# The Economic and Technical Impacts of Houston's Electric Vehicles on the Texas Transmission System: A Case Study

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***Abstract*—As electric vehicles are being increasingly integrated into the transportation system, it is important to model their impact on the electric grid. This paper analyzes the impacts of the electrification of vehicles in the greater Houston area within the context of the synthetic 7,000-bus Texas grid on locational marginal pricing and line loading. The case study models vehicle electrification levels of up to 15%. The results show an increase in the number of highly loaded lines after modeling electric vehicle charging load to the grid but surprisingly, a decrease in line loading of the most heavily loaded lines in the system during peak load hours. The inclusion of electric vehicle charging load resulted in marginal changes to LMPs overnight, a slight decrease to most LMPs during the morning and early afternoon, and a significant decrease in system LMPs during the peak load hour.**

***Index Terms*—Electric vehicles, locational marginal price, line loading, transmission system**

## I. Introduction

Due to maturing technology, declining costs, and increased support for clean transportation, electric vehicles (EVs) are on the rise. As of 2020, the transportation sector represented only around 2% of global electricity demand. However, recent studies show that by 2050, transportation is expected to account for 10% of total global electricity demand [1]. This trend toward increased electrification of the transportation sector requires extensive planning to prepare the electric grid for a variety of possible adoption scenarios. The impacts of transportation electrification varies depending on aspects of the adoption scenarios such as the penetration of EV integration and the charging models used. Therefore, there exists a need to model EV integration scenarios so that researchers can identify possible problems to various aspects of power grid planning and operations.

One area of particular interest pertains to identifying the infrastructure changes that are necessary to support an increased EV integration. Particularly, one identified impact of EV charging is a change to the peak demand under certain charging models [2]. These sudden changes in peak demand can lead to the line overloading as current increases to maintain power supplies. The line overloading and congestion results in huge changes in the locational marginal price (LMP) of electricity [3] and can lead to an accelerated component aging, increased resistive losses, and fire safety issues from overheating lines or transformers that impact the reliability of the components of the electric grid. However, if EV charging load schedule is encouraged during off-peak hours, LMPs may even decrease as a result of congestion prevention in peak hours [4].

Because many factors must be considered with the increasing integration of EV charging into the power grid, it is imperative that studies integrate realistic models of both the transportation and electric systems. This work relies on an established coupled infrastructure approach using detailed models of both a realistic electric grid and actual transportation network to analyze the impact of EV integration on line loading and LMPs of the transmission system for multiple levels of EV penetration. Publicly available data of transportation system is used for estimating EV charging patterns based on their type, location and schedules and the charging demand is integrated to a realistic but not real synthetic power grid that is created over the footprint of Texas, United States. This research provides a fundamental insight into the impact of incorporating electric vehicles into a realistic large-scale electric system with more than 7,000 buses considering reliability and system costs.

## II. Modeling

### A. Transmission System Modeling

In North America, electric grid models are considered critical energy infrastructure information (CEII) and access to those are restricted and detailed results often cannot be published. As such, this study leverages a synthetic grid that is created over the Texas footprint that is realistic enough to mimic actual grids. Synthetic grid models are publicly available at [5] and have been validated to be functionally similar to the built grids in North America [6] without compromising CEII. The development methodology of these grids is documented in [7]–[10], and [11] details the inclusion of generator cost curve information, a feature of the synthetic grids which is essential for the performance of economic studies in this paper. The associated load time series are based on an estimated composition ratio of residential, commercial, and industrial customer load. Publicly available prototypical residential/commercial building, and industrial facility load time series are then aggregated to the buses through a heuristic optimization process [12], [13].

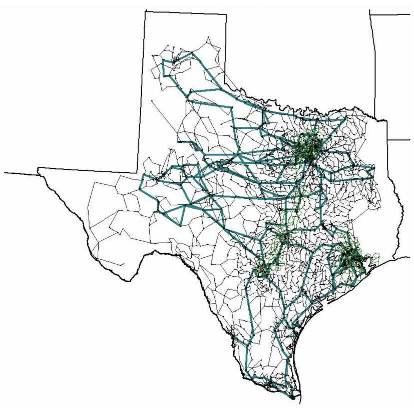

Fig. 1: TX7k transmission system

The transmission system used in this study is the TX7k network, a system comprised of nearly 7,000 buses geographically sited on the Electric Reliability Council of Texas (ERCOT) footprint using the same voltage levels as the built ERCOT system, shown in Figure 1. An overview of case information is provided in Table I. This grid has a corresponding synthetic distribution system [14], the topology of which is leveraged in mapping EV loads to the transmission-level grid.

TABLE I: System Information for TX7k Grid

| Attribute | Value |
|---|---|
| Buses | 6717 |
| Transmission Voltage Levels | 69 kV, 138 kV, 345 kV |
| Peak Load | 80 GW |
| Generation Capacity | 100 GW |

### *B. EV Load Modeling*

Due to a presently low market penetration of EVs (in Texas in 2021, only 0.24% of vehicles registered in Texas were EVs [15]), there exists a lack of availability of widespread EV charging data. Thus, simulations are useful for generating EV charging data. The modeling of EV loads relies on an underlying transportation network model and traffic flow simulations coupled with charging behavior models. This modeling process was demonstrated in [16] and is applied in this paper for the greater Houston region.

A dynamic traffic assignment (DTA) model provides a mesoscopic analysis of traffic flow over a spatio-temporal resolution. The DTA model uses the transportation network and travel demand models to generate a trip trajectory and calculates on-road energy consumption of EVs. For a defined market penetration of EVs, trips are randomly assigned to be EV or non-EV trips. The vehicle range of those designated to be EVs is assigned based on the proportion of 100-mile, 200-mile, and 300-mile ranges from EV sales data [17].

Charging behavior was modeled with the goal of creating a realistic EV load profile. This was accomplished using a microscopic charging behavior model that accounts for characteristics of daily travel as well as various levels of anxiety of drivers. Thus, the resulting charging load incorporates variation based on time-of-day, remaining battery range, and trip characteristics. The outcome of using this behavior model is a charging load that is higher overnight, reflecting people charging their vehicles towards the end of the day when their batteries are more depleted after their daily travel.

The outcome of the EV modeling is a charging load time series at various locations in the synthetic system. These loads are incorporated to the electric grid model by the procedure developed in [16]. In summary, substation service areas are created using Voronoi polygons around the geographic location of the substation and the EV charging loads are mapped to the substations serving their respective locations. The EV charging loads are represented by loads added to buses within the substations in the electric grid model.

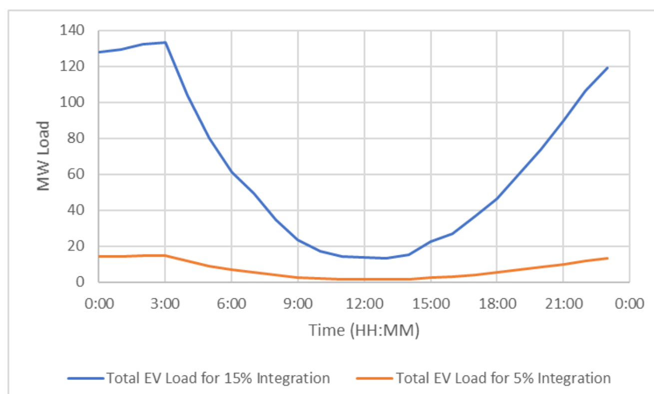


Fig. 2: Charging profiles for 5% and 15% of EV integration

## III. Case Study

The case study presented in this paper involves the electrification of a fraction of light-duty vehicles in the greater Houston area (located in eastern Texas along the Gulf Coast) within the context of the TX7k system. The case study simulates the grid during a sample peak load day (August 5). During this 24-hour time period, non-EV load varies between 45 and 80 GW through a typical daily cycle. This load profile for the base case is shown in Figure 3.

This paper considers the impacts of charging demand at 5% and 15% EV market penetration in Houston by comparing the EV integration scenarios with a base case that does not include EV integration. The EV charging profiles are based on the EV modeling discussed in Section II and are shown in Figure 2.

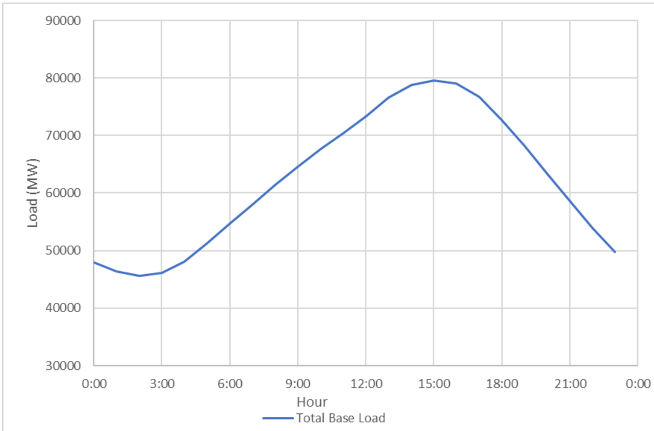


Fig. 3: Load profile for the base case

Each scenario (base case, 5% EV integration, 15% EV integration) is run using a time step simulation that solves an AC optimal power flow for each hour of the simulation using a unit commitment designed for each case's peak load. The LMP and line loading results for the EV integration scenarios are compared to the base case to determine the impact of the added EV charging load.

## IV. Results

### A. Locational Marginal Pricing

The results for the LMP study are shown in Figure 4 displaying time points of interest during the day. In particular note that, 3 am contains the peak of the EV charging load, and 12pm demonstrates the minimum EV charging load. There is a pattern of decreased cost with the inclusion of EV charging during the afternoon hours, particularly from around 12pm to 6pm. Otherwise, the marginal prices remain relatively the same across the scenarios throughout the night and early morning. There are not great variations between the 5% and 15% cases though these cases can differ significantly from the base case.

The greatest differences correspond to the peak system load period during the day. During the peak load of the selected sample day (in 3 pm model), the marginal cost decreased up to 1000%/MWh with the inclusion of electric vehicle load. At 3pm, the greatest negative variations occurred in the northern Texas area, as shown in Figure 6. Both levels of EV integration demonstrate that a small EV load may significantly reduce LMP at peak hours. This observation is discussed in Section IV-C.

### B. Line Loading

The percentage of MVA limit of the most heavily loaded lines were compared across the scenarios. In both of the EV integration cases, the same set of lines were the most heavily loaded lines. These lines are high voltage lines within the synthetic electric grid system (138 kV and 345 kV). They are located in the East of Texas as shown in Figure 7.

Even though most of the charging demand occurs overnight, the greatest changes as a result of EV integration occur between 6am and 8pm as shown in Figure 5. In general, the lines in the 15% EV penetration case had more variation from the base case than the 5% case. However, the overall shape of both cases remain relatively the same.

From 6am to 8pm, the 15% case greatly reduces the loading of several of the most heavily loaded lines. During these hours, the most heavily loaded lines experience a decrease in loading or remain fairly constant when compared to the base case.

With the EVs added, the amount of lines that are over 95% MVA Capacity changes as shown in Figure 8. Five percent integration of EVs causes a shift of heavily loaded lines to the peak hours of the system (between 1pm and 7pm). However, the addition of 15% EV leads to less heavily loaded lines during the peak load of the system. In general, there are more variations during the morning hours of 3am to 6am for the 15% case.

From the comparisons in Figure 5, and 8, adding EV load has slightly changed the power flow without any negative impact on line loading in this EV charging scenario. Interestingly, for both levels of EV integration, the loading on the most heavily loaded lines are even slightly decreased during a high load day simulation. Please note that if the MVA flow in the lines are not close to the line capacity, slight changes in the flow does not impact LMPs but changes near line capacity and line congestion can significantly increase LMPs.

### C. Discussion

The decrease in LMP is consistent with a decrease in line loading on the most heavily-loaded lines. Figure 8 shows a chart with the number of branches loaded in excess of 95% of the rated MVA capacity. Although there was a decrease in loading on the most heavily-loaded branches, the count of all heavily-loaded branches remains high. This may indicate that the inclusion of EV loads in this case study has acted to distribute the power more evenly across the lines in the system, reducing the congestion on the most heavily loaded lines and increasing the congestion on more moderately-loaded lines.

Generally, for both the 5% and 15% integration case, a decrease during the peak hours in the heaviest loaded lines in the system as shown in Figure 5. These lines are mostly located in eastern Texas (Figure 7) and connect the wind-rich northwest portion of the system with the high load region of the system to which the additional EV load was added. The decrease of LMP being most prevalent in northern Texas (Figure 6) is indicative of the inexpensive generation in the north west and congestion along some of the major branches that would carry the generation to other regions of the system.

## V. Conclusion and Future Work

The impact of EVs on line loading and bus LMPs were studied on the synthetic Texas 7k grid using a realistic EV charging load model approximated based on spatio-temporal travel patterns. The studied was implemented on a sample high load day with a peak load of approximately 80 GW. The studied EV charging scenarios included 5% and 15% EV market penetration in the Houston area (located in eastern

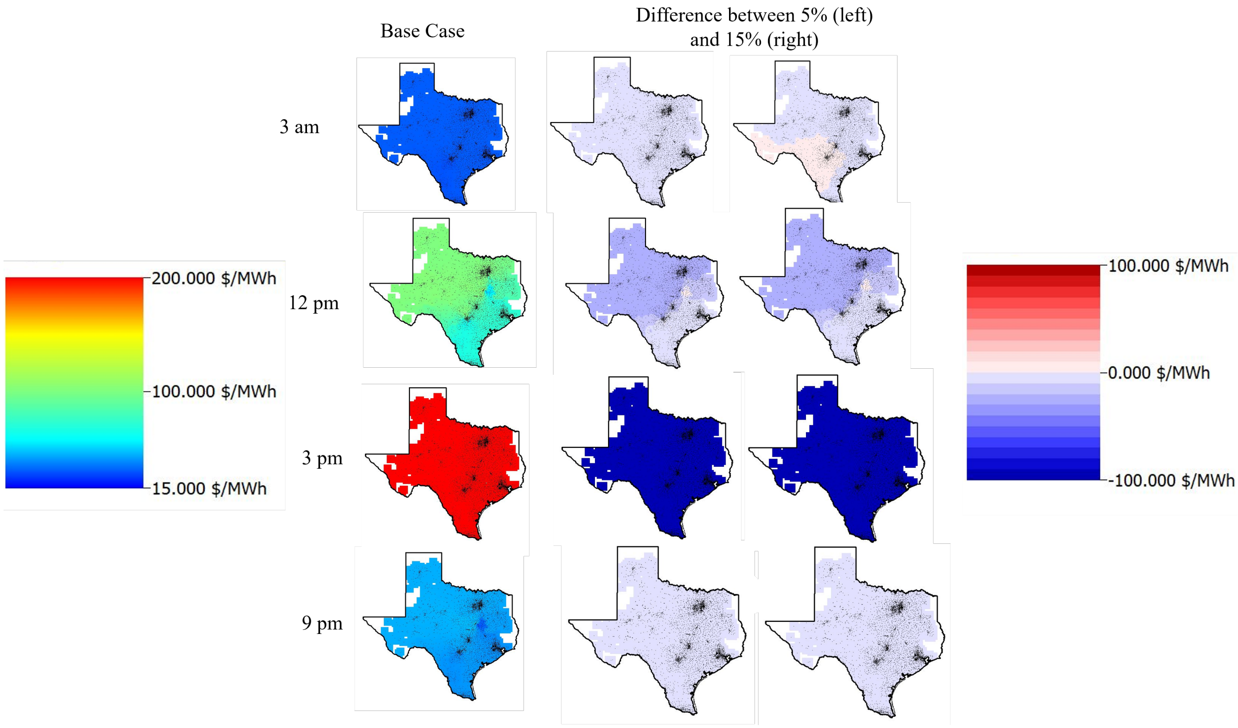


Fig. 4: LMPs for the base case (left). Difference contours with comparison to base for 5% EV integration (center), and 15% EV integration (right) at 3am, 12pm, 3pm and 9pm for the day of simulation.

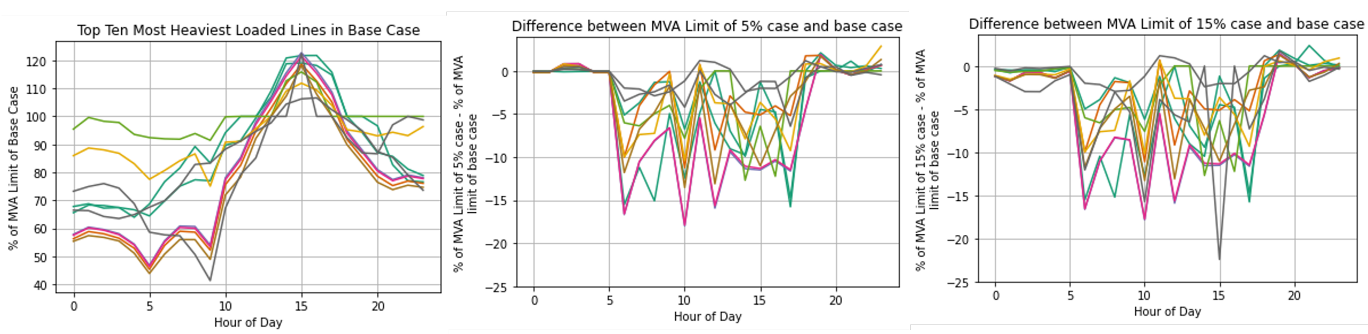


Fig. 5: Variations in line loading on the most heavily-loaded lines from 5% and 15% integration compared to the base case.

Texas along the Gulf Coast). The results show that a suitable charging schedule leads to reduction in the loading of the most heavily loaded lines during the peak load hours. The lines which were most heavily loaded belong to the two highest voltage levels in the system and are among those which connect the wind-rich northwest portion of the grid to the eastern portion and experienced the additional loading. As the congestion was alleviated on these lines during peak hours, bus LMPs decreased. This analysis presents a case study of the behavior of the grid on a peak summer day with the inclusion of EV charging in the greater Houston area. Results may vary for different regions of study or under different grid conditions.

In the future, additional case studies will be conducted to evaluate the impact of EVs under different loading conditions and weather scenarios, and with EV integration modeled in different regions of the grids. Further insights can be gained from considering the impact of EV integration with modelling the increase in the renewable energy sources. For example, Texas has a huge capability of wind farms with around 17% of the overall general being supplied through wind turbines in 2019 [18].

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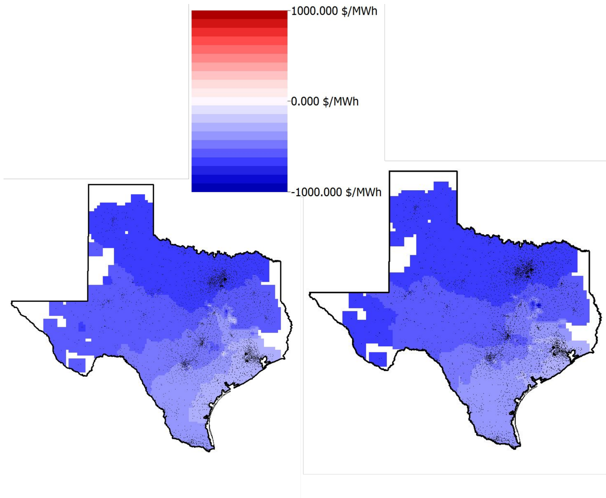


Fig. 6: Difference of LMP in comparison with base case at 3pm. The left side shows the difference between 5% integration and the base case and the right side shows the difference between 10% integration and the base case.

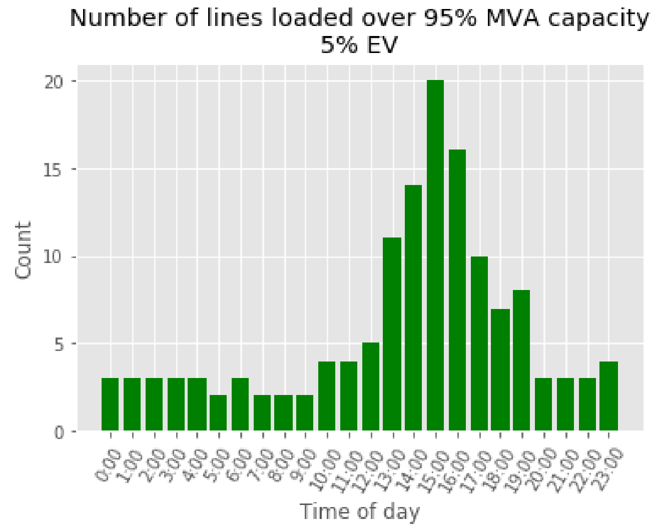


Fig. 8: Number of heavily loaded lines (≥95% MVA capacity) at 5% EV integration.

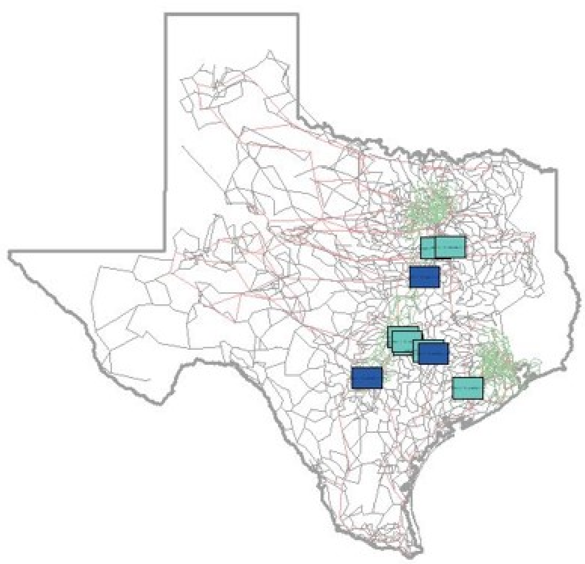

Fig. 7: Locations of heaviest loaded lines in the Texas 7000 Bus System. The dark blue boxes represent 345 kV lines while the light blue ones represent 138 kV lines.

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