Impact Analysis of Electric Vehicle Charging on Distribution System

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***Abstract*—With the growing penetration of various types of electrical vehicles (EVs) such as Plug-in Hybrid Vehicles/ Battery Electric Vehicles (PHEVs/ BEVs), EV charging has the potential to affect the existing distribution system, especially the service lifetime of distribution components. This paper aims at analyzing the potential impact of EV charging on distribution transformers at residential level. Based on the load consumption in East Texas and different assumptions of EV charging scenarios, the impact is demonstrated and compared on monthly basis.**

***Keywords*—EV charging scenarios, Transformer loss of life**

I. Introduction

Power transformers are one of the most expensive components in a distribution network. With the increasing penetration of electric vehicles, new load peak may be created, which may exceed the transformer capacity. Therefore, in a residential house, owning an electric vehicle may mean a need to upgrade the utility's local transformer or lead to early replacement [1]. Reduction in transformer life expectancy will result in an increase of costs to utilities and consumers. Hence, the reduced transformer life becomes a very important impact when extra load is taken into consideration. According to the latest IEEE guide, the relationship between insulation life and transformer life still remains a question. However, percent loss of total insulation life is usually used to evaluate transformer's aging [2].

To analyze the impact of electric vehicle (EV) penetration on transformers, three models are required: base load model, non-base load (electric vehicle load) model, and transformer model.

Non-EV loads are obtained from different sources. Since there are no actual data for distribution of electric vehicle chargers, EV models are based on assumptions of charging scenarios with different charging start times and different penetration rates, or in some cases statistical methods are used to build models. To analyze the impact on distribution transformers, different factors are used to evaluate and compare the impacts. Paper [3] published in 2012 developed a probabilistic model for vehicle arriving time and charge left on arrival. Paper [4] in 2012 considered both loss and thermal models of transformer and analyzed load loss due to current harmonics. The importance of ambient temperatures to the impact on transformer aging was illustrated in [5]. In this paper, the authors combined single residence hourly load from RELOAD database and travel demand data from the National Household Transportation Survey for EV demand, but they applied the same daily base load repeatedly to 365 days through a year. Paper [6] analyzed the impact over a year under different charging scenarios, i.e. simultaneous charging, staggered charging, and proportional charging. A Monte-Carlo scheme simulated each day of the year, evaluating 100 load scenarios, in [7]. In these papers, however, the results for four seasons were not separately discussed.

Our paper focuses on the impact of electric vehicle charging on distribution system, especially distribution transformers. The actual 15-minute load profiles around College Station area (East Texas) available from ERCOT website are used as base load [8]. Various charging scenarios are assumed under different charging start times, penetration rates and usage ratios. Several EV cases are defined based on actual routes in College Station. A MATLAB program is developed to simulate aging acceleration factor and loss-of-insulation life of distribution transformer through a year. The simulation results for four seasons are compared and analyzed.

The paper is organized as follows: Section II describes and summarizes base load model, EV model, and transformer thermal model, which are used for the impact analysis. Based on the total load profiles for different EV charging scenarios provided in Section II, the aging acceleration factor and the transformer loss-of-life are simulated in MATLAB. The simulation results for different load profiles are tabulated and illustrated in Section III, and compared with the original base residential load. Also, a comparison is made between the results through different seasons. Section IV concludes the impact analysis (considering potential scenarios of EV charging in East Texas).

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II. MODELS

In this paper, three models are built: base load model, EV load model, and transformer's thermal model.

A. Base Load Model

Base load is obtained from ERCOT website [8]. Fig. 1 demonstrates 15-minute interval load consumed by an average residential individual customer for different seasons in East Texas. Fig. 2 is the daily peak load per residential customer through 2011. The red points are labeled with the amount and the exact time of the peak load in that day. In East Texas where College Station is located, the load consumed in summer is higher than the load consumed in winter in general. However, different from the load profile obtained from "RELOAD Database Documentation and Evaluation and Use in NEMS" [5], for some days in February, the peak load happens in the early morning and is pretty high (For instance, in 2009, the peak load of the year happened in winter [8]). Hence, in some winter days (e.g. Feb.11th), the load consumed in the early morning is higher than that in summer days. For the purpose of fair analysis, the load consumption in Feb.11th is added to Fig. 1. The results of this phenomenon will be presented in Section III.

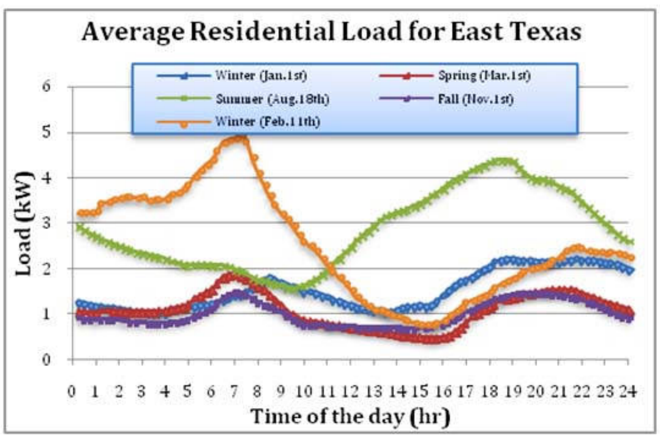

Figure 1. 15-minute interval data of average residential individual customer in East Texas

B. EV Load Model

The EPA estimation results of two representative auto models, Nissan Leaf and Chevy Volt, are employed in this study (in Table I).

TABLE I. EPA ESTIMATION RESULTS

Auto Model	EV Type	Battery Size	Electricity Consumption	Electric Range	Charging Time
Nissan Leaf	EV	24 kWh	34 kWh / 100 miles	73 miles	7 hours (240 V)
Chevy Volt	EREV	16 kWh	36 kWh / 100 miles	35 miles	6-6.5 hours (240 V)

Eight EV cases are defined in Table II. Charging duration indicates the time required to fully charge the battery. The driving cycle for each case is based on the actual routes in College Station [9]. The cases differ in state of charge (SOC), vehicle type, or charging duration. For instance, case 1 differs from case 3 because case 1 vehicle charges only at home

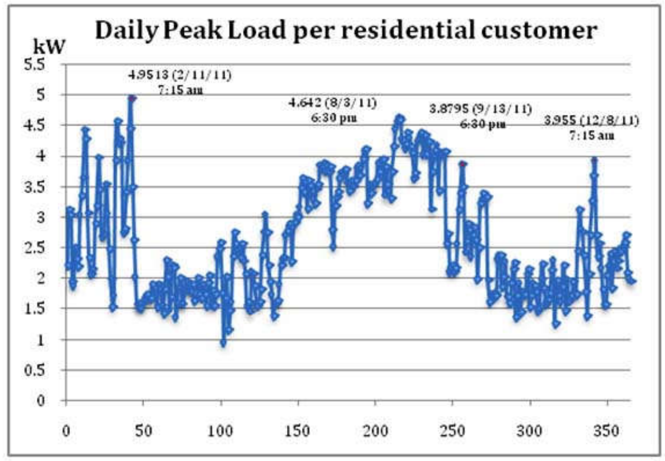

Figure 2. Daily peak load per residential customer in East Texas

TABLE II. EV MODEL CASES

Case	Vehicle Type	Daily Route	Charging Location	SOC (%)	Energy Needed (kWh)	Charging Duration (hour)
1	Chevy Volt	Home-Work (9 miles) Work-Shop-Home (9.2 miles)	Home	59	6.552	2.457 (2.5)
2	Nissan Leaf	Home-Work (9 miles) Work-Shop-Home (9.2 miles)	Home	74.2	6.188	1.805 (2.0)
3	Chevy Volt	Home-Work (9 miles) Work-Shop-Home (9.2 miles)	Home & Work	79.3	3.312	1.242 (1.25)
4	Nissan Leaf	Home-Work (9 miles) Work-Shop-Home (9.2 miles)	Home & Work	87	3.128	0.912 (1.0)
5	Chevy Volt	Home-Work (22.5 miles) Work-Shop-Home (22.7 miles)	Home	X	X	X
6	Nissan Leaf	Home-Work (22.5 miles) Work-Shop-Home (22.7 miles)	Home	36	15.368	4.482 (4.5)
7	Chevy Volt	Home-Work (22.5 miles) Work-Shop-Home (22.7 miles)	Home & Work	48.9	8.172	3.065 (3.0)
8	Nissan Leaf	Home-Work (22.5 miles) Work-Shop-Home (22.7 miles)	Home & Work	67.8	7.718	2.25

whereas case 3 vehicle charges both at work and home. Hence case 1 vehicle when reaching home has less state of charge compared with case 3 vehicle.

Since the electric range of Chevy Volt is only 35 miles (from Table I), the EV case 5 (from Table II) for Chevy Volt involving driving from home to work for 22.5 miles and from work to home via supermarket for 22.7 miles, while charging only at home, is not considered.

Based on different charging start time, three charging assumptions are defined: charging on arriving home, charging at 1 am, and charging at distributed timing. Generally speaking, the peak load of a day happens at early evening (Fig.1). Thus, without any power management and charge distribution, charging on arriving (starting to drive back at 5 pm and charging on arrival) may be the worst case of EV penetration [6]. Usually, it is recommended to charge electric vehicles at midnight since the load consumption is low then and it may avoid increasing the existing load peak of the day. Moreover, the impact of EV charging with a controlled charging strategy (e.g. distributed charging through a day) will be analyzed. For each charging assumption, four charging scenarios are analyzed. In our case study, assuming that the distribution transformer serves 14 residential households, 4 scenarios are proposed (in Table III):

Scenario 1 includes 7 electric vehicles (corresponding to EV cases in Table II), only considering driving to and from work via supermarket. Scenario 2 includes 14 electric vehicles (considering each case in Table II twice). Scenario 3 includes 7 electric vehicles, with zero charge at the beginning of charging. Scenario 4 includes 14 electric vehicles, with zero charge before charging starts.

TABLE III. CHARGING SCENARIOS

Scenario	Vehicle Quantity	Usage
1	7	Limited to Home-Work-Shop-Home
2	14	Limited to Home-Work-Shop-Home
3	7	Charge depleted on arriving home
4	14	Charge depleted on arriving home

TABLE IV. DRIVING TIME FOR EACH DRIVING CYCLE

Cycle	Cycle 1	Cycle 2	Cycle 3	Cycle 4
Route	Home-Work (9 miles)	Work-Shop-Home (9.2 miles)	Home-Work (22.5 miles)	Work-Shop-Home (22.7 miles)
Driving Time (s)	778	1723	1406	2361
Driving Time (min)	13	29	23	39

The SOC, energy needed, and charging duration in Table II which indicate limited usage of electric vehicles are used in scenarios 1 and 2. For charging on arriving home, the charging start time is defined based on the driving time in Table IV by assuming people start driving home from workplace at 5 pm and charge on arriving home. EV load model for charging on arriving home is shown in Fig. 3, which will be added to everyday base load data. Figures 4 and 5 show the daily total load in one typical day per season for scenarios 2 and 4 with EV charging on arriving home. Figures 6 and 7 show the total load of a specific day for charging at 1 am and charging at distributed timing.

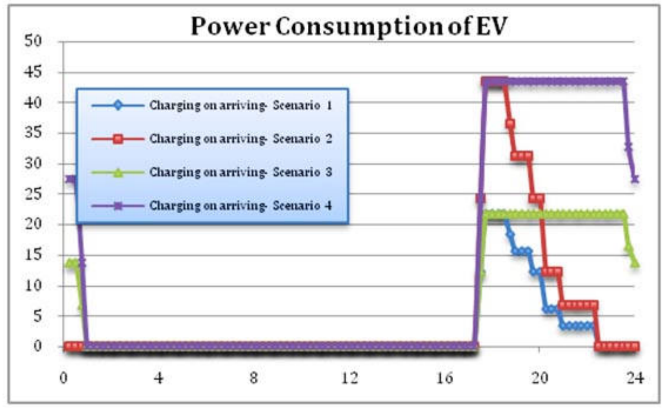

Figure 3. EV load for charging on arriving

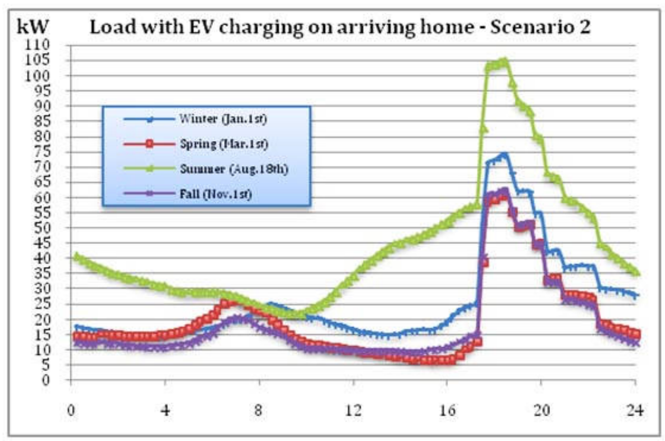

Figure 4. Load with EV charging on arriving home - Scenario 2

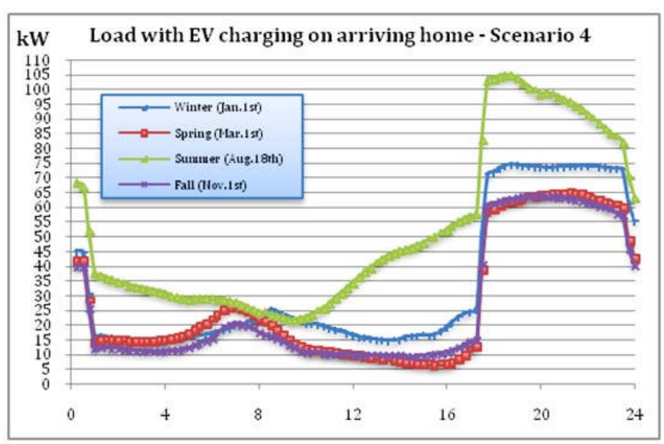

Figure 5. Load with EV charging on arriving home - Scenario 4

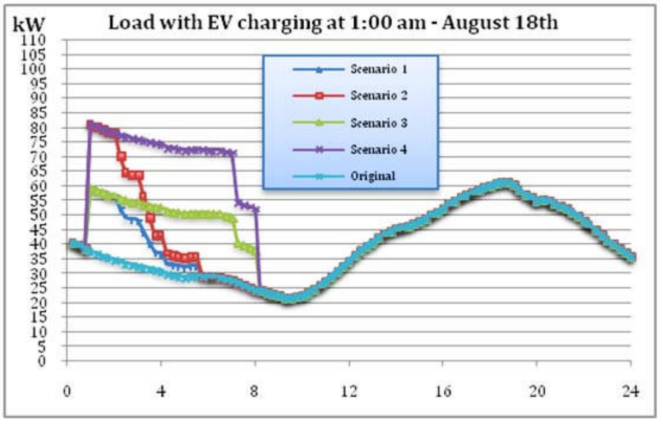

Figure 6. Load with EV charging at 1 am – August 18th

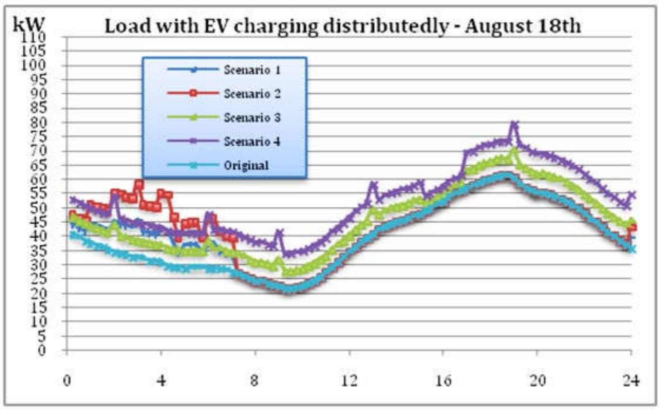

Figure 7. Load with EV charging at distributed timing – August 18th

C. Transformer Thermal Model

1) Correlation between load and ambient temperature: Ambient temperature is an important factor in determining the load capacity of a transformer since the temperature rise for the load should be added to the ambient temperature to determine operating temperature [2].

$$\theta_H = \theta_A + \Delta\theta_{TO} + \Delta\theta_H \tag{1}$$

where θ_H is the winding hottest-spot temperature which is used to calculate loss-of-life factor. θ_A is the average ambient temperature. The average temperature used in this paper is the actual data obtained from Weather Channel website [10]. $\Delta\theta_{TO}$ is the top-oil rise over ambient temperature, $\Delta\theta_H$ is the winding hottest-spot rise over top-oil temperature.

- Positive correlation: The electric cooling load is dominant in summer. Higher temperature will lead to more power consumption, and thus will result in higher temperature rise.
- Negative correlation: The temperature is lower in winter. If the temperature decreases, the electric heating will increase accordingly.

Therefore, generally, the positive correlation provides more severe transformer duty than the negative one.

2) Aging acceleration factor and percent loss-of-life: Aging acceleration factor is a function of ambient temperature, transformer loading, and certain specific transformer parameters. Loss of life (LOL) is the equivalent aging in hours over a time period times 100 divided by the total normal insulation life in hours at the reference hottest-spot temperature. Normal insulation life for a transformer is the expected lifetime when operated with a continuous hot-spot temperature of 110°C, which is 180,000 hours in this paper. Table V shows the specifications used for the transformer's loss of life calculation [2].

Procedure for calculating the thermal factors:

a) Hottest-spot temperature

b) Aging acceleration factor for every 15 min

$$F_{AA} = e^{\left[\frac{15000}{383} - \frac{15000}{\theta_H + 273}\right]} \tag{2}$$

c) Equivalent aging factor for each month

$$F_{EQA} = \frac{\sum_{n=1}^{N} F_{AA,n}\Delta t_n}{\sum_{n=1}^{N} \Delta t_n} \tag{3}$$

d) Annual average factor and the corresponding percent loss of insulation life

$$\%\text{Loss of life} = \frac{F_{EQA} * t * 100}{\text{Normal insulation life}} \tag{4}$$

TABLE V. DISTRIBUTION TRANSFORMER PROPERTIES

Symbol	**Property**	**Units**
R	Ratio of load loss at rated load to no-load losses	
τ_{TO}	Oil time constant	hr
τ_w	Winding time constant	min
$\Delta\theta_{TO,R}$	Top-oil temperature rise at rated load	°C
$\Delta\theta_{H,R}$	Winding hottest-spot rise at rated load	°C
n	Empirically derived exponent	
m	Empirically derived exponent	
$\Delta\theta_{TO}(t)$	Time variable Top-oil rise	
$\Delta\theta_{TO}$	Top-oil rise over ambient temperature	
$\Delta\theta_H(t)$	Time variable winding hottest-spot rise	
$\Delta\theta_H$	Winding hottest-spot rise over top-oil	
	Normal insulation life	hr

III. SIMULATION RESULTS

Results of transformer aging acceleration factor and loss of life according to different EV charging assumptions are tabulated in Table VI-VIII. The actual load data for every 15 minutes through a year are used. The original column in these tables refers to the scenario with no EV charging.

TABLE VI. FEQA AND LOL (CHARGING ON ARRIVING HOME)

	Original	Charging on arriving home			
	Base Load	***Scenario 1***	***Scenario 2***	***Scenario 3***	***Scenario 4***
FEQA	0.0021	0.0757	7.1464	0.1631	20.2431
LOL	0.0104	0.3685	34.779	0.7935	98.5163

TABLE VII. FEQA AND LOL (SCENARIO 2)

	Original	Scenario 2		
	Base Load	***Charging on arriving at 5:00 pm***	***Charging at 1:00 am***	***Distributed Charging***
FEQA	0.0021	7.1464	0.1001	0.0039
LOL	0.0104	34.779	0.4871	0.0192

TABLE VIII. FEQA AND LOL (SCENARIO 4)

		Original	Scenario 4		
Month		***Base Load***	***Charging on arriving at 5:00 pm***	***Charging at 1:00 am***	***Distributed Charging***
Jan	FEQ_1	0.00012	0.785033	**1.357234**	0.002730
Feb	FEQ_2	0.00057	2.377044	**8.422275**	0.015482
Mar	FEQ_3	1.87E-05	0.028636	**0.008801**	0.000109
Apr	FEQ_4	5.62E-05	0.219824	**0.013729**	0.000446
May	FEQ_5	0.00021	1.180658	**0.039392**	0.002139
Jun	FEQ_6	0.00271	26.33804	**0.320498**	0.040787
Jul	FEQ_7	0.00468	42.80368	**0.557542**	0.069685
Aug	FEQ_8	0.01597	158.4035	**1.090655**	0.263961
Sep	FEQ_9	0.00121	10.38140	**0.122107**	0.016797
Oct	FEQ_10	5.21E-05	0.103050	**0.008600**	0.000313
Nov	FEQ_11	2.29E-05	0.046522	**0.037412**	0.000176
Dec	FEQ_12	3.99E-05	0.249521	**0.242704**	0.000646
Year	FEQA	0.0021	20.2431	1.0184	0.0344
Year	LOL	0.0104	98.5163	4.9563	0.1676

Table VI and Fig. 8 indicate that when charging on arriving, scenario 4, which has the highest penetration ratio of EV and requires the most amount of electricity, has much higher aging acceleration factor and loss of life. And for scenario 2, as shown in Table VII and Fig. 9, charging on arriving home tremendously increases loss-of-life factor, while controlled EV charging will help reduce transformer's loss of life.

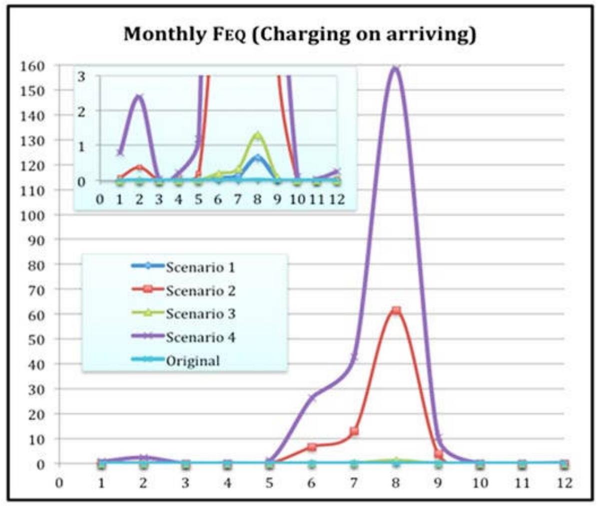

Figure 8. Monthly FEQ results for Charging on arriving

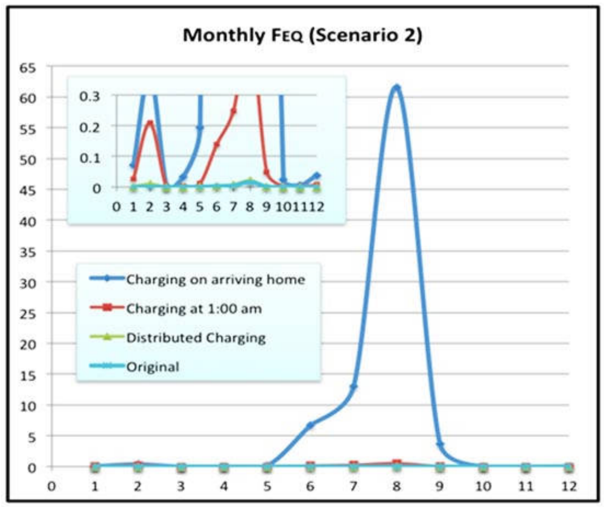

Figure 9. Monthly FEQ results for Scenario 2

Figures 8 and 9 indicate that under the same time-of-charge, higher penetration rate of electric vehicles will significantly increase transformers' loss-of-life factor. With higher penetration rate, the rise of usage ratio will exert even more influence on transformers; under the same penetration rate of electric vehicle, charging at midnight will considerably decrease the loss-of-life factor, while distributed charging through the day will help to almost eliminate the impact of EV charging on distribution transformers.

The monthly data in Table VIII are the equivalent aging factors per month, which are the average value of all the 15 min load data of the month (as given in (3)). The fifth column in Table VIII shows the results for charging scenario 4 and charging at 1 am. It has been mentioned that some days in February have very high daily peak load and the peak load occurs in the early morning. As shown in this column, it is obvious that the aging acceleration factor in February is higher than that in summer. The reason may be that the charging event, which begins at 1am with zero charge left in the battery before charging, will last till early morning, when the peak load of the day happens. Even though the correlation between ambient temperature and load in winter is negative, charging at 1 am in February will have more severe impact on transformer life.

IV. Conclusion

In this paper the potential impacts of different EV penetration scenarios with different usage and charging start time are discussed and compared. The actual load data, the driving routes in College Station, and the real ambient temperature data are employed to simulate the transformer factors. The result data demonstrate the effect of possible EV penetration on the existing distribution transformer lifespan and provide suggestions to eliminate or reduce the negative impact regarding the situation in Texas. According to the discussions presented in this paper, the following conclusions can be drawn:

a) Higher penetration rate of electric vehicle will significantly increase transformers' loss-of-life factor by up to 10,000 times. With the rise of penetration rate, the increase of usage will exert much more influence on transformer life.

b) Charging at midnight will help to considerably decrease the loss-of-life factor for all the scenarios defined in this paper. While with distributed charging, the impact can be almost eliminated. Though charging at distributed timing may lead to charging at peak hour, it is still a better way to alleviate the impact on transformers. However, it remains a challenge to realize this charging strategy, as the utilities need to coordinate with customers and charging stations.

c) Generally, the impact of extra load on transformers in summer is much greater than that in winter. However, as mentioned above, in Texas, some winter mornings with peak load may be an exception. Charging from midnight through early morning in those days may exert strong impact on transformers. Therefore, it is not always appropriate to charge electric vehicles at 1 am in those days. How to develop a control strategy may depend on the actual load profile in a particular area for a particular time period.

d) For charging on arriving home, the most severe impact occurs in June, July, August and September. Thus, steps should be taken to reduce the impact in these months. For charging at 1:00 am, besides the abovementioned summer months, winter months with peak load (e.g. February in 2011) should also be considered.

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