ECONOMIC AND ENVIRONMENTAL IMPACTS OF ELECTRIC VEHICLE SMART-CHARGING PROGRAMS ON THE U.S. POWER SECTOR

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ABSTRACT

Electric vehicle (EV) charging patterns significantly influence power grid operations and investment needs. This study utilizes the Regional Energy Deployment System (ReEDS) model to assess various EV charging strategies in the U.S., including unmanaged charging, daytime and nighttime smart-charging programs with two different participation rates, and fully managed EV charging. These strategies are examined under two EV demand projections: TEMPO and Fast Adoption. The analysis focuses on their effects on grid emissions, the power capacity and generation mixes, and associated investment and operating costs. Key findings reveal that with the TEMPO EV demand projection, fully managed charging could reduce system costs by 2% and carbon emissions by 6% over 25 years, assuming that all new light-duty vehicles in the U.S. are EVs by 2035. In contrast, unmanaged charging necessitates a significant increase in battery storage capacity compared to smart-charging or fully managed strategies, highlighting the critical role of strategic charging management in addressing the infrastructural challenges posed by rising EV penetration. The smart-charging program definitions presented in this study are based on Dean and Kockelman's (2024) online survey results, from assessing U.S. adults' perspectives on plug-in electric vehicles (PEVs) and their preferences for smart-charging initiatives. The novelty of this paper resides in its comprehensive comparison of costs versus benefits of smart-charging programs and their impact on the U.S. power sector. In the TEMPO case, the highest avoided emissions costs per participating-EV-year are realized in the Central and Midwest regions ($69 and $67 per EV-year), while the lowest are observed in the Arkansas-Louisiana region (at a loss of $81 per EV-

year). Nighttime charging is preferred over daytime charging to minimize emissions. The Central region (containing North Dakota, South Dakota, Nebraska, Kansas, and Oklahoma) enjoys significant smart-charging benefits under both the TEMPO and FA cases. Conversely, the lowest avoided electricity system costs per EV are experienced in the Florida and Texas regions in the FA case. Per EV-year, the benefits from grid savings are likely to be much larger than emissions costs savings.

Keywords: Electric Vehicles, Power Sector, Smart-Charging, Capacity Expansion, Energy System Modeling

1. 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 (Liang et al., 2019). 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 (Powell et al., 2020). EVs are projected to account for 58% of all vehicle sales globally by 2040 (Goldman Sachs, 2022). Forecasts tend to rise every year as more nations unveil ambitious targets and policies (S&P Global Mobility, 2023).

Cars and light-duty trucks are responsible for 17% of total U.S. greenhouse gas emissions (Pan et al., 2023). 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 (Zawacki et al., 2018). 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 (USDOT, 2023). California is leading the nation with a roadmap to sell only ZEVs by 2035 (CARB, 2022). Ten other U.S. states have mandated that certain shares of passenger-vehicle sales be EVs (Ou et al., 2021).

Rapid growth in EV ownership, use, and charging may stress existing electricity networks (Coignard et al., 2019). When EVs start charging as soon as customers plug them in (unmanaged charging), power demand may require turning on peaker power plants and releasing more emissions per kWh generated (Gschwendtner et al., 2023). If EV charging can be managed and timed to match wind, solar, and other clean 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 generation is dominated by non-dispatchable/intermittent generators (e.g., solar and wind).

To decarbonize the electricity sector, there has been increased penetration of RE, making demand management (including EV smart-charging, smart thermostat controls, and variable power pricing) fundamental to maintaining a reliable power grid with low-cost electricity. The main objective of this study is to evaluate the impact of EV charging strategies on the U.S. electricity grid in terms of emissions, future capacity expansion, generation dispatch, and investment and operating costs. It particularly concentrates on smart-charging strategies, examining both the detrimental and beneficial impacts of EVs on the grid with and without these strategies.

This paper evaluates different charging strategies for EVs across two cases for EV adoption: Transportation Energy and Mobility Pathway Options (TEMPO) and Fast Adoption (FA). NREL's ReEDS model is employed to project the capacity expansion of the U.S. power sector for each scenario of EV adoption and charging strategy. This study considers six charging scenarios for each EV adoption case: unmanaged charging, daytime and nighttime smart-charging programs, each with two different participation rates, and fully managed EV charging. Unmanaged and fully managed charging scenarios represent the extremes of the spectrum from no intervention to complete control over EV charging times, providing insight into the potential impact on grid investments, costs, and emissions. The smart-charging program definitions presented in this study are based on (Dean and Kockelman, 2024), who conducted an online survey assessing U.S. adults' perspectives on plug-in electric vehicles (PEVs) and their preferences for smart-charging initiatives. These programs involve shifting 25% to 50% of EV demand between daytime and nighttime periods. The novelty of this paper resides in its comprehensive comparison of costs versus benefits of smart-charging programs and their impact on the U.S. power sector. The costs analyzed in this study encompass future investments in generation and storage capacity, dispatch costs, and incentives provided to customers for participating in EV smart-charging programs. Conversely, the accrued benefits are measured in terms of avoided installed capacity, reduced storage requirements, emissions reduction, and effective demand-supply management, thereby alleviating grid stress.

2. RELATED LITERATURE

In recent years, a significant number of studies have been conducted to assess the impact of EV charging on power grids. These studies utilize market-based modeling tools and are often tailored to a specific country's context, focusing on evaluating emission reductions, maximizing RE penetration, and understanding the implications for electricity pricing with the integration of EVs into the electricity system. Table 1 lists a variety of recent EV charging-strategy papers with the regions of study and tool or methodology used. Some of these papers emphasize emissions reductions and flexibility potential for European settings. For example, Bellocchi et al. (2018) analyzed EV-RE synergies in Italy in terms of 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 (Bellocchi et al., 2019). With a sixfold expansion of RE capacity and complete electrification of private transportation, Italy and Germany could reduce CO_2 emissions by 22% and 39%, respectively, by aligning EV charging with periods of RE generation. Lauvergne et al. (2022) simulated the costs of large-scale EV adoption in France using uncontrolled charging, time-of-use tariffs, and smart unidirectional (grid to vehicle) 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 was 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 (Gschwendtner et al., 2023).

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

Author and Year	Study Focus	Country Focus	Tools/Methods
Bellocchi et al. (2019)	Emissions reduction	Germany & Italy	EnergyPLAN (Lund et al., 2021)
Bellocchi et al. (2018)	Renewable energy penetration	Italy	EnergyPLAN
Booysen et al. (2022)	Solar energy use maximization	Uganda	simulation model
Broadbent et al. (2022)	Emissions reduction	Australia	system dynamics
Ullah et al. (2023)	Solar energy maximization	Pakistan	scheduling model
Sambasivam and Sundararaman (2023)	Emissions reduction	India	optimization & simulation model
Jones et al. (2022)	Charging's response to TOU pricing	Synthetic network	simulation model
Gschwendtner et al. (2023)	Demand flexibility potential	Switzerland	agent-based demand modeling
Lauvergne et al. (2022)	Technical & economic impacts	France	Antares-Simulator (RTE, 2022)
Jenn (2023)	Emissions reduction	California	Grid Optimized Operation Dispatch (GOOD) model (Jenn et al., 2020)
Li et al. (2021)	Emissions reduction	China	Switch model (Johnston et al., 2019)
Powell et al. (2022)	Grid impacts	U.S. Western Interconnection	economic dispatch model
Jones and Leibowicz (2019)	SAEV contribution to climate mitigation	Austin, Texas, U.S.	OSeMOSYS (Howells et al., 2011)
Brozynski and Leibowicz (2018)	Electricity & transport sector decarbonization	Austin, Texas, U.S.	OSeMOSYS
This Study (Sambasivam et al. 2023)	Grid & emission impact	Entire U.S.	ReEDS model (Ho et al., 2020)

Other studies focus on the world's two biggest emitters: the U.S. and China. For example, Li et al. (2021) 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 (Gallagher et al., 2019). The result shows that in the long term, large-scale deployment of EVs with unmanaged charging requires 14% additional storage capacity in China, as 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 leads the U.S. in long-term EV integration targets. Jenn (2023) evaluated the impact of managed and unmanaged EV charging strategies in the Western Electricity Coordinating Council (WECC) interconnect, with California as the main 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. (2022) 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 and Leibowicz (2019) 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 results show 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 and Leibowicz (2018) 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 would add system-wide value to the electricity system.

The next set of studies highlights the importance of aligning EV charging with periods of high RE generation, using case studies from Africa, Asia, and Australia. A simulation environment was 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 (Booysen et al., 2022). Using a case study from India, the impact of passenger EV charging on a renewable energy-dominated electricity system is investigated through optimization and simulation approaches. Two charging scenarios are examined: day and night charging. The study reveals that encouraging night charging can effectively reduce emissions within the electricity system (Sambasivam and Sundararaman, 2023). Ullah et al. (2023) 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 results show 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, Broadbent et al. (2022) conducted a nationwide study to project Australia's future road transport demand and transition to renewable electricity by 2050 using five scenarios considering the growth in the economy, population, and RE targets. The results show that a rapid transition to RE 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 time-of-use (TOU) pricing using a synthetic grid. TOU pricing is implemented in electricity systems to reduce peak system demand. Jones et al. (2022) 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 carried out by Dean and Kockelman (2024), who conducted an online survey to characterize U.S. adults' attitudes toward PEVs and their preferences for smart-charging programs. The survey was completed by 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 and persons). The survey was 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 were 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 their electric utilities. Americans with less education prefer unmanaged charging compared to those with Master's and Ph.D. degrees. 45% of the respondents cite privacy concerns as a reason to not cede EV charging control to the utilities. Meanwhile, 60% of people believe that smart-charging is good for society. Finally, gender has no role in characterizing the preferred PEV charging method compared to unmanaged charging.

This study's objective is to compare the economic and environmental benefits of the implemented EV smart-charging programs to the costs that electric utilities would have to incur to incentivize customers to participate in these programs, based on the survey results from (Dean and Kockelman, 2024). The novelty of this paper lies in its comprehensive costs vs. benefits comparison of smart-charging programs and their effects on the U.S. power sector. The costs considered in this analysis encompass future generation and storage capacity investments, dispatch costs, and incentives paid to customers to participate in EV 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 combines survey results with energy system modeling outputs to provide a novel estimation of the costs versus benefits of EV smart-charging programs in the U.S.

3. METHODS

3.1 Summary of the ReEDS Model

As noted earlier, this study uses NREL's ReEDS model (Ho et al., 2020), which is a capacity expansion model that determines the least-cost capacity investments and dispatch operations for the U.S. electric power system through 2050. Many others have used ReEDS for various applications. For example, researchers have employed ReEDS to study the cost implications of increased RE (Cole et al., 2021a), explore pathways to achieve a 100% RE system (Cole et al., 2021b), evaluate the impacts of solar PV (Cole et al., 2020) and wind energy (Mai et al., 2021b) in the electricity system, assess the role of battery storage as a peaking capacity resource (Frazier et al., 2020), examine the impacts of clean energy standards and emission policies (Mai et al., 2021a), investigate planning reserve margins for future capacity additions (Reimers et al., 2019), and examine cost targets for zero-emission nuclear, concentrating solar power, and offshore wind in system planning (Mai et al., 2019).

In ReEDS, the U.S. is divided into 134 balancing areas where the model helps in planning capacity expansion and grid service requirements (Ho et al., 2020). Figure 1 shows the regional representation of the 134 model balancing areas (represented by bold black lines) in the ReEDS model. Utilizing a least-cost optimization paradigm, the model accounts for technological, resource, land use, and policy constraints to assess the trade-offs among different generation technologies, transmission, and storage options. It captures the uncertainty, variability, and geographic constraints of wind (both onshore and offshore) and concentrating solar power across 356 regions. Within the model, two types of EV charging demand are integrated: a constant 'static' demand distributed evenly over 24 hours, and a 'dynamic' demand that varies hour by hour but remains constant within each hour. The 'static' demand represents a base load that cannot be time-shifted, while the 'dynamic' demand is flexible and can be shifted to different times of the day.

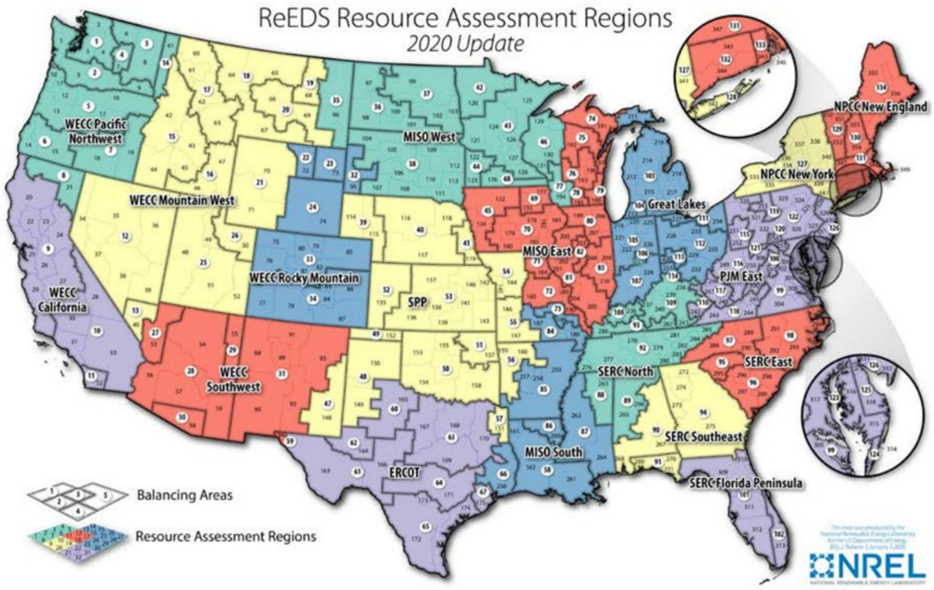

Figure 1 Regional representation (balancing areas and resource assessment regions) used in the ReEDS model (Ho et al., 2020)

The objective of this study is to evaluate the transformation of the U.S. electricity system with EV integration using the ReEDS model. By default, in ReEDS, the model's starting year is set to 2010, and the analysis will cover the timeframe from 2025 to 2050, with a five-year decision-making time step for each model period. Simulations conducted before 2025 function as a warm-up phase, essential for accurately projecting demand growth and capacity additions, setting the stage for the main analysis period. The focus is to project EV growth and evaluate its impact on key elements of the U.S. electricity system, including the generation and capacity mixes, storage requirements, emissions, and investment and operating costs. This research considers 12 distinct scenarios to explore the varied outcomes and implications of EV integration on the electricity grid. Given that the analysis extends to 2050, a 5% discount rate is utilized for converting all future costs to present value, ensuring a consistent economic assessment over time.

3.2 EV Demand Projections

In this study, scenarios are based on two distinct pathways of future EV adoption: TEMPO and Fast Adoption (FA). The projected EV demand up to 2050 is derived from the TEMPO model developed by NREL (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. The FA scenario explores the potential for all vehicles in the U.S. to be electric by 2030. To calculate the EV demand for 2030, the average per capita vehicle miles traveled (VMT) in the U.S. and the amount of electricity required per mile traveled are used. This demand profile is based on the American average per capita VMT, approximately 10,000 miles per year (Bureau of Transportation Statistics, 2021; Huxley Reicher, 2022), assuming an EV efficiency of 5 miles per kilowatt-hour (kWh). For consistent comparisons, the FA EV demand is normalized to the TEMPO model's 2050 projections, with demand gradually increasing to match this level. Figure 2 illustrates the projected EV demand progression up to the year 2050 as assumed by the TEMPO and FA cases.

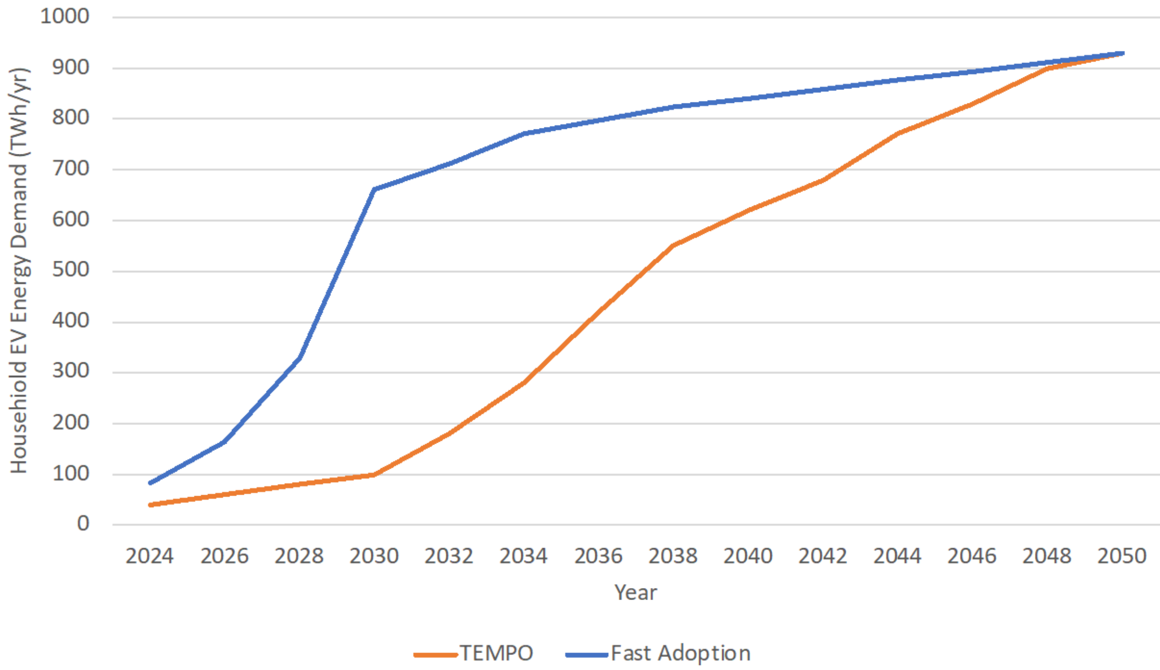

Figure 2 Projected EV demand over the years up to 2050 for the TEMPO and Fast Adoption cases

The determination of the number of EVs in both scenarios assumes that an average EV requires 10 kWh of energy per day. Utilizing this average, the total number of EVs is calculated. Figure 3 illustrates the annual number of EVs for each decision-making year in both the TEMPO and FA cases.

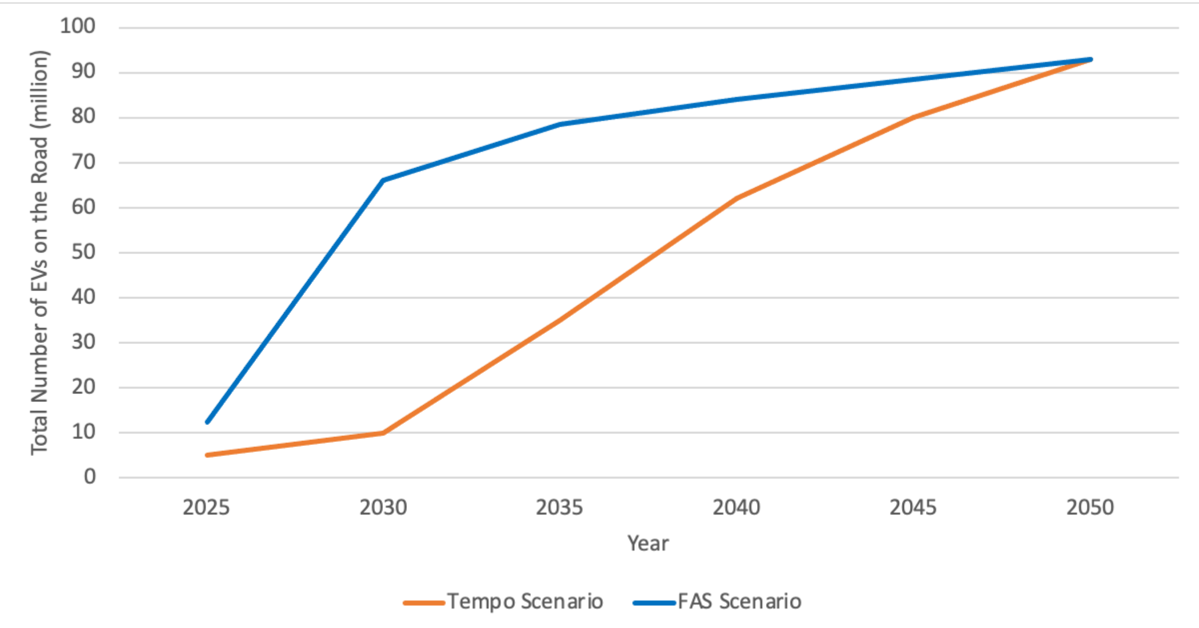

Figure 3 Annual counts of EVs in TEMPO and FA cases

3.3 Scenarios Tested

In this study, 12 distinct scenarios use one of three EV charging strategies: unmanaged, smart-charging, and fully managed (or super-smart-charging). These strategies are applied across two EV adoption cases: TEMPO and FA. In an unmanaged charging strategy, EVs are charged immediately upon being plugged in, without any consideration for the grid's current status. In contrast to the unmanaged approach, the fully managed strategy places complete control over EV charging times in the hands of electric utilities. The smart-charging strategy represents a middle ground, where utilities have control over the timing of EV charging but are constrained to particular times of day and must adhere to a deadline by when EVs must be fully charged. In the two smart-charging setups, consumers are offered incentives to participate in the program and allow the utility to schedule their charging during either the daytime or nighttime. More details are provided below.

The current study is limited to household EVs. The EVs considered for controllable charging include personal vehicles parked at homes (both single-family and multi-family residences), workplaces, and public charging stations. To facilitate the analysis, a day is segmented into five distinct time blocks: overnight (9 PM–6 AM), morning (6–10 AM), midday (10 AM–1 PM), afternoon (1–5 PM), and evening (5–9 PM). Key assumptions for this study are as follows. Across all charging scenarios, it is assumed that the number of EVs available for charging remains constant. This assumption is crucial to ensure a fair comparison across different charging strategies. Whenever EV charging is shifted from one hour to another, it is presumed that the vehicle is plugged in and ready for charging. This reflects a realistic scenario where vehicles are often parked and plugged in but not necessarily charging continuously. In the daytime and nighttime charging scenarios, it is estimated that 25% to 50% of household EVs are plugged in and available for charging. Under all 12 scenarios considered in the study, it is assumed that adequate EV charging infrastructure is available at all key locations, including homes, workplaces, and public places. This assumption is vital for assessing the feasibility and impact of various charging strategies without the constraint of infrastructure availability. These assumptions are integral to the study's methodology, providing a standardized framework for evaluating the impacts of different EV charging strategies on the electricity grid.

3.3.1 Unmanaged Charging (UMC)

In the two Unmanaged Charging scenarios, the model gives complete autonomy to EV owners/users in terms of charging their vehicles. There is no consideration or influence from the grid's status in these scenarios. Utilities do not exert any control over when users charge their EVs. The key assumption here is that users will plug in their EVs for charging at their convenience, and the charging process will continue until the vehicle's battery reaches its full capacity or maximum state of charge. In the ReEDS model, for the purposes of these UMC scenarios, it is assumed that 100% of all EV demand is static within the electricity system. This means that the model does not consider any variability or flexibility in the timing of EV charging. Essentially, the EV load is represented as an exogenously specified demand profile, regardless of other conditions or demands within the electricity system. This scenario offers a baseline for understanding the impacts of EV integration without any form of demand-side management or smart-charging initiatives. It reflects a situation where the increasing EV adoption does not correspond with changes or adaptations in grid management and user behavior, providing a useful benchmark for evaluating the benefits of more managed charging approaches.

3.3.2 Fully Managed Charging (FMC) or Super-Smart-Charging

In the two fully managed charging scenarios of this study, the utilities are granted complete control over the charging times of all EVs. This implies that the entire EV charging demand is controllable and adjustable according to the needs and capacities of the electricity grid. This allows for the most efficient use of grid resources, as utilities can optimize charging times based on grid conditions, RE availability, and overall electricity demand. While this situation might be considered unrealistic in current practice, especially for household vehicles, it represents a theoretical extreme opposite to the unmanaged charging scenario. In this setting, 100% of the EV demand is assumed to be dynamic within the electricity system. In summary, the fully managed charging scenarios in this study enable a theoretical exploration of the potential upper limits of grid optimization through complete control of EV charging, serving as a valuable counterpoint to the unmanaged charging scenario for understanding the full spectrum of possibilities in EV-grid integration. The total dynamic EV charging energy consumption across all time slices in each representative day equals the aggregate EV energy demand for that day and is captured in the equation

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

In addition to fully managed charging, this study explores two smart-charging strategies: nighttime and daytime charging, each with varying customer participation rates. In these smart-charging strategies, 50% of the EV demand is categorized as static, forming the base load that remains constant and unmanaged. The remaining 50% is dynamic, offering flexibility in terms of when this portion of the demand can be met. Two different customer participation rates are considered for these smart-charging strategies: 25% and 50%. The 25% rate implies that 25% of the total EV demand is subject to management and can be shifted to optimize grid performance. With the 50% participation rate, 50% of the total EV demand is manageable, allowing for greater flexibility in shifting charging times. The concept of a base EV demand, present throughout the day and remaining unchanged, is essential for realistic modeling. It recognizes that not all customers with EVs will participate in a smart-charging program, even if the utility offers one and incentivizes participation.

3.3.3 Nighttime Smart-Charging (NSC)

In this program, the EVs are charged only during the nighttime hours (9 PM – 6 AM), i.e., the utilities shift EV charging from daytime to nighttime. In the two NSC scenarios, 25% and 50% of the EV demand during nighttime participates in the smart-charging program. Here, the participating customers in the EV charging program consist of both the shifted customers from daytime charging and some customers who already charge their EVs during nighttime. Therefore, the objective is to have 25% and 50% of customers participate in the EV charging program. The 25% and 50% adoption rates in the NSC scenario are denoted as NSC-25 and NSC-50, respectively. To induce customers to participate in this program, incentives are provided to those who allow the utilities to control their EV charging. The calculation of these program participation incentive payments is done outside the model. The utilities assure the participating customers in this program that their EVs will be fully charged 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 schedule EV charging optimally based on generation capacity availability and cost. The shift in dynamic EV demand in each region r, year t, from daytime to nighttime within the same region r for the same year t, is represented by the following equations, where δ denotes the participation rates. The equations capture the extent of demand shift based on the selected participation rate.

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

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

3.3.4 Daytime Smart-Charging (DSC)

This program contrasts with the nighttime smart-charging program. Here, some EV charging from the nighttime is shifted to the daytime between 6 AM and 9 PM. Similar to the NSC scenarios, in the two DSC scenarios, 25% and 50% of the EV demand during daytime participates in the smart-charging program. Here, both the shifted demand and the existing customers who charge their EVs during the daytime also participate in the smart-charging program. Like the NSC scenarios, in the DSC scenario, the adoption rates of 25% and 50% are denoted as DSC-25 and DSC-50, respectively. Users are incentivized to participate in this program. In the DSC program, the model has the flexibility to optimally schedule EV charging between 6:00 AM and 9:00 PM, which spans four ReEDS time slices: morning (6–10 AM), midday (10 AM–1 PM), afternoon (1–5 PM), and evening (5–9 PM). The following equations delineate the reallocation of dynamic EV demand, transferring a specified proportion of the demand from nighttime to daytime within the same region *r* for a given year *t*. As discussed before, δ denotes the participation rates.

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

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

These charging strategies, spanning unmanaged to fully managed, are evaluated to understand their respective impacts on the electricity grid under different EV adoption pathways. By exploring these scenarios, the study aims to provide insights into how various levels of charging management can influence grid performance in the context of increasing EV penetration.

4. RESULTS AND DISCUSSION

This section presents and discusses the results obtained from ReEDS for scenarios with different EV adoption pathways and charging strategies. Sections 0-0 discuss the TEMPO and FA case results, focusing on the impacts of EV charging strategies on electricity emissions, generation and capacity mixes, and system costs. Sections 0 and 0 present regional results for emissions and costs, with the continental U.S. broken down into 13 different regions based on state boundaries (see Figure 4) as defined in (Jayadev et al., 2020). These regional definitions align with the reporting protocols for electricity system operating data by the Energy Information Administration (EIA), based on the jurisdictions of load balancing authorities and independent system operators (ISOs). Jayadev et al. (2020) implemented several adjustments to these regions to ensure that states grouped together exhibit roughly similar energy resources and demand profiles.

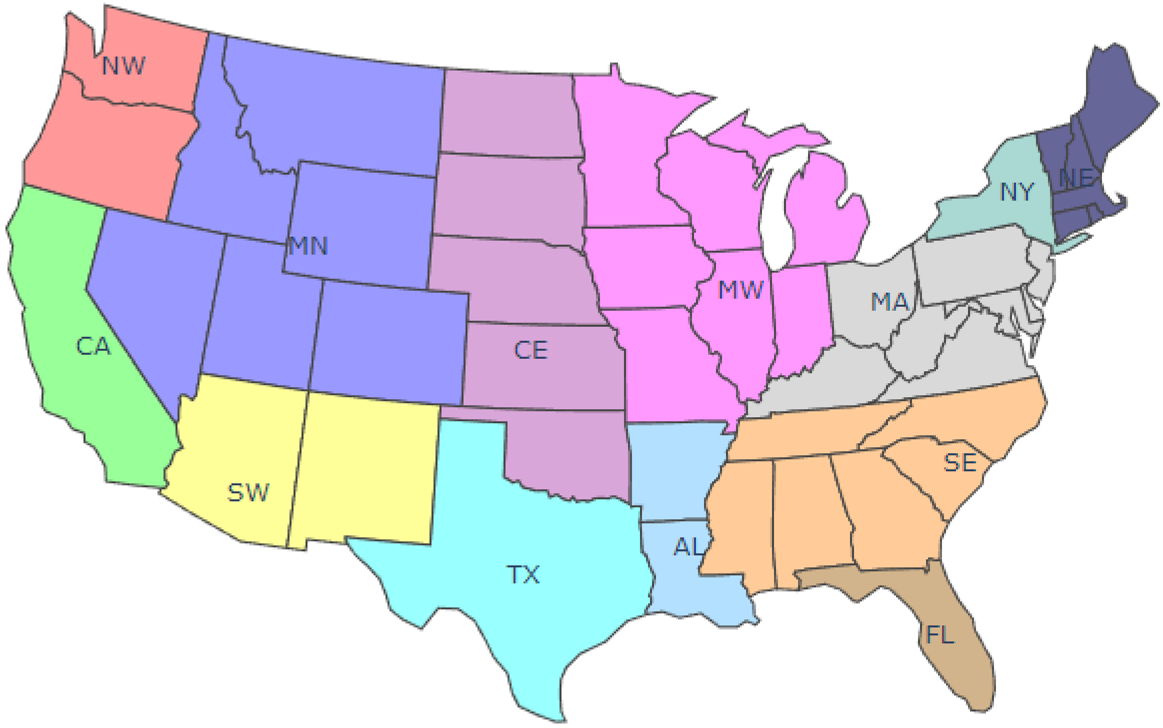

Figure 4 United States'13 Power Regions (Jayadev et al., 2020)

4.1 Emissions Impacts

The long-term adoption of EVs is likely to help reduce the tailpipe emissions from the transportation sector, but may increase emissions from electricity generation in the power sector. Figure 5 and Figure 6 present the total cumulative cost savings per EV due to avoided emissions for the TEMPO and FA cases in comparison to the UMC benchmark scenario from year 2025 to 2050. In the analysis, the social costs of CH_4, NOx, SO_2, and CO_2 emissions are assumed to be \$1500, \$532, \$200, and \$51 per ton, respectively (Environmental Protection Agency, 2023). For both the TEMPO and FA cases, the avoided costs associated with each EV are calculated by multiplying the social cost of a pollutant by the number of tons of that pollutant. The costs are converted to present values using a 5% discount rate. The present value for each scenario is divided by the discounted number of EVs to find the emissions savings per EV-year. Figure 5 shows that the per-EV avoided discounted costs in the TEMPO case range from \$6 to \$29. The highest savings are observed in the FMC and NSC-50 strategies, while the lowest are in DSC-50, all compared to the UMC baseline scenario. In contrast, it can be observed from Figure 6 that in the FA case, the per-EV avoided costs are highest with the NSC-50 strategy at \$150, followed by NSC-25 at \$128.

In the TEMPO case with FMC, compared to UMC, the cumulative CO_2 emissions from 2025 to 2050 are lower by 6% (268 million metric tons (MT)). Since power suppliers have complete control over EV charging in the FMC scenario, they schedule it to coincide with high RE availability, thereby avoiding emissions from fossil fuel power plants. The cumulative CH_4 emissions are 1% lower in the FMC scenario compared to UMC between 2025 and 2050. Over the same timeframe, NO_x and SO_2 emissions are reduced by 4% and 6%, respectively, with the FMC strategy. Although the per-EV emissions cost savings are modest, the smart-charging and FMC strategies play a significant role in grid management and facilitate the strategic expansion of installed capacity.

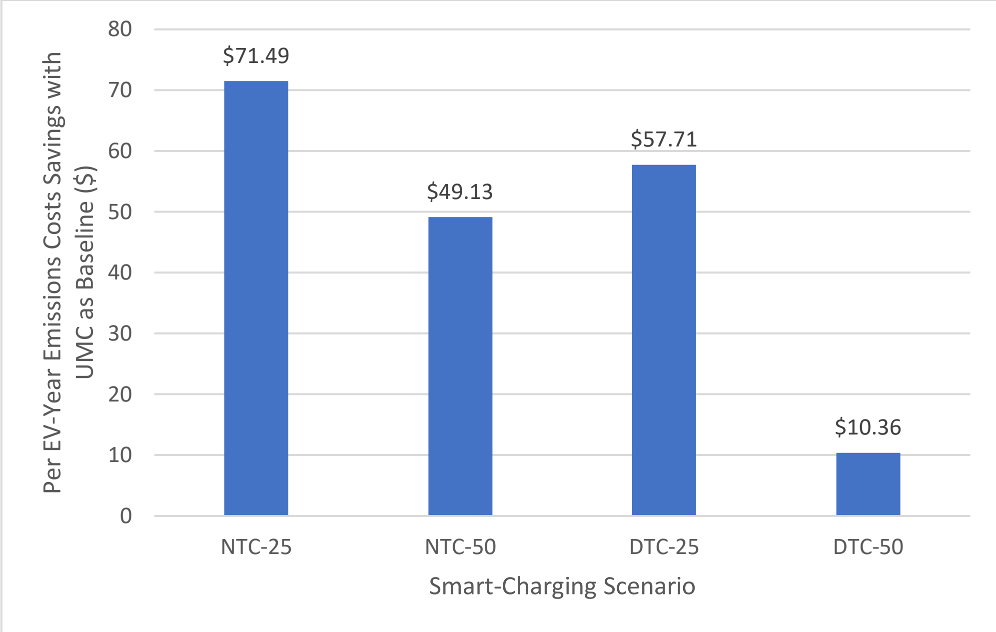

Figure 5 Total (discounted) avoided emissions costs per EV-year in 2025 dollars for each scenario with TEMPO EV adoption rates, relative to the UMC benchmark scenario, over year 2025 to 2050

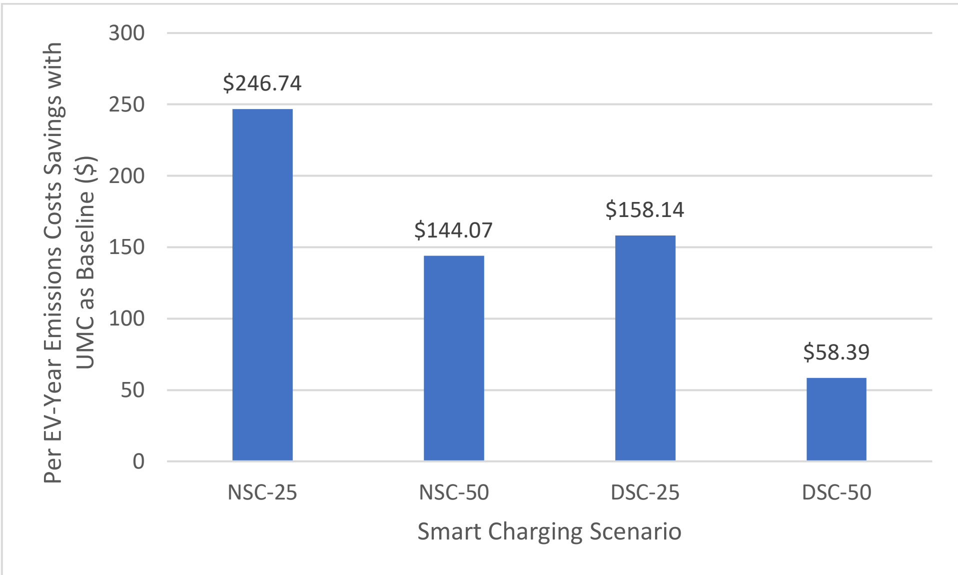

Figure 6 Total (discounted) avoided emissions costs per EV-year in 2025 dollars for each scenario with FA EV adoption rates, relative to the UMC benchmark scenario, over year 2025 to 2050

4.2 Generation and Capacity Mix Impacts

Figures Figure *7* and Figure ***8*** illustrate the generation mixes in 2050 for all TEMPO and FA scenarios. For the TEMPO case, coal power generation is at least 14% greater in the UMC scenario than in all other charging scenarios. For nuclear energy, the FMC strategy leads to a 9% increase in nuclear generation relative to the UMC strategy by the year 2050. Compared to current levels, the lowest decreases observed in coal and natural gas are 91% and 44%, respectively, across all scenarios. Notably, solar power generation in the UMC scenario is projected to be 9% higher in 2050 than in the FMC scenario. When comparing the smart-charging strategies, DSC-25 and DSC-50 result in roughly 4% and 2% more solar power generation, respectively, than NSC-25 and NSC-50. Wind power generation is highest in the FMC scenario, with NSC-50 and NSC-25 trailing closely behind. This suggests that it is generally less costly for the power sector to schedule EV charging during the nighttime compared to the daytime in order to leverage more wind generation for EV charging. This wind power is low-cost and emission-free.

Figure 8 indicates that in the FA case, coal power generation remains a significant component of the energy mix in 2050, with only a 62% reduction from current levels. Further, in all of the FA scenarios, natural gas generation remains significant. While the FA case represents a less realistic EV adoption pathway, a more gradual integration of EVs into the electricity grid (as featured in the TEMPO case) appears advantageous for the long-term reduction of coal and natural gas power generation. Additionally, solar generation in the FA scenario with UMC is similar to that in the corresponding TEMPO scenario.

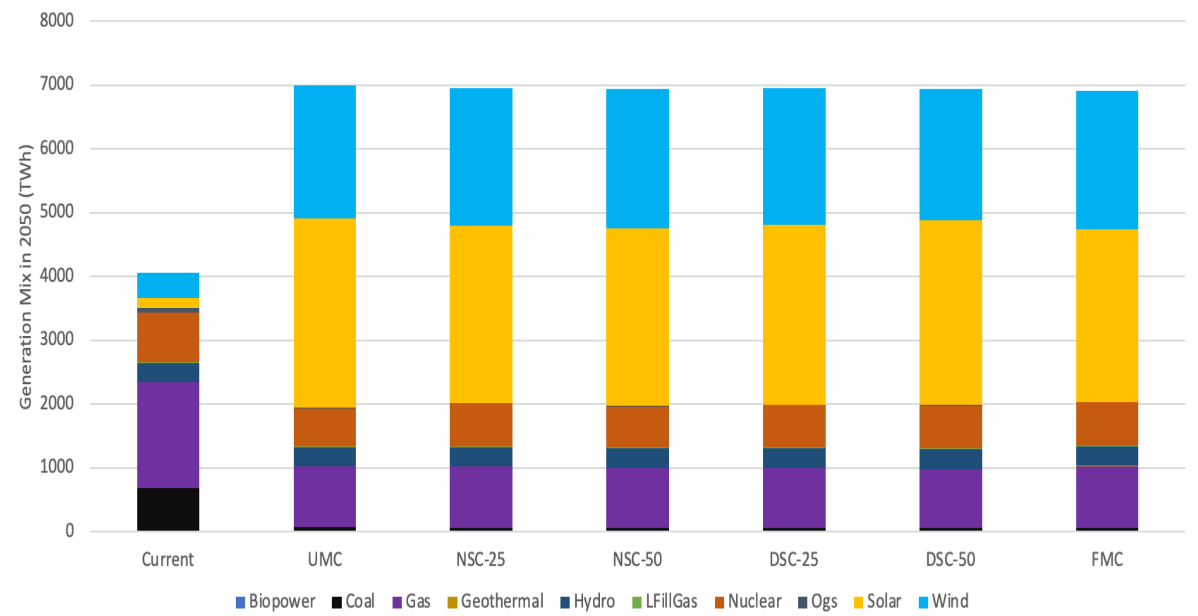

Figure 7 Generation mixes in 2050 for the TEMPO case, across EV charging scenarios

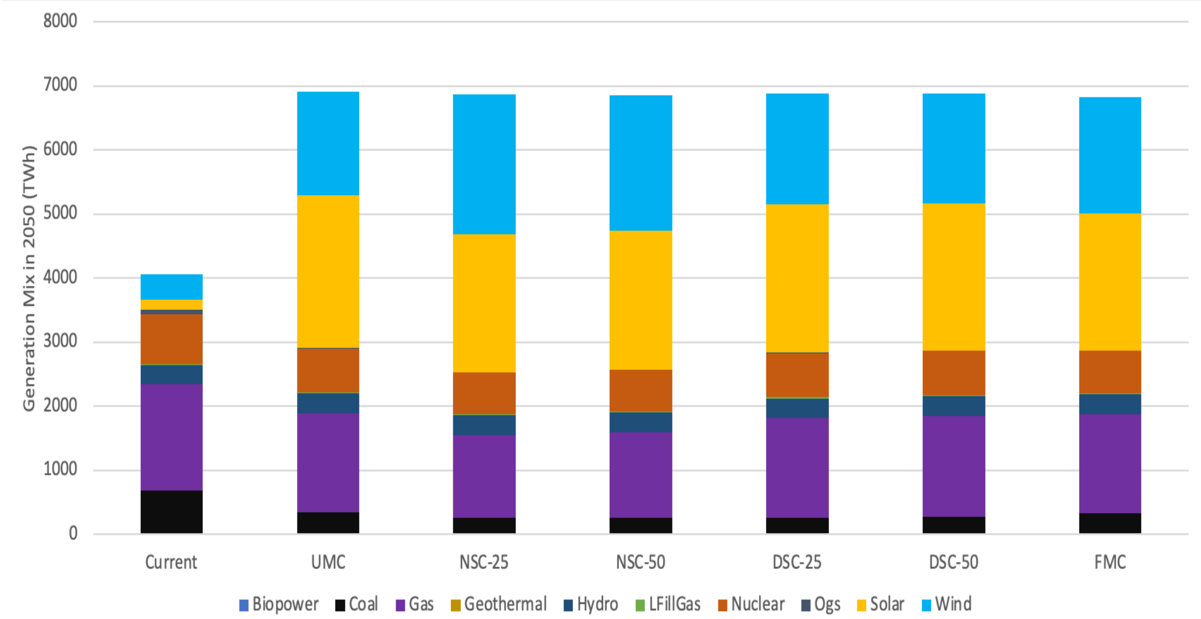

Figure 8 Generation mixes in 2050 for the FA case, across EV charging scenarios

Figures Figure ***9*** and Figure ***10*** present a comparative analysis of the installed capacity mix in the year 2050 for the various EV charging scenarios in the TEMPO and FA cases. In the TEMPO case, the installed coal capacity is consistently reduced by approximately 63% from its current level across all charging scenarios. Figure 9 highlights a modest increase in natural gas capacity across all scenarios, with the most significant increase of 9% observed in the DSC-50 scenario. This trend suggests that as the grid incorporates more solar and wind power, natural gas plants are increasingly relied upon to provide backup power and satisfy peak net loads. In all smart-charging scenarios, 2050 nuclear power capacity is lower than its current capacity. Solar power installations witness a 12% decline in the FMC scenario compared to UMC. Interestingly, solar capacity is expanded in the DSC-25 and DSC-50 scenarios by 4% and 5%, respectively, compared to their NSC counterparts. Wind power capacity sees its greatest increase in the FMC scenario, exceeding its value in UMC by 7%. The NSC-25 and NSC-50 scenarios introduce 9% and 8% more wind capacity, respectively, than the DSC-25 and DSC-50 scenarios. Moreover, there is a notable demand for battery storage in the UMC scenario, reaching a high requirement of approximately 38% (199 GW) more than what is required under the FMC charging strategy. The results also suggests that the NSC-25 and NSC-50 scenarios necessitate 2% and 7% more battery capacity, respectively, than the DSC-25 and DSC-50 scenarios.

Figure 10 illustrates that in the FA case, the demand for battery storage capacity under the FMC scenario is significantly higher (49% greater) than that in the UMC scenario. Additionally, the installed capacity for natural gas sees a substantial hike, with the UMC scenario showing an increase as steep as 19% above current levels. Other scenarios also reflect considerable increases in natural gas capacity. This trend is rationalized by the rapid adoption of EVs, where utilities require the natural gas power plants in meeting the baseline demand.

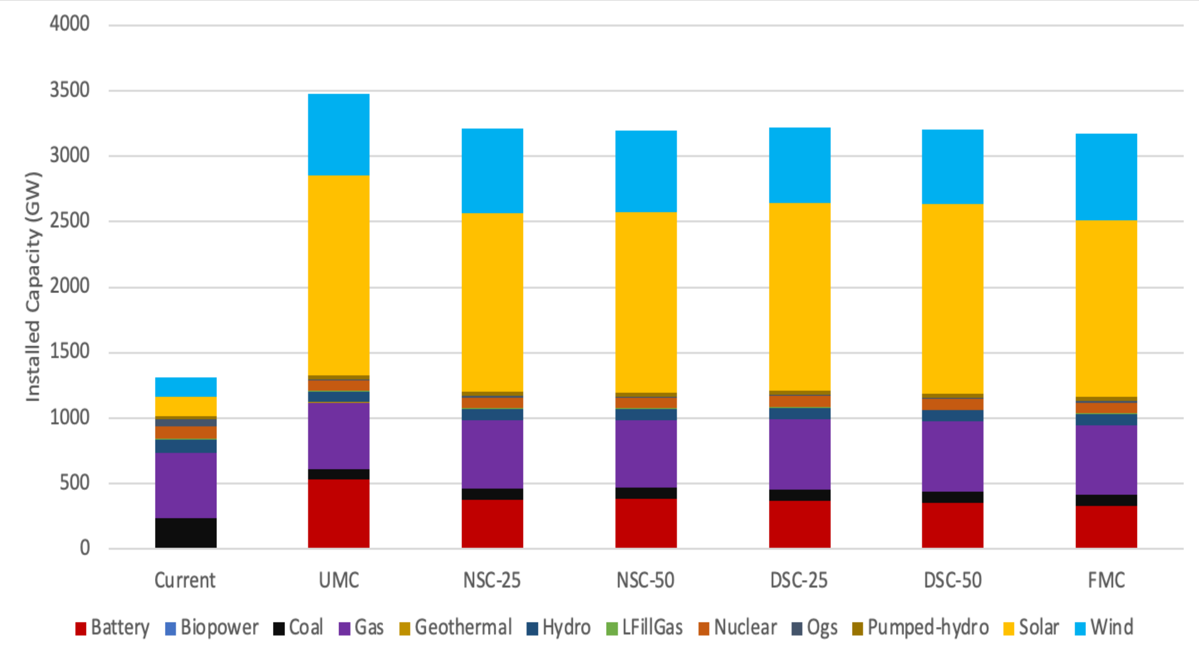

Figure 9 Installed capacity mix in 2050 in the U.S. for the TEMPO case, across scenarios

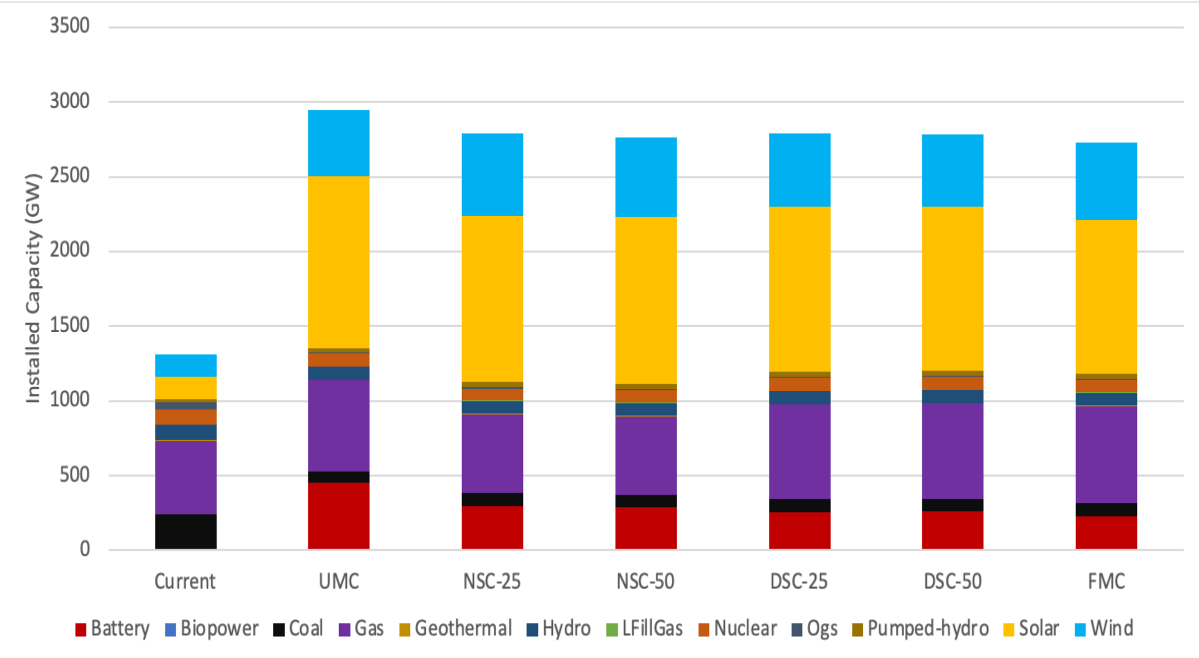

Figure 10 Installed capacity mix in 2050 in the U.S. for the FA case, across scenarios

4.3 Power System Cost Impacts

Figures Figure ***11*** and Figure ***12*** provide a detailed breakdown of the total system costs for each EV charging scenario in the TEMPO and FA cases, respectively, with the costs discounted to their present values. These costs are categorized into capacity investments, fuel expenditures, operation and maintenance (O&M) costs, and transmission costs (transmission expenses & new transmission investments). Across both cases, capacity investment accounts for the largest share of total cost in all scenarios, which is anticipated due to substantial land, construction, and labor expenses. O&M costs follow, reflecting ongoing requirements for system upkeep. Fuel and transmission costs contribute smaller fractions of total costs when compared to capacity investment and O&M. Comparing total costs in different scenarios with the TEMPO case, the FMC scenario demonstrates a cost saving of approximately $61 billion relative to the UMC scenario, which equates to a 2.3% reduction in overall system costs. This translates to an average per capita cost saving of around $187 when adopting the FMC strategy. The total costs of the smart-charging program scenarios are closer to that of the FMC than that of the UMC scenario, with projected systemwide cost reductions ranging from 1.5% to 2% when compared to the UMC baseline. These results indicate that EV smart-charging programs can yield significant economic benefits in the power sector and achieve most of the benefit that fully managed charging — the optimistic extreme in terms of utility control of EV charging — could obtain.

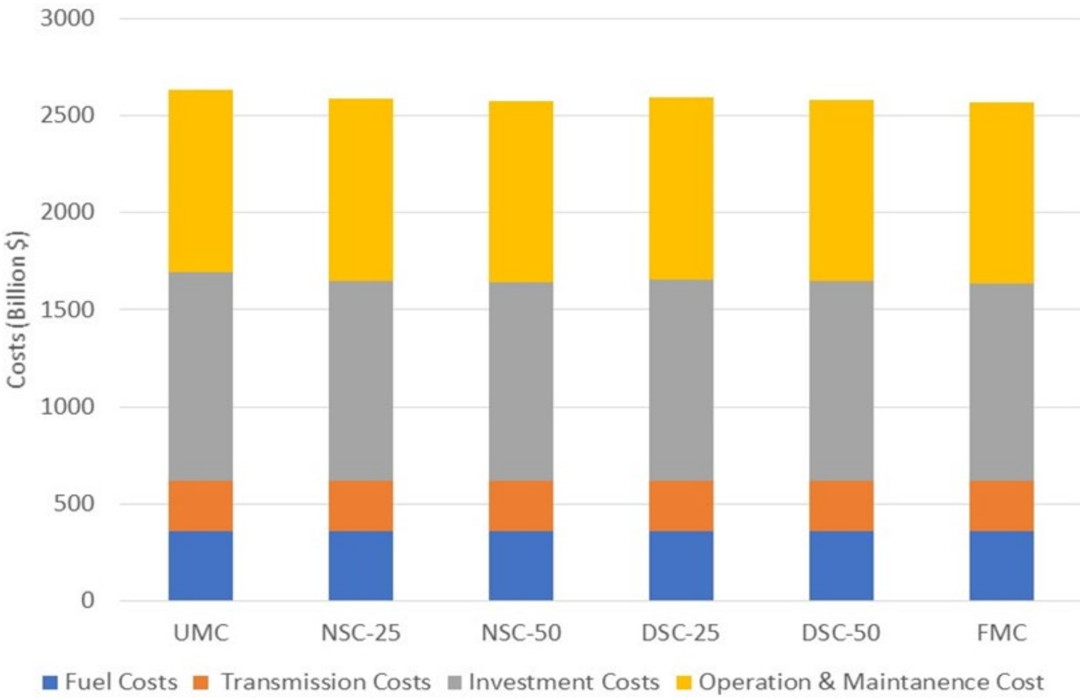

Figure 11 Total (discounted) system cost breakdowns for the TEMPO case, across scenarios, from 2025 to 2050

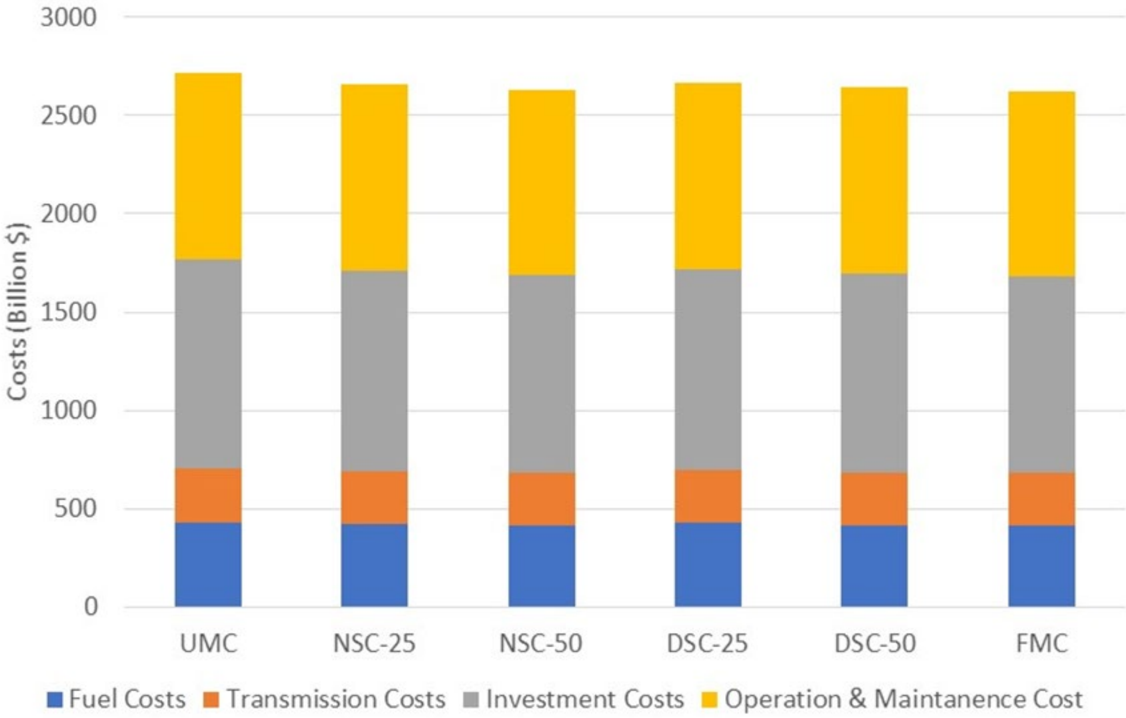

Figure 12 Total (discounted) system cost breakdowns for the FA case, across scenarios, from 2025 to 2050

4.4 Regional Analysis of Emissions Impacts

Section 4.1 detailed the avoided discounted emission costs due to smart-charging on a per-EV basis for the whole continental U.S. In this subsection, we decompose results by region, with the U.S. divided into the 13 regions depicted in Figure 4, in order to analyze how much the environmental benefits of EV smart-charging vary across the country and identify places where its climate change mitigation impact would be strongest. Figures Figure ***13*** and Figure ***14*** depict the regional analysis of discounted per-EV avoided emission costs for each scenario relative to the UMC baseline in both the TEMPO and FA cases of EV adoption. Positive values indicate that the smart-charging and FMC scenarios reduce emission costs compared to the UMC scenario, whereas negative values indicate the opposite. In the TEMPO case as observed in Figure 13, taking California as an example, both the FMC and smart-charging strategies result in a reduction in emissions when compared against the UMC scenario. When evaluating the NSC-25 and DSC-25 scenarios, their performance in per-EV emissions avoidance is essentially identical, showing no discernible difference between the two. In the TEMPO case, the most significant reduction in emissions is observed in the FMC and smart-charging strategies when compared to the UMC base scenario, particularly in the Central and Midwest regions. Within the Central region, the FMC scenario demonstrates the highest avoidance of emission costs per EV ($33), followed closely by the DSC-25 scenario ($28). Conversely, in the Midwest region, NSC-25 and NSC-50 exhibit notable performance in emission reduction compared to all other scenarios (Figure 13). This outcome can be attributed to the preference for nighttime EV charging, which increases wind power consumption, thereby lowering emissions. Specifically, smart-charging strategies such as NSC-25, DSC-25, and DSC-50 show the lowest emission reduction in the Arkansas and Louisiana region, where the avoided emission costs are all below -$25 in these three scenarios when compared to the UMC baseline, as observed in Figure 13. This observation can be attributed to increased coal power consumption in the smart-charging strategies, consequently leading to higher emissions. In Texas, the avoided emissions costs per electric vehicle are positive in all scenarios except for

DSC-50, when compared to the UMC baseline. This phenomenon can be attributed to the high availability of wind power during nighttime, making it suitable for EV charging.

In the TEMPO case, California does not exhibit significant differences between daytime and nighttime charging in terms of their impact. Daytime charging is favored in the Central region, owing to its high solar availability and lower EV demand. Nighttime charging is preferred in the Midwest and Texas regions due to the high availability of wind power. Smart-charging programs have a detrimental effect on electricity system emissions in the Arkansas-Louisiana region, largely due to their heavy reliance on coal.

Further observations can be made from Figure 14, where it is evident that the avoided emission cost per EV for NSC-25 and NSC-50 night charging scenarios exceeds \$60, while for day charging scenarios it hovers around \$30. This can once again be attributed to the abundance of wind resources and the preference for night charging in the Texas region. In contrast, in the Central region, the avoided emission cost per EV in all scenarios surpasses \$80 compared to the UMC baseline, with night charging being the preferred option, followed by FMC and daytime charging strategies. In New York, the avoided emission costs are negative in all scenarios except for NSC-25 (Figure 14). This can be attributed to the high demand for EVs in the region, necessitating the use of baseload power plants to meet this demand. Interestingly, with the FA case, the highest avoided emissions cost is observed in the Arkansas-Louisiana region, amounting to \$156 and \$179 in NSC-25 and NSC-50 scenarios, respectively (Figure 14). Here, the dependence on coal power is offset by the availability of wind power during nighttime charging scenarios. Figure 14 indicates that the avoided emissions cost per electric vehicle (EV) exceeds \$40 and \$20 in all scenarios in the Southeast and Southwest regions, respectively. In both of these regions, nighttime charging demonstrates the highest avoided emission benefits, which can be attributed to the high availability of wind power, particularly since these regions are situated near the coastline.

In conclusion, within the FA case, night charging emerges as the preferred option across most regions, showcasing positive avoided emission benefits. However, exceptions are noted in the New York region, as well as in the DSC-50 scenario in Arkansas and Louisiana, and the Mountain North region.

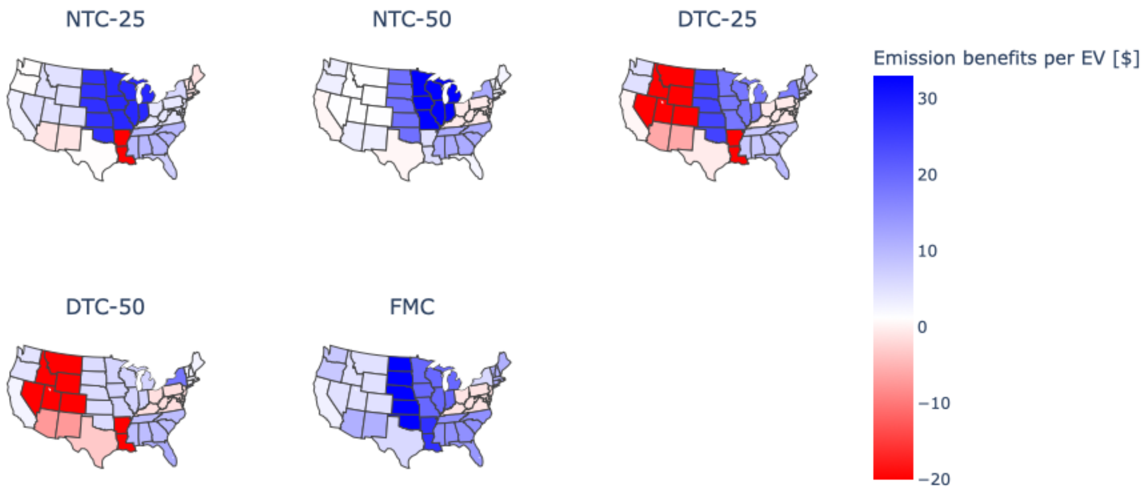

Figure 13 Regional analysis (discounted) of avoided emissions costs per EV for each scenario with the TEMPO case, vs. the UMC baseline scenario, from year 2025 to 2050

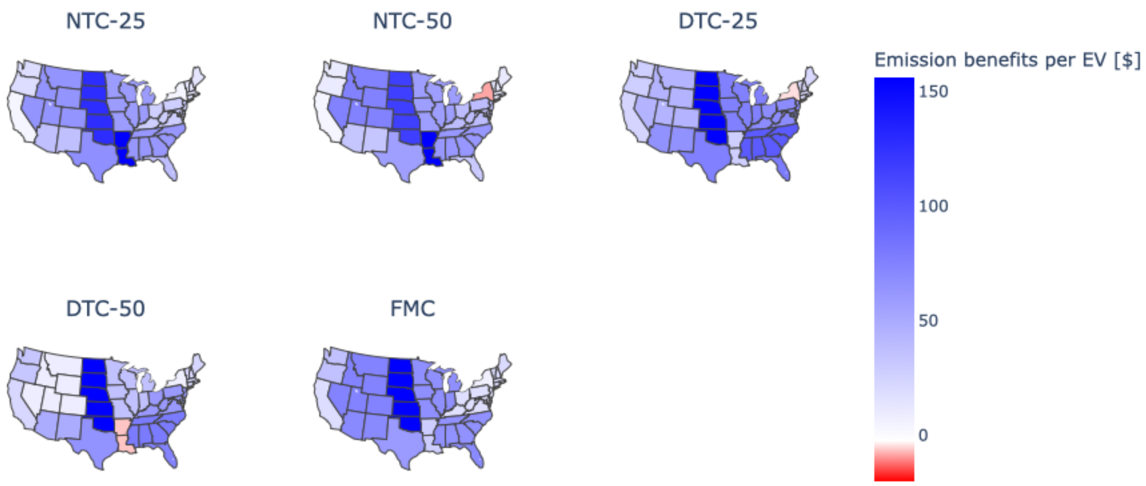

Figure 14 Regional analysis (discounted) of avoided emissions costs per EV for each scenario with the FA case, vs. the UMC baseline scenario, from year 2025 to 2050

4.5 Cost Savings by Region

Section 0 provided a comprehensive overview of the discounted electricity system costs across all scenarios for the continental U.S. In this subsection, a regional analysis of avoided electricity system costs is presented for the FMC and smart-charging scenarios, with the UMC serving as the baseline, from 2025 to 2050. The values are discounted at a 5% discount rate for 2023dollar values. Figure 15 and Figure ***16*** depict the regional breakdown of discounted avoided electricity costs per EV for each scenario within the TEMPO and FA cases, compared to the UMC benchmark. Examining Figure 15, it is apparent that in the TEMPO case, the FMC scenario yields the maximum avoided system costs per EV, reaching $1950 in the Central region when compared to the UMC baseline. Except for DSC-25, all other scenarios exhibit avoided system costs greater than $900, indicating that the strategic implementation of smart-charging programs is likely to significantly reduce system costs in the long term. Additionally, the low number of EVs in the Central region, attributed to its low population, is another significant factor contributing to the high per-EV benefits observed. The lowest avoided system costs per EV compared to the UMC benchmark are observed in the New York region, ranging from \$130 to \$300. Across all regions, the FMC scenario consistently demonstrates the highest benefits, which is understandable as the power supplier has complete control over EV charging demand. Furthermore, NSC-25 and NSC-50 outperform their DSC counterparts in all regions. This can be attributed to the preference for nighttime charging for EVs due to the addition of high wind power. During daytime, electricity demand peaks must be met by more costly generation units, making nighttime scheduling of EV charging the preferred option for power suppliers. Moreover, it is intriguing to note from Figure 15 that even in California, EV charging is preferred during nighttime. This preference can be attributed to high grid stress during the daytime from other loads, making nighttime charging a more viable option. Furthermore, California exhibits the highest total benefits. However, due to its high population and corresponding high number of EVs, the cost avoidance in California is not as pronounced compared to other regions.

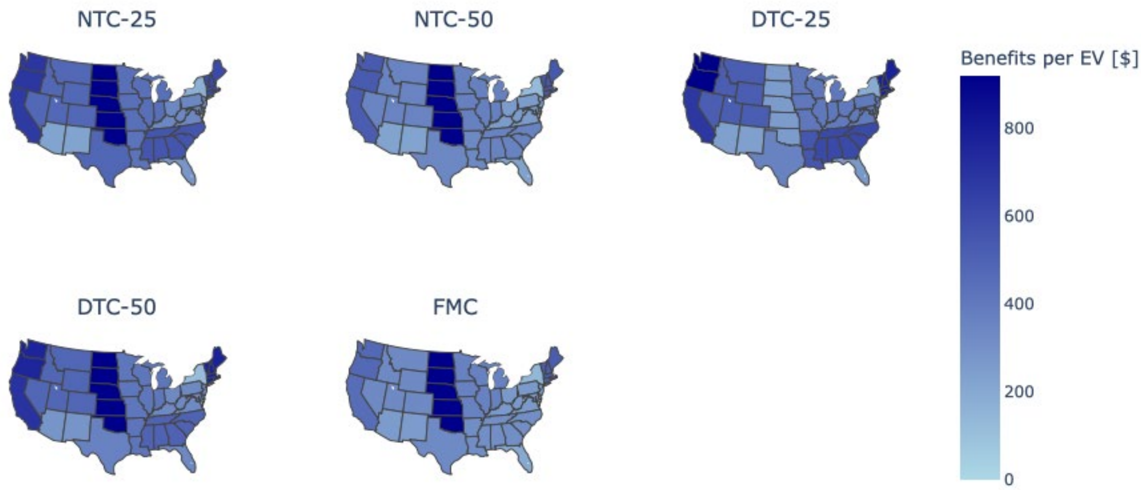

Figure 15 Regional analysis (discounted) of avoided electricity costs per EV for each scenario with the TEMPO case, vs. the UMC baseline scenario, from year 2025 to 2050 (in year 2023 USD)

Furthermore, from Figure 16, it is evident that in the FA case, the Central region exhibits significant benefits in both FMC and smart-charging scenarios compared to the UMC baseline, followed by the Arkansas-Louisiana, Mid-Atlantic, and Mountain North regions. Conversely, the lowest cost avoidance in the various scenarios compared to the UMC baseline is observed in the Florida and Texas regions. Florida, being a coastal region with high availability of wind power, is utilized to its maximum potential in all scenarios, leading to high wind capacity additions across the board. Additionally, the high population of Texas, coupled with a corresponding high adoption of EVs, is another factor contributing to the lowest avoided system costs per EV in the region.

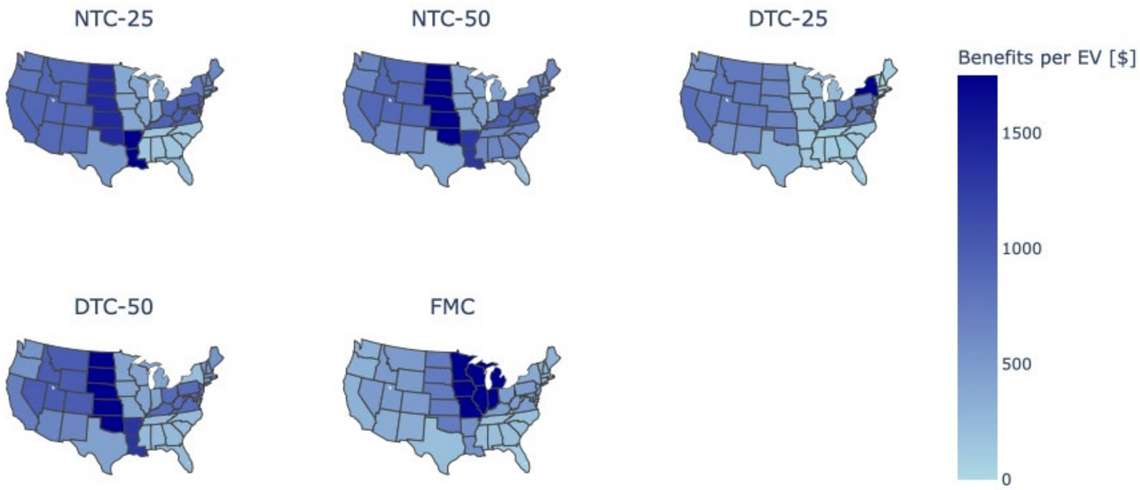

Figure 16 Regional analysis (discounted) of avoided electricity costs per EV for each scenario with the FA case, vs. the UMC baseline scenario, from year 2025 to 2050 (in year 2023 USD)

4.6 Comparison of the Costs and Benefits of EV Smart-Charging Programs

In this section, a comprehensive comparison of costs versus benefits of the smart-charging programs is presented for the TEMPO and FA cases, as shown in Table 2 and Table 3, respectively. The net present value (NPV) of grid cost savings and environmental benefits relative to the UMC baseline are calculated assuming a 5% discount rate for both the TEMPO and FA cases. The grid-cost-savings benefit is the reduction in ReEDS' objective (total discounted grid cost in 2025) relative to the UMC baseline plus the environmental benefits (value of lowered CH_4, NO_x, SO_2, and CO_2 emissions' social costs, discounted to year 2025). As previously discussed, the social costs of CH_4, NO_x, SO_2, and CO_2 emissions are assumed to be $1500, $532, $200, and $51 per ton, respectively–in year 2025 (Environmental Protection Agency, 2023). The highest benefit compared to UMC is observed in the NSC-25 scenario, followed by the DSC-20, NSC-50, and DSC-50 scenarios. Tables 2 and 3 also show the NPV of benefits per participating EV per year with UMC as the baseline for both the TEMPO and FA cases. The NPV of benefits and costs per EV-year are calculated by dividing the NPV of benefits and costs by a discounted number of EVs; all values are discounted by 5% to the year 2025. Discounting the number of EVs accounts results in a net present value of number of EVs in the year 2025, which accounts for the growth in the EV fleet and allows for the benefits and costs to be normalized over the changing number of EVs over 25 years. Additionally, as the size of the EV fleet grows, such as from the NSC-25 to the NSC-50 case, where the number of participating EVs doubles from the first case to the second, the benefits and costs per EV-year fall. Assuming that changes in other factors are negligible, the benefits and costs are spread out across a larger number of vehicles, resulting in a lower value per EV-year.

Table 2 Net present benefits and costs in year 2025 dollars, both total and per participating EV per year, of the smart-charging strategies in the TEMPO EV adoption case

Smart-Charging Strategy	Total Discounted Benefits with UMC as base ($ B)	Total Discounted Costs ($ B)	NPV of Benefits per SMC EV per year with UMC as Base ($)	NPV of Costs per SMC EV per year ($)
NSC-25	$184.56 B	$4.14 B	$6063.09	$136.08

NSC-50	$99.66 B	$8.28 B	$1636.97	$136.08
DSC-25	$125.36 B	$4.01 B	$4118.30	$132.03
DSC-50	$69.13 B	$8.04 B	$1135.60	$132.03

The cost of the smart-charging programs is derived from the survey conducted by Dean and Kockelman (2024). One question in the survey asked:

"What is the smallest one-time bill credit ($) you would accept to allow your local power company to modify your EV charging when plugged in?"

According to this program, customers need to stay enrolled for at least one year. Customers are offered the option to enroll in either the nighttime or daytime SC program. The mean willingness to accept values reported by survey respondents for the nighttime and daytime SC programs are $100.38 and $96.33, respectively. Additionally, customers are given the option to choose a yearly enrollment incentive ranging from $0 to $20.

Table 3 Net present benefits and costs in year 2025 dollars, both total and per participating EV per year, of the smart-charging strategies in the FA EV adoption case

Smart-Charging Strategy	Total Discounted Benefits with UMC as base ($ B)	Total Discounted Costs ($ B)	NPV of Benefits per SMC EV per year with UMC as Base ($)	NPV of Costs per SMC EV per year ($)
NSC-25	$293.33 B	$6.02 B	$5496.20	$112.78
NSC-50	$203.56 B	$12.04 B	$1907.04	$112.78
DSC-25	$236.74 B	$5.83 B	$4435.73	$109.50
DSC-50	$175.33 B	$11.69 B	$1642.62	$109.50

Using the survey responses, the 50th percentile value, which is $13 for yearly enrollment, is chosen as the preferred expectation for continued enrollment on an annual basis. The costs are calculated by multiplying the mean value of daytime and night-time smart-charging for the years 2025 to 2050 at 5-year intervals. A customer who enrolls in 2025 is assumed to remain enrolled until 2029. In 2030, a new one-time credit is provided ($100.38 for nighttime and $96.33 for daytime), and for new enrollments every four years thereafter, the utility needs to pay the yearly enrollment incentive. This process continues until 2050. The NPV of costs in 2025 dollars, calculated using a 5% discount rate, is shown in Tables 2 and 3.

Again, the costs per EV per year are calculated using the discounted number of EVs in the year 2025. For both cases, Tables 2 and 3 suggest that benefits will exceed costs, suggesting that SC programs require substantial utility expenditure, but the value of grid and emissions benefits outweigh the expenditure. Additionally, in both the TEMPO and FAS cases, the value of grid benefits is significantly larger than emissions benefits. Smart-charging programs provide the grid with flexibility to manage demand fluctuations arising from high demand and the variability associated with RE sources, and they offer long-term benefits by helping the grid effectively manage supply and demand in the electricity system.

5 CONCLUSIONS AND POLICY IMPLICATIONS

This study used ReEDS to anticipate light-duty EV charging's impacts on U.S. power grid costs, emissions, and generation and capacity mixes over the period from 2025 through 2050.

ReEDS uses a least-cost approach to determine optimal capacity investments and grid operations based on technology costs and policy constraints. Different scenarios were designed to evaluate the impact of EV charging strategies on the U.S. electricity grid and its emissions. In the TEMPO and FA cases, utilizing the FMC strategy, relative to the UMC baseline, the U.S. grid is projected to achieve emission cost savings of $29 and $80 per EV, respectively. However, in the FA case, the highest emission cost savings of $246 per EV-year are realized in the NSC-25 scenario. A particularly notable (and intuitive) difference between a future electricity system with managed EV charging and one with unmanaged charging is that the latter would require significantly more stationary storage (e.g. batteries) in the grid. This is highlighted by the fact that in the TEMPO and FA cases, 38% and 49% more battery capacity is required in unmanaged charging compared to FMC, respectively.

The analysis reveals several key findings. First, both the FMC and NSC scenarios result in notable increases in wind power generation, with significant reductions in coal installed capacity as compared to current levels in the year 2024. Additionally, the long-term adoption of EVs in the TEMPO scenario is expected to deliver an average emissions cost savings of approximately $187 per EV-year when implementing the FMC strategy. This is accompanied by projected system-wide power-cost reductions (ranging from 1.5% to 2%) when compared to the UMC baseline. Moreover, for California, there are minimal differences in avoided emissions costs per EV between the various scenarios. Regarding emissions benefits in the TEMPO case, daytime charging is favored in the Central region, while nighttime charging is preferred in the Midwest and Texas regions. However, smart-charging programs have a negative impact on electricity system emissions in the Arkansas-Louisiana region, largely due to the region's heavy reliance on coal. In the FA case, night charging emerges as the preferred option across most regions, showcasing positive avoided emission benefits. Exceptions are noted in the New York region, as well as in the Arkansas-Louisiana and Mountain North regions under the DSC-50 scenario. Furthermore, the FMC scenario yields the maximum avoided system costs per EV, reaching $1950 in the Central region compared to the UMC base. Conversely, the lowest avoided system costs per EV compared to the UMC base are observed in the New York region, ranging from $130 to $300. Lastly, in the FA case, the Central region exhibits significant benefits in both FMC and smart-charging scenarios compared to the UMC base, followed by the Arkansas-Louisiana, Mid-Atlantic, and Mountain North regions. Conversely, the lowest cost avoidance in the various scenarios compared to the UMC base is observed in the Florida and Texas regions.

This work suggests several policy implications for various stakeholders. Although smart-charging strategies entail additional costs for grid planners, they are likely to prove invaluable in grid management. Planners should prioritize scheduling the majority of EV charging during nighttime to alleviate grid stress and subsequently minimize investment costs. Moreover, the adoption of smart-charging strategies can lead to substantial reductions in required battery capacity, thus playing a pivotal role in mitigating investment expenditures. As the proportion of intermittent solar and wind power in installed capacity is anticipated to rise, it becomes imperative to implement smart-charging strategies to effectively manage grid stress amidst the widespread adoption of EVs. These strategies serve to balance the variability inherent in renewable energy generation, ensuring grid stability and reliability. Regional variations in charging preferences underscore the importance of tailored planning. For instance, in terms of avoidance of emissions, while daytime charging is favored in the Central region, nighttime charging is preferred in Texas and the Midwest. By aligning charging schedules with regional preferences, system planners can optimize infrastructure deployment and scheduling.

Nighttime charging emerges as the preferred option for cost savings across the majority of regions in the long term, including California, despite its substantial solar capacity. This preference can be attributed to heightened grid stress during daytime periods from other loads, rendering nighttime charging a more economically viable option. Policymakers should prioritize policies and incentives that promote nighttime charging to capitalize on cost-saving opportunities and alleviate daytime grid stress.

This study adds impetus to faster EV adoption with different smart-charging strategies. Allowing for variations in smart-charging practices over space (e.g., state by state) and time of year (and day of year, to match grid stress) will enable even greater benefits, anywhere such policies are pursued. The findings of the study should be considered within the context of certain limitations. The outcomes of this study must be interpreted with the understanding that current trends in EV investments and ongoing research and development could lead to significant improvements in EV efficiency in the future. Beyond not allowing different strategies by day of year and location or vehicle type, this study also does not anticipate new technologies (like fuel cells) or changes in miles per kWh (which can fall thanks to greater efficiency but also rise due to Americans' long-term adoption of heavier or bigger vehicles). Nevertheless, this study offers significant insight to planners, policymakers, grid managers, and equipment manufacturers by providing important insights into the future of the U.S. electricity infrastructure and the role of electric vehicles within it.

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