Generation Dispatch and Power Grid Emission Impacts of Transportation Electrification

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***Abstract*—Generators in the bulk power grid are having to meet the growing demand for electric vehicles (EV) charging. This can affect emissions arising from these generators, which should be accounted for in analyzing the benefits of EVs over internal combustion engine vehicles. This paper describes the impacts of EVs on generator emissions, considering different scenarios of EV penetration, charging strategies, and wind curtailment. It discusses the sensitivity of generation dispatch and emissions to the system generation mix, and the EV charging strategy. Using a synthetic grid model based on the footprint of the state of Texas shows that even a 5% EV penetration in one part of the system can change the dispatch far across the network, highlighting the importance of using large, regional models in EV grid integration assessments. The paper also shows how different methods of modeling wind generation such as wind curtailment affect the emissions, especially in the presence of EVs.**

***Index Terms*—EV charging, coupled infrastructure simulation, emissions**

I. Introduction

In recent years, there has been rapid growth in the development and adoption of electric vehicle (EV) technologies, right from the vehicles themselves to charging infrastructures. A major driver behind this is the growing push for clean energy, which is offered by EVs with their zero tail-pipe emissions. However, there may be other sources of emissions attributed to the growing number of EVs. Specifically, the concern is with the emissions from generators in the bulk power grid that now to have supply the additional EV load. Hence, an environmental analysis of the benefits of EVs over internal combustion engine (ICE) vehicles should account for the increase in generator emissions for charging the EVs compared to the ICE tail-pipe emissions.

In regards to EV benefits, reference [1] provides a comprehensive review of existing literature on the economic benefits of EV integration to different energy market players, namely power generation companies, distribution system operators, EV aggregators, and end users. While economic benefits are important, environmental benefits are a primary function of EVs and should be evaluated. Though not explicitly discussed in [1], generating unit emissions are often considered as one of the generator "costs" that problems such as OPF or SCOPF seek to minimize. These emissions could be minimized with strategic charging strategies such as avoiding charging during peak times, and taking advantage of high renewable generation output periods.

With this in view, this paper describes the impacts of EVs on generator emissions, considering different scenarios of EV penetration, charging strategies, generation mix, and wind curtailment. A synthetic grid representing the footprint of Texas is used as the case study. Hourly EV charging load for multiple cities in this footprint is considered in hourly SCOPF simulations. This charging load from on-road EV operation is developed based on a regional-level transportation simulation and charging behavior simulation, considering different EV penetration levels, congestion levels, and charging strategies. This EV load is then mapped to the appropriate grid substations leveraging the geo-mapping method developed in our prior work [2] to map nodes between transportation and grid networks. The previous paper also provided some preliminary results on grid impacts such as transformer loading and change in generation dispatch by fuel type due to the inclusion of EV charging load. The focus there was on a much smaller footprint, i.e. Travis Country, TX and the grid model used consisted of around 160 buses.

Hence, building on the work of [2], this paper has the the following new contributions:

- Regional, statewide analysis for a comprehensive system study, i.e. modeling the entire transmission grid to account for realistic generation profiles and flows
- Multi-city EV load analysis
- Wind curtailment modeling in the dispatch problem
- Geographic visualizations of generator emission changes

The rest of the paper is organized as follows. Section II describes the test system used for the analysis. Section III details the methodology right from calculating the EV load to mapping it to transmission substations, and finally the dispatch and emission studies. The results of this process for two different test systems are shown in Section IV. The paper

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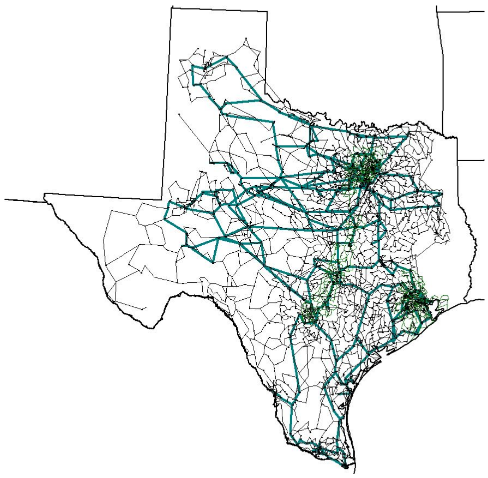

Fig. 1. Texas 7000 Bus System Oneline

concludes with a summary and directions for future work.

II. Test System

Data regarding the actual power grid is considered confidential and is hence not publicly available for research. Instead, we use synthetic electric grids, which are realistic but fictional power network models. Based on publicly available data, and the statistics of the real grid models, synthetic electric grids include detailed representations of grid elements such as generators, loads, transmission lines, and transformers [3], [4]. Some synthetic grids are also geographically sited, which enables the possibility of modeling coupled infrastructures such as transportation networks and the power grid.

This paper uses a synthetic grid geographically representing the ERCOT portion of the Texas electric transmission grid as the study system [5], [6]. It consists of around 7000 buses and serves 75 GW of peak load across the majority of the state of Texas. It uses the same transmission system voltage levels as the actual ERCOT grid. The generators in this synthetic grid are actual generators in the ERCOT grid, the data for which is publicly available from the Energy Information Administration (EIA) Form 860. The grid was developed using a (345/138/69 kV) network that connects with around 5000 distribution substations around the entire footprint.

In Section IV, the 160-bus synthetic system from [6] representing the Travis county portion of Texas, which was also used in [2] is briefly discussed to present emissions results associated with generation mixes from two different years, i.e. 2020, and 2030 which considers a generation mix that is 90% carbon-free (i.e. wind, solar, nuclear, battery, hydro).

III. Methodology

A. EV Load Calculation

The EV load calculation builds on our prior work in [2] which is summarized here for the readers' convenience. Due to the low market penetration (0.12% of registered vehicles in Texas in 2019 [7]) and the lack of observed EV charging data, the charging demand is estimated under hypothetical scenarios, with different assumptions made for the spatial and temporal distributions of charging load. The charging load profile by the hour and by location is generated using two methodologies – a simplified method and a realistic method. The simplified method assumes the charging load equals the trip-level energy use and is charged immediately at the end of the trip. In this case, the charging load is directly aggregated at the trip end by each hour (Scenario 1 - 'trip-end'). An off-peak charging profile is also constructed based on the 'trip-end' scenario by postponing the charging load assigned to peak hours (2:00 PM – 8:00 PM) to non-peak hours (10:00 PM to 4:00 am of the next day) to reduce electricity cost and peak demand (Scenario 2 – 'off-peak').

The realistic charging demand generation method uses a microscopic charging behavior model which accounts for diversity in people's range anxiety and the characteristics of daily travel. The individual-level charging load at different locations depends on the time-of-day, trip characteristics, remaining battery range, and the minimum range needed by individuals to complete trips. We estimate this spatially and temporally resolved charging demand through a stochastic simulation that relies on three sources of data: 1) the statistical properties of daily tours from the National Household Travel Survey (NHTS); 2) the synthetic daily trip roster at a regional scale obtained from a dynamic traffic assignment (DTA) model; and 3) a model of charging behavior based on an empirically obtained distribution of EV range acceptance. In this case, people are more likely to charge by the end of all travels within a day with battery closer to depletion, instead of charging the vehicle in the middle of the day with sufficient ranges left (Scenario 3 – 'most likely').

This EV charging demand is then provided as an input to the grid simulation, as hourly load at different geographic nodes of the transportation network.

B. Mapping EV Load to Substations

The geographic data of the electrical nodes (i.e. transmission and distribution substations, buses, feeders) available in these synthetic networks is leveraged to map the EV charging

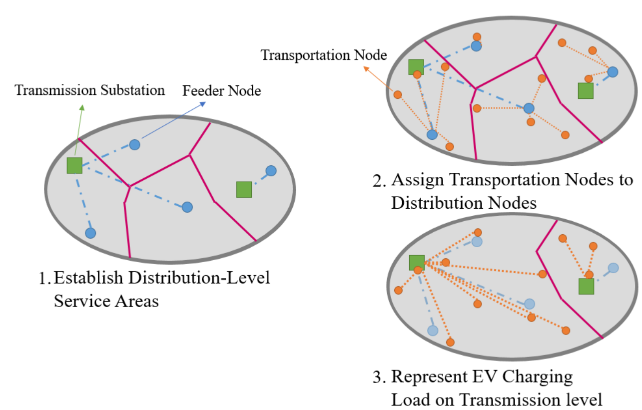

Fig. 2. Mapping Procedure

demand as load into the grid model. As discussed next, the mapping can be done at the transmission level even if feeder network data is not available.

First, substation service areas are defined in the grid model to simplify the mapping of the EV load from a transportation node to a transmission-level substation and to provide an understanding of the geographic service of the system. Figure 2 depicts the overall mapping process. A service area is established for each feeder node using Voronoi polygons. This yields tessellated service areas with the feeder node central to each region. Next, the transportation nodes are assigned to specific feeder nodes depending on the polygon i.e. the service area they fall within. At this point, the EV load has been mapped to a feeder. Finally, using the topological data of the network, the EV load from the feeders is aggregated to each substation at the transmission level. This aggregation is especially useful and important while simulating a large system such as the entire Texas grid. If the distribution system topology is not available, service areas can be approximated by creating Voronoi polygons for each of the transmission-level substations.

Figure 3 shows the hourly EV load profile using Charging Scenario 3 and assuming 5% EV penetration in Austin and Houston, for the TX 7000-bus network study discussed ahead.

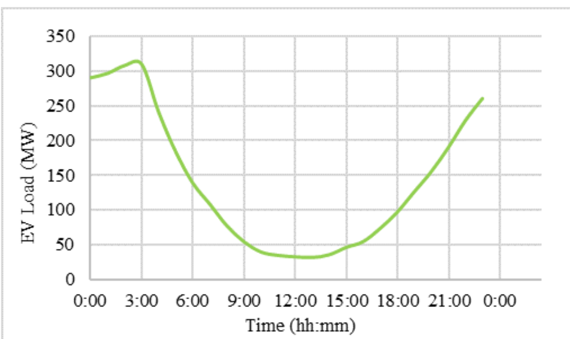

Fig. 3. Austin + Houston 5% EV Load Profile

C. Dispatch and Emission Studies Inputs

Once the EV charging load at each transmission substation has been determined, SCOPF simulations are run to determine the generation dispatch values, followed by computing the emissions for the different generators based on their output, fuel type, and the corresponding emission factors. For the SCOPF analysis, time series data about grid variations such as load and renewable generation is needed. Hourly time series of individual loads and renewable generators are created to represent the electric grid variation. The load time series creation involves estimation of the residential/commercial/industrial ratios for the bus load, and then aggregating publicly available prototypical building, and industrial facility load time series to the transmission bus level through a heuristic optimization process [8]. For the renewable generation time series, the wind and solar integration toolkit from the National Renewable Energy Laboratory is utilized [9], [10]. Given the generator type and geographic location, a unique MW output pattern is synthesized, reflecting the capacity factor, seasonal variation and regional features of a specific renewable unit. A peak load day of the year was chosen for designing the scenario.

The load and renewable time series for the 160-bus system are given in [2]. Figure 4 shows the hourly renewable generation profile used in the TX 7000-bus system study, which corresponds to a low wind day. For the same system, Figure 5 shows the load profile of the base case or the "base load", i.e. the load before the EV charging is considered.

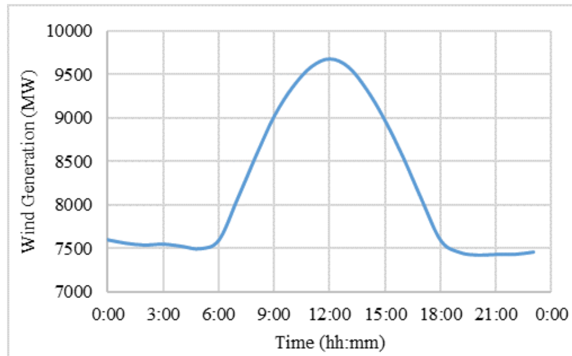

Fig. 4. Texas 7000-bus System Renewable Generation Profile

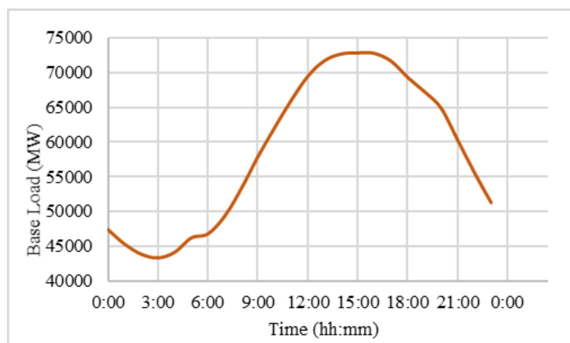

Fig. 5. TX 7000-bus Case Base Load Profile

The next section will discuss two different approaches used to include renewable generation in the dispatch problem. In the first method, also used in [2], the wind power output is considered as a negative load, which is a commonly used simplification approach. This paper uses an additional, different method to model wind generation. The wind units are allowed flexibility between 80% and 100% of their maximum output. This was done in order to model potential wind curtailment, and its impacts in the presence of EVs on grid emissions.

The emissions are calculated based on the values provided in lbs/MWh for different generator fuel types and pollutants from the Greenhouse gases, Regulated Emissions, and Energy use in Transportation (GREET®) model [11]. The emissions of focus in this paper are NOx and CO_2, with the corresponding emission factors shown in Table I.

TABLE I
EMISSION FACTORS FROM GREET®

Fuel Type	NOx (lb/MWh)	CO_2 (lb/MWh)
Coal	0.46	406.87
Natural Gas	0.085	165.56
Petroleum Coke	2.98	2619.5
Nuclear	0	0

IV. RESULTS

A. 160-bus Travis County 2020 vs 2030 Assessment

We first consider the impact on emissions considering two drastically different generation mixes. This example uses the Travis county 160-bus system. The key difference between the 2020 and 2030 generation mix is the proportion of carbon-free (including nuclear, renewables, and storage) generation increasing from 40% to 90%, only within the Travis county footprint. This scenario was studied according to the goals laid out in Austin Energy's Climate Protection Plan [12]. As an example, for the 2030 generation mix, the left part of Figure 6 shows the different hourly EV charging load values for the different charging schemes and EV penetration (5, 10, 15, and 20%). The right side shows the corresponding change in generation dispatch for the just the 20% EV scenario for illustration, color coded by the generator fuel type. It is interesting to note the significant proportion of the EV load that is picked up by carbon-free sources such as wind and storage, and how this changes drastically from one charging scenario to the other.

Next, hourly emission values are calculated for each generator to yield a total daily value in lbs. The results of this analysis show that increasing the carbon-free generation in the system from 40% to 90% causes 77% reduction in CO_2 (Figure 7) and an 85% reduction in NOx (Figure 8) emissions. Also, in the 2020 case, the Charging Scenario 1 shows the largest emissions among the charging strategies. This changes in the 2030 study, where Charging Scenario 3 is now with the largest emissions. This calls for special attention to this "most likely" scenario, the modeling of which should improve as more data on travel behavior and charging infrastructure becomes available and evolves over the next decade.

B. 7000-bus TX Case, Austin and Houston EV Load, 2020

The previous case was a simple example to show the sensitivity of the dispatch and emissions to different generation mixes, and more importantly to the different charging scenarios. The goal of the remaining cases is to assess the emissions on a spatial scale, and on a larger footprint i.e. the state of Texas. Note that here we focus on the 2020 generation

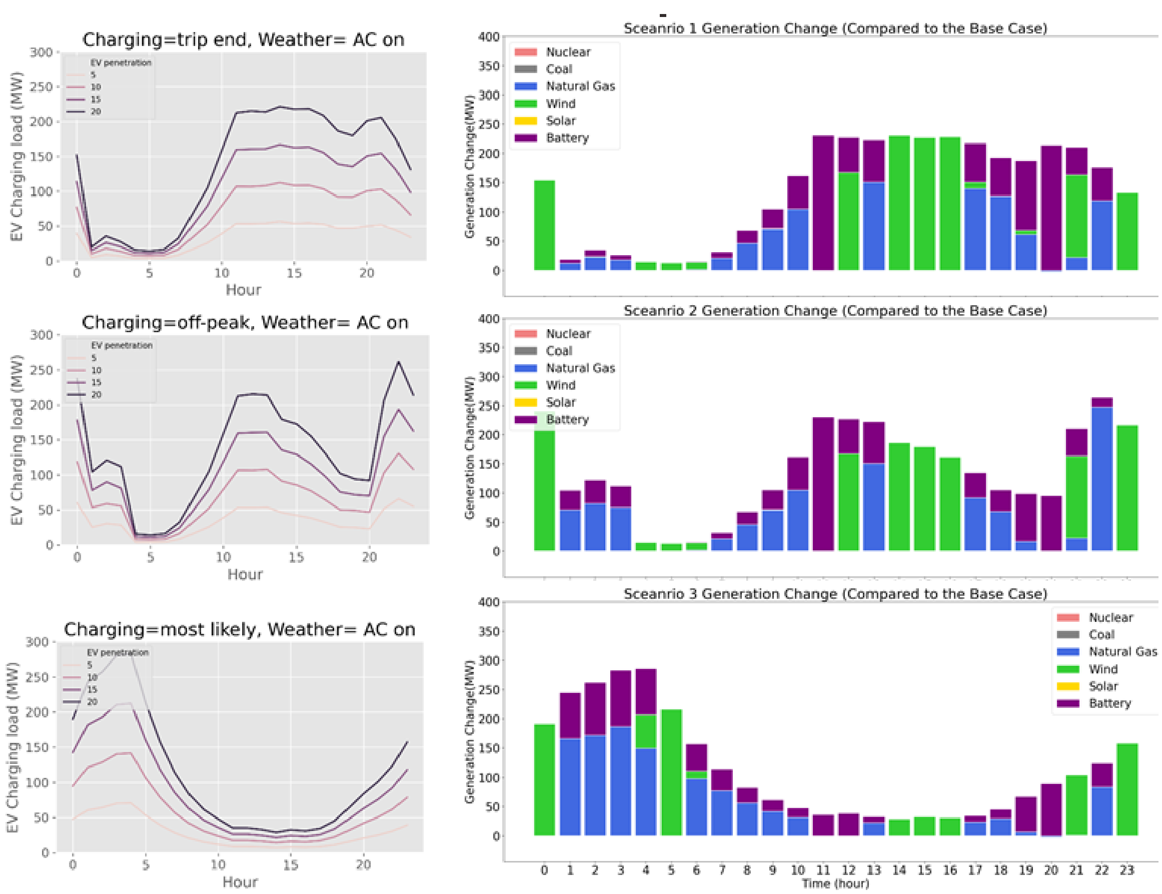

Fig. 6. Charging load for different % EV penetrations and change in generation dispatch for the 20% EV scenario for Travis county in 2020

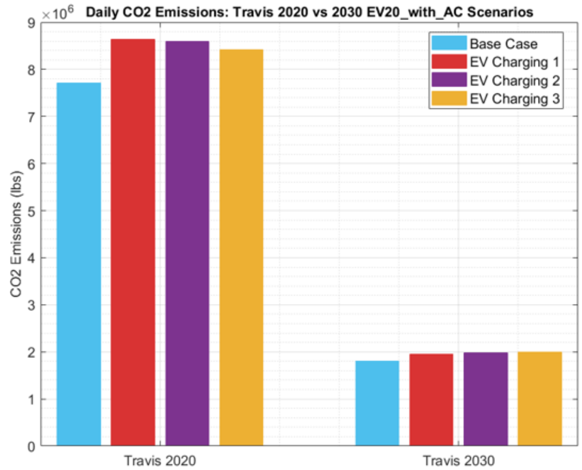

Fig. 7. 2020 vs 2030 generation mix CO_2 emissions

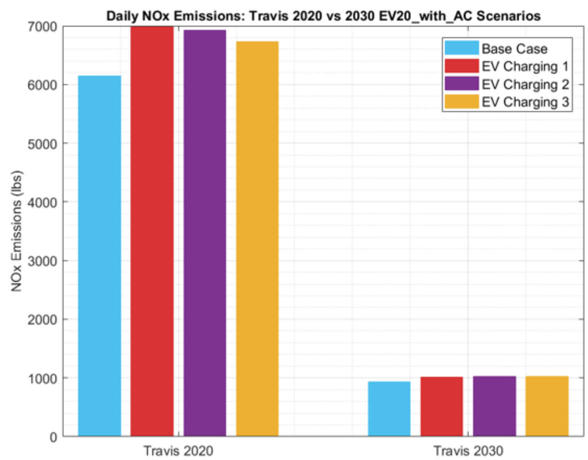

Fig. 8. 2020 vs 2030 generation mix NOx emissions

mix only as the emphasis is more on the regional differences and the sensitivity of results to renewable energy modeling.

As described in Section III.C, we first perform the dispatch and emissions analysis with the base load, and then with the EV load considering the wind generation "Fixed" in the SCOPF solution. Figure 9 shows the change in generation in MWh over the day after considering the EV load from Figure 3. The colors represent different generator fuel types. A key observation here are that considering just 5% EV penetration in the Austin and Houston areas can change the dispatch of electrically and geographically distant generators. Hence it is might be important to use such large, regional, or transmission networks to fully assess the impacts of EV integration, in addition to the commonly used distribution networks.

C. 7000-bus Case with Wind Flexibility

This part also shows results for the change in dispatch and emissions from the base case to one where 5% EV penetration is considered in Austin and Houston. However the key difference with the prior subsection is that here the wind is not treated as a negative load but rather it is allowed to have some flexibility between 80% and 100% of the maximum

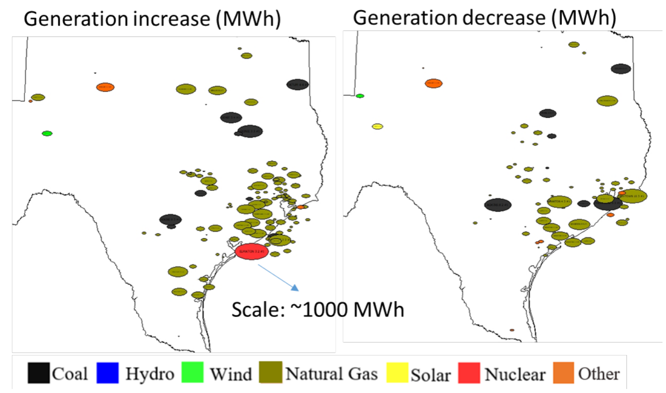

Fig. 9. Change in generation in MWh over 1 day due to 5% EV load in Austin and Houston (Wind Fixed)

output i.e. the forecast for each wind generator. This is done in order to account for possible wind curtailment, which can affect an SCOPF solution.

This method of modeling wind generation with flexibility creates more changes in the generator dispatch compared to

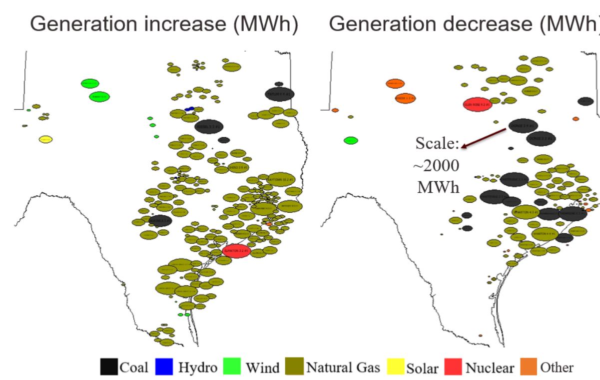

Fig. 10. Change in generation in MWh over 1 day due to 5% EV load in Austin and Houston (Wind Flexible)

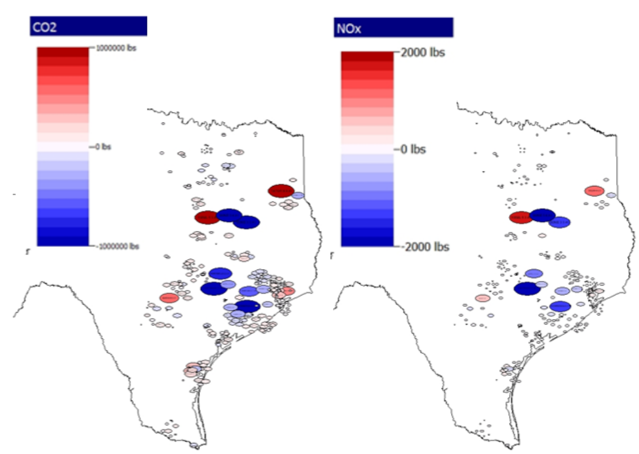

Fig. 11. Change in generation CO_2 and NOx emissions in lbs over 1 day due to 5% EV load in Austin and Houston (Wind Flexible)

the fixed wind scenario, as seen in Figures 9 and 10. Figure 11 shows the resulting change in CO_2 and NOx emissions in lbs, where red indicates an increase and blue a reduction. The sizes of the ovals and intensity of their colors are proportional to the magnitude of the emission changes. The numerical results are summarized in Table II, where "Base Case" refers to emissions without EV load included, and "Change" is the difference between the emissions calculated considering EV load and the Base Case emissions. The Net Change is the change in emissions caused by changing the wind modeling from fixed to flexible plus the emissions change caused by including EV load in the flexible wind case.

TABLE II
EMISSIONS RESULTS SUMMARY

Type	Wind Fixed		Wind Flexible		
	Base Case	Change	Base Case	Change	Net Change
NOx (lbs)	177560	237	181160	-3814.96	-215
CO_2 (lbs)	241,855,394	45673	242,137,102	-163,897	117,811

Adding wind flexibility causes larger variations in the outputs of several other generators compared to the fixed wind case. While adding this element of variation and realism does increase the base case emissions, it is interesting to note the NOx and CO_2 change in the flexible wind case with the inclusion of EVs. This is attributed to the reduced wind curtailment occurring in the EV inclusion case as opposed to the base case. Figure 12 shows the additional wind utilization every hour with the inclusion of the EV load. The spatio-temporal characteristics of both the EV load and the free renewable generation throughout the system optimized in the SCOPF solution process enable more wind utilization, displacing the "not free" conventional generators. What is most notable here is the despite an increase in the base case NOx emissions due to the wind modeling, there is a net (altbeit modest) drop, when the additional EV load is included. This shows promise to pursue the co-optimization of renewable generation and EV charging strategies to minimize grid emissions.

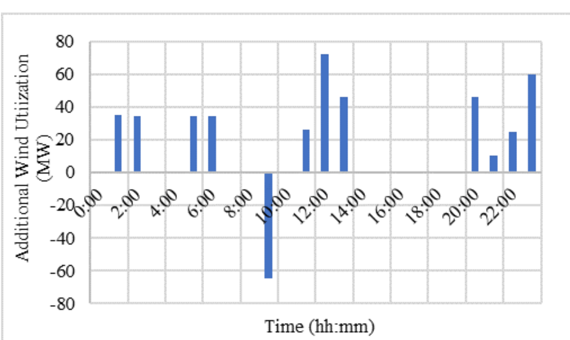

Fig. 12. Additional wind utilization

V. CONCLUDING REMARKS

This paper aimed to highlight some of the key factors that can affect generator dispatch and emissions in the presence of EVs. It discussed the sensitivity of generation dispatch and emissions to the system generation mix, and the EV charging strategy. Simulating a regional, transmission network model showed that even a 5% EV load in one part of the system can affect the dispatch far across the network, highlighting the importance of using such models and analyses in EV grid integration assessments. The paper also showed how different methods of modeling wind generation affect the emissions in the presence of EVs, which shows potential for reducing them.

Work is ongoing to add more EV charging datasets from more regions in Texas and from more types of EVs such as those from fleet vehicles, which are poised to create a significant demand with very different temporal characteristics compared to passenger EVs, in the near future. Improvements can also be made to the overall SCOPF solution process used here by adding complexities such as multi-period optimization, and probabilistic modeling of renewable generation, etc.

ACKNOWLEDGMENT

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