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Considerations for Residential Transformer Sizing Due to Electric Vehicle Adoption

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SUMMARY

Projected rapid electric vehicle (EV) adoption has created a challenge for utilities, including how to plan for an unpredictable future. As EVs gain market share and lawmakers encourage adoption through EV-friendly policy, utilities must prepare for unknown increases in residential loads. Historically, single phase residential transformers have been sized based on an established design process using a diversity factor and typical residential load. As EV adoption increases, utilities may need to change their design parameters to accommodate increases in load. In this paper, a Synthetic Model for Advanced Realistic Testing – Distribution Systems (SMART-DS) model from the National Renewable Energy Laboratory (NREL) and CYME 9.0 was used to perform quasi-static time series analysis (QSTS) to understand the effects of EVs on residential transformer diversity factor and loading at different levels of EV adoption. Using the models, a method to forecast and create residential EV charging time series profiles was developed and used in the QSTS analysis. The changes in diversity factor, load factor, average residential load, and the upgrades needed based on the outlined criteria are reported. This paper provides considerations for the evaluation of current transformer sizing procedures with respect to the predicted growth of EV loading.

KEYWORDS

Diversity factor, load factor, electric vehicles, quasi-static time series analysis, single-phase transformers, residential loads

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I. Introduction

According to the U.S. Department of Energy, in 2022, 28% of the country's energy was used for transportation, equal to approximately 10 billion kWh [1]. As the transportation industry expands its consumption of traditional petrochemical energy sources into power for electric vehicles (EVs), that energy will be generated, transmitted, and distributed through the bulk energy system to vehicle charging locations. This increased demand for power is expected to require large, costly, and time-consuming infrastructure upgrades within the electrical utility industry. Electric utilities are now facing very difficult tasks of accurately forecasting the effect of this increased demand on their existing infrastructure and prioritizing their upgrade efforts.

Adding to the complexity of these tasks is record demand for transformers due to extreme weather events and supply chain bottlenecks resulting from the COVID-19 pandemic. This material scarcity makes precise sizing of future transformer deployment more critical. The impacts of EVs on the existing utility system must also be correctly understood if planned replacements are needed at different adoption levels. Lastly, rising interest rates in the US are creating pressure for utilities to spend wisely and without delay. All these issues make accurate prediction of future asset needs and timely procurement even more important.

One of the most instrumental factors in power system planning is the diversity factor. Because the effect of EVs on the diversity factor of the distribution system is currently not well understood, electric utility planners do not have the information they need to accurately forecast and model future requirements of their systems.

The primary input into system models is the diversity factor. It allows a system designer to take the overall system load addition in kilowatt hours and spread that demand over time, resulting in lower peak usage for the system overall. This can be extrapolated to individual components of the grid, such as substation transformers, service transformers, and feeder/service conductors.

Because of increased demand for power, unreliable supply of assets and capital pressure, accurate information obtained from effective modelling of diversity factors and how they impact the distribution system is more important now than ever. To better estimate future impacts of EVs on residential transformers, SMART-DS models from the National Renewable Energy Laboratory (NREL) and CYME 9.0 software were used to study the impacts of EVs on residential transformers [2]. The studies were performed using QSTS at different adoption rates to determine the appropriate load and diversity factors for these important assets.

a. What is Diversity Factor?

Diversity factor is the ratio of the sum of the individual maximum demands of all connected loads of the system to the maximum demand of the whole system. Diversity factor can be calculated using Equation 1.

$$f_{diveristy} = \frac{\sum Individual\ Load\ Peaks}{Maximum\ System\ Demand} \tag{1}$$

Diversity factor is the measure of how coincident load peaks are to one another, or how diversified loads are. When referring to an individual feeder, connected loads rarely have coincident peaks. Therefore, most feeders have a diversity factor greater than 1. A diversity factor equal to 1 would indicate that all connected loads have peaks occurring at the same time. Since this is not typical, a diversity factor greater than 1 is often used to size equipment such as transformers and conductors. Each connected customer is assumed to have an average peak load. That peak load is divided by a diversity factor. Then, the newly identified diversified load is used to size equipment instead of assuming that equipment would be sized to accommodate all loads peaking at the same time.

For example, a new transformer might be expected to have three connected residential customers and the expected peak load for each residence is 7kW. If a diversity factor of 1.6 and an assumed power factor of 0.98 is used, following the calculations shown in Equation 2, a 15kVA transformer would be adequate for that situation.

$$S_{diversified} = \frac{(7kW/0.98) * 3}{1.6} = 13.4\ kVA \tag{2}$$

If a diversity factor of 1 had been used in that example, the total apparent power would have been 24.5 kVA, meaning a 25 kVA transformer would be needed. While that would be the most conservative choice, it is highly unlikely that all three residences would experience their peak at the same time. The transformer would have unused capacity which can lead to higher losses and increased purchase and installation costs.

b. What is Load Factor?

Load factor is the ratio of the average load in a given time period to the maximum load in that same time period, shown by Equation 3. Load factor is typically used to gauge equipment utilization. Load factor should always be less than or equal to 1.

$$f_{load} = \frac{Average\ Load\ in\ Given\ Time\ Period}{Maxiumum\ Load\ in\ Given\ Time\ Period} \tag{3}$$

A high load factor is typically viewed as good, meaning a high level of equipment utilization and low chance for idle capacity. Utilities often use load factor to indicate when and how to apply demand side management strategies such as time of use rates. By shifting high load residential activities such as charging an EV, drying clothes, or running an HVAC system to non-peak times, overall system peaks can be reduced.

II. Challenges of EVs for Distribution Systems

The distribution grid is a dynamic, ever-changing system that requires constant upgrades and re-designs. The challenge of upgrading the distribution grid is often compared to attempting to repair a plane as it flies. Distribution planners have the difficulty of planning for system upgrades multiple years in the future relying only upon forecasted and predicted conditions. EVs add even greater challenge when planning future upgrades because adoption levels and charging habits of customers are unknown.

a. Market Projections

"In the fourth quarter of 2021, hybrid, plug-in hybrid, and electric vehicles collectively accounted for 11% of light-duty vehicle sales in the United States", according to data from Wards Intelligence [3]. The Biden-Harris administration has "set an ambitious target of 50% of electric vehicle (EV) sale shares in the U.S. by 2030" [4], with a large infrastructure law to help build charging infrastructure across the United States, including rural areas. Some sources project U.S. EV sales' market share to be around 35% by 2030 [5], others say over 50% [6]. All 50 states have some form of tax credit or incentive for the purchase of an electric vehicle. Current projections of EV sales vary widely, but all of these statistics point to the rapid adoption of EVs throughout the world in the next decade. The directed efforts from lawmakers, manufacturers, and policymakers point to increased electrification of the transportation sector resulting from future penetration of EVs.

b. Planning Challenges

Many utilities estimate and evaluate load growth for upwards of 30 years, but most projects are planned around 10-year load growth projections. To prepare the system to handle the forecasted large additions of EV charging load, distribution upgrades must begin now.

Despite many policymakers' lofty goals of getting greater numbers of EVs on the road, many utilities are not ready. One of the biggest challenges of planning for EVs is that much of the EV load forecast is highly dependent on consumer behavior. People's charging habits will shape EV load peaks, and unfortunately, current levels of EV adoption across the United States make it difficult to develop long term growth models based on realistic charging habits of EV drivers. During the past 10 years, many studies have been published that address building realistic load profiles for EVs to use in load growth simulations, but many of these are based on small sample sizes within a handful of cities. While these studies lay a good foundation for EV modelling, they will not be realistic for all areas because EV charging habits vary by demographic.

Another planning challenge is projecting where charging will occur. While also a factor of people's charging habits, charging location could greatly affect system peaks. Based on an EPRI report, 80% of charging currently occurs at home [7]. With the current lack of public chargers, most consumers will continue to use chargers at home for the foreseeable future. Public chargers often collect data such as car type and charging duration, which a user consents to sharing when using a public charger. But a home charger that plugs into a standard 240v outlet does not always collect data like a public charging station. Most data from home charging is collected via smart meters provided by entities who have private agreements with their customers. The data is then used to develop models of charging habits in the specific area being studied. While these studies can be used by utilities, they may not provide a realistic picture for EV charging in a different area.

III. Testing

a. Method

To test the effects of EV residential charging, models from SMART-DS datasets were used [2]. These models provided a test bed to implement residential EV loads in a realistic but synthetic model. CYME 9.0 Rev 7 with the time-series with profiles module was used to QSTS using the created time-series data with three different levels of EV adoption, as shown in Table 1. The time-series load profiles used were created using the methods and assumptions outlined in later sections.

Table 1. Percentage of EV adoption per customer for each simulation case.

Case	Percentage of Loads selected for First EV	Percentage of Loads Selected for Second EV
Low	5%	0%
Medium	30%	0%
High	60%	15%
Medium TOU	30% with 50% adoption of a TOU rate plan	

i. Assumptions

As discussed, there are current challenges to developing realistic residential charging load profiles. Due to these challenges, assumptions were made to develop the testing methodology. Residential loads were determined as an EV charging location based on the adoption levels shown in Chart 1, but 70% of the EV loads were assigned a battery electric vehicle (BEV) and 30% of customers were assigned a plugin hybrid electric vehicle (PHEV). BEV batteries were assigned a 68.4kWh capacity, while the PHEV batteries were assigned a 13.5kWh capacity. Each house is assumed to have a level 2 charger with a 7.2kW charging rate.

Probability density functions from [7] for both the BEV and PHEV were used to determine the probability of a customer starting to charge their car based on their current battery level. Probabilities from [8] were used to determine the time of day a customer begins charging. These probabilities were different for weekdays and weekends. An average discharge rate of 9.4 kWh/day for BEV with a standard deviation of 10.25 kWh/day was assigned to BEVs, and an average discharge rate of 0 kWh/day with a standard deviation of 7.3 kWh/day was assigned to PHEVs. Logically, the discharge rate was limited to positive values. These values were based on the average kWh/mile rating of two common models of EVs, a Tesla Model X and a Chevy Volt. The daily miles driven and standard deviation are extrapolated from data presented in [7].

These probabilities, discharge rates, and driving habits were assumed to be a realistic representation of residential customer charging habits. Information around residential charging habits is limited, so assumptions were made using reliable sources and informed judgement based on those sources to ensure that realistic data is presented.

ii. EV Time-series Loads

To create residential EV charging time-series load models, Python 3 was used to make realistic residential EV charging time-series load profiles. Each individual customer was assigned a PHEV, BEV, or no EV based on the test adoption rate. Each customer was assigned a unique loading profile with a 15-minute resolution for the 365 days simulated. These individual loads were directly allocated in CYME to each customer who was assigned an EV. The method scripted in Python to create the time-series load profiles is outlined in Figure 1.

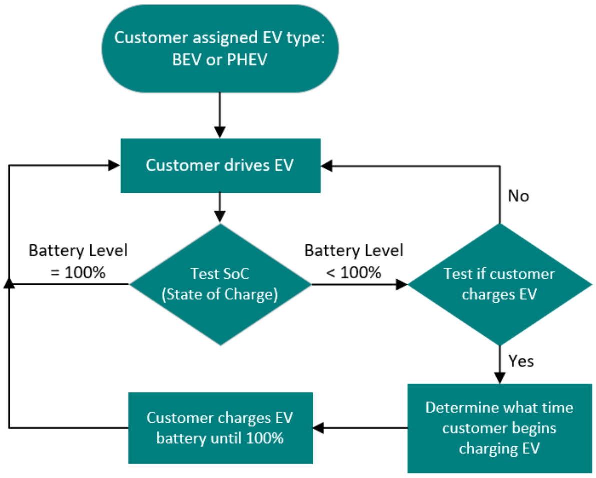

Figure 1. EV time-series code flow chart.

Two different probability density functions (PDF) from [7] for BEV and PHEVs were used to determine if a customer charged their EV based on the SoC (State of Charge) of their battery, as shown in Figure 2. On a given day, if the customer did charge, based on the SoC PDF, a normalized time profile for weekdays and weekends was used to determine when the vehicle started charging. The normalized time profiles are shown in Figure 3. A time of use (TOU) rate plan was also evaluated by shifting the weekday probability of charging start time to peak at 23:00. The weekend charging profile remained the same for the TOU plan.

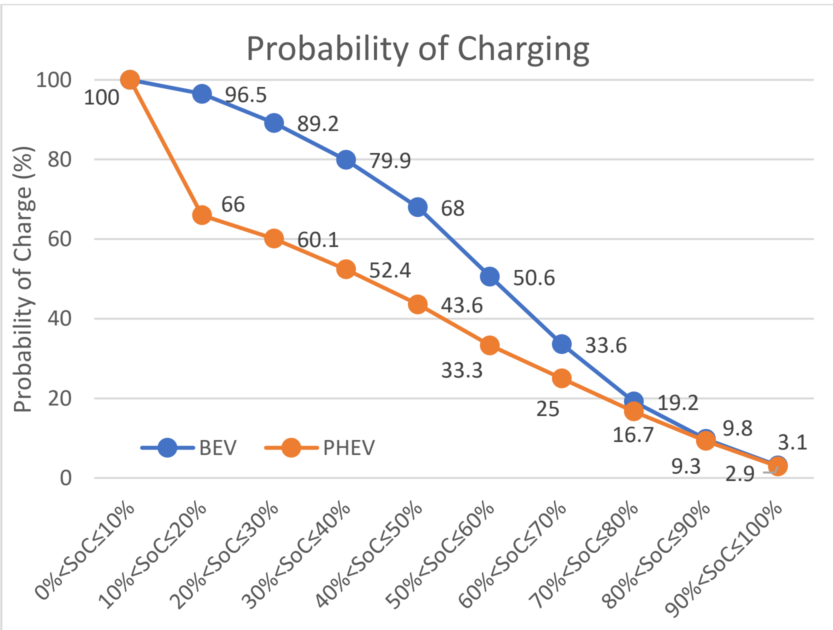

Figure 2. Probability of charging based on present SoC.

iii. Modelling and Data Processing

The feeder topology shown in Figure 4 was analyzed to see the effects of EV loads on residential transformers. The different levels of adoption and EV load placements were defined by JSON placement files provided with the SMART-DS models with randomly chosen placements of EV loads. The EV adoption levels were defined based on the percentages shown in Table 1. The high case has the addition of a possible second EV adopted at residences where a first EV was already adopted. CYMEpy was used to efficiently place the EV loads on the models at the selected residential locations. Residential customer time-series load data was also provided with the models defined as a percentage of their total possible load for 15-minute intervals for 365 days.

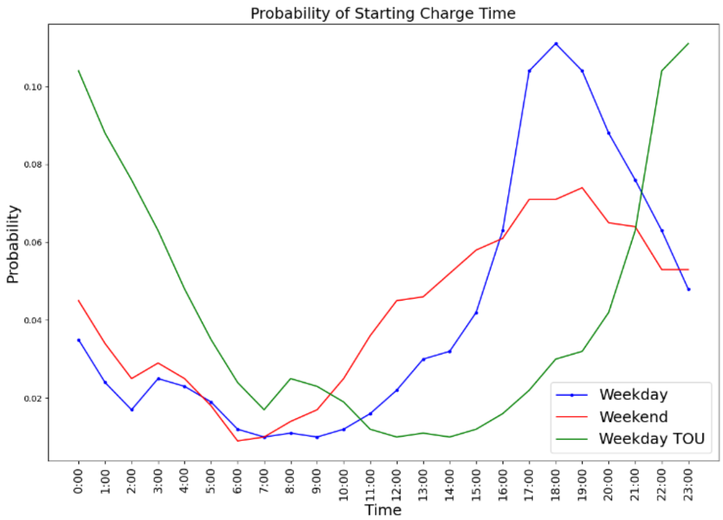

Figure 3. Probability of charge starting time for weekdays, weekends, and weekday TOU plan.

Figure 4. Feeder topology used for simulation.

CYME 9.0 Rev 7 with the time-series with profiles module was used to run QSTS analysis with the generated time-series data with the three different levels of EV adoption. Load data was collected at 15-minute intervals for a total of 365 days for each transformer with connected residential load. This granular load data was then processed using a Python script to compare the customer time-series load files to the total load seen on the transformer high side. This script then provided the diversity factor on each transformer over the entire 365-day period.

To relate the change in diversity factor to transformer loading, the load factor for each transformer was also calculated seasonally for summer and winter. Summer months were June, July, and August, and winter months were December, January, and February.

To fully understand the effects of the increase in EV loads on the overall loading of residential transformers, a function to determine the potential for transformer damaging events was developed based on percentage of loading over nameplate rating and the amount of time at that rating. Equation 4 was defined based on criteria set out by Eaton for single phase transformers, as required by ANSI [9].

$$f(t) = \begin{cases} -100 \times t + 250, & t < 1.0 \\ -8.333 \times t + 158.33, & x \geq 1.0 \end{cases} \tag{4}$$

Equation 4 was integrated over 12 hours, and if at any time a transformer's loading integrated over time surpassed this function, it was considered a potential for damage. The integration was reset if the loading fell below 110%. While the criteria used to develop this function does not account for things such as ambient temperature, insulation life, or aging, it gives a simplified view of potential transformer damage based on increase in EV load. This function could be modified for specific situations if a manufacturer's load curve is used to define when failure could occur, not just potential damage.

IV. Results

Figure 5 shows the change in diversity factor for each adoption case when compared to the base case for all transformers with at least two or more customers. Transformers with only one customer were excluded from the diversity factor analysis.

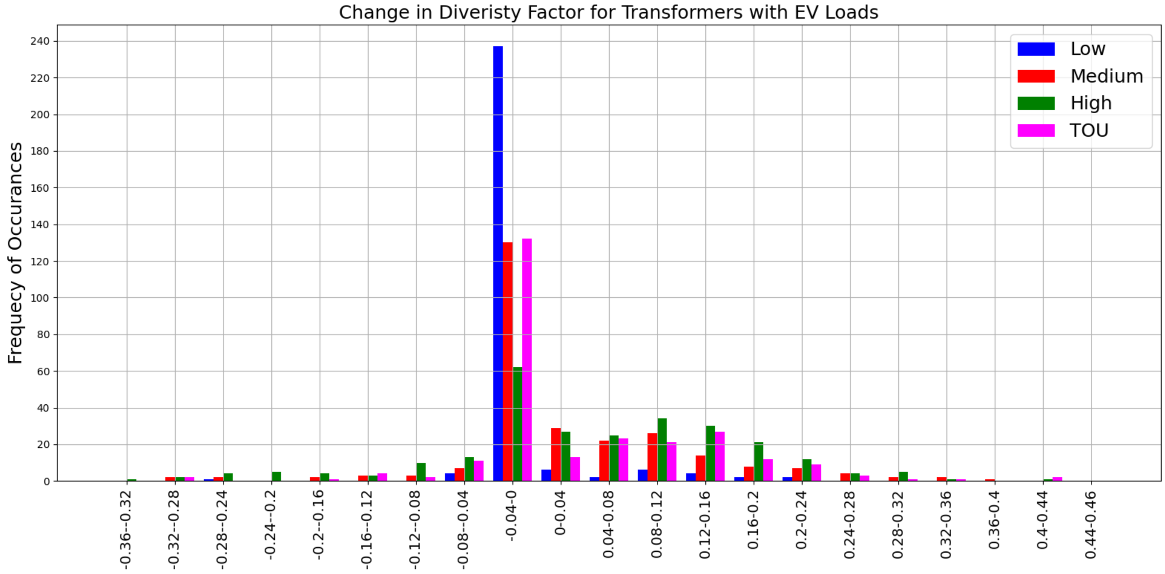

Figure 5. Change in diversity factor for transformers with EV loads

In all three adoption cases, the vast majority of transformers saw an increase in diversity factor. Of the transformers in the high level of adoption, 60% saw an increase in diversity factor, another 21% saw no change. Therefore, if current design practices of sizing transformers based on a set diversity factor has proven to be adequate and lead to no transformer overloading, in over 81% of cases, the diversity factor used should not need to be changed up to a high percentage of EV adoption. In 60% of cases, it could even be conservative, leading to underutilization of transformers. Table 2 shows the overall average diversity factor for all transformers studied with more than one customer. With the increase in EV adoption, there is a trend of increasing diversity factor. The medium adoption TOU plan had no effect on the diversity factor compared to the medium case.

This predominant increase in diversity factor is most likely due to the high diversification of charging possible using the forecasting method implemented with this simulation. Since predicting charging times depends on many factors, using a diversified charging model presents a ‘one size fits all’ method that could be applied to any system and revised based on charging data collected in a specific area that accounts for demographics.

To fully understand the effects of EV loads on transformer loading, Equation 4 was used to determine the number of potential transformer damaging events due to the increase in EV load. Table 3 shows the increase in potential transformer damaging events per adoption case for all 688 transformers studied.

Table 2. Average diversity factor for the base case and each adoption level.

Average Diversity Factor for Each Case	
Base	1.25
Low	1.25
Medium	1.28
High	1.29
Medium TOU	1.28

Table 3. Increase in potential transformer damaging events per adoption case compared to the base case.

Increase in Potential Transformer Damage Events per Adoption Case	
Low	19
Medium	157
High	415
Medium TOU	136

While the function used is not a guarantee of failure, it is an indicator that damage has more than likely occurred, increasing likelihood of later failure of the transformer.

To mitigate these occurrences, transformer upgrades were tested to remove these instances of potential damage. Overloading was still allowed below Equation 4 since many utilities allow for equipment overloading in emergent situations, but all instances of potential damage were mitigated. Figure 6 shows the number of transformer upgrades needed in each adoption case specified by transformer rating in kVA, with the average customer count on all transformers being 1.82. Both the medium and TOU adoption cases were comparable in total number of upgrades, 50 and 45 respectively. A total of 110 transformer upgrades were needed to mitigate all potentially damaging events in the high adoption case. This is 16% of the total residential transformers studied.

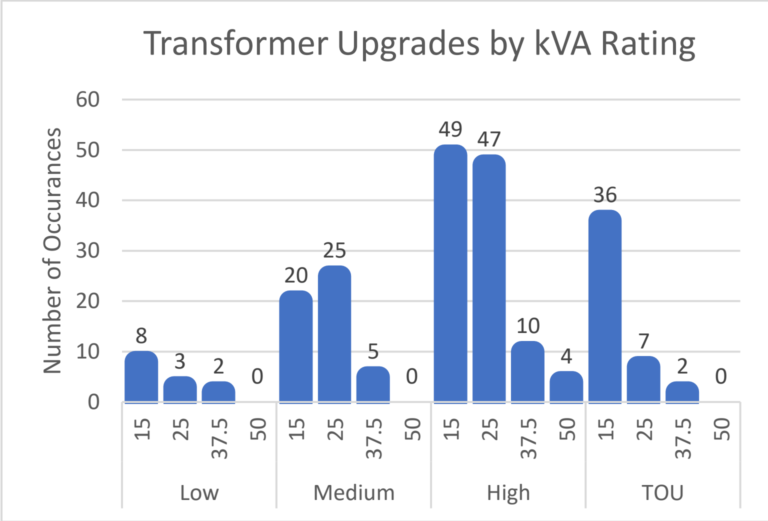

Figure 6. Number of transformer upgrades to mitigate any potential for overloads.

Table 2. Average increase in residential peak load for each adoption case compared to the base case.

Average Increase in Residential Peak Load	
Low	0.174 kW
Medium	1.10 kW
High	2.74 kW
Medium TOU	0.95 kW

The average increase in residential customer peak load is shown in Table 4. The high adoption case saw a 2.74kW increase in peak load, a 19% increase in peak load compared to the base case. The medium adoption case saw a 7.6% increase from the base case. The addition of a level 2 charger in an average residential home could likely introduce a new peak load in many cases. While an increase in peak load is observed, it can be seen in Figure 7 that there was little change in load factor for all adoption cases. The summer load factor did see a greater decrease in load factor for all cases compared to the change in winter load factor. The decrease in load factor for both seasons is likely due to the increase in peak.

load. When using an assumed 7.2kW level 2 charger for all EV loads, a change in load factor would not be expected since the average load and peak load would both likely increase.

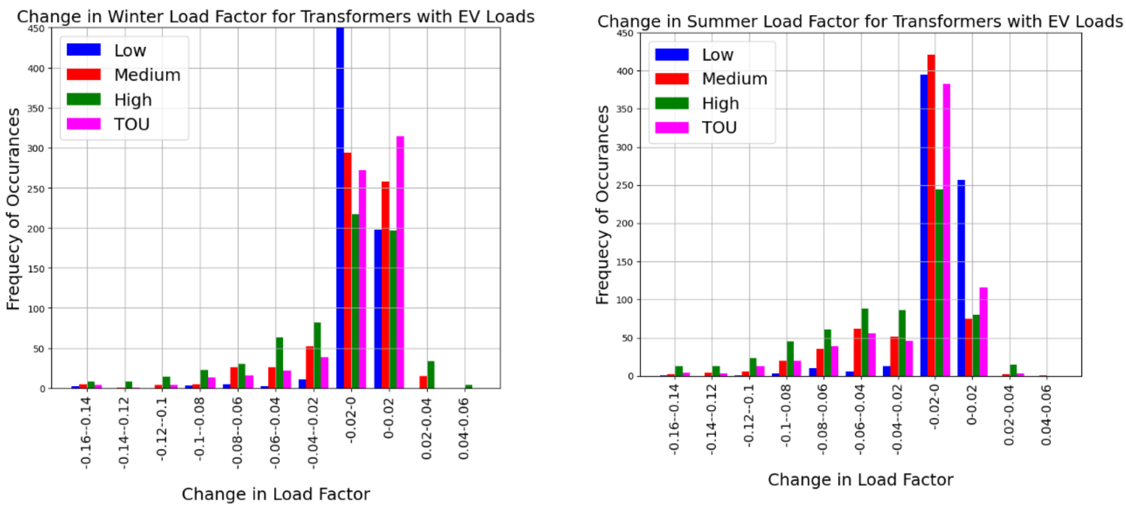

Figure 7. Change in load factor for transformers with EV load.

V. Considerations and Conclusion

Utilities are presently focused on developing plans for large system upgrades for the projected increase in EV loads. However, practical steps can be taken now to plan for increased loads by changing current design practices with the future in mind. Evaluating the way transformers are presently being sized for new construction and routine maintenance could lead to cost savings down the road. A summary of findings can be seen in Table 5. In the medium EV adoption case, 7.3% of transformers needed upgrades to prevent potentially damaging events; 16% of transformers needed upgrades in the high adoption case.

Table 3. Summary of findings.

	Average Diversity Factor	Average Change in Diversity Factor	% of Total Transformer Replacement	Average Increase in Residential Load
Low	1.25	0.01	1.9%	0.174 kW
Medium	1.28	0.04	7.3%	1.10 kW
High	1.29	0.05	16%	2.74 kW
TOU	1.28	0.04	6.5%	0.95 kW

The United States has an estimated 50 million distribution transformers in operation [10]. If it is assumed that only 30 million of those are residential transformers, at an EV adoption level of only 30%, 2.2 million transformers nation-wide could potentially need to be replaced. At 60% EV adoption, 4.8 million transformers could need replacement. Due to the current supply chain issues causing massive delays in transformers delivery, many utilities are experiencing challenges in simply keeping up with supplying transformers for new construction. Many utilities have also been forced to delay large capital projects due to supply chain restrains, with lead times for single phase transformers being multiple years in some cases. If these conditions were to persist into the future, even made worse by increased demand due to EV adoption, it is more important than ever to consider ways existing design and planning methods can be changed to plan for EV adoption.

Beyond just the increased demand driven by EV adoption, many cities are also pushing to decrease the use of natural gas for heat and cooking in residential homes. This electrification of heating and cooking will also lead to further increased demands. Changes in demand due to climate change could also affect peak demands in the future. Recovering from wildfires has already proven to be a challenge many utilities are facing, and many have already chosen to change their design and operation methods to account for the increased risk of wildfires being seen in recent years.

EVs are an inevitable part of a future where society is not dependent on fossil fuels. With the push from lawmakers, manufactures, and utilities alike to make them more obtainable and appealing, EVs will eventually become the sensible choice for the average consumer. Current challenges around obtaining transformers makes it more important than ever for utilities to strategically plan for future increase in load when installing new transformers. Present design practices must be evaluated with the future in mind to ensure a grid that is prepared for a more sustainable and electrified future.

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