Economic and Environmental Impacts of Electric Vehicle Smart-Charging Programs on the U.S. Power Sector

Balasubramanian Sambasivam Ph.D.
Postdoctoral Research Fellow
Department of Civil, Architectural and Environmental Engineering, UT Austin
balasubramaniansa@austin.utexas.edu

Kara M. Kockelman, Ph.D., P.E.
Dewitt Greer Professor in Engineering
Department of Civil, Architectural and Environmental Engineering, UT Austin
kkockelm@mail.utexas.edu
Tel: 512-471-0210

Benjamin D. Leibowicz Ph.D.
Associate Professor
Operations Research and Industrial Engineering, UT Austin
bleibowicz@utexas.edu
Tel: 512-475-9550

Word Count: 5,483 words + 1Table x 150 words = 5,633 words

Submitted for presentation at the 103rd Annual Meeting of the Transportation Research Board to be held in Washington DC in January 2024.

ABSTRACT
Electric Vehicle (EV) charging patterns have direct and indirect impacts on power grid operations and investments. Unmanaged EV charging can intensify peak power demand, creating local and widespread supply-demand imbalances while engaging coal-fired and other high-emitting power sources. This study evaluates a series of coordinated or EV smart-charging programs for the U.S. using the Regional Energy Deployment System (ReEDS) model. The six scenarios are unmanaged charging, daytime and nighttime smart-charging programs with two different participation rates, and fully managed EV charging. The impact of these scenarios on grid emissions, power generation (feedstock) mixes, and capacity, along with the associated system investment costs, is anticipated and compared. Results suggest that fully managed charging should lower new investment costs by 5% and grid emissions by 4% over the next 25 years, assuming the nation's light-duty adoption of EVs is 100% as soon as 2035. Fully managed charging also speeds the nation's shift to renewable energy sources, with new additions of 1200 GW of solar power and 500 of GW of wind power by 2050. Additionally, the system would see an increase of 100 GW in new battery capacity to support managed charging.

Keywords: Electric Vehicles, Power Grid, Unmanaged Charging, Smart-Charging

INTRODUCTION

Climate change is a major threat, with many nations, cities, and organizations working to decarbonize transportation and power systems as quickly as possible. Electric vehicle (EV) adoption is a major intervention for decarbonizing the transport sector and reducing other emissions (*1*). The number of EVs on world roads rose to 10 million in 2020 from nearly zero a decade earlier, and is expected to hit 250 million by 2030 (*2*), with new vehicle sales expected to be 58% EV, globally by 2040 (*3*). Forecasts tend to rise every year as more nations unveil ambitious targets and policies (*4*).

Cars and light-duty trucks are responsible for 17% of total U.S. greenhouse gas emissions (*5*). Passenger vehicles were directly responsible for 60% of $PM_{2.5}$ and 43% of NO_x emissions from on –road U.S. transportation sources in 2017 (*6*). The Biden Administration set a target for half of all U.S. vehicle sales to be zero-emission vehicles (ZEVs) by 2030, and pledged $7.5 billion for EV charging station provision, under the Bipartisan Infrastructure Law (*7*). California is leading the nation with a roadmap to sell only ZEVs by 2035 (*8*). Ten other U.S. states have mandated that certain shares of passenger-vehicle sales be EVs (*9*).

Rapid growth in EV ownership, use, and charging may tax existing electricity networks (*10*). When EVs start charging as soon as customers plug them in (uncontrolled charging), power demand may require turning on peaker power plants and releasing more emissions per kWh generated (*11*). If EV charging can be managed and timed to match wind, solar, and other online power sources, EVs can become an asset to the electricity grid (thanks to coordinated or "smart"-charging). When EV charging is coordinated, EVs can be charged during times of low demand and/or surplus generation. EV charging can be started during times of excess renewable energy (RE) generation, which reduces RE curtailment. In this way, smart-charging adds stability and flexibility to the power grid. Such demand management is especially valuable when a region's power generation is dominated by non-dispatchable/intermittent generators (solar and wind).

To decarbonize the electricity sector, there has been increased penetration of RE, like solar and wind, making demand management (including EV smart-charging, smart thermostat controls, and variable power pricing) fundamental to maintaining a reliable power grid with low-cost power. The main objective of this study is to evaluate the impact of EV charging timing on the U.S. electricity grid in terms of emissions, future capacity expansion, generation dispatch, RE curtailment, and investments. The study focuses on smart-charging strategies and evaluates the harmful and helpful effects of EVs on the grid with and without the proposed strategies.

In this study, six scenarios have been designed to assess the influence of EV smart-charging on the U.S. electricity grid. These scenarios consist of unmanaged charging, daytime, and nighttime smart-charging programs, each with two different participation rates, along with fully managed EV charging. The unmanaged and fully managed charging scenarios represent two opposite spectrums, one with no control and the other with complete control over EV charging on the electricity grid. In the daytime and nighttime smart-charging programs, 50% and 100% of the EV charging demand is shifted between these two time periods. These proposed programs are carefully evaluated to understand the grid impacts of EV charging and provide valuable insights for decision-makers to manage the grid efficiently. With the fast adoption of EVs into the market, it is essential to understand the grid impacts and prepare for appropriate grid investments and storage requirements. The results from the study will help a smoother transition to EVs while maintaining grid reliability and stability.

The remainder of the paper is organized as follows: Section 2 discusses the literature examples of EV charging in different countries, section 3 discusses the methodology, with summary of the ReEDS model and smart-charging program description, section 4 discusses the study results, and section 5 concludes.

Relevant Literature

In recent years there has been a significant number of studies focused on evaluating the impact of EV charging in the power grids. The studies employ market-based modeling tools with a specific country focus on evaluating emission reduction, maximizing RE penetration, and electricity pricing in the electricity system with EV integration. Table 1 lists a variety of recent EV charging-strategy papers with the regions of study and tool names or methodology used. Some of those papers emphasize emissions reductions and flexibility potential for European settings. For example, Bellocchi et al. (*12*) analyzed EV-RE synergies in Italy on power-system costs, CO_2 emissions, and RE curtailment through 2050. A year later, they used EnergyPLAN to simulate different futures for both Italy and Germany, assuming increases in RE generation and EV penetration (including vehicle-to-grid [V2G] strategies) (*13*). Even with very similar RE generation and EV adoption in these two countries, Germany was forecasted to experience a 17% decrease in emissions per GW of RE generation. Lauvergne et al. (*14*) simulated the costs of large-scale EV adoption in France using uncontrolled charging, time-of-use tariffs, and smart unidirectional (vehicle to grid, or V1G) charging. They estimated that smart-charging lowers power costs by €16.2 per capita per year. With the mass integration of EVs into the power grid, the flexibility of the network needs to be taken care of appropriately. An agent-based model is employed to study the flexibility goals of EV charging based on four metrics: peak reduction, flatness of the load curve, increase in midday load, and total load shift under unmanaged and managed charging strategies for the case of Switzerland (*11*).

Others focus on the world's two biggest emitters: the U.S. and China. For example, Li et al (*15*) use the Switch-China model to anticipate feedstock use and emissions from high EV penetration rates (70% of private light-duty vehicles, buses, and taxis), while targeting Paris Agreement goals (*16*). The result shows that in the long term, large-scale deployment of EVs with unmanaged charging requires an additional storage capacity of about 14% compared to employing a smart-charging strategy. Also, smart charging helps to save between $43 and $123 per vehicle annually in 2050 compared to the unmanaged charging strategy. California is the leading state in the U.S. with long-term EV integration targets. Jenn (*17*) evaluated the impact of managed and unmanaged EV charging strategies in the Western Electricity Coordinating Council (WECC) interconnect with California focus using the Grid Optimized Operation Dispatch (GOOD) model. In the light-duty transportation sector in California, with a managed charging strategy, there is a potential for 1 billion tons of cumulative CO_2 reduction through 2045. Using an economic dispatch model, Powell et al. (*18*) analyzed the impacts of different EV adoption levels on the U.S. WECC interconnect region. The results show that EV smart-charging can increase RE consumption and consequently reduce emissions, storage, and ramping requirements. Jones et al. (*19*) developed an energy system optimization model to evaluate the charging patterns of electric shared autonomous vehicles (SAEVs) and electric privately owned vehicles (ePOVs) with two scenarios for Austin, Texas. In one scenario, SAEVs and ePOVs are charged only during night hours; in the other, SAEVs are charged anytime during the day, and ePOVs only at night. The study result shows that if SAEV charging is optimally aligned with renewable electricity generation, there are significant economic and environmental benefits. With Austin, Texas, as a case study, Brozynski et al. (*20*) developed an energy system optimization model to study EV charging and V2G discharging. They conclude that optimal EV charging aligns with solar PV availability, and thus providing charging infrastructure availability at workplaces adds system-wide value to the electricity system.

The next set of studies highlights the importance of mapping EV charging time during high RE generation, using case studies from Asia, Africa, and Australia. A simulation environment is developed to maximize solar PV consumption in public charging of minibus taxi public transport in Kampala, Uganda. The authors used spatiotemporal and solar PV analyses to evaluate the required number of stops needed for the taxis to maximize the available solar energy (*21*). Ullah et al. (*22*) simulated an optimal scheduling algorithm for the maximum utilization of solar PV for EV charging in a solar-based grid-tied charging station in Islamabad, Pakistan. The result shows that the scheduling model can increase the annual solar PV consumption by around 60% and reduce the system cost by around 25%. With a macroeconomic model, Boradbent et al. (*23*) conducted a nationwide study to project Australia's future road transport demand and transition to renewable electricity for 2050 using five scenarios considering the growth in the economy, population, and RE targets. The results show that a rapid transition to renewable electricity generation and 100% battery EVs in new vehicle sales could help to achieve net-zero emissions for Australia by 2050.

There is also an EV charging study with a time of use (TOU) pricing using a synthetic grid. TOU pricing is implemented in electricity systems to reduce peak system demand. Jones et al. (*24*) analyzed the impact of customer EV charging demand on TOU rates for a synthetic grid using a simulation approach. The study results show that unmanaged EV charging immediately after peak hours can increase peak demand by 20%. If the demand is spread across off-peak hours, the peak demand can be reduced by 5% compared to simulations that did not employ TOU rates.

All the EV charging-related studies discussed above are based on optimization and simulation methods. The definitions of the EV smart-charging programs proposed in this study are based on a survey conducted by Dean et al. (*25*) who conducted an online survey to characterize U.S. adults' attitudes toward plug-in electric vehicles (PEVs) and their preferences for smart-charging programs. The survey was conducted among 1050 people across the U.S. between November and December 2022. The respondents were spread across the U.S., and the chosen sample for the study closely resembles the U.S. census data (households & persons). The survey is designed to understand respondents' perceptions of owning EVs, PEV-power grid integration, and the benefits of user-managed and supplier-managed charging. In the survey, questions are asked about respondents' demographics, travel patterns, primary vehicle parking location at home, car buying/leasing decisions, perceived barriers to PEV buying/leasing and home charging, preferred PEV charging style, willingness to participate in utility-managed charging programs and expected compensation for participating in those programs, attitudes towards climate change and consequent clean energy transition, attitudes towards benefits of smart-charging, and grid reliability. The results show that 37% of Americans are willing to cede EV charging control to the utilities. Americans with less education prefer unmanaged charging compared to those with Master's and Ph.D. degrees. 45% of the respondents prefer privacy considerations against ceding EV charging control to the utilities. Further, 60% of people believe smart-charging is good for society. Finally, gender has no role in characterizing the preferred PEV charging method compared to unmanaged charging. Compared to the previous studies in this study, the grid and emission impact arise due to the integration of EVs for the entire U.S. is evaluated using the ReEDS model.

The study's objective is to compare the economic and environmental benefits of the implemented smart-charging programs to the costs of the compensating programs of the survey participants. The novelty of this paper lies in its comprehensive cost vs. benefits comparison, which effectively analyzes the impact of smart-charging of EVs on the U.S. electricity grid. The costs considered in this analysis encompass future capacity investments, storage requirements, and the compensation needed for customers participating in smart-charging programs. On the other hand, the accrued benefits are measured in terms of avoided installed capacity, reduced storage needs, emissions reduction, and alleviating grid stress through effective demand-supply management. This study is one of the earliest to propose such a methodology by juxtaposing the survey results with model outputs to manage EVs.

Table 1 Literature related to EV charging & focus of the current study

Author and Year	Study Focus	Country Focus	Tools/Methods
Bellocchi et al. (*13*)	Emissions reduction	Germany & Italy	Energy Plan
Bellocchi et al. (*12*)	Renewable energy penetration	Italy	Energy Plan
Booysen et al. (*21*)	Solar energy use maximization	Uganda	simulation model
Broadbent et al. (*23*)	Emissions reduction	Australia	system dynamics
Ullah et al. (*22*)	Solar energy maximization	Pakistan	scheduling model
Jones et al. (*24*)	Charging's response to TOU pricing	Synthetic network	simulation modeling
Gschwendtner et al. (*11*)	Demand flexibility potential	Switzerland	agent-based demand modeling
Lauvergne et al. (*14*)	Technical & economic impacts	France	AntaresSimulator
Jenn 2023 (*17*)	Emissions reduction	California	Grid Optimized Operation Dispatch (GOOD) model
Li et al. (*15*)	Emissions reduction	China	Switch model
Powell et al. (*18*)	Grid impacts	U.S. Western Interconnection	Economic Dispatch (ED) model
Jones et al. (*19*)	SAEV contribution to climate mitigation	Austin, Texas, USA	OseMOSYS
Brozynski et al. (*20*)	Electricity & Transport sector decarbonization	Austin, Texas, USA	OseMOSYS
This Study	Grid & emission impact	US	ReEDS model

METHODS

The summary of the ReEDS model is discussed in this section, followed by the description of the smart-charging programs.

Summary of the ReEDS Model

This study has been conducted using NREL's ReEDS model. ReEDS, or Regional Energy Deployment System, is a capacity expansion model developed to produce scenarios for the evolution and operation of the future U.S. electricity system until 2050. In the literature, several studies with varying objectives have used the ReEDS model. ReEDS has been employed to study the cost implications of increased RE (*29*); explore pathways to achieve a 100% RE system (*31*); evaluate the impacts of solar PV (*27*) and wind energy (*32*) in the electricity system, assessing the role of battery storage as a peaking capacity resource (*26*); examine the impacts of clean energy standards and emission policies (*33*), planning reserve margins for future capacity additions (*28*); and examine cost targets for zero-emission nuclear, CSP and offshore wind in system planning (*30*).

In ReEDS, the U.S. is divided into 134 balancing areas where the model helps in planning capacity expansion and grid service requirements. Figure 1 shows the regional representation of the 134 model balancing areas (represented by bold black lines) in the ReEDS model. The model uses a least-cost approach considering technology, resource, land use, and policy constraints to evaluate the trade-offs between the various generation technologies, transmission, and storage. The uncertainty, variability, and geographic resource constraints of onshore and offshore wind, concentrating solar power, are characterized across 356 regions. The model allows for a layering of two EV charging demand types: the first is a base, flat, or minimum load across all 24 hours of the day (which ReEDS calls "static" demand), and the second is a "dynamic" set of values that vary for each of the 24 hours of the day (and are constant loads within each hour). The base load, or "static" EV demand, is not allowed to shift across different time slices (hours of the day), whereas the dynamic demand can be shifted.

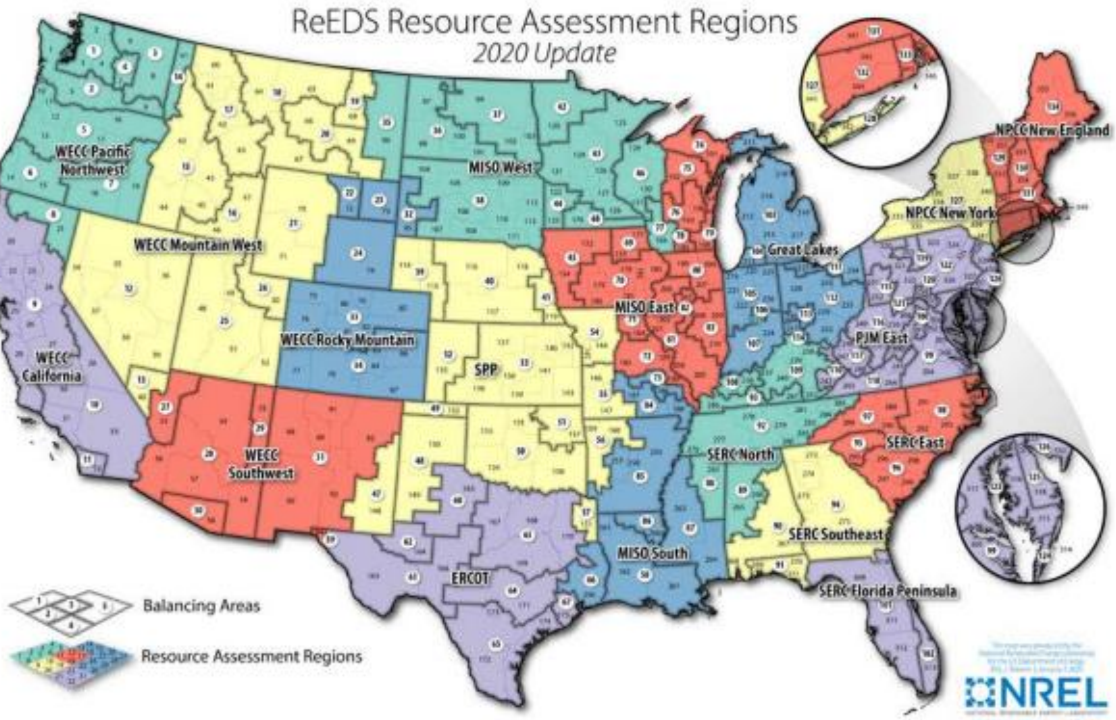

Figure 1 Regional representation (balancing areas and resource assessment regions) used in the ReEDS model

The objective of this study is to evaluate the transformation of the U.S. electricity system with EV integration using the ReEDS model. The analysis will cover the timeframe from 2025 to 2050, with a five-year decision-making time step for each model period. The study aims to project the growth of EVs and assess its impact on various aspects of the U.S. electricity system, including generation & capacity mix, storage requirements, emissions and investment costs. The analysis will consider six different scenarios to explore the potential outcomes and implications of EV integration.

The projected EV demand up to 2050 is derived from the Transportation Energy & Mobility Pathway Options (TEMPO) model developed by NREL (Arthur Yip et al. 2023). The TEMPO model considers different EV adoption rates in future years and estimates the EV demand from 2020 to 2050 with two-year time steps. For the current study, the EV demand based on the "All EV sales by 2035" scenario in the TEMPO model is utilized as the input. In alignment with various announced targets, this scenario assumes reaching 50% and 100% of light-duty EV sales in the U.S. by 2030 and 2035, respectively. Figure 2 presents the projected EV demand over the years up to 2050 given by the TEMPO model.

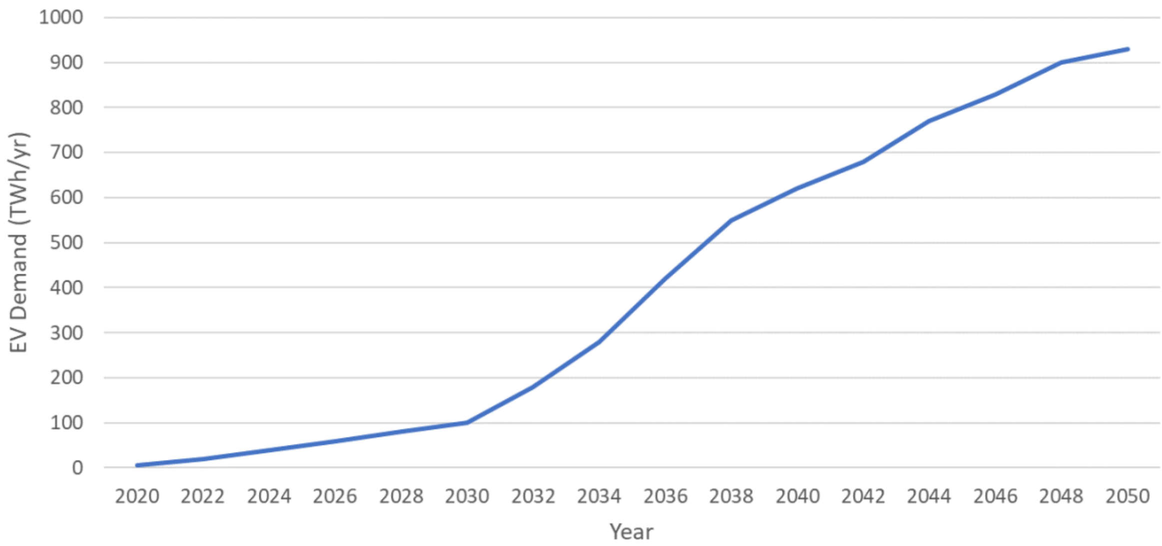

Figure 2 Projected EV Demand over the years up to 2050: TEMPO model

SMART-CHARGING PROGRAMS

The study considers three types of EV charging strategies: unmanaged, smart-charging, and fully managed. In an unmanaged charging strategy, EVs are charged as soon as they are plugged into the grid without concerning the grid's status. In the fully managed charging strategy, the utilities have full control over EV charging time. In a smart-charging strategy, utilities control the timing of EV charging with specific assured deadlines to achieve a full charge; consumers are offered two charging programs (nighttime and day time charging) to cede control of their EV charging to the utilities.

The current study is limited to household EVs. The EVs whose charging times are controllable are personal vehicles parked at homes (both single- and multi-family residences), workplaces, and public charging stations. For this study, a day is divided into five-time blocks: morning (6–10 AM), midday (10 AM–1 PM), afternoon (1–5 PM), evening (5–9 PM), and overnight (9 PM–6 AM). It is assumed that in all the charging scenarios, the number of EVs available for charging is the same. Further, it is assumed that when EV charging is shifted from the present hour to the future hour, the vehicle is plugged in for charging. In the night charging scenario, the EVs are plugged in and available for charging. EV charging infrastructure is assumed to be available in all locations (homes, workplaces, and public places).

Unmanaged Charging (UMC)

This unmanaged-charging scenario simulates charging whenever EV owners/users charge, without any concern for grid status. Here, the utilities do not have any control over user charging times. This scenario assumes that users plug in their EVs for charging whenever desired and unplug them once the vehicle reaches maximum charging capacity.

Fully Managed Charging (FMC)

In this scenario, the utilities have full control over the time of charging of all the EVs, i.e., the entire EV demand is controllable. The utilities schedule the EV charging demand as per supply-side requirements. Though this situation is unlikely to happen, this scenario is simulated to show the opposite of the unmanaged charging scenario.

Smart-Charging

In this study, we have proposed two smart-charging strategies: night-time and day-time charging with two participation strategies (50% & 100%).

Night-Time Smart-Charging (NSC)

In this program, the EVs are charged only during the nighthours (9 PM – 6 AM), i.e., the utilities shift EV charging from daytime to nighttime. The program considers two types of customer participation: 50% and 100% of the EV demand are shifted from the daytime to the nighttime. To encourage customers to participate in this program, incentives are provided to those who allow the utilities to control their EV charging. The calculation of these EV incentives is done outside the model. The utilities assure the participating customers in this program will have a full charge by 6 AM, i.e., all the EV demand that is shifted will be met during this time. Between 9 PM and 6 AM, utilities chose the optimal time for EV charging based on generation capacity availability and cost.

Day-Time Smart-Charging (DSC)

This program contrasts with the nighttime charging program. Here, the EV charging from the night-time is shifted to the daytime between 6 AM and 9 PM. Similarly, two participation rates are considered: 50% and 100% of the EV demand are shifted from the nighttime to the daytime. Users are incentivized to participate in this program. The utilities schedule the EV charging during the day, considering generation availability and reducing system costs. The proposed mathematical model and the related indices are elaborated in the following section.

Indices

r $\quad region\,, r = 1, 2, \dots, R = 134$

h $\quad timeslice, h = 1, 2, \dots, H, (1 - Overnight\ (9\ PM - 6\ AM), 2 - Early\ Morning\ (6\ AM - 10\ AM), 3 - Morning\ (10\ AM - 1\ PM), 4 - Afternoon\ (1\ PM - 5\ PM), 5 - Evening\ (5\ PM - 9\ PM),$

t $\quad year$

Decision variable

$EVD_{r,h,t}$ $\quad EV\ demand\ in\ region\ r\ at\ timeslice\ h\ for\ year\ t$

Parameters

$D_{r,h,t}$ Current EV Demand in region-r at timeslice-h in year-t

δ $\quad Percentage\ of\ EV\ demand\ allowed\ to\ shift\ from\ one\ timeslice\ to\ the\ other$

Fully Managed Charging

$$\sum_{h=1}^{5} EVD_{r,h,t} = \sum_{h=1}^{5} D_{r,h,t} \quad \forall(t,r) \tag{1}$$

Night-time Charging

$$EVD_{r,h_1,t} = D_{r,h_1,t} + \delta * \sum_{h=2}^{5} D_{r,h,t} \qquad \forall(r,t) \tag{2}$$

$$EVD_{r,h,t} = D_{r,h,t} - \delta * D_{r,h,t} \qquad \forall(r,t,h \in \{2,3,4,5\}) \tag{3}$$

Day-time Charging

$$\sum_{h=2}^{5} EVD_{r,h,t} = \sum_{h=2}^{5} D_{r,h,t} + \delta * D_{r,h_1,t} \quad \forall(r,t) \tag{4}$$

$$EVD_{r,h,t} = D_{r,h,t} - \delta * D_{r,h,t} \qquad \forall(r,t,h \in \{1\}) \tag{5}$$

Results and Discussion

In this section, we discuss the operational results of the ReEDS model power system simulation to meet the electricity and EV charging demand. Here, the results of the unmanaged smart and fully-managed EV charging scenarios are discussed elaborately with respect to emissions, generation mixes, costs, and new capacity additions.

Impacts on Emissions

The long-term adoption of EVs is likely to help reduce the tailpipe emissions from the transportation sector but may increase the emissions from power production in the electricity sector. Figure 3 presents the cumulative CO_2 emissions until 2050 between UMC and FMC charging scenarios. Compared to UMC, with FMC, the cumulative CO_2 emissions from 2025 to 2050 are expected to reduce by 4% (126 million metric tons (MT)). Since utilities have full control over EV charging, majorly, they schedule it during times of high RE availability, thereby avoiding emissions from conventional power plants. Figure 4 presents the difference in CH_4, NO_x, and SO_2 emissions between unmanaged and managed charging scenarios. With managed charging of EVs in all the years until 2050, there is a reduction in these emissions. The cumulative CH_4 emissions are 1% less in the FMC strategy compared to UMC between 2025 and 2050. In the same study period, the NO_x & SO_2 emissions were reduced by 4% and 6% with the FMC strategy.

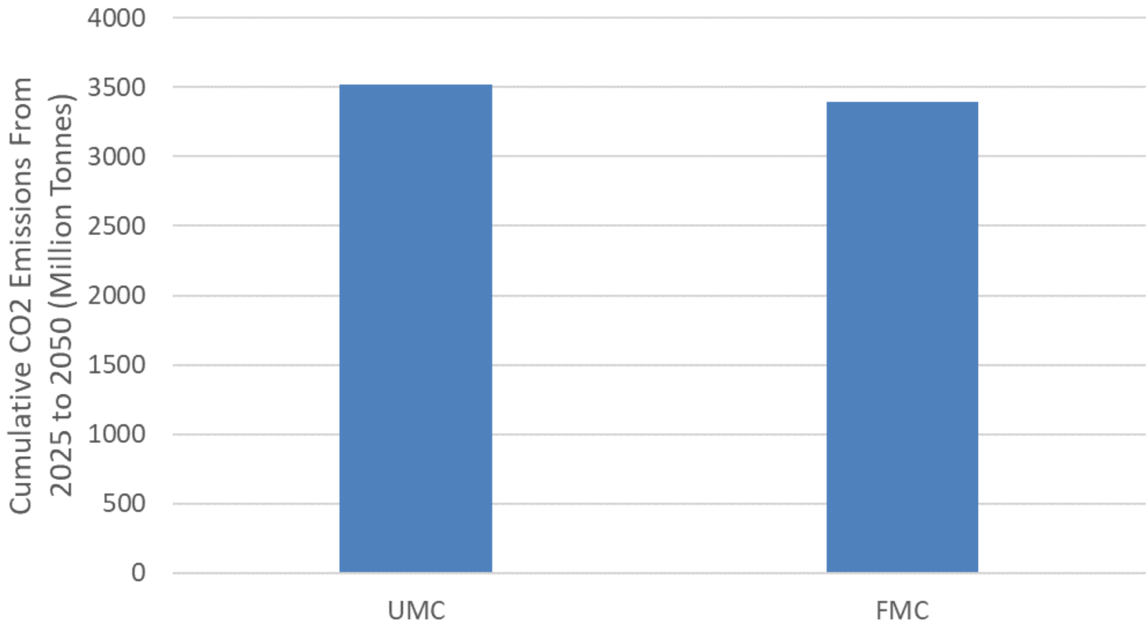

Figure 3 Cumulative CO_2 emissions in 2050, by scenario

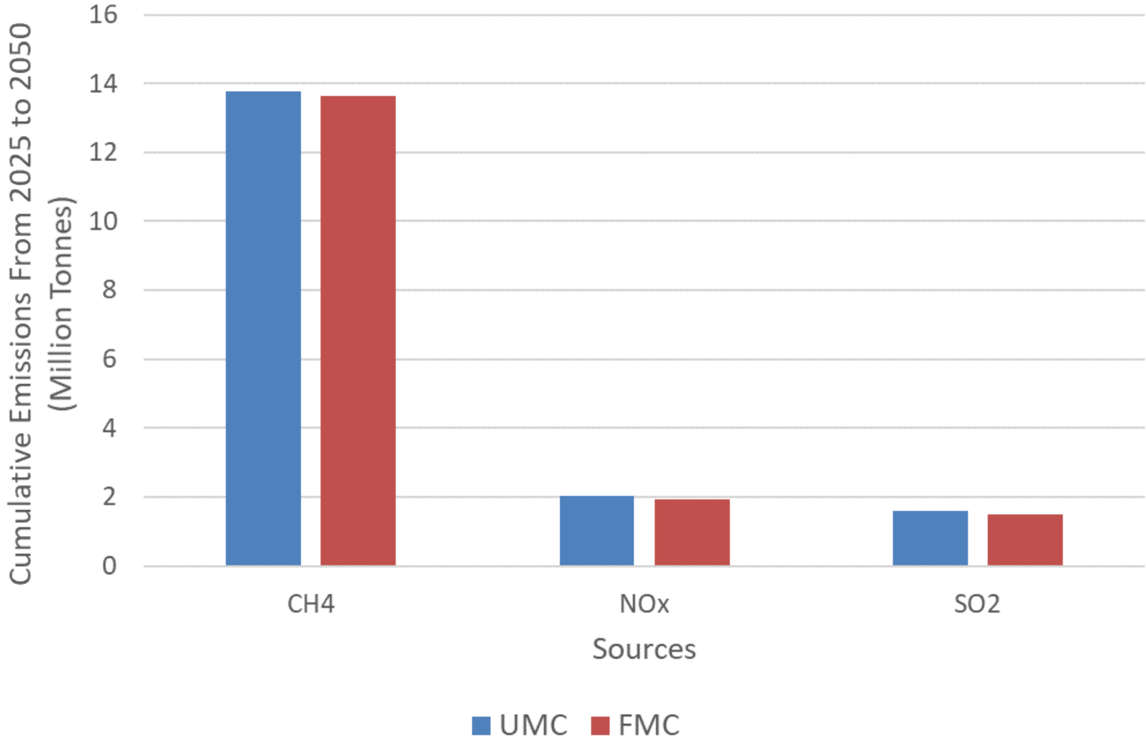

Figure 4 Cumulative other GHG emissions in 2050, by scenario

Impacts on Generation and Capacity Mix

Figure 5 provides an overview of the cumulative electricity generation mixes in 2050 in different scenarios. Regarding nuclear power, FMC generates 8% more nuclear power than UMC strategy in 2050. However, coal generation in the FMC reduces by 62% (32 GWh) compared to UMC which is very helpful for reducing the harmful pollutants. On the other hand, natural gas generation lowers in the FMC compared to the UMC by 5%. One significant advantage of the managed charging scenario is its facilitation of increased uptake of wind power (8%), whereas UMC has more solar power intake (8%). This shows that utilities prefer to schedule EV charging during the nighttime compared to the daytime and thus have more wind power uptake. This can be attributed to the low-cost power available during the night.

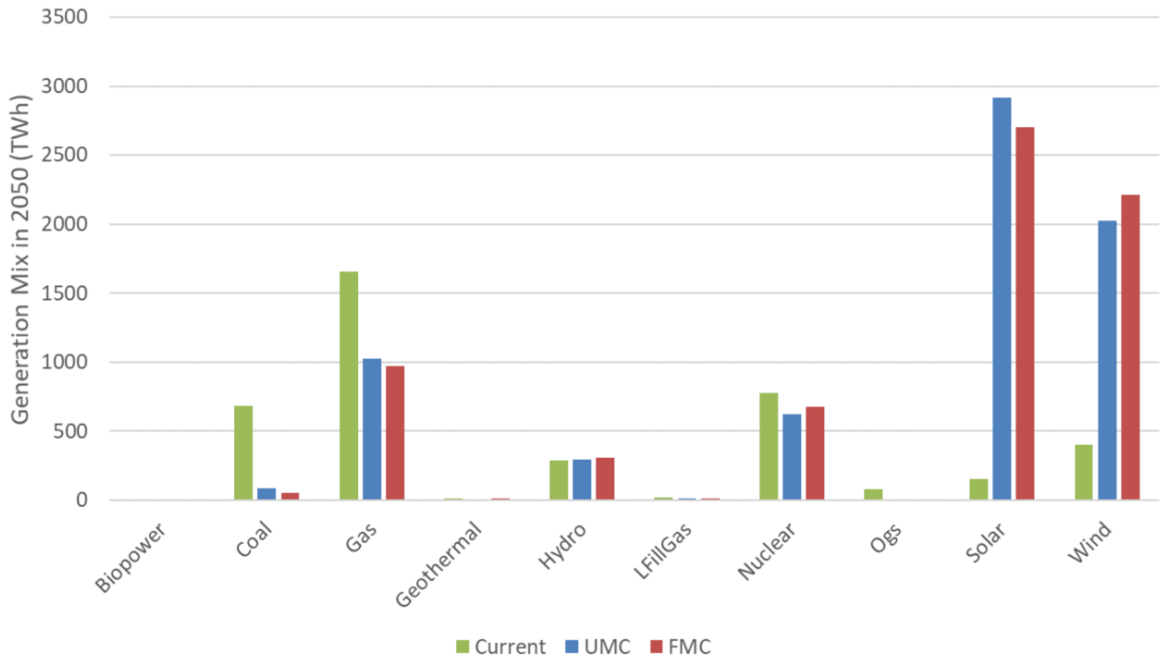

Figure 5 Generation mixes in 2050, by scenario

Figure 6 shows the installed capacity in 2050 in the two charging strategies compared to the current situation. It can be observed from Figure 6 that the nuclear power plant installed capacity is reduced in both scenarios in 2050 as compared to the status quo. Figure 7 shows the cumulative new capacity addition in 2050 in the different scenarios. The negative value in the figure indicates that installed capacity in the FMC is higher than in the UMC, and the positive value indicates the opposite. The solar and wind power installed capacity in 2050 resembles the corresponding generation mix with more solar and less wind power added in the UMC compared to the FMC. Also, there is a significantly high battery capacity requirement of about 28% in UMC compared to the FMC charging strategy.

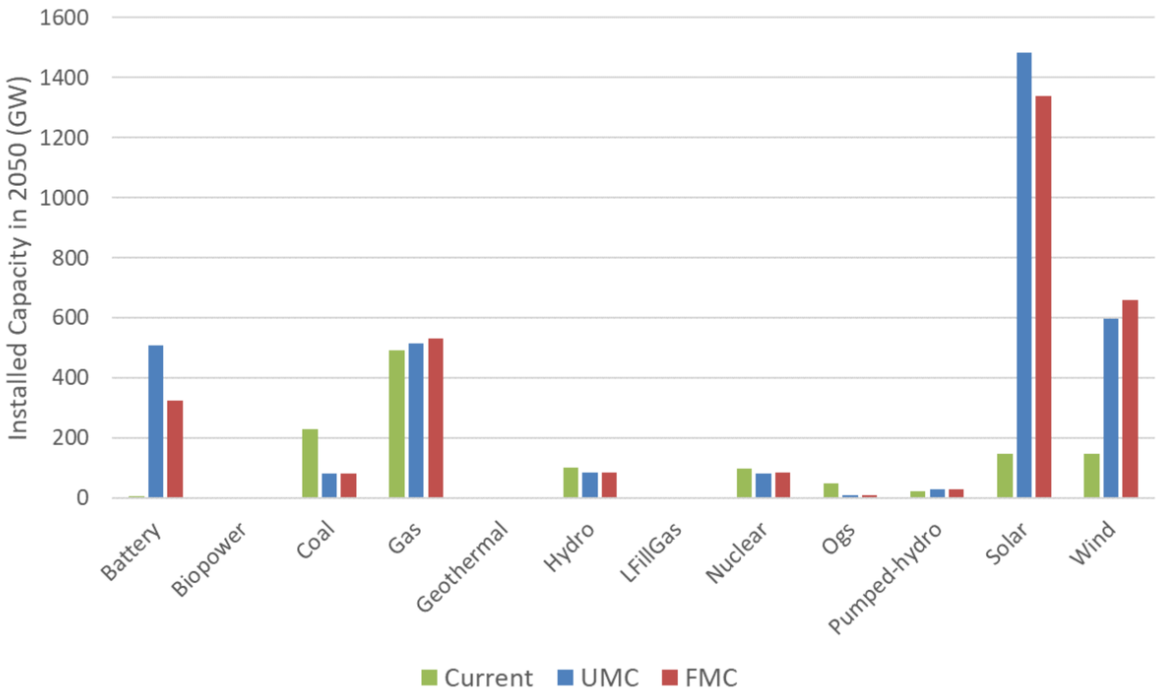

Figure 6 Installed capacity mix in 2050 in the U.S., by scenario

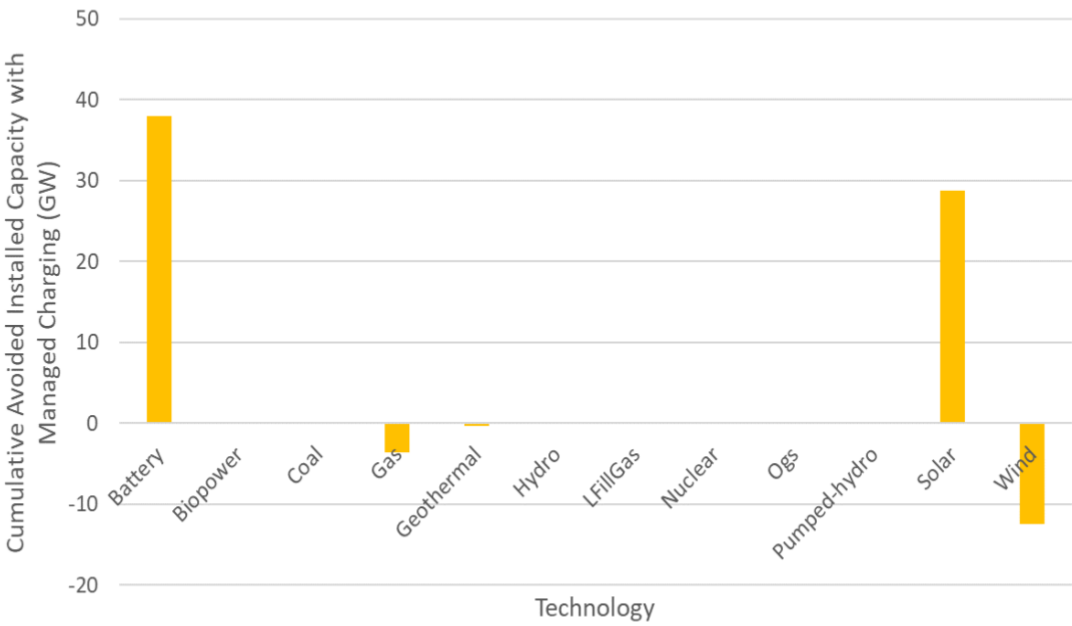

Figure 7 Cumulative new capacity addition in 2050, by scenario

Impacts on Costs

The total system costs are broken down into capacity investment costs, fuel costs and operation & maintenance costs and transmission costs. Figure 8 shows the difference in costs between unmanaged, smart and managed charging scenarios. With FMC the system has a savings of $100 billion which is 5% of the total system costs. New investment costs forms the major part of the cost breakdown which is expected with land, construction and labour costs. Further

FMC helps to save the fuel costs of about $23 Billion which amounts to 2% of total fuel costs. The O&M and transmission costs savings are in the range of $ 8 and $ 6 billions respectively which is less than 1% of their respective costs.

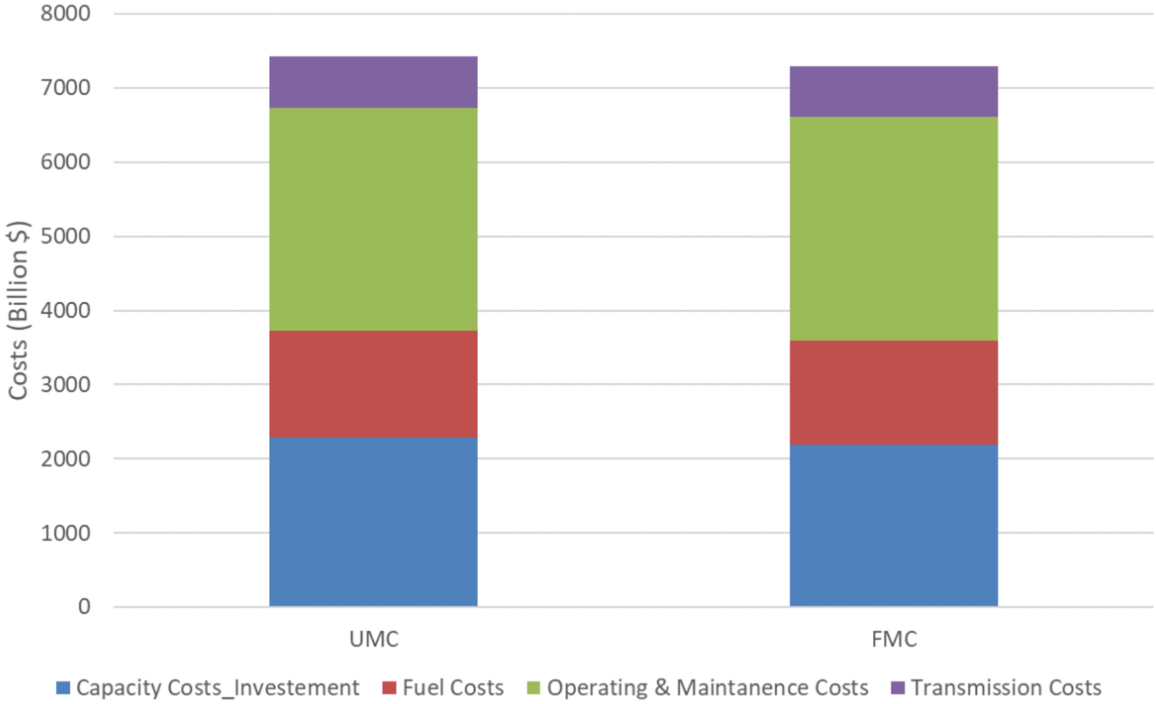

Figure 8 Cumulative cost breakdowns, by scenario

CONCLUSIONS

In this study, NREL's ReEDS model is used to evaluate the impact of EV charging on the U.S. electricity grid's emissions, generation, capacity mix, and new capacity additions. ReEDS helps in planning capacity expansion and grid service requirements using a least-cost approach considering technology, resource, land use, and policy constraints. Different strategies are developed to evaluate the impact of EV charging on the U.S. electricity grid. With the FMC strategy, the utilities have significant cost and emission reduction in the long-term. Also, as expected, UMC requires higher battery capacity compared to FMC. The current results highlight the addition of less solar power and more wind power in FMC compared to UMC. The utilities are likely to schedule the majority of the EV charging during the nighttime and thus reduce the stress in the grid. With the federal government plans to achieve different levels of EV penetration in the near future, this study adds impetus to its faster adoption.

REFERENCES

1. Liang, X., S. Zhang, Y. Wu, J. Xing, X. He, K. M. Zhang, S. Wang, and J. Hao. Air Quality and Health Benefits from Fleet Electrification in China. *Nature Sustainability*, Vol. 2, No. 10, 2019, pp. 962–971. https://doi.org/10.1038/s41893-019-0398-8.
2. Powell, S., E. C. Kara, R. Sevlian, G. V. Cezar, S. Kiliccote, and R. Rajagopal. Controlled Workplace Charging of Electric Vehicles: The Impact of Rate Schedules on Transformer Aging. *Applied Energy*, Vol. 276, 2020, p. 115352. https://doi.org/10.1016/j.apenergy.2020.115352.
3. Goldman Sachs. *Electric Vehicles: What's Next VII: Confronting Greenflation*. 2022.

4. S&P Global Mobility. Electric Vehicle Trends.

5. Pan, S., W. Yu, L. M. Fulton, J. Jung, Y. Choi, and H. O. Gao. Impacts of the Large-Scale Use of Passenger Electric Vehicles on Public Health in 30 US. Metropolitan Areas. *Renewable and Sustainable Energy Reviews*, Vol. 173, 2023, p. 113100. https://doi.org/10.1016/j.rser.2022.113100.

6. Zawacki, M., K. R. Baker, S. Phillips, K. Davidson, and P. Wolfe. Mobile Source Contributions to Ambient Ozone and Particulate Matter in 2025. *Atmospheric Environment*, Vol. 188, 2018, pp. 129–141. https://doi.org/10.1016/j.atmosenv.2018.04.057.

7. U.S. Department of Transportation. Electric Vehicles & Rural Transportation.

8. California Air Resources Board. California Moves to Accelerate to 100% New Zero-Emission Vehicle Sales by 2035.

9. Ou, Y., N. Kittner, S. Babaee, S. J. Smith, C. G. Nolte, and D. H. Loughlin. Evaluating Long-Term Emission Impacts of Large-Scale Electric Vehicle Deployment in the US Using a Human-Earth Systems Model. *Applied Energy*, Vol. 300, 2021, p. 117364. https://doi.org/10.1016/j.apenergy.2021.117364.

10. Coignard, J., P. MacDougall, F. Stadtmueller, and E. Vrettos. Will Electric Vehicles Drive Distribution Grid Upgrades?: The Case of California. *IEEE Electrification Magazine,* Vol. 7, No. 2, 2019, pp. 46–56. https://doi.org/10.1109/MELE.2019.2908794.

11. Gschwendtner, C., C. Knoeri, and A. Stephan. Mind the Goal: Trade-Offs between Flexibility Goals for Controlled Electric Vehicle Charging Strategies. *iScience*, 2023, p. 105937. https://doi.org/10.1016/j.isci.2023.105937.

12. Bellocchi, S., M. Gambini, M. Manno, T. Stilo, and M. Vellini. Positive Interactions between Electric Vehicles and Renewable Energy Sources in CO2-Reduced Energy Scenarios: The Italian Case. *Energy*, Vol. 161, 2018, pp. 172–182. https://doi.org/10.1016/j.energy.2018.07.068.

13. Bellocchi, S., K. Klöckner, M. Manno, M. Noussan, and M. Vellini. On the Role of Electric Vehicles towards Low-Carbon Energy Systems: Italy and Germany in Comparison. *Applied Energy*, Vol. 255, 2019, p. 113848. https://doi.org/10.1016/j.apenergy.2019.113848.

14. Lauvergne, R., Y. Perez, M. Françon, and A. Tejeda De La Cruz. Integration of Electric Vehicles into Transmission Grids: A Case Study on Generation Adequacy in Europe in 2040. *Applied Energy*, Vol. 326, 2022, p. 120030. https://doi.org/10.1016/j.apenergy.2022.120030.

15. Li, B., Z. Ma, P. Hidalgo-Gonzalez, A. Lathem, N. Fedorova, G. He, H. Zhong, M. Chen, and D. M. Kammen. Modeling the Impact of EVs in the Chinese Power System: Pathways for Implementing Emissions Reduction Commitments in the Power and Transportation Sectors. *Energy Policy,* Vol. 149, 2021, p. 111962. https://doi.org/10.1016/j.enpol.2020.111962.

16. Gallagher, K. S., F. Zhang, R. Orvis, J. Rissman, and Q. Liu. Assessing the Policy Gaps for Achieving China's Climate Targets in the Paris Agreement. *Nature Communications*, Vol. 10, No. 1, 2019, p. 1256. https://doi.org/10.1038/s41467-019-09159-0.

17. Jenn, A. *Green Charging of Electric Vehicles Under a Net-Zero Emissions Policy Transition in California*. Davis, 2021.

18. Powell, S., G. Vianna Cezar, E. Apostolaki-Iosifidou, and R. Rajagopal. Large-Scale Scenarios of Electric Vehicle Charging with a Data-Driven Model of Control. *Energy*, Vol. 248, 2022, p. 123592. https://doi.org/10.1016/j.energy.2022.123592.

19. Jones, E. C., and B. D. Leibowicz. Contributions of Shared Autonomous Vehicles to Climate Change Mitigation. *Transportation Research Part D: Transport and Environment*, Vol. 72, 2019, pp. 279–298. https://doi.org/10.1016/j.trd.2019.05.005.

20. Brozynski, M. T., and B. D. Leibowicz. Decarbonizing Power and Transportation at the Urban Scale: An Analysis of the Austin, Texas Community Climate Plan. *Sustainable Cities and Society*, Vol. 43, 2018, pp. 41–54. https://doi.org/10.1016/j.scs.2018.08.005.

21. Booysen, M. J., C. J. Abraham, A. J. Rix, and I. Ndibatya. Walking on Sunshine: Pairing Electric Vehicles with Solar Energy for Sustainable Informal Public Transport in Uganda. *Energy Research & Social Science*, Vol. 85, 2022, p. 102403. https://doi.org/10.1016/j.erss.2021.102403.

22. Ullah, Z., S. Wang, G. Wu, H. M. Hasanien, A. U. Rehman, R. A. Turky, and M. R. Elkadeem. Optimal Scheduling and Techno-Economic Analysis of Electric Vehicles by Implementing Solar-Based Grid-Tied Charging Station. *Energy*, Vol. 267, 2023, p. 126560. https://doi.org/10.1016/j.energy.2022.126560.

23. Broadbent, G., C. Allen, T. Wiedmann, and G. Metternicht. The Role of Electric Vehicles in Decarbonising Australia's Road Transport Sector: Modelling Ambitious Scenarios. *Energy Policy*, Vol. 168, 2022, p. 113144. https://doi.org/10.1016/j.enpol.2022.113144.

24. Jones, B., W. Vining, M. Lave, T. Haines, C. Neuman, J. Bennett, and D. R. Scoffield. Impact of Electric Vehicle Customer Response to Time-of-Use Rates on Distribution Power Grids. *Energy Reports*, Vol. 8, 2022, pp. 8225–8235. https://doi.org/10.1016/j.egyr.2022.06.048.

25. Dean, M. D. . K. K. American Preferences for EV Charging. *Under Review*, 2023.

26. Frazier, A. W., W. Cole, P. Denholm, D. Greer, and P. Gagnon. Assessing the Potential of Battery Storage as a Peaking Capacity Resource in the United States. *Applied Energy*, Vol. 275, 2020, p. 115385. https://doi.org/10.1016/j.apenergy.2020.115385.

27. Cole, D. Greer, J. Ho, and R. Margolis. Considerations for Maintaining Resource Adequacy of Electricity Systems with High Penetrations of PV and Storage. *Applied Energy*, Vol. 279, 2020, p. 115795. https://doi.org/10.1016/j.apenergy.2020.115795.

28. Reimers, A., W. Cole, and B. Frew. The Impact of Planning Reserve Margins in Long-Term Planning Models of the Electricity Sector. *Energy Policy*, Vol. 125, 2019, pp. 1–8. https://doi.org/10.1016/j.enpol.2018.10.025.

29. Cole, N. Gates, and T. Mai. Exploring the Cost Implications of Increased Renewable Energy for the U.S. Power System. *The Electricity Journal*, Vol. 34, No. 5, 2021, p. 106957. https://doi.org/10.1016/j.tej.2021.106957.

30. Mai, T., W. Cole, and A. Reimers. Setting Cost Targets for Zero-Emission Electricity Generation Technologies. *Applied Energy*, Vol. 250, 2019, pp. 582–592. https://doi.org/10.1016/j.apenergy.2019.05.001.

31. Cole, D. Greer, P. Denholm, A. W. Frazier, S. Machen, T. Mai, N. Vincent, and S. F.

Baldwin. Quantifying the Challenge of Reaching a 100% Renewable Energy Power System for the United States. *Joule*, 2021. https://doi.org/10.1016/j.joule.2021.05.011.

32. Mai, T., A. Lopez, M. Mowers, and E. Lantz. Interactions of Wind Energy Project Siting, Wind Resource Potential, and the Evolution of the U.S. Power System. *Energy*, Vol. 223, 2021, p. 119998. https://doi.org/10.1016/j.energy.2021.119998.
33. Mai, T., W. Cole, N. Gates, and D. Greer. The Prospective Impacts of 2019 State Energy Policies on the U.S. Electricity System. *Energy Policy*, Vol. 149, 2021, p. 112013. https://doi.org/10.1016/j.enpol.2020.112013.
34. Arthur Yip, Christopher Hoehne, Paige Jadun, Catherine Ledna, Elaine Hale, and M. M. *Highly Resolved Projections of Passenger Electric Vehicle Charging Loads for the Contiguous United States*. Golden, USA, 2023.
35. Jonathan Ho, Jonathon Becker, Maxwell Brown, Patrick Brown, Ilya Chernyakhovskiy, Stuart Cohen, Wesley Cole, Sean Corcoran, Kelly Eurek, Will Frazier, Pieter Gagnon, Nathaniel Gates, Daniel Greer, Paige Jadun, Saroj Khanal, Scott Machen, Madeline Macmilla, and E. Z. *Regional Energy Deployment System (ReEDS) Model Documentation: Version 2020*. DENVER, 2020.