lifetime throughput LT can be obtained by averaging LT_i in the allowable depth of discharge range.

$$LT_i = E_{BESSmax} \times DOD_i \times nc_i \quad (15)$$

The optimization period considered is 24 hours with a 30-minute sampling interval. The proposed method uses day-ahead information to take optimal decisions. The expected PV generation, building load and EV demand are assumed to be known 24-hour day-ahead. The constraints that must be satisfied during the optimization process are as follows:

1) Transformer capacity limit:

The transformer rating capacity must not be exceeded after adding EVs and BESS, avoiding high transformer temperature and lifetime deterioration.

$$S_T^t \le S_{nom}\ , \forall t = 1 \dots N \quad (16)$$

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where S_{nom} is the transformer nominal rating and $S^t{}_T$ is the total apparent power of the transformer at time t after the integration of EVs, PV and BESS.

2) Transformer demand:

The total transformer demand at any time t after the integration of EVs, PV and BESS is given by:

$$P_T^t = P_{base}^t + \sum_{i=1}^{N_{EV}} P_{EV}^{i,t} - P_{BESS}^t - P_{PV}^t, \forall t = 1 \dots N \quad (17)$$

where $P^t{}_{base}$ is the building load at time t, $P^{i,t}{}_{EV}$ is the charging power of the i^{th} EV at time t, $P^t{}_{BESS}$ is the BESS charging/discharging power at time t, $P^t{}_{PV}$ is the photovoltaic power at time t, all in kW, and N_{EV} is the number of electric vehicles. The sign convention adopted to the BESS is negative power while charging and positive power when discharging.

3) Electric Vehicle SOC:

Equation (18) represents the SOC of charging the i^{th} EV in period Δt. Also, the vehicles should have a desired departure state of charge according to customer preferences, as shown in (19). The required SOC considered in this study is 80%.

$$SOC^{i,t} = SOC^{i,t-1} + \eta_{EV} P_{EV}^{i,t} \Delta t / C_b \,, \ \forall i = 1 \dots N_{EV} \quad (18)$$

$$SOC^{i,t_{dep}} = SOC^{req}, \quad \forall i = 1 \dots N_{EV} \quad (19)$$

where $SOC^{i,t}$ is the state of charge of i^{th} electrical vehicle at time t, t_{depart} is the departure time, SOC^{req} is the required state of charge, C_b is EV battery capacity in kWh, and η_{EV} is charging efficiency.

4) BESS Energy balance equation:

Equation (20) represents the BESS energy balance, and (21) forces the battery storage value for the last time instance to be the same at the beginning of the optimization period. The charger efficiency η is assumed to be 95%.

$$E_{BESS}^t = E_{BESS}^{t-1} - \eta P_{BESS}^t \Delta t \,, \forall t = 1 \dots N \quad (20)$$

$$E_{BESS}^{t_{end}} = E_{BESS}^{t_o} \quad (21)$$

5) Electric Vehicles and BESS operation limits:

The SOC and charging power allocated to each EV i must be within its operational limits in every step of the simulation. The same applies to the BESS.

$$SOC_{min}^i \le SOC^{i,t} \le SOC_{max}^i \,, \forall t = 1 \dots N \quad (22)$$

$$0 \le P_{EV}^{i,t} \le P_{EVmax}^i \,, \forall t = 1 \dots N \quad (23)$$

$$E_{BESSmin} \le E_{BESS}^t \le E_{BESSmax} \,, \forall t = 1 \dots N \quad (24)$$

$$P_{BESSmin} \le P_{BESS}^t \le P_{BESSmax} \,, \forall t = 1 \dots N \quad (25)$$

The proposed optimization model is solved using the linear programming solver LINPROG from MATLAB with matrix formulation as follows.

$$\begin{gathered} \min_x c^T x \\ A_1 x \le b \\ A_2 x = d \\ x_{min} \le x \le x_{max} \end{gathered} \quad (26)$$

V. Simulation Results

The proposed smart charging method was applied to the commercial building garage and different scenarios are analyzed to verify the impact on peak load reduction, electricity consumption costs and transformer life expectancy. In addition, an economic analysis of the proposed PV-BESS charging system is performed to determine the viability of the approach, and the results are presented next.

A. Peak Load Reduction

In order to verify the effectiveness of the proposed smart charging method, the following scenarios are investigated.

- Uncoordinated charging: EV starts charging as soon as vehicle-owner arrives at work with a charging power of 3.3kW without PV-BESS;
- Uncoordinated charging with PV: EV starts charging as soon as vehicle-owner arrives at work with a charging power of 3.3kW, connected with PV under different weather conditions;
- Smart charging with PV-BESS: proposed charging scheme with PV-BESS under different weather conditions.

The uncoordinated charging scenario was used as a baseline solution for comparison with the other scenarios. Fig. 6 shows transformer load under uncoordinated charging and connected with PV. The transformer exceeds its maximum capacity even during sunny days with high levels of solar production, since electric vehicle peak demand occurs right after noon, at the same time the building load is at its maximum value.

Fig. 7 shows transformer load with smart charging and PV-BESS. With the proposed smart charging strategy, even during cloudy days with lower levels of solar production, the transformer does not exceed its limit and operates under its maximum loading capacity. Fig. 8 shows EV, PV and BESS operation on a sunny day in summer season. The BESS charges during off-peak hours and supplies energy to the building while the transformer is operating at its maximum capacity. The EV energy consumption reduces during peak hours, reducing as a consequence the transformer load during this period. Is it important to note that the minimum and maximum levels of BESS state-of-charge (50% and 100%) are maintained to preserve battery life. Also, the number of BESS charging/discharging cycles per day is only one avoiding battery degradation with unnecessary cycling.

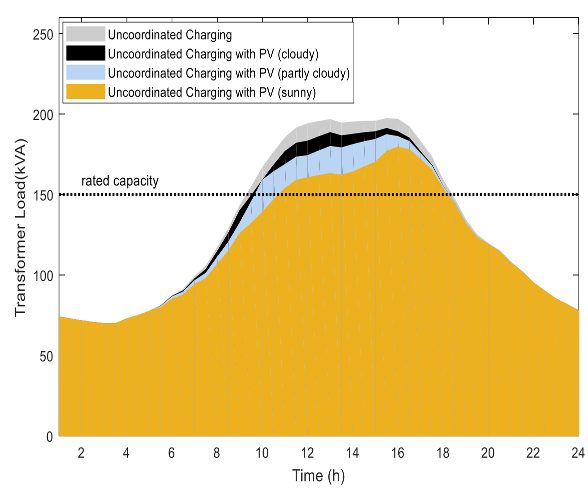

Fig. 6. Transformer load with uncoordinated charging and PV.

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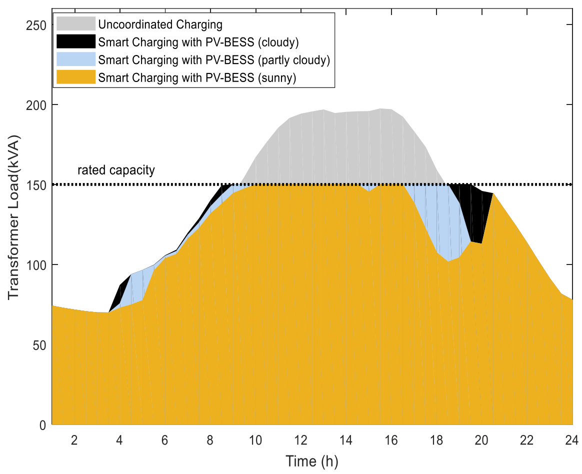

Fig. 7. Transformer load with smart charging and PV-BESS.

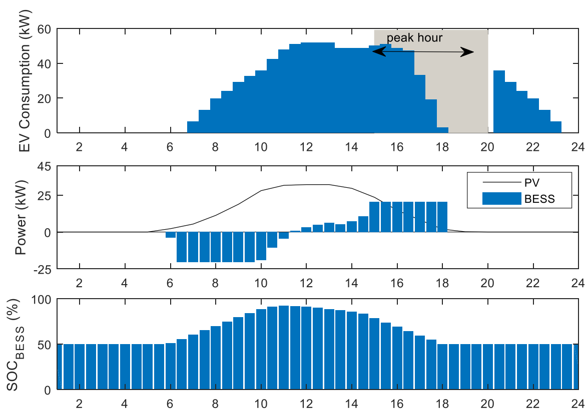

Fig. 8. EV consumption, PV and BESS operation on a sunny day in summer.

B. Effect on Transformer Life Expectancy

Fig. 9 and 10 show transformer hottest-spot temperature and accelerated aging factor respectively to all scenarios analyzed. Under the uncoordinated charging scenario, the transformer hottest-spot temperature goes beyond the normal operating temperature limit even when PV is connected. As a consequence, the instantaneous aging factor exhibits a period with values above one, indicating that transformer is experiencing accelerated aging. During the period that EVs exhibit higher arrival rate, the building load and the ambient temperature are both high, making the conditions even worse. The proposed smart charging scheme significantly decreases transformer hottest-spot temperature for all scenarios analyzed (sunny, partly cloudy and cloudy), staying below the reference temperature of 110°C during the entire day.

Table III shows transformer equivalent aging factor and loss-of-life to the scenarios analyzed considering a single operating day. It is observed that F_{EQA} changes significantly with transformer load profile variation. For the uncoordinated charging scenario, the results show an equivalent aging of 1.479 days, which is equivalent to 35.50 hours of life lost in one day indicating accelerated aging. When PV is added to the uncoordinated charging, the equivalent aging is lower than one for all weather conditions, even though transformer operates overloaded. In these cases, the overloaded period has no detrimental effect on transformer life since the increased loss-of-life during overload is balanced by the slower-than-normal ageing when transformer operates underloaded [26]. However, overloaded operation is not a recommended practice unless in emergency situations. With the smart charging scheme a significant improvement in transformer aging can be achieved, prolonging transformer lifetime. Regarding the transformer loss-of-life, the results show the uncoordinated charging strategy presents bigger loss-of-life compared to the normal loss-of-life, and the smart charging strategy preserves transformer lifetime for both sunny and cloudy days.

In order to evaluate the remaining transformer life when subjected to the uncoordinated charging scenario, typical load and ambient temperature profiles are used for each season of the year (summer, winter, spring and fall), and a moderate annually growth rate of 1.5% is assumed for the building load. Transformer retained tensile strength (RTS) and loss-of-life are evaluated over the years and the results are presented in Fig. 11. After the end of the twelfth year, the transformer reached a RTS of 19.7% and used 17.36 years of its normal life. Since the end of life criteria considered is a RTS of 20% and a normal life of 17.12 years, the expected transformer life in this case is only 12 years, a much shorter lifetime requiring early replacement.

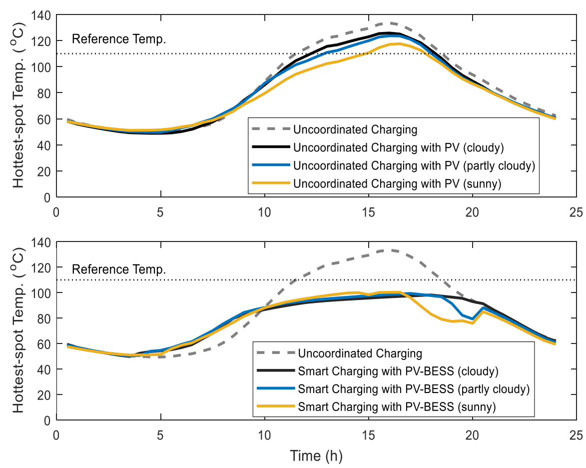

Fig. 9.Transformer hottest-spot temperature to all scenarios.

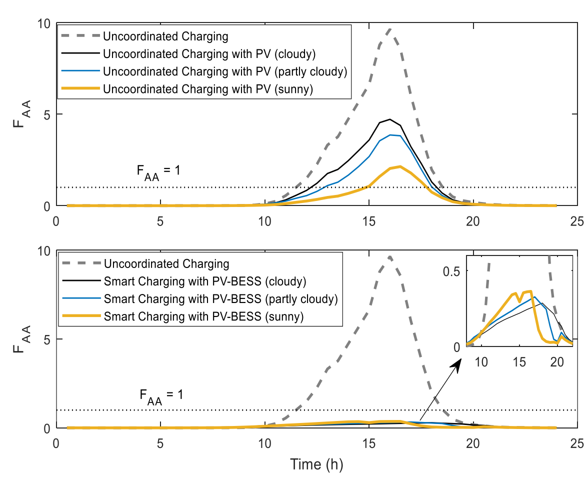

Fig. 10. Transformer accelerated aging factor F_{AA} to all scenarios.

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TABLE III
EQUIVALENT AGING FACTOR AND LOL TO DIFFERENT SCENARIOS

Scenarios	F_{EQA}	LOL%
Uncoordinated Charging	**1.4790**	**0.0237**
Uncoordinated Charging with PV (sunny)	0.3171	0.0051
Uncoordinated Charging with PV (partly cloudy)	0.6177	0.0099
Uncoordinated Charging with PV (cloudy)	0.7914	0.0127
Smart Charging with PV-BESS (sunny)	0.0937	0.0015
Smart Charging with PV-BESS (partly cloudy)	0.0996	0.0016
Smart Charging with PV-BESS (cloudy)	0.0971	0.0016

C. Effect on Energy Consumption Cost for the Garage Owner

Table IV shows the daily energy consumption cost to all scenarios analyzed. The results show higher costs with the uncoordinated charging, and a cost reduction when PV is added. Even more significant cost reduction is obtained for all weather conditions when the proposed smart charging scheme is applied. As expected, lower costs occur when there is more availability of PV generation (sunny day) and less energy is imported from the grid.

D. Economic Viability Analysis

The installation of EV chargers in the commercial building represents a daily increase of 23% in energy consumption. Then, it is important to perform a detailed economic analysis to evaluate the viability of the project, considering the installation costs of PV generation, BESS, and EV charging stations. The economic analysis was based on the results obtained with the smart charging strategy with PV-BESS. Cash flow analysis and three frequently used financial indicators are adopted in this analysis: net present value, internal rate of return and payback period [27,28].

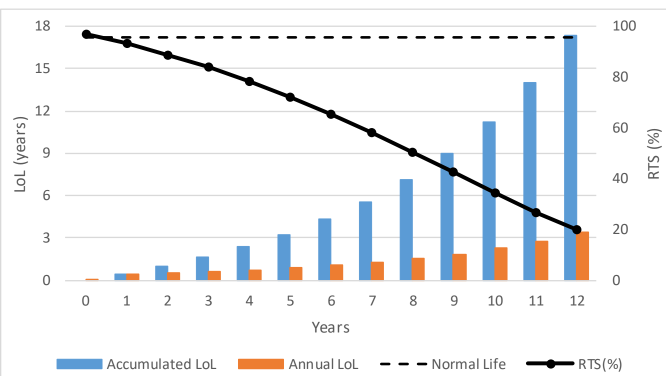

Fig. 11.Transformer RTS and used life over the years.

TABLE IV
ENERGY CONSUMPTION COSTS

Scenarios	Daily Costs ($)	Daily Savings (%)
Uncoordinated Charging	280.43	--
Uncoordinated Charging with PV (sunny)	259.53	7.45
Uncoordinated Charging with PV(partly cloudy)	271.06	3.34
Uncoordinated Charging with PV (cloudy)	275.87	1.62
Smart Charging with PV-BESS (sunny)	239.50	14.59
Smart Charging with PV-BESS (partly cloudy)	257.52	8.16
Smart Charging with PV-BESS (cloudy)	265.64	5.27

The net present value (NPV) represents the cumulative balance of revenues and expenses for every year of the project considering the changing value of money over time, and can be evaluated as shown in (27). A negative NPV indicates the project investment does not bring financial benefits.

$$NPV = -C_0 + \sum_{t=1}^{T} CF_t(1+r)^{-t} \tag{27}$$

where C_0 is the initial investment cost in \$, r is the discount rate in %, T is the period over which the investment is analyzed in years, and CF_t is the cash flow at year t in \$, defined as the difference between incomes and expenses.

The internal rate of return (IRR) is the expected return generated by the project, and can be evaluated finding the discount rate that makes the net present value of all cash flows equal to zero, as shown in (28). Projects with higher internal rate of return are considered a more attractive investment.

$$NPV = -C_0 + \sum_{t=1}^{T} CF_t(1+IRR)^{-t} = 0 \tag{28}$$

The payback (PB) is the time necessary to recover the initial investment in a project, obtained when the cumulative cash flow becomes a positive number. Shorter payback periods are more attractive than those with longer payback periods.

The project duration time considered is 25 years, which is the lifetime of PV modules, the component with longest service life in the project. The PV installation costs are based on USA national average costs [29]. All other information regarding equipment costs and rates were collected from manufacturers and different websites [30,31,32]. Table V shows the summary of the data used in the economic analysis. It is important to mention that some utilities and municipal governments are currently offering incentives to install EV charging stations. As an example, Austin Energy utility offers a rebate of up to $4,000 or 50% of the cost to install EV charging stations Level 1/2, and rebates up to $10,000 to install DC Fast Charger. Since the availability of these incentives depend on the city, they were not included in the analysis to get more conservative results.

Although some places offer free charging while you are parked (shopping centers, department stores, hotels etc.), most charging points are not free and the price varies by state and station, and some adopt kWh pricing while others adopt time-based charging fees. Table VI shows examples of EV charging fees currently adopted by USA charging providers. The EV charging fee initially considered in this study is $0.39 $/kWh.

TABLE V
INVESTMENT COST AND FINANCIAL PARAMETERS

Equipment Costs	
PV system	2.13 $/W
Converter	0.7 $/W
Battery	$1,326.47/unit
EV charger	$1,000.00/unit
O&M	0.5 %/ year
Financial parameters	
Inflation rate	1.6% /year
Discount rate	5.0% /year
Energy price increase rate	2.5% /year

TABLE VI
CHARGING FEES ADOPTED BY SOME CHARGING PROVIDERS

EV Charging Provider	Fee (Level 2)		
	Based on kWh	Based on time	Flat rate
Blink	$0.39 to $0.79/kWh	$0.06/min	-
EVgo	-	$1.50/hour	-
AeroVironment	-	-	$4.00
Circuit Electric	-	$1.00/hour	$2.50

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Fig. 12 shows the accumulated cash flow for a period of 25 years with a charging fee of $0.39/kWh, considering the yearly increase in electricity prices and the replacement of converter and battery system after the end of their lifetime. Under this condition, the project payback time is 7 years, which means that after this period the investor will recover the money. After 25 years, the project IRR is 15%, and the NPV is positive with a value of $236,321.18, meaning that this investment is economically attractive.

Since the charging fee is completely established by the owner, a sensitivity analysis is performed to verify its impact on the project payback time considering three charging fees: $0.29/kWh, $0.39/kWh, and $0.49/kWh. In addition, a positive and negative variation of 20% is considered in the daily amount of vehicles in the parking garage.

Fig. 13 shows the NPV, IRR and Payback to all scenarios. As expected, the higher the charging fee, the higher NPV and IRR are with lower payback time. The daily variation on the number of vehicles parked in the garage represents a maximum variation of 50% in the IRR and 50% in the payback time. The worst scenario is when the charging fee is $0.29/kWh and the daily amount of vehicles is reduced in 20%, leading to negative NPV, lowest IRR and payback time of 15 years, which is a long period to recover the investment.

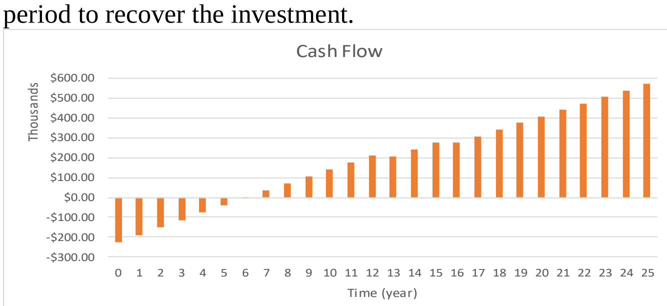

Fig. 12. Cash flow with EV charging fee of $0.39/kWh.

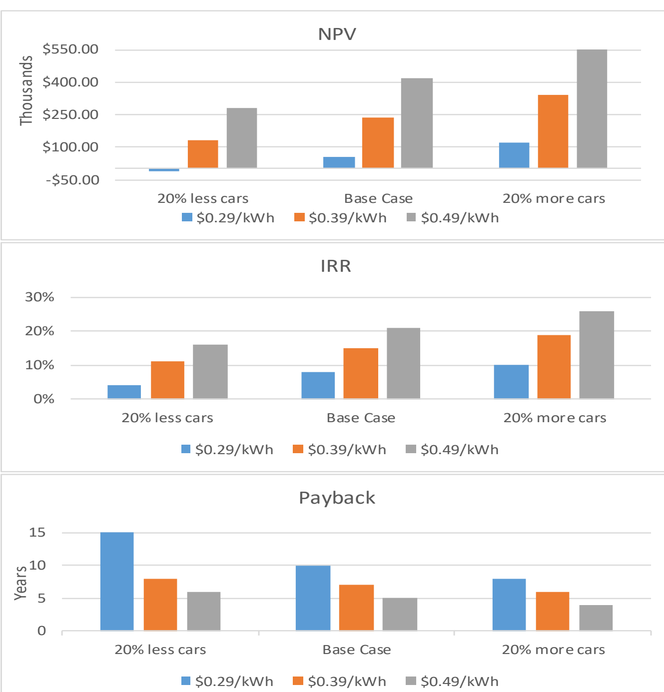

Fig. 13. Sensitivity analysis results (NPV, IRR and Payback).

Considering the worst scenario with 20% less vehicles in the parking garage, the results show that a charging fee bigger than $0.30/kWh should be applied in order to recover the initial investment in the project, otherwise, the project will have negative NPV and should be rejected, as shown in Fig. 14. Different charging fees bigger than 0.30/kWh were analyzed for the worst scenario (20% less cars), and the payback, NPV and IRR are shown in Fig. 15. Based on this analysis, the most adequate charging fee can be selected according to the minimum IRR, which is a profitability threshold fixed by the investor.

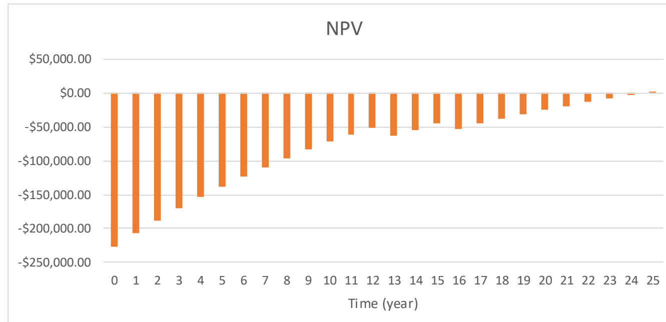

Fig. 14. NPV with charging fee of $0.30/kWh considering 20% less cars.

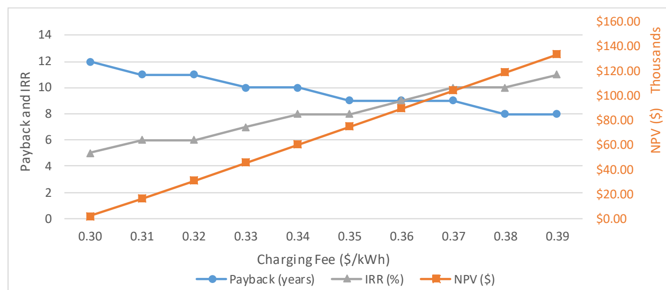

Fig. 15. Payback, IRR and NPV for different charging fees for 20% less cars.

VI. Conclusions

This paper proposed an optimal charging scheme to minimize the impact of electric vehicles charging demand on a distribution transformer that serves a commercial building parking garage integrated with PV generation and BESS. The model considers time-of-use rates in order to minimize energy consumption costs and avoid transformer overloading and loss-of-life, based on load and meteorological data from Texas, USA. The investigation is performed by means of both technical and economic viability analysis, and important conclusions were obtained:

- Under EV uncoordinated charging scheme the transformer is subjected to overloading condition during summer season due to high ambient temperatures, exceeding its thermal limits and experiencing accelerated aging;
- The proposed smart charging scheme and PV-BESS system can prevent transformer overloading and loss-of-life. PV generation can reduce the energy purchased from the grid, while BESS can assist during peak hours;
- The PV-BESS parking garage is a feasible and profitable investment, as long as a minimum charging fee is adopted to recover the project costs.

VII. References

[1] International Energy Agency – IEA (2017, June). Global EV Outlook 2017: Two million and counting. International Energy Agency. France. [Online].Available:https://www.iea.org/publications/freepublications/publication/GlobalEVOutlook2017.pdf

[2] M. Kezunovic and S. Travis Waller, "Vehicle-Power Grid Interaction for Multi-fueling (EBV, PHEV)", in *Encyclopedia of Sustainability Science and Technology*, New York: Springer, 2012.

[3] A. Dubey, and S. Santoso, "Electric Vehicle Charging on Residential Distribution Systems: Impacts and Mitigations", *IEEE Access*, vol. 3, pp. 1871 - 1893, Sept. 2015.

[4] A. D. Hilshey, P. D. H.Hines, P. Rezaei, and J. R. Dowds, "Estimating the Impact of Electric Vehicle Smart Charging on Distribution Transformer Aging", *IEEE Trans. on Smart Grid*, vol. 4, no. 2, pp. 905–913, June 2013.

[5] M. Muratori, "Impact of uncoordinated plug-in electric vehicle charging on residential power demand", *Nature Energy*, vol. 3, pp. 193–201, March 2018.

[6] Sherif F. Abdelsamad, Walid G. Morsi, and Tarlochan S. Sidhu, "Probabilistic Impact of Transportation Electrification on the Loss-of-Life of Distribution Transformers in the Presence of Rooftop Solar Photovoltaic", *IEEE Trans. on Sustainable Energy*, vol. 6, no. 4, pp. 1565-1573, Oct. 2015.

[7] C. M. Affonso, M. Kezunovic, "Probabilistic Assessment of Electric Vehicle Charging Demand Impact on Residential Distribution Transformer Aging", in *Proc. Int. Conf. on Probabilistic Methods Appl. Power Syst. (PMAPS)*, Boise, ID, 2018.

[8] M. K. Gray, and W. G. Morsi, "On the role of prosumers owning rooftop solar photovoltaic in reducing the impact on transformer's aging due to plug-in electric vehicles charging", *Electric Power Systems Research*, vol. 143, pp. 563–572, 2017.

[9] H. Turker, S. Bacha and A. Hably, "Rule-based charging of plug-in electric vehicles (PEVs): impacts on the aging rate of low-voltage transformers", *IEEE Trans. Power Delivery*, vol. 29, no. 3, pp. 1012-1019, June 2014.

[10] M. R. Sarker, D. J. Olsen, and M. A. Ortega-Vazquez, "Co-Optimization of Distribution Transformer Aging and Energy Arbitrage Using Electric Vehicles", *IEEE Trans. on Smart Grid*, vol. PP, no. 99, pp. 1–11, Mar. 2016.

[11] E. R. Munoz, G. Razeghi, L. Zhang, F. Jabbari, "Electric vehicle charging algorithms for coordination of grid and distribution transformer levels", *Energy*, vol. 113, pp. 930-942, 2016.

[12] R. Godina, E.M.G. Rodrigues, N.G. Paterakib, O. Erdinc and J.P.S. Catalão, "Smart electric vehicle charging scheduler for overloading prevention of an industry client power distribution transformer", *Applied Energy*, vol. 178, pp. 29-42, Sept. 2016.

[13] S. A. El-Batawy, and W. G. Morsi, "Optimal Design of Community Battery Energy Storage Systems with Prosumers Owning Electric Vehicles", *IEEE Trans. Ind. Informat.*, vol. 14, no. 5, May 2018.

[14] G. Merei, J. Moshövel, D. Magnor, D. Sauer, "Optimization of self-consumption and techno-economic analysis of PV-battery systems in commercial applications", *Applied Energy*, vol. 168, pp. 171–178, 2016.

[15] Electric Reliability Council of Texas (ERCOT). [Online]. Available: http://www.ercot.com/mktinfo/loadprofile/alp

[16] National Renewable Energy Laboratory (NREL). PVWatts Calculator. [Online]. Available: http://pvwatts.nrel.gov/

[17] Hoppecke Batterien [Online]. Available: https://www.hoppecke.com/fileadmin/Redakteur/Hoppecke-Main/Products/Downloads/OPzS_en.pdf

[18] CoServ: Electricity Prices [Online]. Available: http://www.coserv.com

[19] A. Santos, N. McGuckin, H.Y. Nakamoto, D. Gray, and S. Liss. (2011, June). Summary of travel trends: 2009 National Household Travel Survey (NHTS). US Department of Transportation, Washington DC. [Online]. Available: https://nhts.ornl.gov/2009/pub/stt.pdf

[20] A. Keyhani, M. Marwali, *Smart Power Grids 2011*. Berlin, German: Springer, 2011.

[21] SAE Electric Vehicle and Plug-in Hybrid Electric Vehicle Conductive Charge Coupler, SAE J1772, Jan. 2013.

[22] T. A. Short, *Electric power distribution handbook*, 2nd ed., Boca Raton, FL: CRC Press, 2004.

[23] *IEEE Guide for Loading Mineral-Oil-Immersed Transformers and Step Voltage Regulators*, IEEE Std. C57.91-2011, Mar. 2012.

[24] P. K. Sen, S. Pansuwan, "Overloading and Loss-of-Life Assessment Guidelines of Oil-Cooled Transformers", in *Proc. IEEE Rural Elect. Power Conf.*, Little Rock, AR, 2001, pp. 1-8.

[25] C. Bordin, H. O. Anuta, A. Crossland, I. L. Gutierrez, C. J. Dent, D. Vigo, "A linear programming approach for battery degradation analysis and optimization in offgrid power systems with solar energy integration", *Renewable Energy*, vol. 101, pp. 417-430, 2017.

[26] C. R. Bayliss, B. J. Hardy, *Transmission and Distribution Electrical Engineering*, 4th ed. Waltham, MA: Elsevier, 2012.

[27] ENERGY STAR (2007, July). Building Upgrade Manual Chapter 3: Investment Analysis. U.S. Environmental Protection Agency. [Online]. Available:https://www.energystar.gov/sites/default/files/buildings/tools/EPA_BUM_Full.pdf

[28] V. Stoiljkovic, "Net present value analysis—Comparing engineering projects by financial return", *IEEE Potentials*, vol. 29, no. 3, pp. 17-21, 2010.

[29] Ran Fu, D. Chung, T. Lowder, D. Feldman, K. Ardani, and R. Margolis. (2016, Sept.). U.S. Solar Photovoltaic System Cost Benchmark: Q1 2016. National Renewable Energy Laboratory (NREL), CO. [Online]. Available: https://www.nrel.gov/docs/fy17osti/68925.pdf

[30] Z. T. Taylor, N. Fernandez, R. G. Lucas. (2012, Apr.). Methodology for Evaluating Cost Effectiveness of Residential Energy Code Changes. Pacific Northwest National Laboratory. Richland, Washington. [Online]. Available:https://www.energycodes.gov/sites/default/files/documents/residential_methodology.pdf

[31] AeroVironment. [Online]. Available: http://store.evsolutions.com/all-products-call.aspx

[32] Inutec solarcenter [Online]. Available: http://inutec-int.com/shop/brands/hoppecke/opzs-battery/20-opzs-solar-power-3610-hoppecke.html

VIII. Biographies

Carolina Mattos Affonso (S'03-M'07) received the B.S. degree in electrical engineering from Federal University of Para, Brazil, in 1998, the Master's degree from Federal University of Santa Catarina in 2000, and the Ph.D. degree from State University of Campinas, Brazil. Since 2004 she is a Professor at Federal University of Para, Brazil, and her current research interests include smart grids, electric vehicles, distributed generation, power system operation and planning. Currently, she is a Visiting Professor at Texas A&M University, College Station, Texas.

Mladen Kezunovic (S'77-M'80–SM'85–F'99, LF'17), received the Dipl. Ing., M.S., and Ph.D. degrees in electrical engineering in 1974, 1977, and 1980, respectively. He has been with Texas A&M University for 31 years.

Currently, he is Regents Professor and Eugene E. Webb Professor, Director of the Smart Grid Center, and Site Director of "Power Engineering Research Center, PSerc" consortium. His expertise is in Protective Relaying, Automated Power System Disturbance Analysis, Computational Intelligence, Data Analytics, and Smart Grids. He has published over 550 papers, given over 120 seminars, invited lectures and short courses, and consulted for over 50 companies worldwide. He is the Principal of XpertPower™ Associates, a consulting firm specializing in power systems data analytics. Dr. Kezunovic is an IEEE Life Fellow, a CIGRE Fellow and Honorary Member, and a Registered Professional Engineer in Texas.