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Influencing Factors for Light Duty Electric Vehicle Adoption and Anticipated Impacts on the Electric Reliability Council of Texas

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Influencing Factors for Light Duty Electric Vehicle Adoption and Anticipated Impacts on the Electric Reliability Council of Texas

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Dedication

To my parents and my dear friends who have been my support system for my entire life.

Thank you for everything.

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Abstract

Influencing Factors for Light Duty Electric Vehicle Adoption and Anticipated Impacts on the Electric Reliability Council of Texas

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Electric vehicles (EVs) are becoming a more prominent portion of Texas's light duty vehicle (LDV) fleet as they become more attractive to consumers and as relevant governing bodies work to incentivize further adoption rates in an effort to reduce emissions within the transportation industry. Meanwhile, the Electric Reliability Council of Texas (ERCOT), the electric grid that services about 90% of the state's residents, has been seeing increases in power demand. This has been due to factors such as a growing population, increased air conditioning use, and pushes for electrification across other industries, all factors that are expected to continue contributing to power demand increases within the foreseeable future. As more vehicles in the state are electrified, they will add further power demand increases on top of the existing contributing factors.

This work focuses on evaluating different EV adoption, charging management, and policy scenarios in order to then evaluate how they may be expected to impact ERCOT, particularly regarding peak demand increase within two time horizons: one into 2030 and one into 2050. Peak demand is an important consideration because as it increases, it presents challenges for maintaining the electrical grid's reliability when it exceeds generation capacity. After constructing and refining models which predict EV presence at the county level based on socio-economic and infrastructure related feature variables, the anticipated impacts of a growing EV fleet are quantified using historical data from ERCOT, planned installations and reserve margins, EV charging patterns, and travel patterns. Additionally, this work includes results from a collaboration which culminated in applying relevant EV fleet growth predictions to a DC-OPF simulation for Austin Energy, serving as a case study for the future of EV fleet impacts on relatively small-scale utilities.

The results of this study showcase the fact that it is possible to accurately predict EV presence at the county level with 6 publicly available feature variables. In examining adoption pathways, it importantly finds that current incentives will very likely be insufficient for the achievement of the Biden Administration's 50% market share goal by 2030. Should this market share goal come to fruition, however, it is expected to be manageable at the state level and within the Austin Energy case study regarding electricity supply in 2030. Sustained growth from this scenario, however, will necessitate ambitious charging management strategies in order to limit the potentially heavy impact of a growing EV fleet on peak demand looking forward into and beyond 2050.

Table of Contents

List of Tables

List of Figures

Chapter 1: Introduction

1.1 Motivation and Objectives

Electric vehicles (EVs) contributed to under 1% of the state of Texas' light duty vehicle (LDV) fleet at the end of 2021, which corresponds to about 120,000 EVs on the state's roads at the time. Though this is a small portion of cars in a state of nearly 30 million people where most residents own cars, the 2020s' is already a decade experiencing a dramatic rise in EV adoption rate (Ruder, 2022). This trend is a result of the culmination of many factors: EVs are rapidly approaching price parity with conventional gas powered LDVs (Ewing, 2023), their battery capacity has expanded leading to an increase in trip range available from a single charge, and they offer owners a method of reducing greenhouse gas (GHG) emissions associated with personal transportation. This is because emissions from gasoline powered cars are virtually unavoidable, but the power sector has alternative ways of producing the electricity that can power these EVs GHG emissions. All of these factors have led to an overall increase in intrinsic demand for EVs from those in the market for a new LDV.

This intrinsic demand has also been accompanied by externally implemented policies from both the state and federal level. Such policies have been implemented in order to help the Biden Administration achieve their goal of a 50% reduction in greenhouse gas emissions (relative to emission levels from 2005) by the year 2030 in accordance with their rejoining of the Paris Climate Agreement (The White House, 2021). Therefore, the Biden Administration has also targeted achieving a 50% nationwide market share of EV's by 2030. (The White House, 2021b). Achieving this goal will be driven by the aforementioned Federal policies put into place such as tax credits for the purchase of EVs, funding for the expansion of public charging infrastructure, and other incentives at the state level such as rebates.

Reaching this market share goal by 2030 would indeed reduce emissions from the substantial portion of the transportation industry that is made up by LDV's, however, justifiable concerns have been raised about the potentially negative impacts that these EVs can have on the electric grids servicing them (Ziegler, 2022). As market share rises in the country and in Texas, more energy that was traditionally provided by gasoline will now have to come from additional power plants in the Electric Reliability Council of Texas (ERCOT), the independent system operator that services electricity to 90% of the state’s population.

Such grid impacts would most notably include an increase in electricity demand, meaning that across the state, utilities will have to accommodate by increasing generation capacity. If this demand increase from EV charging aligns with times when ERCOT already experiences peak load, it would have a disproportionately large impact on the necessary increase in generation capacity to maintain grid serviceability. ERCOT’s peak demand, which occurs during hot summer days, has already been increasing over the past decade due to factors such as the electrification of other commonly used appliances and population growth that is projected to continue into and beyond 2030. This is also expected to be exacerbated by increasingly hot summers attributable to climate change (EPA, 2016). This means that any large-scale efforts for electrification must be carefully evaluated with regards to their impact on ERCOT.

Furthermore, an increase in peak demand often leads to a disproportionate increase in emissions. This is because at times of unusually high demand, peaking power plants that can produce easily rampable but relatively inefficient electricity must come online, and these often operate with a carbon footprint as high as twice that of conventional natural gas combined cycle (NGCC) plants (Clark Energy, 2019). This means that despite one of the main driving forces behind the push for EV adoption incentives being to curtail emissions, they have the potential to increase the carbon intensity of the grids that service them such as ERCOT.

In order to best foresee and mitigate this effect, this study evaluates the driving forces behind EV adoption within ERCOT serviced counties in Texas and shows that they can be predicted using publicly available data. It then examines how different adoption scenarios translate to quantifiable grid impacts and showcases the need for charging management strategies in the coming decades. The study's findings can be used as a framework for informing utility and policy decisions in order to maximize the benefits of electrifying transportation in Texas without adding undue stress to ERCOT or other local utilities.

1.2 Literature Review

As a relatively new technology which has only penetrated the mainstream automobile market within the past decade, public attitude towards EV adoption has been evolving rapidly over this time frame. Due to this, there are many available works which have sought to identify, isolate, and quantify different variables' influences on EV adoption. Most of these works, however, have found that at their time of writing it's very difficult to quantify the influence of demographic and socioeconomic factors on an individual's decision to purchase an EV. This is likely due to the fact that EVs adoption until very recently has been very minimal, leading to smaller sample sizes and lack of available data. Still, some notable predictors from the literature have been identified and noted in order to inform the modeling techniques used in this study. (Nasir, 2022) specifically examines two indices that can be used to predict EV adoption rates; Technology Readiness Index (TRI), and Desire for Unique Consumer Products (DUCP). Though it relies heavily on survey results from the United Kingdom, the many similarities in attitudes between citizens of the UK and the US means that the findings still provide relevant insight to how the TRI and DUCP could play a role in EV adoption within the ERCOT serviced counties of Texas. In particular, the influence of the TRI justifies this work's examination of public charging infrastructure availability as well as researching if current EV battery capacity is likely to meet range demands from travel patterns within the state.

(Sierzchula, 2014) uses an ordinary least squares (OLS) regression using EV registration data from 2012 across over 20 different countries to identify factors that are expected to be influential for EV adoption. It is worth noting that this study is nearly a decade old and is not specific to the United States, meaning that its scope is rather broad. However, these insights are advantageous to have as they span a broader spectrum of socioeconomic factors and show their influence on EV adoption prior to many of the incentivization initiatives that have since taken hold in the United States. It ultimately found that charging infrastructure and financial incentives were the most effective predictors of EV adoption. It also found that in its modeling, socioeconomic factors such as income, education level, and concerns environmentalism were not accurate predictors of EV adoption, though it states that this may be due to the relatively small market share of EVs when the used data was collected. A more recent study, (Xue et. al, 2021), found that household income did indeed play an important role in EV adoption. This work, however, also used analyses on a global level using aggregated data from individual countries.

While these studies are helpful for guiding this work's methodology, the evaluation of their breadth reveals a substantial gap in the literature when it comes to local analyses. Because this study is motivated in large part by providing insight to maintain ERCOT's resiliency, additional and novel analyses of factors influencing adoption on a local level across Texas are crucial to ensuring its findings and takeaways are well informed.

At this time, most available information on forecasted EV adoption rates and their anticipated impacts on ERCOT come in the form of brief news articles, interviews, and editorials. Many of these publications lack robust analyses and also focus on the present-day threat of EV charging to grid conditions, which is negligible due to the presently low presence of EVs in the state, and does not accurately reflect the changes that will result from rapidly increasing adoption rates. There is a significant presence of discussion about the future of EVs and the grids that service them, such as in (Ziegler, 2023) and in (Charette, 2023), however none focus on ERCOT specifically.

A discussion of the future of EVs and Texas's grid was posted to Green Tech Media's website (Deign, 2017). It is, however, intentionally vague about its key takeaways, which is understandable when considering its time of publication, stating that "due to inconsistent demand for electric cars, it's still unknown how quickly these changes might take effect." It was still, however, a timely publication that provided necessary insight to the general public about the electrification of the transportation industry.

These broad level studies have led to in depth simulations of ways to mitigate the negative effects of a growing EV fleet, often in the form of optimization or control problems. (Debnath et. al, 2020) investigates the optimization of EV charging via smart grids in order to achieve peak load shaving. Similarly, (Gilles et. al, 2021) uses model predictive control in order to investigate its potential effectiveness on peak load shaving and found that depending on which of its proposed strategies are used, it can achieve a reduction in peak power of between 14.6% to 33.7%. The knowledge that peak demand increases from EV charging can be successfully reduced by manipulating charging profiles and how much shifting can reasonably be expected is relied upon in chapters 3 and 4 of this work. These chapters briefly examine the difference between the aggregated effects of BAU charging scenarios and controlled charging scenarios. Though no novel applications of optimization and control strategies are included in this work, this is certainly of interest for future research and will be in part driven by the key takeaways and findings of this study, which will show how charging management could be used for peak demand reduction.

1.3 Scope

The scope of this study deals with evaluating the predicting socioeconomic and demographic factors of the adoption of light duty electric vehicles (LDEVs) within the ERCOT serviced counties of Texas. These evaluations are paired with a subsequent analysis of how different EV fleet growth patterns can be expected to impact ERCOT, making it suitable for informing decisions regarding statewide policy, operation, and infrastructure plans in Texas.

The predicting factors for EV adoption are all evaluated using data available on a county level. This means that it would be useful for informing local utilities of how they can expect demand to change due to the potentially highly disruptive growing presence of EVs within their service. It could also provide insight to the level of flexibility they might expect to have with V2G (vehicle-to-grid) technology, which in turn could help mitigate this demand increase if managed properly, however specific V2G strategies are beyond the scope of this particular study.

Additionally, this paper examines the difference between the aggregated effects of uncontrolled and controlled statewide charging profiles. The profiles used for this work were determined primarily using the Alternative Fuels Data Center's EV-Lite tool (Alternative Fuels Data Center, 2022), though as mentioned previously in the literature review, the simulation of specific charging management strategies are of interest for future studies.

1.4 Structure and Organization

The remainder of this work will cover the methodology for building predictive models for determining EV presence within ERCOT serviced counties in Texas based primarily off of socio-economic and infrastructure related factors. It then covers the intuition and process behind fine-tuning, cross validating, and simplifying these models so that they can be applied more generally and effectively.

It then covers how expected statewide EV market shares are determined from different financial, policy, and infrastructure related incentives. Once these expected market shares are identified, they are translated into expected grid impacts using historical data of the travel patterns and tendencies of Texas drivers, as well as different charging management scenarios. Following the sections on methodology, the results are presented and discussed, along with a case study regarding the population serviced by Austin Energy and what anticipated EV penetration scenarios could look like in the context of a direct current optimal power flow (DC-OPF), performed in collaboration with a colleague from my lab group. Lastly, the study is summarized and the key findings and takeaways are presented.

Chapter 2: Modeling EV Adoption Rates

2.1 Identifying important feature variables

In order to identify potential influences or predicting factors on EV adoption rate within a population, learning algorithms were used to create regression models for a combined data frame. This model incorporates data from the 2021 American Communities Survey (ACS), EV Atlas, and the alternative fuels data center (ACS, 2022), (Ruder, 2022), (AFDC, 2022). The ACS dataset provided information for the demographic and socioeconomic makeup of each county, such as the presence of different racial and ethnic groups, median household value, and education level. EV AtlasHUB provides information for the total number of registered EVs in Texas by county in the year 2021, and the data from AFDC provides the locations of all registered public charging stations across Texas. They were indexed by county using ArcGIS Pro and a shapefile of each Texas county from the US Census Bureau.

After this data was combined, it was cleaned using a variety of methods, such as manually addressing typo in the county names by index inspection, dropping columns which contained mostly N/A values, and replacing remaining N/A values with the column's average.

Initially, multiple learning algorithms were chosen in order to benefit from their differing advantages: linear regression, random forest regression, and decision tree regression. Linear regression was attempted first due to its ease of interpretability, but demographic data in particular is prone to exhibiting multicollinearities. This is why random forest and decision tree regression were also used based on their ability to learn non-linear relationships. For each model, a grid search was performed in order to identify the best hyperparameters for each model using 5-fold cross validation. This helped to eliminate overfitting to the training data and create more robust, generalized models that still perform well with new data.

Using a standard 80/20 train-test split, once each model was created with the best identified hyperparameters, each model's top ten important feature variables were examined along with each model's performance metric. The split also arbitrarily set the random seed to 1 so that the results would be reproducible. These features, along with intuition gathered from the previously discussed literature review, which identified property value and TRI as being particularly important factors for EV adoption, were used to create a finalized and more targeted list of feature variables. The known importance of the TRI in particular was the primary reason for including a variable which indicates the presence of public charging infrastructure.

Many of the feature variables listed here from the 2021 ACS dataset are collinear with each other. For example, median value, which refers to the median value of the occupant's home, is strongly tied to the median rent to rent out such a property.

Demographics regarding race and ethnicity were not taken into consideration due to their relatively sporadic presence in highly important feature variables. Additionally, the number of feature variables was limited in order to show that EV presence can be predicted with relatively few known variables, making data availability less of a concern when looking to apply the results to adoption predictions. With all of this considered, a finalized model was created using six feature variables.

2.2 Simplified Modeling

As discussed in chapter 2.1, six target variables were chosen to predict the presence of EVs within ERCOT serviced counties. These variables are: (i) the presence of public level 2 chargers, (ii) county classification (urban vs. rural), (iii) presence of single-family housing, the (iv) population 25 years or older holding a bachelor's degree, (v) the population between ages 44 and 55, and (vi) the county's median household value. 5-fold cross validation was also used to find the best performing version of each model, and the same arbitrary random seed of 1 was used to ensure the reproducibility of results.

One of the goals of creating simpler, lower dimension, models was to eliminate the influence of multicollinearity between feature variables. Because of this a heat map was created in order to visualize any potential multicollinearity. For a more quantifiable approach, a principal component analysis (PCA) was performed on each pair of variables to determine if there were any high loadings (close to -1 or 1) on a particular component. It is often acceptable to include variables with a PCA score at or below .3, meaning that there is not a particularly strong multicollinearity between the chosen variables (Perez, 2017).

For all three modeling methods the root mean squared error (RMSE), mean squared error (MSE), mean absolute error (MAE), and R^2 were determined in order to assess overall performance as well as performance both before and after many of the feature variables were removed.

Chapter 3: Understanding the grid impacts of different adoption scenarios

3.1 EV Adoption incentives and growth rate scenarios

Figure 3.1 is a flowchart of the broad steps taken to evaluate how a specific set of incentives may affect EV adoption, and by extension, ERCOT. Information that didn't require significant analysis or extrapolation meaning that it was readily available is highlighted in gray. The first three boxed steps outline the first general steps of the process, which help to determine an EV adoption rate that results from a given set of incentives. This rate can then be used to find the EV percentage (the percentage of the LDV fleet made up of EVs) for a given year.

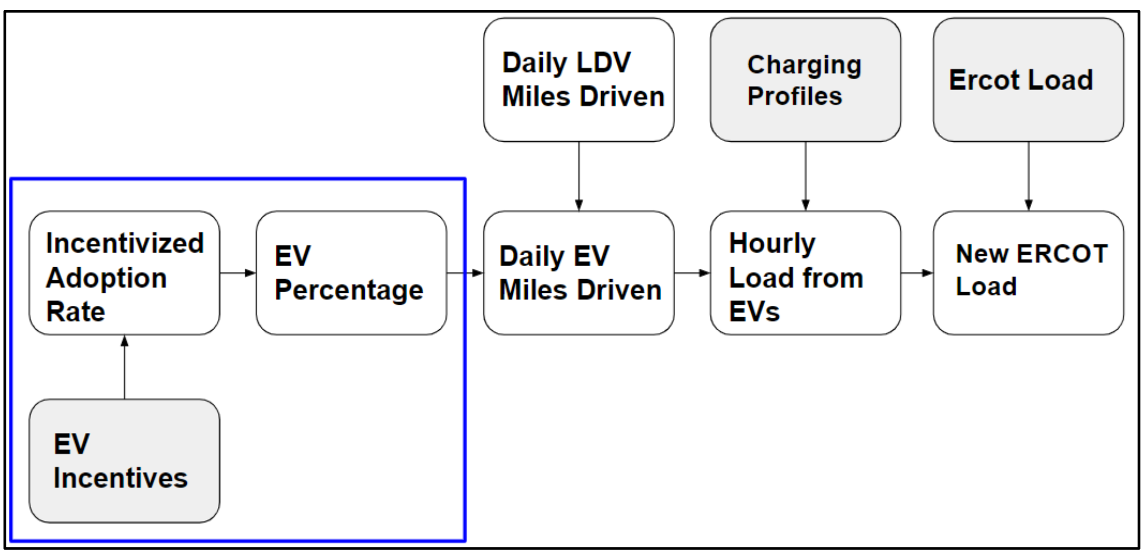

Figure 3.1: Overview for finding incentives' resultant impacts on ERCOT with highlighted steps for determining EV percentage

3.1.1 2030 Projections for EV fleet size

Some of the projections into 2030 rely on the examination of existing, explicitly stated market goals or reputable projections. The market share goal examined is the Biden Administration's goal of achieving a 50% market share by 2030. Additionally, ERCOT's relatively conservative projection for approximately 1 million EVs on Texas roads by 2030 is examined as well as the IEA's much more generous projection of 3 million.

This work also sought to evaluate how current, existing incentives might translate to future EV percentages and by extension grid impacts. Such evaluations relied on differences between BAU (business as usual) scenarios (where EV growth is only driven by intrinsic demand from the consumer) and their incentivized counterparts (where EV adoption is manipulated through incentives). Trends for EV adoption in the US were analyzed in (Archsmith et. al, 2021) in order to outline three potential BAU scenarios which differ by level of intrinsic demand (low, medium, and high). Low growth corresponds to a 15% YoY (year on year) growth rate decline, medium growth corresponds to a 10% YoY growth rate decline, and high growth corresponds to a 5% YoY growth rate decline. In this case, a lower decline in growth rate between years leads to a higher overall growth rate for each year.

Once the BAU scenarios were evaluated, data on incentives for EV adoption and their estimated effectiveness on increasing adoption rates from the findings in (E. Narassimhan and C. Johnson, 2018) were used to project a new, incentivized market share and corresponding EV percentage. These projections, along with the previously discussed projections from ERCOT, the IEA, and market share goals, directly translated into an EV percentage that could then be applied to the LDV usage patterns of Texas drivers analyzed later in this chapter.

3.1.2 2050 Projections for EV fleet size

Due to increased uncertainty that is inherent to increasing a prediction's time horizon, an altered approach was used for projections beyond the year 2030. Also taken into consideration is the fact that the largest incentive regarding EV adoption (a $7,500 federal income tax credit) is currently a result of the inflation reduction Act of 2022, which will only be in place through 2031. Therefore, projections for 2050 did not rely on estimates from a specific set of incentives, as it is too difficult to know what public attitude, policy, fleet makeup, etc. will look like beyond this time frame (Inflation Reduction Act, 2022). Instead, market share achievements were evaluated at face value, without any consideration for the specific pathway used to accomplish that goal. Despite increased levels of uncertainty, these distant market shares are still important, especially because as the EV fleet grows its effects will be even more prominent in later years.

For a market share benchmark for the year 2030, a corresponding market share benchmark for the year 2050 was estimated using existing projections scenarios from (Grid Integration Tech Team, 2019). These market share benchmarks between 2030 and 2050 were modeled as being approached linearly over time, and the total number of EVs registered at the end of each year were determined using Eq. 3.1. In this equation, n is the year, EV is the total number of registered at the end of year n, $MS_n$is the EV market share in year n, and LDV_n is the total number of EVs registered it the end of year n.

$$EV_n = \frac{15}{16}EV_{n-1} + MS_n \times \frac{1}{16}LDV_n \quad \text{(Equation 3.1)}$$

Only 15/16ths of year $n-1$'s EVs carry over into year n because the average turnover time (length of time that LDVs are used before being discarded or scrapped in the United States) is 16 years (Keith et al, 2019). The is also why 1/16 appears in the second term, as it allows the equation to use this turnover time to estimate how many LDVs are going out of commission in year n and being replaced by either an EV or another non-electric LDV. Multiplying the LDVs going out of commission by the market share yields the number that will be replaced by EVs in that year.

3.2 LDV Usage patterns and electricity demand from EV fleets

The next steps of methodology to be discussed is determining the daily LDV miles driven. This is then combined with the EV percentage that results from the incentivized adoption rate to find daily EV miles driven and then the hourly load from these EV miles by applying known charging utilization ratios (GridPIQ, 2022). This hourly load is then combined with the BAU ERCOT hourly load in order to identify changes in peak demand.

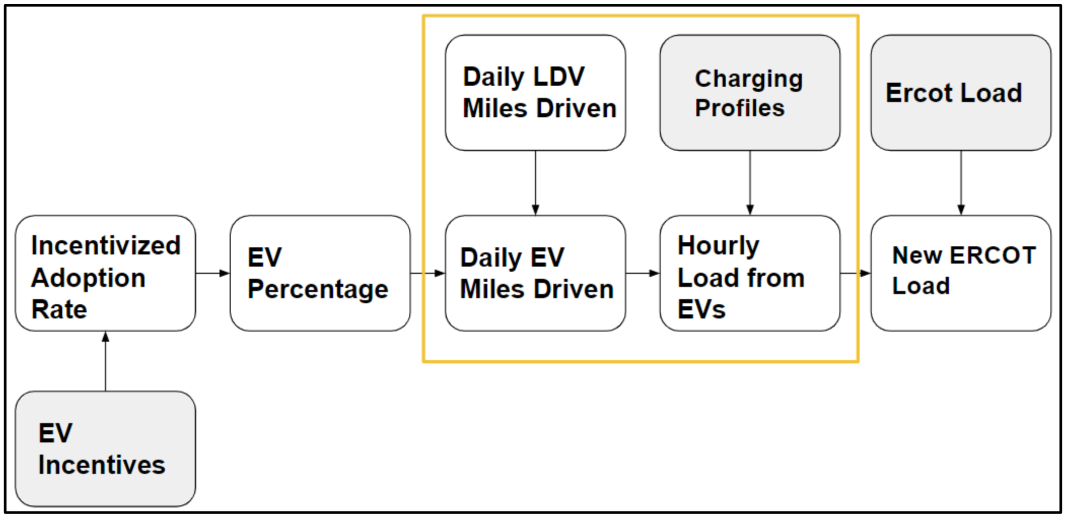

Figure 3.2: Overview for finding incentives' resultant impacts on ERCOT with highlighted steps for determining travel patterns that an EV percentage will then be applied to.

In order to translate EV adoption rates to an electricity demand, it is important to understand the travel patterns of LDV users within ERCOT serviced counties. By understanding how many trips are taken by LDV each day and the average mileage achieved depending on the length of the trip, the amount of electricity required to power the states' EV trips in kilowatt-hours can be determined using Eq. 3.2. This equation states that the total electricity demand from the statewide EV fleet for a given day is equal to the current EV percentage (P_{EV}) multiplied by the summation of each LDV's trips' miles traveled ($MilesTraveled_{LDVFleet}$) multiplied by the mileage for the trip's distance in kWh/mile ($Mileage_{TripDistance}$).

$$kWh_{EVs} = P_{EV} \times \sum_{n=1}^{\#\,of\,trips} MilesTraveled_{LDV\,Fleet_n} \times Mileage_{TripDistance_n}$$

(Equation 3.2)

The EV percentage of interest for a given scenario will have already been identified using the methodology of chapter 2. Depending on the trip's length, a different value for mileage was used. This was done in order to account for the fact that EVs mileage tends to decrease as speed increases. Longer trips were assumed to have been taken primarily via highway at faster speeds, meaning that the assigned mileage was lower than shorter trips, which were assumed to have been taken on residential roads at slower speeds. (Duan, 2013).

A given day's miles traveled by LDV was determined using data from (BTS, 2022), which provides data sets for daily travel in the United States down to the county level. Data from 2019 was used in order to avoid the influence of covid lockdown measures on typical travel patterns. Because the Bureau of Transportation (BTS) data set was created from GPS tracking, it only logs each person trip and not each vehicle trip, which is a more immediate concern because they can directly show the percentage of distance traveled that can be electrified within the LDV Fleet by changing the transportation mode to its electric counterpart.

In order to estimate the trips taken by LDV, this data was supplemented with additional data from the Federal Highway Administration (FHWA) as well as additional data from BTS (FHWA, 2015), (BTS, 2011). These data sets both provided more information on how many Americans choose to drive by car for a given trip distances versus taking a plane, walking, using public transportation, or other alternative modes. The BTS dataset specifically focused on long distance transportation modes, and the FHWA dataset encompassed a wider breadth of trip distances. Taking into account all of these studies and data sets allowed for the creation of multipliers for different categories of trip distances which facilitate a conversion from person trips (PT) to vehicle trips (VT), eliminating the person trips not taken by vehicle and accounting for carpooling.

The FHWA dataset provided data for the distribution of trips taken by purpose classifications as well as the distribution of trips taken by distance classifications. In order to then find the distribution of transportation modes by trip purpose, Baye's theorem was applied as shown in Eq. 3.3.

$$P(Purpose|Distance) = \frac{P(Distance|Purpose) * P(Purpose)}{P(Distance)} \quad \text{(Equation 3.3)}$$

In this equation, $Purpose$ is the category of trip purpose, and $Distance$ is the distance range that the trip falls under. The trip purposes by distance were then paired with data for party size by purpose, allowing the multipliers to also account for carpooling.

As shown in Eq. 3.2, the estimated daily miles traveled, anticipated EV percentage, and the assumed average mileage of each trip taken by EV can all be used to estimate the daily demand from a given EV fleet percentage in Texas.

The daily demand for a hypothetical EV Fleet in Texas can then be converted to an hourly demand by applying business as usual (BAU) charging profiles from data collected by Grid Project Impact Quantification in order to appropriately distribute the electricity consumption over the course of day (Grid PIQ, 2022). The charging profiles from GridPIQ were presented both for weekdays and weekends, allowing for this analysis to take into account the variance in electricity demand throughout the week. Once this hourly demand was found, it was added to historical data from ERCOT for hourly load over the duration of a year (ERCOT, 2020). The year's peak demands, both before and after the EV Fleet load was added to historical data, were identified and then compared in order to determine a peak load increase factor (PLIF). This factor describes the average ratio between a one-point increase in EV percentage ($EV\%$) and a one percentage point increase in peak load ($PeakLoadIncrease\%$) as described by Eq. 3.4.

$$PLIF = \frac{PeakLoadIncrease\%}{EV\%} \text{ (Equation. 3.4)}$$

Though projections for peak load and vehicle registrations within the state show probable growth into 2030 and 2050 (ERCOT, 2022), the PLIF as a percentage for a given adoption scenario is assumed to be applicable to future years (TDC, 2021). This is because a predictable driver for both the change in a state's LDV fleet size and electricity usage is its change in population. The relationship of the PLIF to both the state's LDV fleet size and electricity usage is shown in Eq. 3.4, where $PLI_{\%}$ is the peak load increase as a percentage of business as usual (BAU) demand, $\Delta EV_{\%}$ is the change in EV percentage, EV_{load} is the charging demand from the EV fleet during the grid's time of peak load from a fully electrified LDV fleet, LDV is the number of light duty vehicles in Texas, and PL_{BAU} is the ERCOT's BAU peak load.

$$PLI_{\%} = \frac{\Delta EV_{\%} \times LDV \times EV_{load}}{PL_{BAU}}$$ (Equation. 3.5)

Here it is apparent that as the PL_{BAU} and LDV both scale at similar rates according to population, population growth into future years does not change the $PLIF$ from Eqn. 3.2.

It is important to note that the PLIF is obtained by analyzing BAU charging patterns. However, as mentioned in the literature review, many utilities and aggregators are interested in the implementation of charging management in order to reduce peak demand increases while still providing the same total amount of energy to the EV fleet. This study does not introduce any new proposals for charging management, but does seek to demonstrate its usefulness in the future, and is also of great interest for future works.

For each simulation's determination of peak demand, a complementary scenario was simulated with all parameters and methods remaining identical except for the EV fleet charging load profile, which was replaced with an example of a shifted profile obtained from AFDC, which assumes greater public charging availability, the strategic use of delayed charging, and the use of even spread charging. Its results showcase the potential for charging management to play a key role in limiting a growing EV fleet's costly effects on electricity users and utilities.

3.3 Austin Energy case study

To demonstrate how the modeling of predicting factors and EV growth can be paired with data on the effectiveness of incentivization to translate into grid impacts, a smaller scale case study was performed for the utility company that services much of Travis County, Austin Energy. This was done in collaboration with my colleague, Dipanjan Ghose, a master's student in the electrical engineering department at The University of Texas at Austin. This case study uses an estimated EV fleet size to run a direct current optimal power flow (DC-OPF) for the years 2030 and 2050 in order to see if the utility's grid fails under the simulated conditions. My colleague's contribution is running the DC-OPF for Austin Energy and generating relevant figures using the projections from this study.

We first needed to identify which intrinsic demand values (low, medium, or high growth) would be appropriate to use for Travis County. This was identified using the modeling methods outlined in chapter 2.

In order to apply these models to a categorical criteria of low, medium, or high, a new categorical target variable was created in order to classify each county with EV presence below the 33rd percentile as low, each county with EV presence between the 33rd and 67th percentile as medium, and each county in the 67% percentile as high. A random forest classifier model was then created using this data with the same 6 feature variables. After applying the model to Travis County, an appropriate growth rate was selected to simulate. Additionally, data on EV presence is available down to the zip code level (Ruder, 2022), so these growth rates were applied to each zip code in order to distribute EV presence to nearby buses as accurately as possible.

Chapter 4: Results and Discussion

4.1 Influences on EV adoption rates - results & discussion

The top identified feature variables for predicting EV presence within Texas counties from each modeling technique are presented in Table 4.1, which helped to inform the training of simplified regression models, with random forest regression in particular having the best performance in 3 out of the 4 evaluation metrics: RMSE, MSE, and R^2 value. Also of important consideration was the proven importance of TRI for EV adoption (Nasir, 2022), which is tied to the ability of current infrastructure to handle the adoption of new technologies, making public charging an important factor to investigate.

Table 4.1: Initial identification of Important Feature Variables to predict EV presence

	Top 10 Feature Variables
Ridge Regression	1. Classification (Urban vs. Rural) 2. Population 45 to 54 Years of Age 3. Not Hispanic or Latino: Asian Alone 4. Population 55 to 64 Years of Age 5. Population 10 to 14 Years of Age 6. Population Aged 25 Years and Over with Bachelor's Degree 7. EV Level 1 Chargers 8.Population Under 5 Years of Age 9. Housing Units: 2 10. Not Hispanic or Latino: Black or African American Alone
Decision Tree	1. Median Home Value 2. Median Gross Rent 3. Population Aged 25 Years and Over with Bachelor's Degree 4. Population 5 to 9 Years of Age 5. Housing Units: 1 Unit: 1, Attached 6. Housing Units: Mobile Home 7. Population Aged 25 Years and Over with Doctorate Degree 8. Population Aged 18 to 24 Years 9. Median Year Structure Built 10. Not Hispanic or Latino: Some Other Race Alone
Random Forest	1. Median Home Value 2. Median Gross Rent 3. Population Aged 25 Years and Over with Bachelor's Degree 4. Population Aged 25 Years and Over with Doctorate Degree 5. Population Aged 45 to 54 Years Old 6. EV Level 2 Chargers 7. Population Aged 25 Years and Over with Master's Degree 8. Housing Units: 20 to 49 9. Median Year Structure Built 10. Housing Units: 50 or More

The following feature variables were selected for a second round of more simplified modeling for more practical use. Classification (urban vs. rural) was chosen due to its heavy influence on the average number of EVs per person. The average is nearly four times higher for counties in MSAs than for rural counties. EV level 2 charger presence was selected due to the clear influence of charging availability on EV adoption. Level 2 chargers were chosen over their level 1 or 3 counterparts due to their much higher prevalence in Texas and to avoid skewing the model with two heavily correlated feature variables. Population aged 25 years or older with a bachelor’s degree was chosen for similar reasons; higher education is clearly an influencing factor and bachelor’s degrees are inherently more common than those earned after an undergraduate degree is earned. Housing Units: 1 Unit was chosen due to the high likelihood of those living in single family households having access to garages with charging ports.

The results from the PCA between these variables were all under 0.3, which as mentioned in chapter 2 is acceptably low. Additionally, a heatmap of the six variables is shown in figure 4.1.

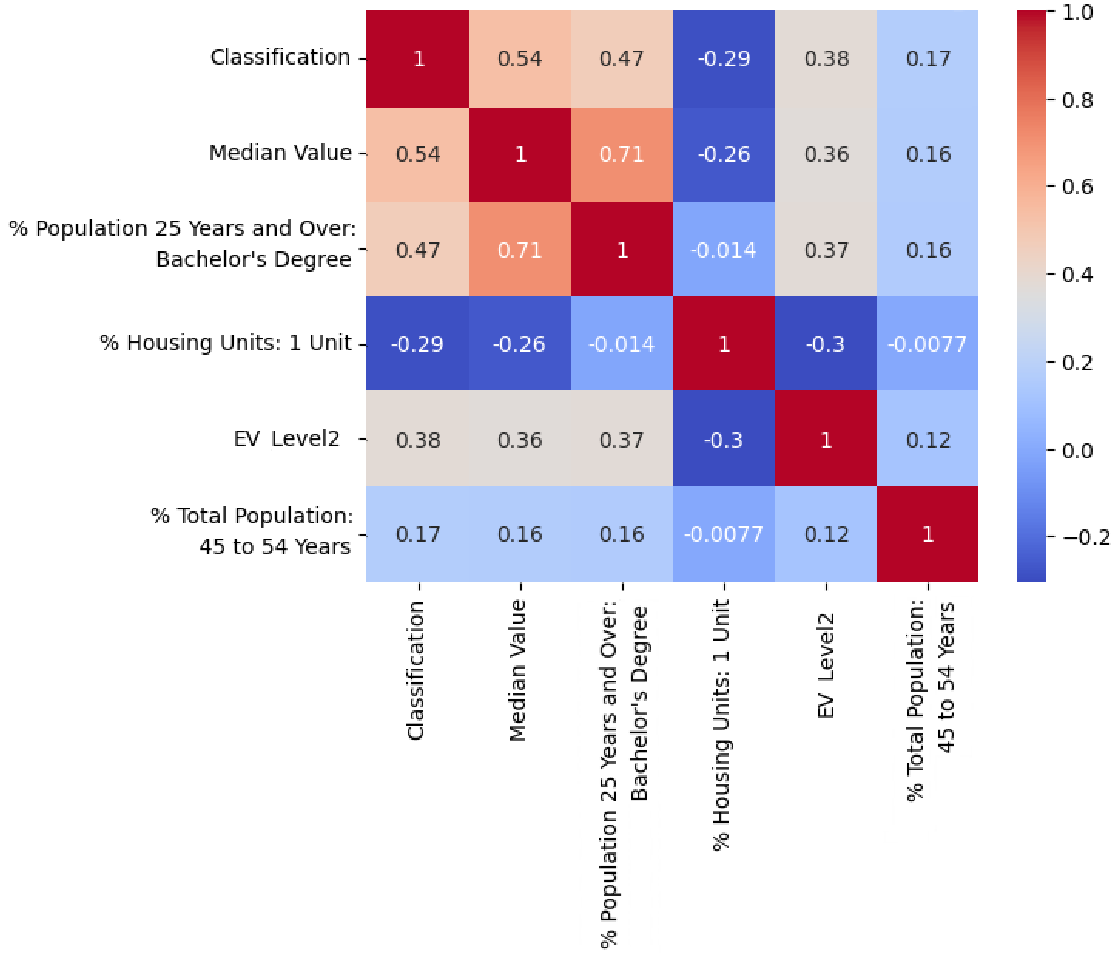

Figure 4.1: Heatmap of feature variables used for the targeted modeling of EV presence by socioeconomic factors.

It is apparent that the median value, which refers to the median house value of the county, is somewhat strongly correlated with the urban vs. rural classification as well as the variable chosen to represent the education level of the community members. However, none of these variables have such strong correlations that they can't still be used to build and train informed models. The correlation between the population 25 years or older with a bachelor's degree and median value is substantial, however both of these represent uniquely important potential drivers of EV adoption, so all 6 variables shown in the heatmap were included in the final modeling process. The performance of the simplified models using these feature variables are summarized in table 4.2 and directly compared with the performance of the models which used all available feature variables.

Table 4.2 Model performance before and after reduction of the number of feature variables

	All available feature variables				6 common feature variables			
Model	R^2	MSE	RMSE	MAE	R^2	MSE	RMSE	MAE
Ridge Regression	.95	5.41E-7	7.36E-4	4.34E-4	.80	8.56E-7	9.25E-4	6.73E-4
Decision Tree	.67	1.26E-6	1.10E-3	6.89E-4	.75	9.39E-7	9.66E-4	6.21E-4
Random Forest	.87	4.81E-7	6.93E-4	4.80E-4	.84	5.78E-7	7.6E-4	4.97E-4

These results show that despite a substantial reduction in feature variables, EV presence can still be accurately predicted without a significant decrease in model quality with the lowest R^2 value of .75, indicating that the predictors (the 6 used feature variables) explain 75% or more of the response variable's (EV presence) variance depending on the model. The errors can be contextualized by providing the scale of the target variable of the number of EVs per person. The average of this target variable for urban counties, where the majority of Texans reside, was 4.6E-3, making the lowest MAE, which is the MAE for random forest regression, about 14% of the target variable in question for urban counties.

Though most models showed a slight decline in performance metrics, the performance metrics of the decision tree regression model improved, possibly in part due to the elimination of erroneous variables. This means that, in Texas, even in cases of limited data availability, it is still meaningful and helpful to use estimations of demographics and infrastructure presence (e.g., public level 2 charging presence) to anticipate EV presence within a community of interest.

4.2 Policy discussion

In August of 2022, the Inflation Reduction Act (IRA) was passed by the 117th United States congress (H.R.5376, 2022). This congressional bill continued and also modified measures in place by the federal government to incentivize the adoption of EVs, most notably in the form of tax credits. Tax credits are of particular importance, because historically the lack of price parity between EVs and traditional gas fired vehicles has been a barrier for adoption (Sierzchula et al., 2014). Before the IRA's passing, there was already a tax credit in place from 2008 (H.R.6049 - 110th Congress, 2008). This credit was worth up to $7,500 for newly purchased EVs and was only claimable for the first

200,000 EVs sold by any manufacturer. Since then, major manufacturers such as Tesla and General Motors have already sold 200,000 vehicles, meaning that their EVs no longer qualify for the credit from 2008.

The IRA put a new $7,500 tax credit in place with some key changes. Called the Clean Vehicle Credit, it implements a requirement for the EVs to be assembled domestically as well as a requirement that will phase in through 2028 requiring increasingly high percentages of the battery and mineral components to be sourced domestically (H.R.5376 - 117 Congress, 2022).

Though these new assembly and sourcing requirements may seem like they will make the tax credit less accessible to consumers as several models of EVs don’t presently meet these requirements (US Department of Energy & Environmental Protection Agency, 2023), it importantly eliminates the 200,000 vehicles per manufacturer limit that was applied to the credit from 2008. This means that companies such as Tesla and General Motors can once again qualify for the credit as they assemble their vehicles in the United States. Tesla alone accounts for over half of the EVs on the road in Texas today, meaning that the Clean Vehicle Credit will likely be more effective than its 2008 counterpart as it now applies to the heavily favored EV manufacturer of Texas (Ruder, 2022).

4.3 Grid impacts

4.3.1 Impacts on ERCOT by adoption scenario

The multipliers for vehicle trip per recorded person trip by distance category are presented below in table 4.3. These were used to put the BTS dataset of travel behavior in a usable format to apply EV percentages to and then find electricity demand and associated increase in peak demand as characterized by the PLIF, shown in eq. 4.1.

Table 4.3: Average vehicle trips per person trip in Texas by trip distance

Trip Distance (miles)	>3	3-100	100-250	250-500	500+
VT/PT	.684	.922	.515	.513	.508

The average PLIF, or the ratio between a one-point increase in the fleet's EV percentage and the percentage point increase in ERCOT peak demand, was found to be 0.41.

$$PLIF(\%) = 0.41 \quad \text{Eq. 4.1}$$

Table 4.4 provides a summary of the results from existing, and explicitly stated market goals or reputable projections mentioned in section 2 of chapter 3. In this Table, ERCOT and TXDOT refers to ERCOT and the Texas Department of Public Transportation's projection of 1 million EVs on the road by 2030, and Biden Administration and IEA refer to the goal and projections respectively by these entities of achieving a 50% market share by 2030. All projections or targets have also been extended into 2050 for a more generalized look at what certain growth patterns could look like for ERCOT's peak demand.

Table 4.4: Peak load increase associated with various specific market share or fleet size projections and goals

Projection Scenario	2030 Peak Demand Increase	2050 Peak Demand Increase
ERCOT and TXDOT	1.59%	8.82%
Biden Administration and IEA	4.65%	33.6%

ERCOT and TXDOT's conservative predictions show that the peak demand increase would be minimal into 2030, but would at least require consideration should these trends continue. Meanwhile, sustained growth from a 2030 50% market share achievement would result in over a ⅓ increase in peak demand. Given historical ERCOT reserve margins, this would result in blackouts and brownouts without significantly expanding generation capacity or implementing the charging management strategies discussed in chapter 3 (ERCOT, 2022).

Looking at current policies and trends, however, the EV fleet's potential impact looks much different. Current incentives for Texans include a federal income tax credit of $7.5k from the IRA of 2022 and a $2.5k rebate available through the state (TXDOT, 2023). Additionally, there is a plan to install public charging stations along major highways no more than 50 miles apart (Texas Department of Transportation, 2022). With these incentives considered against the three different BAU or baseline scenarios discussed in chapter 3.2, table 4.5 presents the results for peak load increases. As mentioned earlier, the scenarios stemming from specific incentives and legislation are only examined into the year 2030, after which it becomes too difficult to meaningfully predict their impact.

Table 4.5: Peak load increase in 2030 due to current EV policies under different growth scenarios

Baseline Growth Scenario and current incentives	2030 Peak Demand Increase
Low	1.74%
Medium	2.04%
High	2.47%

Here, the peak demand increase in 2030 remains in between 1 and 3%, which is well within ERCOT's reserve margins (ERCOT, 2022). The scenario above also results in a 30% market share for the high growth scenario, falling short of the 50% market share goal the nation is targeting despite assuming the most optimistic levels of intrinsic demand from the consumer. This indicates that continued incentivization and advocating for EVs will be necessary to reach this target.

4.3.2 Grid Impacts with Charging Management

Next, the potential of charging management to reduce peak demand increase was evaluated using a managed charging profile from AFDC. Figure 4.2 shows the differences between the BAU charging profile and managed charging profile and how they line up with ERCOT's peak demand.

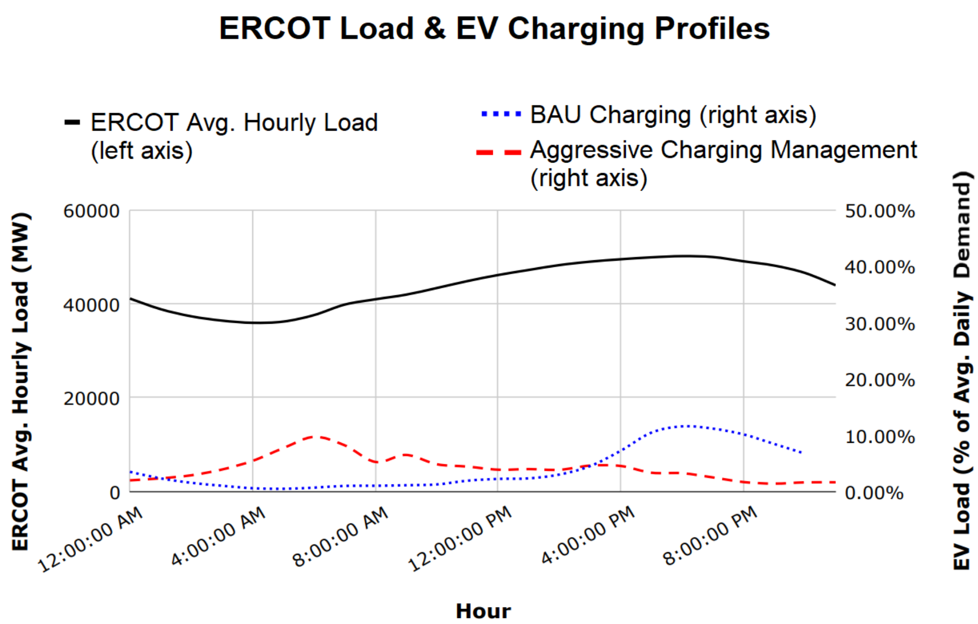

Figure 4.2: ERCOT average hourly demand (left axis) and the BAU and managed charging profiles (right axis)

It is apparent that daily BAU charging patterns overlap by a substantial amount with ERCOT's typical time of summer peak demand as they both peak at 6pm, while the managed charging profile, which shifts much of the EV load between the hours of 12am and 6am, limits this overlap. To examine the potential for charging management to limit peak demand, the managed charging profile was applied to the most ambitious of the evaluated EV growth scenarios, in which a 50% market share is achieved by the year 2030 and follows the growth projections from this point obtained in (Grid Integration Tech Team, 2019).

Table 4.6: Peak load increases from BAU charging and managed charging for the 50% market share achievement in 2030 scenario

		Peak Demand Increase	
Year	Market Share	BAU Charging	Managed Charging
2030	50%	8.82%	2.94%
2050	90%	33.6%	11.5%

As mentioned in the previous section, sustained growth from the Biden Administration's desired 2030 market share achievement would result in a 33.6% increase in peak demand, which given historical ERCOT reserve margins would result in blackouts and brownouts barring significant expansions of generation capacity under BAU charging conditions (ERCOT, 2022). With managed charging, however, it will be possible to limit this peak demand increase to just under ⅓ of what it would have been originally, showing how valuable and important charging management strategies will become to grid operators in the coming decades.

4.3.2 Case Study: EV fleet projections applied to Austin Energy DC-OPF

As discussed in chapter 3, a random forest prediction model trained on data from AFDC, 2021 ACS, and EV Atlas was applied to Travis County in order to decide which growth scenario would be most appropriate to use for simulating a 2030 and 2050 DC-OPF which accounts for EV fleet growth.

When the model was applied to Travis County as a whole, it predicted a high EV presence based on the selected feature variables. Therefore, it was justifiable to use the YoY demand decline rate for a high growth scenario of 5% from (Archsmith et. al, 2021). Under these conditions for 2030, the DC-OPF does not fail, meaning that the generators were able to supply enough power to meet demand at all times, even for that year's anticipated peak demand. The conditions at each generator for that year's expected peak demand are shown in figure 4.3

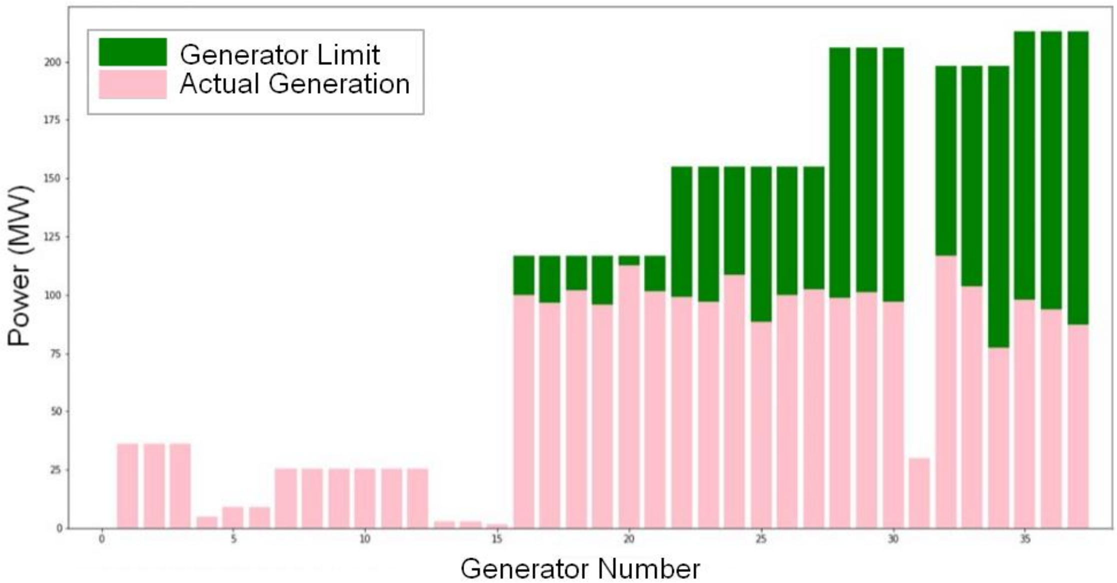

Figure 4.3 Generator conditions for Austin Energy DC-OPF under a 2030 high growth scenario. Green is the remaining generator limit and pink is the utilized power generation during peak demand.

This figure (4.3) shows that the collective required generation to meet the expected peak demand in 2030, which includes an EV presence from a high growth scenario, does not exceed generation capacity.

For the more distant 2050 predictions, we began with using ERCOT's more conservative estimate for 2030 EV presence. The DC-OPF for this scenario immediately failed, meaning that any increase in EV presence to match other predictions, such as ours from the chosen YoY adoption rate, Austin Energy's predictions, or predictions from a market share achievement would also result in failures. It is, however, important to note that due to high levels of uncertainty, we did not account for increases in generation capacity for this DC-OPF, meaning that failures can be avoided, especially taking into consideration the amount of time that still remains to prepare for such a scenario.

Chapter 5: Summary and Conclusions

This study is motivated by the need to address the threats that the electrification of the transportation industry will pose to ERCOT as well as local utilities. It does so by using publicly available data in order to build and refine models which can predict EV presence at the county level within Texas in order to best anticipate which counties will experience the highest growth rates as EV market shares increase. Additionally, it evaluates a variety of EV adoption scenarios within ERCOT serviced counties into 2030 and 2050, taking into consideration current federal and state policy.

These adoption scenarios are then used to quantify the impacts that this grid can be expected to experience from a growing EV fleet. It does so by closely examining Texas's unique LDV travel patterns, ERCOT's historical and projected grid conditions, and using different charging profile scenarios to simulate the effects of management strategies such as price signaling and delayed charging. After assessing the aggregated impact on ERCOT, a collaborative case study is conducted, which simulates a DC-OPF for both 2030 and 2050 EV fleet conditions for a local utility company within ERCOT, Austin Energy.

The scope of this study is limited in part by the fact that no specific charging management methods were developed, and the utilized charging profiles have contextual scaling limitations due to the uncertainty of future charging behavior. Because of this, the development of more flexible modeling and charging management methods are of great interest for future work in order to introduce more directly applicable and achievable strategies for mitigating the grid impacts of a growing EV fleet. The results also need to be taken within the context of an ever changing policy framework and rapidly shifting public opinion regarding the importance of emissions curtailment, especially for the later time horizon of 2050. Nevertheless, the results still provide a basis from which to make informed policy decisions regarding EVs.

This study found that for predicting EV presence at the county level, it is possible to do so with 6 publicly available feature variables while still maintaining high levels of accuracy with an R^2value above .75 and mean absolute error on the order of 10^{-4}, or about 14% of the average EV presence in urban counties, where the majority of EVs are registered. This is in contrast to existing published literature, which largely found no strong correlation between surrounding demographics and EV presence (Sierzchula, 2014). This shift is likely due to the fact that though EV percentages are still low (in Texas's case below 1% in 2021), they are substantially higher than they were when most of the examined literature was published, allowing for larger sample sizes. Additionally, the substantial drop in average price along with continued EV tax credits from the IRA has made adoption more accessible to a larger population (Ewing, 2023), meaning that updated analyses are crucial to understanding these growth patterns.

In evaluating EV adoption pathways, this study notably found that even when assuming the continuation of all current state and federal policies to incentivize EV adoption along with a high intrinsic demand, Texas is likely to fall short of the Biden

Administration's 50% market share target by 2030. This means that barring an abrupt and major shift in public attitude, more action will be required to improve the desirability and accessibility of EV ownership, such as making public charging more accessible.

By evaluating the grid impacts of these EV adoption pathways, this study found that peak demand increases from EV charging will be minimal enough to accommodate with current grid conditions for all growth scenarios in 2030, for both ERCOT and Austin Energy, even without efforts to manage charging profiles. Looking forward into 2050, however, it becomes apparent that more aggressive measures regarding charging management will have to be implemented in order to avoid the potentially costly impacts of a growing EV fleet.

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