Economic Analysis of Transformer Loss of Life Mitigation Using Energy Storage and PV Generation

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Abstract—**High penetration of electric vehicles (EVs) can potentially put the utility assets such as transformers under overload stress causing decrease in their lifetime. The decrease in PV and battery energy storage system (BESS) prices has made them viable solutions to mitigate this situation. In this paper, the economic aspect of their optimal coordination is studied to assess transformer loss of life and hottest spot temperature (HST). Monte Carlo simulation is employed to provide synthetic data of EVs load in a residential complex and model their stochastic behavior. For load, temperature, energy price and PV generation, data for City of College Station, Texas, USA in 2018 is acquired and a case study is developed for one year. The results illustrate using BESS and PV is economically effective and mitigates distribution transformer loss of life.**

Index Terms—**battery energy storage, economic analysis, photovoltaic generation, electric vehicle, transformer loss of life.**

NOMENCLATURE

$P_{Ti,j}$	Average power that flows through the transformer excluding the effect of battery in the last 10 days before the jth day in the ith hour
P_{avg}	Average power that flows through the transformer in the last 10 days excluding the effect of battery
P_{B_i}	Power of the battery, charged (+) and discharged (-)
η	Efficiency of the battery and inverter
E_C	Capacity of the battery in KWh
t_{C_1}, t_{C_2}	Starting and ending time of charging
t_{D_1}, t_{D_2}	Starting and ending time of discharging
SOC_t	Battery state of charge at time t
SOC^{EV}	EV battery state of charge
E_D^{EV}	Electricity consumption in KWh/mile
T_{CH}^{EV}	Required time to charge PEV
θ_H, θ_a	Hottest spot and Ambient temperatures
$\Delta\theta_h$	Winding hottest spot temperature rise over the top oil
$\Delta\theta_{to}$	Top oil temperature rise over the ambient
R	Ratio between loss at rated load and no load
K_u	Ratio of ultimate load to the expected load
F_{AA}	Aging acceleration factor
F_{EQA}	Equivalent aging factor
TP	Time period under analysis in hour
L	Normal insulation life
τ_ω, τ_{to}	Winding and oil time constant
Ini, ult	Refers to the initial and ultimate values
Inv_0	Initial investment
PR_t	Profit at time interval t
r	Discount rate
PB	Payback period

I. INTRODUCTION

Electric vehicles (EVs) have been considered as a promising solution to reduce greenhouse gas emission and fossil fuel consumption. The EV global market is rising. Thus, in the near future, power system will face a new challenge from high penetration of EVs. It is challenging since it is expected that a large number of EVs will be connected to get charged in residential buildings with considerable overlap in charging time. This will expose assets such as transformers to overloading stress.

Increasing presence of EVs will lead to more electricity consumption and this can cause several issues such as power quality deterioration [1], under-voltage condition [2] and extra demand on distribution transformers [3]. Usually distribution transformers do not have on-line monitoring and when they operate in an overload condition continuously, they will face accelerated aging and risk of their failure will rise [4]. In addition to an unexpected outage, their more frequent failure will cause more repair or replacement expenses.

Battery energy storage system (BESS) cost has reduced and paved the path to be considered as a promising solution to mitigate the negative impacts of EVs' high penetration. BESS can be employed for different applications such as energy arbitrage [5], frequency and voltage support [6], peak shaving

[7] and congestion management [8]. One of the additional benefits of using ES, considered in this paper, can be reducing the accelerated aging of the transformers.

The adverse effect of EVs on the transformers is studied in [9], [10]. Reference [3] illustrates how different level of EV penetration will negatively affect the transformers in a residential complex. In [11], a probabilistic approach is proposed to investigate the impact of EV on transformers loss of life when PV generation is present.

Reference [9] is the only one among the abovementioned papers that takes stationary battery energy storage into account. However, the main focus is proposing a smart charging approach in a presence of a predetermined BESS. Moreover, the economic analysis in [9] employs a dynamic pricing method for the customers and schedules BESS charging/discharging by optimizing the price for the customers. The contribution of our paper is studying the economic benefits of employing BESS and PV generation considering the mitigation of transformer loss of life that has not been studied before and yet it is shown that it is essential to consider it.

For this purpose, one year data of EVs demand is created using a probabilistic approach. Load [12], irradiation [13], temperature [14] and electricity price data in the city of College Station, Texas, USA in 2018 are used to provide a realistic evaluation. The payback period of different scenarios is calculated and it is shown that employing BESS and PV generation yields tangible financial benefits.

The rest of the paper is organized as follows. Section II shows the battery scheduling methodology. In section III, the utilized data is introduced. In Section IV, the employed method for generating EVs demand is illustrated. Section V presents the transformer aging model. In Section VI, the utilized economic model is proposed. In Section VII, the results are demonstrated and discussed and finally, in Section VIII, the main conclusions are outlined, followed by list of references.

II. BATTERY CHARGING/DISCHARGING OPTIMIZATION

The residential building that is used in this paper is shown in Figure 1. The nominal power of the transformer is 63KVA and PV system size is 10KW. The building load is connected to the same bus as PV panel, battery storage, and charging station. It is assumed that EV can only be charged, i.e. it operates in the grid to vehicle mode. The fixed BESS operates both in charging and discharging modes. The charging station is located in the parking lot of the residential building.

In this paper, the assumed role of the battery is peak load shaving. It is assumed that the battery scheduling is day-ahead and the minimum state of charge is 20%. To prevent battery accelerated ageing, one cycle a day maximum is considered for battery charging/discharging. The following is total power flowing through the transformer in the absence of BESS during ten consecutive days before the current day.

$$P_{T_{i,j}} = \sum_{k=1}^{10} \frac{(P_{Load_{i,j-k}} + P_{EV_{i,j-k}} - P_{PV_{i,j-k}})}{10} \quad (1)$$

For simplification, index j in further equations is removed. The optimization problem for the current day (j^{th} day) is formulated as follows:

$$Min \; C = \sum_{i=1}^{24} \left| P_{T_i} + P_{B_i} - P_{avg} \right| \quad (2)$$

The battery should not be charged more than 100% and should not be discharged to less than 20% of selected state of charge. Hence, constraints (3) and (4) can be defined as follows:

$$\sum_{i=t_{C1}}^{t_{C2}} P_{B_i} \leq \eta E_C (1 - SOC_{t_{C1}}) \quad (3)$$

$$\sum_{i=t_{D1}}^{t_{D2}} -P_{B_i} \leq \eta E_C (SOC_{t_{C3}} - 0.2) \quad (4)$$

Furthermore, the charging or discharging power should not be more than the nominal power of the battery charger that leads to the constraint (5).

$$\left| P_{B_i} \right| \leq P_n \quad (5)$$

The starting time of charging and discharging must be positive and should not exceed the ending time. The problem should obey the following constraints (6) – (8).

$$t_{C1} \leq t_{C2} \quad (6)$$

$$t_{D1} \leq t_{D2} \quad (7)$$

$$t_{C1}, t_{C2}, t_{D1}, t_{D2} \geq 0 \quad (8)$$

Constraint (9) and (10) are defined for when charging is scheduled before discharging and when discharging is scheduled before charging, respectively.

$$If \; t_{C1} < t_{D1} \Rightarrow SOC_{t_{D1}} = SOC_{t_{C1}} + \frac{\sum_{i=t_{C1}}^{t_{C2}} P_{B_i}}{\eta E_C} \quad (9)$$

$$If \; t_{C1} > t_{D1} \Rightarrow SOC_{t_{C1}} = SOC_{t_{D1}} + \frac{\sum_{i=t_{D1}}^{t_{D2}} P_{B_i}}{\eta E_C} \quad (10)$$

Since the planning is day-ahead, heuristic optimization methods can be utilized to solve this optimization problem. In this paper, genetic algorithm is deployed.

III. LOAD, SOLAR GENERATION AND TEMPERATURE DATA

The load data is acquired from National Renewable Energy Laboratory (NREL), OpenEI [12]. The dataset contains the hourly load profile for different types of commercial and residential buildings. The data for the residential buildings is synthesized based on Building America House Simulation Protocols [15] and Residential Energy Consumption Survey (RECS) [16]. In the under study, there are 10 total customers from which energy consumption of 3 is low, 6 is medium and 1 is high. PVWatts Calculator [17] is employed to calculate the hourly generation of the PV considering panel, inverter and solar irradiation. This system employs the newest data from National Solar Radiation Database and by receiving the information of the PV panel, can provide hourly data of PV generation for a specific location.
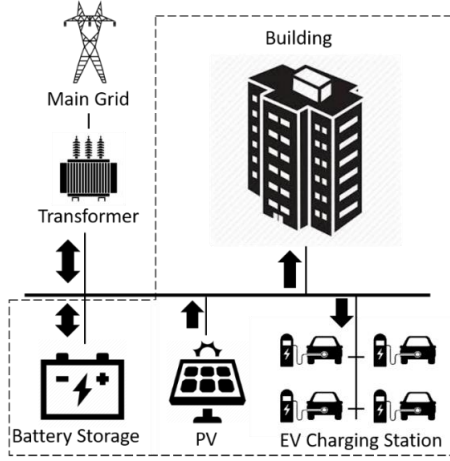
Figure 1. Schematic of the system under study.

The hourly temperature data is obtained from Iowa Environmental Mesonet [14]. The temperature data are collected using Automated Surface Observing Systems. The temperature of each hour is assumed to be fixed.

IV. MODELLING UNCERTAINTIES OF EV CHARGING DEMAND

To model the uncertainty of the demand imposed by EVs, the approach introduced in [9] is used. In order to estimate EV load profile several variables such as driving distance, arrival time and EVs' characteristics are considered.

In a residential building, it is more probable that EV owners leave the building in the morning and return in the evening. Thus, the following distribution function is used. The time of arrival is modeled with a normal distribution with the mean value of $\mu_d = 17:00$ and standard deviation of $\sigma_d = 2.28$.

$$AT = Gauss(\mu_{AT}, \sigma_{AT}^2) \qquad (11)$$

The daily driving distance is modeled using log-normal distribution with the mean value of $\mu_d = 3.37$ and standard deviation of $\sigma_d = 0.5$. The distribution is defined as follows:

$$d = Ln(\mu_d, \sigma_d^2) \qquad (12)$$

The SOC when EV is driven home can be calculated using equation (13):

$$SOC_{ini}^{EV} = 1 - \frac{E_D^{EV} \cdot d}{E_C} \qquad (13)$$

It is assumed that the required SOC is 0.95. Thus, considering the EVs are charged with constant power, the required time to charge the vehicle can be calculated as follows:

$$T_{CH}^{EV} = \frac{(SOC_{req}^{EV} - SOC_{ini}^{EV}) \cdot E_C^{EV}}{\eta^{EV} \cdot P} \qquad (14)$$

Nissan Leaf is the studied electric vehicle in this paper. The battery capacity in this car is 24KWh and it consumes 340Wh/mile. It is assumed the residents own 12 EVs cars and there are 10 charging slots in the building parking area.

V. TRANSFORMER AGEING

Loading and ambient temperature are the main factors that affect hot spot tememperature (HST) and transformer loss of life. When transformer is working under overload stress, the temperature adjacent to the winding of transformer increases and deteriorates winding insulation. It causes accelerated ageing for the winding insulation and decreases the life of the asset. IEEE Standard C57.91 [18] thoroughly explains quantification of this effect on loss of life. Firstly, the hottest spot temperature can be calculated:

$$\theta_H = \theta_a + \Delta\theta_{to} + \Delta\theta_h \qquad (15)$$

For which the changes in temperature can be calculated as follows:

$$\Delta\theta_h = (\Delta\theta_{h,ult} - \Delta\theta_{h,ini}) \cdot (1 - e^{-\frac{t}{\tau_w}}) + \Delta\theta_{h,ini} \qquad (16)$$

$$\Delta\theta_{to} = (\Delta\theta_{to,ult} - \Delta\theta_{to,ini}) \cdot (1 - e^{-\frac{t}{\tau_{to}}}) + \Delta\theta_{to,ini} \qquad (17)$$

$$\Delta\theta_{h,u} = \Delta\theta_{h,rated\_load} \cdot K_u^{2m} \qquad (18)$$

$$\Delta\theta_{to,ult} = \Delta\theta_{to,rated\_Load} \cdot \left[\frac{K_u R + 1}{R + 1} \right]^n \qquad (19)$$

For which m and n are empirically derived exponents and their values depend on the cooling of transformer, the aging acceleration factor and the equivalent aging factor are F_{AA} and F_{EQA}. They can be calculated as follows:

$$F_{AA}(t) = e^{(\frac{15000}{110+273} - \frac{15000}{\theta_H+273})} \qquad (20)$$

$$F_{EQA} = \frac{\sum_{n=1}^{N} F_{AA,n} \Delta t_n}{\sum_{n=1}^{N} \Delta t_n} \qquad (21)$$

And loss of life can be calculated using the following equation:

$$Loss\ of\ Life = \frac{F_{EQA} \cdot TP}{L} \qquad (22)$$

VI. ECONOMIC MODEL

PV and BESS are relatively expensive equipment and it is essential to evaluate the viability of deploying them. Due to energy loss in the charging/discharging procedure, it is significant to evaluate the economic benefits. Several energy pricing and selling methods to residential customers exist and this may vary in different areas or cities. In the College Station area, which is the subject of study in this paper, the customers buy electricity from College Station Utility with fixed prices. In addition to a $7 monthly service fee, the electricity price is $0.1369/KWh from May to October and $0.1323/KWh from November to April including tax and transmission fees [19]. The College Station Utility buys the electricity based on the

prices announced by Electric Reliability Council of Texas (ERCOT) every 5 minutes.

The utilities are usually the owner of distribution transformers and they are the beneficiary of loss of life mitigation effect of PV and BESS utilization. Considering the electricity price, it is clear that the beneficiary of employing BESS is the utility and not customers, but utilities do not necessarily benefit from PV generation. In this context, customers should receive incentives from utilities to make using BESS economically attractive for them. Incentive determination is out of scope of this paper and the profit for both customer and utility is calculated to obtain the payback period of the investment regardless which parties share the investment.

Net present value (NPV), shown in (23), is the difference between the present value of cash inflows and the present value of cash outflows over a period of time i.e. it is the difference between the current value of all incomes and investments. NPV is a usual index in investment planning to analyze the profitability of a project or investment. The payback (PB) period is the required time to recover the initial investment and can be obtained using (24).

$$NPV = -Inv_0 + \sum_{t=0}^{T} \frac{PR_t}{1+r} \qquad (23)$$

$$if \quad \exists T_{PB} : NPV \geq 0, \forall T > T_{PB} : NPV < 0$$
$$\Rightarrow PB = T_{PB} \qquad (24)$$

Table I shows the summary of the parameters values used in the economic analysis. Transformer remaining life is assumed to be 112000 hours out of 180000 hours for a new one. Information regarding costs and rates are acquired using different available sources [20], [21]. Energy price increase rate is taken as the average of this value in USA in the last 20 years. Used discount rate is announced by the U.S. Federal Reserve Board of Governors effective December 2018.

TABLE I.　　COSTS AND FINANCIAL PARAMETERS

Equipment Costs		Financial Parameters	
PV System	$2.13/W	Energy price increase rate	2.6% /year
BESS	$0.4/W		
Transformer NPV	$5000	Discount Rate	3.0% /year

To include transformer loss of life in the economic calculations equivalent annual cost (EAC) is used. EAC is the cost per year of owning and operating an asset over its entire lifespan and is calculated using the equation (25). In this equation, t is the expected life of the asset and NPV is the net present value of that.

$$EAC = \frac{NPV_{transformer} \cdot r}{1 - \dfrac{1}{(1+r)^t}} \qquad (25)$$

The actual extra cost caused by transformer loss of life is the difference between EAC before investment on BESS and/or PV and after that. Therefore, PB can be calculated using equations (24) and (26).

$$NPV = -Inv_0 + \sum_{t=0}^{T} \left(\frac{PR_t + EAC_2 - EAC_1}{(1+r)^t} \right) \qquad (26)$$

VII.　　SIMULATION RESULTS

The method is implemented in MATLAB, the transformer loss-of-life evaluation and economic calculations is performed for the following scenarios.

　a)　No PV generation, no EV, and no energy storage.
　b)　No PV generation , high penetration of EVs and no energy storage.
　c)　PV generation, high penetration of EVs and no energy storage.
　d)　No PV generation, high penetration of EVs and several levels of energy storage.
　e)　PV generation, high penetration of EVs and several levels of energy storage.

The results of one year study of 7 cases are shown in Figure 2. In this table, it can be clearly seen how high penetration of EVs can negatively impact the life of the transformer and the effect can be mitigated using PV generation and BESS.
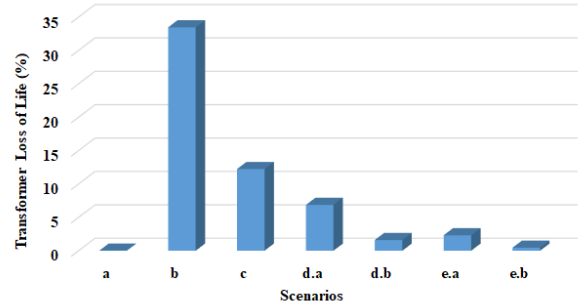

Figure 2. Transformer loss of life for different scenarios.

The introduced algorithm is used to manage the battery charging and the average load of this one year study is shown in Figure 3. Using the data, simulation results and the introduced economic model, payback periods of the abovementioned scenarios, for when loss of life is considered and when it is not, are calculated and shown in Figure 4.
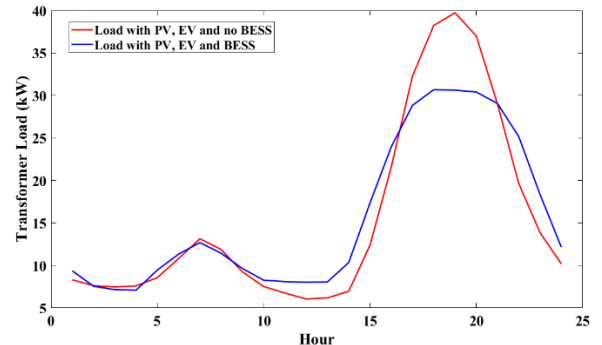

Figure 3. The average load with and without BESS.

In Figure 5, it is shown how considering the economic impact of transformer loss of life can dramatically change the economic calculations. The conspicuous difference is in scenario d for which only BESS is employed. If the effect of BESS in transformer loss of life is not taken into account in the economic evaluations, utilizing BESS may look an unfeasible

solution, but when its impact on transformer life is considered, it shows a promising solution to overcome the changes in the load curve for future grid with high penetration of EVs. Total annual savings in this case study are shown in Figure 5. It can be seen that increasing the BESS capacity from 20kWh to 40kWh has almost no impact on savings in scenario e. In this study, battery capacity can only be used to feed the load downstream from the transformer. The load and generation in this part of the grid is limited, thus impact of increasing the battery size on loss of life mitigation is negligible.
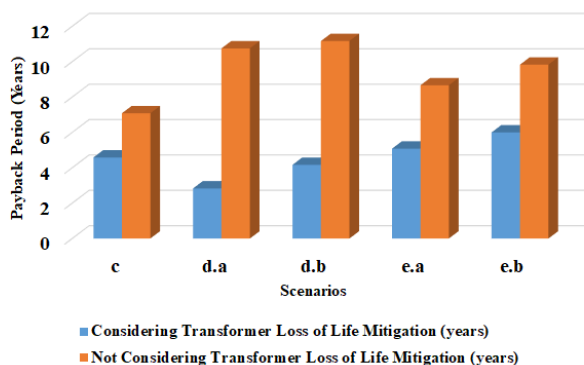

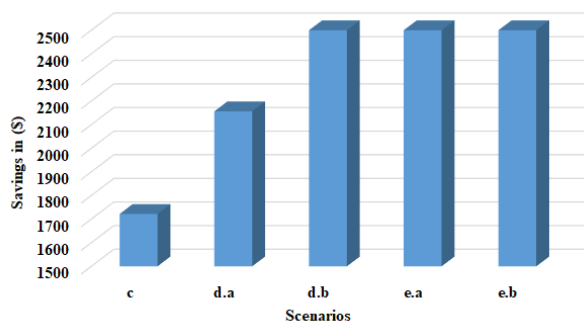Figure 4. Payback period for different scenarios

Figure 5. Total Annual Savings Due to Transformer Loss of Life Mitigation for Different Scenarios

VIII. CONCLUSION

We have studied how the impact of BESS and PV generation on transformer loss of life can vary the economic evaluation of the total investment by simulating a residential building demand for different scenarios of PV generation and EV charging penetration. Specifically, we have shown that ignoring positive effect of BESS on transformer's life can be misleading. The demand for EV charging, generated using a probabilistic method based on data for the city of College Station, TX. The results show that:

- Inclusion of 12 EVs and 10 parking spaces with charging stations in a building with 10 residents will greatly accelerate the aging of the transformer and reduce its life.
- An EAC economic model of the costs of transformer loss of life shows that if only the profit from BESS energy storage is considered, payback period will be rather long
- Increasing the capacity of battery or using both PV generation and BESS may make the payback period longer since the value of mitigation does not offset the cost of investment.

- Utilizing the proposed approach for optimal use of PV generation and BESS will mitigate the transformer loss of life caused by EVs, and at the same time the payback period is short enough making the arrangement not only viable but also profitable.

REFERENCES

[1] M. K. Gray and W. G. Morsi, "Power Quality Assessment in Distribution Systems Embedded With Plug-In Hybrid and Battery Electric Vehicles," in *IEEE Transactions on Power Systems*, vol. 30, no. 2, pp. 663-671, March 2015.

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

[3] M. Soleimani, C. Affonso, M. Kezunovic, "Transformer Loss of Life Mitigation in the Presence of Energy Storage and PV Generation," 2019 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe), Bucharest, Romania, September 2019.

[4] Godina, Radu, et al. "Effect of loads and other key factors on oil-transformer ageing: Sustainability benefits and challenges." *Energies*, vol. 8, no .10, pp. 12147-12186, 2015.

[5] D. Krishnamurthy, C. Uckun, Z. Zhou, P. R. Thimmapuram and A. Botterud, "Energy Storage Arbitrage Under Day-Ahead and Real-Time Price Uncertainty," in *IEEE Transactions on Power Systems*, vol. 33, no. 1, pp. 84-93, Jan. 2018.

[6] M. Farrokhabadi, S. König, C. A. Cañizares, K. Bhattacharya and T. Leibfried, "Battery Energy Storage System Models for Microgrid Stability Analysis and Dynamic Simulation," in *IEEE Transactions on Power Systems*, vol. 33, no. 2, pp. 2301-2312, March 2018.

[7] D. Gayme and U. Topcu, "Optimal power flow with large-scale storage integration," in *IEEE Transactions on Power Systems*, vol. 28, no. 2, pp. 709-717, May 2013.

[8] H. Pandžić, Y. Wang, T. Qiu, Y. Dvorkin and D. S. Kirschen, "Near-Optimal Method for Siting and Sizing of Distributed Storage in a Transmission Network," in *IEEE Transactions on Power Systems*, vol. 30, no. 5, pp. 2288-2300, Sept. 2015.

[9] C. M. Affonso and M. Kezunovic, "Technical and Economic Impact of PV-BESS Charging Station on Transformer Life: A Case Study," in IEEE Transactions on Smart Grid.

[10] M. A. Awadallah, B. N. Singh, and B. Venkatesh, "Impact of EV Charger Load on Distribution Network Capacity: A Case Study in Toronto", Canadian Journal of Computer Engineering, vol. 39, 2016.

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

[12] OpenEI, "Commercial and Residential Hourly Load Data," [Online]. Available: https://www.openei.org

[13] NREL, "National Solar Radiation Data Base," Available: https://www.nrel.gov.

[14] Iowa State University, "Iowa Environmental Mesonet", Available: https://mesonet.agron.iastate.edu/request/download.phtml?network=TX _ASOS

[15] R. Hendron and C. Engebrecht, "Building america house simulation protocols (revised)." No. DOE/GO-102010-3141. National Renewable Energy Lab.(NREL), Golden, CO, United States, 2010.

[16] Residential Energy Consumption Survey (RECS), Available: https://www.eia.gov/consumption/residential

[17] NREL, "PVWatts Calculator", Available: https://pvwatts.nrel.gov/index.php

[18] *IEEE Guide for Loading Mineral-Oil-Immersed Transformers*," IEEE Std. C57.91-1995), March 1995.

[19] City of College Station, "Electric Rates", Available: http://cstx.gov/index.aspx?page=3852

[20] Kittner, Noah, Felix Lill, and Daniel M. Kammen. "Energy storage deployment and innovation for the clean energy transition." Nature Energy vol. 2, no. 9, 2017.

[21] 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.