Integrated T&D Impact Assessment of EV Charging Using a Co-Simulation Framework

Jacob Hastings and Anjan Bose
Washington State University, Pullman, WA

Monish Mukherjee and Trevor Hardy
Pacific Northwest National Laboratory, Richland, WA

***Abstract*—The rapid growth of electric vehicle (EV) adoption is reshaping the operational dynamics of distribution systems, necessitating reevaluation of and innovation in grid infrastructure and management strategies. With increased EV penetration, utilities face increased uncertainty regarding feeder loads, voltage regulation, and capacity for EV charging infrastructure. Hosting capacity analysis has become a crucial tool in assessing the maximum level of EV penetration that feeders can support without violating system limits. However, evaluating the impacts solely at the distribution level is no longer sufficient, as charging behaviors also influence transmission-level operations, including ramping requirements, reserve scheduling, and congestion. This paper presents a multi-level co-simulation framework that integrates transmission and distribution system dynamics with a high-fidelity EV charging model to explore how coordinated charging incentives, such as Time-of-Use programs, affect both local distribution systems and the broader transmission market.**

Simulation results demonstrate the broader implications of localized charging schemes, with time-based incentives showing effects on load profiles and locational marginal prices (LMPs) at the distribution level. Overall operational cost effects, however, were not meaningfully seen until the transmission level. This work emphasizes the need for multi-scale simulation tools that can support grid planning and operational decision-making in high-EV adoption scenarios. It also lays the foundation for future studies on transactive energy models and their potential to optimize grid operations across multiple domains.

***Index Terms*—Electric vehicles, co-simulation, economic dispatch, wholesale markets**

I. Introduction

Electric vehicle (EV) registration counts in the United States have increased substantially, with the U.S. DOE reporting annual growth rates of over 20% for each year from 2016 to 2023 [1]. The rapid adoption of EVs is driving substantial changes to the operational behavior of distribution systems and amplifying interdependencies across the transmission–distribution (T&D) interface. As EV charging becomes increasingly concentrated at residential and commercial nodes, utilities face growing uncertainty in feeder loading patterns, voltage regulation requirements, and provisioning of capacity for fast-charging infrastructure. Hosting capacity analysis has become a critical tool for quantifying the maximum EV penetration that feeders can accommodate without violating thermal limits, voltage bounds, or protection constraints. Studies have shown that uncoordinated charging can significantly reduce hosting capacity—driving transformer overloading, voltage deviations, and reverse power flows—particularly in feeders with high residential clustering or limited voltage support [2], [3]. These constraints grow more pronounced with the introduction of DC fast chargers (DCFC), which can exceed feeder headroom even at low adoption levels.

However, evaluating EV impacts solely at the distribution level is increasingly insufficient. Charging behavior directly alters the net-load profiles observed by transmission operators, influencing ramping requirements, reserve scheduling, and regional congestion patterns. To capture these interactions, integrated T&D co-simulation has emerged as an essential methodology, enabling the concurrent modeling of unbalanced distribution feeders and transmission-level economic or dynamic simulations. Co-simulation platforms such as HELICS allow researchers to evaluate how distribution constraints affect system-wide peak formation, or how transmission-level locational marginal prices (LMPs) induce synchronized V1G charging that stresses local feeders [4], [5]. This cross-domain feedback highlights the need for multi-scale simulation frameworks to support accurate planning and operational decision-making under high EV adoption.

At the same time, the evolution from unidirectional charging (V1G) towards bidirectional vehicle-to-grid (V2G) capabilities introduces both operational complexity and new opportunities for flexibility. V1G managed charging can mitigate operational violations by shifting load away from peak periods, reducing feeder congestion, and improving load-ability margins. V2G extends these capabilities by enabling EVs to inject power back into the grid, providing fast-response services such as frequency regulation, peak shaving, and localized voltage support [6], [7]. When modeled within integrated T&D co-simulation frameworks, V2G resources demonstrate the potential to relieve both transmission-and feeder-level constraints, thereby expanding effective hosting capacity. Yet widespread deployment requires detailed modeling of user availability, charger behavior, degradation costs, and coordination strategies that account for constraints across both system layers.

Overall, the combined assessment of hosting capacity, T&D co-simulation, and V1G/V2G flexibility is essential for understanding the holistic impacts of transportation electrification. Such integrated studies enable utilities and system operators to identify infrastructure needs, develop coordinated operational strategies, and ensure reliability and economic efficiency in future high-electrification scenarios.

Towards that goal, this paper presents a method for the inclusion of these components in a multi-level co-simulation incorporating transmission market, distribution system, and high-fidelity EV charging simulations; demonstrating the importance of capturing the interaction between these levels. Specifically, this work looks at how a decision at the individual

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user level (when to charge a personal EV), influenced en masse through an incentive program, can translate to effects at the transmission market level. The key contributions of this study are (1) A high fidelity EV response modeling approach that can capture vehicle availability at feeder connection points, charging characteristics for a range of EV chargers, and incorporate EV-management solutions, (2) Integration with a co-simulation framework to evaluate the impacts of EVs across the T&D boundary and (3) Demonstrating, through a Texas-based use-case, the integrated T&D impacts of uncoordinated EV controls at varying penetration-levels.

II. Modeling EV Response

A. Charger Model

When charging batteries, the rate at which they can be charged is a function of the electronics involved as well as the battery chemistry. This effect is most notable when charging batteries quickly, leading to a rapid drop off of charging rate as the battery becomes full. This behavior can be seen in figure 1, which demonstrates how charging rate is affected by the battery SOC. P and C rates refer to the rate of charging scaled to the capacity of the battery. P refers to the energy delivered to the battery (W/WH) while C refers to the current (A/AH) with a rate of 1 being the rate at which the battery would charge completely in an hour. The exact design of this charging behavior is based on Caldera: Electric Vehicle Charging Simulation Platform [8].

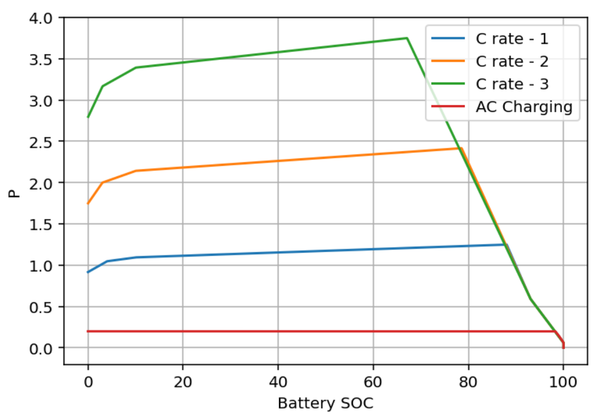

Fig. 1. Charging rate as a function of battery SOC for NMC batteries

This model covers behaviors during both the constant current and constant voltage modes of DC EV chargers. These transition points and the exact behavior before and after the transition are dependent on both the charging rate and the type of battery being charged. At the charger level, the details of each vehicle and charger are kept in order to properly keep track of exactly where the electric vehicle loads are occurring. Customer behavior and vehicle technical specifications are captured in order to model the vehicle's battery and schedule both use and charging availability.

B. Controls

When broader management of EV-charging is reasonable, such as for commercial chargers at a single station, fleet charging stations, or for DER aggregation, multiple chargers are placed under a management entity. These managers can then set charging schedules taking into account the limitations set by the vehicle schedules as well as the technical specs of both the vehicles and chargers themselves. This allows for simulation of various charging schemes in order to analyze their impact on the transmission and distribution systems within the other components of the co-simulation. Demonstrated in the results section of this paper is an example of residential EV controls that restrict charging during a set period of time.

III. Overview of the Simulation Components

This co-simulation is separated into three individual simulation components coordinated by the co-simulation tool HELICS. This coordination involves maintaining a consistent simulation time across the components as well as the transfer of necessary data between components. Coordination between the components allows for control schemes informed by the state of the system (e.g. voltage control at the distribution level or altering loads based on prices from the real time market).

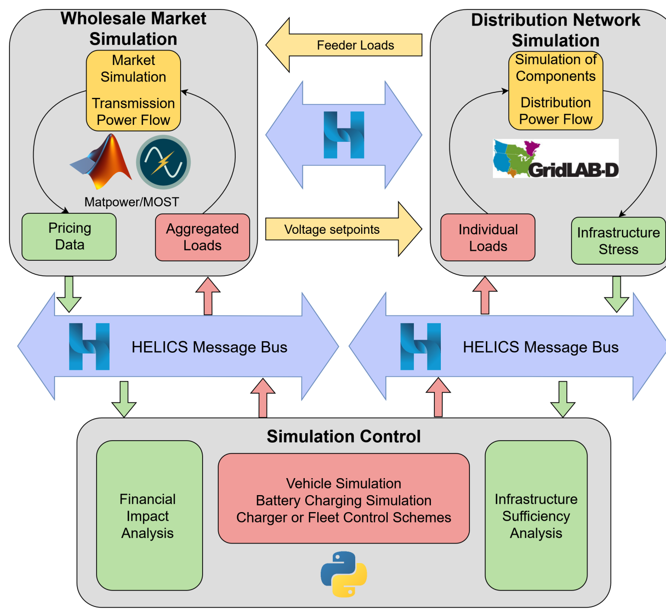

Fig. 2. Architecture of the co-simulation framework

A. Transmission Simulation & Market

At the transmission level, the transmission grid is simulated to capture network and generation limits, perform a power-flow analysis of the grid, and communicate back the resulting voltages to the distribution level simulation. The transmission market is also simulated in order to set generation schedules, determine LMPs, and communicate those prices back to aggregators and EV-controllers at the more granular levels of the co-simulation in order to better inform their decisions.

The inclusion of the transmission market simulation captures when and how behaviors and controls at the more granular levels of the co-simulation have an effect on the market and allow for a feedback loop where meaningful communication can occur between a control scheme and the market. Electric vehicle controls can have an effect on prices and those prices in turn can affect the electric vehicle controls.

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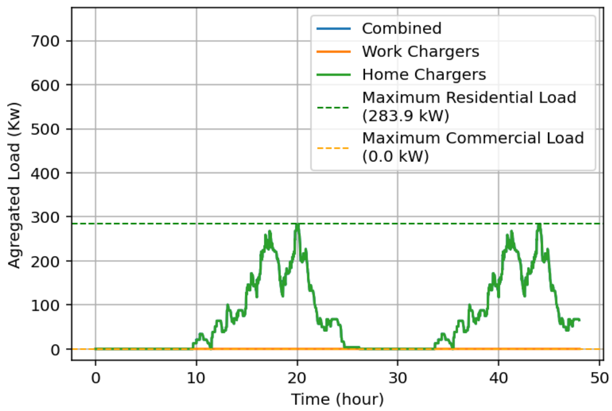

Fig. 3. EV example charging simulation: residential chargers only

B. Distribution Simulation

At the distribution level, regular residential and commercial loads are simulated as part of a distribution network. The loads simulated at this level are combined with the electric vehicle loads simulated elsewhere in order to simulate full substation loads to be communicated to the transmission level.

This is where stresses on distribution components such as transformers, lines, and substations can be analyzed. These stresses can also be communicated back to the EV controls to simulate real-time adjustments meant to alleviate said stresses.

C. EV Charging Control Simulation

At the simulation control level, the coordination and monitoring of the individual EVs, chargers, and management entities are handled. These details are simulated at the EV-control level and communicated back to the other levels in the form of loads. For the distribution system, individual loads from chargers are communicated by location. For the transmission market, any aggregated DERs that participate in the market can send updated bids and capacity limits. This charging control covers EV chargers that are part of DER aggregation, commercial chargers, and fleet chargers; leaving residential chargers that are not a part of DER aggregation to act independently.

An analysis of the impacts of the features included at the charging control level is seen in figures 3, 4, and 5. For this demonstration, 57 EVs are included which initially only have residential AC chargers available.

The inclusion of commercial DCFCs in Fig. 4 demonstrates the expected reduction in residential loads. The much higher load associated with DC chargers results in a significant peak for commercial chargers. With the inclusion of more accurate charging limitations in Fig. 5, the likelihood of multiple chargers simultaneously charging at their maximum rate is significantly reduced, leading to a more accurate commercial load peak while maintaining the residential load reduction associated with the commercial charger addition.

The inclusion of both the commercial chargers and the battery chemistry charging limitations enables the simulation to accurately reflect both the reduction in stress that commercial chargers can provide to the residential load and the increased stress caused by the same chargers elsewhere on the network.

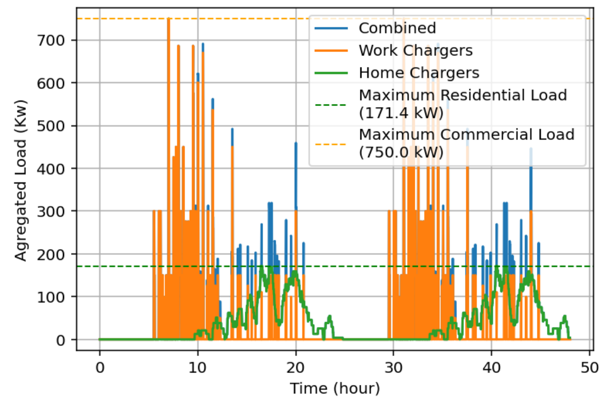

Fig. 4. EV example charging simulation: commercial DC chargers included with no battery chemistry charging limitations

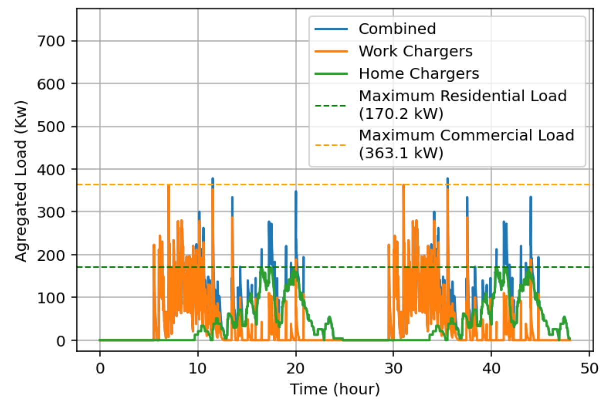

Fig. 5. EV example charging simulation: residential and commercial chargers included with battery chemistry charging limitations

IV. Test System Description

A. ERCOT Model

To provide the transmission component of the co-simulation, an 8-bus transmission model of ERCOT was utilized (see fig. 6). This model includes 606 generators as well as actual load data of the ERCOT weather zones and variable renewable energy (solar & wind) generation data for 2021 obtained from [9]. The test system was simulated for four sample days in August 2021 and the market operations were emulated as a day ahead market executing a multi-period security constrained economic dispatch every 24 hours, a real time market executing an optimal power flow every 5 minutes adjusting resource commitments based on the day ahead market, and a power flow followed by adjusting slack and communicating system voltages every minute.

Demonstrating the efficacy of this transmission model, the generation mix and the LMPs were compared to the actual mix of dispatched generators and historical LMPs from the ERCOT ISO in previous work [10]. The dispatch of the generation mix obtained from the wrapper-simulation aligns closely with the actual generation mix of ERCOT.

Since the majority of the computational burden for the transmission market optimization comes from the nonlinear constraints and mixed integers introduced by the 606 generators, scaling to a more detailed transmission model would be possible without excessive computational load as the transmission constraints can be reasonably linearized.

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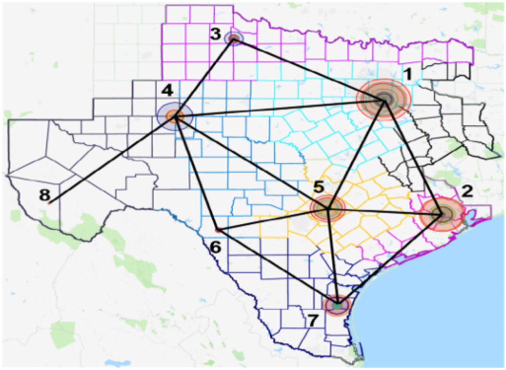

Fig. 6. 8-bus model of ERCOT

B. Distribution Model

To appropriately represent regional demand characteristics, GridLAB-D based distribution grid models have been used. The distribution system was modeled using an urban prototypical feeder (R4-12.47-1) [11] as the system was considered to be connected at a transmission bus at the South Central (SC) weather zone of Texas, which is mostly urban in demographics. The feeder has been configured with an SC-specific customer mix and end-user loads including temperature-sensitive loads like HVAC systems, water heaters, other plug loads and EVs. To appropriately represent typical regional responses, the customer asset parameters are based on an energy consumption survey further details of which are presented in [12]. The authors' prior work in [12] also quantifies the fidelity of the distribution grid models through a set of statistical metrics comparing the simulated load with actual ERCOT load including R^2 values of 0.91 (summer). The residential EV behavior is represented using residential car driving schedules gathered from the 2017 National Household Travel Survey [13].

V. Impact of Charging Schemes

For the combined simulation, a simple time-based control was modeled where an adjustable percentage of the EVs in the system would not charge during peak hours, which were defined as 5:00 pm to 10:00 pm. The details of how to achieve these levels of participation are outside the scope of this work, so the adjustable percentage of participants acts as a stand-in for the willingness of customers to participate. Surveys suggest solutions such as time-of-use tariffs may be a more popular solution than they currently are when EV ownership is higher and customers feel more in control of their own energy usage [14]. For maximum impact, commercial chargers were not available during this simulation, meaning that the charging of all EVs in this simulation occurred at the residential level.

Figure 7 demonstrates the effect of the control scheme. The notable features are the decreased loads during the controlled period (highlighted in green) and the prominent peak that occurs just after the end of the controlled period when the EVs that were restricted to charge due to the controls suddenly reconnect together. Both of these features can be seen to increase in magnitude as program participation increases.

The simulated substation load including all residential, commercial, and EV chargers is shown in figure 8. At all levels of program participation, it can be seen that the peak load during the disincentive period decreases. At the highest 75% participation level, the load following the disincentive period is large enough to become the new peak load each day.

Demonstrating the market effects of the control-program, the LMPs at the bus containing the simulated EVs are shown in figure 9. During the restricted period, prices decreased in response to the corresponding decrease in load. Following the restricted period, prices rose in response to the EVs participating in the program coming back online simultaneously. Both of these effects increase with increasing participation.

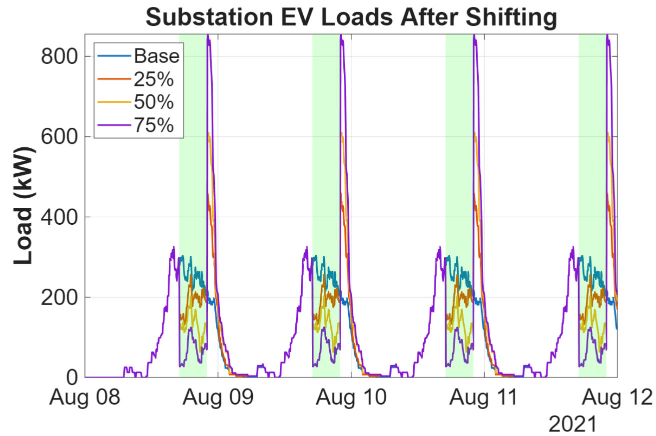

Fig. 7. EV residential loads at a single substation at increasing levels of participation in a restricted charging period (5:00-10:00pm, in green)

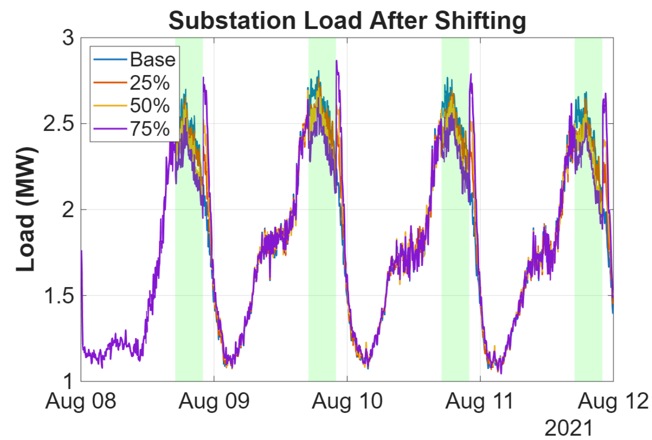

Fig. 8. Full substation loads at increasing levels of program participation.

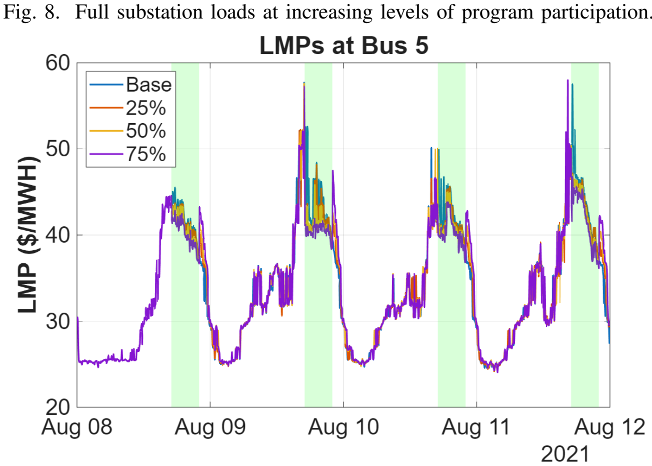

Fig. 9. LMPs at bus 5 at increasing levels of program participation.

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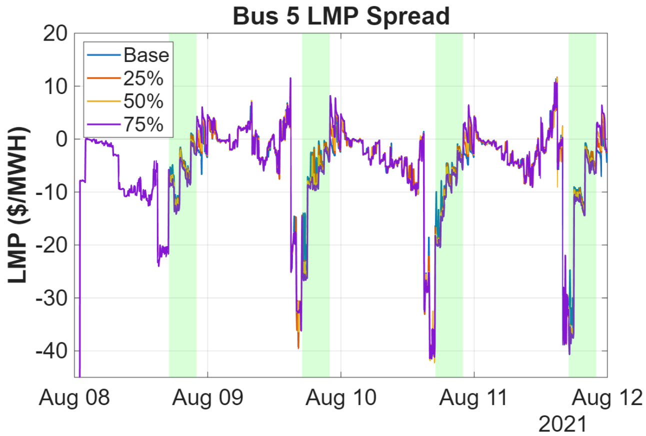

Fig. 10. (Day ahead market prices) - (real time market prices) for bus 5

LMP spread, or the differences in price between the day ahead market and the real time market, is an indicator of market inefficiency. In this case, the inefficiency is partially a result of the program participation not being reflected in the day ahead market load prediction. LMP spreads were most pronounced at the highest levels of participation (Fig. 10).

Operational costs were calculated according to (1), combining the predicted loads $\left(P^{DAM}\right)$ and LMPs from the day ahead market assessment with the actual loads $\left(P^{Actual}\right)$ and cleared prices $\left(LMP^{RTM}\right)$ from the real time market simulation. Costs were summed over all buses (i) and time periods (t) for the full simulation duration (T).

$$\text{Cost-of-Operation} = \sum_{t}^{T} \sum_{bus=i}^{8} \left[\text{LMP}_i^{DAM}(t) \times P_i^{DAM}(t) \right] + \sum_{t}^{T} \sum_{bus=i}^{8} \left[\text{LMP}_i^{RTM}(t) \times \left\{ P_i^{Actual}(t) - P_i^{DAM}(t) \right\} \right] \tag{1}$$

Table I includes the operational costs at the simulated bus level as well as at the full ERCOT system level. It should be noted that smaller levels of restricted charging participation (25% and 50%) resulted in reduced costs from peak shedding, however, at higher levels (75%) the effect of the sudden load increase at the end of the restricted period began to outweigh the peak shedding effects and costs began to rise instead.

TABLE I
OPERATIONAL COSTS FOR THE 4-DAY SIMULATION

EV Program Participation	Simulated Bus Costs		System Costs	
	Total	Change	Total	Change
0%	$31,653,856	-	$285,172,857	-
25%	$31,653,364	-$492	$285,124,883	-$47,974
50%	$31,653,158	-$698	$285,087,340	-$85,517
75%	$31,653,256	-$600	$285,098,393	-$74,464

At both levels, the cost change associated with program participation was a small percentage of overall costs, but the far-reaching consequences of the program ended up being more notable than they may have appeared at the local level. At the individual bus level, the savings from 50% participation were only $698, but at the system level this effect ballooned to $85,517; far beyond a proportional effect that one might expect. This shows that the bulk of the change in cost was due to effects outside the bus where the program occurred.

VI. Conclusions

This study underscores the importance of multi-level co-simulation in capturing the complex interactions between transmission and distribution systems under high EV penetration. By integrating detailed EV charging behavior, distribution system constraints, and transmission market dynamics, we demonstrate how local control schemes, such as time based controls and incentives, can have significant, far-reaching effects on grid operations, including both local and system-wide economic impacts. The results reveal that even simple charging incentives can lead to noticeable changes in load patterns, voltage regulation, and system-level LMPs.

While this work demonstrates the value of integrated simulation for understanding the steady-state impacts of EV charging behaviors, further research is needed to explore more complex charging schemes and the role of commercial and fleet charging stations. Additionally, the development of transactive energy models and advanced distribution grid service controls will be crucial for optimizing grid reliability and efficiency in future electrified energy systems.

References

[1] U.S. Department of Energy, Office of Energy Efficiency and Renewable Energy, "Change in U.S. Light-Duty Vehicle Registration Counts," https://afdc.energy.gov/data/10881, 2024.

[2] P. Richardinson, D. Flynn, and A. Keane, "Impact of electric vehicle charging on residential distribution networks: A probabilistic analysis," *IEEE Transactions on Power Systems*, vol. 26, no. 1, pp. 82–93, 2010.

[3] K. Clement-Nyns, E. Haesen, and J. Driesen, "Coordinated charging of multiple plug-in hybrid electric vehicles in residential distribution grids," *IEEE Transactions on Power Systems*, vol. 25, no. 1, pp. 371–380, 2010.

[4] B. Palmintier, D. McCorkle, J. Fuller, and et al., "Design of the helics high-performance co-simulation framework for electric power systems," in *Proc. IEEE Power and Energy Society General Meeting*. IEEE, 2016, pp. 1–5.

[5] M. Almassalma, D. Van der Meer, and M. Gibescu, "Co-simulation of integrated transmission and distribution systems: A review and outlook," *Electric Power Systems Research*, vol. 189, p. 106614, 2020.

[6] W. Kempton and J. Tomic, "Vehicle-to-grid power fundamentals: Calculating capacity and net revenue," *Journal of Power Sources*, vol. 144, no. 1, pp. 268–279, 2005.

[7] Y. Bichiou and M. Krarti, "Vehicle-to-grid frequency regulation services: A comprehensive review," *Renewable and Sustainable Energy Reviews*, vol. 132, p. 110054, 2020.

[8] INL Software, D. Scoffield, M. Cebol Sundarrajan, and P. Rumsey, "Caldera charge icm: Vehicle and supply equipment charging library," 2022.

[9] Electric Reliability Council of Texas, "Ercot weather zone map." [Online]. Available: https://www.ercot.com/news/mediakit/maps

[10] J. Hastings, A. Bose, M. Mukherjee, and T. Hardy, "Wrapper-based interfaces to enable wholesale markets simulation for transactive energy studies," in *2025 IEEE PES Grid Edge Technologies Conference & Exposition (Grid Edge)*. IEEE, 2025, pp. 1–5.

[11] K. P. Schneider, Y. Chen, D. P. Chassin, R. G. Pratt, D. W. Engel, and S. E. Thompson, "Modern grid initiative distribution taxonomy final report," Pacific Northwest National Laboratory, Tech. Rep., 11 2008. [Online]. Available: https://www.osti.gov/biblio/1040684

[12] S. Hanif, M. Mukherjee, S. Poudel, M. G. Yu, R. A. Jinsiwale, T. D. Hardy, and H. M. Reeve, "Analyzing at-scale distribution grid response to extreme temperatures," *Applied Energy*, vol. 337, p. 120886, 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0306261923002507

[13] U.S. Department of Transportation, Federal Highway Administration, "National Household Travel Survey," https://nhts.ornl.gov/, 2017.

[14] M. Nicolson, G. Huebner, and D. Shipworth, "Are consumers willing to switch to smart time of use electricity tariffs? the importance of loss-aversion and electric vehicle ownership," *Energy research & social science*, vol. 23, pp. 82–96, 2017.

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