# THE IMPACT OF ELECTRIC VEHICLE ADOPTION IN NORTH CAROLINA

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# Contents

**EXECUTIVE SUMMARY ....................................................4**

**INTRODUCTION ....................................................6**

**LITERATURE REVIEW ....................................................7**

**CLIENT....................................................8**

**OBJECTIVE....................................................8**

**BACKGROUND....................................................9**

ELECTRIC VEHICLE DEFINITIONS ....................................................9

CHARGERS CONFIGURATION....................................................10

**METHODS & RESULTS....................................................10**

**SCENARIO DESIGN....................................................10**

**LOAD CURVE MODEL ....................................................12**

DATA INPUTS AND ASSUMPTIONS....................................................13

**REAL-TIME SIMULATION MODEL....................................................16**

MODEL INPUTS ....................................................16

**DISCUSSION....................................................19**

**ECONOMY IMPACTS....................................................19**

BASELINE ....................................................19

COMPARISON ....................................................20

ENVIRONMENTAL IMPACTS....................................................**22**

BASELINE ....................................................22

EMISSIONS COMPARISON ....................................................24

ICE VEHICLE COMPARISON ....................................................27

**NORTH CAROLINA GOVERNOR'S ORDINANCE NO. 80 ....................................................31**

CONCLUSION ....................................................................................................................33

ECONOMIC ....................................................................................................................33
ENVIRONMENTAL ..........................................................................................................33
SOCIAL ........................................................................................................................33

REFERENCES ....................................................................................................................35

## Executive Summary

The U.S total annual sales of Battery Electric Vehicles (EVs) and Plug-in EVs increased from 16 thousand in 2011 to 190 thousand in 2017; a 12 fold increase in size over 6 years (Fitzgerald). The expansion of EVs becomes almost an irreversible trend when one considers the variety of rebate programs, tax incentives and state level EVs penetration goals being implemented. Consequently, the demand for electricity has increased rapidly, which creates new challenges and opportunities for the electricity generation system and the power grid. On the one hand, this additional electricity demand from EVs could significantly increase the peak load. Some studies state that daily peak demand would increase by over 15% if the market share of EVs exceeds 10%, which might have enormous and comprehensive impacts on supply-side energy management (Qian, Kejun et al). On the other hand, the increasing use of EVs could offer a number of opportunities to reduce carbon emissions and pollutants, increase integration of renewable energy resources, and promote advanced metering infrastructure and smart grids if suitable policy and economic instruments are implemented on the demand side.

The North Carolina Sustainable Energy Association and The Nicholas Institute of Environmental Policy Solutions are the clients sponsoring this project. They are interested in identifying the impacts of EVs if they are to advocate for state-level EV incentives in the future. The North Carolina Governor’s Executive Order No. 80 that states a goal of 80,000 Zero Electric Vehicles (ZEV) by 2025 is also taken into consideration in this project.

This project assess the impacts of different scenarios of penetration of EVs in the Duke Energy Carolinas/Duke Energy Progress (DEC/DEP) region in 2030. Specifically, the project simulates the real-time operation of EVs in 2030 and provides economic, environmental and social insights. To achieve these goals, the project consists of the following approaches:

1) Characterizing scenarios of EVs penetration in the region that take EV growth and charging patterns into consideration.

2) Creating a model to generate the additional demand caused by the different scenarios
3) Utilizing Aurora, an electric modeling, forecasting, and analysis tool, to simulate the impact of the additional demand on the DEC/DEP system in 2030.

From an economic standpoint, research indicates that the charging behavior will only lead to a small change in the levelized cost of electricity (LCOE) - the influence is negligible. However, demand shows a significant positive relationship with LCOE. The higher the demand, the higher the LCOE.

From an environmental standpoint, the research implies that under the predicted energy mix in 2030 at DEP/DEC area, the higher the EV penetration, the higher the annual $CO_2$, $NO_2$, and $SO_2$ emissions will be. Also, day-and-night charging behavior generate slightly fewer emissions than night-only charging behavior. Moreover, compared to the internal combustion engine (ICE) vehicle, EVs do not necessarily emit less $CO_2$ and $NO_2$ than the ICE in the scenarios modeled, and EVs consistently lead to higher $SO_2$ emissions than ICEs.

Lastly, the project underlines the relationship between the impact of electric vehicles and the generating fleet. Both economic and environmental impacts are connected to the generating fleet and will not improve until coal and natural gas are not the primary fuels used to meet additional demand.

## Introduction

The growing concern over carbon emissions and the greenhouse effect has prompted a resurgence in the development of battery-powered electric vehicles (EVs). EVs are expected to play a key role in reducing the transportation sector's carbon footprint. 28% of all 2016 greenhouse gas (GHG) emissions came from the transportation sector – this is primarily carbon dioxide emissions from the combustion of petroleum-based products (EPA, Greenhouse Gas Emission Sources). Passenger cars and light-duty trucks are the largest sources of transportation-GHG emissions accounting for more than half of them in this sector. Electric vehicles are a potential solution to the transportation sector's emissions problem. The Natural Resources Defense Council reports that, in 2050, there would be 430 million to 550 million metric tons carbon pollution reduction annually with the different light-duty EV penetration, which is equivalent to 80 – 100 millions of current conventional vehicles' emissions (Tonachel, 2015).

Many states in the US are trying to advocate for increased electric vehicle adoption as they recognize the potential benefits of a more electrified vehicle fleet. California (CA) is probably the staunchest advocate for EV adoption. The California Air Resources Board (CARB) created the Zero Emissions Vehicle (ZEV) program to help reduce the effects of air pollution affecting the state's main metropolitan areas. The ZEV program is part of CA's Advanced Clean Cars package of coordinated standards that controls smog causing pollutants and greenhouse gas emissions of passenger vehicles in CA. The latest development in the ZEV regulation requires auto manufacturers to produce a number of ZEVs and plug-in hybrids each year, based on the total number of cars sold in CA by the manufacturer (Zero Emissions Vehicle Program, CARB). The required sales volume is based on a percent credit system where each vehicle is assigned credits based on its electric driving range – the greater the range, the more credit it receives. CA also has a Clean Vehicle Rebate Program that offers rebates up to $7,000 for the purchase or lease of new eligible zero-emission vehicles (About CVRP).

When considering advocating for a new policy to increase EV adoption, it is important to understand the implications of the perceived change. The scenario-based analysis is necessary to better interpret the consequences of different adoptions rates of electric vehicles in the future. The challenge to accurately model the effect of increased EV adoption becomes important as more and more states look to advocate for adoption. There are a number of variables that will affect the future of electric vehicles that need to consider: vehicle models and specification, charging infrastructure, and customer perception to name a few. A better understanding of what the future of EV adoption looks like can aid in future planning to support the effort.

## Literature Review

The initial focus of this project was on transforming the expectation of EVs market share into the hourly load curve before generating real-time simulations in Aurora. In other words, the goal was to calculate microscopic additional load stimulated by EVs charging and its distribution based on the macroscopic prediction of EVs. Some studies have developed several methods to do this. Moon conducted a survey of Korean EV user charging patterns, and used multiple linear models to predict the additional electricity consumption and its distribution. (Moon, HyungBin, Stephen Youngjun Park, Changhyun Jeong, and Jongsu Lee, 2018).

P. Zhang developed a model to solve the optimization problem of charging distribution, and it showed that EV charging load has significant potential to improve the daily load profile of power systems if the charging loads are optimally distributed. (Zhang, Peng, Kejun Qian, Chengke Zhou, Brian G. Stewart, and Donald M. Hepburn, 2012). K. Qian simulated three scenarios, comprising of uncontrolled charging, controlled off-peak charging and smart charging to determine the EV battery charging load on the power system load profile. (Qian, Kejun, Chengke Zhou, Malcolm Allan, and Yue Yuan, 2010). Li and Zhang modelled overall charging demand at an EV charging station and in a local residential community respectively. (Li, Gan, and Xiao-ping Zhang, 2012). Finn, Fitzpatrick and Connolly set a goal at 10% EV penetration by

2020, and then examined how to optimize the charging cycles of an electric car using DSM (Demand Side Management). (Finn, P., C. Fitzpatrick, and David Connolly, 2012)

The project then shifted to look into the real-time simulation in Aurora and examine if the Aurora outputs can address economic and environmental issues. Gabel Associates proved that Aurora enabled the company to provide a wide range of rigorous modeling and forecasting services to clients by offering emission, fuel prices, dispatching information and case studies. (Gabel Associates, 2018). Also, Conejo et al used Aurora to study the distributed energy resources market. (Antonio J. Conejo, Juan M. Morales, and Juan A. Martinez, 2011)

## Client

The North Caroline Sustainable Energy Association (NCSEA) and the Nicholas Institute for Environmental Policy Solutions are clients for this project. In early 2017, NCSEA created an Electric Vehicle and Charging Infrastructure Policy Working Group (EV Working Group), to help facilitate the development of a clear and consistent policy framework to accommodate the growth in EV sales. They are interested in the understanding the economic and environmental impact of EV adoption if they are going to advocate for state-level incentives.
They are interested in identifying the impacts caused by increasing EVs penetration if they plan to advocate for state-level incentives.

## Objective

This analysis will provide a comprehensive evaluation of the economic, environmental, and social impacts of an increase in electric vehicle adoption in the Duke Energy Carolinas / Duke Energy Progress (DEC/DEP) North Carolina territory in 2030. It will model multiple different growth scenarios and charging behavior patterns in order to better understand the effect of different variables on an electrified transportation future.

The economic impact is evaluated in terms of the shift in clearing prices in the wholesale market and the additional costs incurred to meet growing electricity demand. The environmental impacts are assessed by comparing the additional generation emissions to potential tailpipe emissions as well as changes between different growth rate scenarios. The social impact is reflected in the different charging scenarios chosen and their impact on demand.

## Background

Although electric vehicles made up only 2.1% of new car sales in the US in 2017, this number will continue to grow as battery prices decline, the charging infrastructure is expanded, and customer purchasing behaviors begin to change (EV Volumes-USA). According to Bloomberg New Energy Finance, 54% of new car sales and 33% of the global car fleet will be electric by 2040 (BNEF EV Outlook). It appears that the increasing penetration of EVs is a global trend and supported by most of the countries. According to the data from Plug-in NC, there are more than 7,500 electric vehicles and 1,000 public charging sites in North Carolina, and 200 new charging ports are expected to be added soon (Plug In NC 2017 Annual Report). There are currently 17 models of electric vehicles available for purchase in North Carolina, with many more models expected in the coming years. Travel range for these vehicles are increasing dramatically, while vehicle costs are declining.

## Electric Vehicle Definitions

In this research, EVs refer to Plug-in Electric Vehicles, which include Plug-in Hybrid Electric Vehicles (PHEV) and Battery Electric Vehicles (BEV). PHEVs have an electric motor and an internal combustion engine, so they use electricity and other fuels such as gasoline or diesel for power (AFDC). BEVs only have an electric motor and battery, deriving all the power from electricity (USCUSA). According to the most recently available EVs sales data provided by Argonne National Laboratory, the top three PHEVs are the Toyota Prius Prime, Chevrolet Volt and Honda Clarity Plug-In, and top three BEVs are the Tesla Model S, Nissan Leaf and Tesla

Model 3 (ANL.gov). On average, a PHEVs' battery capacity is 11 kWh with a range of 16 miles while BEVs have 50 kWh battery capacity and a range of 172 miles.

### Chargers configuration

There are three charging station levels: Level 1, Level 2 and DC Fast Charge (DCFC). In general, Level 1 charging stations' charging load is 1.4 to 1.9 kW with a 120 voltage outlet. A Level 2 charging station typically has a load of 6.6 kW and a 240-volt outlet. And a DCFC load is typically 50 kW (Plug in NC). Level 2 charging stations are also known as Electric Vehicle Supply Equipment (EVSE). Charging time varies by charging types. Currently, Level 2 charging stations account for the majority among those three, which is around 88% of the total, followed by 8.5% DCFC, and 3.5% of level 1. Level 1 and Level 2 charging stations are installed more for home use rather than in workplaces, while DC fast charging stations are located at workplaces. Also, not all EVs models can charge at DCFC. To charge at DCFCs, the EV has to be compatible with Tesla Supercharger's, SAE Combo or CHAdeMO connector (Go Electric Drive).

## Methods & Results

### Scenario Design

There were two key characteristics used to develop the scenarios: charging behavior and rate of adoption. When developing the load curves for vehicle charging there were two scenarios considered:

1. Night only charging
2. Day and Night charging.

The night charging scenarios assume that charging infrastructure has remained primarily residential and that owners are charging their cars at home in the evening. The day and night charging scenarios assume that charging infrastructure will become more readily available in public places and therefore EV owners will charge both during the day in public (for example at work) and in the evening at home. More details on how the load curves were developed can be found in the next section titled Load Curve Model.

When modeling the rate of adoption there were two factors used to develop the scenarios. First states were chosen based on their policy programs. The goal was to model adoption rates for states that had different policy programs and compare. It is important to note that this project is not drawing conclusions between policy programs and rates of adoption but is just using the policy program as a selection criterion for each scenario. The three states in addition to North Carolina selected for this project are California, Colorado, and Texas.

The rates of adoption were then calculated based on historical annual new car sales. The Auto Alliance's Advanced Technology Vehicle Sales Dashboard has historical data of EV new car sales by state from 2011 to present and this was used to calculate the cumulative number of EVs on the road in each successive year. The cumulative number of EVs was divided by the total number of vehicles registered in each state, provided by the Federal Highway Administration, to determine its percentage of the state car fleet. The percentage of EVs were plotted over time and fit to a linear curve. The slope of the line generated is the adoption rate used for this project's scenarios. An important note that this is not necessarily an accurate percentage of EVs in the car fleet – the sales data used only dates back to 2011 and it is possible PHEVs and BEVs were on the road prior to then. But it is enough to determine a rate of growth over the 7 years of data available.

North Carolina historically has not had EV incentives and has experienced a growth of 0.03% per year. Texas had a $2,500 rebate program for EVs and experienced growth at 0.04% per year (Light-Duty Motor Vehicle Purchase or Lease Incentive Program). Colorado has had a $5,000 tax credit program since 2010 and have experienced growth at 0.09% per year (Tax Credits, Drive Electric Northern Colorado). Lastly California has had the most aggressive incentive program – a $7,000 incentive program for eligible EVs and has had on average 0.35% growth per year (About CVRP). Table 1 below lists the matrix of scenarios that are modeled in this project.

*Table 1 Scenario Matrix*

| | Night Only Charging | Day & Night Charging |
|---|---|---|
| NC Growth Rate | Scenario1_Base | Scenario2_Base |
| TX Growth Rate | Scenario1_Low | Scenario2_Low |
| CO Growth Rate | Scenario1_Mid | Scenario2_Mid |
| CA Growth Rate | Scenario1_High | Scenario2_High |

## Load Curve Model

The load curve model aims to predict the hourly electricity demand profile from EV charging based on different EV penetration level and charging behaviors. The model takes the data inputs described in the following section and generates load curve for charging demand during weekdays and weekends respectively. Figure 1 below depicts the flow chart = used to create this model.

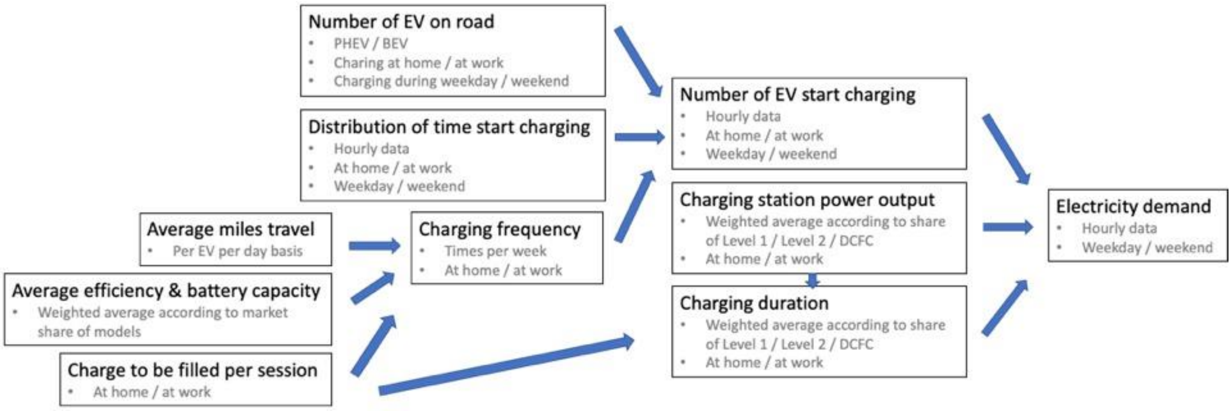

*Figure 1 Load Curve Model Flow Chart*

Average miles travel, EV efficiency, battery capacity and “charge to be filled per charging session” are used to calculate EV owner’s charging frequency. This charging frequency, together with the number of EV on road and “distribution of charging start time” are then used to determine the number of EV start charging for each hour of the day. From the “charge to be filled per charging session” and the charging station power output, the duration of each session is estimated. The final electricity demand is calculated from the number of EV start charging, charging station power output and charging duration.

To avoid excessive dimensions in the model, several inputs or intermediate data were simplified using average numbers. For instance, the battery capacity and miles per gallon equivalent (MPG-e) of different models of BEV and PHEVs were averaged by the weight of the market share of models. The charging station power output and charging duration are also average numbers weighted by the share of charging station types. The only categories kept strictly separate throughout the model is the location of charging (at home / at work) and the time of week (weekday / weekend).

### Data inputs and assumptions

**Number of EVs on road:** this number is obtained by applying each growth scenario to the number of registered vehicles currently in North Carolina to get a projection of EVs on the road for 2030.

**Market share and configuration of EV models:** the new car sales of popular EV models in North Carolina in 2018 from Argonne National Laboratory were used to estimate the market share of each EV model (Argonne National Laboratory, 2018). The configurations of each EV model, including battery capacity and MPG-e, are obtained from the US Department of Energy (DOE, 2018a). A similar market landscape and constant configuration of EVs in 2030 as the current situation was assumed given the limited information on the future trends.

**Market share and configuration of charging station types:** similar market share of Level 1 / Level 2 / DCFC charging stations in 2030 as of the current situation were assumed again given limited information on the future plan. The share of types of charging stations in North Carolina is collected from GoElectricDrive Foundation for both workplace and home charging in the sense that DCFC is less affordable for private owners (GoElectricDrive Foundation, 2018).

**Charging station power output:** The power output of each type of charging station is referenced from PluginNC (PluginNC, 2018). A constant power output at maximum level during each charging session is assumed, neglecting the short period of power ramping at the beginning and end of the charging period.

**Average miles travel:** this project assumes no difference in the average miles travel between EV drivers and traditional ICE drivers since more people are turning to driving EVs in the future. Therefore, the current vehicle miles traveled (VMT) of light-duty vehicle from DOE is used as the average VMT of EVs in our study (DOE, 2018b).

**Charging behavior:** the behavioral part includes data on “charge to be filled per charging session”, “percentage of charging happens at home or at workplace”, and “distribution of charging start time”. 35% and 45% “charge to be filled per charging session” for charging happens at home and at workplace respectively are assumed based on the model parameter in Rocky Mountain Institute’s report (Fitzgerald & Nelder, 2017). 80% of charging, it is assumed, happens at home during weekdays and 95% during weekends for our scenarios, and assume all the charging sessions happen at home for night charging scenarios. Those assumptions are used to calculate a more accurate average charging duration of each session that contributes to the final load curve. For the distribution of charging start time, it is assumed that it obeys a Gaussian distribution around each charging peak according to the assumptions in Cao et al.’s study (Cao et al. 2012).

Figure 2 below shows the results after running each scenario through the load curve model. Upon first glance, there is not enough of a difference in the growth rates of NC and TX in either charging scenario 1 or 2. Therefore, TX was removed from future modeling in order to provide more useful results. The new set of scenarios is listed below in Table 2 and plotted again in Figure 3.

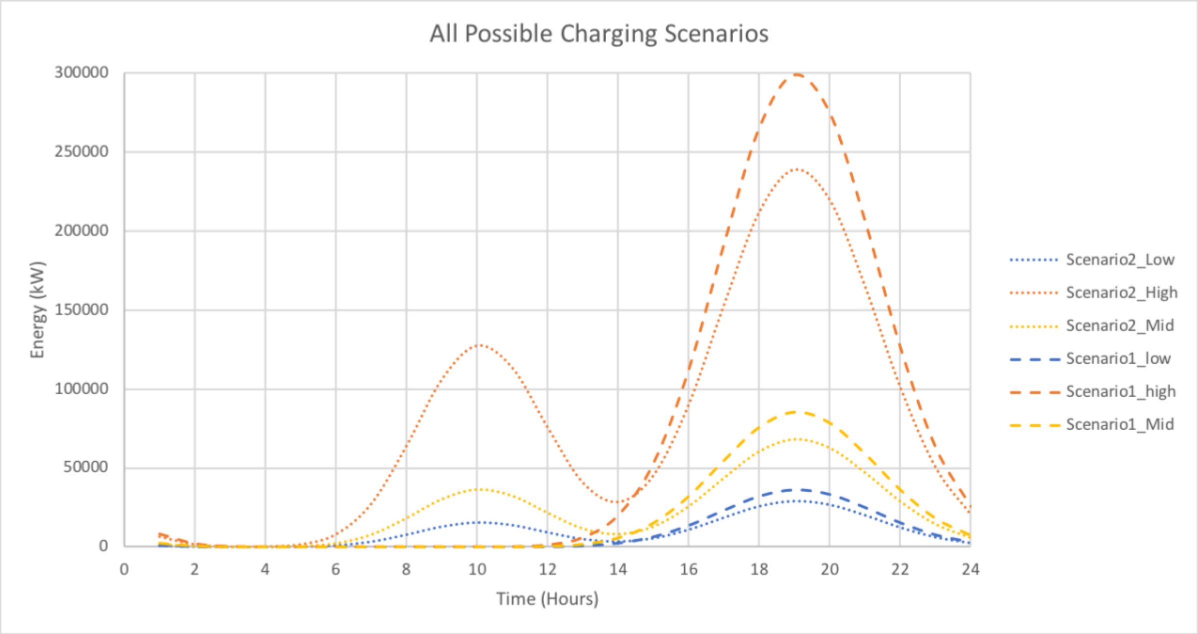

*Figure 2 All Possible Charging Scenarios Graph*

*Table 2 Updated Scenario Matrix*

| | Night Only Charging | Day & Night Charging |
|---|---|---|
| NC Growth Rate | Scenario1_Low | Scenario2_Low |
| CO Growth Rate | Scenario1_Mid | Scenario2_Mid |
| CA Growth Rate | Scenario1_High | Scenario2_High |

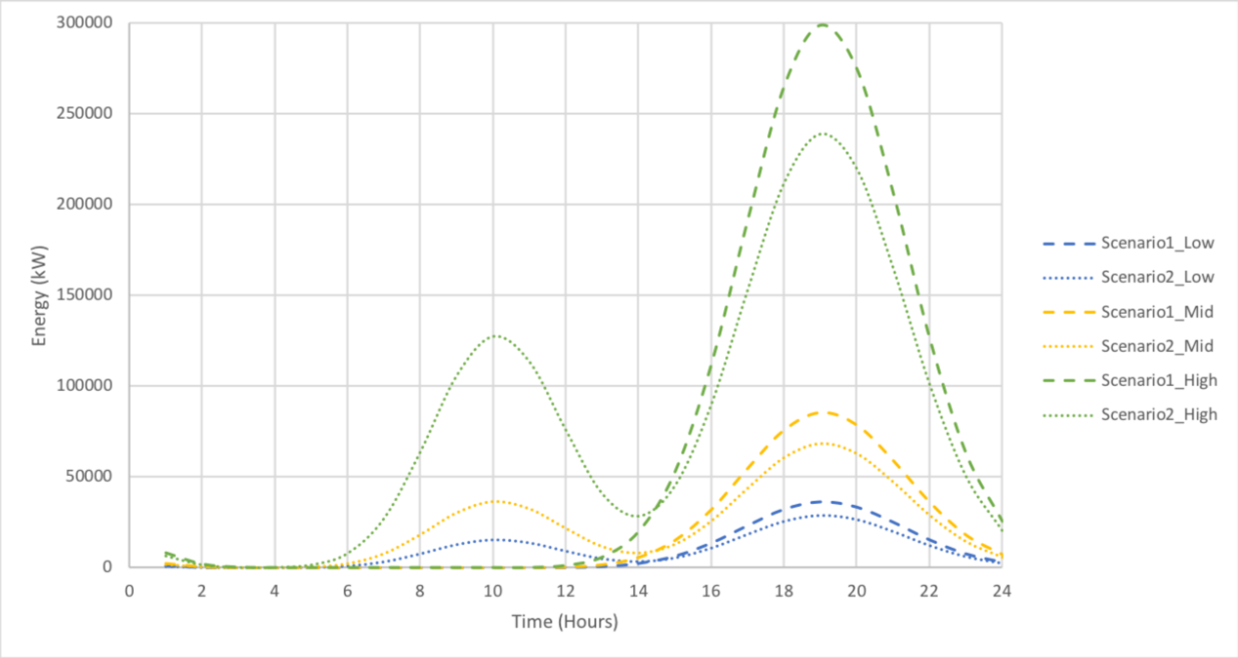

*Figure 3 Updated Charging Scenario Graph*

## Real-time Simulation Model

This project utilized the software AURORA Electric Modeling Forecasting and Analysis Software (version13.1.1039) developed by Energy Exemplar to conduct the simulation of the electricity market. The software can generate hourly-basis unit commitment and economic dispatch results based on its built-in database of the energy system and user's inputs. the built-in database of AURORA was used to obtain the basic parameters of the energy system including the parameters of the current generation fleet, transmission constraints, wind and solar modelling and hydroelectric power production. The inputs include the hourly electricity demand and the expansion and retirement of resources. Given the scope of this study, the North Carolina area was separated out from the eastern interconnection in the simulation model to avoid excessive assumptions.

## Model inputs

The main variable to the energy system in this study is the changing electricity demand in North Carolina due to additional EV charging. To get the electricity demand for the scenarios, the weekday/weekend load from charging generated in the previous section is added to 2030 forecasted demand. For the 2030 demand forecast, the demand forecast in AURORA is used which is predicted through the use of historical demands. As shown in figure 4, the annual demand escalation rate is predicted to fluctuate between year 2019 and 2026, and remain 113% after the year 2026.

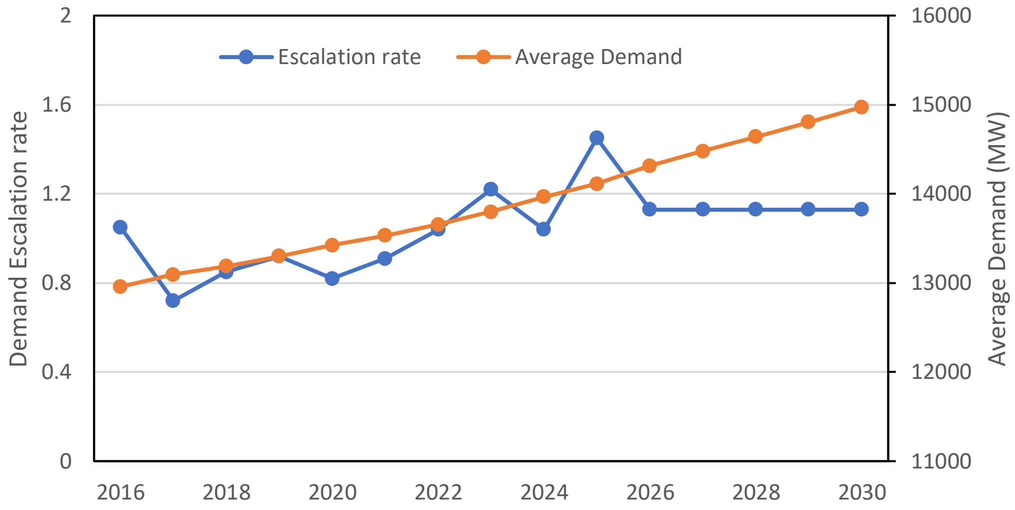

*Figure 4 Annual demand escalation in North Carolina over the years from Aurora*

The figure 5 below shows the yearly average demand curves without EV charging, with EV charging under high adoption rate day and night charging scenario, with a comparison to the 2018 demand curve. It is evident that the demand increase due to EV charging is very small compared with the natural growth of demand. The 2030 demand curve shown below is what is use as a baseline scenario to compare all other EV related scenarios to.

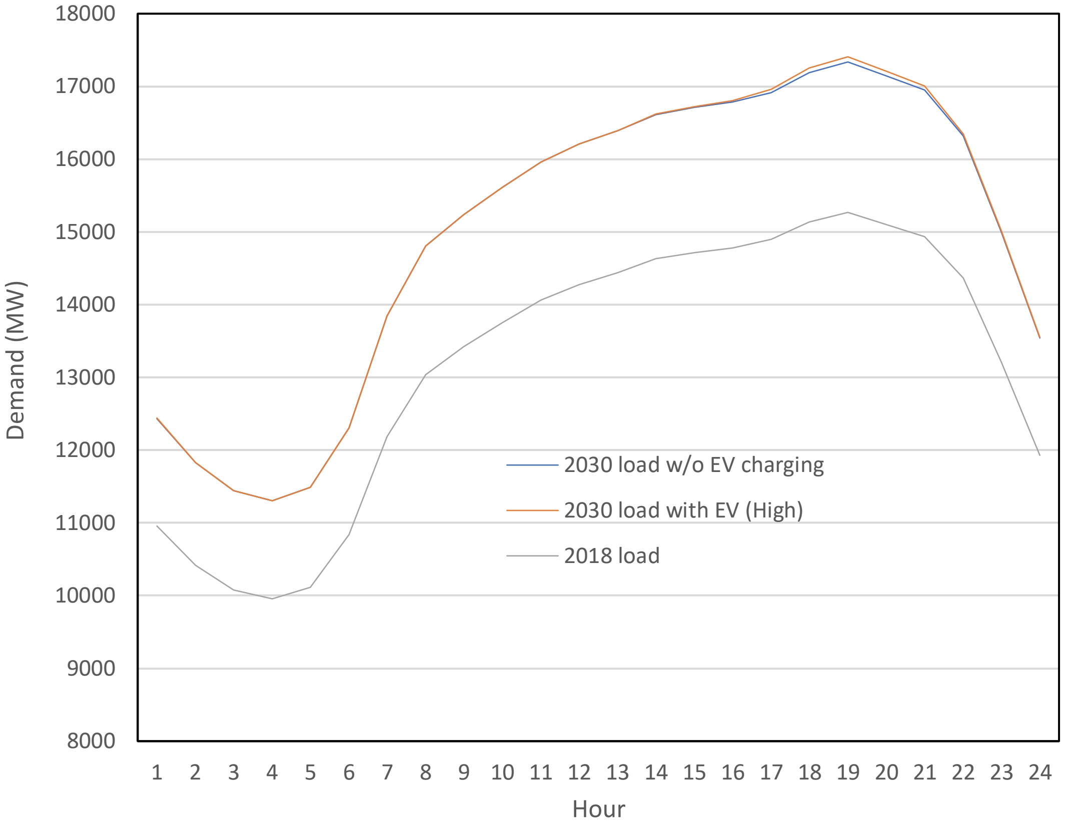

*Figure 5 Load curve of North Carolina under different scenarios (Scenario 2_high is shown in graph for 2030 load with EV)*

The expansion and retirement of resources in North Carolina was updated for the model used in the project based on the 2017 annual report regarding long range needs for expansion according to which the state plans to add over 6000 MW of natural gas combined cycle capacity by 2030 and have 10% - 12.5% renewable generation by 2021 (NC Utilities Commission, 2017). Those planned new resources are taken into consideration in this model assuming similar heat rate and costs as of the current generation unit of the same type.

# Discussion

## Economy Impacts

### Baseline

The graph below (Figure 6) shows the energy mix in our baseline scenario with DEC/DEP in 2030 and the 2018 energy mix. The natural gas accounts for the largest portion with 50% of the generation mix, followed by nuclear power and renewable energy. The proportion of coal in the whole energy mix would decrease from 19% (in 2018) to 6%, while renewable energy would almost double its percentage.(from 6% in 2018 to 11% in 2030) Oil would be only used for dealing with summer peaks.

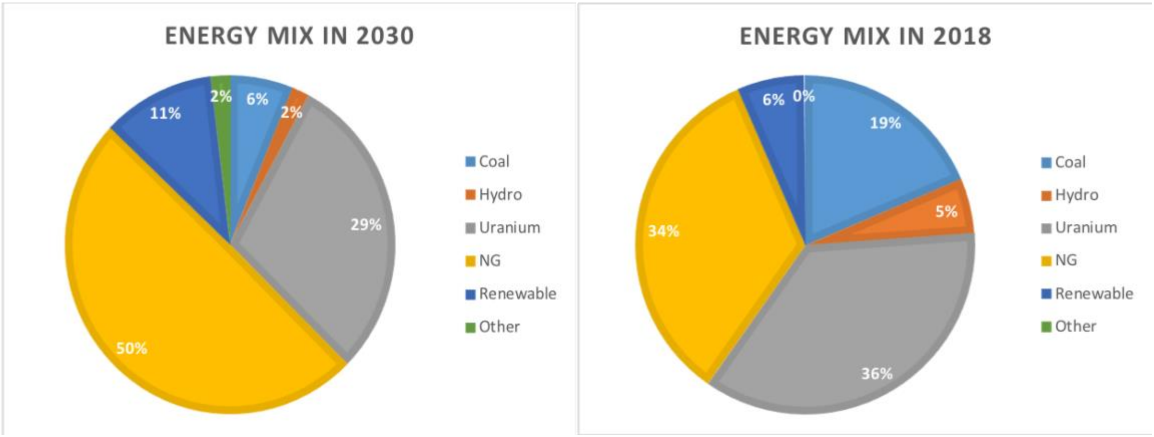

*Figure 6 Energy Mix in Baseline*

The graph below (Figure 7) shows the monthly average electricity prices in the baseline scenario within DEC/DEP. Apparently, prices would peak at January and August when the demands are the highest and reach their lowest points in April and October when weather is mild. The annual average wholesale price is 61.8$/MWh.

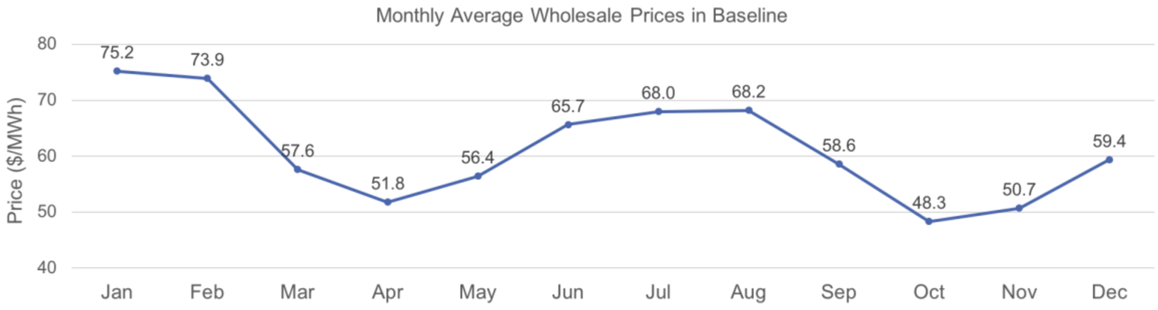

*Figure 7 Monthly Average Wholesale Electricity Price in Baseline*

Besides prices, the results indicate that monthly levelized costs of electricity (LCOE) in baseline scenario also follow similar tendency as shown below in Figure 8. Due to the complexity of bidding mechanism simulation, LCOE could be an appropriate substitute to help understand the overall generation costs in the whole grid. In 2030 baseline scenario, average monthly total generation costs in DEC/DEP is $51.5/MWh.

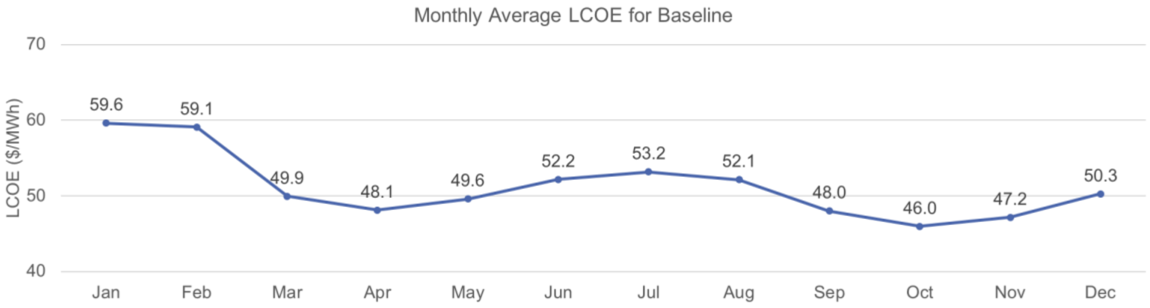

*Figure 8 Monthly LCOE for Baseline*

## Comparison

The graph below (Figure 9) shows the monthly average price changes in DEC/DEP of the all 6 charging scenarios. In most months, the price differences are lower than 0.6$/MWh, which is lower than 1%. It is also evident that there is an obvious price difference in July for two high-charging scenarios. However, in some months (like September and December), there is a negative price difference which means that there are lower prices even if additional EV charging demand is added. It is mainly because for some generators, higher demands would lead to lower heat rates, which means that overall generation efficiency is improved.

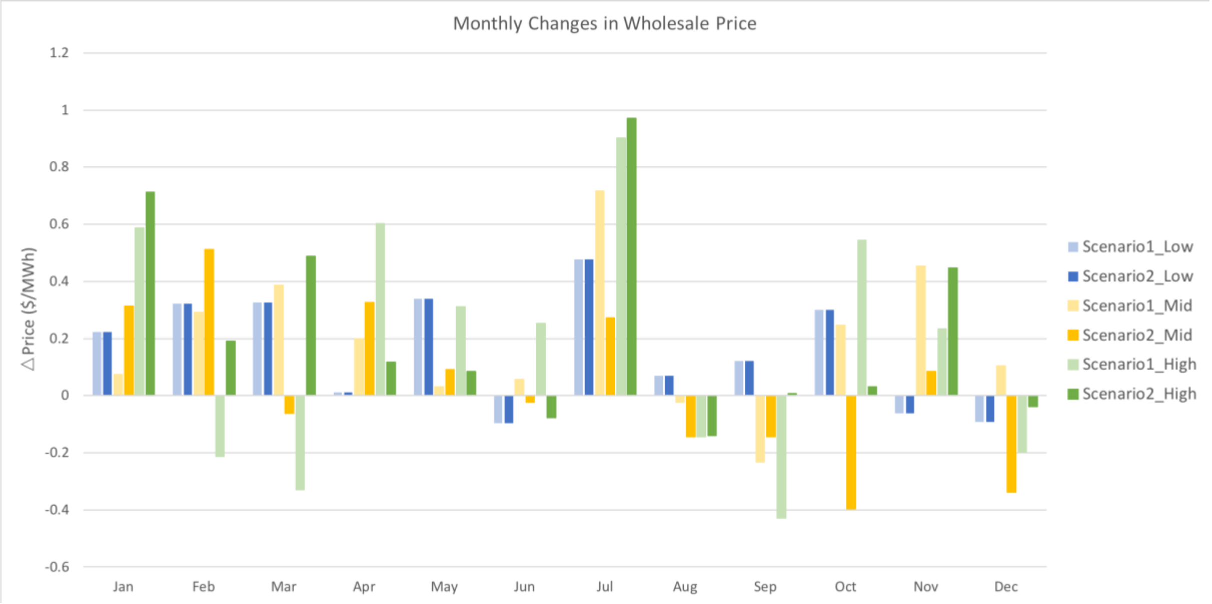

*Figure 9 Monthly Wholesale Price Change in DEC/DEP*

The graph below (graph 10) shows the LCOE changes for all scenarios. Though wholesale prices are relatively unpredictable, the LCOE changes for all scenarios show a clear trend that LCOE would be higher with higher demand. In addition, it’s hard to say which charging behavior pattern (night only or day and night) would lead to higher LCOE increase because the differences are too small.

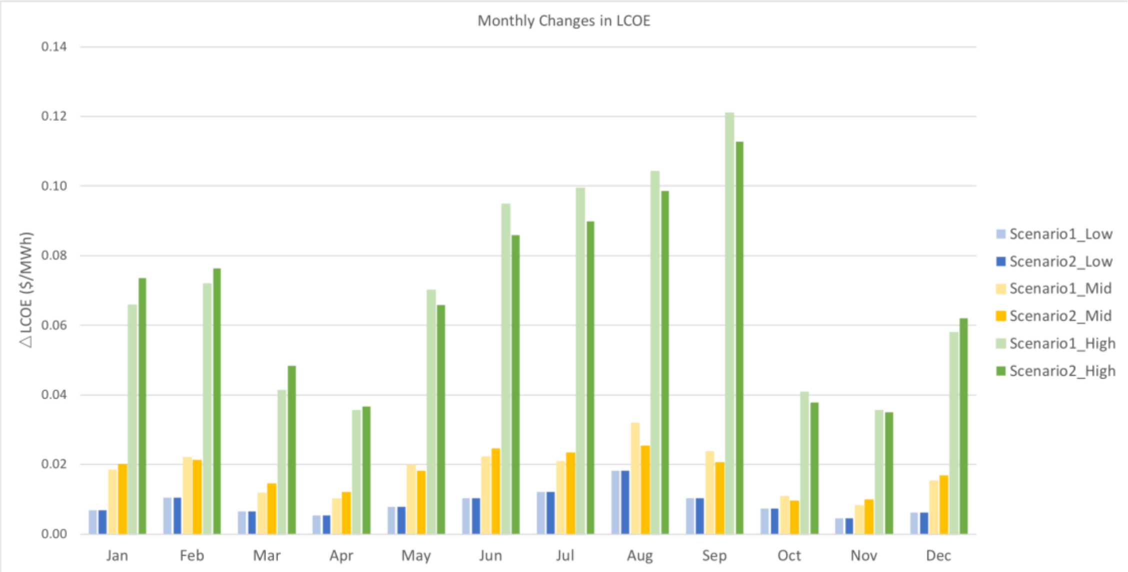

*Figure 10 Monthly LCOE Change in DEC/DEP*

## Environmental Impacts

### Baseline

This project aims to evaluate $CO_2$, $SO_2$ and $NO_x$ emissions to reflect environmental impacts of additional EV charging behaviors. The three graphs below (Figures 11, 12, and 13) show the monthly $CO_2$, $SO_2$ and $NO_x$ emissions for the baseline scenarios respectively. The annual $CO_2$ emissions are about 34.5 million ton. And the annual $SO_2$ and $NO_x$ emissions are 11.8 and 19.7 thousand ton respectively.

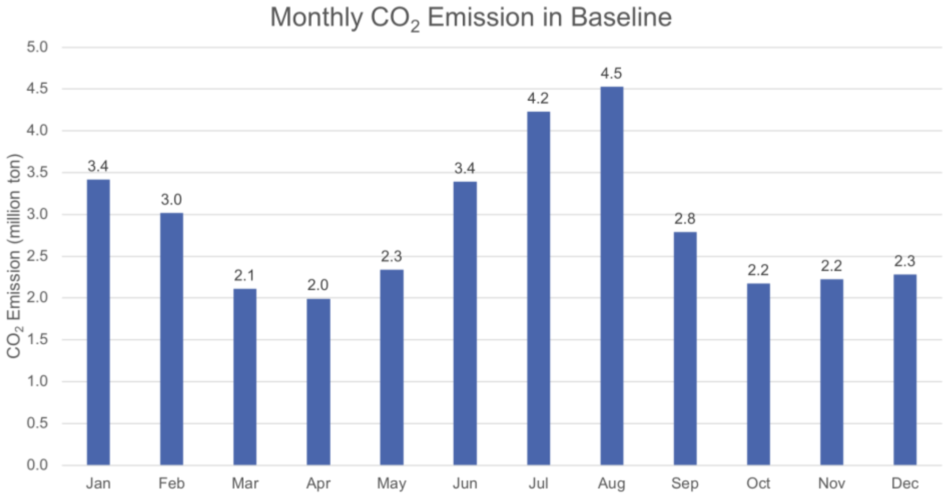

*Figure 11 Monthly CO2 Emission for Baseline*

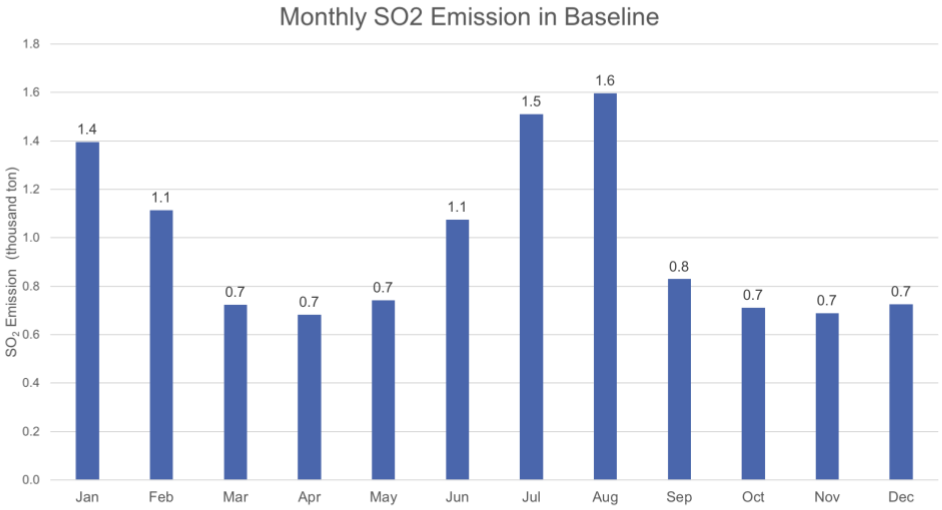

*Figure 12 Monthly SO2 Emission for Baseline*

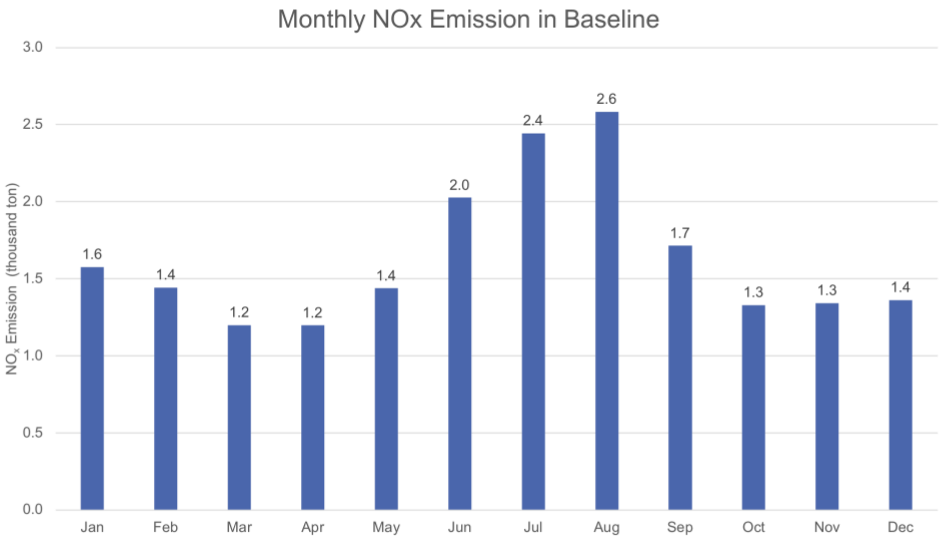

*Figure 13 Monthly NOx Emission for Baseline*

## Emissions Comparison

Figure 14 below shows the change in monthly $CO_2$ emission in DEC/DEP in scenarios compared to the baseline discussed above. The annual $CO_2$ emission rates for all scenarios vary from 0.1% to 1% increase. The emission increases for Low and Mid charging scenarios are very close while it would experience a dramatic increase in the high charging scenarios. In addition, almost in each month and for each charging demand, day-and-night charging would cause slightly more emissions.

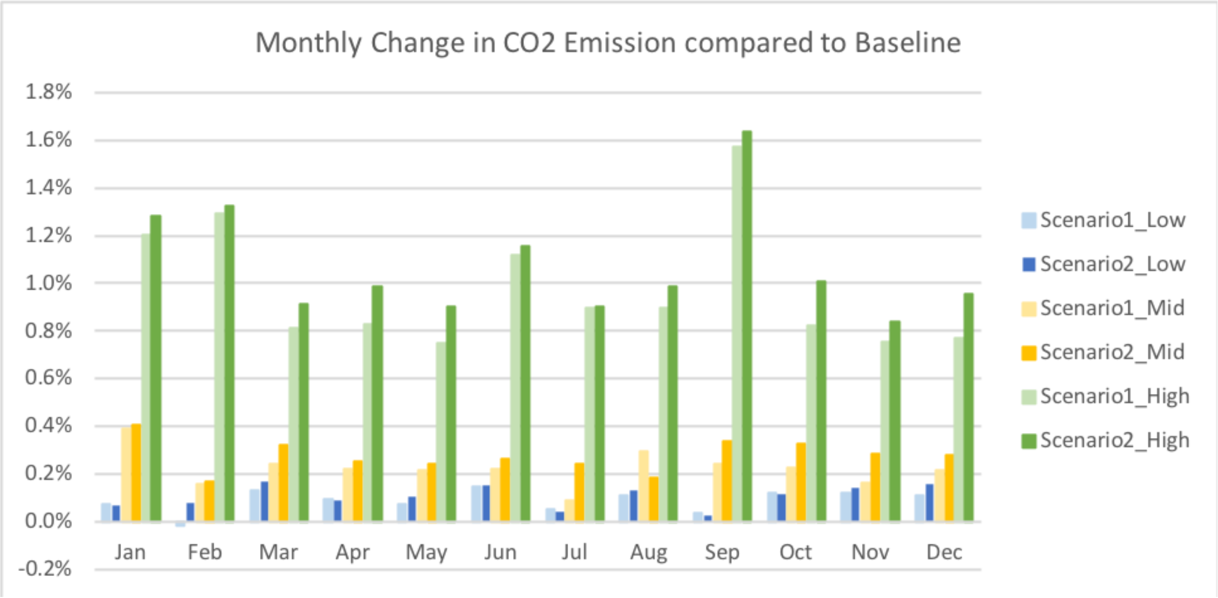

*Figure 14 Monthly CO2 Emission Change in DEC/DEP compared to Baseline*

Two graphs below show the monthly changes in $SO_2$ and $NO_x$ emission compared to baseline. The annual $SO_2$ emission increase rates for all scenarios vary from 0.1% to 1.2% and are depicted in Figure 15 below. The annual $NO_x$ emission increase (Figure 16) rates also vary from 0.1% to 1.2%. Compared to $CO_2$ emissions, monthly $SO_2$ and $NO_x$ emission data show some negative changes due to increased generation efficiency. Especially in $SO_2$ emissions, the increase rate of emissions would be higher as the additional charging demand grows, which means the emission would increase faster as the demand goes up.

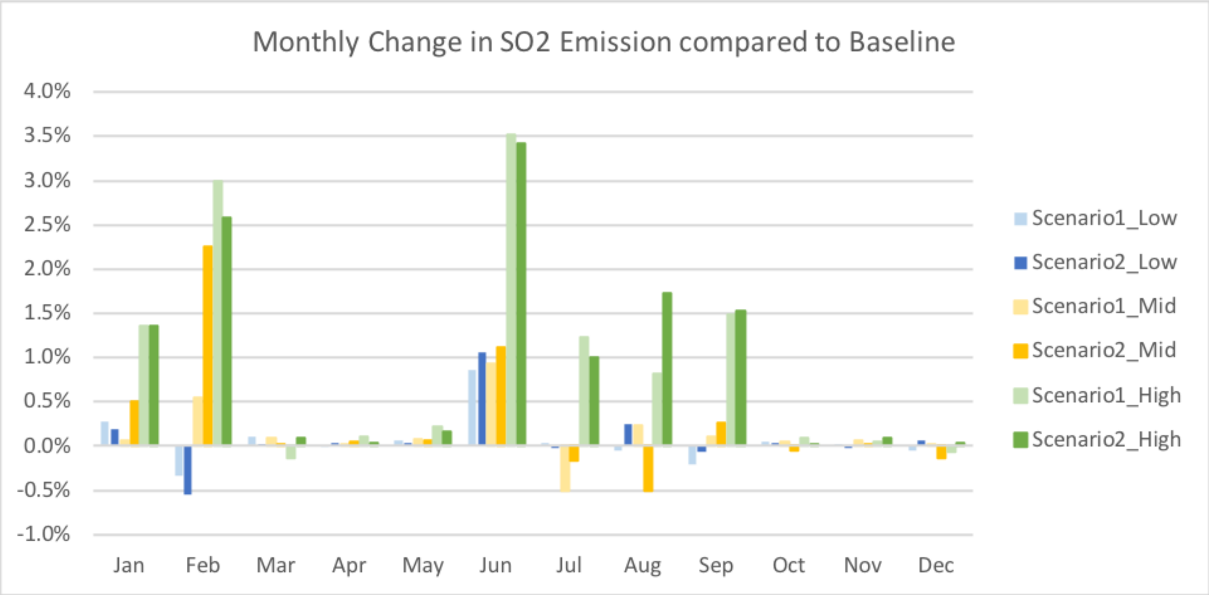

*Figure 15 Monthly SO2 Emission Change in DEC/DEP compared to Baseline*

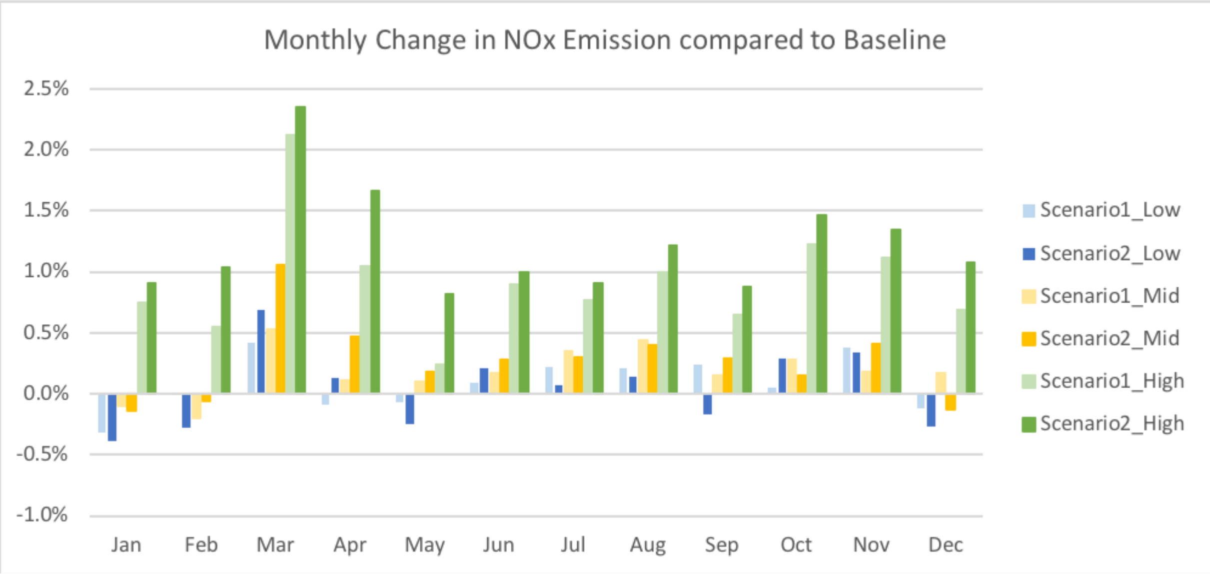

*Figure 16 Monthly NOx Emission Change in DEC/DEP compared to Baseline*

To better understand this phenomenon, the energy mix for additional generation was plotted, which represents the energy mix of marginal generators. significant differences of energy mix in different hours were not discovered, but as shown in the graph below (Figure 17), the marginal generator would be more likely to be a coal plant with increasing demands. That explains why high charging scenarios have higher emission increase rate compared to other scenarios.

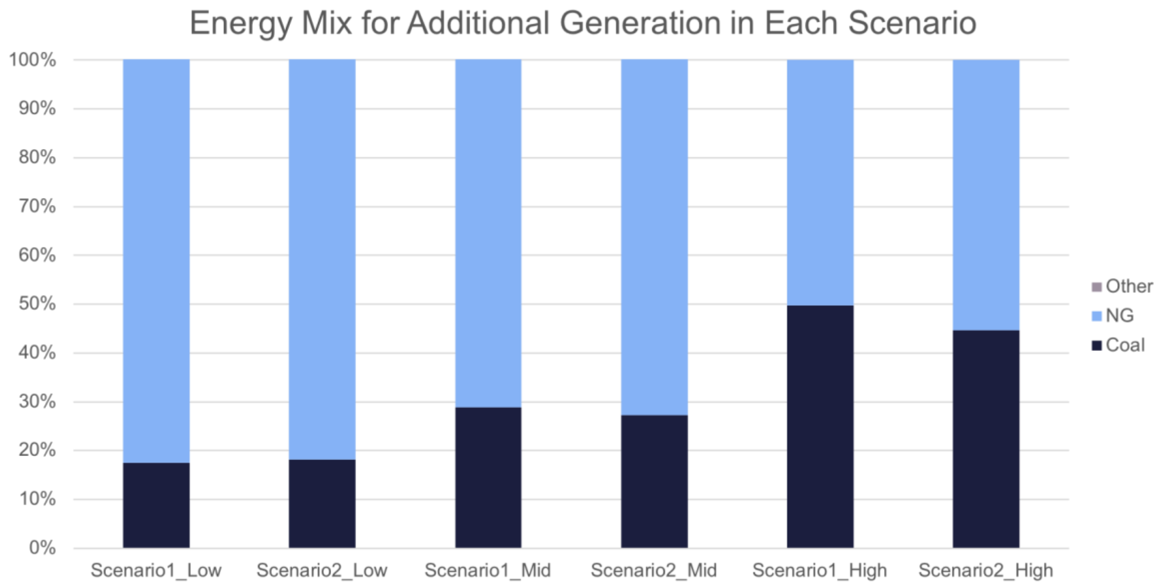

*Figure 17 Energy Mix for Additional EV Charging Behaviors*

## ICE Vehicle Comparison

The environmental impact also includes comparing indirect emissions from EVs to direct tailpipe emissions from their potential alternative, internal combustion engine (ICE) vehicles. ICE vehicles that use petroleum-based fuels (gasoline or diesel) emit similar air pollutants as generation facilities. The EPA regulates greenhouse gas emissions standards and fuel economy standards for all new engines and vehicles. But even with stricter standards and more efficient ICE vehicles, tailpipe emissions are still a problem. In a generating facility, emissions can be monitored more closely and control technologies can be implemented to capture greenhouse gas before they enter the atmosphere. Control technologies are expensive and only feasible at the generating facility scale and are not a viable solution to tailpipe emissions.

Emission factors – pollutant per combusted unit of fuel – from the EPA were used to convert vehicle miles traveled (VMT) to $CO_2$, $SO_2$, and $NO_x$ emissions (tons). The average fuel economy of an ICE bought after 2018 was assumed to be 22.04 miles per gallons-gasoline equivalent (AFDC). It was assumed when building the load curve that the VMT for a light duty vehicle was 11,346 annual miles travelled (AFCD). To determine the carbon emissions from ICE vehicles, the emissions factor from the EPA's Greenhouse Gas Inventory Guidance report for Direct Emissions for Mobile Combustion Sources– 8.78 kg $CO_2$ per gallon gasoline equivalent - was applied. When determining the $SO_2$and $NO_x$ emissions the emissions factors from the EPA's Greenhouse Gas Regulated Emissions and Energy use in Transportation (GREET) model – 0.12 g $NO_x$ per mile and 0.0042 g $SO_2$ per mile were applied. The total emissions from each scenario were obtained using the three equations listed below and the results for the three different growth scenarios are listed in Table 3 below.

$$\frac{\#\ of\ new\ Vehicles}{in\ 2030} * \frac{Annual\ Miles}{Vehicle} * \frac{Gallons\ Gasoline}{Miles} * \frac{kg\ CO_2}{Gallons\ Gasoline} * \frac{1\ mtonne}{1000\ kg} = \frac{mtonne\ CO_2}{in\ 2030}$$

$$\frac{\#\ of\ new\ Vehicles}{in\ 2030} * \frac{Annual\ Miles}{Vehicle}\ \frac{0.0042\ g\ SO_x}{Mile} * \frac{1\ mtonne}{1000000\ g} = \frac{mtonne\ SO_X}{in\ 2030}$$

$$\frac{\#\ of\ new\ Vehicles}{in\ 2030} * \frac{Annual\ Miles}{Vehicle}\ \frac{0.12\ g\ NO_x}{Mile} * \frac{1\ mtonne}{1000000\ g} = \frac{mtonne\ NO_X}{in\ 2030}$$

*Table 3 Results for ICE Air Pollution*

| Growth Scenario | Estimated new Vehicles in 2030 | $CO_2$ Emissions (metric ton) | $SO_x$ Emissions (metric ton) | $NO_x$ Emissions (Metric Ton) |
|---|---|---|---|---|
| Low | 25,438 | 114,976 | 1.21 | 34.63 |
| Mid | 31,244 | 141,128 | 1.49 | 42.51 |
| High | 60,154 | 271,888 | 2.87 | 81.90 |

Table 3 also lists the estimated new vehicles in 2030 for each load growth scenario. These are the same estimations used to develop the demand curve for each scenario previously discussed. The graphs below compare the annual total emission in metric tons of ICEs to the additional emissions caused by EV growth in each scenario (difference from baseline total emissions). Figure 18 below shows the comparison for $CO_2$.

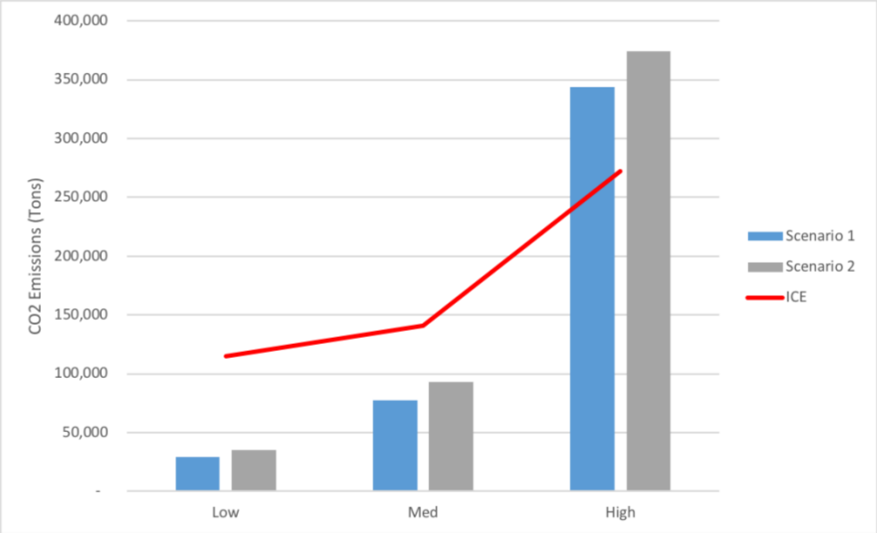

*Figure 18 CO2 Emissions ICE Comparison*

The ICE scenario is shown by the red line while the blue bar is scenario 1 in each growth rate and the grey bar is scenario 2 in each growth rate. The carbon emissions from ICE vehicles are not uniformly higher than emissions from electricity generation. As the number of EVs on the road increase, their emissions will exceed those of ICEs given the current fuel mix of the grid. As seen in Figure 17 in the previous section the high growth rate scenarios have more coal in their additional generating mix which generate more carbon emissions than natural gas. Figure 19 below shows the comparison for $SO_2$.

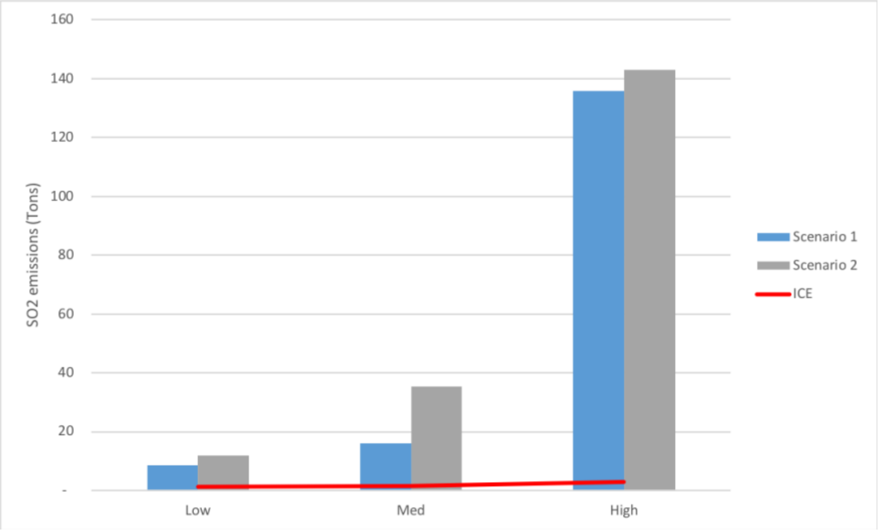

*Figure 19 SO2 Emissions ICE Comparison*

Figure 19 shows how $SO_2$ in ICEs is consistently much lower than any generating facility. Emission standards have successfully reduced $SO_2$ tailpipe emissions to the point where they are hardly comparable to those from a coal or natural gas generating facility. $SO_2$ control technologies like limestone scrubbers are only viable for coal generating facilities that have a sulfur content less than $3\ lbs\ SO_2/MMBtu$, their efficiency significantly decreases after this benchmark. Therefore, this technology is only provided to plants that use coal with a lower sulfur content – like anthracite which is in limited supply (Emission Control Technologies). Figure 20 below shows the emissions comparison for $NO_x$.

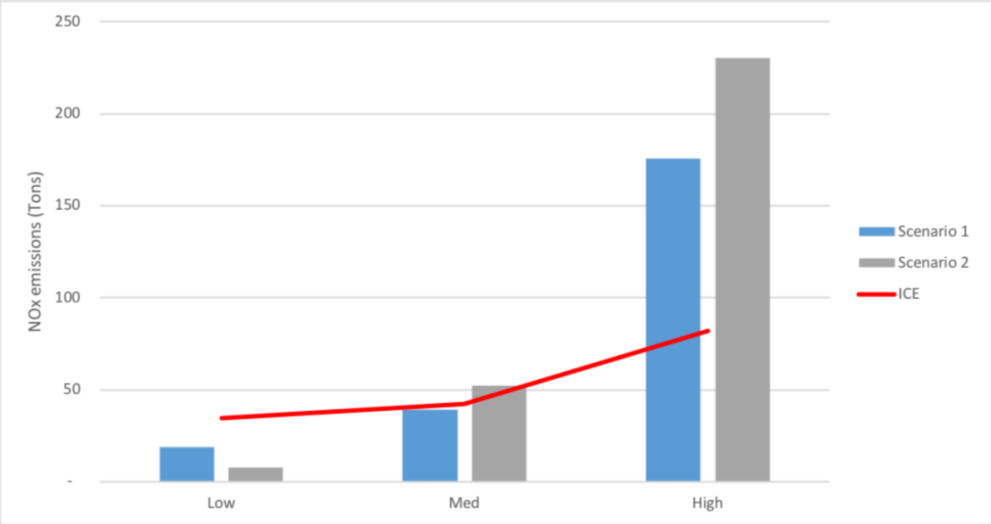

*Figure 20 NOx Emissions ICE Comparison*

$NO_x$ exhibits a similar trend as carbon emissions from above – emissions from electric vehicles are lower until adoption increases. Figure 20 above reiterates how dependent emissions are on the fuel mix. In the med and high scenarios there is more coal in the generating mix than in the low scenario and it makes emissions from EVs exceed the tailpipe emissions from ICEs.

## North Carolina Governor's Ordinance No. 80

In October of 2019 Governor Roy Cooper announced Ordinance No. 80: North Carolina's Commitment to Address Climate Change and Transition to a Clean Energy Economy. In this ordinance states a goal for the state to reach 80,000 ZEVs by 2025 – that is 2% penetration given the size of the 2017 car fleet. In comparison to the scenarios that have been modeled in this scenario, this level of adoption would require a growth rate between med and high. Figure 21 below displays all three growth rates used in this study and the growth rate required for North Carolina to reach this goal displayed in red.

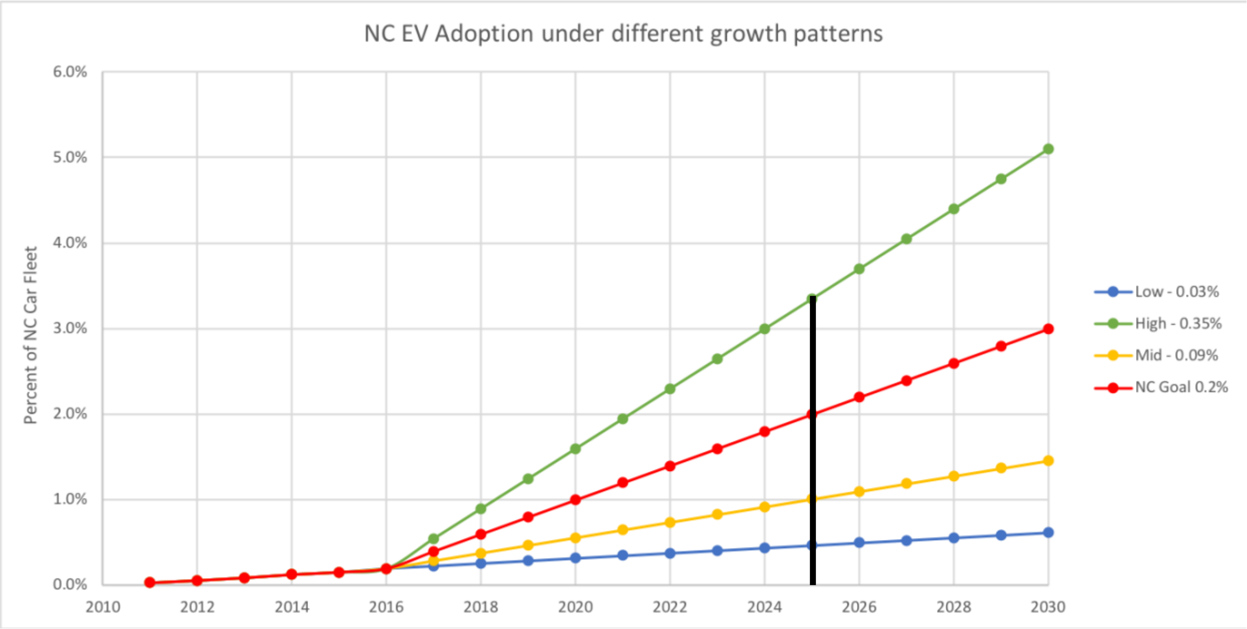

*Figure 21 Growth Rate Scenarios*

This project is not drawing any correlations between state policy and EV adoption as there are many more variables that will influence residents decision to buy an EV such as the price of gasoline and the buildout of charging infrastructure. But it is important to recognize that in order for North Carolina to meet this goal, it will have to mimic the level of growth that progressive states like California and Colorado have been experiencing after years of incentives and EV advocacy. Annual EV growth of 0.2% increase in the car fleet is a substantial increase from the 0.03% that North Carolina has traditionally experienced.

# Conclusion

## Economic

One of the primary objectives of this paper is to determine the economic impact of electric vehicles – will they increase clearing prices and incur additional costs on generators? The analysis above suggests that the clearing prices would hardly increase (barely 1% in most months) and LCOE would increase slightly as generation increases. An important note here is that cost and prices are dependent on generators. And the peaker plants that are being used to meet the additional demand from electric vehicles are mainly coal and natural gas which are traditionally more expensive to operate.

## Environmental

The environmental component of this study focused on emissions from the additional generation caused by electric vehicles. Electric vehicles will cause an increase in $CO_2$, $SO_2$, and $NO_x$ emissions. But the magnitude of change varies by pollutant and does not exceed a 4% increase. When compared to internal combustion engines, electric vehicles in the lower adoption scenarios had fewer tons emissions. But as adoption rates increase, so did the emissions and exceeded those of ICEs. Again, emissions are a direct results of the marginal generation fleet used to meet the increasing demand and that mix is predominantly coal and natural gas. With further research, the effect of the generating fleet could be determined by modeling these scenarios under different future fuel mixes. A rapid increase in residential solar and storage, or utility scale renewables and storage could have a significant impact on the emissions from EVs.

## Social

The social impact is no something that can be empirically evaluated in the same way as economic and environmental impact. Social impact has to do with changes in behavior which can only be modeled by including varying assumptions in the scenarios modeled. This study chose to model charging at night only and during the day and night. Charging only at night is intended to include the assumption that society has not adopted electric vehicle charging and created a demand for public charging infrastructure. Charging split between day and night is intended to depict a shift in societal behavior that has created a demand for public charging and gives EV owners the option to charge at work or somewhere non-residential. And the results in every impact show that scenario 2 – the scenario that splits charging between day and night options – has less of an impact than scenario 2. It spreads out the demand so costs and emissions decrease slightly compared to scenario 1. This suggests that increased advocacy for charging availability could reduce some of the impacts shown in this study. Further analysis that evaluates managed vs. unmanaged charging, incentivized rates/time of use rates, and magnitude of charging infrastructure development will help to determine the behavior changes EVs could bring about.

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