New Loads and Service Factors for Distribution Transformers Following the Transition to High-Efficiency Heat Pumps, Solar PV, and EV Charging

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***Abstract*—Replacement of conventional high-power appliances including heating ventilation and air-conditioning (HVAC) and resistive electric water heaters (EWHs) with heat pumps is expected to be implemented long-term to increase energy efficiency. Even with efficiency upgrades, future residential power demand may rise due to increasing electric vehicle (EV) penetration. Extensive experimental data from field demonstrators and regional utilities as well as thousands of synthetically generated loads are utilized to investigate the effect of heat pumps, EV charging, and distributed solar PV on residential power demand and distribution transformers. Values are established for typical rating distribution and connection to multiple houses to study and quantify the impact seen by residential transformers with load and diversity factor calculations. At the residence level, uncontrolled EV charging on a circuit with 100% heat pump water heater (HPWH) penetration significantly decreased average load factor across all transformer ratings, decreased average diversity factor for transformers rated 75kVA and higher, and caused more frequent transformer overload.**

***Index Terms*—Electric power distribution system, electric vehicle (EV), heat pump water heater (HPWH), load factor, diversity factor**

I. Introduction

The replacement of conventional heating ventilation and air-conditioning (HVAC) and resistive electric water heaters (EWHs) with high-efficiency heat pumps is expected to further increase in the United States. On the other hand, increased deployment of electric vehicles (EVs) may offset demand reduction caused by the transition to heat pumps, so the overall resulting change is yet to be determined in terms of instantaneous power demand. Adoption rate of EVs has increased in the United States and around the world in recent years due to technological advancement, decreasing prices, and major policy changes [1].

Growing EV ownership may increase residential peak demand due to simultaneous charging when commuters arrive home in the evening, intensifying distribution transformer overload [2]–[4]. Transformer overloading causes hot-spot temperature to rise, leading to winding insulation degradation and accelerated aging [5]. Possible transformer lifespan deterioration due to EV charging could further increase an already substantial lead time for distribution transformer orders, which was 12-30 months in 2023 [6].

Several control strategies in literature could mitigate EV grid impact and reduce charging overlap. The authors of [7] proposed a vehicle-directed smart charging concept that issues random charging start times within a time window after evening peak has reduced. A simulation in [8] reduced projected peak demand by 80-99% utilizing a valley-filling optimal charging scheme. Bidirectional charging, or vehicle-to-grid (V2G), is another potential strategy where stationary EV batteries are dispatched to provide grid auxiliary services including load balancing and peak demand reduction. A V2G simulation by the authors of [9] demonstrated long-term support for load balancing without any EV batteries dropping below 50% state of charge. With increasing EV ownership and emerging technologies like heat pumps and distributed solar PV, it may be beneficial to analyze future load shapes for appropriate planning of infrastructure upgrades and control schemes.

Proposed in this paper are techniques to estimate community load shapes based on individual house trends with EV adoption and upgrades to high efficiency heat pump systems for HVAC and water heating. Extensive experimental data was used to analyze impact on distribution transformers at the residence and main feeder level quantified with calculations for load and diversity factor. A further contribution of synthetically-generated loads includes application of a new artificial intelligence (AI) machine learning (ML) method to separate HVAC from total load, deployment of a heat pump water heater (HPWH) power demand model, and generation of EV charging profiles using National Household Travel Survey (NHTS) data. The analysis focused on the southeastern region of the United States for which such studies are scarce.

II. Experimental and Synthetic Big Data for Distribution Systems

Within this conference paper, four major data sources are employed for use in the case studies. Two of the sources are a substation aggregate load for a neighborhood from a utility in the southeast region of the United States [10] and the CBECC-Res hot water draw (HWD) profiles for 150 homes from 2019 and 2022 [11]. The additional experimental field demonstrators have individual houses with extensive monitoring of appliance loads, i.e. the TVA Robotic house data shared by the Tennessee

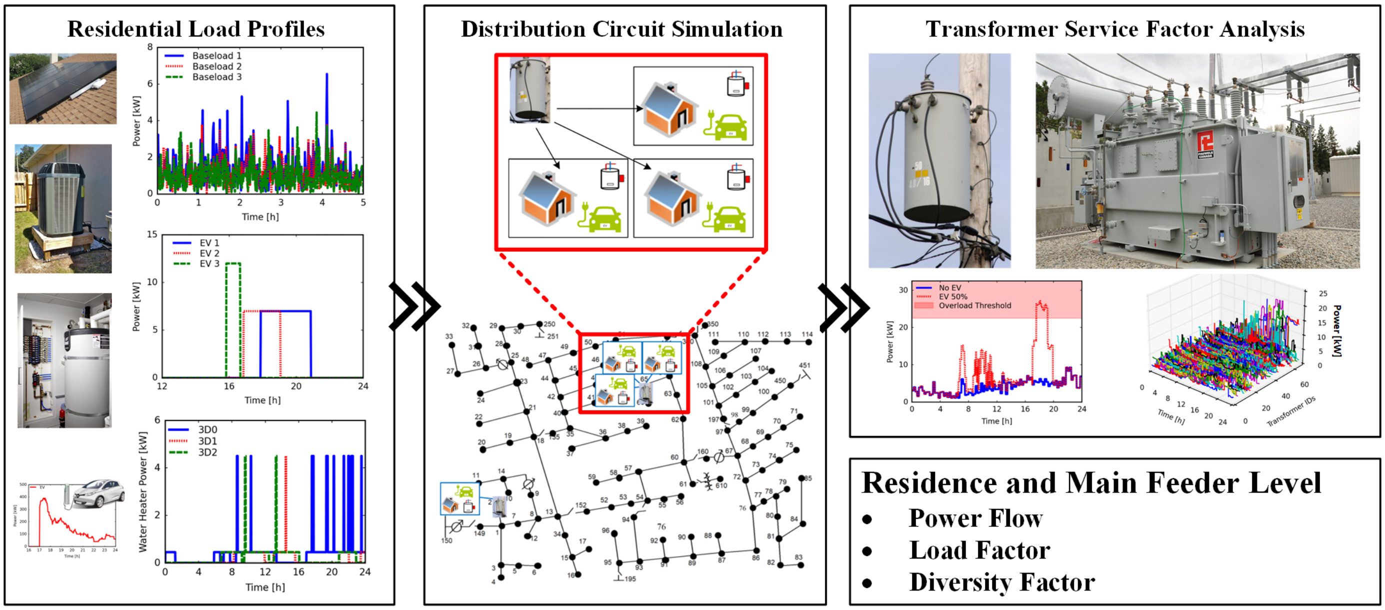


Fig. 1. Experimental data from field demonstrators as well as synthetically generated datasets based on human behavior patterns and ML are utilized to study the effect of emerging technologies on the service factors of distribution transformers. Diversity factor, load factor, and power flow are calculated at the residence and main feeder level.

Valley Authority (TVA) [12], and the Glasgow, Kentucky Smart Energy Technologies (SET) data [13].

Public availability of big data from residential load field demonstrations is typically limited due to widely acknowledged consumer privacy and security concerns. These field demonstrators provide residential load data for the southeast region of the United States, which is less-studied in comparison to western states like California. Experimental and synthetic data used for this study as well as technologies deployed by field demonstration projects to report experimental load data are shown in Fig. 1.

A 12-node stratified tank temperature model of the type in [14] was employed to generate hundreds of realistic synthetic daily power profiles for HPWHs. Given residential HWD profiles from the 2019 and 2022 CBECC-Res data, the model outputs heat pump compressor and resistive element operation status at one-minute resolution with rated input powers of 0.45kW and 4.5kW, respectively. Assumptions for the HPWH model include a temperature setpoint of 125 deg F (51.7 deg C) as well as nominal tank sizes of 50 and 75 gallons dependent on number of occupants. Water draw profiles with less than five occupants were assigned a 50 gallon tank, while those with five and six occupants were assigned a 75 gallon tank.

The developed HPWH model was simulated with all 150 original CBECC-Res HWD profiles, and the operation status for each profile is visualized in Fig. 2. To further expand the profile dataset for large-scale distribution systems with thousands of houses, each of these unique HWD profiles were fed into the model multiple times after being shifted in time by +/- 15, 30, and 45 minutes to increase the total number of HPWH power profiles to 1,050. The aggregated power demands for the original 150 profiles and 1,050 profiles have the same general shape with different magnitudes. Both demand curves follow human behavior patterns peaking in the morning and evening when occupants leave and return home, and have a similar shape in comparison to the HPWH demand curve presented in [15].

The 2017 NHTS includes data for residential arrival times and daily driving distances for the southeast region of the United States [16]. This dataset along with Gaussian Kernal Density Estimation as described in [9] was used to generate residential EV charging profiles. Charging duration was established based on miles driven with start time determined by vehicle home arrival times. For the case study, it is assumed each EV has 100kWh battery capacity, 85% round-trip charging efficiency, and that all EV owners charged their vehicle upon arrival. An example typical distribution of EV charging levels based on regional adoption was used with rated powers of 3, 7, 12, and 19kW. The majority of charging levels were set to the most common values of 7 and 12kW.

Experimental data from the TVA SET project was used to populate the IEEE 123 node test feeder with 1,765 residential loads. Additionally, the homes were assigned synthetically-generated CBECC-Res and NHTS-based HPWH and EV modules. The HPWH modules were designated HWD profiles using 2020 United States Census data to reflect an accurate distribution of occupants per home [17]. Homes on the circuit were grouped into residential transformers using a typical distribution of transformer ratings in electric power distribution systems with large majority of residential consumers shown in Fig. 3. The amount of homes assigned to each transformer was determined by transformer rating, with more homes connected to transformers of higher kVA ratings.

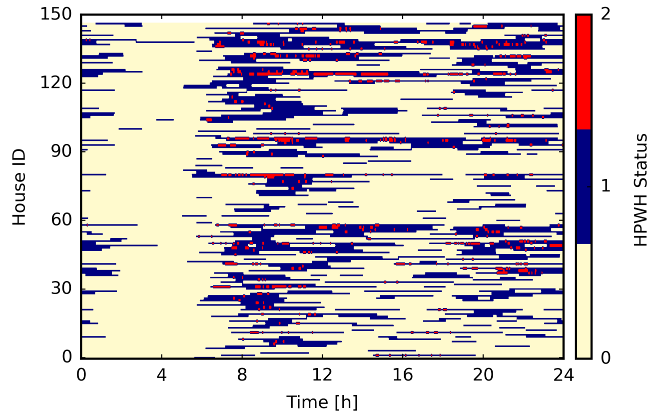


Fig. 2. Operation status at each timestep for the 150 original HPWH profiles generated from the CBECC-Res 2019 and 2022 data. Status "1" represents heat pump compressor operation while status "2" represents resistive element operation.

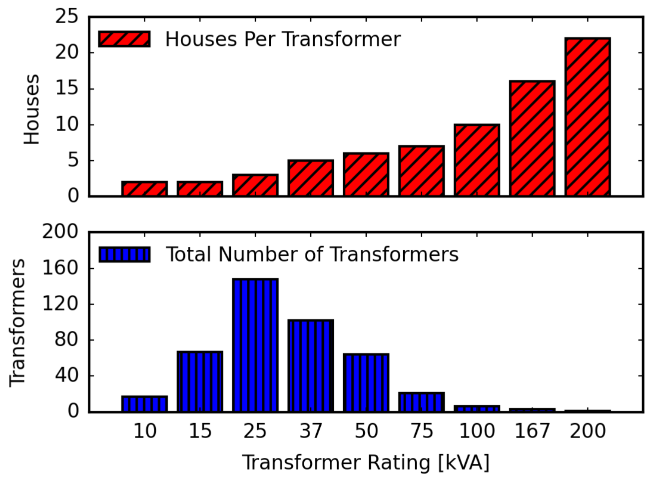


Fig. 3. Typical house connections for each transformer rating (top) and typical distribution of transformer ratings (bottom) used to assign residential transformers on the IEEE 123 node test feeder.

III. Service Factor Metrics for Distribution Transformer Impact

Service factors are metrics used by utilities to assign transformer ratings based on load data. Those used for analysis in this study are load factor and diversity factor. Load factor is defined as the ratio of average load to peak load during a specified time period [18]. From the utility perspective, a high load factor is beneficial, as a more constant demand allows for higher capacity factor with less overload. In common practice most residential loads are variable, so power transformers often operate with a load factor between 50 and 70%.

Diversity factor is a metric that can be utilized to capture the probabilistic and time-dependent characteristics of the multiple residential loads connected to a distribution transformer. It is defined as the ratio of the sum of individual maximum non-simultaneous loads to their simultaneous peak demand. Values of diversity factor are typically between 1.0 and 8.0 [19]. Higher diversity factor is also beneficial from the utility perspective. Greater diversity between residential loads decreases peak demand seen by their transformer due to minimized overlapping of individual peak loads in time. This may decrease overloading and hot-spot temperature, leading to a longer transformer lifespan.

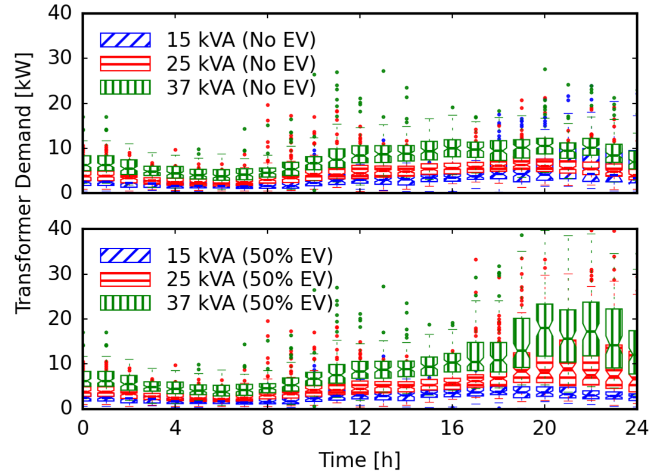


Fig. 4. Box plot for power demand seen by 15, 25, and 37kVA transformers on the circuit with and without EV charging. The evening demand significantly increases for the EV charging case.

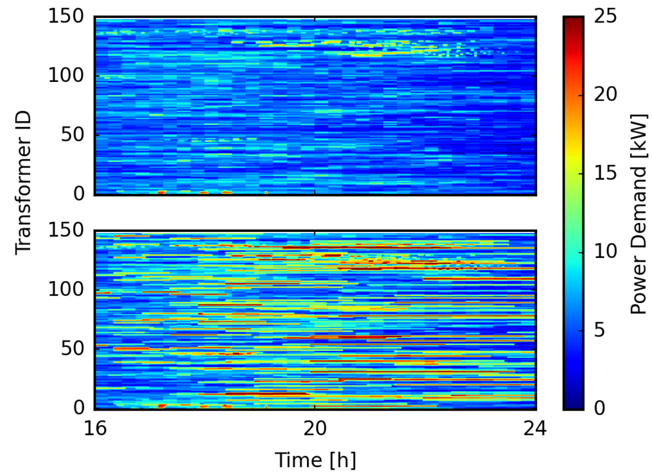
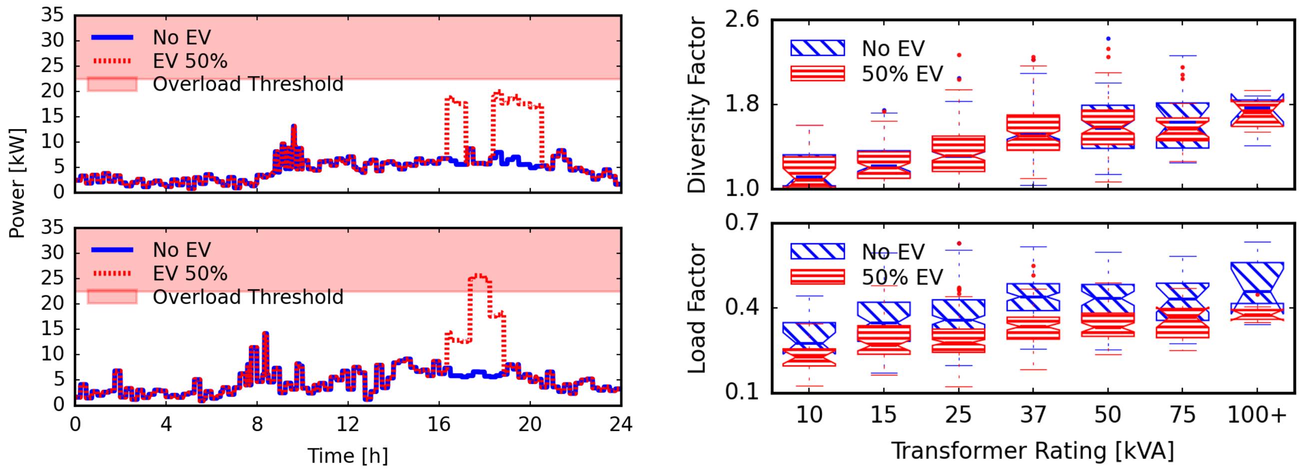


Fig. 5. Evening demand for each 25kVA transformer without (top) and with EV charging (bottom). Addition of EV charging to the distribution circuit resulted in more frequent transformer overload during evening hours, indicated by the increase in dark red spots in the bottom subplot.

Load factor and diversity factor were calculated and compared to analyze impact of EV charging and heat pump adoption on distribution transformers in the case studies. The following equations were used to calculate load factor and diversity factor:

$$LF = \frac{P_{avg}}{P_{max}}, \quad (1)$$



(a)

(b)

Fig. 6. Power demand for two 25 kVA transformers in the 0% and 50% EV penetration cases (a) and service factors for all transformers in both the EV penetration cases (b). Residential transformers could often service multiple EVs without experiencing overload when charging occurred at different times (top a). Simultaneous charging of multiple EVs often caused overload (bottom a). High EV penetration caused a significant decrease in load factor across all transformer ratings, while a decrease in diversity factor was only seen for those rated 75kVA and higher, likely due to higher probability of EV charging overlap for transformers servicing a high number of homes.

$$DF = \frac{\sum_{i=0}^{L} P_{M,i}}{P_{max}}, \tag{2}$$

where P_{avg} and P_{max} are the average and peak power demands seen by the transformer respectively during the specified time period, in this case 24 hours, and $P_{M,i}$ represents the individual non-simultaneous peak demands of the loads i connected to the transformer.

IV. Case Studies: EV, HPWH, HVAC, and Solar PV

The modified IEEE-123 node test feeder was used to study the effects of high-penetration residential EV charging on distribution transformers. Two 24-hour simulations were conducted: one without EV charging and one where 50% of homes charge an EV. In both cases, 100% penetration of HPWHs was assumed to represent a long-term case with a high adoption rate of high-efficiency appliances.

As expected, the addition of EV charging on the circuit resulted in significantly higher evening demand seen by residential transformers, illustrated in Fig. 4. This resulted in more frequent overload, as 35% of residential transformers experienced overload during the EV charging case, up from only 4% without EV charging. The increase in evening overload for 25kVA transformers is depicted in the color map shown in Fig. 5. At the main feeder level, load factor and diversity factor greatly decreased, changing from 72% to 53% and 1.85 to 1.70 respectively.

For 10 and 15kVA residential transformer ratings, supplying charging demand for just one EV was enough to cause overload in many cases. Some higher rated transformers sufficiently serviced multiple EVs without overloading when the charging times did not overlap. In other cases, overloading occurred on transformers of higher ratings due to simultaneous charging of multiple EVs, as shown in Fig. 6a.

A significant decrease in the average load factor was noted across all residential transformer ratings in the EV charging case, as shown in Fig. 6b. While the addition of EV charging load had very little effect on diversity factor of lower-rated transformers, there was a small yet notable decrease for those rated 75kVA and higher. This is likely because transformers with more EVs connected have higher probability of simultaneous charging. Overlapping charging of multiple EVs on the same transformer heavily decreases load diversity, and consequentially diversity factor.

In addition to the EV charging case study, demand reduction due to long-term adoption of distributed solar PV and high-efficiency heat pumps was estimated using experimental data from a regional utility circuit with approximately 5,000 home loads. To demonstrate the impact of heat pumps at the main feeder level, an AI ML model of the type in [20]–[22] was applied to extract HVAC load from the total load. Next, the HVAC demand at each timestep was decreased by 26% to represent installment of high-efficiency heat pump systems across all houses in the community, then recombined with the baseload. This percentage comes from findings in [12] where the authors used experimental data and calibrated EnergyPlus models considered to be representative of the southeastern Untied States.

The forecasted demand reduction due to heat pump adoption is illustrated in Fig. 7 and compared to the original demand. The substation transformer load factor was only marginally increased from 70% to 73%, and energy consumption during the day was reduced by 7.20MWh (approximately 9%). The anticipated demand reduction resulting from transition to

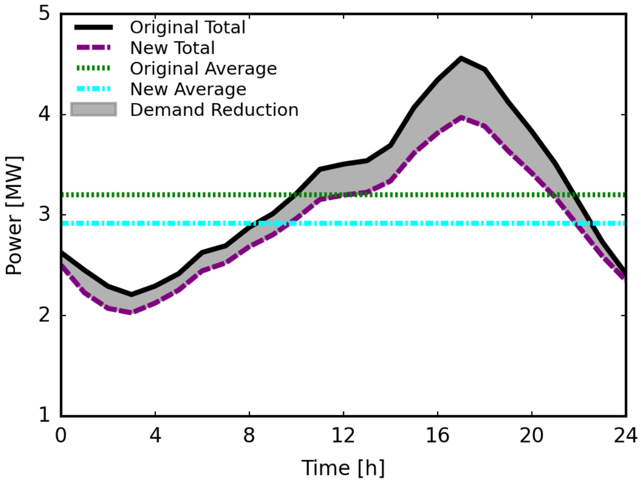


Fig. 7. Demand reduction estimation for the large-scale utility distribution feeder resulting from replacing conventional HVAC systems with high-efficiency heat pumps. The demand reduction is highest during evening peak, which could help offset some of the expected demand increase due to EV charging.

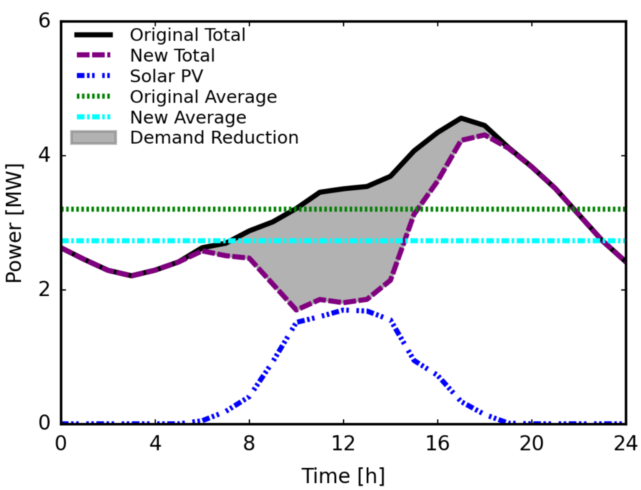


Fig. 8. Estimation of demand reduction from the addition of 2,500 distributed solar PV residential sites on the large-scale utility distribution system. Solar PV generation does not align with typical EV charging hours, so load shifting may be necessary to balance demand.

higher efficiency HVAC may help offset some of the demand increase caused by growing EV penetration.

Distributed solar PV generation measurements from the aforementioned TVA SET project were used to consider a scenario with 50% distributed solar PV penetration. Data for a sunny day with high PV output was purposefully selected to demonstrate the largest potential demand reduction. Effective energy demand decreased by 11.78MWh (approximately 12%), and the substation transformer load factor decreased from 70% to 64%. System demand with solar PV is compared to the original demand in Fig. 8. In this case, load factor still decreased due to the misalignment of solar PV generation with peak demand.

V. Conclusion

A systematic study of future load shapes and distribution transformer impact was conducted. The analysis focused on the southeastern region of the United States, for which such studies are scarce. Extensive experimental and synthetic data as well as an AI ML separation method were employed to forecast community load shapes based on heat pump and solar PV adoption. Results indicate that high adoption rates may significantly decrease residential demand, which could help balance the increased demand from growing EV adoption. Since solar PV generation and residential peak demand occur at different times, load shifting strategies may be needed to balance demand of distribution feeders with high PV penetration.

An EV charging case study was conducted utilizing a modified IEEE 123 node test feeder populated with experimental and synthetic home loads. The analysis shows that high penetration of EV charging may increase the cases of transformer overload even with high adoption rate of heat pumps. High EV penetration also significantly decreased average load factor of distribution transformers. While in the case studies EV charging had little impact on diversity factor of residential transformers with lower ratings, those of higher ratings saw a significant reduction in average diversity factor due to simultaneous charging of multiple EVs. These findings confirm that future distribution systems may benefit from smart charge scheduling strategies to maintain load diversity, reduce transformer overload, and decrease required infrastructure upgrades at high EV penetration levels.

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References

[1] C. R. Forsythe, K. T. Gillingham, J. J. Michalek, and K. S. Whitefoot, "Technology Advancement is Driving Electric Vehicle Adoption," *Proceedings of the National Academy of Sciences*, vol. 120, no. 23, 2023.

[2] J. Dixon, I. Elders, and K. Bell, "Electric Vehicle Charging Simulations on a Real Distribution Network Using Real Trial Data," in *2019 IEEE Transportation Electrification Conference and Expo, Asia-Pacific (ITEC Asia-Pacific)*, 2019, pp. 1–7.

[3] Q. Gong, S. Midlam-Mohler, V. Marano, and G. Rizzoni, "Distribution of PEV Charging Resources to Balance Transformer Life and Customer Satisfaction," in *2012 IEEE International Electric Vehicle Conference*, 2012, pp. 1–7.

[4] A. Bin-Halabi, A. Nouh, and M. Abouelela, "A Simple and Effective Strategy to Prevent Power Transformer Overloading," *American Scientific Research Journal for Engineering, Technology, and Sciences (ASRJETS)*, vol. 48, no. 1, pp. 201–214, 2018.

[5] P. Roy, R. Ilka, J. He, Y. Liao, A. M. Cramer, J. Mccann, S. Delay, S. Coley, M. Geraghty, and S. Dahal, "Impact of Electric Vehicle Charging on Power Distribution Systems: A Case Study of the Grid in Western Kentucky," *IEEE Access*, vol. 11, pp. 49 002–49 023, 2023.

[6] M. Pesin, "DOE and Industry Team Up to Keep the Lights On for America," February 2024. [Online]. Available: https://www.energy.gov/oe/articles/doe-and-industry-team-keep-lights-america#:~:text=It%20is%20crucial%20to%20ensure,to%2030%20months%20in%202023.

[7] M. H. Mobarak and J. Bauman, "Vehicle-Directed Smart Charging Strategies to Mitigate the Effect of Long-Range EV Charging on Distribution Transformer Aging," *IEEE Transactions on Transportation Electrification*, vol. 5, no. 4, pp. 1097–1111, 2019.

[8] C. Crozier, D. Apostolopoulou, and M. McCulloch, "Mitigating the Impact of Personal Vehicle Electrification: A Power Generation Perspective," *Energy Policy*, vol. 118, pp. 474–481, 2018.

[9] H. Gong, R. E. Alden, and D. M. Ionel, "Stochastic Battery SOC Model of EV Community for V2G Operations Using CTA-2045 Standards," in *2022 IEEE Transportation Electrification Conference & Expo (ITEC)*. IEEE, 2022, pp. 1144–1147.

[10] E. S. Jones, N. Jewell, Y. Liao, and D. M. Ionel, "Optimal Capacitor Placement and Rating for Large-Scale Utility Power Distribution Systems Employing Load-Tap-Changing Transformer Control," *IEEE Access*, vol. 11, pp. 19 324–19 338, 2023.

[11] B. Wilcox, P. Wilcox, R. Wichert, S. Criswell, and T. Chaou, "Residential California Energy Commissiom Performance Compliance," 2019 and 2022, https://sourceforge.net/p/cbecc-res/code/HEAD/tree/trunk/CBECC-Res-64/CSE/.

[12] E. S. Jones, R. E. Alden, H. Gong, A. G. Frye, D. Colliver, and D. M. Ionel, "The Effect of High-Efficiency Building Technologies and PV Generation on the Energy Profiles for Typical US Residences," in *2020 9th International Conference on Renewable Energy Research and Application (ICRERA)*. IEEE, 2020, pp. 471–476.

[13] R. E. Alden, H. Gong, T. Rooney, B. Branecky, and D. M. Ionel, "Electric Water Heater Modeling for Large-Scale Distribution Power Systems Studies with Energy Storage CTA-2045 Based VPP and CVR," *Energies*, vol. 16, no. 12, p. 4747, 2023.

[14] J. Rendall, F. Karg Bulnes, K. Gluesenkamp, A. Abu-Heiba, W. Worek, and K. Nawaz, "A Flow Rate Dependent 1D Model for Thermally Stratified Hot-Water Energy Storage," *Energies*, vol. 14, no. 9, p. 2611, 2021.

[15] H. Gong, T. Rooney, O. M. Akeyo, B. T. Branecky, and D. M. Ionel, "Equivalent Electric and Heat-Pump Water Heater Models for Aggregated Community-Level Demand Response Virtual Power Plant Controls," *IEEE Access*, vol. 9, pp. 141 233–141 244, 2021.

[16] F. H. Administration, "National Household Travel Survey," 2017, https://nhts.ornl.gov/.

[17] V. Korhonen, "Distribution of Households in the United States from 1970 to 2022, by Household Size," 2022, https://www.statista.com/statistics/242189/disitribution-of-households-in-the-us-by-household-size/.

[18] V. M. Montsinger, "Effect of Load Factor on Operation of Power Transformers by temperature," *Electrical Engineering*, vol. 59, no. 11, pp. 632–636, 1940.

[19] G. T. Heydt, "Distribution Transformer Loading: Probabilistic Modeling and Diversity Factor," *IEEE Transactions on Power Delivery*, vol. 38, no. 2, pp. 842–849, 2022.

[20] R. E. Alden, H. Gong, E. S. Jones, C. Ababei, and D. M. Ionel, "Artificial Intelligence Method for the Forecast and Separation of Total and HVAC Loads with Application to Energy Management of Smart and NZE Homes," *IEEE Access*, vol. 9, pp. 160 497–160 509, 2021.

[21] F. Hafiz, M. Awal, A. R. de Queiroz, and I. Husain, "Real-Time Stochastic Optimization of Energy Storage Management Using Rolling Horizon Forecasts for Residential PV Applications," in *2019 IEEE Industry Applications Society Annual Meeting*. IEEE, 2019, pp. 1–9.

[22] E. Cadete, R. Alva, A. Zhang, C. Ding, M. Xie, S. Ahmed, and Y. Jin, "Deep Learning Tackles Temporal Predictions on Charging Loads of Electric Vehicles," in *2022 IEEE Energy Conversion Congress and Exposition (ECCE)*, 2022, pp. 1–6.