Integration Challenges for Fast-Charging Infrastructure to Support Electric Vehicle Adoption

by

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Abstract

Highway fast-charging stations located between major population centers are necessary to address consumer charging concerns and thus to support the continued adoption of electric vehicles to meet decarbonization policy targets. Yet such stations, if sized to support anticipated demand, may cause operational difficulties on the power grid.

Using a spatially resolved model of the power transmission network and a detailed market simulator, we characterize the effects of large-scale EV fast-charging on the Texas ERCOT system. We further explore three strategies to mitigate these effects – energy storage co-location, network reinforcement, and demand flexibility – and quantify their costs. This analysis is unique in its focus on highway fast-charging, in its nodal representation of the power grid, and in its measurement of transmission-level impacts.

We find that highway fast-charging stations do have the potential to cause transmission-level impacts, especially by exacerbating local transmission constraints. Inter-zonal transfer constraints and increased costs due to the dispatching of more expensive generation also contribute to system costs. We develop a general method to identify the most impactful charging stations, but we find that the determination of cost-effective mitigation strategies for each station requires a more tailored approach. Our analysis indicates that transmission reinforcement and battery co-location are relatively competitive mitigation strategies, but that demand flexibility is not.

When considering policies to promote fast-charger development, policymakers should focus on involving multiple stakeholders who can contribute different expertise to identify cost-efficient solutions. Specifically, we suggest a central role for power utilities due to their experience planning transmission reinforcement, but we also highlight an important role for private developers, especially in the United States, for political feasibility and overall cost controls.

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Terminology

Abbreviation	Elaboration
EV	Plug-in Electric Vehicle, including plug-in hybrids
ICEV	Internal Combustion Engine Vehicle
EVSE	Electric Vehicle Supply Equipment
Fast-Charging	EVSE at Level 4 or above (See Table 2)
Slow-Charging	EVSE at Level 3 or below (See Table 2)
ISO	Independent System Operator
ERCOT	Electric Reliability Council of Texas
LTSA	Long-Term System Assessment
CRR	Congestion Revenue Rights

Table 1: Terms and abbreviations used in this document.

EVSE Level	Current Type	Average Power (kW)	Miles Charged per Minute
Level 1	AC	1.4	0.06
Level 2	AC	6.6	0.30
Level 3	DC	50	2.25
Level 4	DC	150	6.76
Level 5	DC	350	15.77

Table 2: Common SAE designations for EVSE power levels. Adapted from (Lee and Clark 2018), who assume an EV efficiency of 0.37 kWh per mile, representative of a Tesla Model S.

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Chapter 1

Introduction

1.1 A Policy Mandate for Electric Vehicles

National and local governments around the world have established electrification goals for their transportation sectors, with policies ranging from fuel economy standards, vehicle purchase subsidies, and support for technology standards to achieve them (IEA 2019, pages 11-12). Reasons to expend political and financial capital on these targets vary, but include: decelerating climate change, for which tailpipe emissions are an important driver[1]; and continuing to reduce local air pollution, to which EVs contribute nothing at point-of-use (Ajanovic and Haas 2018).

EV sales are expected to dominate by mid-century, but must overcome both demand and supply barriers. In response to government policies, to declining EV production costs (Wofram and Lutsey 2016) (largely driven by battery pack economics (Hsieh et al. 2019)), and to private consumer preferences, EV sales in both the light-duty and heavy-duty sectors are widely expected to accelerate through the mid-century. Although specific forecasts differ substantially according to methodology, reputable estimates of passenger EV sales range from 15% (IEA's business-as-usual "New Policies" scenario (IEA 2019, page 16)) to 30% (BNEF's baseline scenario (BNEF 2019, page 1)) of total global passenger vehicle sales in 2030, with much higher estimates for China, Europe, and the USA. Organizations such as OPEC that have interests in promoting oil demand also predict sales within these bounds (OPEC 2019, page 100).

[1] "Transport accounted for 28% of global final energy demand and 23% of global energy-related CO2 emissions in 2014." (IPCC 2018, page 142)

Despite the positive drivers, many countervailing factors must still be overcome to meet the forecasts. They can be grouped into three categories. First, *demand-side factors* that limit consumer interest in purchasing EVs, the most salient of which are high upfront costs, range anxiety, and access to charging (Mattila 2019, page 59). Second, *supply-side factors* that limit producer interest in offering EVs and EVSEs, including reduced after-sales revenues to dealers from maintenance, lower profit margins to manufacturers from production, and the uncertain nature of EVSE business models (Rubens et al. 2020). Third, *societal factors* that limit the politically acceptable pace of change in socio-technical systems due to their adverse effects on other systems. Examples here include the effect of personal mobility on urban transit systems, the effect of battery chemical demand on resource supplying areas, and, notably here, the effect of charging demand on power systems.

A convenient charging solution is instrumental to overcoming these barriers. At the intersection of demand-side, supply-side, and societal limitations to continued transportation electrification lies the question: How to charge the vehicles? From a demand perspective, charging should be affordable, accessible, and fast. These are attributes that characterize the existing dense fueling network for ICEVs.[2] From a supply perspective, the charging needs either a profitable business model or a compelling case for cost-socialization as a public good. From a societal perspective, the charging should have a low impact on other systems, or else its externalities should be internalizable via impact analysis and transfer payments.

This research focuses on the challenges of EV charging, and it specifically seeks to address a current gap in the literature around the impacts of highway fast-charging stations on the supporting power system. Are there significant operational impacts? How can they be mitigated, practically? And how will the answers to those two questions affect progress towards the policy goal of a fully electrified transportation fleet? As I show further on, interaction with the power network will become a key consideration when designing a charging network to support EVs at a massive scale.

[2]There are over 150,000 retail petroleum fueling sites throughout the USA according to a fueling industry group (NACS 2020), compared to fewer than 3,000 DC fast-charging sites (EVAdoption 2019). A typical ICEV fueling pump may have a power output of 20 MW (MIT Energy Initiative 2019), compared to 100-300kW DC fast-charging plug.

1.2 Looming Challenges: A Thanksgiving Case Study

Operational problems at the EVSE-grid interface exist already. At 3:30 PM on Saturday, November 30th, 2019, Steven Conroy drove by the Madonna Inn in San Luis Obispo, California with his camera rolling. His subject: a Tesla Supercharger station packed beyond capacity. Though hosting over a dozen individual Supercharger EVSEs, the station plaza had turned into a makeshift parking lot of almost twenty Tesla vehicles queueing up for their turn to charge. Conroy's video, uploaded to YouTube (Conroy 2020), joined a chorus of complaints launched on Twitter about long wait times all over the country as people embarked on annual holiday visits to friends and family. The story was picked up in mainstream outlets like Business Insider (Meisenzahl 2019).

San Luis Obispo is approximately halfway between Los Angeles and San Francisco, two automobile-rich metropolises in California about 400 miles apart. This distance is notably greater than even the longest-range quoted on Tesla's website for its "Long Range" edition premium Model S, implying the need for an EV to recharge at least once between the two cities (Tesla 2019). During holiday travel periods it is understandable that fast-charging stations along major transportation corridors, although distant from population centers, could become more congested than usual. Surprisingly, however, the problem of long wait times and fast charger access has not become any less of a consumer headache over the past two decades of EV industry maturation.[3]

Approaching this problem from the perspective of the three categories of limitations introduced in the previous section – demand-side, supply-side, and societal – brings important trade-offs into focus. In the case of the San Luis Obispo charging station, Tesla has not built its charging network to handle peak demand. Given that Tesla has been operating in California for more than a decade, and given the amount of data it collects from its EVs, it is even appropriate to say that Tesla has *chosen* not to handle peak demand. This choice has resulted in a lessened supply-side problem — the charging station has a higher utilization rate and so has better profit margins — but a heightened demand-side problem — consumer frustrations over unavailable charging may limit future purchases. From a societal perspec-

[3] See reports in, for example (Crothers 2019) and (Mish 2019).

tive, Tesla's decision has lessened the impact of charging on the power network: by limiting the number of simultaneous charging events, Tesla is reducing strain on the distribution and transmission elements connecting its station to the broader grid. Given consumer anxieties and the policy goal for continued EV adoption, however, the present solution is unlikely to be an equilibrium.

To meet future policy goals, operational burdens will necessarily shift to the power grid. In order for EV penetration to extend to mandated levels, fast-charging stations on major transportation corridors will need to more gracefully meet peak demand. It is unreasonable to expect holiday travelers to wait in long queues for charging.[4] In a market with competitively priced alternatives to EVs, as exist now with ICEVs, too few people will make the electrification switch if this problem persists. To meet electrification targets through consumer choice (that is, not through fiat by making ICEVs illegal[5]), the demand-side problem will need a solution.

If the demand-side capacity constraints relax, though, the supply-side and societal will effects worsen. A business model must be found to profitably support up-sized charging stations with lower utilization rates, and more capital will need to be invested in grid infrastructure to meet the new large and variable power demand. Even if the current ratio of EVSEs to EVs remained the same, charging stations along transportation corridors will need to increase in size many times over to keep pace with increasing EV penetration.[6] This increase by itself may bring significant operational problems to the power grid.

Waiting for these problems to materialize before studying them is irresponsible. This research attempts to shed light on the effects of EVSE-power grid interaction at highway fast-charging stations with the goal ultimately of more efficiently supporting the global electrification of

[4]Attempting to eliminate 100% of queueing would be an overreaction. A recent NREL report that investigated the aggregate need for highway fast-chargers assumed that meeting 90% of peak demand would suffice. (Wood et al. 2017)

[5]Phasing out ICEVs through direct legislation may occur. After 2025 in Norway, most households will only be permitted to purchase EVs. A recent research report on the topic determined that "traffic on peak travel days can become a major barrier. It may not be economic to build out charging infrastructure capacity to absorb these peaks. Users will thus confront a trade-off between daily cost and time savings and longer stops and charging queues on long distances." (Figenbaum 2018)

[6]See further sections.

transportation.

Chapter 2

Mitigating Impacts of Highway Fast Chargers on the Power Grid

2.1 Literature Review

The literature surrounding EVSE is rich, covering topics from the demand perspective (how drivers will use charging infrastructure), from the supply perspective (how developers can plan and operate charging networks) and from the power utility's perspective (how grid infrastructure and electricity rates should adapt). The literature shrinks considerably, however, when focusing on highway fast-charging EVSE. This type is characterized by (1) large-scale demand from many EVs simultaneously charging at high power levels[1], (2) locations on transportation corridors distant from load and population centers, and (3) relative inflexibility, since drivers stop en-route to a destination. Such charging, despite intense focus from utilities in recent years, is relatively poorly studied.[2] What efforts have been published are surveyed below.

[1] Power levels for highway fast-charging generally is greater than 100kW. See Table 2 on page ii.

[2] "As fast charging networks expand and new technology enables greater charging power, their extremely concentrated and stochastic loads are likely to cause more of an issue for the electrical grid, and typical smart charging programs are less suited to this application. Further exploration of the impacts of DC fast charging and potential models to mitigate these effects could help to reduce costs and spur sustainable growth of fast charging networks, which would ultimately benefit electric vehicle owners." Excerpted from (Hall and Lutsey 2017).

Research on distribution-level impacts and in abstract transmission networks.

A first category of literature examines the impact of EV charging on distribution-level power networks. This research is focused on the vulnerabilities of specific pieces of equipment, such as low-voltage transformers, when exposed to unmanaged or managed EVSE demand. Such research is often formally structured in terms of power systems engineering, but it is inherently limited in its applicability to system-level operational costs. Several utilities have sponsored research in this area, for example studies conducted by Xcel Energy of Colorado, the My Electric Avenue project in the UK, and the Sacramento Municipal Utility in California (Hall and Lutsey 2017). Affonso and Kezunovic investigate the impact that different charging schemes for a parking garage EVSE has on the local distribution transformer. They find that certain smart charging plans can prevent transformer overloading (Affonso and Kezunovic 2018). Humayd and Bhattacharya simulate stochastic charging load within a model network to determine the maximum EVSE penetration that current distribution systems can accommodate (Humayd and Bhattacharya 2018).

A second category of literature, related to the first in its power systems engineering approach, seeks to characterize EV charging as a distinct type of demand using idealized network models. Although such modeling does extend analysis to the transmission scale, it does not attempt to make economic or policy conclusions or to assess demand-side behavior, instead characterizing purely technical operational difficulties. Staiger et al. perform a risk analysis on the New England IEEE-39 bus test system, seeking specifically to understand how the stochastic nature of EVSE demand exposes the transmission grid to cascading failure-style faults (Staiger et al. 2019). Anderson and Nair develop a model that minimizes the system-level costs of EVSE demand by managing EV travel routes in a centralized, controllable fashion across an abstract network model. This results in a stylized problem of the sort we investigate (Anderson and Nair 2019).

Research characterizing system-level costs from EV charging.

Over the past few years an increasing amount of literature has been published that quantifies system-level costs on real-world power networks due to EV charging at large scale. However, these studies are often more focused on novel or powerful methods of simulating demand-side EV charging behavior than on a detailed understanding of the power grid impacts.

Xu et al. exploited a massive and granular personal mobility data set to produce spatially and temporally highly resolved charging simulations that could interact with a metropolitan-scale power network (Xu et al. 2018). The paper treats charging as a flexible demand, however, and does not interact it with a comparably detailed power network. Zhuge et al. similarly showcase highly resolved mobility data to create credible charging profiles on the scale of the Beijing metropolitan area (Zhuge et al. 2019). Focus on power system effects is lacking, however, and does not extend to the transmission scale. Wolinetz et al. use a more realistic power system model that includes hourly generation dispatch, but they use a copper-plate approximation for the transmission network that cannot account for locational effects from specific EVSE stations (Wolinetz et al. 2018). Additionally, short-term costs are derived from levelized costs of electricity from the power supply stack and not from a realistic operational model.

Sheppard comes closest to developing a truly detailed picture of the interaction between (a) a spatially and temporally resolved charging network and (b) a spatially and temporally resolved power network. He couples a transportation model (BEAM) of the San Francisco Bay Area to a realistic power systems simulator (PLEXOS), which precisely models unit commitment and economic dispatch of power generation (Sheppard 2019). Though he does model hourly system operations over the course of a year, his power system is only spatially resolved into regional load zones, and so localized power constraints cannot be simulated. This is appropriate given his focus is on the aggregate effects of distributed charging behavior, but does not allow, for example, the detailed modeling of specific highway fast-chargers. Additionally, such an approach underestimates the costs of EVSE integration; as he states, “the electricity prices produced by the model generally under-estimate hourly prices” due to the reduced operational constraints. Still, his detailed exploration of the effect of different electricity tariffs on charging behavior, and how that charging behavior translates into power grid operational impacts, is in the theme of the present research.

There is a gap in the literature around detailed power systems modeling. The above brief review shows that, although existing literature has begun to explore the utility of finely detailed EVSE demand models for measuring transportation and power system-level effects, similar attention is still lacking for the power system. Literature that does finely represent grid equipment is generally quite abstract or restrained to distribution-level effects. This research seeks to address this gap by offering a more detailed operational model of a power grid in which to assess the (necessarily locational) impacts of highway fast-charging.

2.2 Research Questions

Above we have discussed the policy goals for rapidly increasing electrification of the road transportation system over the coming decades, and we have shown that the dearth of inter-city fast-charging EVSE stations is a potentially limiting factor to achieving these goals. Extrapolating into the future presents operational risks at the EVSE-power grid interface, and we have shown that existing literature has not yet looked at this topic from the perspective of a realistic, spatially- and temporally-resolved power system. This study takes that perspective.

We hypothesize that there will be significant operational costs to the power grid from integrating highway fast-charging infrastructure as EV penetration increases, and that it will manifest as local power network congestion that requires spatially-resolved modelling to effectively study. From this basis we investigate three questions in succession:

1. Will there be significant operational costs on the power grid from future highway EV fast-charging?
2. If so, how can these costs be efficiently mitigated?
3. How do the preceding two conclusions locate within ongoing business and policy debates surrounding the attainment of transportation electrification?

2.3 Methodology

2.3.1 Overview

We use a scenario analysis approach to model plausible future system behavior. The essence of our research topic is not just to identify possible behaviors in the interaction of an abstract charging network and power network, but further to make some claim about whether these behaviors will manifest in our future reality. We construct a modeling pipeline as described below that attempts to represent *plausible* future states of the world and how they interact. We will often repeat the word "plausible" in our descriptions since it is the core consideration in our modeling approach. While much of the system we describe is generically recognizable as an apparatus to simulate the operations of a future power grid in a realistic electricity market simulator, we do detail important interpretations and caveats in Section 2.3.5 that help to maintain plausibility and to combat the inherent problems of credibility that accompany detailed predictions about the future.

We choose Texas in the year 2033 as our base scenario. Our selection of a future scenario in which to base our analysis is guided both by suitability and practicality. A suitable system should: (1) be based tightly on an existing, real-world system; (2) be large and varied to encompass the important behaviors in power and transportation networks; (3) be closed, so that endogenous modeling does not exclude important exogenous effects; (4) have sufficiently advanced EV penetration to drive visible system effects. A practical system should have sufficient data available to allow modeling at the high levels of temporal and spatial resolution we desire. For our purposes, that means hourly time increments and resolution down to at least the 69kV level on the transmission system.

A coupling of today's Texas ERCOT power system with today's Texas Tesla Supercharger network is a convenient joint system candidate for the above considerations. As for suitability, it (1) is already an existing system in the present, (2) manages power for over 26 million people and at 45 different highway fast-charging locations, and (3) operates electrically as its own interconnection. It only lacks in (4) EV penetration, although compared to other US markets it does not lag far behind.[3] As for practicality, ERCOT makes copious amounts of operational data available down to the 15-minute and 13kV levels, and information on Tesla Superchargers is available readily online. To mitigate the weakness in EV penetration, we will forecast this joint system into the year 2033, as discussed in detail below.[4]

We use commercial grade market simulation software. Our analysis focuses on the hypothetical outcomes that arise from the interaction between our system components over time, according to common electricity market rules. With plausibility in mind, we select a simulation method that approximates the real-world operational mechanics in the ERCOT power system. Instead of building such software from scratch to implement production cost modeling, generation commitment, and security constrained economic dispatch, we rely on commercial-grade market simulation software for a fully detailed and credible simulation.

An overview of our modeling pipeline is presented in Figure 2.1, and will be elaborated in the following sections.

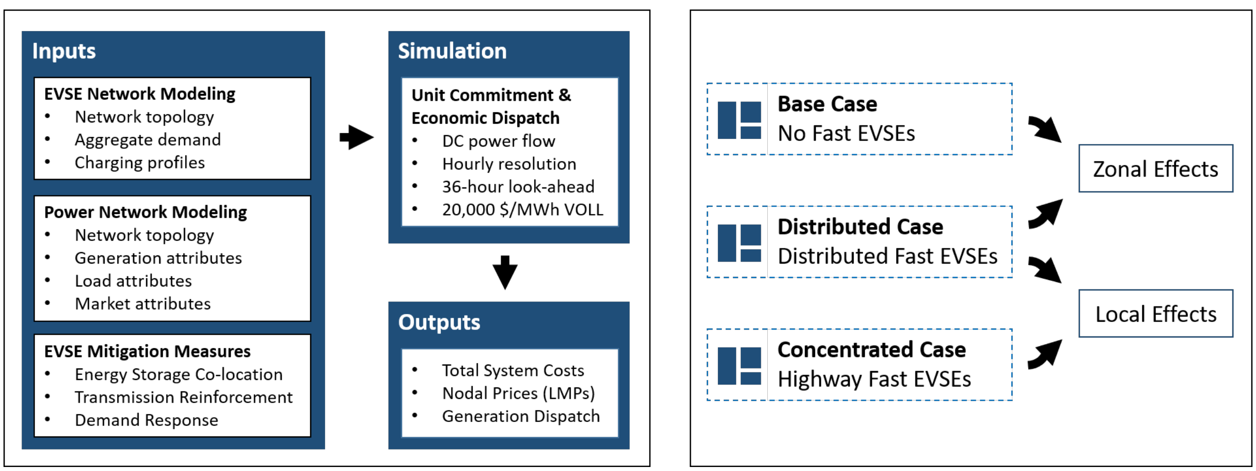

Figure 2.1: Schematic representation of our scenario modeling approach.

We perform our analysis over two time frames. The main results of this paper are computed over a full year of data, but for computational convenience we limit our sensitivity

[3]According to (US DOT 2020), Texas had the fourth largest share of new EV registrations in 2017 among the states in the USA, behind California, Washington, and Florida.

[4]Although we aim for "plausibility", we do not attempt equal levels of precision for all adjacent systems in 2033 Texas. Fuel prices as generation operating cost inputs, for example, as well as market rules, are simplified.

analysis to a period of only one week. Because a motivating assumption of this study is that highway fast-charging stations will need to be sized for peak demand, and because the grid impacts of EVSE use will also be most severe during times of peak demand, a narrow simulation window should capture the most important dynamics. For our sensitivities we focus either on the eight-day period of peak demand in our 2017 load data, from August 10th through August 17th, or on the eleven-day period around Thanksgiving, from November 20th through November 30th. A short discussion of these time windows is in Appendix A.1.

2.3.2 Scenario Design: The Power Network

We develop a topological model of ERCOT using data from ISO auctions. An advantage of choosing ERCOT for this study is the availability of high-quality transmission[5] network models produced by the system operator for its monthly Congestion Revenue Rights (CRR) auctions.[6] This model is available as an unencrypted RAW file formatted according to Siemens' PSS®E format.[7] The RAW data file contains all the necessary information to create a high-fidelity and technically complete topological model of ERCOT suitable for powerflow studies, including control area definitions, transmission lines, substations, transformers, load buses, and generation. With basic data mapping we extract the data into a non-proprietary format.

We extend the network model using external data sources for generation and load. To simulate the electricity market operations, generation characteristics and load profiles must supplement the topological model. For thermal generation we need production cost data – commitment costs, variable operating costs, fuel types, and heat rates – as well as simplified operational characteristics like ramp rates and maximum power output. We obtain this data from from S&P Global's Power Plant Briefing Book, a subscription data

[5] For the purposes of this research, we consider "transmission" to include 60kV lines and higher, which comports with ERCOT's definition.

[6] The specific model we use is from the June 2018 CRR auction.

[7] PSS®E is a power system analysis platform in some ways similar to Polaris' PSO, the simulator used in this research.

source and standard for industry analysts.[8] Fuel costs are also needed for thermal generation. Daily natural gas prices follow the history at Henry Hub from 2017.[9] Uranium, coal, and biomass prices are set at constant levels that reflect average levels in 2017 and appropriately locate the respective generation in the total ERCOT supply stack. Wind and solar facilities were specified similarly, although instead of solar irradiation and wind speed data, we used historical capacity factors that follow 2013 history.[10]

Load profiles are also based on 2017 ERCOT historical hourly data, which is only available in zonal aggregate form. Since spatial resolution plays an important role in our model, the zonal load data must be plausibly apportioned between each load bus in our topology. To accomplish this, we exploit a feature of the CRR model that ERCOT provides. It is a "snapshot" of the grid at a moment in time, and as such contains not only topological information, but also momentary power flow information. Thus, each load bus has momentary demand information associated with it. We assume that the CRR snapshot demand information is representative, and apportion historical zonal load data to each bus according to its share of total zonal demand in the model. The distribution of load is visualized in Figure 2.7.

We extrapolate the transmission, generation, and load models into the year 2033 using ERCOT's 2018 LTSA Report. The power network resulting from the steps above is certainly a plausible facsimile of the current-day ERCOT grid, and its simulation as-is replicates the real-life patterns in ERCOT: peak hour pricing, West-to-East congestion patterns, responsive thermal generation commitment according to renewable energy production, etc. Because we are considering this system in the future, however, we must make reasonable alterations to the transmission network, generation stack, and load profiles that are expected to occur over the next decade.

We use ERCOT's 2018 Long-Term System Assessment (LTSA) report to accomplish this. This report is a bi-annual publication required by the state legislature to forecast "increased

[8] Like all external data sources in this research, the S&P data was integrated into the CRR model via manual name matching and field mapping.

[9] Data obtained from the US EIA. Using 2017 data matches our data for electrical load, though for natural gas prices it is scaled such that the annual average matches ERCOT's LTSA report projection for 2033 (annual average of \$4.5/MMBtu) (ERCOT 2018).

[10] The historical capacity factor data is only available on an aggregate basis by ERCOT's nine "Weather Zone" definitions, and so is not resolved to individual facilities.

transmission and generation capacity" over a "10- to 15-year planning horizon" to provide a "longer-term view of system reliability and economic needs" (ERCOT 2018). There are two main advantages to using this report as the basis for our system modifications. First, ERCOT is arguably the best-positioned organization to study and identify infrastructure modifications, given it is the grid operator and planner. Although many other organizations make predictions about Texas' power systems (e.g. NREL, BNEF, EIA), ERCOT is the most familiar with the real assets. Second, ERCOT's LTSA necessarily synthesizes predictions about economic load growth, electrification, and technology changes when considering infrastructure changes. A major problem when assembling predictions to inform a system model can be the disparate methodologies leading to each one. In this case, the individual predictions are guaranteed to be coherent, which lends additional plausibility to our future scenario. So, we use this same source both for informing power network changes as well as highway EV fast-charger network changes (as detailed in the next section).

The Base Case scenario for our analysis uses the "Current Trends" scenario from ERCOT's LTSA to inform transmission, generation, and load expansion. This scenario, which studies "the trajectory of what is known and knowable today", is the only scenario for which ERCOT conducted a detailed transmission expansion analysis. ERCOT predicts almost 22 GW of new nameplate capacity in this scenario, most of it wind and solar located in the far west and north of the state, as figured in Table 2.1. (For reference, ERCOT predicts an increase in peak demand of 20 GW from 74.5 GW in 2019 to 94.5 GW in 2033 in the same report.) About 3 GW of coal generation retirements are also expected to occur. ERCOT predicts that the cross-state transmission network will become constraining as the forecasted renewable power flows from the north-west to the Dallas, Houston, and San Antonio load pockets. It identified ten high-voltage transmission corridors that would need reinforcement over the next decade.

We implemented the LTSA report's predicted generation capacity changes in our system model. Retiring coal capacity was subtracted from the nameplate capacities of existing coal-powered facilities in proportion to their size. New generation was handled similarly: we split the incremental capacity over existing facilities of the same technology and zone. (This is analogous to the load-distribution process described above.)

(MW Change)	Natural Gas	Solar	Wind	Coal
WZ_COAST	0	0	0	0
WZ_EAST	0	0	0	0
WZ_FAR_WEST	0	9200	500	0
WZ_NORTH	0	1600	5000	0
WZ_NORTH_CENTRAL	0	0	0	0
WZ_SOUTH_CENTRAL	0	0	0	0
WZ_SOUTHERN	0	0	0	0
WZ_WEST	0	1900	900	0
other	2750	0	0	-3000

Table 2.1: Generation expansion according to ERCOT's 2018 LTSA "Current Trends" scenario. (ERCOT 2018)

Our load forecasting methodology does not rely solely on the LTSA report since the predictions therein are only presented on an annual aggregate basis, which is insufficient for scaling our hourly load data. Instead, we built a simple forecasting model from forecasts produced by ERCOT's long-term load forecasting team.[11] These forecasts are available on a monthly basis for both total energy demand and peak power demand from the year 2019 through 2028. This data is sufficient to build twelve predictive regression models, containing linear and quadratic terms, for monthly energy and power demand into the year 2033. With these monthly models we can scale the historical hourly load from 2017, as shown graphically in Figure 2.2. Re-aggregated to yearly totals, the predicted ERCOT energy and demand in our model closely match the predictions in the LTSA report for the "Current Trends" scenario, validating our approach.[12]

Serving increased energy demand from upsized generation requires a reinforced transmission network relative to what exists today. Although the ERCOT LTSA report does gloss over congested transmission corridors that will need attention in order to satisfy projected demand reliably in 2033, it does not identify specific, implementable upgrades. To model the 2033

[11] By using ERCOT sourced data, we attempted to maintain the underlying assumptions that fed into the LTSA report. See details at http://www.ercot.com/gridinfo/load/forecast.

[12] Our models report an annual peak power demand of 96.6 GW and a total annual energy demand of 544 TWh, compared to the LTSA's predicted 94.5 GW and 530 TWh.

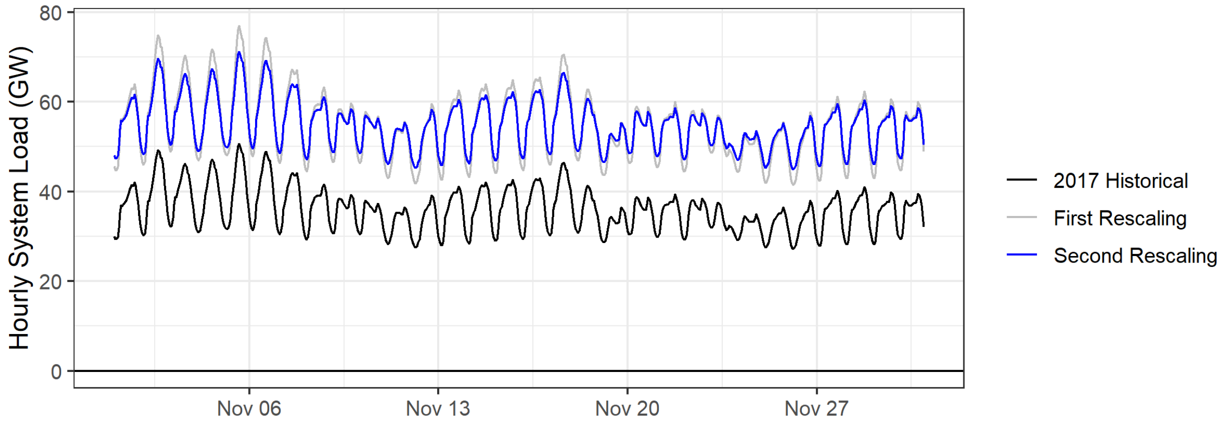

Figure 2.2: Load extrapolation method. Here we show the two step process for extrapolating hourly historical load into hourly future load just for the month of November. The historical data (in black) is first uniformly scaled up to match the projected monthly energy demand, resulting in the gray line. Then this timeseries is rescaled around its mean to match projected monthly peak demand while holding total monthly energy constant.

system, then, we back into a minimum feasible upgrade solution by successively simulating the power grid during strained conditions to identify problematic transmission lines. These lines are upgraded just enough to prevent thermal operational constraint violations. The results from this process are showed in Figure 2.3. The problematic lines identified by this process are predominantly those that interconnect upsized generation and upsized load. Some higher voltage transmission lines that serve to transfer power from the west to the east are also upgraded.[13]

2.3.3 Scenario Design: The Charging Network

Fast-charging EVSEs and slow-charging EVSEs are modeled separately in this research. The fast-charging EVSEs, which are the focus, are modeled in detail with independent

[13] With large amounts of available land and high wind and solar resource in the northern and western areas of the state, Texas has seen massive amounts of generation development in areas far removed from load centers. The accompanying need to move power from north-west to south-east has led to large-scale and persistent transmission congestion and renewables curtailment. This phenomenon is widely discussed and documented. It is sometimes called the "Panhandle Constraint" or "Western Export Constraint" or bundled up under the name "CREZ" (Competitive Renewable Energy Zone). See (ERCOT 2019).

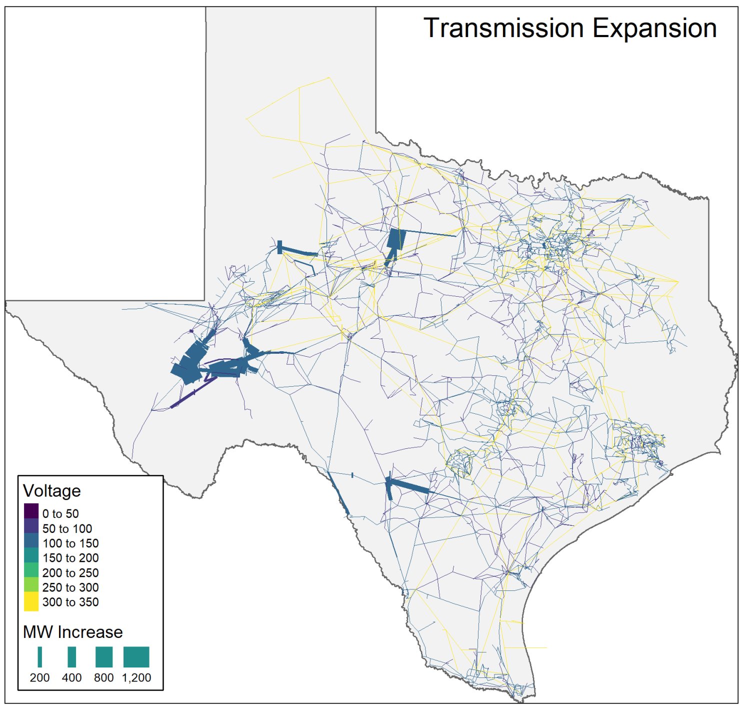

Figure 2.3: Upgraded transmission lines. The depicted statistics are thermal powerflow limit increases relative to the June 2018 CRR model.

interconnects to the power network. The slow-charging EVSEs, which are not, have their charging demand appended to the load profiles at existing load buses. The two types of EVSE are discussed in detail below.

The fast-charging load is treated as defined, time-varying load. The operation of the charging network as a whole, including residential and workplace slow-chargers as well as fast-chargers, is expected to be dynamic according to drivers' scheduling constraints and the rate structures in place at the charging stations. Since our research questions focus on highway fast-charging only, which is expected to be largely inelastic to price signals, the charger network model can be simplified and remain plausible.[14] There does not need to be a full supply-and-demand model as in the power network, but just a spatially-resolved network of fast-chargers and an expected power demand profile at each. The fast-charging stations can then be treated as other load buses in the power system from an operational perspective.

The modeled charging network is derived from the present-day Tesla Supercharger Network. As with the power network topology, our model of the charger network topology is derived from present-day systems to maintain plausibility. We use the locations and sizes of the existing 48 Tesla Supercharger stations in Texas as the basis for our model. We use this network for its convenience and sufficiency. It is convenient because the data is readily available online.[15] We argue that these locations are sufficient because since Tesla must already support inter-state travel along major corridors with the existing network. Although in the future there will undoubtedly be charging capacity expansion at and around charging stations, the locations of each will not shift over the time frame of our predictions since major population centers will not shift.

There are 48 charging stations, with a median EVSE count of 8 at each location. We use a 150kW power rating per EVSE as a conversion factor to go between EVSE count and station power rating.[16]

[14]We relax the assumption of inelastic demand in Appendix A.1.

[15]Our data was taken from www.supercharge.info.

[16]This number is inconsequential for the analysis, since station power demand is treated as a continuous function.

To connect the charging network to the power network, each charging station is assumed to connect directly to the nearest 69kV substation on the transmission network. This ignores the possibility that the stations access the transmission network through a lower voltage distribution network first, which would only exacerbate the impacts of too much demand on the system. The charging network topology with grid connections is shown in Figure 2.7.

Overall level of EV penetration is taken from ERCOT's LTSA report, which maintains consistency between assumptions. After modeling the topology of the charging network, the load at each charger must be determined. This load forecasting occurs in three steps: the first is to predict the overall amount of transportation electrification in Texas in the year 2033, the second is to determine how this maps onto aggregate charging demand, and the third is to assign hourly load profiles to each of the charging stations.

To maintain an overall consistency in our set of assumptions, the aggregate level of electrification in 2033 is taken from the same ERCOT LTSA report that drove our power system modeling.[17] ERCOT predicts 3,000,000 cars, 80,000 "Short Haul" and 200,000 "Long Haul" commercial vehicles to be electrified by 2033, as shown in Table 2.2.

Type	Number of Vehicles in 2033	Per Vehicle Charging (kWh)	Peak Charging Demand (MW)
Cars	3,000,000	20	5,940
Short Haul/Buses	80,000	350	2,800
Long Haul Trucks	200,000	600	10,200

Table 2.2: Forecast for transportation electrification in Texas, from (ERCOT 2018).

Division of EV load between fast- and slow-charging is informed by present day patterns. We derive two relationships, one between the number of passenger EVs in a jurisdiction and the number of EVSEs in the jurisdiction and one between the number of fast-chargers and the number of slow-chargers in a jurisdiction. These two relationships are

[17] It should be noted that the EV predictions from the ERCOT LTSA report are only included in the "Emerging Technologies" scenario, not the same "Current Trends" scenario used for generation, transmission, and load expansion in our power system model. Since transportation electrification is the only major modification between these scenarios, this distinction is not important.

shown in Figure 2.4. Together they allow us to estimate the total number of fast-chargers and slow-chargers that correspond to the 3 million EV cars forecasted by ERCOT. (See Table 2.3 for descriptive statistics of the scaled up charging network.) The data for these relationships is taken from the IEA's "Global EV Outlook 2019", and covers 9 countries and 5 years of data, giving 45 observations.

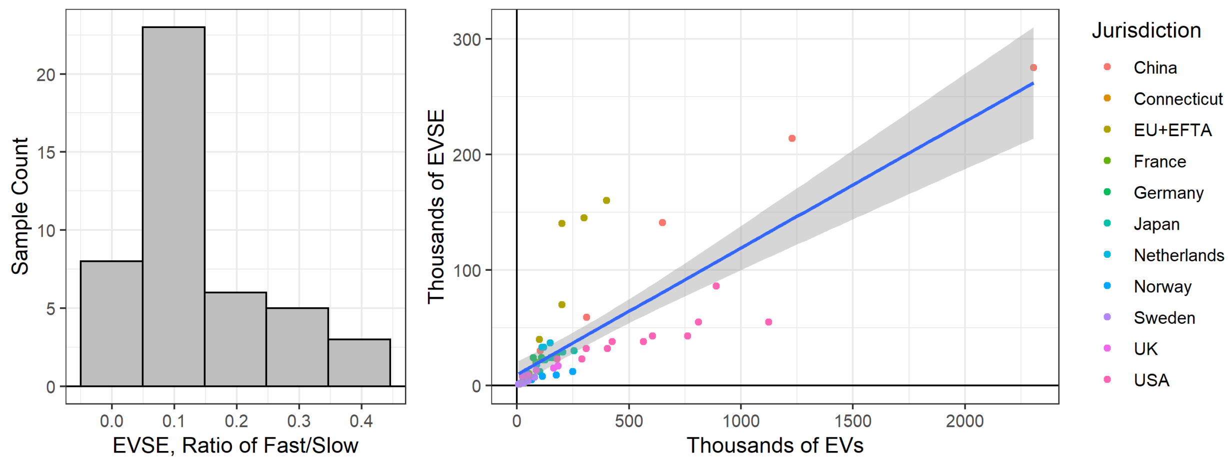

Figure 2.4: (Left) Distribution of public EVSE power ratings: (Fast-Chargers / Slow-Chargers). Assembled from 45 data points from (IEA 2019). (Right) Estimated linear relationship between the number of EVSE and the number of EVs in a jurisdiction. Assembled from 57 data points from (IEA 2019).

Zone	Station Count	EVSE/Station	Total MW	Median Voltage (kV)
WZ_SOUTH_CENTRAL	8	803.00	963.15	138.00
WZ_FAR_WEST	6	998.00	898.05	103.50
WZ_COAST	7	724.00	760.35	138.00
WZ_EAST	5	995.00	745.95	138.00
WZ_SOUTHERN	4	1014.00	608.40	138.00
WZ_NORTH	4	784.00	470.70	207.00
WZ_NORTH_CENTRAL	12	237.00	427.05	138.00
WZ_WEST	2	1014.00	304.20	207.00

Table 2.3: Summary of our extrapolated EVSE network in the year 2033.

Hourly charging profiles are derived from empirical data. We use data from the Idaho National Laboratory's "The EV Project" to determine typical hourly weekend and weekday charging profiles both for fast-chargers and for slow-chargers. The INL tracked "over 12,000 AC Level 2 (208-240V) charging units and over 100 dual-port DC fast chargers in 20 metropolitan areas" for the entirety of 2013, resulting in rich, public data sets (INL 2013). One of the data sets produced contains distributions of daily utilization rates at charging stations, broken out by type of EVSE and whether weekend or weekday. These distributions are available on a 15 minute basis, and are plotted in Figure 2.5.

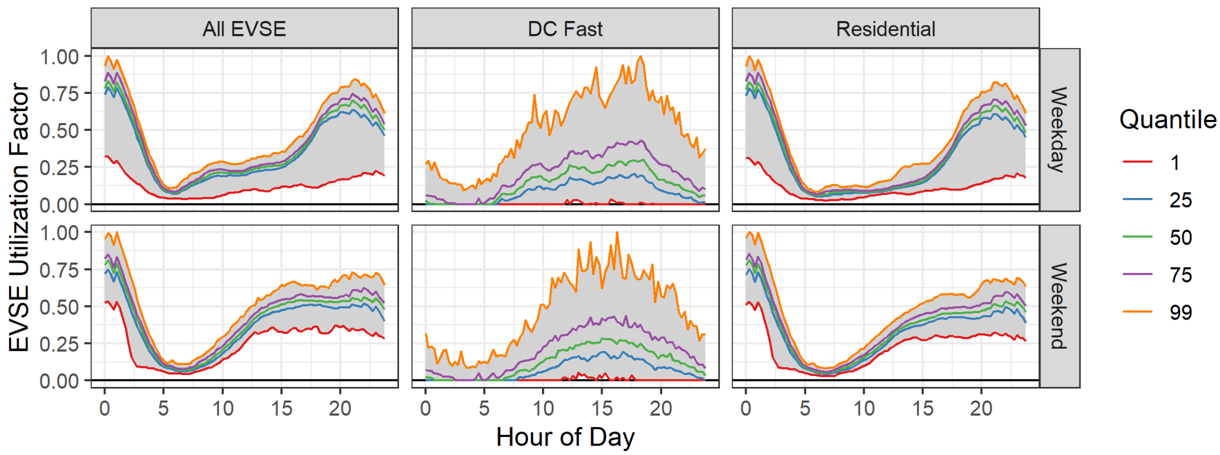

Figure 2.5: Hourly distributions of ESVE utilization from the study by (INL 2013). Here we show distributions from the 100 publicly accessible DC fast-chargers and the 6,474 private residential Level 2 chargers that were tracked. The "All EVSE" category includes an additional 3,522 public and private Level 2 chargers that we do not picture.

Using the total stock of slow-chargers derived above and the median aggregate charging profile from INL (the "all" profile in Figure 2.5) we determine the hourly charging load in ERCOT not due to highway fast-charging infrastructure. This charging load is distributed among all ERCOT load buses in proportion to those buses' load. When aggregated, this incremental charging load matches the prediction from ERCOT's LTSA report for a roughly 15% increase in peak system load.

The highway fast-charging demand is handled slightly differently in order to introduce noisier, more realistic demand profiles at the stations. First, the projected stock of fast-chargers are assigned to the existing stations in the topological model proportionally to the existing number of chargers at those stations. Then, a normal distribution is fit to every 15 minute interval of INL's "DC Fast" charging profile, from which each individual fast-charging EVSE samples. Thus, each projected EVSE generates its own weekday and weekend charging profile. An example of this is shown in Figure 2.6. At each station these individual charging profiles are aggregated (according to the total number of charging ports at the station) to present one hourly demand profile to the power system.

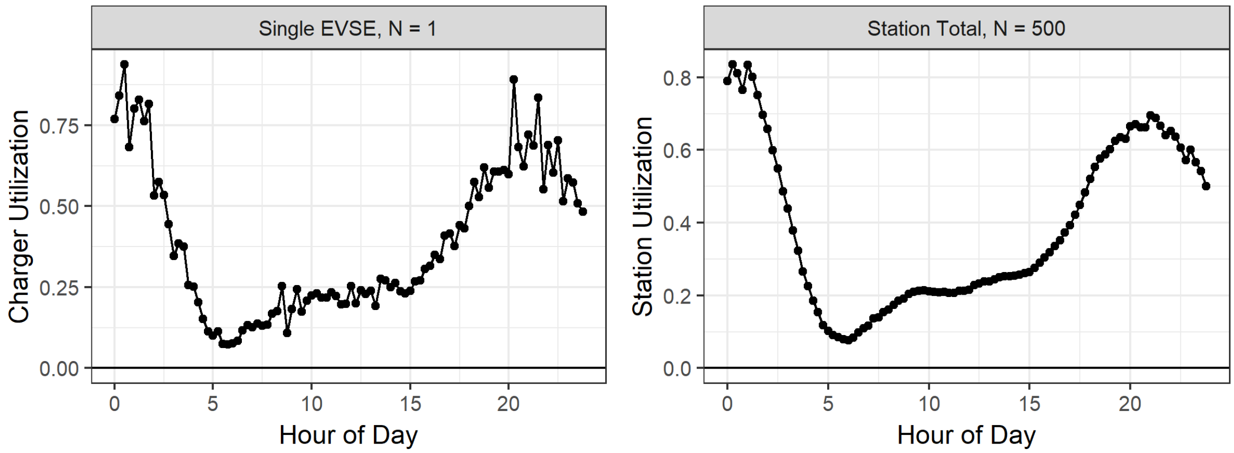

Figure 2.6: An illustration of our construction process for (weekday) highway fast-charger station demand profiles. For each EVSE at the station, we sample a demand realization for each 15-minute interval of the day (left). (The sampled distributions are those shown in Figure 2.5.) These individual EVSE realizations are then combined into the aggregate station load (right).

2.3.4 Simulation approach

The core of our analysis is to identify and quantify the impacts of incremental electrical loads – the EV fast-chargers – on a power network. The metrics we will care most about are the ability of the system to server these loads, and the incremental cost to do so. Most power systems, including ERCOT, operate on the principle of cost minimization: the cheapest set of power producers that that can reliably serve load is the set that is dispatched. The many operational constraints present, such as generation ramp-rates and transmission power flow limits, make the determination of this set a complex, multi-period optimization.

We use the Polaris Power System Optimizer to manage the optimization. To generate plausible solutions, we turn to Polaris' Power System Optimizer (PSO), which is a commercial-grade production cost market simulator based on mixed integer programming

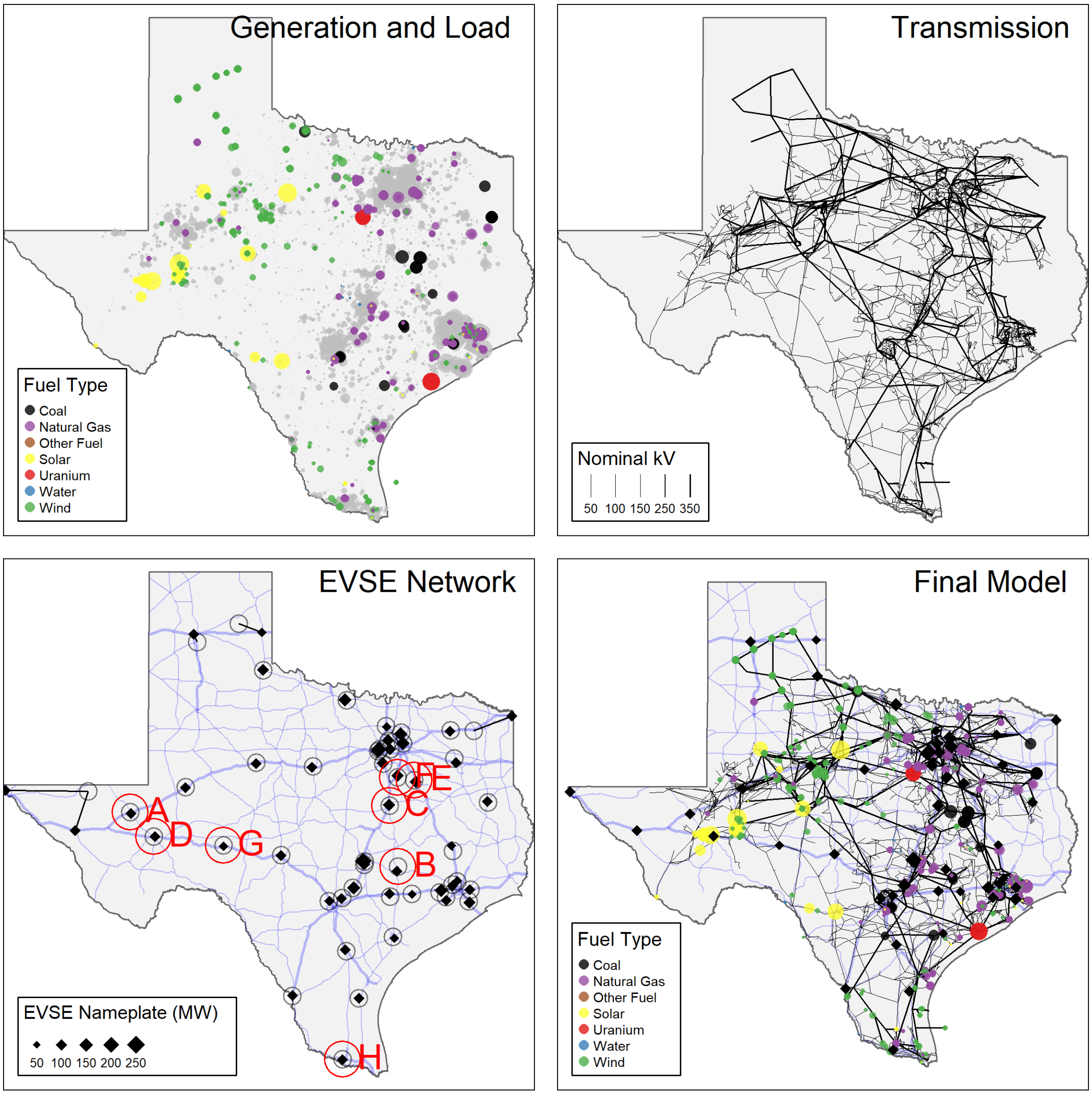

Figure 2.7: Power: Generation (colored circles) and load (gray circles) that are modeled, and the transmission lines (black) that interconnect them. **EVSE:** Highway fast-charging stations that we model (solid diamonds), along with the feeder lines that interconnect them to the nearest transmission load bus (gray rings). The highway network is shown in light blue. The red labelled EVSE stations are referenced in the text.

implemented in AIMMS.[18] It uses a DC power flow approximation to solve the commitment and security-constrained economic dispatch problems in the power system. This approach is consistent with the operation of real-world markets, such as those that ERCOT administers. PSO has been showcased at FERC technical conferences (Tuohy, Yong, and Philbrick 2013; Goldis et al. 2014), used in academic work (Tabors, He, and Birk 2016; Goldis 2015), and used as a benchmark for the development of other tools, such as Sandia National Laboratory's Prescient PCM (Siirola et al. 2018).

We configure PSO with a simplified set of market rules. PSO is fully flexible and can be configured for a variety of market designs. We choose a simplified set of rules that eases the interpretation of results, with the understanding that they are conservative assumptions: they will generally decrease the system operation cost. We specify an energy-only market with day-ahead commitment using a 36-hour look-ahead window. There is no real-time market. Ancillary markets, for example in reserves or frequency regulation, are not modeled. Uncertainty and stochasticity in forecasts is also not modeled. We set a $15,000/MW value for load shedding and a $9,251/MW penalty for exceeding transmission thermal limits, but otherwise use default operational parameters.

PSO produces a comprehensive series of reports for each simulation, representing the physical and financial outcomes on the grid at various spatial and temporal resolutions, as well as mathematical results from the optimization solver. Physical results include generation schedules, line-by-line power flows, fuel consumption, generation emissions, and renewable energy curtailment. Financial results include nodal prices (LMPs), generator revenues, and costs to load. Optimization results include the shadow prices for thermal line limit constraints and the overall solution cost including and excluding the value of operational constraints.

Our analysis focuses on nodal LMPs, line-specific power flow, and overall system costs. The most relevant quantities for our evaluation of the system will be the overall system solution cost, the LMPs at charging stations, and the shadow prices of transmission line constraints. The system solution cost is available from the optimization solver as the objective function score for each time step's minimization problem. (In our case this is every

[18] See details at http://psopt.com/pso/.

24 hours as the Day-Ahead market clears.) In general this solution cost includes "real costs" such as the revenue received by dispatched generation as well as "penalty costs" from the violation of system constraints. These penalties range from violating a line flow limit to shedding load. The LMPs are reported for each charging station individually, and we will always use the "bundled" LMP with its energy, congestion, and loss components.[19] The shadow prices of transmission line constraints, or in other words the dollar improvement in total system solution if a line limit is relaxed by one MW, will be important for understanding the limiting elements of the power system around the introduced fast-charging stations.

2.3.5 Mitigating methodological challenges

Granular system modeling in the medium-term future is unavoidably inaccurate. Although we have stressed the plausibility of our scenario construction and simulation design throughout the above sections, we do not assert that this scenario will come to pass nor manifest operational outcomes as we simulate. This does not fatally weaken our analysis or conclusions, however, provided that we take precautions. The first precaution is to dispense with a predictive mindset; to reiterate the research questions, we are seeking to identify potential problems and their solutions, not to predict their exact magnitude, timing, or location. We take two additional precautionary steps to mitigate the inaccuracy inherent in our research design.

First, we mitigate inaccuracy by measuring the differences in scenario outcomes. We almost never use the results from any simulation in particular, but usually consider the difference between two different scenarios. We will be interested in, for example the change in electricity prices at a specific location as the result of the change in the size of a charging station. It is much easier to convince ourselves of the validity of conclusions based on these differences rather than of those based on absolute results. Further, we are most concerned with trends and modes of behavior between many such differences, as will become clear in the Results chapters. By thus paying attention to the overall behavior of the system, and

[19] Note that ERCOT operational prices include the costs for reserves, and are bundled as Settlement Point Prices (SPPs). We do not include a reserve market and so do not mention SPPs.

not to any particular outcome, we take advantage of the precision of our methodology and avoid the pitfalls of its inaccuracies.

An intuitive understanding of this differencing approach is important to understand the results. As a simple example, we point to Figure 2.8. Here we show three time series of generation dispatch schedules for the entire ERCOT footprint over the ten-day simulation period. They are the results of two simulations and their difference. In this case, Scenario 2 has EV fast-chargers, while Scenario 1 does not. The time series of the difference between the dispatches for Scenarios 1 and 2 clearly shows the addition of this load, and also what compensating generation was dispatched to serve it. (In this case, primarily the fast-ramping natural gas units, with some coal support as well.)

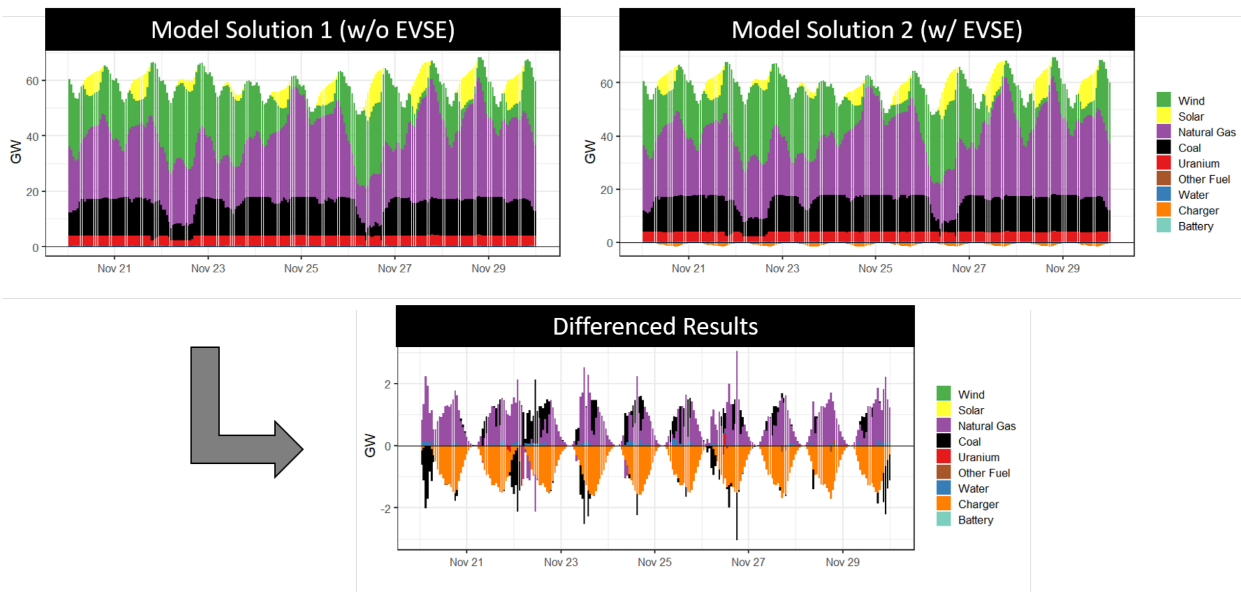

Figure 2.8: An illustration of the differencing approach we use in this analysis. Two cases are run, and the main result is found by subtracting the second case's metrics from the first's.

More generally speaking, we will concentrate on three broad scenario types during this analysis, and report results for the differences between them. These are shown on the right side of Figure 2.1. The first scenario class is the "Base Case". It consists of a grid scenario with no highway fast-charging. (TO be clear, there is still slow-charging in this class.) The second scenario class is the "Distributed Case". In this class, the incremental load from adding a particular fast-charging station is distributed among all load buses in its zone, i.e.

there is fast-charging, but it is not happening at single stations on the highways.[20] The third scenario class is the "Concentrated Case", and is a full model of highway fast-charging at a few specific locations, in our model the Tesla Supercharger sites. To be clear, the Distributed and Concentrated Cases have identical *aggregate* fast-charging loads, but the spatial distribution of the fast-charging demand on the network is significantly different between them.

Since our analysis is concerned with the impact of highway fast-charging specifically, and not EV charging broadly, we will predominantly focus on the difference between the Concentrated Case and the Distributed Case. This isolates the impact of the locational aspect of highway fast-charging, which we term as "Local Effects", and ignores the impact of just adding more load to the system, which we term as the "Zonal Effects"[21]. Occasionally we will represent both impacts to look at the full system effects of adding highway fast-chargers.

Second, we make assumptions that tend to underestimate charging impacts. We have made several assumptions in the design of the inputs and operational model so that any results we do see will be more likely to manifest in reality. The most important of these assumptions are:

- The underestimation of EV charging demand. The charging profiles from INL that we have used to model the power demand at the EV fast-charging stations are, in aggregate, representative of the average day's charging profile. However, transportation networks surge in usage during peak holidays. Whereas our modeled charging profiles peak around 35% utilization factor, the motivating example of the Tesla Supercharger station during Thanksgiving showed multiple hours of 100% utilization with additional, unserved demand. Thus we have good reason to believe the charging profiles we have used to model the EV fast-charging stations are underestimates of reality, and thus what power system impacts we do model are more plausible.
- The exclusion of ancillary markets and contingency constraints from power system

[20] As a heuristic, this Distributed fast-charging can be thought of as happening at thousands of very small, local fast-charging stations.

[21] "Zonal Effects" is a slight misnomer, since the expected difference from adding zonally-distributed fast-charging is not just to exacerbate existing inter-zonal transmission congestion, but also to systematically force more generation online. Thus there are expected real operational costs as well as penalties from observing system security constraints in this differencing.

operations. As discussed during the “Simulation Approach” section of this Chapter, we have configured PSO to execute a stripped down energy-market. It is thus missing many of the market mechanisms that make system operation during volatile and uncertain demand periods, as peak travel periods with high EV penetration will become, quite expensive. These mechanisms include procurement of reserves to mitigate uncertainty in next-day demand forecasts, and procurement of frequency response to mitigate short-duration demand fluctuations. Additionally, we do not model contingency constraints for our economic dispatch solutions, and so another mechanism that makes system operation in congested areas even more expensive is missing. Thus not only are we underestimating the physical demands on the system, but we are also underestimating the financial costs of those demands that we are simulating.

- The direct coupling of charging stations to the 69kV network. We choose to directly connect the fast-charging stations to the nearest 69kV load buses in our power network model. This is rational in most cases, since the charging stations we model are often drawing multiple MW off of the power network, but in a few cases, the 69kV buses are far from the stations. (See Figure 2.7 on page 2.7.) In these situations, the charging stations might more realistically connect to the distribution networks, but if so, operational challenges could be even more severe than we show in this research.

2.4 Our Results

2.4.1 Identification of Impacts from Fast-Chargers

As fast-charger penetration increases, Local Effects increase, while Zonal Effects do not. Our first result characterizes the impact of adding the fast-charging stations to our Base Case scenario model, which simulates the Texas transportation and power systems in 2033 through an entire year. In Figure 2.9, we present the change in the system objective cost function from the Base Case scenario to the Concentrated Case scenario for different levels of EVSE deployment in Texas. We benchmark these deployments levels as percentages of the overall EV penetration predicted by ERCOT’s LTSA report.

The change in the system objective cost function, which should be interpreted as the incremental operational cost imposed on the power grid by the EVSE infrastructure, is presented in \$/MWh. We normalize the total cost by the annual energy served in the Base Case. This incremental cost is decomposed into the Local Effects and Zonal Effects introduced in the previous section: the Zonal Effects are the change in costs from the Base Case to the Distributed Case, and the Local Effects are the change in costs from the Distributed Case to the Local Case. Each of these Effects is further decomposed into "Costs" and "Penalties": Costs refer to actual economic costs in the optimized solution, while penalties refer to violated "soft constraints". The most important such constraint is the thermal power flow limit across transmission lines. (This can be violated if an EVSE with a defined power demand exceeds the capacity of its feeder line, for example.)

There are two features to notice. First, the overall cost to operate the system in each set of simulations is higher with fast chargers, and second, the Zonal Effects are dominated by Costs while the Local Effects are dominated by Penalties. The first is an expected outcome: all else equal, increased load will require more generation to be dispatched and paid. The second, however, adds significant nuance that could requires simulation to uncover. Without further context, we can begin to interpret these results. The Zonal Effects monotonically increase as EVSE penetration increases, and they are entirely composed of Costs. We can interpret that the additional loading from fast charging, when not concentrated at few specific interconnections, does not strain the ability of the grid to deliver capacity but does cause more (and perhaps more expensive) generation to be dispatched. The Local Effects also monotonically increase, with less than 10% attributable to Costs. Thus, the concentration of fast charging demand along highways does cause a redispatch of generation towards a more expensive solution, and more importantly it also causes operational problems for the grid. The Penalty component of the Local Effects is likely the product of the \$9,251/MW thermal power flow constraint being violated.

The impact of each fast-charger is not equal. Our second result exploits the underlying spatial resolution of our power network model to show the specific impacts caused by the addition of each fast-charging station. When modeling all of the fast-charging stations on the system, it is not possible to split out the marginal contributions to total incremental

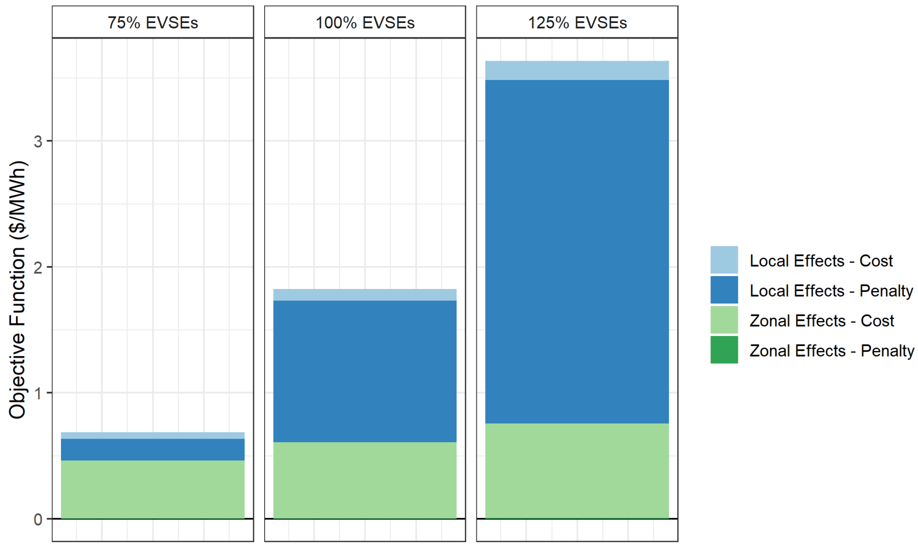

Figure 2.9: Our main results, showing the incremental system costs due to the addition of EVSE fast chargers in the modeled system. The incremental cost is decomposed into "Local Effects" and "Zonal Effects".

system cost from each one of them, due to the integrated nature of the system operation optimization. As a proxy for the impact of highway fast-chargers, however, we can examine the difference in LMP at the same node in the power system before and after the addition of the fast-chargers. Figure 2.10 shows the change in hourly LMP distributions at each of the 47 charger stations, focusing on the 100% EVSE deployment case and the "Local Effects" that are derived from comparing the Distributed Case and the Concentrated Case.

The important pattern in these results is the range, spanning four orders of magnitude, of the average LMP differences at each charging station, indicated by the solid dots. We associate these average differences with the network impact of the respective charging station. Thus the charging station "47191_chg" with an average (absolute) LMP difference of less than $1/MWh has an insignificant impact on the power grid, while the charging station "38131_chg" with the same statistic approaching $10,000/MWh has a very significant impact. All but four charging stations have this statistic underneath the $100/MWh level, which is a useful threshold for serious operational costs. (For reference, the average day-ahead LMP in ERCOT for November 2018 was just over $30/MWh (PE 2019)).

The differential impacts between charging stations is a function of the local network topolo-

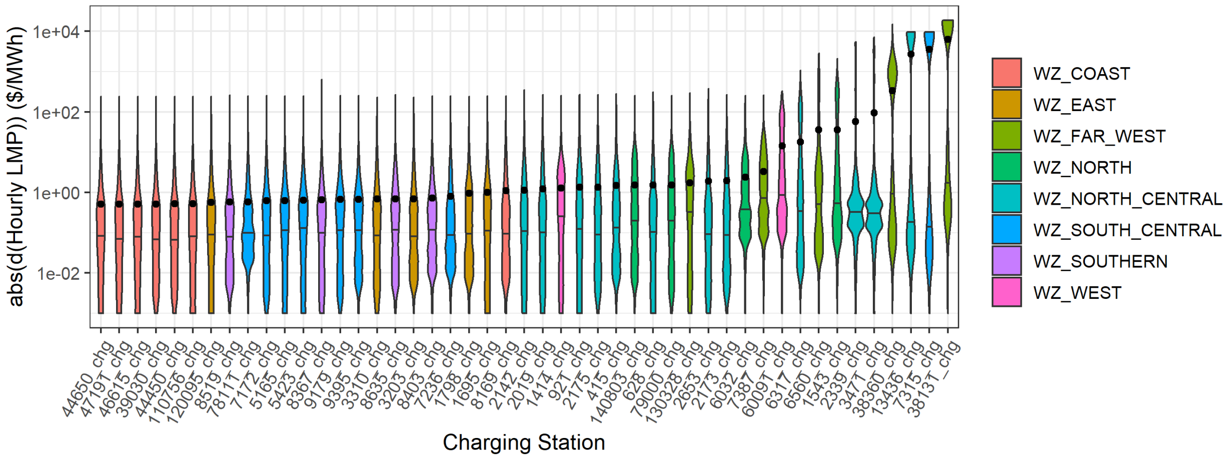

Figure 2.10: Distributions of the *differences* in LMPs at each charging station. Note the log axes and absolute values. The values are the differences from the Distributed Case to the Concentrated Case ("Local Effects").

gies at each.[22] This is not a surprising conclusion: we expect (and indeed hypothesized) that charging stations located in electrically weak or stressed areas where either (a) low voltage lines with low-gauge conductors do not provide sufficient power transfer capability or (b) already congested lines due to existing power transfer constraints would be problematic. Still, it is only because we use a spatially resolved model of the power network that these effects can be identified and measured.

We briefly demonstrate this explanation by showing the neighborhoods of two of the most "problematic" charging stations in Figure 2.11. The case of the "38131_chg" station, located in the Far West zone and labelled "A" in Figure 2.7 is trivial. The charging station is connected at the end of a low-kV spur line that is not rated, even in absolute terms, to handle the load that the charging station requires at peak times. "7315_chg" (labelled "B" in Figure 2.7) is largely similar, but it sits at the end of a much higher capacity line. In this case, however, the loads it is co-located with are already substantial, and its incremental demand overloads the transmission lines. "38360_chg" (labelled "D") is the most interesting, since it exists in a meshed part of the network but still causes significant amounts of congestion.

[22]Generally speaking this is a definitional relationship: differences between LMPs is due to differing congestion and loss contributions, which arise from transmission line losses and voltage constraints or thermal line limits.

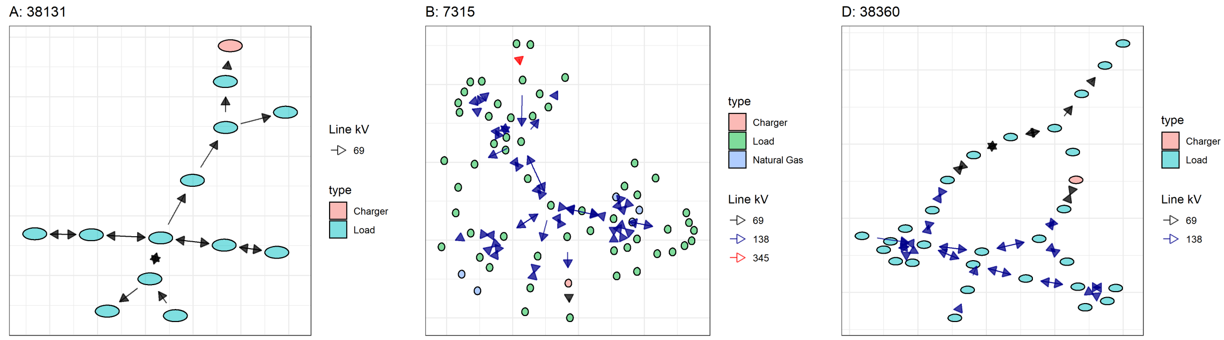

Figure 2.11: Network topologies for the neighborhoods around three congested charging stations. From left to right, they are stations 38131, 7315, and 38360. These stations are also circled in Figure 2.7.

In summary, most fast-chargers will not create substantial operational issues, but those located in weak parts of the transmission network will. With these two basic results we have answered the first research question: whether there will be significant power system impacts from the increased deployment of highway fast-charging EVSEs. We conclude "yes", with the caveat that most charging stations will be almost entirely non-problematic. The existence a few very impactful charging stations, however, means that developers, utilities, and system operators should pay attention to potential integration challenges.

2.4.2 Characterization of Mitigation Strategies

NOTE: While the above "Main Results" section covers a Base Case that extends for an entire calendar year using the power network and EVSE network described in Section 2.3, the rest of this Section focuses only on the eleven-day period from November 20th through the 30th, and it uses an un-upgraded transmission line set. This narrowed scope was chosen for reasons of computational convenience, given the many model runs needed to generate the results.

We consider both network reinforcement and energy storage solutions. We next explore mitigation strategies that can reduce the operational challenges of integrating the most problematic charging stations on the power system. Although the simplest strategy would seem to be to develop the EVSE elsewhere, this is impractical since major transportation corridors are fixed and charging stations must be located at regular intervals.[23] It is unavoidable that some large charging stations will be built in areas that are currently not able to cope with the demand. For our analysis, we focus on energy storage and transmission reinforcement as viable mitigation strategies.

(Demand flexibility by drivers is another potential mitigation measure. Just as drivers of ICEVs who need to refuel may pass by gas stations with high posted gasoline prices, so too might drivers of EVs be persuaded to change the location or time of recharging based on electricity rates. We view the amount of flexibility available from drivers as not significant: highway fast-charging EVSEs will be used by drivers with fixed routes and a desire to refuel quickly. Nevertheless, we explore demand flexibility as another mitigation strategy in Appendix A.1.)

Energy storage co-located at a highway fast-charging station mitigates grid impact by, heuristically, making demand more flexible without inconveniencing drivers. Although energy storage cannot reduce aggregate energy demand on the grid[24], it can reduce peak power demand during the day by charging during low demand hours and discharging during high demand hours. This solution is not perfect: aside from upfront capital costs, chemical energy storage – the most likely type – suffers from degradation over time. Due to the stochastic nature of demand, energy storage may also need to operate very conservatively in order to "shave" peak demand in all situations (Richard and Petit 2018). Despite this, EVSE developers have a strong incentive to install storage on-site because it has the potential to dramatically reduce upfront and ongoing interconnection service from the utility and/or grid operator in the form of "demand charges" that scale with perceived peak usage. Industry participants report actively using storage to find relief from "demand charge rate structures that inhibit fast charging deployment and EV adoption" (EVgo 2019).

In our analysis, we consider battery energy storage with 4-hour duration such as the Tesla Powerpack, which we use to specify the model.[25] For convenience we assume that these

[23]See A for a discussion of some relaxation in the charging station location constraint.

[24]In fact, energy storage increases aggregate energy demand due to storage losses.

[25]4-hour duration, 89.5% round-trip efficiency, and 100% depth of discharge. For details see https://www.tesla.com/powerpack.

batteries are available in any capacity size. We use Lazard's Levelized Cost of Storage report for an approximation of capital costs: considering the application (commercial/industrial, behind-the-meter) and scale (4-hour duration on the order of 10 MW of nameplate capacity), we choose \$1.5M/MW.[26] We note that the choice of a capital cost does not impact model dispatch; it is only a sensitivity for the post-processing.

Transmission upgrades, despite being the traditional method of accommodating new electrical load, have received almost no consideration in the literature for integration of EVSE. Distribution-level, and sometimes transmission-level, power flow constraints are often cited as a difficulty at high levels of penetration (IEA 2019). This fact, however, is often used as motivation to analyze alternative mitigation strategies, such as managed charging or energy storage. However, in line with other literature in the power system planning space that seeks integration of, for example, renewable generation, transmission new build and reinforcement should be considered as viable strategies (Conlon, Waite, and Modi 2019).

The problem of reinforcing the transmission network to lower operational costs from a new EV fast-charging station is multi-dimensional. New transmission lines be considered alongside the upgrading of existing lines. In a meshed network, different sets of line upgrades can accomplish the same alleviating effect. If considering the reinforcement of an existing line to handle more power flow, a new conductor with larger diameter and ampacity can be retrofitted, the structures can be raised to accommodate more line sag, or line-end equipment can be upgraded so that the existing line can be up-voltaged at the same current flow. For this analysis, we simplify the options by considering only the reconductoring of existing lines with the justification that this is a common solution (Mills, Wiser, and Porter 2009; Jackson et al. 2015).

To develop capital cost estimates for reconductoring we took estimates from system operator planning process documents, performed cost buildups, and spoke to utility representatives. There is wide disagreement on high level cost estimates, ranging from \$50K/mile to \$2M/mile or more. On the low side, our cost buildup of line costs – including conductor, optical ground-wire, shielding, and overhead expenses – was as low as \$53K/mile for a 30MW 69kV

[26] This is on the high side of both the 1 MW, 2-hour C&I systems and the 100 MW, 4-hour wholesale systems that Lazard covered. See (Lazard 2019).

line.[27] On the high side, WECC planning documents showed an average high-level estimate of \$2M/mile for a 230kV new-build, ranging past \$10M/mile for areas with rough terrain (Mason, Curry, and Wilson 2012). We settle on a cost of \$1M/mile with large uncertainty bounds: this is lower than our conversations with a utility indicated, but higher than the \$100K/mile - \$500K/mile range from an LBNL survey in 2009 (Mills, Wiser, and Porter 2009).

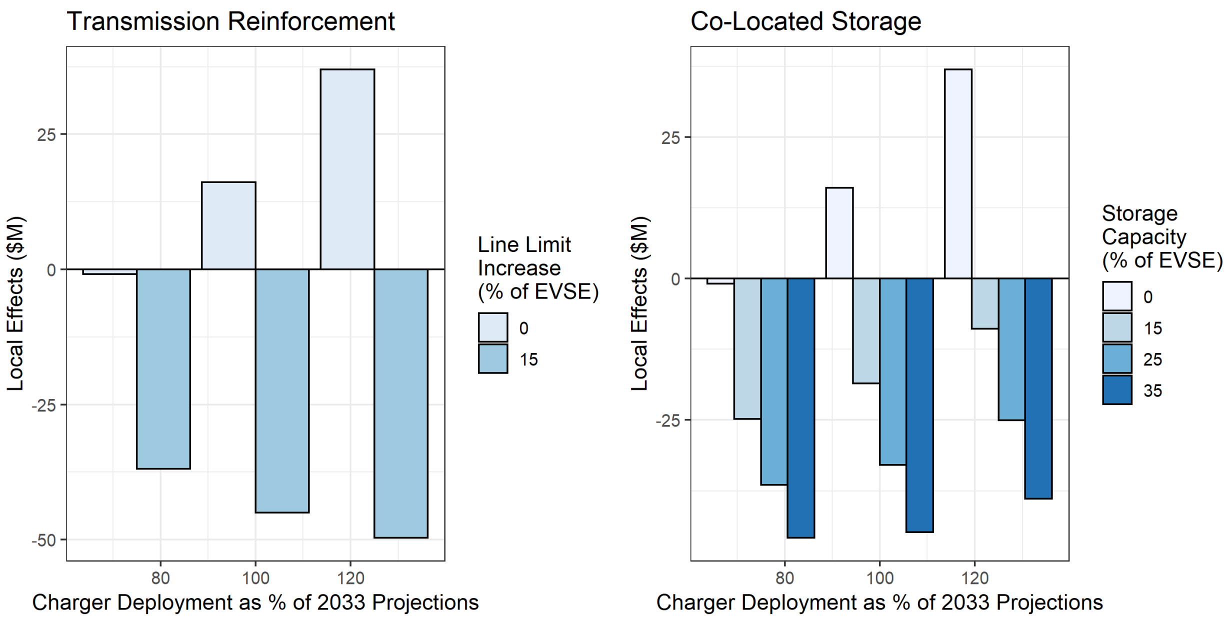

Figure 2.12: An overview of how Local Effects change (here represented as \$M of incremental objective function value) in response to mitigation measures at various levels of EVSE deployment.

It is simple to show the efficacy of either solution, energy storage or transmission reconductoring, using our model. Figure 2.12 shows the results from a set of simulations that test increasing levels of both types of mitigation. Energy storage is deployed only at four of the most problematic EVSE stations: 38131 (A in Figure 2.7), 38360 (D), 60091 (not highlighted), and 7315 (B). The capacity of the storage solutions are set as a percentage of the nameplate level of the EVSE station. Transmission mitigation is simply modeled here as a global (i.e. applied to all transmission lines) increase in thermal line limits of 15%. The main result is that both mitigation strategies can successfully mitigate the incremental system costs associated with the deployment of highway fast-chargers. In fact, at sufficient deployment levels, both solutions can bring system cost reductions below the Base Case

[27] Using conductor ampacity specs from (PJM 2010) and line costs from (MISO 2019).

scenario.

2.4.3 Analyzing Mitigation Strategies

We illustrate the energy storage and transmission reinforcement mitigation techniques with a case study of one of the most problematic charging stations, 38131, in the Far West zone. (Refer back to Figure 2.10 to see its large impact on the system relative to other stations'.) As pictured in Figure 2.13, this charging station exists at the end of a radial branch on the 69kV network. This makes it a particularly easy case to analyze, though the case study is instructive for more complex cases. Figure 2.13 depicts that during peak demand periods, the feeder lines delivering power from the main network to the charging station become overloaded. This charging station has a nameplate capacity of 152 MW, and during our peak simulated hours it is drawing around 50MW off the network. Given the rated 37 MW and 32 MW feeder lines, it is no wonder this station is causing operational issues.

To mitigate this station's impact on the local grid, we can simulate co-located energy storage to "shift" power demand from the afternoon peak to the mornings and evenings, or we can simulate upgrades to the two congested transmission lines to handle more power flow. In both cases we need to offset the same amount of *incremental* peak power demand: 29 MW on line 38360-38120, and 25 MW on line 38120-38129. For convenience we set our targeted incremental upgrade to 15% of the charging station's nameplate capacity, or about 23 MW. So far as simulation goes, these scenarios are simple to construct, and their results are shown in Figure 2.14 in terms of congestion relief on the two impacted transmission lines.

The figure clearly shows that the transmission solution is much more effective than the energy storage solution, even at the same nominal incremental peak power. (The magnitude of congestion on lines is less in the Transmission Reinforcement case than in the Co-Located Storage case.) This is due to the duration of the congestion events caused by this charging station. Figure 2.15 illustrates the greater than 10-hour period of operational difficulties, day-after-day. Since the energy storage systems we model are rated for only 4-hours, they are not sufficient to shift the aggregate energy demand, despite having the appropriate peak rating. In fact, to achieve the same amount of system mitigation as the transmission

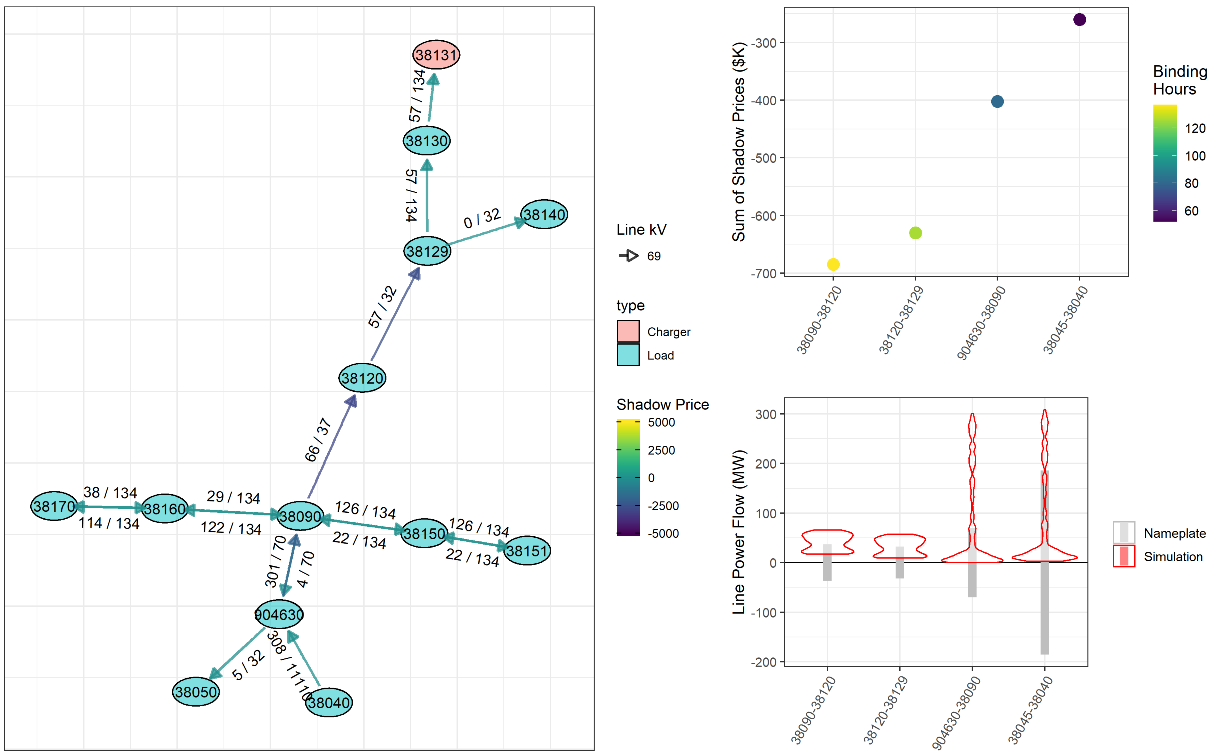

Figure 2.13: An illustration of the transmission congestion leading into the highway fast charger "38131" for the Concentrated Case at 100% EVSE deployment relative to the ERCOT LTSA. The left panel shows an abstract network model of the station's neighborhood. The line annotations indicate the maximum power flow during the simulation (MW) as a fraction of the line's thermal power flow limit (MW). The top right panel quantifies the levels of congestion on the four most affected lines as the sum of the hourly shadow prices on the thermal line constraints over our simulation. The bottom right panel shows the simulated hourly power flow distributions on these same lines, overlaid on the operating limits. The lines "38090-38120" and "38120-38129" suffer from chronic congestion.

reinforcement, we would need to simulate energy storage sized well over 35% of the charging station's nameplate capacity, as Table 2.4 shows.

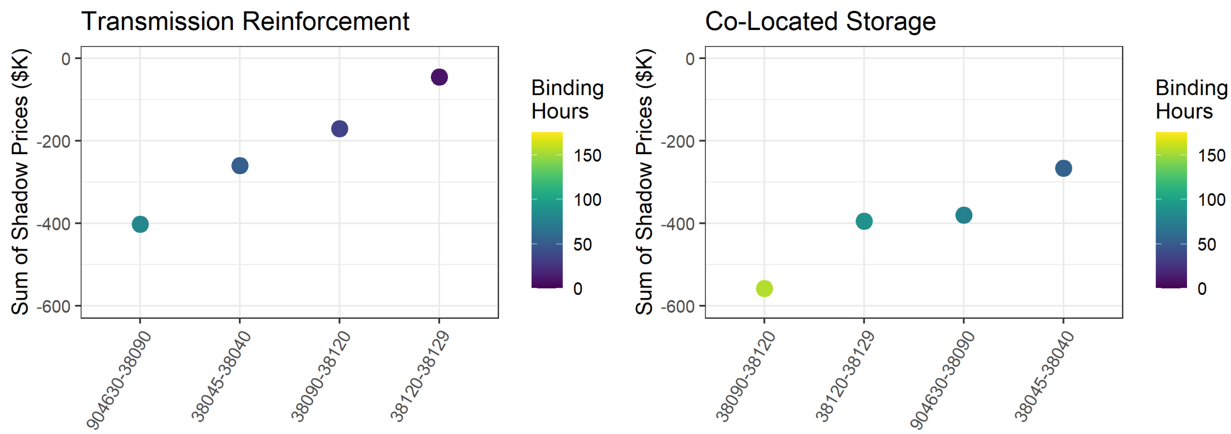

Figure 2.14: A comparison of two mitigation strategies for reducing transmission congestion. The left panel replicates the information in Figure 2.13 but with the two most congested lines uprated by 15% of the charging station's nameplate capacity. The right panel shows the same but for a 15%-sized co-located energy storage solution. The differing magnitudes between panels indicates the persistent congestion in the energy storage solution.

This exercise show far has shown that in the case of fast-charging station 38131, an incremental 15% (relative to the charging station) of transmission capacity or 35% of energy storage can both largely mitigate the station's grid impacts, thought the transmission solution to a much greater extent. To understand which is a more efficient solution, we must next consider their costs. The transmission line upgrade we assume is a reconductoring of the two lines already mentioned. To perform a reconductoring, new conductor with an ampacity appropriate to the *total* new power flow limit must be purchased. In this case we cannot only consider the 15% incremental but the existing 35 MW line, for a total of about 60 MW, which implies a medium sized conductor of about 1000A at 69kV. [28] After the line rating, the line length must be considered, which is where transmission costs can grow dramatically. Lines 38090-38120 and 38120-38129 are, respectively, approximately 10 miles and 7 miles in length. Using our prior developed costing estimates, these transmission upgrades could cost around $17M, with wide uncertainty bounds anywhere from $5M to $40M and higher.

[28] This difference between incremental and absolute power capacity is not so consequential here, but in other cases may make a large difference to cost. The cost of a 1600A "Kiwi" ASCR conductor and a 460A "Linnet" conductor is about 500% (PJM 2010).

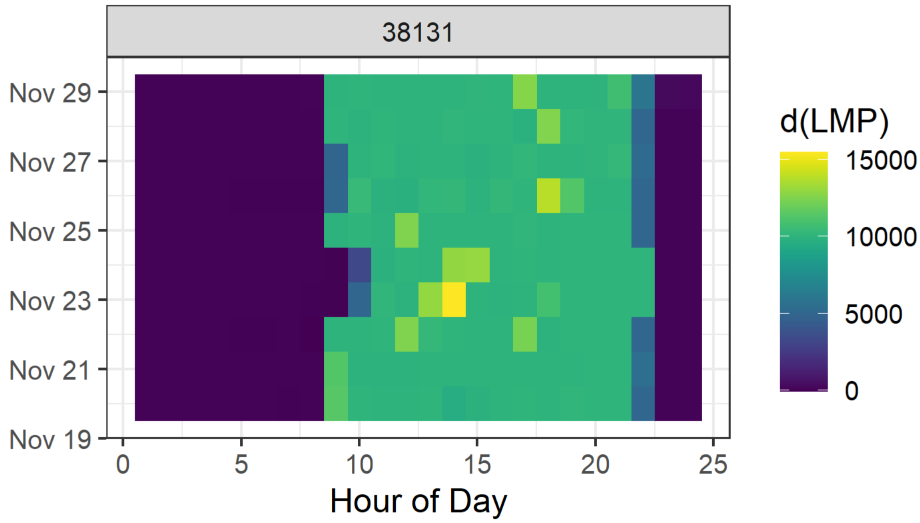

Figure 2.15: Illustration of the duration of congestion events at charging station 38131. This heatmap of LMPs (the difference in LMPs between the Distributed Case and the Concentrated Case) starkly shows a greater than 10 hour congested period at this charging station.

The cost to implement energy storage is independent of topology. Using the previous cost estimate from (Lazard 2019) of \$1.5M/MW, the 35% battery system (or about 50 MW) comes out to a capital cost of about \$75M. This is much higher than even the high range of the transmission costing estimate, for a lesser amount of amount of system cost reduction. In this case, transmission reinforcement is the more cost-effective option. For the energy storage solution to have come out ahead, the number or length of the transmission lines needing upgrades would have had to been about triple, or the duration of congestion events been much shorter.

We develop a general framework for mitigation in terms of power and duration of local congestion events. The case study above illustrates two principles that can be combined into a general framework for understanding whether energy storage or transmission reinforcement is the best mitigation choice for a particular charging station. First, reconductoring has increasing returns to scale: when replacing a thin conductor with a thicker one to improve a line's ampacity, one does not only pay for the incremental power rating of the new line. To upgrade from a 50 MW line to a 75 MW line, one must pay for a 75 MW line.

Measure	Transmission 15%	Battery 15%	Battery 25%	Battery 35%
EVSE impact and mitigation	-4.39	5.18	2.75	0.91
Just mitigation	-20.49	-10.91	-13.34	-15.19

Table 2.4: System cost reduction according to two measures (rows) due to four different mitigation strategies (columns) at charging station 38131. The four strategies are transmission reinforcement to increment line capacity by 15% of the EVSE nameplate, and energy storage collocation with nameplate power ratings at 15%, 25%, and 35% of the EVSE nameplate. The first row, 'EVSE impact and mitigation', measures the incremental system operation cost (increase in objective function score) in $M between the Dispersed Case and the Concentrated Case with mitigation. The second row isolates the effect of mitigation by comparing the Concentrated Case with and without mitigation.

On the other hand, to perform a 25 MW battery installation at a 50 MW site, one must only purchase a 25 MW battery. Thus smaller projects, in terms of peak power mitigation required, favor energy storage.

Second, energy storage's net value diminishes quickly as the duration of peak demand events lengthens. In our analysis, energy storage is assumed to have a 4-hour discharge duration. Thus, for a given power rating, one must double the number of battery cells on site to fully mitigate a peak demand event that extends past 4-hours. (Using longer duration energy storage solutions is more expensive, and so does entirely circumvent this problem.) The efficacy of transmission, on the other hand, is agnostic to the duration of peak demand events. Since EV fast-charging demand peaks (recalling Figure 2.5) could feasibly last for 10 hours, energy storage may not always be the most cost-effective solution.

These two principles are combined into the chart shown in Figure 2.16. This figure shows, conceptually, regions of relative competitiveness for energy storage and reconductoring. It ignores several considerations. One, that the y-axis for energy storage should be measured in incremental MW of mitigation required, whereas for reconductoring it must be in incremental MW of mitigation and existing MW of capacity. Two, there is some lumpiness to investments in reconductoring. Unlike for battery energy storage systems, transmission solutions may only be available in increments of 10-15 MW, which increases the risk of over-building. Three, energy storage solutions are inherently more flexible, in that there components can be repurposed for other sites more easily, if grid conditions change. Despite these and other gaps, Figure 2.16 is a good starting point.

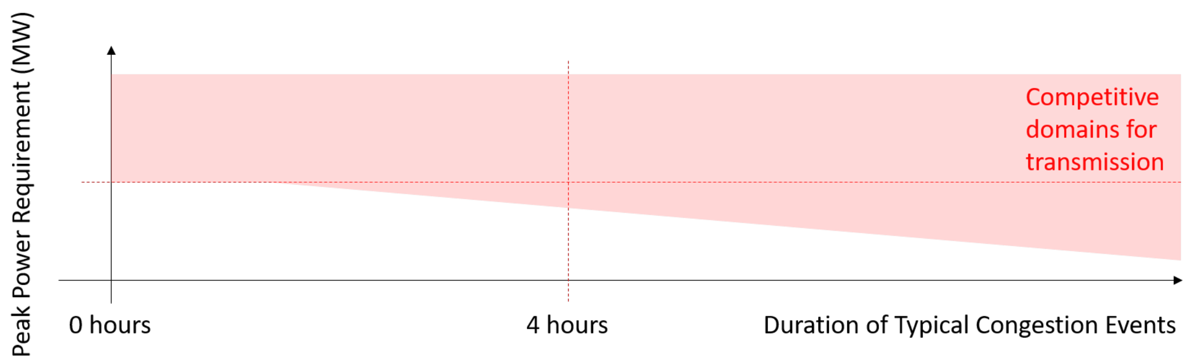

Figure 2.16: Conceptual framework to consider the relative competitiveness of transmission reinforcement and energy storage to mitigate EVSE-related operational costs. The y-axis refers to the total power requirement from the EVSE. The x-axis refers to the duration of operational challenges that the EVSE imposes on the grid.

Attempting to extend this framework quickly shows the pitfalls of generalization. A clean implementation of this framework is, however, elusive. It is difficult to quantify, for a given highway fast-charging station, either the "Peak Power Requirement" for mitigation or the "Duration of Typical Congestion Events". As an illustration we present Figure 2.17. Here we attempt to algorithmically determine the average duration of congestion events at each charging station by averaging the hourly LMPs across days and measuring the "width" of the daily peaks. This approach works cleanly for the most problematic four-to-five charging stations, but it is problematic for others where the daily LMP patterns are far more irregular. Quantifying the other variable in our framework, the "Peak Power Requirement", is also challenging, for reasons already covered above in the case study.

In summary, it can only be said that the choice between energy storage and transmission reinforcement depends on the specifics of the power system at the charging station. Although the general framework is useful as a way of thinking through the problem, the variety of topologies and situations that highway fast-charging stations will be located in defy analysis with simple heuristics. Instead, they demand more detailed analysis using the tailored approach shown above for the single charging station. This is indeed

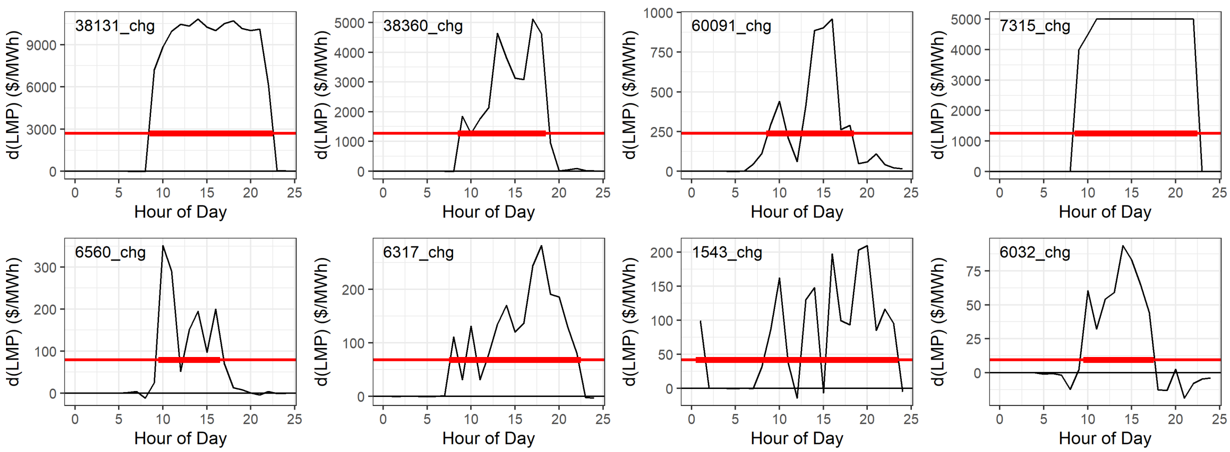

Figure 2.17: Determining the duration of congestion events at EVSE from LMP data. Here we plot the average LMP for each hour over the simulation period in black. (The y-axis is more accurately the difference in LMP at the EVSE between the Distributed and Concentrated Cases.) The thick red line measures the LMP "peak width", but only succeeds in the simplest cases. What duration battery would be needed to effectively arbitrage prices at, for example, "7387_chg"? It is not obvious from visual inspection.

one of the primary hypotheses and motivations for the present study, which is equipped with a very complex model of the power system. We conclude from the above that in-depth case-studies (of the sort used above) with detailed network models are irreplaceable for actual mitigation decisions. And, although identification of potentially problematic charging stations can be done in one shot (as our lineup in Figure 2.10 shows), identification of mitigation solutions cannot be done at such a high-level.

2.5 Future Work

The analysis that we have completed is a novel application of detailed transmission modeling to the problem of EVSE-grid interaction, and yet the analysis is fairly simple. Simplicity in analysis can be a worthwhile goal, but here we look forward to adding additional complexity. Our modeling pipeline can be expanded to simulate more attributes of realistic power market operations than the day-ahead, energy-only markets we have here implemented. With additions, we could better differentiate the highway fast-charging EVSEs of interest from other types of load that might be studied in similar ways. Specifically we aim to add real-time energy markets and reserve markets while incorporating forecasting uncertainty into the EVSE demand. Since stochasticity and volatility are characteristic aspects of fast chargers, enabling markets that have been designed with these traits specifically in mind will be useful.

We also wish to analyze mitigation strategies other than network reconductoring and energy storage collocation. A particularly promising one is the dynamic relaxation of voltage constraints in congested areas of the grid to relieve temporary or mild operational difficulties. Such an analysis would require moving beyond a DC powerflow approximation and modeling the full system, or portions of it, with a full AC powerflow model. Because such a mitigation solution would be nearly free, entailing only software tweaks from the system operator and perhaps minor loss-of-life to grid equipment, it could be an attractive solution where EVSE integration issues are small in magnitude.

There are additional, minor expansions to our analysis left to do that are briefed in Appendix A: performing a sensitivity analysis on the design of the Base Case; adding an additional case between the Concentrated and Distributed cases; performing targeted transmission expansion to complement the generation expansion to the year 2033; and a replication of our results throughout an entire calendar year.

Chapter 3

Policies to Support EVSE Development

This thesis began by detailing the widespread policy mandate for increased electrification of transportation and the obstacles that remain in the path of achieving our ambitious targets. How to overcome these obstacles is not just a matter of technical fact-finding, but a political decision about the proper way forward. This holds as well for the particular topic of this paper's research, the deployment of high-way fast-charging EVSEs and their efficient integration into the existing power infrastructure, which must be accomplished to ease EV owner range anxiety. In this chapter we review the ongoing policy debate, contextualize our results inside of it, and conclude with recommendations for productive paths forward.

3.1 Policy debate around EVSE deployment

Governments have been actively supporting EV adoption for decades. The most well known federal policy in the US is the tax credit program passed in 2008, granting a credit of up to $7,500 per sold vehicle to EV manufacturers. Other programs have existed, including R&D grants to national labs and fleet acquisition incentives. Internationally, governments are experimenting with similar measures: Norway and China both have had success implementing mixtures of tax relief and relaxed regulations and fees for vehicle ownership. (Cattaneo 2018) Policies aimed at supporting EVSE deployment specifically also exist, although in the US they are more limited: the federal government operates the knowledge-sharing Workplace Charging Program to encourage business-financed EVSE, and several states have some form of financing available for EVSE. (ibid.) Norway has also used public financing to support EVSEs. (Figenbaum 2018)

Review of the Deployment Challenge

Why are government policies needed? The root of the debate around EVSE deployment is that there is not an obvious market-based solution: EVSE chargers are not currently profitable for pure-play developers to operate. Although conceptually similar to ICEV refueling stations, an EV recharging station has higher capital costs[1] that must be recovered through the same sales of a cheap, competitive commodity: in this case wholesale power. In a pure business model, estimate that charging station utilization rates at or above 30-40% are necessary before an EVSE operator can push charging prices down to a level competitive with ICEV refueling while still breaking even. The dependency of a viable business model on the station utilization rate introduces the circular trap: without increased EV penetration, EVSEs will not exist; without more EVSEs, EV penetration will not increase.[2]

Restricting the conversation only to highway fast-charging EVSE stations, the problem is exacerbated. These stations have even higher capital costs: as this research shows, their far-flung locations in weak areas of the grid necessitate more expensive mitigation investment; the higher ratio of peak demand draw to aggregate energy usage can also lead to high demand charges that dominate operating revenues (Lee and Clark 2018). Recalling our motivating case study on page 3, utilization rates seem doomed to persist at very low levels if the stations are adequately sized for peak holiday travel periods. Reports like those from (NRC 2013) that are "unaware of any case in which private firms have recovered the installation costs" for fast-charging stations are unsurprising. Of course, highway fast-charging stations *do exist*; our analysis is built around the Tesla network. But the existing stations are not profitable and anyway are undersized to support peak demand.[3]

Despite these difficulties, the policy goals demand a solution, and given the unlikelihood of one presenting itself organically within existing market structures, the government must proactively design one. New structures must be politically palatable and efficient enough to

[1] Not only is the cost of EVSE itself expensive, but the cost of integrating the charging station into the power network can be prohibitive once needed network upgrades are considered. (Lee and Clark 2018)

[2] This is a very well documented "chicken-and-egg" problem. See (NRC 2013) and (MIT Energy Initiative 2019).

[3] Tesla handles the situation more generously on its website "Tesla is committed to ensuring that Supercharger will never be a profit center." https://www.tesla.com/support/supercharging?redirect=no.

operate sustainably. Who are the correct agents to develop and to operate stations? What subsidies and incentives do they need? What business model should they pursue? We cannot answer these questions here, but we hope to constructively contribute to the conversation – which even in relatively advanced markets remains fractious[4] – with our results on integration costs and mitigation strategies for EVSEs.

Discussion of Potential Solutions

The academic and professional literature that examines fast-charging stations often takes the perspective of one of three groups: private business, government entities, and power utilities. These categories each contain many entities with different goals and incentives. Examples of key participants in the realization of EVSE development include: power utilities, pure-play private developers, the federal government, state governments, municipalities, and brick-and-mortar businesses. To frame our discussion about our results and recommendations, we briefly describe the specifics of each category.

Business In market economies like the USA's, solutions generated by existing market structures are generally preferred, even if their results generate inequitable outcomes. As described above, these solutions are not apparent, though not for lack of trying. Over the past decade many businesses, existing and new, have participated in the EVSE market. Generally we can categorize these businesses into "pure play", where the enterprise depends only on revenues from charging operations, and "adjacent", where there are other revenue streams to the business that are ancillary to charging. In order to recoup the fixed costs associated with the EVSE infrastructure and any non-variable demand charges, pure play operators must rely either on a subscription model plus commodity pricing (for example ECOtality, EVgo, and BetterPlace) or on charging significantly above marginal cost (for example ChargePoint). Adjacent businesses have more flexibility. At its simplest, an adjacent business would mimic the gas station model of a convenience store attached to the charging station. Other models include subsidization through vehicle sales (the Tesla model),

[4](Rubens et al. 2020) survey of Scandinavian industry was revealing. An Icelandic respondent said, "... Government doesn't know its role; energy companies don't know their role and the oil companies don't know their role. The question is how to build these [charging] plugs."

subsidization through advertising revenue (such as Enel has pursued), and integration into existing brick-and-mortar businesses as a customer convenience.[5] (NRC 2013) Most of these business models could scale to the inflexible demand scenario of highway fast-charging, where a customer still must wait more than ten minutes for a charge. (Refer back to Table 2.) Yet still no business has developed a sustainable model (Rubens et al. 2020, page 7).

Government In the face of market failure society must turn to alternative means of coordination, such as a government led effort. The USA has a strong track record of sponsoring early-stage technology research and development through various mechanisms including ARPA-E grants, national laboratory sponsorship, and financial incentives. Electric vehicle technology is no exception, and indeed several of the data sources and references for this research come from government-backed sources. With EVSE specifically, federal and state governments were early promoters of the necessary public infrastructure, having provided in some cases 100% financial grants to infrastructure partners (NRC 2013). Although in some countries – notably China – state-backed EVSE deployment continues to be the norm, most countries do not intend for public ownership and support to be a long term solution to the EVSE market-failure. The federal government's policy interest in an electrified transportation sector seems like a powerful synergy and reason for its continued leadership, but it is politically infeasible (Rubens et al. 2020). Considering highway EVSEs specifically, some have claimed that municipal governments have an additional interest in stimulating development: increased transportation to and from their cities. The economic benefits from this are unlikely to outweigh the political and budgetary costs, however.

Power Utilities The power utility represents an interesting in-between compared to private business and administrative approaches, "walking a thin line between markets and government" (Perez-Arriaga 2013). Investor-owned utilities of the type common in the USA especially blend the economic incentives of business with the direction of government in potentially useful ways for the deployment of highway fast-chargers. On one hand, they present the most compelling adjacent business imaginable, as under the most common regulation regimes the power utility profits from increased end-point power sales, including through

[5] The Target chain of retail stores has, according to (NRC 2013), estimated that store-located EVSEs will be profitable given the extra time that customers will spend in stores.

EVSEs.[6] Additionally, utilities have the precedent to socialize the upfront capital costs of EVSE among most residents in a jurisdiction through the rate-basing mechanism, achieving a similar cost spreading as direct governmental intervention. This makes a compelling case for utility involvement in EVSE deployment, and many are already active where their respective utility commissions allow such cost recovery: Hydro Quebec operates DC fast-charging infrastructure in Ontario and Quebec; municipal utilities in the USA such as Austin Energy and Kansas City Power & Light are building regional EVSEs; regulators in California and Hawaii have also approved rate-basing (Hall and Lutsey 2017). Not everyone agrees that a utility led model is the best, however. Regulators in Massachusetts, for example, have declined to allow the rate-basing and ownership/operation of EVSE by National Grid over concerns that, among others, that utility ownership of EVSE is needed and that there may not be a true market failure (Holahan 2019). Even where regulators have given approval, utility mandates have only been for a specified number of chargers (Hall and Lutsey 2017). Once rate-basing is approved, the distinction between direct government operation and utility involvement becomes significantly blurred, and critics worry that "healthy competition could be crowded out" (Alexander-Kearns and Cassady 2016).

Thus each of the actors – business, government, and power utility – has its own advantages and disadvantages for the deployment of EVSE. Private business is the clear political preference in western countries, yet so far has not been able provide sufficient infrastructure. Direct government administration of programs has diminished greatly in recent years under political pressure as EVs have reached non-negligible market penetration, though this strongly on the backs of those who rely primarily on residential charging solutions. Utility management has a powerful case at present, but is pressured both by advocates of more and less government involvement in the transportation industry. The investor-owned utility is just one example of a generalized public-private partnership, of course, and coalitions of actors between and within these groups will likely be the eventual solution.

[6]Traditional utility regulation models set a \$/MWh volumetric rate once every several years. The more unit sales of electricity a utility books, the greater are its returns. As energy efficiency and other policies come to the fore, "revenue-sales decoupling" are increasingly common in the USA, which attempt to reduce this incentive for increased power sales. See (Gomez 2013).

3.2 Integrating Our Results

Before presenting our recommendations we present the contributions of our own results from Chapter 2. Original research into this domain should aim to inform the policy debate by highlighting the relative costs and benefits of EVSE development to the different sets of actors.

Our research focuses on the *locational* aspects of EVSE integration with the power grid. Location is one of the defining attributes of highway fast-chargers (the others being scale and demand inflexibility, as highlighted in Section 2.1). The inter-city location is simultaneously what makes these EVSEs so important for overall EV adoption and what makes them so troublesome to integrate, given the often "infrastructure poor" regions nearby rural interstates. Our main results are that: (1) highway fast chargers do cause integration issues in some areas of the grid where they will plausibly be connected, and (2) although energy storage and transmission reinforcement both plausibly mitigate grid operational costs, the range of costs for transmission solutions necessitates analysis of potential stations on a case-by-case basis. We have developed a systematic methodology for thinking about the impacts of these chargers and assessing mitigation strategies to support their deployment. This framework, applied for example in the case study in Section 2.4, illustrates that finding a least-cost solution for the integration of highway fast-charging EVSE is not trivial, and that granular modeling of the infrastructure is necessary to appreciate the net benefits of the different approaches. Artificially restricting the choice in solution to reconductoring of existing lines or installing energy storage does not make the problem much easier.

These results emphasize the need for coordination between whichever actor is planning and developing the EVSE infrastructure and the local power transmission entity: the power utility. The power utility has the data, expertise, and experience about the power infrastructure to much more efficiently (or at least heuristically) identify high-value transmission network solutions. The natural extension of this line of reasoning is that power utilities should own the entire EVSE infrastructure development pipeline, and not merely partner with another party, be it government or business. This solution has not proven politically feasible, however, as covered above. A cooperative approach, then, that involves the private sector as much as possible while retaining the technical expertise of the utility must be found.

One potential solution is to build EVSE under a joint venture model between a private owner/operator and the power utility incorporating a conditional ownership flip, in some ways similar to tax equity flips in the renewable generation development market. With regulatory approval, a utility would take the majority stake in project company with partners from the private sector. The project company would undertake the construction and operation of an EVSE, the upfront and ongoing costs of which would be subsidized through traditional rate-basing mechanisms. This solves the immediate policy need for EVSE deployment while increasing the chances of a cost-efficient power systems outcome through utility buy-in. The joint venture agreement would specify a threshold utilization rate or profit metric, that, upon realizing, would trigger a majority ownership flip from the utility to the private partner, up to 100%. In the case of a future with high-enough EV penetration to support highway EVSEs, this turns into the politically desirable private ownership model.

In the case of a future that fails to support highway EVSEs, the ratepayers subsidizes the network operation.[7] Given the expected low utilization rates for a highway fast-charging station that is sized for peak demand, this proposal may result in perpetual public ownership. Unless EVSE truly becomes a public good, this will be problematic. Maximizing the private sector partner's involvement in operations, e.g. through concessions and maintenance contracts, could assuage political backlash against this. Another alteration to keep this solution politically attractive is to ex-ante limit these sorts of partnerships only to highway fast chargers in rural "energy poor" locations where utility coordination is most important. Such a restricted program, like the current limited rate-basing ongoing today, will promote easier buy-in (Hall and Lutsey 2017).

In the absence of a comprehensive solution like the above, there are numerous steps that the state and federal governments can take to promote continued investment in this market by the private sector, even at the risk of inefficient outcomes.

First, the government should strive to clarify the impact of certain regulations on the op-

[7] One of the controversies about power utility involvement in EVSE networks is that not all residential ratepayers should be subsidizing a recharging network for the minority of EV owners. Cost socialization is important for this proposal, however, and substitute financing mechanisms, e.g. state budgetary grants, seem unlikely.

erations of EVSE stations. (NRC 2013) has raised the question of the Americans with Disabilities Act as an area of potential liability and uncertainty. New regulations should be designed in open cooperation with business and utility interests. The federal government's fact-based rule-making is an appropriate mechanism here.

Second, the government should act early to aid the establishment of industry standards. (Li 2019) shows how the lack of EVSE standards has led to an unproductive over-investment in duplicative EVSE infrastructure by some firms (primarily vehicle manufacturers). While this "format war" may end in higher returns to the winner, it is likely not useful in the short term for encouraging riskier investments in infrastructure like highway fast chargers. Standards around smart-charging and power supply would benefit from utility involvement. Standard setting in the USA has traditionally not involved the government, but in the case of significant utility involvement in EVSE, there could be a stronger case for top-down regulation.

Third, the government should revive the pro-innovation initiatives that helped to support the first wave of EVSE construction in the early 2000s. The most beneficial programs to maintain are those that offer grants and technical support to new business models or platforms. As stated above, the best solution to EVSE deployment will be the private model if it can be found. Along a similar vein of market support, state and federal governments should make prime transportation- and transmission-accessible real estate readily available to interested developers, and potentially consider tax incentives to develop EVSE there. Where the government cannot help, it should at least not hurt development efforts with too much red tape.

In summary

Governments have made bold commitments over the past decade towards a cleaner future that includes carbon-free power generation and an electrified transportation industry. Although current policies, technological learning, and changing consumer tastes are organically driving industry conversion already, reaching the end goal will require continued innovation from our policymakers as well as our technologists. This research has identified just one group of challenges that lie in our path, but they are not insurmountable. If government takes a proactive coordinating role, existing market structures can be re-harnessed to lead society into the future.

Appendix A

Model Assumptions and Sensitivities

This appendix considers the effects of several sets of assumptions that we made while conducting this research. We think of each of these as a "sensitivity analysis". We conducted them throughout our research to convince ourselves that our results were robust to different specifications of our model.

A.1 Sensitivity to the time of year

We constrained our sensitivity and mitigation analysis to the 11 days at the end of November, encompassing the Thanksgiving Day holiday, which is a peak travel period in the US. This ties our analysis into the motivating case study in Section 1.2 and also reinforces the conservativeness of our assumptions around fast-charging demand profiles and utilization, as discussed in Section 2.3. Further, November is a "shoulder season" in the power industry, when the large power demand from HVAC systems is at a minimum, leading to a less constrained power system with fewer systemic operational challenges. Despite these points, one may ask if our results extend more generally to other times during the year.

We show in Figure A.1 a replication of Figure 2.9 expanded into a year-long time series. This series can somewhat support the above point: November effects are not atypical, and the magnitude of system-level impacts is well below the peaks in the summer. Although this speculation cannot stand in for fuller analysis, it is provocative that November looks to have much the same pattern as the rest of the year.

To an important extent, of course, the relevance of our results to policy is not impacted even if the results do not extend to all periods of the year. The power and transportation

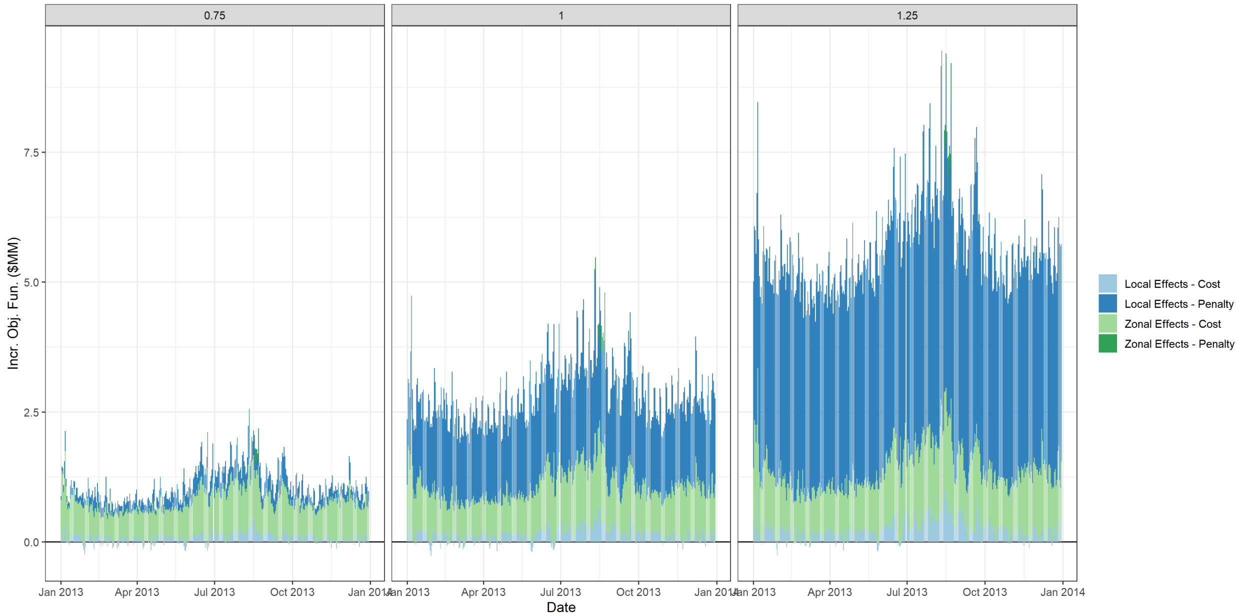

Figure A.1: The incremental effects of EVSEs calculated over the course of the full year.

networks must be sized and maintained for peak demand periods, whether those occur in July or in November. And for EVSE developers, whose primary operational costs can be the demand charges levied by utilities, it is the peak impact that matters most, not the average impact over the year.

A.2 Sensitivity to demand inflexibility assumption

A primary motivation for conducting this research was that one of the much discussed features of EV charging, the supposed demand flexibility and even "V2G" potential of EVs and their owners, will be absent at highway fast-charging stations. This demand flexibility, realized either through dynamic rate structures or utility-controlled residential charging stations, is an inherent mitigant for power network stress from incremental charging load. Some may doubt that highway fast-charging load is truly inflexible. Indeed, business plans to combine shopping, grocery, and entertainment facilities with charging stations[1] may well allow station operators to flexibly shift load up to an hour in either direction. Are our results robust to this potential?

[1]See, for example, Volta's business plans (Korosec 2019).

Although our market simulation approach using PSO does not include any potential for vehicle demand co-optimization, we can still believably simulate a flexible demand scenario with an iterative simulation approach.[2] We conduct a sequence of Concentrated Case simulations where a certain percentage of charging demand each hour is permitted to shift earlier or later by one hour in an attempt to minimize its cost to charge. For example, we run a first simulation where 5% of the load each hour is flexible. This 5% of load reacts to the charging station LMPs resulting from the inflexible demand case. If the station LMPs are lower in the hour preceding or succeeding the default charging time, that 5% of demand will shift to take advantage of it. In the same way, we then run a 10% demand flexibility simulation that reacts to the outcomes from the 5% demand flexibility simulation.

The results from this analysis are reasonable and do not change our main conclusions. There is a shift in aggregate charging demand from the early afternoon hours (when the system as a whole is experiencing peak demand) to the late morning and late afternoon hours (when the system as a whole has less demand), as shown in Figure A.2. The impact of this (exogenous, distributed, driver-led) cost optimization is a steady reduction in system operation costs as demand flexibility increases, as shown in Figure A.1. However, even when 1 in 5 EVs is flexible enough to shift its charging demand by one hour, the system as a whole only benefits from a $5M reduction in operation costs. This number should be compared to the nearly $50M increase in operation costs from adding the highway fast-chargers in our main results, as shown in Figure 2.9. So, although demand flexibility reduces operation costs, it alone cannot mitigate the transmission impacts of at-scale fast-charging.

A.3 Sensitivity to the concentration of EVSE stations

Our Concentrated Case scenario models over 5 GW of incremental fast-charging nameplate capacity[3] in Texas spread over 48 charging stations and 47 electrical nodes, for an average of 720 chargers per station.[4] (Refer back to Figure 2.3 for summary statistics.) This concentra-

[2]This is the basis for the "feedback" arrow in Figure 2.1.

[3]Though with our INL-based EVSE demand profiles, peak EVSE power draw is closer to 2 GW. Refer back to Figure 2.5

[4]At present-day fast-charger demand ratings of 150kW. By 2033 it is projected that EVSE fast-charger power ratings will have increased to the MW scale.

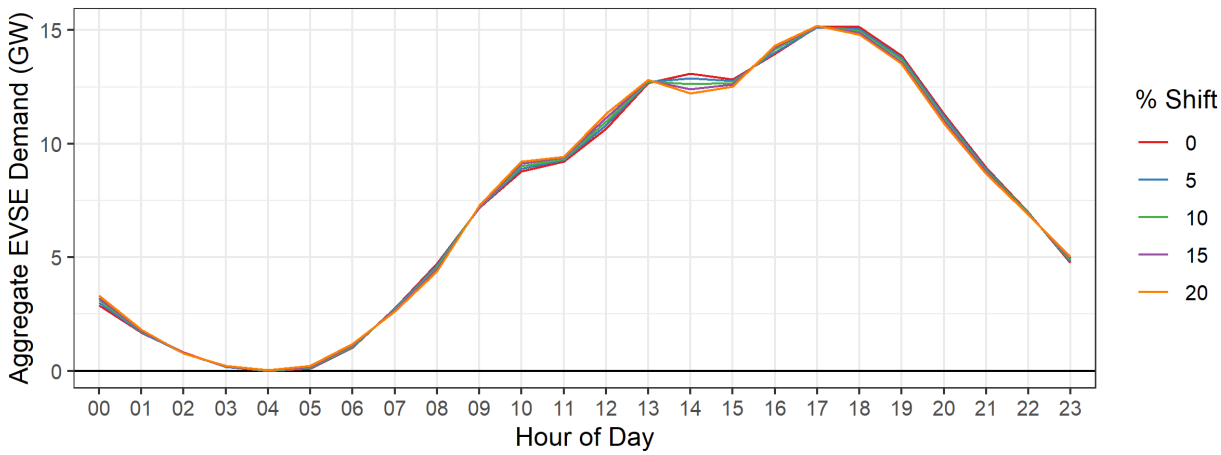

Figure A.2: Demand flexibility results in some shifted load, but the aggregate EVSE demand is relatively unchanged. The red line represents base case fast charger demand without flexibility. The orange line represents EVSEs with 20% of hourly demand able to shift back or forth by an hour. The only meaningful change is about a 1 GW shift away from 2:00pm.

tion of EVSE at specific grid locations is arguably implausible, notwithstanding our earlier justification in Section 2.3 on page 10 that there are only few optimal locations in large transportation corridors to site these stations. Are our results robust to a less concentrated charging topology, with highway fast-chargers spread more evenly along highways in a way that more closely mimics the network of gas stations today?

We have highlighted the analysis of such a topology in the Future Work section, but a re-interpretation of the Distributed Case from our main analysis can be brought to bear on this question. We decomposed the effects of highway fast-charging into "Zonal Effects" and "Local Effects" (refer back to Figure 13) specifically to focus on the impact of the spatially concentrated case. But we argue that the Distributed Case and its "Zonal Effects" can be thought of as the limit to which a more distributed EVSE topology trends. It suffices in a rough sense to analyze just these impacts to understand this sensitivity.

We can also form an informed guess about the "Local Effects" of a less concentrated EVSE topology by leaning on the brief analysis we undertook to connect our modeled EVSE network to the modeled transmission network. As discussed in Section 2.3 we interconnected each charging station to the nearest 69kV load bus on the transmission network. Some of these nearest buses were actually quite distant. The histogram in Figure A.3 shows the distribution

Flexible Demand	Incr. Obj. Fn.
0 %	$ 0.00M
5 %	$-1.31M
10 %	$-2.60M
15 %	$-3.84M
20 %	$-5.05M

Table A.1: Incremental system costs due to different levels of allowed demand flexibility. Increased flexibility lowers the costs of EVSE integration, but not significantly compared to total integration costs.

of the physical length of these interconnecting feeder lines. Immediately apparent is that four-fifths of the charging stations with feeder lines over 20km are located in the problematically congested northern and western regions of Texas whence the majority of the "Local Effects" in our main results are derived. Simple reasoning – that splitting these stations' capacities over a long stretch of highway would not change their interconnecting load bus – leads directly to the conclusion that the power network congestion impacts would be unchanged. This is a compelling hypothesis, but we would like to test it more analytically within the model.

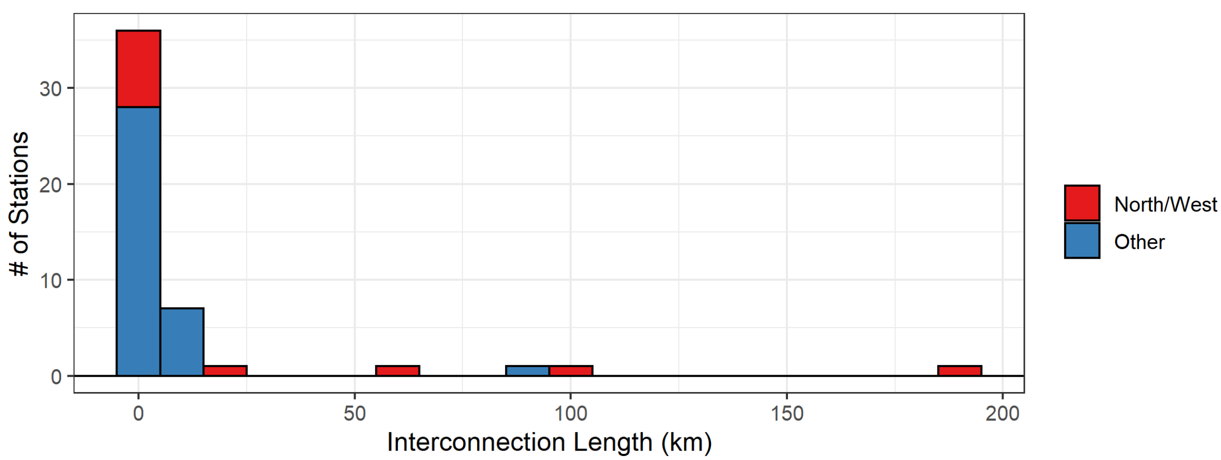

Figure A.3: Histogram of each fast-charging station's feeder line length. Most stations are within 10km of the interconnecting load bus on our modeled network.

Appendix B

Frameworks

Below are three of the organizational frameworks used throughout this paper.

The attributes of barriers to EV and EVSE penetration:

- Demand-side limitations to growth
- Supply-side limitations to growth
- Societal limitations to growth

The attributes of EVSEs focused on in this paper:

- Scale: Massive. (Many chargers together, in the future.
- Location: Highway/rural. Connected to potentially weak grid, with fewer interconnection options.
- Flexibility: Low/No demand flexibility. Uncoordinated, time-of-need charging.

The three entities that drive EV and EVSE penetration:

- Business: pure-play and adjacent
- Government: federal and state
- Utilities: private and public

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