Analyzing Distribution Transformers at City Scale and the Impact of EVs and Storage

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ABSTRACT

Electric vehicles (EV) are rapidly increasing in popularity, which is significantly increasing demand on the distribution infrastructure in the electric grid. This poses a serious problem for the grid, as most distribution transformers were installed during the pre-EV era, and thus were not sized to handle large loads from EVs. In parallel, smart grid technologies have emerged that actively regulate demand to prevent overloading the grid's infrastructure, in particular by optimizing the use of grid-scale energy storage. In this paper, we first analyze the load on distribution transformers across a small city and study the potential impact of EVs as their penetration levels increase. Our real-world dataset includes the energy demand from 1,353 transformers and charging profiles from 91 EVs over a 1 year period, and thus provides an accurate snapshot of the grid's current state, and allows us to examine the potential impact of increasing EV penetrations. We then evaluate the benefits of using smart grid technologies, such as smart EV charging and energy storage, to mitigate the effects of increasing the EV-based load.

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1 INTRODUCTION

Advancements in battery and electric vehicle (EV) technology, combined with public policy initiatives, is rapidly accelerating the electrification of transportation. Major car and truck manufacturers have all announced new EV products, making it likely that EVs will become mainstream in the coming years. Nearly 200,000 EVs were sold in 2017 in the U.S. alone—a 25% increase in sales over 2016 [1]. Reports from Norway indicate that 70% of all new cars being sold are now EVs. Of course, EVs are powered by batteries that must be charged frequently, e.g., often daily, using electricity from the grid. Consequently, as EVs become commonplace, their impact on the electric grid will be profound. At a macro scale, all of the energy used to power automobiles, currently supplied by gasoline, will need to be provided by the electric grid, resulting in a manifold increase in electricity usage. At a micro scale, the residential distribution grid was built in a pre-EVA era and was not designed to account for EV loads. For example, a typical home in the U.S. has an average load 1.2kW, while an electric car such as Nissan Leaf adds an additional load of 6.6kW, effectively doubling or tripling the peak electric demand of the home. As a result, distribution grid transformers that were sized before EVs may become overloaded and not be able to reliably support high EV penetrations.

At the same time, the emergence of the smart electric grid has resulted in new technologies for more flexible demand-side load management and load mitigation in the grid. In particular, grid-level energy storage is emerging as a key technology for supporting future smart grids, since it can smooth out fluctuations from intermittent renewable energy sources, such as solar and wind, as well as enable grid optimizations, such as shaving peak loads and serving as backup power to reduce outage durations [28, 30, 31]. Interestingly, grid-level energy storage can also be used to mitigate the impact of EV loads on distribution transformers. If judiciously deployed adjacent to distribution transformers, energy storage batteries can *reduce or eliminate transformer overloads due to EV charging and increase transformer lifetimes.* A complementary smart grid technology is intelligent load management via load shifting [11, 32]. In the context of electric vehicles, this technique translates to *smart charging* where the EV intelligently coordinates its charging with the distribution grid often by deferring its charging from peak to off-peak periods whenever necessary [39, 41]. Together, energy storage and smart charging have the potential to mitigate the impact of EV loads on the distribution grid, but how much and to what extent is unclear based on actual transformer capacities, projected EV loads, and current demand profiles.

In this paper, we study the impact of residential EVs on the demand experienced by a city-wide distribution grid in the New England region of United States and then analyze whether and how much grid energy storage and smart charging technologies can mitigate this increased demand. Our study is empirical in nature and is based on analyzing real load data from i) 13,523 residential homes and 1,353 distribution transformers gathered at 5 minute granularity over a 2-year period and ii) real charging data from over 91 EVs in use over a one year period. While there has been prior work on analyzing the impact of EV loads [9, 35, 43], our study differs from prior work in several key aspects. For example, Clement-Nyns et al. [9] largely focuses on characterizing the aggregate load impact from EVs, and does not consider the issue of mitigating the load impact using grid storage, while Verzijlbergh et al. [43] focuses on peak load analysis and thus only considers mitigating the one day that experiences the peak annual load.

In contrast, we analyze the impact of EVs on transformer loads throughout the grid over a 2-year period and specifically study how the distribution of loads changes as the penetration of EVs

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increases. As we show later, understanding the impact on the probability distribution of loads is as important as analyzing the peak load alone. While Ramanujam et al. [35] examines a similar problem, it drives its simulations using synthetic estimates of existing loads, rather than real-world empirical data, and is thus not an accurate characterization of real-world conditions. We analyze long-term fine-grained transformer load data across an entire city to characterize the real-world implications of increasing EV penetration, and examine ways to mitigate problems using grid-scale energy storage. In conducting our empirical analysis, this paper makes the following contributions:

Transformer Distribution Analysis. We use a city-scale dataset to conduct an in-depth analysis of the existing transformers and quantify their different load profiles. Surprisingly, we observe that most transformers are not over provisioned in the network and all transformers are already designed to gracefully handle temporary overloads. Moreover, we find that 19.2% of transformers are heavily overloaded, having a utilization of over 100%.

Impact of Electric Vehicles. We analyze the effect of increasing penetrations of EVs and the effect on the load experienced by transformers in the grid and their lifetime under multiple different scenarios, e.g., uniform and skewed distributions of EVs. Our results indicate that the percentage of critically overloaded transformers is low for small levels of EV penetration (1-5% of homes), but increases significantly at higher penetrations levels (20-40% of homes).

Mitigation Strategies. Since our results demonstrate that the current distribution system is not provisioned for high levels of EV penetration, we examine the effect of two mitigation strategies—the use of energy storage and smart EV charging—to reduce transform overloads, extend their lifetime, and improve grid reliability. Our results show that even deployed a small amount of energy storage capacity, e.g., 24kWh, can dramatically reduce the risk of failures in transformers. We also show that smart charging is highly effective at reducing the number of critically overloaded transformers at high EV penetrations levels. In addition, when used in conjunction with energy storage, we show that smart charging can reduce the battery capacity necessary (by 41.3%-69.6%) to prevent transformers from exceeding their capacity.

2 BACKGROUND

In this section, we present background on the distribution grid, grid-based energy storage, and electric vehicles.

2.1 Distribution Electric Grid

The architecture of the electric grid has three key components: generation, transmission, and distribution. In this paper, we are only concerned with the distribution grid. The distribution grid is primarily responsible for supplying electricity to end consumers, which include industrial, commercial, and residential customers. While electricity is transmitted at high voltages through transmission lines, the distribution grid network uses a series of transformers to progressively step down the voltage and supply end-consumers with electricity at voltages of 110V (North America) or 230V (Europe and Asia). The distribution grid comprises sub-stations, feeders, and transformers that are responsible for supplying electricity to end consumers and can be viewed as a hierarchical network [5].

In our work, the exact topology of the distribution grid is not important since we focus specifically on distribution edge transformers — transformers at the edge of the distribution network that are directly connected to the end users. Furthermore, since we are specifically interested in EV charging, we consider the portion of the distribution grid that serves residential and commercial/office customers and ignore industrial users (since EVs are unlikely to be connected to transformers serving an industrial user, such as a manufacturing plant). We assume that distribution edge transformers serving homes or those serving business users are likely to see increasing EV loads — resulting from users charging electric cars at home or in office parking lots with EV chargers.

Such distribution edge transformers come in a range of capacities, varying from small 5-10 kilo-Volt-Ampere (kVA) pole-top transformers to larger 500, 1000 and 1500 kVA transformers. Note that transformer capacity is rated in kVA, which is the unit used for apparent power, i.e., the product of the root mean square (rms) of voltage and current in an AC power system. Small transformers may serve a small number of homes (e.g., 2 to 4 homes), while the larger ones serve apartment complexes or office buildings.

Electric utilities size edge transformers based on their expected load. However, typical capacity planning for transformers in the grid works differently from capacity planning in server farms and data centers, which is a well-studied problem [8, 27]. In particular, server capacities are computed based on their expected peak load, such that a server cannot service a peak load that exceeds its capacity, since they have a fixed computing capacity (based on their clock speed and bus bandwidth) that they cannot exceed. Transformer capacity is also sized based on its expected peak load, but a transformer is an analog device that *can supply electricity that exceeds its rated capacity.* Ultimately, the more power a transformer services, the more heat it generates. However, transformers have built-in safety mechanisms, specifically mineral oil, that can absorb some amount of excess heat generated from being overcapacity. Thus, unlike servers, transformers are sized to operate over a wide range of their rated capacity, e.g., up to 1.25 of their rated capacity [22]. Even so, overloaded periods are undesirable as they reduce transformer efficiency (since the excess heat represents lost energy), and over time they can cause the insulating oil to evaporate. Once there is not enough oil to absorb the excess heat, it can melt the transformers coils and cause it to fail.

Thus, limiting the time periods (and magnitude) when the transformer load exceeds its rated capacity is important in reducing the negative impact on transformer lifetimes. For our analysis, we consider a transformer with a peak load between 0.9 to 1.25 its rated capacity to be highly utilized, a peak load between 1.25 to 1.5 to be overloaded and peak load exceeding 1.5 to be critically overloaded. Transformers with loads less than 0.9 are considered to have low to moderate utilization.

2.2 Electric Vehicles

Electric cars, which are the most common type of EV, are becoming increasingly popular. Many manufacturers now include one or more types of EV in their product line up (see Table 1). Two types of electric vehicles are particularly common — pure EVs, which are solely powered using batteries, and plugin hybrid EVs (PHEV),

EV model	Range (mi)	Size (kWh)	Rate (kW)	Charge Time (hour) at 220V
Nissan Leaf (electric)	150	40	6.6	8h
Tesla Model S (electric)	315	100	10	10.7h
Chevrolet Bolt (electric)	238	60	7.2	9.3h
Chevrolet Volt (hybrid)	53	18.4	3.6	4.5h
Prius Prime (hybrid)	25	8.8	3.3	2.1h

Table 1: Examples of popular electric vehicles with different battery characteristics.

which are powered using a combination of a gas-powered and electric motor. Examples of pure EVs include the Tesla Model S, Nissan Leaf, and Chevy Bolt, while examples of plugin hybrids include the Chevy Volt and the Toyota Prius Prime. Many plugin hybrids tend to have smaller batteries than pure EVs since they can “fall back” to a gas-powered engine when their batteries run out.

The larger battery sizes of pure EVs imply a larger load, which results in a higher peak charging load and a longer charging time to fully charge the battery. Regardless of the type, EVs can impose a significant load on edge transformers in the distribution grid. For instance, electric Type 2 chargers, a standard charger used for charging electric cars, draws roughly 7kW of power, while a central air conditioner, which is typically the “largest” load, draws 3.5kW. In other words, an electric car charger imposes twice the load of largest load, the central AC, in many homes on the distribution grid. Since distribution edge transformers were sized based on pre-EV era peak loads, increasing penetrations of EVs can have a significant negative impact. Thus, in the summer, a home with a central AC and an EV may exhibit a peak load 3× the previous peak load based on central AC alone (e.g. 10.5kW versus 3.5kW).

2.3 Grid-based Energy Storage

Grid-level energy storage, in the form of batteries, has emerged as a promising approach for various grid optimizations. Battery-based grid energy storage can be deployed at various points in the grid’s hierarchy — generation, transmission, or the distribution part of the grid network. Prior studies have shown that battery-based storage is especially appealing to handle the intermittency exhibited by renewable energy sources, such as solar and wind, by using storage to smooth out the fluctuations [6, 23]. Similarly, battery-based storage has been used for peak load shaving [30, 31].

Although the cost of battery-based energy storage remains high, prices are dropping more rapidly than expected even a few years ago, and commercial products and deployments are beginning to ramp up. For instance, Tesla sells PowerWall battery packs to both residential users and to utility companies. The largest deployment of grid batteries, a capacity of 100 MWh, was recently installed by Tesla in Australia [2]. In this work, we consider the deployment of energy storage batteries alongside distribution edge transformers to mitigate overloads caused by EVs and enhance transfer for lifetimes — a use of batteries that has not seen much attention in the distribution network. Utilities are especially interested in using such application in the future as prices continue to fall.

3 PROBLEM AND METHODOLOGY

In this section, we present the problem and key research questions we address in the paper, and then describe the datasets and experimental methodology that we use to answer those questions.

3.1 Problem

The primary goal of our paper is to understand the impact of varying levels of EV penetration on the loads experienced by distributed edge transformers, so as to understand how much slack capacity is currently present and to identify when grid transformers become overloaded. An additional goal is to understand when emerging technologies, such as smart EV charging or battery-based grid storage, can alleviate the overloads or what extra upgrades will be necessary to accommodate the growing number of EVs. Specifically, we seek to answer the following research questions.

(1) What is the distribution of load experienced by edge transformers? What are the daily and seasonal variations in this load, specifically the peak load, seen by edge transformers? What does this load analysis reveal about the current slack present in the distribution grid? For those transformer with little or no slack, how loaded or overloaded are they?
(2) How does progressively increasing the penetration of EVs impact the load distribution seen by edge transformers? How does the resulting load increase change the fraction of highly utilized and overloaded transformers? At what penetration levels does the distribution grid see significant overload problems? How does skewing the deployment of EVs to particular (e.g., affluent) neighborhoods change these results?
(3) Can smart EV charging that defers (or rate limits) charging loads during peak periods help alleviate transformer overloads? How much energy storage is necessary for overload shaving of edge transformers at different EV penetration levels? How much additional benefits can be obtained by combining smart charging and grid-level energy storage? What do these results reveal about the relative size and feasibility of energy storage as a mitigation strategy and how much more penetration can be accommodated?

3.2 Datasets and Experimental Setup

The answers to these questions will vary from region to region, and clearly depend on the current state of the distribution grid in terms of its load over time, transformer capacities, and the resulting slack. In this paper, we use a small city in the New England region of United States and attempt to answer these questions for this city by conducting a city-wide data analysis. Since the distribution grid design in this city is typical of many regions in North America, we believe that our high level insights are broadly applicable.

Distribution Grid Dataset. Our dataset consists of electricity usage (load) data recorded by 15,089 smart meters that serve every residential and commercial user in the city. These 15,089 meters are served by 1,353 distribution edge transformers. Our dataset includes a mapping of each meter to its edge transformer, and also includes a detailed specification of each transformer, including its rated capacity. The load data is recorded at a five minute granularity and spans from 2015 to 2017. Since data from late 2017 was not yet available when performing our analysis, we limit our analysis to two full calendar years—2015 and 2016—for which data is available.

Since these edge transformers are low voltage transformers that are directly connected to end-customers, the load on each transformer can be computed by summing the load recorded by each meter connected to that transformer. Doing so yields highly detailed

Num. of transformers	1353
Num. of commercial meters	1566
Num. of residential meters	13523
Transformer sizes	5kVA to 1500kVA
Electric meter granularity	5 minutes
Duration	2015 to Sep 2017

(a) Grid Distribution Dataset

Total num. of electric cars	91
Num. of Tesla S	12
Num. of Nissan Leaf	18
Num. of Chevrolet Volt	61
Granularity	5 minutes
Duration	2016

(b) Electric Vehicles Dataset

Table 2: Key characteristics of the dataset.

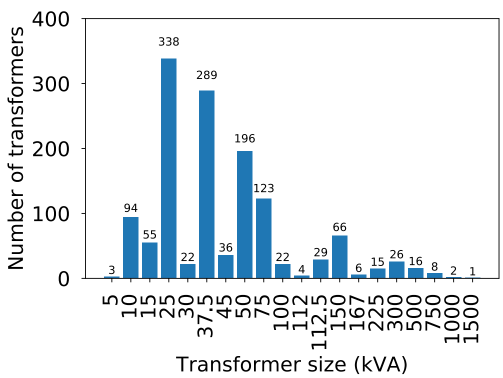


Figure 1: Distribution of transformer capacities.

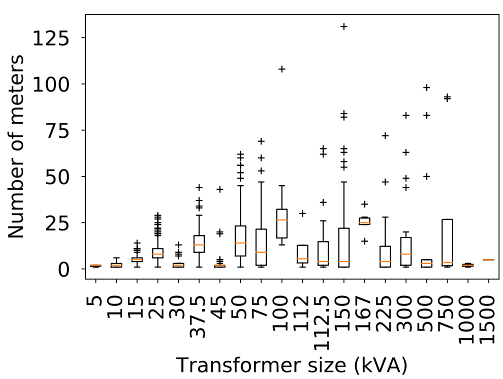


Figure 2: Distribution of smart meters connected to transformers of varying capacities in the distribution grid.

load information experienced by each distribution edge transformer over the two year period of the study. The availability of detailed load information for all 1,353 edge transformer in a city is a distinguishing feature of our study. Prior work has only considered the total grid load across a city rather than transformer-level loads [35]. In contrast, we study probability distribution of loads as well as the time of day/seasonal impacts that other studies did not consider.

Table 2 summarizes the key characteristics of our dataset discussed above. Figure 1 then depicts the diversity of transformer capacities in the distribution grids and the distribution of transformers across varying sizes. Note that, since the rated capacity is

Car Model	Summary (kWh)	Max	Median	Std.
Tesla S	Daily Energy Demand	28.07	13.69	4.25
	#Charging Session	340	235	112.8
Nissan Leaf	Daily Energy Demand	10.41	4.98	1.64
	#Charging Session	337	174.5	122.7
Chevrolet Volt	Daily Energy Demand	7.19	5.01	0.92
	#Charging Session	351	266	123.3

Table 3: Charging Summary of electric vehicle models.

in apparent power as kVA , in our later analysis, we use the average power factor to convert it into kilowatts (kW) to make our results more intuitive. We use the equation below for the conversion.

$$kW = kVA \cdot PF \tag{1}$$

Here, $0 \leq PF \leq 1$ is the power factor. For our analysis, we use power factor of 0.9 and 0.95 for summer and winter, respectively, which represents the average power factor in these seasons.

Figure 1 shows that transformer capacities can vary from 5 kVA all the way to 1500 kVA. Most of the deployed transformers are "small" and have a rated capacity of less than 150 kVA — a few transformer are large with a capacity of 500 kVA to 1500 kVA. Generally, the small transformers serve a small number of residential customers (e.g., 2-4 homes). The larger transformers serve apartment complexes, office buildings, other light commercial customers.

Figure 2 shows the distribution of meters connected to transformers of various sizes. We observe that the number of connected residential meters increases with the increase in transformer capacity. In contrast, fewer meters are connected to transformers that provide electricity to commercial buildings as they tend to consume higher energy. The median number of meters connected to these transformers ranges from 2 to 28.

Electric Vehicle Dataset. Since our study seeks to understand the impact of electric vehicles, we use the Dataport dataset from Pecan St.[1] — a real-world trace that consists of power consumption from 91 electric vehicles gathered at five minute resolution in 2016. The 91 EVs in the dataset represents a mix of 3 popular electric car models — Tesla Model S, Nissan Leaf, and Chevy Volt. Table 3 depicts the different types of EVs in the dataset. The dataset includes detailed information, such as the power drawn and the time and duration the car was connected to the power outlet. Table 3 also shows the statistics of the charging profiles for each car model in the dataset.

Since our dataset only includes 91 EV traces, we supplement our dataset by constructing additional synthetic EV traces as follows. First, we randomly choose a particular car from the existing dataset. We then take the charging data for the entire year and permute the weekdays and weekends over the year for that car. That is, each weekday trace is mapped to a random other weekday and each weekend is randomly mapped to a different weekend. Doing so yields a synthetic trace that is based on permutations of the initially chosen trace. We repeat this process to construct 24,000 synthetic EV traces, 8000 for each model to supplement our real dataset in our analysis of increasing EV penetrations.

To simulate the effect of increased EV penetration on the distribution transformers, unless otherwise specified, we randomly assign EVs to residential homes. We then calculate the net load in each

[1] Dataport dataset. http://dataport.pecanstreet.org

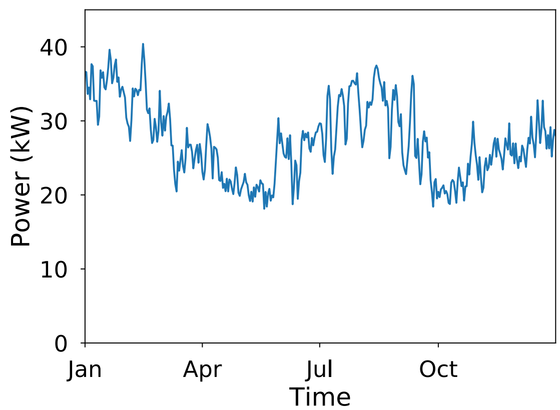


Figure 3: This graph illustrates the seasonal variation in the load profile of a representative transformer.

transformer after the addition of the electric vehicles. We repeat the above simulation 50 times and show the results for the average case over multiple runs. We also study skewed EV deployment, where we concentrate a greater fraction of EVs to specific neighborhoods, such as affluent neighborhoods that are more likely to experience a higher fraction of EV adopters, rather than uniformly distributing them across the whole city.

4 ANALYSIS OF EDGE TRANSFORMER LOADS

In order to understand the impact of EV penetration on transformer loads, we must begin with an analysis of the current (“as-is") loads on edge transformers *before the introduction of* any EVs. Such an analysis reveals the slack available at various transformers, as well as the transformers that are already heavily utilized and have little available slack.

4.1 Demand Profiles of Edge Transformers

We begin with an analysis of the monthly and daily loads seen by the 1,353 edge transformers across the city. Figure 3 depicts the monthly load experienced by a representative transformer over 2016. The figure illustrates the seasonal variation in the load, and is characterized by two peak demand periods — winter and summer. The winter peak occurs due to increased use of electric heaters during the winter, while the summer load coincides with the increased use of air conditioning on hot summer days. Although the winter peak is slightly higher than the summer one, the summer peak has a greater impact on transformer efficiency and lifetimes. Prior studies have shown that a high ambient temperature can have an adverse impact on transformer lifetimes [13, 42], as a high ambient temperature contributes to the effect of overloading by further heating up (and evaporating) the insulation oil, which protects transformers from overheating. With increased energy demand from EVs, summers are likely to have a greater adverse impact on transformers than other seasons. Since the spring and fall seasons see lower peak loads, there is more slack and cooler temperatures, which makes the transformers less vulnerable during these periods.

Next, we analyze the daily load profile of edge transformers to identify the most common types of transformers based on their load profile. For this analysis, we clustered the average daily profile of all transformers using *k-Means* clustering. Since the transformers are of different sizes, we normalize the daily load profile of each transformer to a range between 0 and 1 (e.g., using MinMaxScaler in scikit-learn), and then perform clustering. Figure 4 depicts the five clusters that emerge when using k-means with k=5; the figure shows the result for 2016 (the other years yield qualitatively similar results and are omitted). We selected k=5, since 5 was the highest value of k that yielded clusters that were qualitatively different, and also did not yield an outlier cluster with few transformers. The red line depicts the centroid of the clusters, while the grey line shows the energy profiles of all the transformers in the cluster.

Group Name	Utilization	#Transformers
Low to Moderate	< 90%	976 (72%)
Heavy utilization	≥90% to <125%	283 (21%)
Overloaded	≥125% to <150%	63 (5%)
Critically overloaded	≥150%	31 (2%)

Table 4: Summary of the peak utilization of transformers

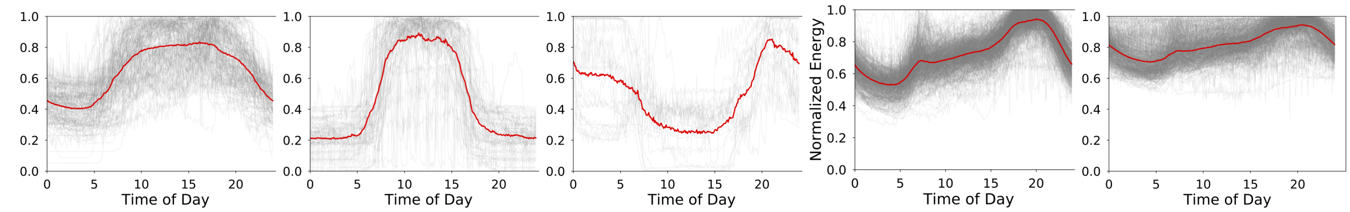
The five clusters reveal interesting patterns. For example, Figures 4(a) and (b) depict transformers that exhibit daytime peaks, while Figures 4(c), (d) and (e) depict transformers that exhibit evening peaks. The captions depict the number and percentage of transformers in each cluster. We hypothesize that the transformers exhibiting daytime peaks, in Figures 4(a) and (b), serve office buildings that have a 9 am to 5 pm workday or businesses, such as retail stores, that have 9 am to 9 pm work hours. These transformers have a low load during the late evening and nighttime hours.

The clusters shown in Figures 4(c), (d), and (e) all exhibit evening peaks and also exhibit a nontrivial amount of nighttime usage — we hypothesize that these are large residential customers with different daily routines. The cluster in Figure 4(c) shows transformers that see a low load during the day — these are likely users who are away from home (i.e., working) during the day and at home in the evening and night. Figures 4(d) and (e) show residential customers with evening peaks, but also a non-trivial amount of daytime and nighttime usage. These are likely to be families where someone is at home during the day, where the increased evening activities result in an evening peak — these two clusters (d) and (e) also account for a large fraction of the transformer, 37.5%, and 46.2%, respectively.

From the perspective of EV loads, these load profiles have interesting implications. Transformers with daytime peaks, which are offices and businesses, may deploy EV chargers in their parking lots that will service users charging their EVs while at work, and thus causing the already-high daytime peaks to rise further. Transformers, such as those in Figure 4(c), where users are away during the day, will likely see evening charging of EVs when users return home, causing evening peaks to increase further. In both cases, EVs may exacerbate the already-high peaks. Transformers in clusters (d) and (e) have the most flexibility, since users may be home during the day and may charge their vehicles at day or night. Of course, charging during the peak load periods, when feasible, exploits more slack in the transformer than the other way around.

4.2 Analyzing Peak Loads

Next, we analyze the peak loads (defined as the 99.9^{th} percentile of the load serviced by a transformer over the year) experienced by the edge transformers. Using raw meter readings as they are



(a) Cluster1: 134 (9.9%) (b) Cluster2: 65 (4.8%) (c) Cluster3: 22 (1.6%) (d) Cluster4: 508 (37.5%) (e) Cluster5: 624 (46.2%)

Figure 4: Demand profile clusters across transformers. The number and percentage of transformers in each cluster is listed in the caption. The clusters are qualitatively different, with some exhibiting daytime peaks and others exhibiting evening peaks.

leads to erroneous estimates of transformer peaks brought about by spurious reads, often way higher than the normal peaks. We use the 99.9^{th} percentile to eliminate these values. Using (1), we compute the rated capacity of transformers in kW and then compute the utilization by normalizing the load observed at the transformer with its rated capacity.

We then group the transformers into four categories, explained in Section 3.2 and depicted in Table 4: low-to-moderate, highly utilized, overloaded, and critically overloaded. Figure 5 depicts the peak load distribution of the transformer across the whole city, while Table 4 shows the number and percentage of transformers that fall in each category. Since transformers have a typical lifetime of 20-30 years, one would expect careful sizing, such that the peak load is well below the rated capacity. However, as shown in Table 4 and Figure 5(a), only 72% of the transformers service a peak load of less than 90% utilization over the course of the year. Around 21% of the transformers are heavily utilized and service a peak load of up to 125% of capacity. Note that this implies that the transformer operated at or above its rated capacity for at least part of the time over the year. Around 3.8% of the transformers are overloaded and see a peak load that exceeds 125% utilization, while an additional 2% of the transformers are critically overloaded with peak load exceeding 150%. As explained earlier, it is not “abnormal" for a transformer to exceed 100% utilization for short periods, since they have mineral oils to insulate them from overheating, although sustained overloads for long periods are dangerous. Therefore, we next analyze the duration of the overloads experienced by transformers.

We consider only the transformers that are in the overloaded and the critically overloaded groups and compute the number hours over the year for which they service a load exceeding 125% of their rated capacity, and also compute the maximum "session duration" over which the transformer is continuously overloaded. Figure 5(b) plots the total number of hours for which transformers are overloaded or critically overloaded over a year. The figure shows that the overload distribution is long-tailed — the majority are overloaded for 162 hours over a year, while a few see overloads of as many as 1000 - 3000 hours. Figure 5(c) analyzes each continuous period that experiences an overload, and plots the longest continuous duration for which a transformer was overloaded. The figure, plotted on a log scale, shows the median duration of overload was 45 min, while some transformers see a sustained overload of 143 hours.

Implications.. Our analysis shows that roughly two-thirds of the transformers have slack due to low-to-moderate peak loads. However, our temporal analysis reveals that the amount of slack has high seasonal variations — i.e., there may be less slack during the summer or winter peaks and less slack during peak hours of the day, which vary based on the transformer's load profile. Conversely, around 21% of the transformers are heavily utilized and have almost no slack to accommodate EVs, while around 6% are already overloaded or critically overloaded. Further, energy storage may be beneficial for these 6% of the transformers to absorb the overloads, even without any EV. Finally, one surprising aspect of our analysis is our finding that shows roughly 19% of the transformers routinely operate over capacity at least for a portion of time each year, with some experiencing long sustained overloads of many days.

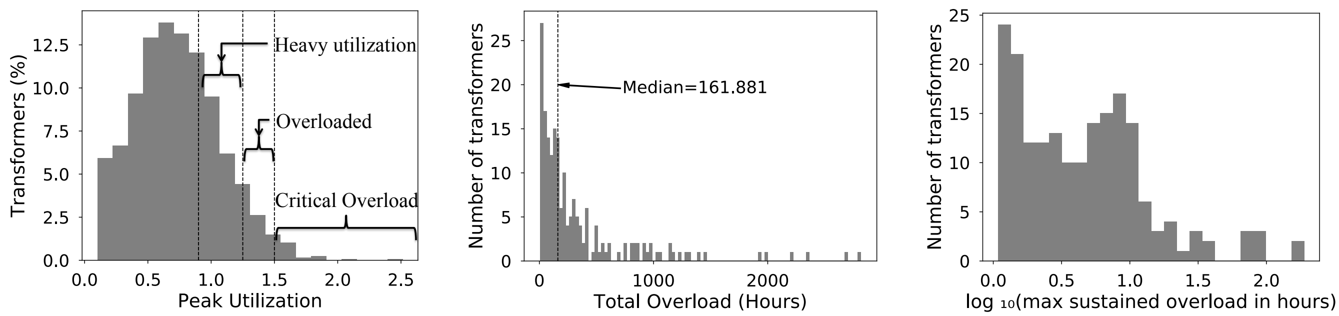
5 IMPACT OF ELECTRIC VEHICLES

In this section, we analyze the impact of increasing EV penetrations on the peak loads experienced by edge transformers. We first assume a uniform distribution of EVs across households (and transformers) in the city, and analyze the impact of varying levels of EV penetration on transformer peak loads. We also examine the impact of a skewed distribution, where EVs are disproportionately concentrated in specific (e.g., affluent) neighborhoods, and study the effects of different penetrations for such skewed distribution.

We first introduce different levels of EV penetration into the grid, namely 1, 2, 5, 10, 20 and 40% — where penetration represents the percentage of smart meters that service an EV load. To do so, we randomly select an EV trace (from our synthetic trace of Tesla, Chevy and Nissan EV, as described in Section 3) and map it to a randomly chosen smart meter (selected from a uniform distribution). The EV charging trace is overlaid on the smart meter trace, and the transformer load is recomputed accordingly. We repeat each experiment for 50 runs with a different random mapping of EVs to transformers to ensure our results have tight confidence intervals.

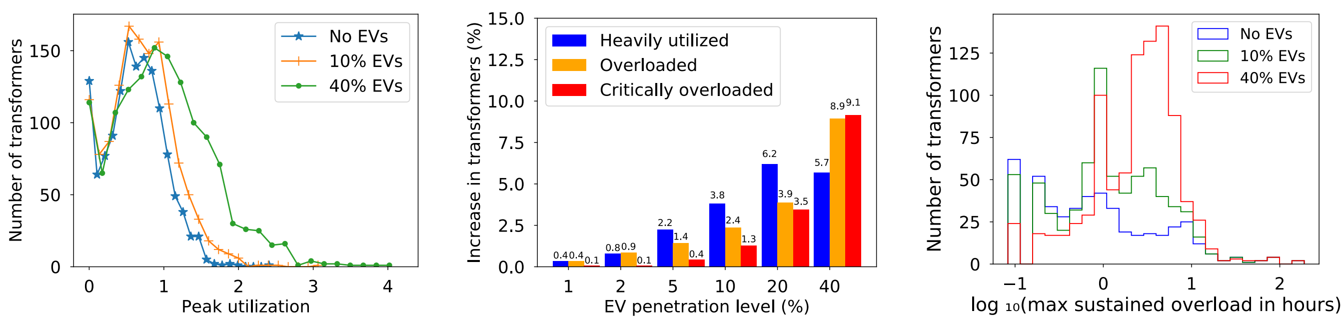
Figure 6 shows the impact of varying levels of EV penetration on the peak loads. Figure 6(a) depicts the distribution of transformers seeing different peak loads for the no EV case (current grid) and at 10% and 40% penetration. As expected, the peak loads experienced by a transformer increases due to EV loads, such that the mass and tail of the distribution shifts to the right. Furthermore, while the median peak load is 0.7 in the no EV case, the median peak load increases to 0.76 and 1.03 at 10% and 40% penetration respectively.

Next, we analyze the increase in the number (and percentage) of highly utilized, overloaded, and critically overloaded transformers at different penetration levels. We assume the current state (from Table 4) as the baseline such that Figure 6(b) reports the *additional* percentage of transformers in each group (over the baseline) at



(a) (b) (c)

Figure 5: Distribution of transformer overloads over a year, based on the peak transformer utilization (a), the number of total hours the transformers experienced overloads (b), and the maximum sustained period of overloading (on a log scale) (c).



(a) (b) (c)

Figure 6: Peak utilization distribution of the transformers for varying EV penetration levels (a). Additional transformers that are at risk of overloading or are overloaded due to EVs (b). As EV penetration increases, the maximum sustained overloading in transformers increase depicted by the distribution shifting to the right (c).

each penetration level. The figure shows that for low penetration levels of 1%, 2%, and 5%, the additional transformers that become heavily utilized or overloaded are relatively small (1-2% in each group). In these cases, since the number of EVs is relatively small, there is sufficient slack in the transformer load to accommodate them. Generally, we see that as penetration levels rise, so does the percentage of transformers in each category. At 10% penetration, an additional 4% transformers become heavily utilized, while an additional 3% transformers see overloads or critical overloads. The peak loads rise quickly at 20% and 40% penetration, with up to 18% of transformers becoming overloaded or critically overloaded. Since many transformers become overloaded, rather than highly utilized, this case yields a slight drop in the heavily utilized transformers.

Figure 6(c) shows the maximum sustained duration of overloads seen by all transformers in 2016 for the no EV case, and for 10% and 40% penetration levels. The figure shows that with increasing EVs, not only do the peak loads rise, the duration for which these peak loads persist also rises. The median overload duration rises from 0.75 hours in the no EV case to 1.1 and 2.8 hours for 10% and 40% penetration respectively.

Implications. Overall, the results show that the distribution grid can easily accommodate up to 5% EV penetration, and potentially up to 10% penetration. The impact of 5% penetration is relatively small, while a 10% penetration level causes an increase in highly utilized transformers (which are still considered within normal operating range) and a moderate 3% increase in the overloaded transformers. Higher penetration levels above 10% cause an increasing problem with overloading, and indicate that mitigation strategies are necessary to accommodate these higher levels of EVs.

5.1 Impact of Skewed EV Penetration

While the above analysis assumes that EVs are uniformly distributed across meters and transformers, it is entirely likely that “early adopters” of EVs may be concentrated in certain neighborhoods (e.g., affluent households can pay the higher price for electric cars). In this scenario, EVs will be concentrated in a certain neighborhood and not uniformly distributed. To understand the impact of a skewed distribution, we repeat the above analysis for a skewed mapping of EVs to transformers. We perform two types of analysis representing both an optimistic best case and a pessimistic worst case scenario. For the optimistic case, we disproportionately skew the assignment of EV to low and moderately utilized transformers — by assigning 75% of the EVs to the group and the remaining 25% to the remainder of the transformers. For the pessimistic case, we do the opposite, and disproportionately skew the assignment of EVs to highly utilized and overloaded transformers. Like before, we conduct at least 50 runs for each penetration level. The two scenarios study the impact of EVs in neighborhoods with transformers with the greatest and the least slack, respectively. Figures 7 and 8 depict our results for the optimistic and the pessimistic scenario, respectively.

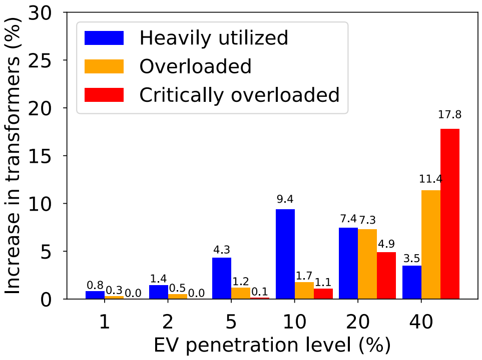


Figure 7: Best case scenario, where EV adoption is skewed to *low-to-moderate* transformers, causing fewer transformers to become overloaded or critically overloaded.

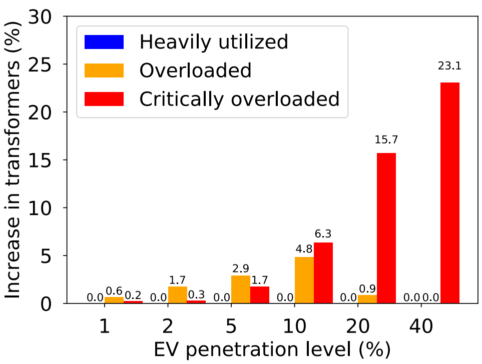


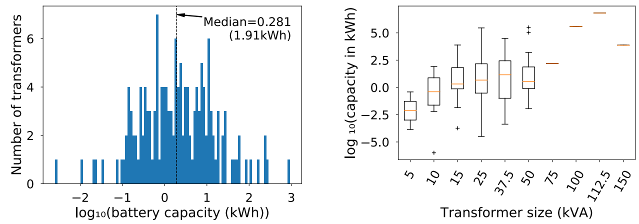
Figure 8: Worst case scenario, where EV adoption is skewed to *highly utilized and above* transformers, causing the number of transformers at risk to increase.

Figure 7 shows that skewing EV adoption to neighborhoods that have transformers with low-to-moderate loads (and the greatest slack) allows a higher penetration level compared to the uniform distribution (Figure 6). Specifically, at low penetration levels of up to 5%, there is minimal impact on overloaded transformers and a small increase in the heavily utilized transformer. Even at 20% penetration level, the increase in heavily-utilized and critically overloaded transformers is minimal, although the number of overloaded transformers nearly doubles. The 40% penetration level sees a dramatic increase in the percentage of critically overloaded transformers, increasing from 9.1% (in Figure 6(b)) to 17.8%

Figure 8 shows that skewing EV penetrations to neighborhoods with highly utilized transformers permits a lower penetration level. Interestingly, even in this pessimistic worst case scenario, there is only a modest rise of 4.6% of overloaded transformers at a 5% penetration level, indicating that there is adequate slack to accommodate up to 5% EVs even in the worst case. However, the percentage of overloaded transformer rises quickly at 10% and higher penetration levels, indicating that additional mitigation strategies are necessary to handle the worst-case scenario.

6 MITIGATION STRATEGIES

Having examined the effect of EV-based loads on distribution edge transformers, we now evaluate mitigation strategies to help alleviate transformer overloads. Specifically, we explore two emerging technologies in the smart grid — energy storage and smart charging to understand how using them in isolation or in combination can help in reducing the number of overloaded and critically overloaded transformers in the grid. We also evaluate how many additional EVs can be accommodated if utilities introduce these technologies.



(a) (b)

Figure 9: Energy storage capacity required to limit utilization to no more than 125% across all transformers (a), and the distribution of energy storage capacity needed to limit overloading based on transformer capacities (b).

6.1 Energy Storage

In Section 4, we show that even in the absence of EV-based loads, a small fraction of the grid consists of overloaded or critically overloaded transformers. Since we are only concerned with how EVs impact the grid, we first examine how much energy storage capacity is required to eliminate the overloaded and critically overloaded transformers. We then examine how much additional energy storage is required when EVs are serviced by the edge transformers.

To calculate the energy storage capacity required per transformer, we propose a simple peak-shaving algorithm that clips the maximum contiguous peak above a given threshold. Specifically, for each transformer, our algorithm scans over its load and computes the contiguous period when the load exceeds the threshold. Our algorithm then computes energy storage capacity by computing the energy above the threshold across the periods, and selects the maximum. Our premise is that the energy storage that can flatten the maximum contiguous peak can also provide energy to flatten the smaller peaks experienced at other periods.

We begin by analyzing the distribution of storage capacity required to limit the maximum transformer utilization to 125%. Figure 9(a) shows that energy storage capacity can vary between 1kWh and 915kWh. We note that the 90th percentile of energy storage is 24kWh, which indicates that even a small battery size can dramatically reduce the risk of failures in transformers. In particular, 85% of overloaded and critically overloaded transformers can benefit from an energy storage capacity of 24kWh or less.

Since, the battery capacity is a function of the size of the transformer capacity, we plot the distribution of battery size against transformer size. Figure 9(b) shows the median energy storage capacity increases with increases in transformer capacity. The larger energy storage capacity can be attributed to the higher number of homes that larger transformers serve.

Figure 10 shows that the median battery capacity required to eliminate overloads in the overloaded and heavily utilized transformers increases from 1.9kWh prior to introduction of EVs to 15.6kWh at 40% penetration. The difference in energy storage capacity between heavily utilized and overloaded transformers is also

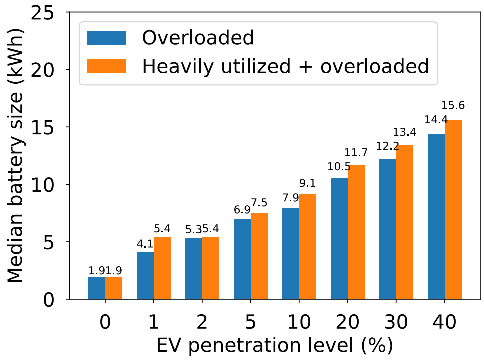


Figure 10: Increase in the median battery size necessary with different EV penetration levels to limit overloaded transformers (above 125%), utilization exceeding 90%

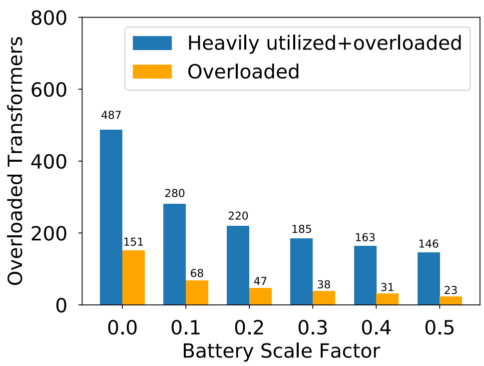


Figure 11: Reduction in number of overloaded and heavily utilized transformers with increasing battery scale factor without EVs.

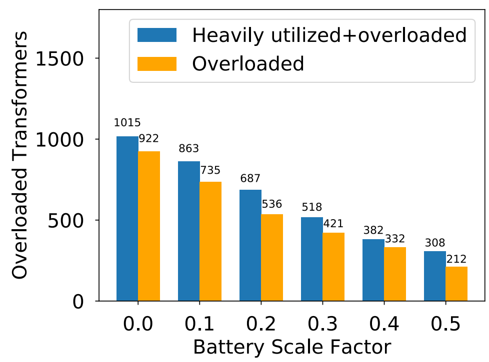


Figure 12: Reduction in number of overloaded and heavily utilized transformers with increasing battery scale factor at 10% EV penetration.

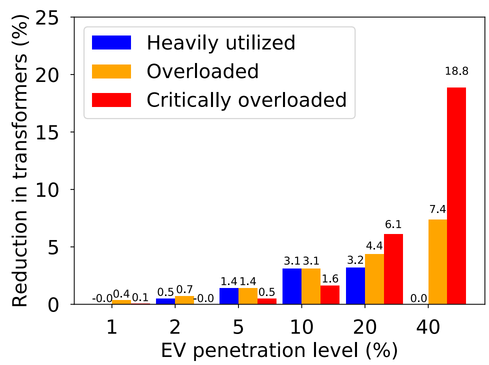


Figure 13: Reduction in the number of transformers that are overloaded when using smart charging policy.

small, not exceeding 2kWh at all penetration levels, showing that most of the transformers are in the overloaded region.

Next, we analyze the effect of adding storage as a function of transformer sizing. We define *battery scale factor* as a 1:1 ratio to a transformer's kVA rating *i.e.* for each kVA, what effect would adding 1kWh of storage to the transformer have on the transformer's overload status. Figure 11 shows the result of adding storage using this factor in the no EV case. By adding a 0.1 factor of storage, we are able to reduce the number of heavily utilized and overloaded transformers by up to 42% and 55% respectively. Figure 12 shows that at 10% EV penetration, the number of heavily utilized and overloaded transformers can be reduced by up to 70% and 76% respectively using a 0.5 factor of storage.

6.2 Smart Charging

We now evaluate the reduction in peak utilization due to smart charging of electric vehicles. The goal of our analysis is to understand how flexibility in EV charging can reduce the number of overloaded transformers. Our hypothesis is that the demand profiles of transformers have sufficient low usage periods, especially during the night, such that EVs can be charged without significantly increasing the peak utilization of the transformers.

For the purpose of our analysis, we assume an ideal EV charging algorithm that has full knowledge of future transformer loads and EV charging profiles. We also assume that transformers and EV chargers are able to communicate over a network. We then compute an optimal threshold that minimizes the transformer's utilization while ensuring that all EV requirements are met ahead of time. In the event that transformers do not have enough future slack for EV charging, our smart charging algorithm allows the threshold to be exceeded in order to meet EV demands. We then allocate EV charging schedules on a first come first serve basis. Whenever the threshold is reached, additional chargers are not allowed to start charging immediately. As additional slack becomes available either due to connected EVs reaching full capacity or general household power usage reducing, the remaining EV chargers are scheduled.

Figure 13 shows the reduction in the number of transformers that are heavily utilized, overloaded, and critically overloaded at different EV penetration levels. The graph demonstrates that smart charging becomes more important as the EV penetration increases. Smart charging has little to no effect on reducing over-capacity transformers at small EV penetrations between 1% and 5%. However, the reductions in over-capacity transformers increases for EV penetrations between 10% and 20%. Once EV penetration reaches 40%, smart charging becomes critical, as it is able to reduce the number of critically overloaded transformers by nearly 20% and the number overloaded transformers by 7.4%. These results demonstrate that smart charging is an important tool for maintaining grid reliability as EV penetration ramps up.

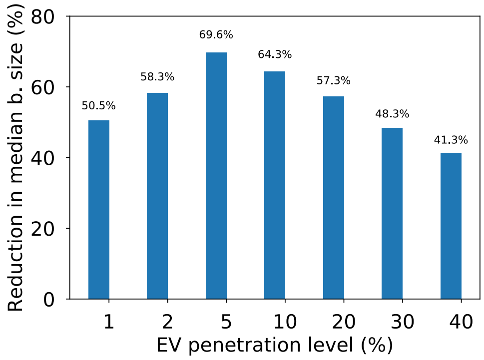


Figure 14: Reduction in the necessary battery capacity when smart charging is combined with energy storage.

6.3 Combing Storage and Smart Charging

Finally, we examine the effect of combining grid-level battery-based energy storage with EV smart charging. Since batteries are still expensive to deploy and maintain, we examine how much battery capacity is necessary to limit utilization to no more than 125% across all transformers when used in conjunction with our smart charging algorithm. Figure 14 shows the results at different levels of EV penetration. The graph shows that smart charging can reduce the battery capacity substantially, ranging from 41.3% to 69.6%. At low penetration, smart charging is able to take advantage of the available slack. As penetration increases, the threshold boundary is crossed, because EVs still need to be charged within the time period, and the reduction in overall battery size reduces. Since smart charging would incur very little capital expenses on the utility side, this reduction would significantly decrease the capital expenses related to deploying and maintaining batteries.

7 RELATED WORK

In this section, we discuss some of the prior work on optimizing the distribution grid network for EVs, smart charging of EVs, and the use of energy storage for grid optimizations.

Distribution Grid Network. There have been numerous studies on the distribution network [4, 26, 40]. For instance, [4] studied the grid's resilience to disruptions in the distribution network. Others have studied the feasibility, or have examined the cost-benefit analysis, of integrating renewables in the distribution network [26, 40]. However, these studies do not analyze the load on distribution edge transformers or examine the effects of EVs on edge transformers. Prior work has also studied the impact of load on transformer lifetimes [7, 17, 18, 38, 42]. These approaches provide thermal modeling of transformers, and examine how load and external factors affect transformer lifetime. Our work is complementary to this work, as we provide a broader analysis of the current state of distribution edge transformers in a city over a 2-year period. In addition, these studies do not characterize the impact of increased penetration of large EV loads. Prior work has also studied demand patterns at both the household and grid level [3, 21, 24, 36]. These include studies to understand the types of demand profiles for setting power tariffs or enabling demand-response programs [29, 44]. Again, our work differs, as we focus on classifying load profiles across edge transformers, and characterize the current state of the grid to study the effect of emerging technologies, such as EVs and energy storage.

Electric Vehicles. There has also been a significant amount of prior research on EVs [5, 10, 15, 16, 18, 25, 33, 37, 43]. While some studies have focused on the effects of EVs on power quality [15, 16, 33, 37], other work has focused on controlled EV charging [5]. In contrast, our work focuses on characterizing the load impact from EVs on edge transformers, and approaches to mitigate these impacts. Prior work has also studied flexible charging or co-ordinated EV charging in the grid [39, 41]. Our work is complementary to this work, as these smart charging methods can be employed reduce the overloading of distribution edge transformers. Prior work has also analyzed the impact of EVs on the distribution grid [9, 35, 43]. However, as discussed in Section 1, our work differs from this work, as the dataset used is limited or synthetically generated. Instead, we use fine-grained load data and provide empirical analysis on potential strategies that can be used to mitigate impact of EVs.

Energy storage. Prior studies have explored the benefits of using energy storage in conjunction with renewable energy [14, 19, 23, 34]. These studies focus on control policies to meet certain cost objectives. In addition, the use of energy storage has been studied in the context of *load shifting*, where energy storage charges itself during periods of excess generation (or off-peak pricing periods) and discharges when the demand is high [11, 12, 20, 32]. Similarly, prior work has proposed algorithms to shave peaks at both the individual home or the grid level [28, 30, 31]. Again, our work is complementary, as this work does not study the use of peak-shaving techniques to mitigate the impact of EVs on distribution edge transformers at city-scale.

8 CONCLUSIONS

This paper analyzes both the current load on transformers from a small city, and the expected load as EV penetrations increase. We find that many transformers are over-provisioned in today's grid, but a significant fraction of them will become overloaded once EV penetrations reach 20% and above. We then examine mitigation strategies for reducing transformer overloads using grid-level energy storage and smart EV charging strategies. Our results indicate that both mitigation strategies can reduce over-capacity transformers at high EV penetration levels, and can also be used in combination to achieve significant reductions. At 40% EV penetration, we can reduce the number of critically overloaded transformers by 18% using smart charging, and up to 90% by deploying energy storage of up to 15kWh per transformer. We expect our work to spur further work on the impact of the changing electric grid, with higher penetrations of EVs and renewable energy sources, on the grid's distribution system and its edge transformers.

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