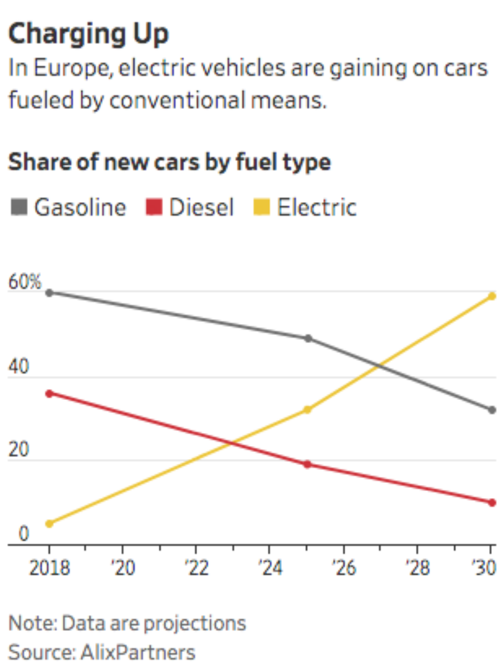
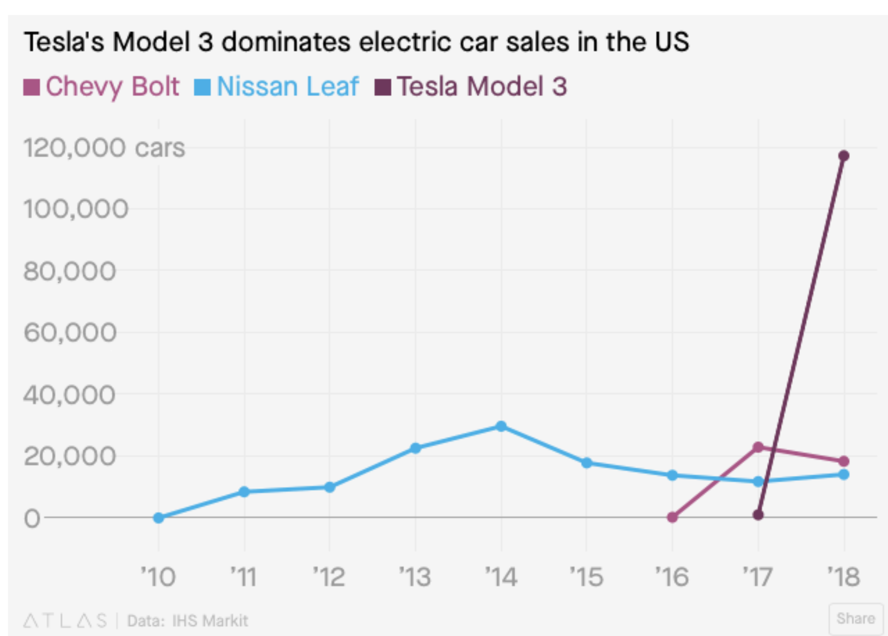
"How Can Utilities Manage Distribution Assets to get Maximum Benefit from EV Growth"

I. ***Executive Summary:*** within the next fifteen years, more than $168 billion may be spent by US electric utilities on "emergency" replacements of half of the existing stock of 40 million pole-mounted local distribution transformers in rural residential areas, as these transformers progressively fail due to overloading and overheating. Materially contributing to this overloading and overheating will be high-rate, "*Level 2*" charging of increasingly-popular battery electric vehicles, such as the Tesla models S, 3, X, Y and B (along with other models introduced over time by competitors). For example, one such battery electric vehicle may charge at a rate of 12 kwh or 20 kwh, while the peak annual power consumption of a household might be only 3-5 kwh. While this might initially appear to pose an insurmountable strain on the grid and a formidable infrastructure challenge, this author believes that with a holistic approach embodying a mixture of old-fashioned "common sense" and Modern Analytics, the transition should be readily manageable, and with a cost $112-134 billion lower than anticipated. The large savings arise in part because the emergency cost of replacing a failed transformer (cited by independent experts at $8,400) is 3-5x the cost of successfully anticipating such failure and replacing it in advance. Moreover, by averting negative outcomes, the growth of electric vehicles should be assured, and the financial prospects of electric utilities, currently clouded by the so-called "*Electric Utility Death Spiral*" (see below), would be materially improved due to the consequent load growth. Since the aggregate equity capitalization of such electric utilities currently exceeds $400 billion, the value of this additional growth may exceed $40 billion. Successfully supporting EV growth and averting the unduly high costs of emergency transformer replacements is therefore an important question.

II. Background and Context

Electric vehicles potentially convey tremendous benefits to society in term of lower transportation-related GHG emissions, the enabling of Renewable forms of energy as sources for EV charging (as Wind energy is often most abundant at night when EV's are at home being charged), and longer term as a platform for autonomous vehicles (which may reduce urban traffic congestion, and free up large quantities of real estate and other resources). An August 13th article in the Wall Street Journal mentioned that *"auto makers are spending $225 billion to develop more than 200 new plug-in vehicles through 2023"*. An August 15th article from the same source reported "*Industry consultants AlixPartners predicts fuel-powered cars will make up just 56% of new cars sold by 2030, down from 95% now. The biggest shift will be in Europe, where regulators are pushing tough restrictions on greenhouse-gas emissions.*" Specifically, EV's will attain a 60% share in Europe by 2030 (see below):

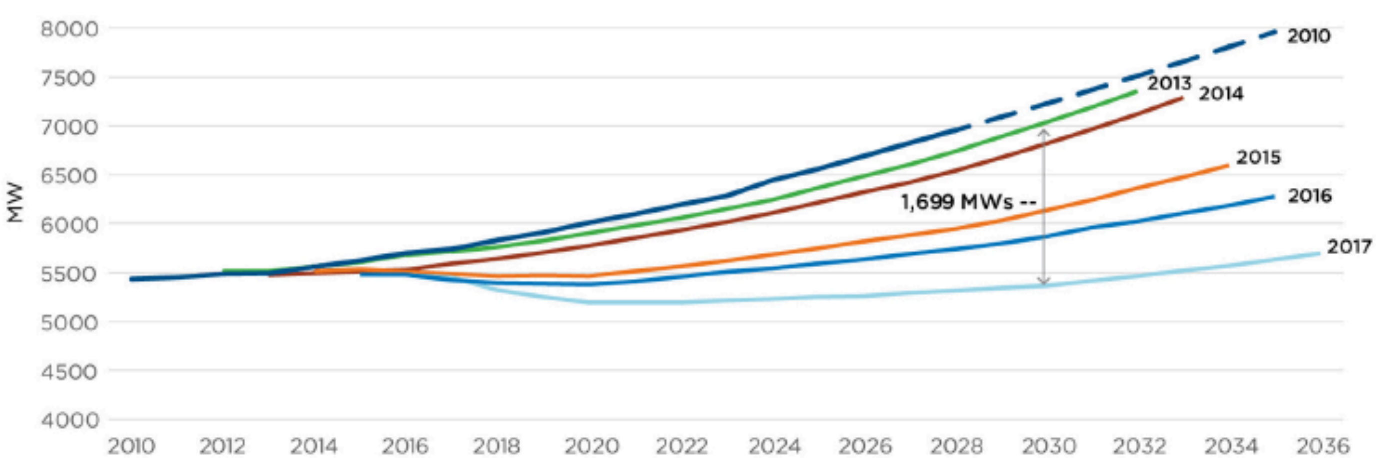




In particular, the recent rapid rise in fast-charging Tesla BEV's represents a sea-change in the stresses imposed on local distribution transformers: the annual production run-rate for the Tesla Model 3 may be as high as 500,000 vehicles by year-end, so these stresses will become increasingly common. Moreover, because of the relatively larger battery size of Tesla's, their charging rate is now usually at a rate of 10 or 15 kW. Given that the thermal stress is in proportion to the square of the electrical current, a single Tesla may impose a stress equivalent to more than four Chevrolet Bolts/Nissan Leafs, and this stress will not be mitigated by differing arrival times and charging times.

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

Long Island's Peak Load Forecast has Declined Since 2010



The Zone K peak load forecast for 2030 has declined by over 24% (i.e., 1,699 MWs) when comparing the 2013 forecast to the 2017 forecast.

Many electric utilities face declining long-term growth prospects, as appliances (including AC and refrigerators) have become markedly more efficient, and Rooftop Solar has become increasingly popular. An illustrative example is provided *above* for Long Island Power Authority, which has consistently revised its estimates of future growth downwards. Some investors have called this the "*Electric utility death spiral*", pursuant to which a utility's fixed costs must be amortized over declining volumes, and compensating price increases simply make matters worse by accelerating future volume declines (https://www.alternativeenergyhq.com/are-electric-utilities-in-a-death-spiral.php). Electric vehicles provide a potential lifeline from the *Death Spiral*, and even a path to prosperity. However, if consumers lose confidence in the reliability of distribution infrastructure due to increased awareness of transformer failures, the opportunity for this growth may yet be missed.

III. __Infrastructure Considerations__

While it is widely acknowledged that in the US there is sufficient excess capacity in power generation and long-distance transmission lines to accommodate the increased demand from EV charging, the situation with rural local distribution is much different (and has been formally designated "*The Last Mile Problem*"). Residences in rural areas are commonly served by cylindrical, pole-mounted local-distribution transformers which lower the voltage from the higher feed levels to the 120V or 240V levels safely used by homes. A single such transformer might commonly serve five households, and the most common sizes are 25 kVA, 37.5 kVA, and 50 kVA. The average hourly consumption of a household is about 1.25 kwh, although this obviously varies with the time of day and the season. The peak annual consumption might be 3-5 kwh per hour, and this is normally recorded during the peak evening hours in the Summer when the air-conditioning load is highest. An unusual feature of these transformers is that they are by design most efficient at a relatively low level of utilization, such as 35%. A transformer may operate at up to 130% of its rated capacity before a fuse may blow (triggering a brown-out), and if no such fuse is present up to 180% before a catastrophic failure such as a explosion or fire from the oil vaporizing under pressure and heat. However, at more than a 100% utilization rate it will tend to overheat, and its insulation may be degraded and its remaining life exponentially shortened, with possible failure (including due to a dangerous fire).

Distribution Transformer Losses

- **Typical 25 KVA Transformer**
  - At 130% Loading
    - Core Losses 51 watts
    - Winding Losses 781 watts
  - At 100% Loading
    - Core Losses 51 watts
    - Winding Losses 462 watts
  - At 30% Loading
    - Core Losses 51 watts
    - Winding Losses 41 watts

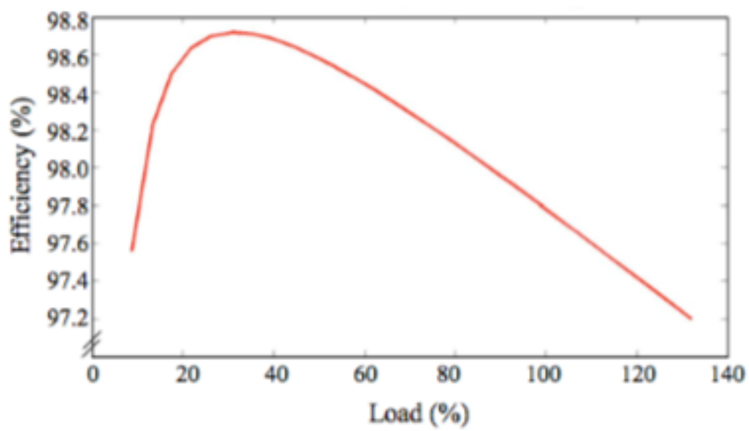


Fig. 3. Transformer efficiency curve.

There are an estimated 40 million such pole-mounted distribution transformers in the US owned by utilities, with another 10 million being owned by businesses. The estimated original life of such a transformer when originally placed in service is 40 years, but the average age of the fleet has been estimated to already be between 38 and 42 years. These transformers are therefore mostly full-depreciated, and now near the end of their lives. Some utilities, such as Memphis Gas, Light, and Water and ComEd in Illinois have in recent years conducted comprehensive audits of their distribution transformers. However, this is rare and most electric utilities just tend to passively wait for their distribution transformers to fail, and then to simply replace the failed unit with one of the same size.

IV. *__The "One Tesla Problem"__*

The relationship between transformers of different sizes and the number of different households that they characteristically serve is illustrated below with data provided by a certain New England electric utility.

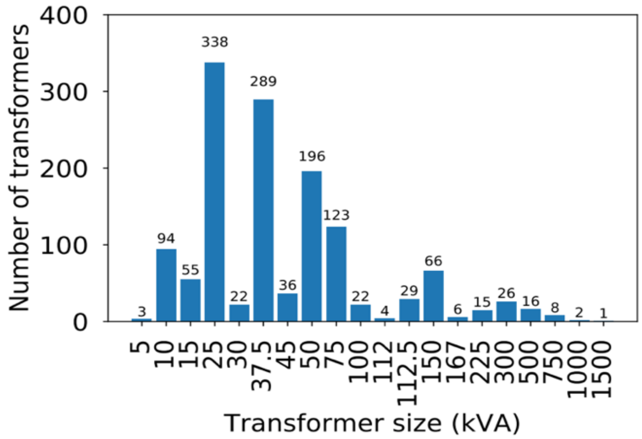
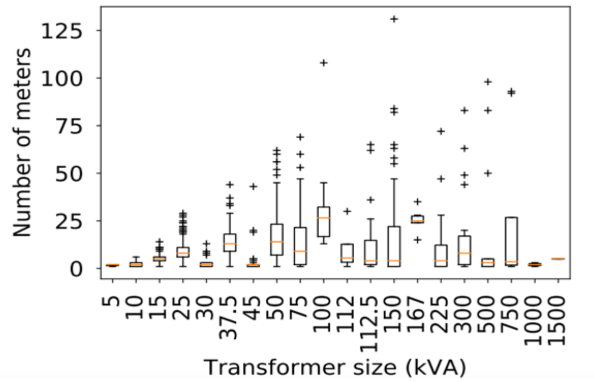
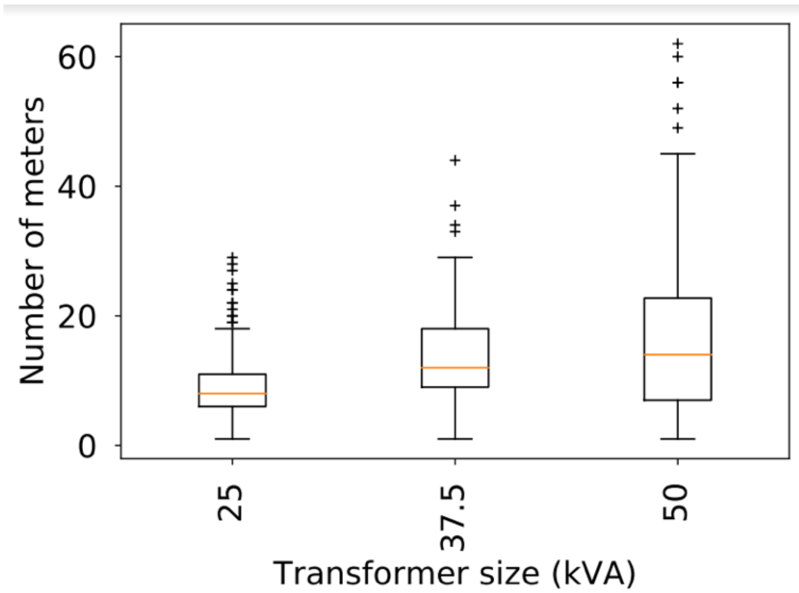


Figure 1: Distribution of transformer capacities.



The charts below are for just the 25, 37.5, and 50 kwh sizes with the actual medians and quartiles in black:



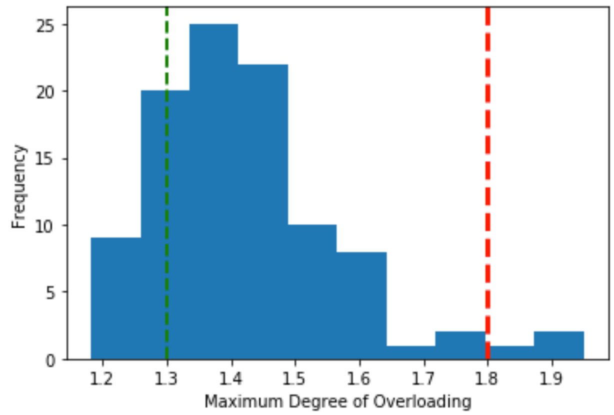

```
25.0 -> Q1 6.0
25.0 -> Q2 8.0
25.0 -> Q3 11.0
37.5 -> Q1 9.0
37.5 -> Q2 12.0
37.5 -> Q3 18.0
50.0 -> Q1 7.0
50.0 -> Q2 14.0
50.0 -> Q3 22.75
```

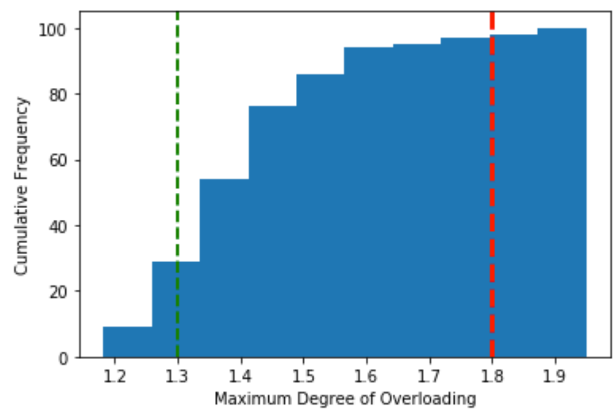
From the above median and interquartile data (with the black background) we can see, for example, that:

1. For the 25 kwh units, half of the transformers serve 8 residences or more (implying c.3kwh average peak)
2. For the 37.5 kwh units, half of the transformers serve 12 residences or more (implying a c.3 kwh avge. peak)
3. For the 50 kwh units, half of the transformers serve 14 residences or more (implying a c.3.5 kwh avge. peak).

This detailed quartile data illustrates the "*One Tesla Problem*": namely that the addition of a single Tesla charging at the most common rates of 30 miles' range/hour and 45 miles' range/hour can on its own overload a transformer, leading to exponential aging. These two charging rates would be pulling from the grid at a rate of 12 kwh and 18 kwh respectively. For example, for a 25 kVA transformer serving the median eight households, the old peak might have been 8 x 3kwh, or 24 kwh: however, with the addition of a single Tesla, the new peak will be now 36 kwh or 42 kwh, corresponding to overcapacity levels of 144%, and 168% respectively. At this latter level, unless a protective fuse is tripped (and they seem not to be always installed), a transformer fire becomes a danger (such as those shown below).

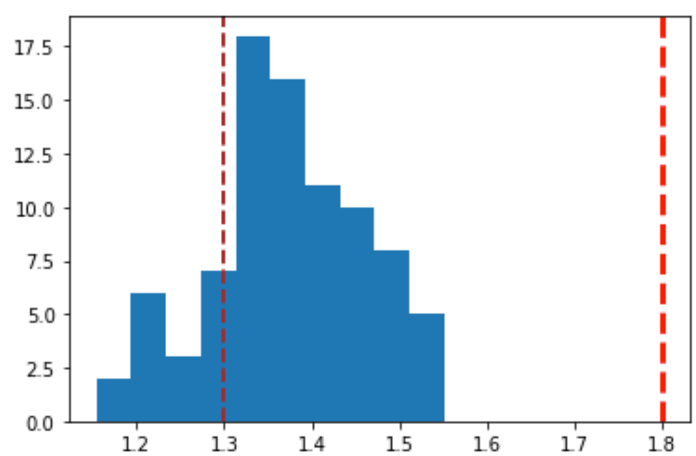
Of course, the reader will quickly realize that the most extreme overloading will occur for the even smaller transformer sizes, such as 10 kVA and 15 kVA: while these are less common (together they comprise c.44% of the number of 25 kVA transformers), they are often located in the most isolated rural areas where scrub is abundant, and the likelihood of a wildfire may be greatest. Provided below are two figures that show the frequency (and cumulative frequency) distribution for different degrees of overloading during the Summer months for 100 transformers, all assumed to be of 15 kVA capacity, each serving five households, just one of which owns a Tesla. The analysis may be deemed conservative, as the energy consumption of each household and of the Tesla are assumed to be statistically independent. In fact, when temperatures are very high, the load for each household is more likely to be high, and moreover the amount of charging may be increased as for a Tesla, AC is a significant energy user.



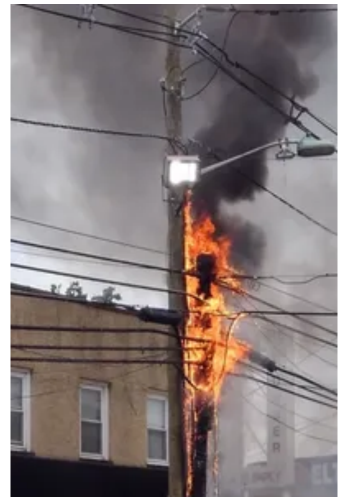


This "*One Tesla*" illustrative analysis suggests that 74% of the 15 kVA transformers will experience a maximum overload of 130% or more, and 3% will experience a "potentially catastrophic" degree of overloading of 180% or more of capacity. While 3% may sound small, one may bear in mind that each utility owns thousands of oil-filled, pole-mounted local-distribution transformers, and all electric utilities own 40 million in total. Given that a single fire can trigger a multi-billion-dollar liability, it may be prudent to be cautious. More fundamentally, the cost of an emergency transformer replacement is reportedly 3-5x that of replacing it in advance, so a modest investment in Analytics to anticipate and pre-empt overloading with appropriate upgrades seems to be well warranted, in terms of avoiding (a) the very-substantial emergency replacement cost premium, (b) reputation damage and a potential acceleration of the *Electric Utility Death Spiral*, and (b) reputation and legal costs associated with catastrophic transformer failures.

While the outlook for 25 kVA transformers is less dire with just a single Tesla, with two Tesla's the likelihood of brown-out's is high, although Catastrophic failures seem unlikely. Specifically, this "*One Tesla*" illustrative analysis suggests that 89% of the 25 kVA transformers will experience a maximum overload of 130% or more, but none will experience a "potentially catastrophic" degree of overloading of 180% or more of capacity. However, two Tesla's for eight households and an average of 16 vehicles owned, corresponds to just a 12.5% EV penetration, which could be achieved in some counties of some states in the not so distant future.

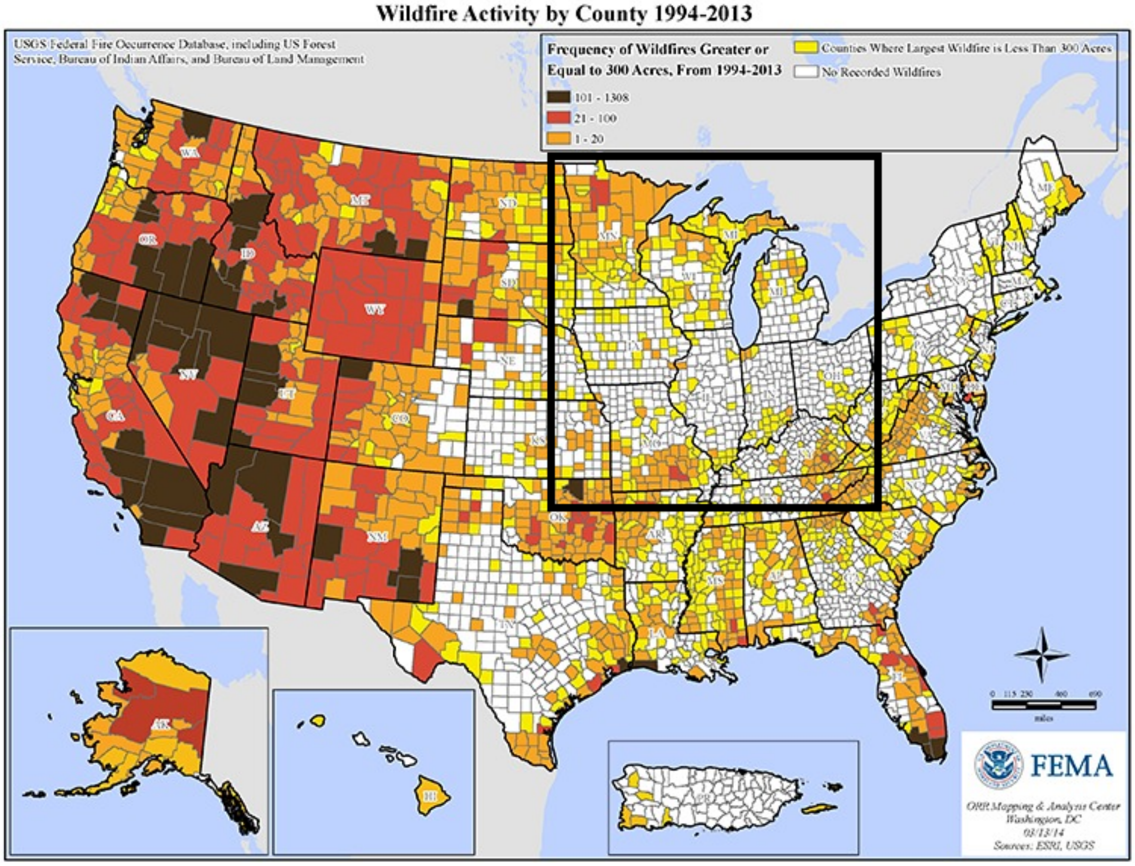


Another risk factor here relates to additional heat from eddie currents as the AC current is converted into DC for charging: some analysts have recommended that the capacity of a transformer by downgraded by c.36% to reflect the additional heat generation due to such non-linear loads. While many transformers are equipped with protective fuses that trigger a brown-out at 130% loading, at a load of 180% or more catastrophic failure (including when the transformer oil vaporizes, potentially causing a gas-explosion and a fire) can occur – see below:



As The Wall Street Journal has commented, *"California law makes utilities responsible for any fire started by their equipment, even if they weren't negligent. Analysts have pegged PG&E's wildfire liabilities as high as $30 billion. That is triple its market value of $9.1 billion, which has plunged from $25.3 billion in mid-October."* See https://www.wsj.com/articles/pg-e-sparked-at-least-1-500-california-fires-now-the-utility-faces-collapse-11547410768 . A national map of wildfires by county is provided below:

Wildfire Activity by County 1994-2013



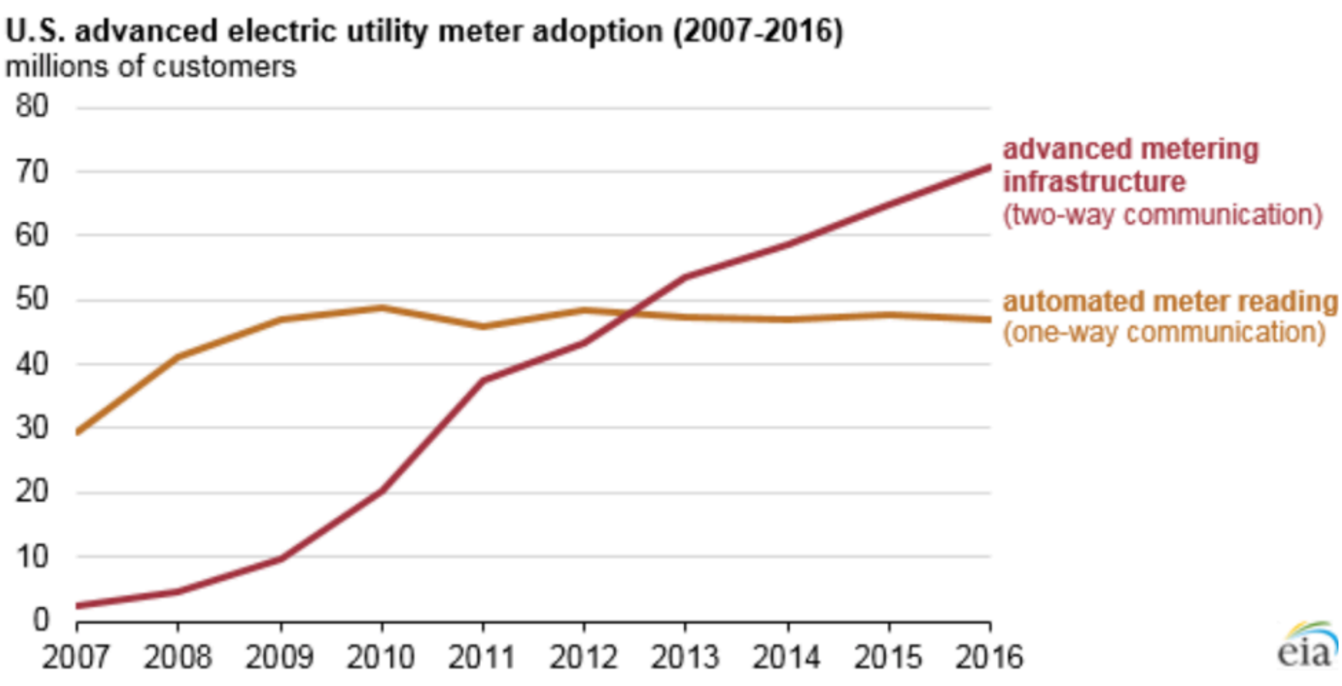
While it may seem unfair for lawyers to even have sought criminal gross negligence against an electric utility such as PG&E in the face of Climate-Change enhanced, ultra-dry 60 mph winds emanating from the Great Basin desert to the east, there is a view that "*The One Tesla Problem*" in retrospect might be deemed to have been well within the responsibilities of highly-paid senior management executives to have anticipated, and to have expeditiously acted upon. As will be argued below and elsewhere, this is not an alarmist study. It just does not seem to be an especially intractable Problem in the face of a seasoned blend of common sense and established analytics. However, so far the attitude of electric utility managements (with fortuitously at least one exception) appears to have been somewhat dismissive.

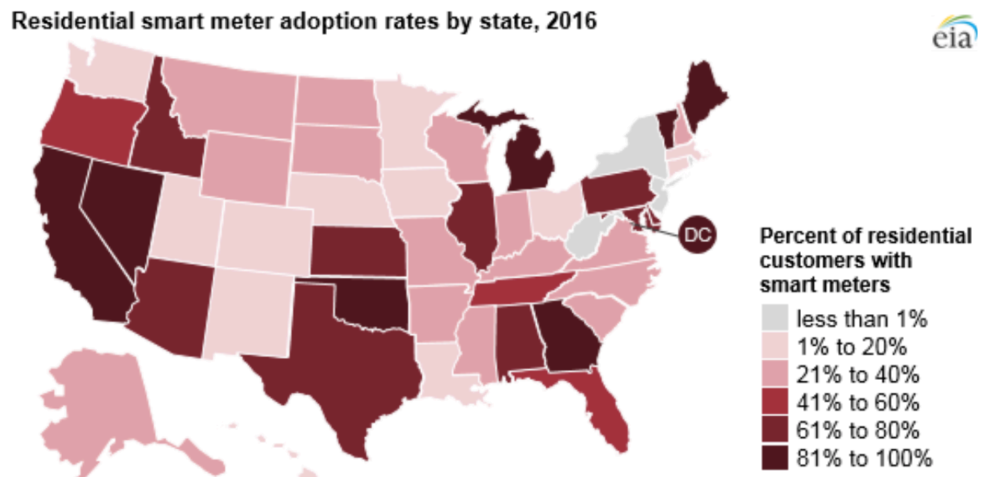
V. Problem Solution

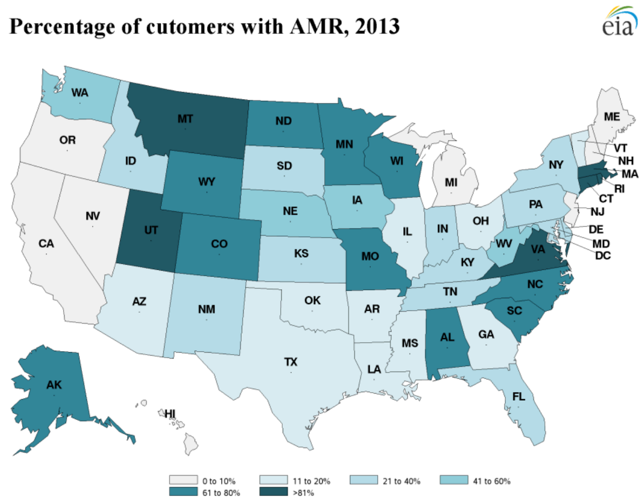
One of the challenges of upgrading the distribution transformer infrastructure to support the growth of battery electric vehicles is that the locations of BEV's still remain largely unknown. The great majority of EV owners contact a local electrician to install their charger, and do not communicate with their host electric utility. Accordingly, even a sophisticated and well-advised electric utility such as SCE in Southern California reportedly only knows the locations of 40% of the EV's within its territory. The question arises, "*Can an algorithm applied to hourly meter readings be constructive in identifying residences that have a high likelihood of owning an EV?*". The answer to this (as will be demonstrated below) appears to be a resounding "*Yes*", moreover so-called two-way "smart meters" are not required: the one-way AMR (Automated Meter Reading) meters are sufficient. This is important, as some states have a dearth of smart meters, but AMR meters are quite widespread.

VI. Availability of AMI and AMR Meters to Provide the Hourly Data Required for the Subject Algorithms

Smart Meters have two-way communication, and therefore potentially offer the possibility of a Utility intervening in the context of EV charging that may be damaging to local transformers. The two-way meters provided by eMotorWerks are tailored to EV charging and are highly sophisticated. Residential smart meter penetration rates vary widely by state. Washington, DC, has the highest AMI penetration rate at 97%, followed by Nevada at 96%. Six other states had a residential AMI penetration rate higher than 80% in 2016: Maine, Georgia, Michigan, Oklahoma, California, and Vermont. In 2016, Texas added the most residential AMI meters of any state, installing smart meters on more than 200,000 customer accounts. Two-Way Smart Metering has grown rapidly: however, Automated Meter Reading (AMR) is at almost 50% nationwide, and this hourly data appears to be valuable, and sufficient for EV detection and monitoring. In the context of an Algorithm, states (such as New York and Connecticut) with low AMI penetration but high AMR penetration are especially interesting: because there is no two-way communication that could facilitate a temporary intervention, it is especially important that pole-mounted residential distribution transformers are configured in advance to avoid expensive permanent damage. Nationwide, almost 50% of residences have AMR-type meters. Moreover, to the extent that the installations of AMR-type meters are positively correlated with the higher income areas more likely to purchase EV's, they could potentially represent 70% of the EV's and 90% of the EV clusters that are of most interest. This however is a purely personal and speculative conjecture.

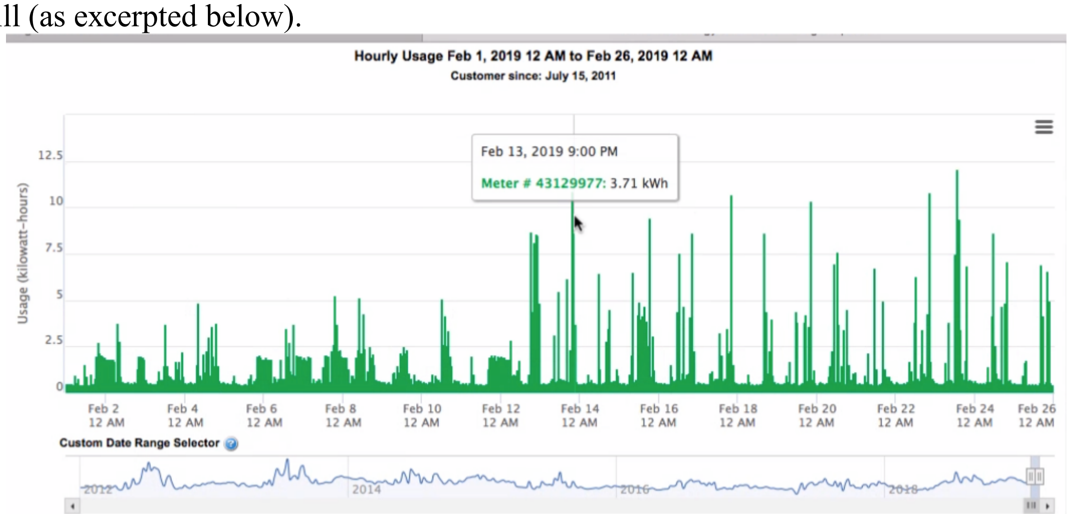






VI. <u>Data Used to Construct the Algorithms</u>

Obtaining hourly metering records for residential households is a challenging task, as utilities are extremely cautious about sharing such information. Even if information is anonymized, there have been much publicized examples of other instances (such as for NYC taxi data) where resourceful reverse-engineering has been publicized with embarrassing consequences, and even potential legal liability. This author's work has been positively received by senior researchers at Columbia University who are also interested in this field: however, notwithstanding the outstanding reputation of Columbia, a certain NYC utility has not yet shared such metering information with Columbia, although the matter remains under consideration. However, an eight-year time series for one residence in Illinois was shared privately, as the owner received a print-out of hourly consumption with his monthly bill (as excerpted below).



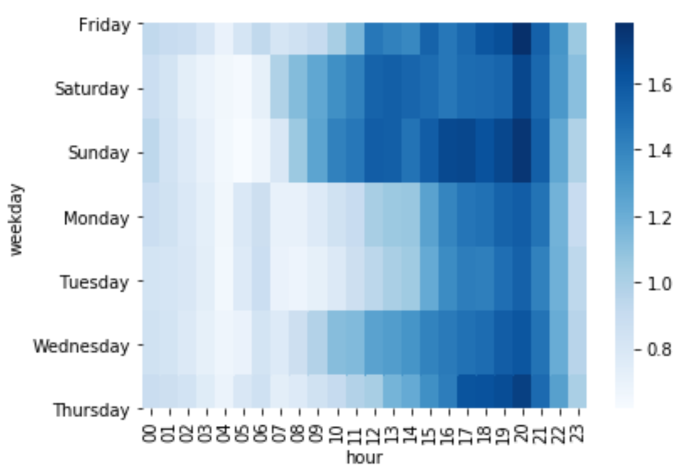
This hourly record encompassed:

(a) six months of hourly metering records for a Tesla Model 3 (acquired in February, 2019),
(b) seven months of records for a (Honda) PHEV immediately preceding that, and
(c) seven years of non-EV ownership, including two with less-efficient A/C's and appliances, and two years without children, and six years with children.

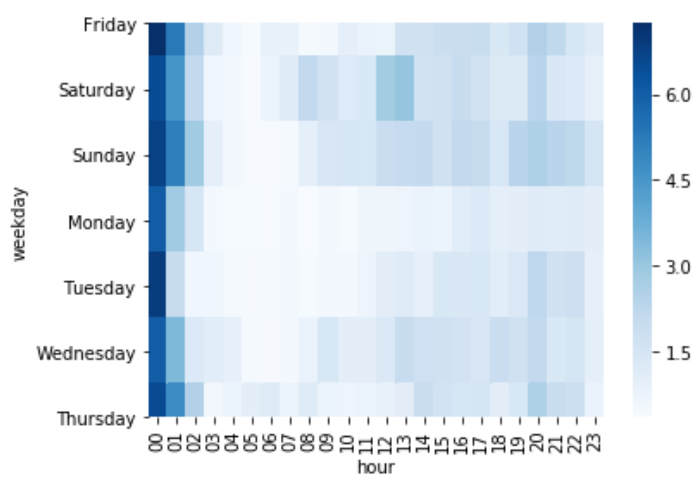
Accordingly, this may be considered a rich dataset, on account of its high level of diversity and eight-year duration. To simulate one hundred distinct non-EV records, the time series was partitioned into weekly data, and allocated to the four seasons. An artificial metering record for each season was then generated by making thirteen draws at random from the lengthy time series, and concatenating them into a continuous time series. This process was repeated one hundredfold for each season, to artificially create a synthetic database of time series records. Interestingly the total energy consumption for a given record could easily vary by +/- 20% for a given season. While the seasonal data for the Tesla did not encompass a full year, it did include the most important month, which is July due to the high A/C load on the residences AND on the EV, and February and March with high heating demands for the EV. This approach is of course a form of statistical "*Bootstrapping*" highly familiar to data scientists (including via an excellent course by a CalTech instructor available online at DataCamp.

While this approach is not ideal, it may be regarded as constructive and has yielded insights which likely transfer to a truly historical dataset of many residences. The author is in discussions with one large utility that is also seeking to discern EV's at residences, and the algorithms developed below can be expeditiously implemented on a third-party dataset should it become available.

Heat Map for Base kwh Use



Heat Map for kwh Use with Tesla Charging

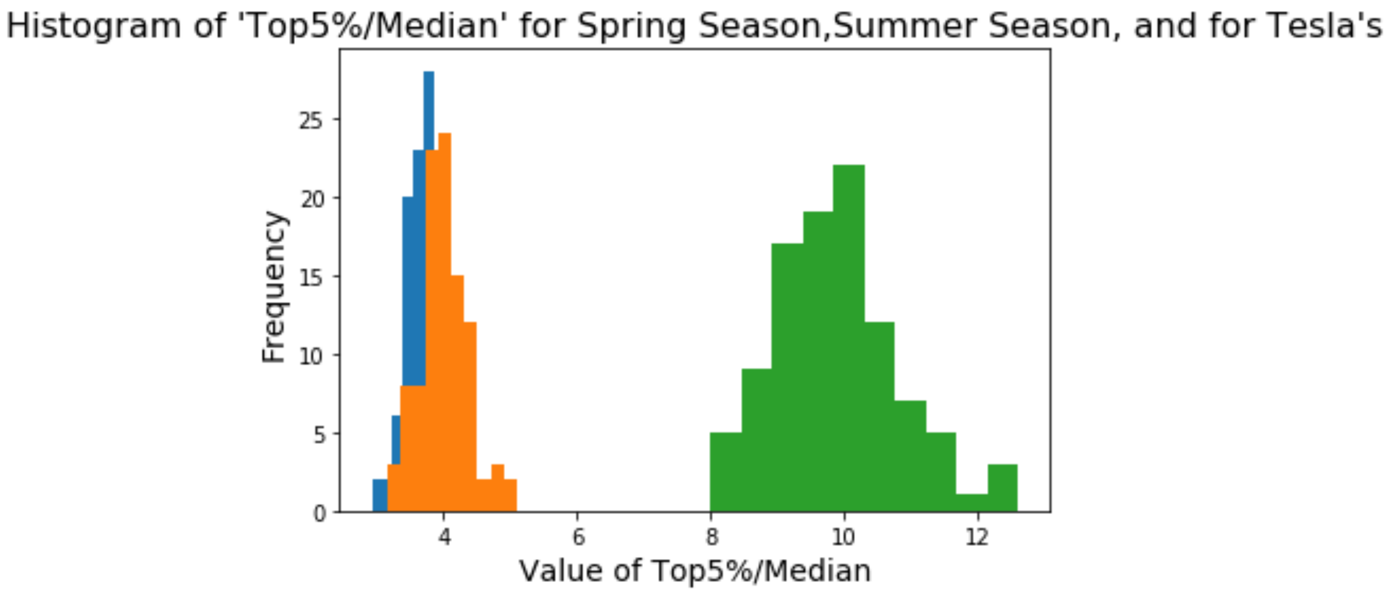


VII. Selected Algorithms, and Opportunities for 'High-Grading'

Time series classification is a somewhat specialized and challenging area. A standard algorithm for time series classification is the Kullbeck-Leibner algorithm. There is also a website at the University of East Anglia in the UK devoted to time-series classification (see http://www.timeseriesclassification.com/).The approach adopted here is a bit different. Specifically, it is domain-specific, and predicated upon the construction of a series of metrics that seem plausible in distinguishing a BEV charging at a '*Level 2*' rate. For example, the high spikes relative to normal household use suggest the use of a maximum for the period considered (although this metric is sensitive to errors in readings or transcriptions). Less sensitive is a metric derived by dividing the quantile for the top 5% (so 95% of readings are below this calculated level) by the median. The thought was that if most users charge at home for two hours (typically providing 40-60 miles of BEV range), but do not happen to start on the hour, then the middle of the charging period will encompass _one_ complete hour. Since 5% of a 24-hour day is approximately one hour, this metric is targeted at capturing that one complete hour of charging.

The Classification was partitioned into the four seasons of the year for a strategic reason. In the Fall and Spring seasons, spikes from cooling and heating are less common, and PHEV electric vehicles with smaller batteries are less obviously apparent. For example, the accuracy of one algorithm was found to be 83% in the Summer, but 100% in the Spring or the Fall: therefore, the common approach of seeking the most current data may not always be the best approach. More generally, algorithms commonly benefit from a cluster-and-predict approach, and the approach above embodies a simple form of clustering. It may also be constructive to first cluster the time series using standard Unsupervised Learning approaches: this may be the subject of future work.

It should be emphasized that the classification approach adopted here is somewhat unusually not based on the time series themselves, each numbering thousands of consecutive meter readings, but rather on seven domain-based metrics derived from the time series. A histogram for one-such metric referenced above, namely '*top5%/median*' makes the approach more intuitive:



In view of the very high degree of separation observed above, it should not be a great surprise to the reader that algorithms seeking to Classify the high-rate, *Level 2* charging of a Tesla BEV have achieved an Accuracy of close to 100%. While the accuracy of Algorithms seeking to classify low-rate, Level 1 PHEV's may vary from 70% (in the Summer with its high A/C load) to even 100% (in the Fall, when charging levels are more conspicuous). Fortuitously, the lower Level 1 rates impose a strain on the grid that is a small fraction of that of a high-rate Level 2 Tesla (or other BEV), and therefore the analysis of PHEV classification is somewhat more academic, with less requirement for management action.

VII. Decision Trees and Random Forest Classification Performance

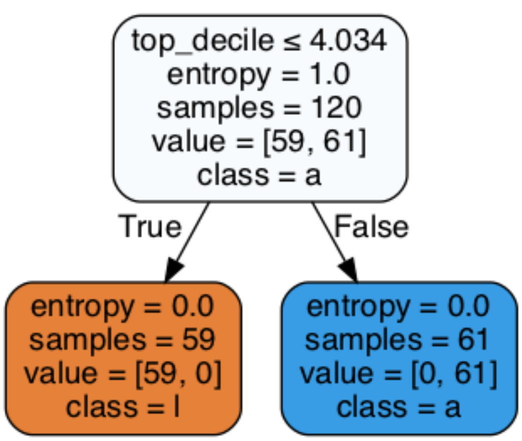
As set forth in detail in the associated Jupyter notebook, three algorithms were initially explored to seek to classify whether a given residence has either a Tesla (charging at a Level 2 rate), or a Plug-in-Hybrid Electric Vehicle (PHEV). The three were namely (a) Decision Trees, (b) Random Forests, and (c) Logistic Regression. Although Decision Trees generally perform less well than Random Forest classifiers, they do have the advantage of being highly intuitive, which is an important benefit for the senior management of an electric utility. One may question whether a "black box" approach will be embraced by management and implemented, if it cannot be satisfactorily explained to senior decisionmakers.

Moreover, on account of the high degree of separation observed for certain of the constructed classification metrics (including the Top 5%/ median outlined above), the Decision Tree for classifying Tesla's achieved 100% accuracy on the Train Set, and 97% accuracy on the Test Set. Important in this context is how might the information and insights best be used by management. The view in this work is that it is highly valuable to identify a fraction (eg 60-80%) of the "unknown" Tesla's/BEV's with a relatively high probability (so the so-called *False Positive* rate is correspondingly low. One may recall that in general less than 40% of the EV's (and sometimes even less than 10%) have generally been identified by an electric utility.

The residences identified as having a high probability of owning a Tesla/BEV can then be targeted by a focused direct mail campaign, and additional data gathering can be invested in to clarify the correctness of the initial classification (such as registration information from the Department of Motor Vehicles, research on Tesla Clubs and the like). Depending on this further information, the subject pole-mounted local distribution transformer may be visited and inspected, and potentially replaced with a larger unit (potentially also serving a larger number of residences through re-wiring the network, which carries the benefit of additional diversification).

It has been much commented that most Data Science Projects are not implemented, or fail in the implementation stage, often due to a neglect of broader business considerations and organizational context. Accordingly, additional background and more detailed recommendations are set forth in Sections A through G of ***Appendix A*** below, entitled *"A Sequenced, Information-Based Approach for an Electric Utility to Most Economically Protect its Distribution Transformers*". This remains a work in progress, as additional feedback is received from practitioners with whom the author is in correspondence (including about a position).

By means of illustration, one particular Decision Tree is provided below (LHS) for Tesla classification (in the Summer, which is for the reasons outlined above a more challenging task). A single branch, here on the "*Top Decile*" metric (specifically when it exceeds 4.034 kwh), is sufficient to achieve 100% accuracy in classifying the Training Set. On the right below is a so-called Confusion Matrix for the more challenging task of classifying PHEV's during the Summer. In this example PHEV's are the Positive Class, and of the Test Set of 80 residences, 30 were predicted to have PHEV's. Of this prediction, 27 were correct. Since there were in fact 39 PHEV's in reality, 70% of the PHEV's, so 27/(27 + 12), were correctly "located". Since most electric utilities know the location of only a small fraction of the EV's within their service territory, this is very constructive from a practical perspective. Moreover, once the 27 correct predictions (in our example) have been confirmed by diligent follow-up analysis, the amount of "labelled" data may have more than doubled, enabling more accurate predictions in the future.



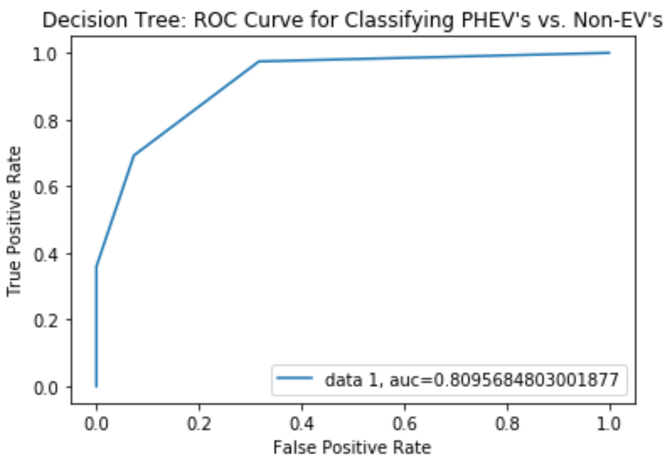
	negative	positive
negative	38	3
positive	12	27

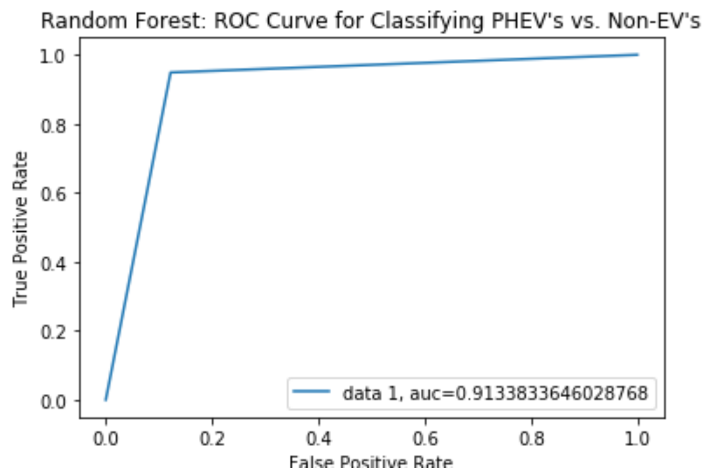
Finally it should be noted that (a) the classification performance for Tesla's/BEV's is far superior than for PHEV's, and (b) some commentators believe that BEV's will eventually dominate the market as charging infrastructure evolves. From an August 11^{th} WSJ article:

"Auto makers for two decades have leaned on hybrid vehicles to help them comply with regulations on fuel consumption and give customers greener options in the showroom. Now, two of the world's largest car

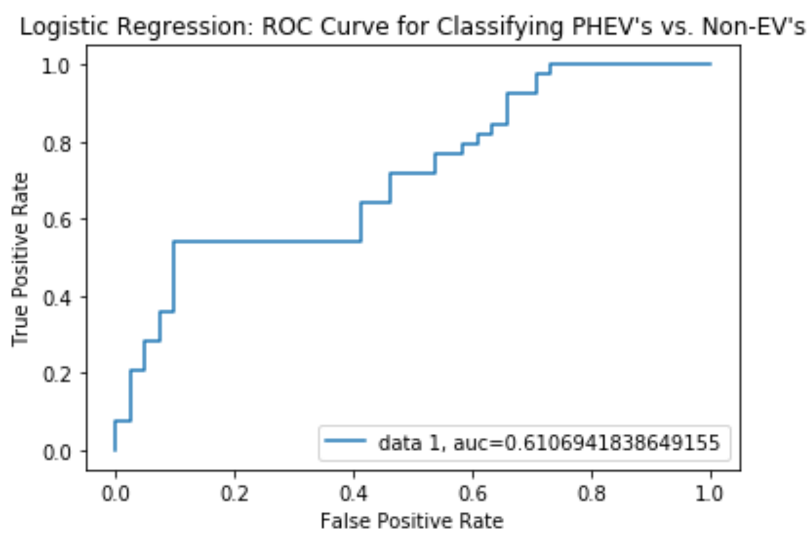
manufacturers say they see no future for hybrids in their U.S. lineups. General Motors Co. and Volkswagen AG are concentrating their investment on fully electric cars, viewing hybrids—which save fuel by combining a gasoline engine with an electric motor—as only a bridge to meeting tougher tailpipe-emissions requirements, particularly in China and Europe. GM plans to launch 20 fully electric vehicles world-wide in the next four years, including plug-in models in the U.S. for the Chevy and Cadillac brands. Volkswagen has committed billions to producing more battery-powered models, including introducing a small plug-in SUV in the U.S. next year and an electric version of its minibus around 2022. "If I had a dollar more to invest, would I spend it on a hybrid? Or would I spend it on the answer that we all know is going to happen, and get there faster and better than anybody else?" GM President Mark Reuss said in an interview."

Provided below are ROC curves for classifying PHEV's versus Non-EV owning residences during the more challenging Summer period for (a) a Decision Tree, and (b) a Random Forest. Consistent with broad experience, the performance of the Random Forest (with a higher *Area Under the Curve* (AUC) of 0.913 vs. 0.809) is superior.





Shown below is an ROC curve for Logistic Regression, which with an AUC of just 0.61 is markedly inferior:



VIII. Summary

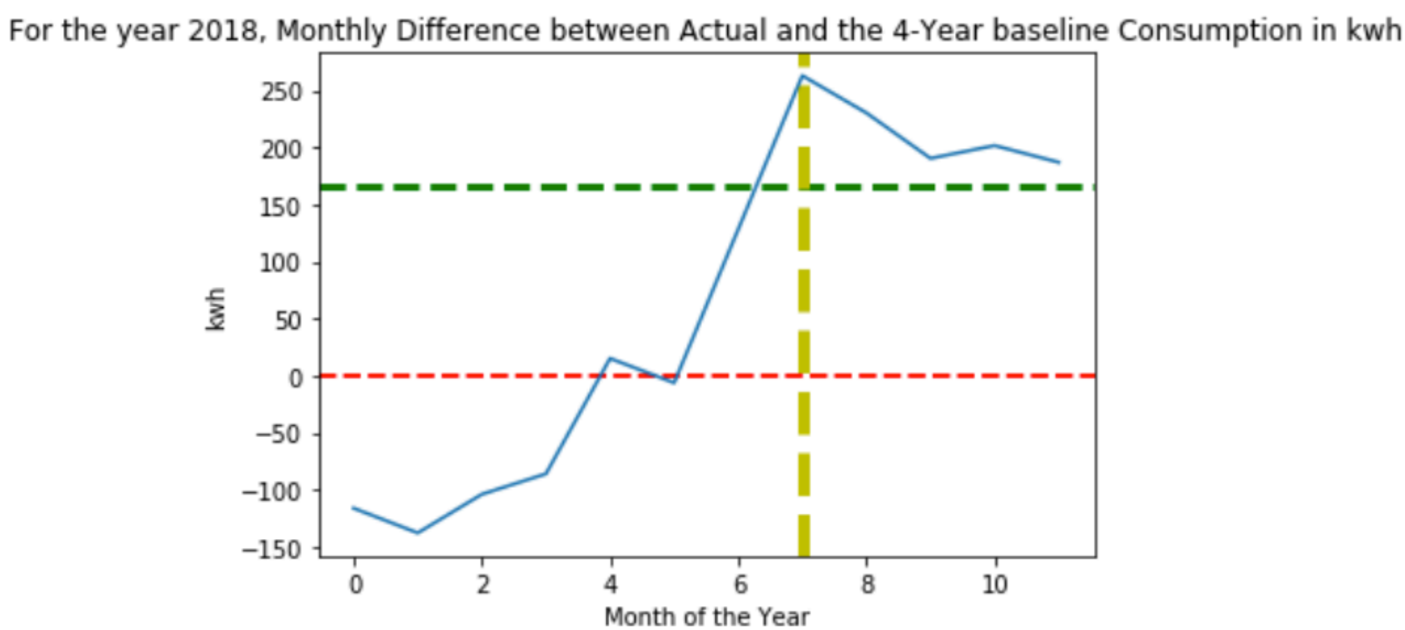
In summary, initial analysis of a limited dataset provides encouragement that high-rate charging Tesla's and other BEV's can be successfully identified from hourly meter reading from AMR meters, which are already widely present today, and also from *Smart Meters*. Standard approaches, such as Decision Trees and Random

Forest classification algorithms yielded relatively encouraging results, with AUC's of 0.8 to almost 1.0 for the test set being recorded.

A program of the type outlined above, that successfully discerns residences which have a high probability of owning an EV, and which is accompanied by appropriate follow-up and action (including the upgrading by various means of the relevant pole-mounted local distribution transformers), may be successful in avoiding most of the burdensome 3-5x premium paid for emergency replacements of transformers. The aggregate cost savings for electric utilities as a whole may exceed $110 billion. Moreover, by acting pre-emptively and maintaining confidence among households that brown-out's will not be experienced, an accelerated rush to rooftop solar PV purely for reliability reasons will not be triggered. The additional growth in residential demand from a successful EV program may increase the stock market valuation of electric utilities by more than 10%, so more than $40 billion in aggregate. In addition, smaller and private cooperatives and municipalities will not have to pass through to their customers large rate and unpopular increases.

Most fundamentally, EV's offer society tremendous benefits, and yet one could easily envision how the adoption process could be stymied by a lack of preparation on the part of electric utilities, when EV owners could become unpopular on account of the brown-out's and other misfortunes imposed on neighbors. One may also note that the reputation of Long Island Power Authority was so questionable that management was at the behest of stakeholders eventually transferred to PSEG, in New Jersey. Those electric utilities whose managements fail to navigate the tremendous changes introduced by EV's may founder, and be similarly replaced.

Future Work: These approaches can surely be improved by incorporating addition information (including with a Bayesian Perspective (or *Naïve Bayes*, for multiple factors including zip-four Tesla ownership, and zip-code related income levels). For example, 40% of Tesla owners have rooftop solar PV, compared to just 1% for the population as a whole). Moreover, the presence of rooftop solar at a residence should be clearly discernable from the same set of hourly metering records: using *Labelled Data*, the "nationwide" 40% figure cited above can be recalibrated for the dataset at hand. In any event, residences owning PHEV's, whose lower-rate charging poses a much-reduced threat to distribution transformers, can also be identified with a high level of accuracy, especially when Spring or Fall is chosen as the classification period. In addition, perhaps the single best metric (based on earlier exploratory data analysis) for a PHEV is the increase in the aggregate kwh consumption over a trailing 30-day period. *See chart excerpted immediately below*



APPENDIX A

A Sequenced Information-Based Approach for an Electric Utility To Most Economically Protect its Distribution Transformers

Prologue: there is a saying, "*The perfect is the enemy of the good*". While it is laudable to achieve perfection, as a practical matter a more realistic and economic initial approach might be to simply (a) identify most of the distribution transformers that appear to be at immediate risk, and (b) pre-empt potential financial and reputational damage by upgrading the relevant transformers in an appropriate manner (such as larger sizing, and two other variations). Historically, some utilities have conducted an explicit policy of waiting until failure, and then replacing the failed unit with one of the same size. Any continuation of such a strategy in the context of increasing EV ownership may incur significant reputational damage, and jeopardize the long-term growth benefits from EV's. For example, EV owners may defensively opt for a *Rooftop Solar + Battery* approach, to avoid exposure to a utility that has a reputation for having failed its customers – see WSJ article on this matter.

A. The Big Picture: Developing a "Baseline"

Memphis Light, Gas, and Water audited its Distribution Transformers (apparently over a period of several years) by performing the non-invasive Furan chemical test, to obtain estimates of the *Degree of Polymerization* of each transformer's insulation, and hence the so-called Remnant Life. Testing every single transformer in this manner seems expensive and time consuming. A more focused approach might therefore be considered. A faster and less expensive approach might be to first start with an independent statistical estimate ("Estimate") of the life of each transformer, and then to later physically sample 5-10% in a structured manner. The Estimate would be derived by (a) first simply noting the year of installation of the transformer, and (b) by adding to this implied age a calculation of the Accelerated Aging. This is obtained by summing the historical hourly kwh of each residence served by that transformer, and dividing that total by the transformer's capacity: each hour in which the capacity was exceeded is then multiplied by an appropriately exponential aging factor, and these are ten summed to derive the cumulative accelerated aging.

This initial "Desk" audit will provide a quick and helpful benchmark. Are some transformers now underloaded because of a combination of more energy-efficient appliances (including AC), Rooftop Solar, and other factors? Conversely, have some transformers become overloaded as residences have been expanded, subdivided, or new residences have been added? New appliances (such as Big Screen TV's, computers, printers, games etc) are also a factor. One variation would then be to notionally add a single Tesla to each transformer charging at either 12kwh or 19 kwh at peak hours, and see if this would result in overloading and accelerated aging. Smaller transformers are likely more vulnerable – see below "*G. Immediate Focus on Smaller Transformers which More Easily become Overloaded".* The advantage of this general approach is that using modern data science techniques (including Panda's), it can potentially (subject to data availability) be accomplished within days, and at a very low cost (less than one cent per transformer analyzed?). It may identify the 5% of transformers that need to be focused on in the short term, and is therefore a constructive "first cut".

B. More Granularity: Zip Code Level

With respect to the specific challenge of potential overloading due to high-rate EV charging, ownership of EV's by zip code is already available for a number of states, with the specific EV model (including Tesla Models S, 3, X, and Y) broken out separately. If not publicly available already, this information may also be purchased. An electric utility can therefore focus on the zip codes within its territory where EV ownership is most prevalent. At the crudest level, we have 40 million pole-mounted distribution transformers in the US, and some 42,000 different zip codes (more than half of which are strictly rural). So, if we suppose that 60% are rural, one guess might then be 1,600 distribution transformers per rural zip code. Of course, if EV ownership by "zip +4" data is available, then the number of transformers per distinct area would be very much lower. There are quite possibly cost advantages derived from sampling within a particular zip code (as travel time would be greatly reduced). The zip code data can be incorporated into the Algorithm's in the context of a so-called ROC Curve. This is a somewhat unusual situation. We have knowledge of a minimum number of EV's, but not which residences own them. The algorithm can be specified to predict the most likely residences, or can return a larger subset (eg twice the number of EV's), so this group can be targeted for further marketing. An important consideration here is that the cost of an overlooked residence is large (in terms of reputational damage or a failed transformer), but the cost of a "False Positive" is relatively low – namely more research and marketing were conducted to seek to clarify the true state of affairs, and this gave rise to modest additional costs.

C. <u>Algorithms to Discern Likely Residential Charging of EV's and at Level 1 or Level 2 Rates</u>

Once an electric utility has identified the zip codes with the highest EV ownership, a suitable statistical algorithm can be applied within those zip codes to the utility's internal metering records to identify particular residences which appear likely to be charging an EV. Of course, these algorithms do best when hourly metering data is available, such as from AMR or AMI ("Smart") meters: where this metering is not available, a lower priority may be assigned, to be reviewed at a later time. While some highly-regarded papers have focused on the Kullback/Leiber algorithm for time series analysis, other algorithms may be demonstrably far superior.

D. <u>Securing Labelled Data:</u> <u>Follow-Up Direct Mail & Marketing Approach with Possible TOU Plan</u>

In order to assess the accuracy of the algorithm's selected, labelled data is of course required. It can be obtained in numerous ways. The simplest is for the utility's EV manager to do a mass mailing to clients, including the possibility of a raffle of attractive prizes (such as highly-discounted charging for a period of one year). As EV owners submit their information, including their address, ownership of EV's is determined for the respondents. A second approach is to initiate a *Time-Of-Use* (TOU) tariff plan. However, some experts question this approach as it has in the past created a significant peak at the onset of the Off-Peak period: conversely, without a TOU Plan, EV owners simply tend to charge when they arrive home, which means the electrical load is more staggered. However, sophisticated SCE has done both of the above actions, and reportedly still only knows the locations of 40% of the EV's within its service area. However, if 40% of the residences <u>are</u> known, then we have a significant sample of labelled data, and this can be used to tune the algorithms to "discover" the other 60% of owners. These estimates of ownership can then be used for follow-up targeted marketing, with further inviting offers made to gather information and ascertain EV ownership.

E. <u>Marijuana Grow House Considerations</u>

It has been commented that in some areas that 85% of the transformer failures have been due to illegal taps of power lines "*before the meter*". One interesting opportunity here is that any such transformer failures that a utility has experienced directly may be used to build a statistical model that predicts the failure of a distribution transformer. The model might include as potential explanatory variables: the age, size, and manufacturer of the transformer, and the aggregate hourly load history in kwh (with this load to retrospectively include any "omitted" (55-85 kwh) load contributed by a Grow House). This model can then be constructively applied to predicting the time to failure due to the lower loads due to EV charging.

More broadly, c.5% of the electricity distributed in the US is stolen, albeit in smaller volumes than a marijuana grow house. One unknown question is whether EV chargers engage in above-average theft rates: they would certainly seem to have above average usage, and the installation of a Level 2 charger by a friendly electrician might surface the opportunity. Although this does seem unlikely, as EV owners are relatively prosperous and public-minded, the possibility cannot be entirely discounted, particularly if the suggestion was proffered by the electrician who installed the Level 2 charger *("You know, the electric utility will never tell as no one comes to visit and look at the meter anymore!"*).

F. Physical Visit to Targeted Transformers with Possible Furan and DTM Tests

The "desk" assessment of potentially overloaded transformers (outlined above in Section A *"The Big Picture"*) is of course predicated upon an accurate mapping between distribution transformers and the residences that they serve. For a number of reasons, this mapping may have become out of date, and may need to be updated (or even re-created, if the original records are not available). A Distribution Transformer Monitor (DTM) device (such as made by Grid20/20 – see www.grid2020.com), used in conjunction with hourly metering records and appropriate analytics, can be constructively used to achieve this. A Furan test on the transformer's oil exhaust might also be done concurrently with the DTM test, to determine the remaining life of the transformer's insulation. This would initially be done for just the less than 5% of transformers targeted pursuant to work program outlined above.

G. Immediate Focus on Smaller Transformers which More Easily become Overloaded

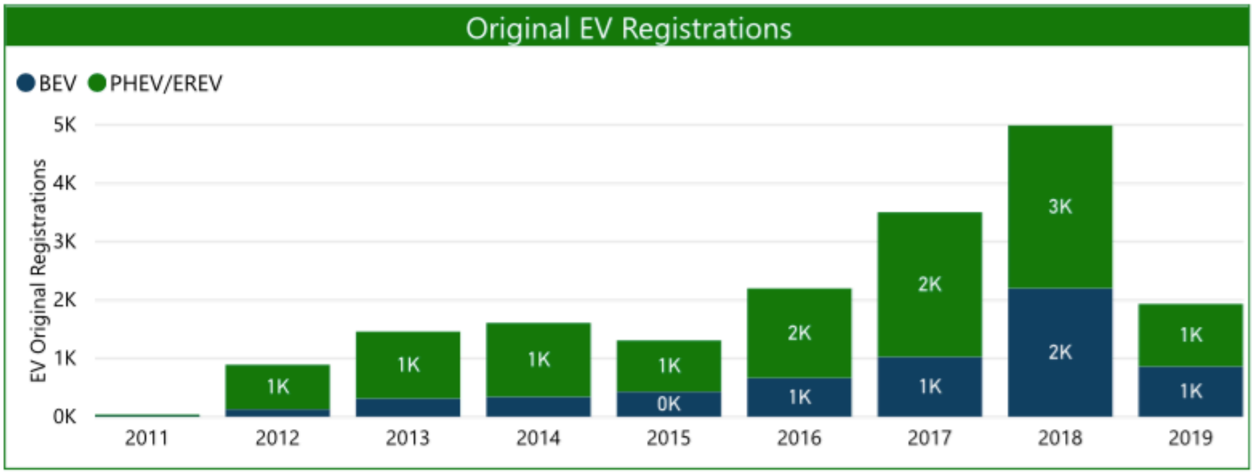
The Transformer-Meter association available for a small New England utility (as discussed above) indicates that more than half of their distribution transformers have a nominal capacity of 37.5 kva or below. One approach is to simply extract the hourly metering records for the residences served by these smaller transformers, and to apply a simple statistical algorithm to screen for likely Tesla ownership. This will likely be a relatively small percentage (eg less than 2% of the residences), and presumably a similarly small percentage of the transformers, which we can call the Target Subset. For the Target Subset, we then go back and add up the hourly kwh consumption figures for each subject transformer, and assess the extent (if any) to which overloading (and hence likely overheating and accelerated aging of insulation via polymerization) may have taken place. Initial analysis suggests that severe overloading is likely for smaller transformers, and this will be the subject of detailed follow-up work.

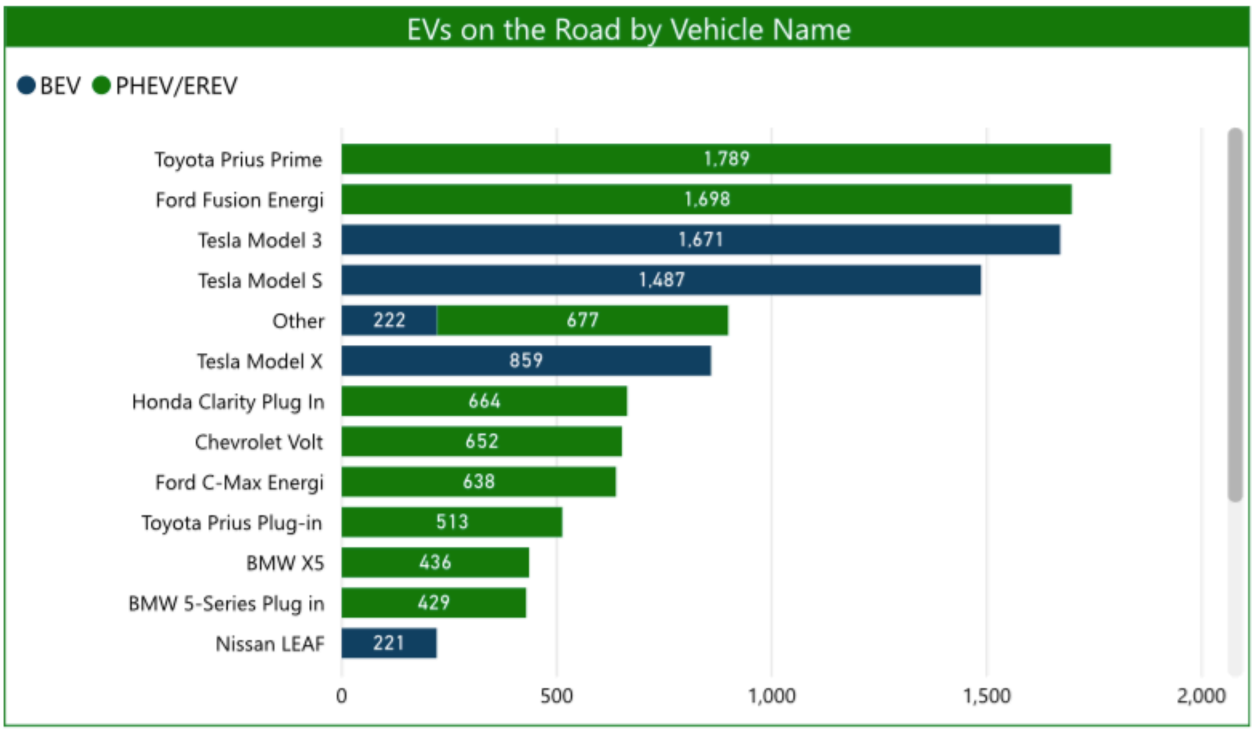
APPENDIX B

Illustrative Case Study: PSEG Long Island/ Long Island Power Authority (LIPA)

PSEG Long Island/Long Island Power Authority (LIPA) is a municipal subdivision of the State of New York that owns the electric transmission and electric distribution system serving all Long Island and a portion of New York City known as the Rockaways. It includes affluent areas such as the Hamptons. Specifically, Suffolk and Nassau counties together have more than 12,000 EV's, of which more than 4,000 are Tesla's (see figures below). Importantly, EV ownership information is also available by county and Zip Code. It appears that LIPA has 15,671 one-way (AMR) meters and 46,365 two-way (AMI) smart meters (see below).

Long Island Power Authority (LIPA): EV Registrations: by Year and by Model





To put LIPA in context with the rest of New York and other states, information on meters is provided below:

utility	state	grid	amr	ami	smeters
Niagara Mohawk Power Corp.	NY	NYIS	1603887	268	1604155
Consolidated Edison Co-NY Inc	NY	NYIS	1174296	0	1174296
Central Hudson Gas & Elec Corp	NY	NYIS	127665	139	127804
Orange & Rockland Utils Inc	NY	NYIS	83229	40047	123276
Long Island Power Authority	NY	NYIS	15671	46365	62036
Village of Fairport - (NY)	NY	NYIS	15618	0	15618

In the context of an Algorithm, states such as New York (and Connecticut) with low AMI penetration but high AMR penetration are especially interesting, because there is no two-way communication that could facilitate a temporary intervention. It is therefore especially important that pole-mounted residential distribution transformers are configured in advance to avoid expensive permanent damage.