Coupled Infrastructure Simulation of Electric Grid and Transportation Networks

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***Abstract*—This paper presents a framework for coupled infrastructure studies between the electric power transmission system and transportation networks. The proposed methodology evaluates the impact of electric vehicle (EV) charging demand on grid operation and power generation. Key modeling and coupling considerations are presented for each network. Case studies for various EV charging schemes are presented on networks situated in Travis County, TX for illustration. System loading and generation dispatch provide examples of two of the many analyses enabled by this coupled infrastructure simulation framework.**

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

I. Introduction

Using the power grid to charge the increasing number of electric vehicles (EVs) is invariably increasing the coupling between two complex and critical infrastructure networks–the power grid and transportation systems. Both have well-established planning and operating principles, yet their nascent coupling offers unique challenges. EVs at scale (high penetration scenarios) affect the grid on two distinct levels [1]:

1) at the point of common coupling; this is usually a connection to the distribution system, either at home, at a workplace, or at a public charging station, and
2) in the bulk power system as an aggregated new load.

Several papers have presented methods to model these coupled networks. For instance, a comprehensive review of different methods to couple transportation and grid networks is provided in [2]. Flow models are used for each network to determine steady-state distributions of vehicular flow on each road in the transportation network and bus voltage and line power flow in the grid network. These models are the traffic assignment problem and the power flow, respectively. The key approximation in [2], however, is the use of static models for traffic simulation, with a recommendation to use dynamic traffic assignment (DTA) for better spatio-temporal estimation of the EV load.

Another common feature of existing work is the focus on distribution systems. While this is warranted due to the prevalence of EV charging at this level, few works such as [1] have looked into the equally significant upstream impacts on the bulk power system. This is important for issues such as generation and transmission resource adequacy, emissions, etc. Even in such studies, some [3] use unit commitment or economic dispatch for generation dispatch analysis, thus ignoring important system constraints. Often, the EV load is approximated from historical travel data from national databases instead of calculating the actual EV energy consumption. Regarding the actual coupling, simulation tools and methods have been developed [4], [5], though implemented only on small test systems or on large synthetic systems without geographic information [6].

In this paper, the charging load from on-road EV operation is developed based on a regional-level transportation simulation and charging behavior simulation, considering different EV penetration levels, congestion levels, and charging strategies [7]. The unique contribution of the paper is the methodology for a detailed geographic mapping between transportation network links and nodes to the power transmission network substations and service territories in order to aggregate the EV load to the transmission substations. The overall objective is to present the modeling considerations and framework for the such coupled infrastructure studies. An overview of the workflow developed for such studies is shown in Figure 1.

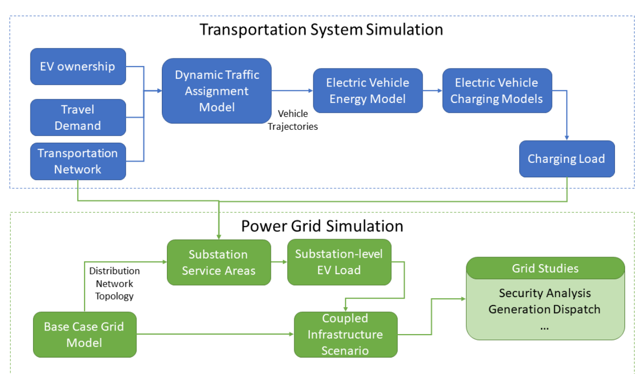

Fig. 1: Workflow overview for coupled infrastructure studies

Section II presents the details of EV modeling using DTA. Section III then outlines the electrical system modeling and

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methodology of realistic integration of EV load to the system. The specifics of the study scenarios are outlined in Section IV and grid impact analysis results are presented in Section V. Section VI concludes the paper by summarizing and outlining future work. To demonstrate the methodology established, this paper presents Travis County as the geographic location for the case study. Located in Central Texas, Travis County is home to the state's capital city, Austin.

II. EV Load Modeling

A. Traffic Flow Modeling

To perform hourly dispatch or OPF simulations, a high spatial and temporal resolution transportation model is needed to supply the spatially resolved electricity demand from EV operation. Mesoscopic DTA models can analyze the movement of individual vehicles while using macroscopic traffic flow theories without complicated vehicle interactions [8]. The equilibrium-seeking DTA methods adopt an iterative approach to simulate individual travel behavior under varying traffic conditions and provide performance measures such as travel time and cost under congestion. In this paper, a mesoscopic simulation-based DTA model, DynusT [9], is used for the analysis. The DynusT model takes the transportation network and travel demand as inputs and generates vehicle trajectories as output which are then used to estimate the on-road energy consumption of EVs.

Using a pre-defined EV market penetration, a fraction of trips is randomly assigned to be EV trips. An activity-based vehicle energy model is needed to assess the impact of various transportation-related attributes on energy use [10]. In this study, a parameterized simulation-based inference approach is followed to predict the energy consumption of EVs based on on-road operating conditions [11]. The vehicle powertrain is represented by a Bayesian Network statistical model, which adopts the domain knowledge a priori, and can be trained using a data-driven approach. The details of model development and validation can be found in [11]. Commonly used energy models for three typical EVs with 100-mile, 200-mile, and 300-mile ranges are utilized.

Finally, for each assigned EV within the network, the range of the EV is randomly assigned based on the market share of EVs that are estimated using EV sales data from 2011 to 2019 [12]. EVs with 100-mile, 200-mile, and 300-mile ranges accounted for 25%, 13%, and 52% of the entire EV fleet, respectively. The energy consumption rates per mile developed from the EV energy models were matched to each trip based on the road link-level driving distance and speed obtained from the vehicle trajectories. As the second-by-second driving profiles are not available in the DynusT output, the driving cycles by different speeds from the Environmental Protection Agency (EPA) Motor Vehicle Emission Simulator (MOVES) model were used as a surrogate of link driving profiles. The total on-road energy consumption is then converted to charging demand using the following charging demand simulation.

B. EV Charging Load Modeling

By 2019, only 0.12% of registered vehicles in Texas were EVs [13]. Due to the low market penetration and the lack of observed EV charging data, the EV charging demand is estimated under different hypothetical scenarios, with different assumptions made for the spatial and temporal distributions of charging load. The charging load profile by the hour and by location is generated using two methodologies, i.e., a simplified and a realistic method. The simplified method assumes the charging load equals the trip-level energy use and is charged immediately at the end of the trip. In this case, the charging load is directly aggregated at the trip end by each hour (i.e., the "trip-end" scenario). An off-peak charging profile is also constructed based on the trip-end scenario by postponing the charging load assigned to peak hours (2:00 PM to 8:00 PM) to non-peak hours (10:00 PM to 4:00 AM of the next day) to reduce electricity cost and peak demand ("off-peak" scenario).

The realistic charging demand generation method will simulate the charging demand using a microscopic charging behavior model which accounts for diversity in people's range anxiety and the characteristics of daily travel. The individual-level charging load at different locations depends on the time-of-day, trip characteristics, remaining battery range, and the minimum range needed by individuals to complete trips. In this case, people are more likely to charge by the end of all travels within a day with battery closer to depletion, instead of charging the vehicle in the middle of the day with sufficient ranges left (referred to the 'most likely' scenario).

C. Transportation Network Model

The traffic modeling provides information on the energy consumption of EVs. Coupled with parameters designed specific to each scenario through EV charging schemes, the location and time of charging is determined. These models provide the EV charging load at geographically-represented nodes each hour of the day for the period of study. This information provides the essential details that enable the coupled-infrastructure modeling completed in this paper: the additional load from EV charging, where, and when this charging occurs.

III. Electric Grid Network Modeling

A. Test Case Overview

Synthetic electric grids are realistic and fictional power network models. Based on publicly available data, and the statistics of the real power networks, synthetic electric grids are created to include detailed representations of grid elements such as generators, loads, transmission lines, and transformers [14], [15]. Some synthetic grids are also geographically sited, which enables the possibility of coupled infrastructure mapping and co-simulation. Publicly available synthetic grids can be used without the data confidentiality concerns [16].

In this paper, a synthetic grid on the footprint of Travis County, TX is used as the test case to demonstrate the coupling of power and transportation networks [17]. The key statistics of the synthetic system, Travis160, are provided in Table I. This test case contains both transmission and distribution networks [17]–[19]. Figure 2 provides a closer look at the Austin downtown area in the synthetic test case, where the gray boxes

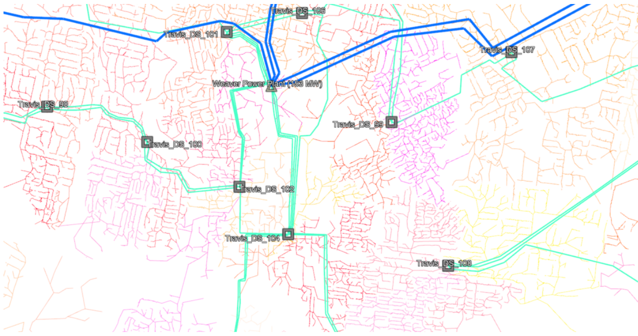


Fig. 2: Zoomed-in view of downtown area in the Travis160 synthetic test case, geo-located in Travis County, Texas [17]

TABLE I: Overview Statistics of the Travis160 Test Case

Customer loads	307,236
Generator units	39
Feeders	448
69 kV transmission lines	229
230 kV transmission lines	34
Transmission buses	160
Distribution electric nodes	1,654,691

are transmission substations, blue and green lines are parts of the transmission grid, and other lines are distribution feeders.

To reduce the computational demand of the coupled infrastructure simulation, the distribution models are simplified to non-electrically modeled elements in the paper. Leveraging the topology of the distribution system, substation service areas are defined to map the locations of EV load to the transmission-level substations.

B. Substation Service Areas

Substation service areas are defined to simplify the mapping of EV load from a transportation node to the transmission-level substation and to provide an understanding of the geographic service of the system. Establishing the service territory of each transmission substation leverages the geographic data on the synthetic system as well as the topology of the distribution system in the Travis160 synthetic case and uses Voronoi polygons to establish tessellating service territories with the electric model's nodes central to each region.

The service area mapping procedure is summarized below:

1) Select a transmission-level substation,
2) Identify which distribution feeders correspond to the selected substation,
3) Obtain geographic coordinates of identified distribution feeder nodes,
4) Create Voronoi polygons to represent the reach of each distribution node,
5) Aggregate Voronoi polygons to represent the selected transmission-level substation's service area,
6) Repeat steps 1 through 5, iterating through transmission-level substations.

If the distribution system topology is not made available, service areas can be approximated by creating Voronoi polygons for each of the transmission-level substations.

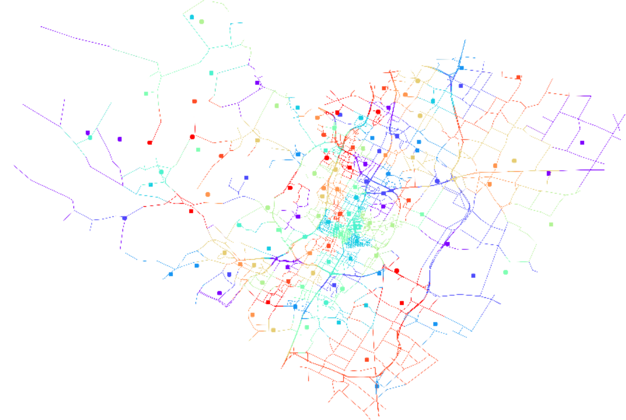


Fig. 3: Transportation segments (lines) and transmission-level substations (dots) colored according to substation service [7].

C. Mapping EV Load to the Electric Grid

The EV charging nodes are mapped to the transmission system according to the substation service areas established in III-B. If the EV charging node falls within the geographic footprint of a substation, it indicates that its most proximate distribution point of interconnection would aggregate to the specified transmission-level substation and thus, its load is best represented as an addition to the identified transmission-level substation.

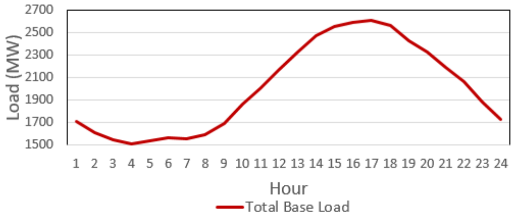
In practice, the mapping of all transportation nodes to the service areas is performed once and the aggregation is customized for varying charging demands informed by different scenarios. Figure 3 provides a depiction of the transmission substations and the roadway links which fall within their service area. The aggregate EV load from charging along these roadway segments are applied to the corresponding transmission-level substation to include the EV charging load in the electric model.

IV. Scenario Design

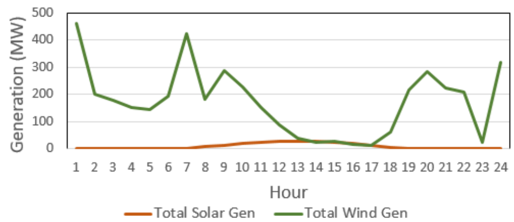
A. Electric Grid Variation

Leveraging the geographic information associated with the Travis160 synthetic test case, hourly time series of individual loads and renewable generators are created to represent the electric grid variation. For the bus-level load, a composition ratio of residential, commercial, and industrial customer is estimated. Publicly available prototypical residential/commercial building, and industrial facility load time series are then aggregated to the transmission bus level through a heuristic optimization process [20], [21]. For renewable generation time series, wind and solar integration toolkit from National Renewable Energy Laboratory is utilized [22], [23]. Given the generator type and geographic location, a unique MW output pattern is synthesized, reflecting the capacity factor, seasonal variation and regional features of a specific renewable unit in the Travis160 test case.

In this paper, the peak load day of the year is chosen for the scenario design. During this 24-hour period, the total system



(a) Base case load time series



(b) Base case renewable generation time series

Fig. 4: Load and renewable generation profile for the base case

load varies between 1511 MW and 2607 MW through a typical daily cycle. The peak solar generation occurs at 1 PM with 27 MW output, and the system wind peaks at midnight with 460 MW generation. The load and generation profile for the base case is shown in Figure 8.

B. *Load Addition from EV Charging*

This paper considers charging demand at 20% EV market penetration. With different assumptions on charging behaviors discussed in Section II, three EV load profiles are added to the existing electric grid variation. Figure 5 shows the time series for the EV charging demand. The three study scenarios with EV charging considered, and one base scenario without EV are summarized in Table II, with the peak and trough values of the system load given.

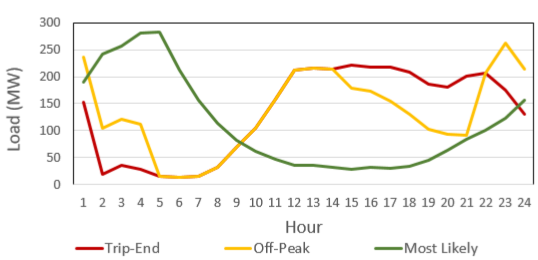


Fig. 5: EV charging demand

TABLE II: Travis160 24-Hour Scenario Summary

Scenario #	EV Charging Scheme	Load Peak	Load Trough
0	–	2607 MW	1511 MW
1	Trip-End	2825 MW	1539 MW
2	Off-Peak	2762 MW	1553 MW
3	Most Likely	2638 MW	1707 MW

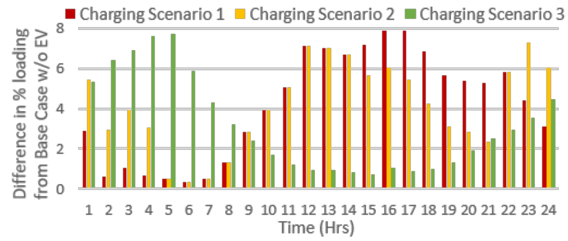


Fig. 6: Impacts on most heavily loaded transformer

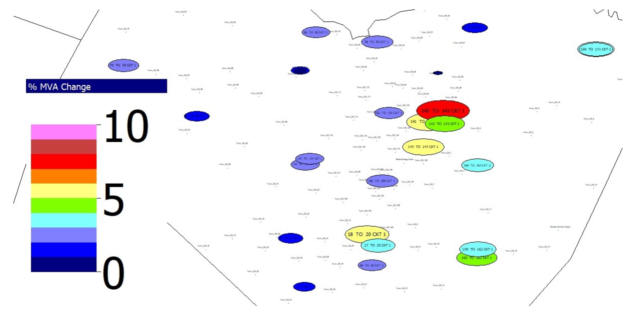


Fig. 7: Change in transformer %MVA load (Scenario 1, 4 PM)

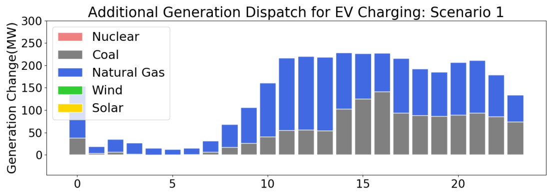
V. Grid Impact Analysis

A. *System Loading*

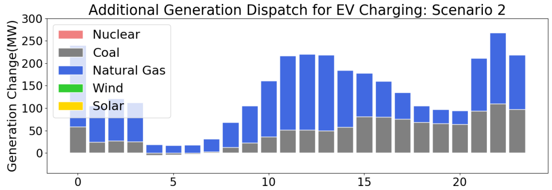
A key question to address while considering increasing EV usage is whether the grid is able to meet the charging demand. If not, system upgrades or special charging strategies may be required. Using the OPF results, the loading on systems elements such as lines and transformers as well as impacts on bus voltages are determined. While 20% EV integration did not cause any violations, the most noticeable effects were on transformer loading. Across different charging scenarios, the same four or five transformers in Travis County showed the most increase in loading. Figure 6 shows the change in MVA loading for the transformer that was the most heavily loaded (i.e., 60%) in the base case, while Figure 7 shows the change in loading for all transformers for scenario 1 at the peak EV load time of the day (i.e., 4 PM). Such studies can help indicate potential weak points or candidate upgrade locations especially for more extreme scenarios of load increase etc.

B. *Generation Dispatch*

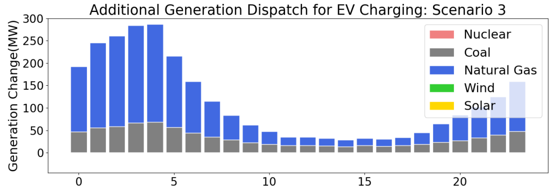
The generation dispatch of each scenario is determined using optimal power flow (OPF) method to minimize the system operation cost at each hour. Figures 8a, 8b, and 8c visualize the additional generation dispatched due to the load increase from EV charging, with three different charging patterns. For all three EV charging scenarios, natural gas and coal generators are dispatched with increased MW output to meet the added electric demand, while the output of nuclear, wind, and solar generators stay constant when compared to the base case, where no EV charging is considered. During the 24-hour period of the simulation for all three EV charging scenarios, no line loading or bus voltage limits are violated. Thus the wind and solar units can generate at their maximum



(a) Additional dispatch for EV charging Scenario 1



(b) Additional dispatch for EV charging Scenario 2



(c) Additional dispatch for EV charging Scenario 3

Fig. 8: Additional generation dispatch for each EV charging scenario, by unit type

for each hour following the pre-defined renewable MW output time series, without being curtailed.

For the "trip-end" charging scenario, the additional MW from natural gas and coal generators are relatively steady throughout the daytime, since the charging is directly aggregated at the end of the trip each hour. The generator dispatch pattern of "off-peak" scenario is similar to that of "trip-end" in the middle of the day. However, compared to the first scenario, the generator output in the second scenario is reduced from 2:00 PM to 8:00 PM, and increased 10:00 PM to 4:00 AM. Both "trip-end" and "off-peak" scenarios have relatively lower generation dispatch during the night. The dispatch pattern for the "most-likely" scenario is unique compared to the first two scenarios. The additional generation dispatch is minimal during the day, and increased drastically at night.

VI. Summary and Future Work

This paper presents a framework of coupled infrastructure studies between the power transmission and transportation networks. The detailed modeling considerations for each network, the points of coupling from EV charging, and the design of testing scenarios are discussed. The grid impact study results using three different charging patterns are also presented and compared to the base scenario without EV charging.

Future work can expand on the methodology outlined in this paper to include:

- Test systems on larger geographic footprints to enable corridor analysis and renewable power purchase agreement simulations for the power transmission network,
- Combined power transmission and distribution simulation for distribution element overload prediction, and
- Smart EV charging patterns informed by grid operation conditions and renewable energy forecasts.

Acknowledgment

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