# AN INTEGRATED TRANSPORTATION-POWER SYSTEM MODEL FOR A DECARBONIZING WORLD

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## ABSTRACT

The increasing demand for electricity from electric vehicles (EVs) will require new paradigms to guarantee reliable and low-cost electricity. This study evaluated an approach to coupling an agent-based travel demand simulator and an electricity grid model to assess the economic costs of supplying power to meet this additional demand in Chicago. The study found that shifting from personal EVs to a fleet of shared, fully-automated all-electric vehicles (SAEVs) could lower per-mile emissions, congestion, and embodied vehicle and charging infrastructure emissions. The results should compel policymakers to shift the cost of providing power onto commercial customers, like electric ride-hail fleets, through price-indexed electricity prices, which can shift charging to off-peak periods or away from resource-scarce hours.

***Keywords*:** integrated modelling, electrified mobility services, electrified transportation systems, infrastructure systems, agent-based modelling, transportation simulations, electric vehicles, shared autonomous electric vehicles

## 1. MOTIVATION

Speeding up the transition from gas- or diesel-powered personal, light-duty vehicles to zero-emission vehicles is necessary for developed countries to meet voluntary climate change targets (Bibra et al., 2022), provided that the power system transitions to low-carbon generation sources. Variable renewable energy (VRE) technology, like solar and wind, with no fuel costs and small variable costs, is economically advantageous to fossil fuel generation, thanks in part to production and investment tax credits and a small levelized cost of electricity (U.S. EIA, 2022a). In addition to supply-side changes, the electrification of heating sources, home appliances, and vehicles will increase electricity demand and change its spatial-temporal distribution pattern. Under aggressive electrification scenarios, the U.S. may need to double or triple its installed generation capacity between 2018 and 2050 (Mai et al., 2018). Large-scale adoption of electric vehicles (EVs), to an extent, also shifts decarbonization responsibility to another sector: the power system. The EV transition increases interdependencies between the transportation and power sectors, which have historically operated independently, despite both impacting household budgets at the individual level and overlapping rights-of-way at the network level.

Charging infrastructure access, electricity rate design, and EV charging control are strategies that can influence charging behavior and the expected rise in electricity demand (Powell et al., 2022). Studies have investigated the effect of EV charging at different scales, from the power distribution system effects of increased personal EV adoption (Clement-Nyns et al., 2010; Coignard et al., 2019; Estandia et al., 2021; Muratori, 2018; Nacmanson et al., 2022; Wert et al., 2021) to transmission and generation-level effects (Cheng et al., 2018; Forrest et al., 2016; Kintner-Meyer et al., 2020; Sheppard et al., 2021; Szinai et al., 2020; van Triel and Lipman, 2020; Xu et al., 2020; Zhang et al., 2020, 2019). The granular scale helps one understand how unmanaged charging may increase co-incident peak loads in residential neighborhoods, age equipment faster, and lead to grid capacity upgrades. On the other hand, macroanalysis shows the importance of load flexibility in avoiding an increase in emissions, deferred capacity expansion to meet peak demand, reduced investment in utility-scale energy storage, and increasing reliability in the system in the face of climate change.

EVs could be important grid assets in smoothing the balance between supply and demand at different time scales. Personal EV owners may allow their local power companies to stagger or directly control charging at their workplaces and/or homes (Bailey and Axsen, 2015; Bauman et al., 2016; Tarroja and Hittinger, 2021). If the cost of electricity is indexed to real-time marginal generation costs (i.e., wholesale power prices), then EV ride-hailing fleets may seek to lower their electric bills by charging during off-peak hours, assuming this coincides with periods of low passenger demand (Dean et al., 2023; Iacobucci et al., 2021; Zhang and Chen, 2020). Price signals are a form of smart or managed charging that can reshape the EV charging demand curve (Anwar et al., 2022), and mitigate co-incident peak demand. The importance of studying the grid impacts of large-scale EV adoption also requires understanding how emerging mobility, like shared, autonomous, electric vehicles (SAEVs), could reshape urban mobility and change charging profiles away from assumptions in previous studies that mainly focused on personal EVs (Dean and Kockelman, 2022).

While many have studied the implications of personal, light-duty vehicle electrification on grid resource adequacy (Anwar et al., 2022), studying EVs within the context of using on-demand SAEVs is a challenge with technological delays in autonomous vehicle (AV) testing and deployment. As recently as the 2016/2017 U.S. National Household Travel Survey (NHTS), 7.3% of households used taxi services or ride-hail vehicles at least a few times a month (and 1.4% used these services a few times a week)[1] (Crossland et al., 2021). Given the slow adoption of ride-hail services and car-dependent land use policies in many American cities, the long-term adoption levels of SAEVs are uncertain. The timing of the transition to SAEVs depends on technology learning curves, human factors, falling costs, and regulations (Litman, 2022). Likewise, the transition to low-carbon power generation depends on declining energy storage technology costs, government mandates, grid interconnection reviews, land use policies, and public-private investments (Susskind et al., 2022). Regardless of the timing, the scientific consensus is that a quick transition from fossil-fuel-powered vehicles and power plants to zero- or low-carbon alternatives is necessary to avoid the catastrophic effects of climate change (Rogelj et al., 2018; Sperling et al., 2020).

SAEV fleet charging decisions, vehicle utilization, battery capacity, and infrastructure investments all impact charging demand. Unlike personal EVs, which are parked for over 95% of an average day (Shoup, 2011), passenger-serving fleet vehicles may be busy 8+ hours per day (Fakhrmoosavi et al., 2024). Moreover, SAEV fleets will need to return to central hubs for cleaning, maintenance, and maybe even charging (if wireless or automatic plug-in adapters at fleet-owned charging stations are not in use) (Gurumurthy et al., 2022). Centralized charging infrastructure can reduce land acquisition or leasing costs but increase deadheading between trip ends and charging hubs. Investing in fewer charging outlets can reduce costs and increase charger use, but limits SAEV fleet use for power grid benefits, like load shifting. In contrast, fleets could co-locate charging infrastructure where personal vehicles are normally parked to align charging with periods of solar-rich power and reduce empty travel between passenger-serving trips. In California and 10 other western U.S. states, daytime charging of EVs provides significant economic and environmental benefits (Powell et al., 2022).

SAEVs can have significant impacts on electricity systems, not only due to added power demands – but also centralized fleet-control's benefits, like charging modulation in response to transmission congestion, VRE generation, and total load on the local transformer. Demand-side flexibility is an important tool in increasing the power grid's reliability, and removing the human driver from charging decisions offers greater certainty when relying on EVs as a grid resource. Future SAEV fleets may offer bi-directional charging (Dean et al., 2023; Iacobucci et al., 2021; Melendez et al., 2020) at select chargers to provide a temporary power supply and help grid operators avoid rolling power outages (Dean and Kockelman, 2022). As the transportation and electricity sectors converge and new modes of transport emerge, integrated models are necessary to identify the opportunities and challenges of this transition.

## 1.1 Literature Review

Several studies have explored EV-grid effects using transportation and power system models at various spatial scales. Often, these analyses emphasize smart charging of EVs to manage the added EV load, with Anwar et al. (2022) providing a critical review of these works. Many studies exogenously define transportation load profiles as inputs to a power system model to quantify the benefits of managing the additional EV load. At the power distribution system level, EV load

[1] Within the Census Bureau's defined Chicago–Naperville–Elgin, IL–IN–WI metropolitan statistical area (MSA), 9.2% of households used taxi services at least a few times a month versus 2.8% using this mode a few times a week.

impacts are primarily quantified in terms of power loss and voltage change, which depend on the location, timing, and magnitude of charging in the network (Dubey and Santoso, 2015; Masoum et al., 2010). At the bulk power system level, power system operators evaluate resource adequacy, including in long-term resource planning, and quantify the benefits of managed charging in terms of reduced operational costs, avoided capacity expansion, and lower emissions (Cheng et al., 2018; Forrest et al., 2016; van Triel and Lipman, 2020; Xu et al., 2020). Although these studies often rely on well-established power system models, such as PLEXOS, the fixed transportation demand approach cannot capture the effect of pricing strategies on traveler charging behavior. As an example, demand-responsive SAEVs that serve passenger demand can also follow grid pricing signals to charge or discharge energy. Thus, there is a need to co-simulate transportation and power system models to capture dynamic EV load profiles[2]. Although a fleet of SAEVs would account for a small share of all vehicles on the road, their higher daily use and need for short downtimes during high travel demand hours of the day may result in new load profiles different from personal EVs (Dean et al., 2023; Sheppard et al., 2021). To date, few have jointly considered travel demand with a production cost model for the power grid.

Sheppard et al. (2021) simulated the economic and environmental costs of electrifying all U.S. daily personal vehicle trips and the effects of serving a higher share of vehicle trips with SAEVs. Smart charging can reduce peak demand by 47%, relative to no EVs (including SAEVs), by valley filling when solar would otherwise face curtailment. Further, they estimated that sharing vehicles and chargers would reduce the total daily light-duty vehicle fleet size from 145 million down to 12 million and the need for chargers from 195 million (to meet 100% personal EVs) to 2.6 million (to meet 100% trips served by SAEVs). Still, their study's SAEV travel demand was adjusted from aggregate mobility flows and used 2016-era generation capacities.

More recently, Panossian et al. (2023) demonstrated a proof-of-concept co-simulation framework to relay charging demand by location between an agent-based transportation model and a distribution system simulation at the same simulation time interval. A suite of future light-duty vehicle fleet compositions (e.g., percent EVs, access to charging infrastructure, and SAEV uptake) was analyzed for Alameda County, California. They found that fast charging at public locations, particularly in urban centers, could overload some distribution feeders and cause voltage excursions, necessitating strategies to mitigate unintended consequences (e.g., grid upgrades, power flow studies before permitting, and smart charging controls). While at a small spatial scale, this co-simulation approach connects high-fidelity models and will allow for future analyses of co-optimized charging control strategies.

Although these two studies contributed to the knowledge of SAEV power system impacts, none of these prior works has used co-simulation frameworks to study the impacts of managed charging for future-year generation capacities at the bulk power system level. This research gap is critical to inform power system operators of future EV load shapes under high automation scenarios and transportation planners on how cost-driven SAEV charging decisions impact system-wide metrics, such as net vehicle miles traveled (VMT).

[2] On the other hand, studies using agent-based transportation models have relied on exogenously defined electricity prices to estimate charging demand, even though large fleets of SAEVs may influence production costs (Dean et al., 2022; Iacobucci et al., 2018).

In this study, an agent-based transportation simulator estimates the daily charging demand for personal (household-owned) EVs and a fleet of SAEVs under different adoption levels for the Greater Chicago metro region, covering 20 counties with nearly 11 million people. The daily charging demand is added to a state-wide power system operational model with least-cost unit commitment and economic dispatch functions to understand changes in wholesale power prices from large-scale vehicle electrification. The study first shows the effect of switching from internal combustion engine vehicles (ICEVs) to EVs while holding Chicago's destination and mode choices constant (a fuel-switching-only scenario). Then a range of scenarios are used to understand how shared, fully-automated, all-electric vehicles (SAEVs), shared rides (with strangers), and smart-charging price signals mitigate increases in power costs for everyone, while lowering per-passenger mile emissions and excess investments in household EVs and chargers. The scenarios simulate the transportation-energy transition in 2035 under different SAEV mode splits within a 2,360 square-mile geofence (service area). Seasonal effects are captured through EV energy consumption, non-transportation power demand (i.e., load), and VRE generation to provide robust results. The results reveal planning insights for future all-electric mobility solutions, like SAEVs, and capture the interdependent relationship between additional EV charging load on wholesale power prices and smart charging decisions.

The following sections describe the modeling framework, assumptions made, data sets used, and charging strategies applied, before showing results and conclusions, along with recommendations for policymakers and future research.

## 2. METHODS

The study's first contribution is a framework for integrating power systems operation model and a discrete-event transportation simulator. The transportation simulation covers the 20-county Greater Chicago region and simulates a 24-hour period of typical weekday travel demand, including urban, freight, and commercial vehicle trips that are internal or external to the region. Charging demand was simulated for the region based on a day's typical travel and assumptions on charging frequency and access to charging stations. The underlying vehicle ownership choice model, calibrated to present-day data and demographics (like household income), was adjusted to increase the probability of choosing an electric powertrain vehicle. Charging control scenarios, including different electric utility rates (i.e., prices) and charging equipment timers to delay charging, were used to compare them to unmanaged charging. The total charging demand was added to the baseload electricity demand curve. The power system model uses unit commitment and economic dispatch to find the least-cost set of generators to dispatch to meet electricity demand at all hours of the day while respecting transmission constraints. The model also determines the marginal generation cost of each node at the transmission network, serving as the electricity wholesale prices.

The workflow for this at-scale power analysis is shown in Fig. 1. The assumption taken was that a large fleet of SAEVs may be price makers (or at least price influencers), with sufficient aggregate charging demand to affect generation costs (and eventually electricity prices) in the power model. The respective scenario inputs for personal EVs and SAEVs are shown in grey boxes on the left-hand side. The results from the power system model (e.g., costs and generator status) are returned to the transportation simulation if electricity prices are indexed to the wholesale market.

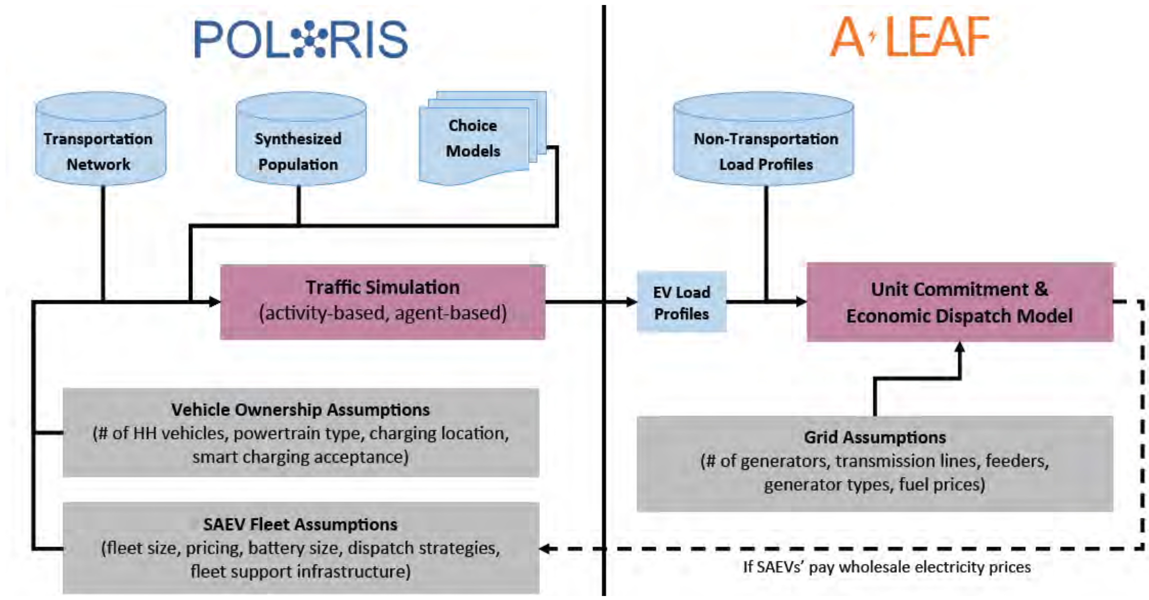


**Fig. 1**: Workflow of the at-scale power analysis.

### 2.1 Electricity Consumption

The state of Illinois has a goal of registering 1 million EVs in the state by 2030 (IDOT, 2022). An estimated 10.4 million private and commercially owned automobiles and trucks were registered in Illinois in 2017 (FHWA, 2021). This study simulates two on-road adoption levels for 2035: 8% and 17% adoption, which would require a high EV sales share through 2035[3]. Since most early adopters of EVs are wealthy residents and urban dwellers (Lee et al., 2019), these targets for the Greater Chicago region may be attainable with accelerated vehicle turnover rates. Using adoption targets and choice models to explain travel patterns, vehicle ownership, and charging options, the transportation simulation tool, POLARIS, keeps track of vehicle movements throughout the region's travel network to reflect heterogeneity in energy consumption based on traffic levels. The traffic flow model with dynamic traffic assignment provides the travel records for the region (Auld et al., 2016). A machine-learning algorithm predicts energy consumption based on vehicle trajectories across the synthetic road network (Moawad et al., 2021) and updates vehicle battery levels throughout the simulation.

To estimate the effects of widespread EV adoption and increasing reliance on SAEVs, the aggregate charging load is added to the non-transportation (or baseload) consumption profile. Population growth, economic output, and cross-sector decarbonization (namely, switching from fuel to electric for heating) will also increase baseload consumption of electricity. This study applies a year-over-year growth factor that varies by month and hour based on estimates from the National Renewable Energy Laboratory (NREL) Cambium model (Gagnon et al., 2023). The average growth factor across twelve months and twenty-four hours is 1.19%, which is less than the 1.23% assumed in the well-cited 2050 medium-rapid electrification scenario in Mai et al.

[3] The turnover rate for a U.S. light-duty vehicle (LDV) is 20 years, which means that high EV sales in a given year will have a delayed response in LDV fleet share. One U.S.-based study estimated that EV sales rising to 89% in 2035 come with a total LDV fleet share of 31% (Woody et al., 2023).

(2018). See Fig. A.5 in the appendix for the monthly- and hourly-varying demand growth factors used in this study.

The grid model, A-LEAF, is a combined least-cost unit commitment and economic dispatch model written in Python that models the generation and transmission of power (Verbas and Zhou, 2020). A mixed-integer linear program determines the commitment status of generators to balance supply and demand for each hour of the day (i.e., unit commitment), followed by a sub-problem that solves a linear program for power levels from each committed generator (i.e., economic dispatch). This study used 2015 generator data to compare a business as usual (BAU) case and a predicted future with coal retirement and VRE capacity generation exceeding natural gas, since wind and solar capacity factors are less than those for thermal power plants (U.S. EIA, 2022b). The increase in VRE can also reduce the cost of power, as shown in the merit order curves for the two feedstock scenarios (see Figs. A.6 and A.7 in the Appendix).

### 2.2 Charging Strategies

Demand-side flexibility is critical to support VRE and avoid costly upgrades owing to steeper demand for electricity. Thus, many power companies are using pricing, such as time-of-use (TOU) rates, to avoid a co-incident peak in electricity demand (SEPA, 2019). To take advantage of these off-peak prices, vehicles or charging equipment use timers to delay or stagger charging (if devices are connected and the power company can shift timing by a few minutes). In contrast, fleets of SAEVs will seek to minimize electricity purchasing costs and downtime of vehicles and increase the utilization of chargers to avoid excess investments in infrastructure. Using wholesale power prices to incentivize off-peak charging or TOU rates is expected instead of timer-based solutions. This study uses an optimization-based control strategy that relays prices into within-day idle vehicle dispatch decisions (Dean et al., 2023). Interested readers are referred to Dean et al. (2023) for details on the methodological framework[4].The flat electricity price in this study, $76.36/MWh, is based on the bundled rate available for medium-load commercial customers with secondary voltage connections in ComEd's service region (ComEd, 2022a). The study assumes the residential TOU rate can apply to commercial customers, of which there are three time-varying prices[5]: off-peak prices apply between the hours of 10 PM and 6 AM ($25.95/MWh), super-peak prices apply between 2 PM and 7 PM ($68.58/MWh), and peak prices between 6 AM and 2 PM and again between 7 PM and 10 PM ($34.19/MWh) (ComEd, 2022b). Customers can also choose to pay a wholesale-indexed rate plan without any markup on the rate, which can reduce the customer's average power bill. Since the additional demand from EVs will require an additional supply of power, the prices of the wholesale market cannot be assumed to be stable, as in Dean et

[4] A metropolitan area like Chicago, with a sprawling suburban area and dense urban core, can benefit from an optimization-based control strategy for SAEVs to rebalance vehicles and ensure equitable short pick-up times. However, the spatial-temporal distribution of trips and sprawling suburban regions creates a challenge in reducing deadheading between paid rides and support trips to charging stations and maintenance depots. Prior work has compared multi-objective optimization-based control dispatch strategies to heuristic-based control strategies (Dean et al. 2022) and found benefits in integrating charging decisions with other idle-vehicle dispatch decisions, like repositioning and vehicle maintenance and cleaning (Dean et al. 2023).

[5] As of April 18, 2023, for non-summer months. The characteristic summer day in this study used the following approved rates for summer days: $33.50/MWh for off-peak hours, $80.10/MWh for super-peak hours, and $42.50/MWh for peak hours.

al. (2023). As a result, the stable wholesale price found in the coupled power-transportation model, shown in Fig. 2, is used in the study results.

In contrast to SAEVs, personal EVs charge between activities, including at-home and at-work activities, provided there are chargers at these locations (i.e., "top-off" charging). Once a personal EV arrives at a destination, a heuristic determines whether to create an unplanned charging trip. If an EV's expected energy consumption for the next planned trip decreases the state of charge (SOC) below an individual's absolute minimum threshold (i.e., a random draw between 3% and 10%), the driver searches for a public charging station that minimizes the total detour and wait delay. Although there are a growing number of EV-managed charging pilots and EV-specific TOU rates (SEPA, 2021), this study assumes drivers of EVs are not influenced by prices.

### 2.3 Scenario Definitions

The study compares the transportation and power system impacts of personal EVs and SAEVs. Scenarios include electricity prices, charging strategies, adoption percentages of new technology, ride-sharing acceptance (for SAEVs), and seasonal effects. Seasonality impacts include adjusting the energy consumption of EVs based on auxiliary loads and the baseline demand for electricity, both of which are driven primarily by heating, ventilation, and air conditioning (HVAC). Personal EV and SAEV electricity consumption changes are assumed to follow real-world all-electric taxi performance. Hao et al. (2020) estimated a 3.3% increase in energy consumption during the summer from HVAC use and a 30% increase in the winter due to poor performance in colder temperatures.

Personal light-duty EV adoption scenarios include low (8%) and high (17%) EV ownership as well as charging infrastructure supply. The public charging station siting scenarios are defined as *low* (1 charger per 35 vehicles) and *high* deployment (1 charger per 13 vehicles). Home charging availability was randomly assigned based on adoption targets of 61% in single-family dwellings and 5% in multi-family dwellings, such that 41% of households with light-duty EVs had a home charger in the Chicago metro.SAEVs are relatively new within the broader context of AV (including shuttle) tests. In this study, SAEVs are defined as on-demand paid ride service on public roads with no fixed routes. Although public acceptance of autonomous ride-hailing (or SAEVs) is uncertain, a growing number of travelers are paying for driverless rides in cities like San Francisco, California (California Public Utilities Commission, 2024), Phoenix, Arizona, and Beijing, China. By redirecting the focus from whether travelers will accept SAEVs and when AV technology will mature to how SAEVs impact transportation and power systems, this study provides information on how large-scale EV and SAEV adoption impact electricity markets and how effective vehicle and ride-sharing strategies are in reducing transportation's energy use. While the use of SAEVs is certain (and currently observed), the future of travel will continue to be a mixture of multiple travel modes, especially with public transit included in the mix (Krueger et al., 2016). SAEV scenarios, as a result, include intra-geofence mode shares of 5%, 10%, 15%, and 20%. The effect of pooling strangers via dynamic ride-sharing (DRS) to increase vehicle occupancy is tested in three scenarios: the SAEV fleet does not offer pooled rides, some customers are willing to share rides (Gurumurthy and Kockelman, 2020), and all customers are willing to share rides. Wholesale-indexed electricity prices are used as the smart charging control strategy, where SAEVs centrally coordinate charging to lower power bill costs. The scenarios include retail prices (e.g., fixed and

TOU) and wholesale prices from ALEAF. The combination of scenarios results in 144 SAEV simulations (Fig. 2).

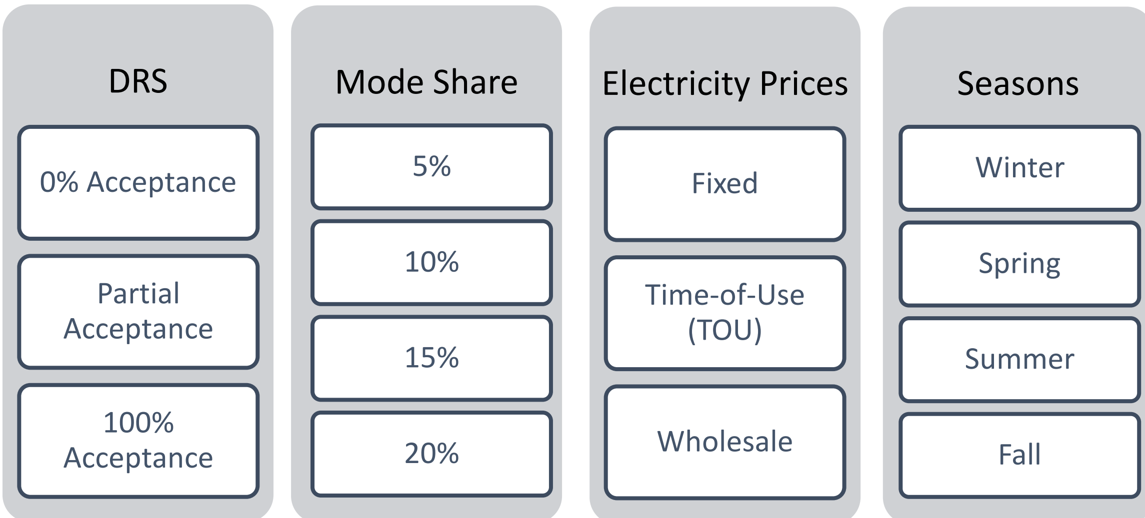


**Fig. 2**: Combination of SAEV sensitivity analysis scenarios.

### 2.4 Network Information

The synthetic transportation network includes 48,400 links and 35,800 nodes across the 20-county metro. The geofenced SAEV fleet is limited to a 2,360 sq-mile region, shown in Fig. 3a, and accounts for nearly 80% of the region's population. The transportation data was obtained from the Chicago Metropolitan Agency for Planning (CMAP). Fleet-owned charging stations with a power rating of 120 kW were generated during a warm-up simulation run to distribute charging stations 5 miles apart (Gurumurthy et al., 2022). The synthetic power grid includes 20 nodes, 45 links, and 250 representative generators, with data inputs obtained from Form EIA-860 generator data. The size of the node, shown in Fig. 3b, represents the share of the average annual daily load of the state. The nodes in Fig. 3b are also the locations of generators in the system. The transmission lines, shown in black, transport power to ensure that each node's demand is met with supply, based on 2015 data. As a result, demand in 2035 may exceed supply in some nodes when local VRE output drops and there is not enough transmission capacity to import electricity. The economic power system model reports the presence of congestion in the system through prices that exceed the marginal cost curves of the power plants. This economic measure is designed to incentivize demand response and energy efficiency measures in the short term and grid capacity expansion in the long term. Readers interested in the development of synthetic bulk power and transmission system networks are referred to Xu et al. (2017) and Birchfield et al. (2017).

**a. Geofenced SAEV service area** **b. Power grid node-link network**

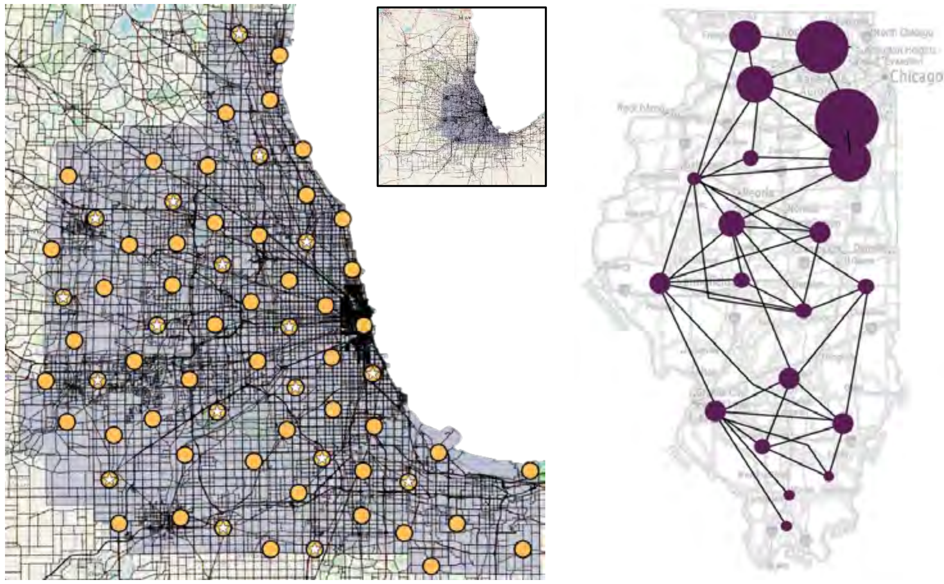


**Fig. 3**: (a) Chicago metro's synthetic road model centered on the geofenced SAEV service area with fleet-owned charging stations (orange circles, *n*=66) and co-located maintenance depots (white stars on orange circles, *n*=18), and the (b) Illinois' synthetic power grid where each node shows the locations of the generation sources and demand sinks (purple circles) and transmission lines (black lines) connect the generation sources to demand sinks.**RESULTS**

The joint framework aggregated personal EV charging demand from the 20-county Greater Chicago metropolitan area. The first half of the results presents the case where fuel switching through fast turnover of personal EV fleets leads to less on-road emissions, but no other actions are taken in the avoid-shift-improve decarbonization framework (Creutzig et al., 2018). The second half of the results presents the case where the presence of on-demand SAEVs reduces household vehicle ownership, leading to mode shift behavior and some avoided travel. There are different scenarios where the fleet offers pooled rides with strangers, and either some or all passengers are willing to share. Like the low and high personal EV adoption scenarios, the results show different levels of SAEV mode share within the 2,360 sq-mile geofence to understand the at-scale impacts of fleet electrification.

### 3.1 Transition to Personal Electric Vehicles

Personal EVs are assumed to charge as needed (i.e., unmanaged), leading to more EVs charging later in the day. In other words, some motorists opportunistically charge their EVs at work and public charging stations, while most EV owners charge after returning home. The baseline demand[6] for electricity in Illinois varies by season (see Fig. 4). Colder months usually have a morning and evening peak, while the summer has a single peak. The baseline demand in Illinois

[6] Fig. 4 plots "baseline demand," which is non-transportation demand minus generation from distributed rooftop solar (seasonally adjusted), since the model does not consider distributed energy resources.

is highest in the summer[7], and the demand curve peaks in the afternoon and early evening hours. The peak demand for a characteristic 2035 summer day is 35.0 GW between 4 and 5 PM (high public charging scenario). The additional demand for electricity from Chicago metro EVs can increase the summer peak demand by 320–580 MW (low vs. high public charging scenario), assuming unmanaged charging and drivers always charge when given the opportunity (i.e., "top-off" charging behavior). In contrast, the winter peak demand between 6 and 7 PM may increase by 410–760 MW. This change in electricity demand stems from worse performance in the winter rather than seasonal changes in activities. Fig. 4 displays the new demand curve for Illinois if just the 20-county Chicago metro were to quickly phase in EVs by 2035, such that the personal fleet of LDVs was 17% EVs. The first column shows results for a high number of public charging stations, and the second column reports results for a low number of charging stations. At 17% EV adoption, unmanaged charging can increase the summer peak demand by 0.9% to 1.6% and the new winter peak demand by 1.2% to 2.2%[8].

The increase in peak demand does not necessarily guarantee a steep increase in the cost of producing electricity. The marginal difference in wholesale energy prices due to Chicago personal EV adoption depends on the season's baseload, VRE output, and the additional demand from EV charging. Wind output changes hourly and seasonally, resulting in a different supply curve. The true cost of electricity in real-time is found at the intersection of the demand curve and the supply curve (i.e., market clearing price or spot price). The shape of the supply curve is determined by the merit order—the least-cost sequence of power plant output capacity based on the marginal cost. VRE, with no fuel costs and very low operating costs, can shift the supply curve left or right, depending on output (see Figs. A.3 and A.4 in the Appendix for the 2015 and 2035 merit order plots for the state of Illinois). To a lesser extent, the new electricity demand from EVs can shift the spot price by altering the operations of thermal power plants, which have minimum up/down times and ramping constraints.

A characteristic winter day in 2035 is likely to see a spike in wholesale prices between 5 and 7 PM, while summer days see a spike at 6 PM due to additional daylight for solar generation. EV charging, if left unmanaged, can increase peak demand during the natural ramp-up in the net load curve. EV charging at home usually occurs at a lower power draw using Level 2 chargers; however, at 17% EV adoption, this additional peak demand is spread out over more hours and may lead to peak prices for an additional *n* hours. This study finds that winter prices may spike between 5 and 8 PM and summer prices may spike between 6 and 9 PM (or an increase in high prices for 1 hour and 2 hours, respectively).

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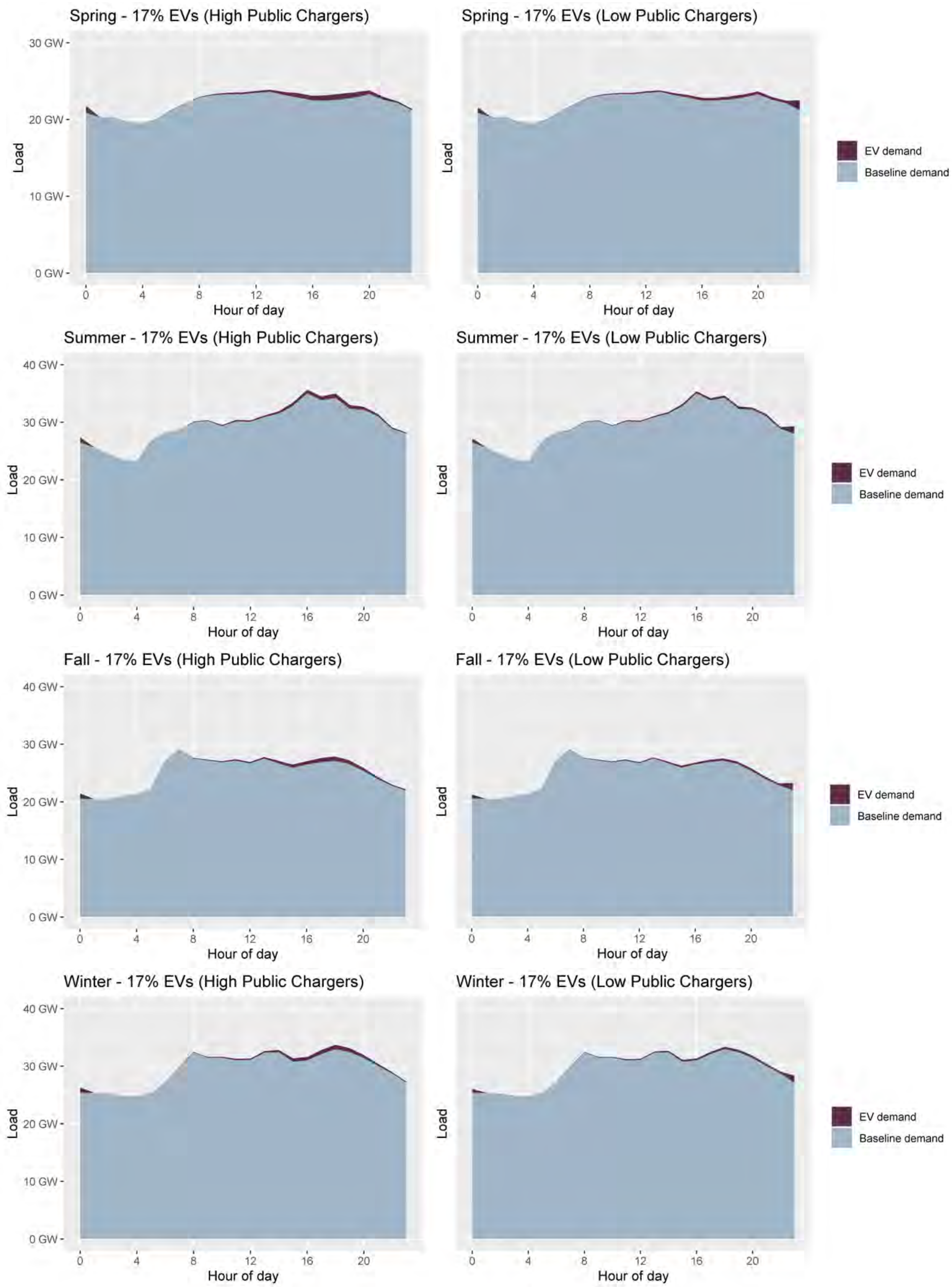
[7] According to the 2020 Residential Energy Consumption Survey (RECS) and the 2019 American Community Survey, around 95% of Illinois households use electric air conditioning, while less than 20% have an electric heating system (U.S. Energy Information Administration, 2022c).

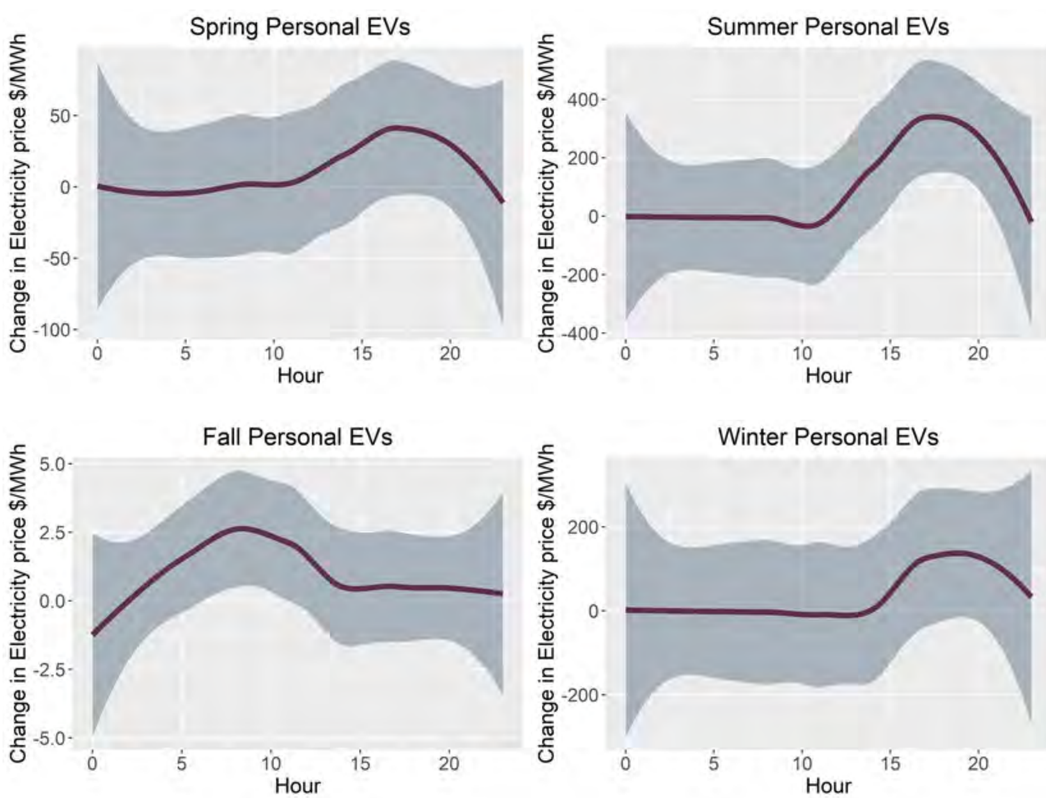
[8] About half of the state's population lives within the Greater Chicago metro area. Assuming that 20% personal EV adoption increases peak demand by 1-2%, a 100% EV scenario might increase peak demand by 10%-20%.




Note: Assuming 17% fleet share and two public charging station density scenarios.

**Fig. 4**: Change in Illinois' projected 2035 power demand curve due to Chicago's unmanaged personal EVs charging in winter, spring, summer, and fall.

The difference in projected statewide wholesale energy prices due to personal EV charging is plotted in Fig. 5 using LOESS regression, where the solid purple line is the average change in price from the four scenarios (2 EV adoption levels times 2 charging access scenarios). The shaded grey region is a 95% confidence interval to account for the high uncertainty in energy price fluctuations in 2035. The statewide wholesale electricity prices will almost certainly increase in the summer and winter months in the evening hours (Fig. 5), when a peak in electricity demand coincides with a drop in solar production. Spring and fall days, with a moderate temperature range, are less likely to see large fluctuations in energy prices due to unmanaged EV charging. Figs. A.1–A.4 in the appendix provide individual joint price and load curves without smoothing data, hence why there are large spikes in prices in the summer and winter months. If transmission capacity is expanded to reduce congestion, then the true increase in price due to the merit order of generators may more closely resemble the projected increase in Fig. 5.




Note: Y-axis scale differs for each subfigure. LOESS regression-generated mean line in purple with 95% confidence interval band captures wide estimate from 4 data points for each hour (2 EV adoption levels x 2 public charger scenarios).

**Fig. 5**: Average change in Illinois' projected 2035 hourly wholesale electricity prices due to Chicago personal EV adoption by season.

### 3.2 Shared Autonomous Electric Vehicles

SAEV fleet operators can make centralized charging decisions and are flexible to price signals that incentivize off-peak charging. The study reports findings from scenarios that used a fixed price, which is equivalent to unmanaged charging, and two price-based managed charging strategies: TOU and wholesale-indexed prices. Table 1 reports mobility and vehicle statistics for an SAEV fleet under different mode share levels, DRS acceptance, and electricity prices for a characteristic spring or fall day (where air temperatures do not increase vehicle energy consumption or increase HVAC loads on the state's electrical grid). Table 2 and Table 3 report results for the same metrics for the characteristic summer and winter days, respectively.

The average SAEV drove between 290 and 310 miles each day (across all mode share scenarios), with empty VMT adding upwards of 3 million VMT for each 5% increase in mode share. On average, 40% of the VMT driven by each vehicle is without a passenger (i.e., empty VMT [eVMT]). Higher duty cycles by fleet EVs lead to more energy consumption on a per-vehicle basis compared to personal EVs. On average, an SAEV that completes over 22 person-trips per day will require between 85 and 110 kWh[9] of electricity (i.e., the average person-trip consumes 3.9 to 5 kWh, including the additional eVMT consumption to support this trip; see Fig. A.9). In contrast, the average personal EV requires less than 12 kWh of electricity each day to operate. The average Chicago person-trip in a personal EV consumes 7.7 to 9.3 kWh, which is 1.9 times more energy than with a fleet of shared SAEVs.

The average vehicle occupancy (AVO) across all vehicle-miles (revenue and non-revenue) for this fleet of SAEVs ranges from 1.4 (5% mode share with no DRS) to 1.8 (20% mode share with DRS). The revenue-miles adjusted AVO metrics are shown in the results tables, which aligns with public data on driver-reported passenger counts in similar cities (i.e., New York City Taxi and Limousine Commission's trip dataset). If fleets offer a DRS option the expected revenue-miles AVO may increase from 2.5 to 2.8. Although percent eVMT (%eVMT) is about 40% across all scenarios, DRS scenarios have about a three-percentage point decrease. If no rides are shared, almost two-thirds of empty travel occurs between customers. As DRS reduces deadheading between trip ends, the relative share of support trips (e.g., charging, maintenance, cleaning, and rebalancing vehicles) will increase from a third to over 40%. If riders take SAEVs in group settings or solo travelers are willing to share rides, the congestion impact of large-scale SAEV service may be minimized. Even with a high empty VMT, sharing vehicles, rides, and centralized dispatch of vehicles to passengers with DRS can lead to more efficient energy use relative to the status quo of driving one's personal vehicle in sprawling regions, like Chicago.

To encourage households to give up their vehicles and use on-demand SAEV service, fleets should minimize the percentage of unmet trips. A trip is declared unmet if a customer waits more than 18 minutes before their smartphone app notifies them of their vehicle assignment. The results in Table 1 indicate that fleet operators adjusting charging decisions to lower the fleet's electric bill, either through a set retail TOU rate or a wholesale-indexed rate, does not decrease the number of trips served per vehicle per day, relative to the unmanaged case of flat prices. Aligning charging with low-cost periods of electricity does not come at the expense of serving passenger trips. Further, there is evidence that a fleet minimizing electricity expenditures could decrease percent empty travel (Fig. A.10).

In comparison to Fig. 4, which shows an increase in the load curve due to unmanaged personal EV charging, Fig. 6 shows the new load curve in the spring if between 5% and 20% of daily Chicago

[9] Assuming a 33% increase in energy consumption during the winter (see methods). See Fig. A.8 for a boxplot of daily energy consumption per SAEV by season.

trips were served by a fleet of SAEVs. These figures assume that all riders are willing to share rides, which decreases energy consumption on a per-trip basis (Fig. A.9). Subfigures on the left assume the region's electricity provider does not charge time-varying electricity prices, while subfigures on the right assume the fleet pays the prevailing wholesale price and adjusts charging decisions based on day-ahead energy prices. At 20% SAEV mode share, the state's springtime peak demand for electricity could shift from 1 PM to 8 PM (representing a 7.9% increase in demand at 8 PM) under flat energy prices. However, a fleet paying wholesale prices will try to avoid charging in the evening hours when energy prices are higher, thereby shifting charging earlier in the day and increasing the 1 PM peak by 8.9%. Shifting charging may also increase empty travel if vehicles are not near charging stations and charging station locations are far from trip pick-ups. The simulation results suggest that with uniform charger placement (see Fig. 3a), the percent of empty VMT does not necessarily increase with time-varying energy prices (Fig. A.10).

Shifts in EV charging patterns can lead to price fluctuations in statewide wholesale energy prices. Fig. 7 plots projected price changes from a Chicago fleet serving 20% of trips in 2035, using LOESS regression to reduce the magnitude of large price increases during hours where demand exceeds supply due to transmission constraints. Prices will increase across all seasons due to an increase in charging from SAEV adoption, which was not observed in the personal EV scenarios (Fig. 5). Spring days have relatively low prices due to less electricity demand, but due to an increase in charging after midnight (Fig. 6), the power grid operator dispatches additional generators to meet this new demand, raising prices for all. However, if this charging demand coincides with the midday peak, prices may rise substantially more than the midnight price increase of nearly $13/MWh, indicating that smart charging decisions can mitigate price increases. At the same time, there is an opportunity for more valley filling after midnight (Fig. 6), which could reduce the expected price increase.

**Table 1**: SAEV Mobility and Vehicle Statistics by Mode Share, DRS Acceptance, and Electricity Price for a Spring (or Fall Day)

| **Metrics** | **Unmanaged Charging: Flat Electricity Prices (Spring/Fall)** | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **SAEV (No DRS)** | | | | **SAEV + DRS Acceptance Model** | | | | **SAEV + 100% DRS Acceptance** | | | |
| **Mode Share** | **5%** | **10%** | **15%** | **20%** | **5%** | **10%** | **15%** | **20%** | **5%** | **10%** | **15%** | **20%** |
| **Avg. Response Time (min)** | 5.0 min | 4.7 min | 4.9 min | 5.9 min | 4.3 min | 4.1 min | 4.2 min | 4.8 min | 4.3 min | 4.1 min | 4.1 min | 4.3 min |
| **Avg Person-Trips/ SAV/day** | 24.3 trips | 24.4 trips | 22.7 trips | 21.2 trips | 26.3 trips | 26.6 trips | 26.1 trips | 23.9 trips | 26.2 trips | 26.6 trips | 26.3 trips | 25.1 trips |
| **Avg. SAV VMT/day** | 292 mi | 308 mi | 303 mi | 298 mi | 285 mi | 301 mi | 303 mi | 300 mi | 284 mi | 300 mi | 304 mi | 295 mi |
| **%eVMT** | 43.6% | 41.4% | 42.2% | 43.0% | 40.6% | 38.0% | 38.2% | 40.0% | 40.5% | 37.9% | 37.8% | 37.9% |
| **Charging (kWh/SAV/day)** | 81.5 kWh | 86.4 kWh | 84.0 kWh | 71.2 kWh | 79.1 kWh | 86.9 kWh | 84.2 kWh | 70.5 kWh | 80.2 kWh | 84.6 kWh | 84.9 kWh | 76.5 kWh |
| **AVO** | 2.50 | 2.50 | 2.50 | 2.50 | 2.69 | 2.74 | 2.77 | 2.81 | 2.69 | 2.74 | 2.77 | 2.79 |
| **Metrics** | **Managed Charging: Time-of-Use (TOU) Electricity Prices (Spring/Fall)** | | | | | | | | | | | |
| | **SAEV (No DRS)** | | | | **SAEV + DRS Acceptance Model** | | | | **SAEV + 100% DRS Acceptance** | | | |
| **Mode Share** | **5%** | **10%** | **15%** | **20%** | **5%** | **10%** | **15%** | **20%** | **5%** | **10%** | **15%** | **20%** |
| **Avg. Response Time (min)** | 5.0 | 4.9 | 6.2 | 4.8 | 4.4 | 4.2 | 4.9 | 4.3 | 4.3 | 4.1 | 4.1 | 4.3 |
| **Avg Person-Trips/ SAV/day** | 25.0 | 24.7 | 21.7 | 23.5 | 27.1 | 27.1 | 24.9 | 25.7 | 26.2 | 27.3 | 26.3 | 25.5 |
| **Avg. SAV VMT/day** | 300 | 313 | 305 | 310 | 295 | 307 | 302 | 302 | 284 | 307 | 304 | 301 |
| **%eVMT** | 43.8% | 41.5% | 44.0% | 41.2% | 40.8% | 38.0% | 39.9% | 37.7% | 40.5% | 37.6% | 37.9% | 38.1% |
| **Charging (kWh/SAV/day)** | 80.3 | 87.9 | 82.4 | 81.7 | 79.8 | 87.8 | 82.1 | 79.5 | 79.0 | 87.9 | 80.2 | 80.3 |
| **AVO** | 2.50 | 2.50 | 2.50 | 2.50 | 2.70 | 2.74 | 2.79 | 2.80 | 2.69 | 2.74 | 2.77 | 2.79 |
| **Metrics** | **Managed Charging: Wholesale-Indexed Electricity Prices, Endogenously Derived (Spring)** | | | | | | | | | | | |
| | **SAEV (No DRS)** | | | | **SAEV + DRS Acceptance Model** | | | | **SAEV + 100% DRS Acceptance** | | | |
| **Mode Share** | **5%** | **10%** | **15%** | **20%** | **5%** | **10%** | **15%** | **20%** | **5%** | **10%** | **15%** | **20%** |
| **Avg. Response Time (min)** | 5.3 | 5.0 | 5.3 | 4.8 | 4.5 | 4.2 | 4.2 | 4.5 | 4.5 | 4.1 | 4.2 | 4.2 |

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Avg Person-Trips/ SAV/day** | 24.3 | 24.2 | 23.5 | 23.4 | 24.7 | 27.1 | 26.3 | 26.3 | 24.5 | 26.9 | 27.0 | 26.5 |
| **Avg. SAV VMT/day** | 296 | 306 | 317 | 311 | 291 | 300 | 310 | 305 | 270 | 300 | 305 | 307 |
| **%eVMT** | 44.4% | 41.2% | 42.9% | 40.9% | 41.5% | 37.1% | 39.1% | 39.9% | 41.8% | 37.1% | 37.5% | 37.7% |
| **Charging (kWh/SAV/day)** | 92.6 | 84.0 | 83.7 | 81.9 | 87.3 | 84.3 | 81.6 | 81.0 | 73.2 | 85.0 | 80.2 | 81.8 |
| **AVO** | 2.50 | 2.50 | 2.50 | 2.50 | 2.70 | 2.74 | 2.77 | 2.80 | 2.69 | 2.74 | 2.78 | 2.80 |

| **Metrics** | **Managed Charging: Wholesale-Indexed Electricity Prices, Endogenously Derived (Fall)** | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **SAEV (No DRS)** | | | | **SAEV + DRS Acceptance Model** | | | | **SAEV + 100% DRS Acceptance** | | | |
| **Mode Share** | **5%** | **10%** | **15%** | **20%** | **5%** | **10%** | **15%** | **20%** | **5%** | **10%** | **15%** | **20%** |
| **Avg. Response Time (min)** | 5.2 | 4.9 | 4.9 | 4.8 | 4.5 | 4.1 | 4.2 | 4.1 | 4.3 | 4.3 | 4.4 | 4.3 |
| **Avg Person-Trips/ SAV/day** | 24.6 | 23.2 | 24.3 | 23.6 | 26.9 | 27.3 | 26.8 | 26.7 | 27.2 | 26.9 | 26.3 | 24.7 |
| **Avg. SAV VMT/day** | 299 | 301 | 319 | 312 | 290 | 302 | 313 | 307 | 294 | 305 | 303 | 291 |
| **%eVMT** | 44.1% | 40.9% | 41.8% | 41.4% | 41.7% | 37.3% | 38.2% | 37.4% | 40.5% | 38.2% | 37.9% | 38.9% |
| **Charging (kWh/SAV/day)** | 85.4 | 81.2 | 83.8 | 82.9 | 75.6 | 88.1 | 76.3 | 79.4 | 83.4 | 87.7 | 80.2 | 69.4 |
| **AVO** | 2.50 | 2.50 | 2.50 | 2.50 | 2.70 | 2.74 | 2.78 | 2.80 | 2.69 | 2.75 | 2.79 | 2.79 |

Note: Fleet size does not linearly scale with mode share within the geofence. The ratios of SAEVs to residents (assuming 5% to 20% mode shares) are 1:300, 1:140, 1:105, and 1:75, respectively. AVO = revenue-miles weighted average vehicle occupancy (accounting for party size), & DRS = dynamic ride-sharing (or pooling).

**Table 2**: SAEV Mobility and Vehicle Statistics by Mode Share, DRS Acceptance, and Electricity Price for a Summer Day

| **Metrics** | **Unmanaged Charging: Flat Electricity Prices (Summer)** | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **SAEV (No DRS)** | | | | **SAEV + DRS Acceptance Model** | | | | **SAEV + 100% DRS Acceptance** | | | |
| **Mode Share** | **5%** | **10%** | **15%** | **20%** | **5%** | **10%** | **15%** | **20%** | **5%** | **10%** | **15%** | **20%** |
| **Avg. Response Time (min)** | 5.0 | 4.7 | 4.8 | 4.7 | 4.4 | 4.2 | 4.3 | 4.0 | 4.3 | 4.2 | 4.3 | 4.5 |
| **Avg Person-Trips/ SAV/day** | 24.3 | 24.1 | 23.6 | 23.7 | 26.2 | 26.6 | 26.7 | 26.7 | 26.2 | 26.5 | 26.5 | 25.2 |

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Avg. SAV VMT/day** | 292 | 306 | 303 | 314 | 285 | 302 | 303 | 308 | 284 | 302 | 302 | 300 |
| **%eVMT** | 43.8% | 41.6% | 41.6% | 41.2% | 40.7% | 38.3% | 36.5% | 37.1% | 40.6% | 38.5% | 36.6% | 38.4% |
| **Charging (kWh/SAV/day)** | 80.5 | 86.3 | 83.4 | 101.1 | 79.2 | 89.6 | 90.2 | 101.1 | 79.1 | 89.5 | 90.2 | 93.2 |
| **AVO** | 2.50 | 2.50 | 2.50 | 2.50 | 2.69 | 2.74 | 2.78 | 2.80 | 2.69 | 2.74 | 2.78 | 2.50 |

| **Metrics** | **Managed Charging: Time-of-Use (TOU) Electricity Prices (Summer)** | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **SAEV (No DRS)** | | | | **SAEV + DRS Acceptance Model** | | | | **SAEV + 100% DRS Acceptance** | | | |
| **Mode Share** | **5%** | **10%** | **15%** | **20%** | **5%** | **10%** | **15%** | **20%** | **5%** | **10%** | **15%** | **20%** |
| **Avg. Response Time (min)** | 5.1 | 4.9 | 5.0 | 4.6 | 4.3 | 4.2 | 4.1 | 4.5 | 4.3 | 4.2 | 4.3 | 4.0 |
| **Avg Person-Trips/ SAV/day** | 25.0 | 24.7 | 23.2 | 23.9 | 27.3 | 27.2 | 26.6 | 25.2 | 26.2 | 26.5 | 26.5 | 26.6 |
| **Avg. SAV VMT/day** | 301 | 314 | 304 | 316 | 295 | 308 | 302 | 304 | 284 | 302 | 302 | 309 |
| **%eVMT** | 44.0% | 41.8% | 40.8% | 41.0% | 40.6% | 38.1% | 36.4% | 38.8% | 40.6% | 38.5% | 36.6% | 37.4% |
| **Charging (kWh/SAV/day)** | 80.2 | 90.5 | 91.5 | 101.6 | 79.8 | 90.8 | 90.6 | 94.2 | 79.1 | 89.5 | 90.2 | 101.7 |
| **AVO** | 2.50 | 2.50 | 2.50 | 2.50 | 2.70 | 2.75 | 2.77 | 2.81 | 2.69 | 2.74 | 2.78 | 2.80 |

| **Metrics** | **Managed Charging: Wholesale-Indexed Electricity Prices, Endogenously Derived (Summer)** | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **SAEV (No DRS)** | | | | **SAEV + DRS Acceptance Model** | | | | **SAEV + 100% DRS Acceptance** | | | |
| **Mode Share** | **5%** | **10%** | **15%** | **20%** | **5%** | **10%** | **15%** | **20%** | **5%** | **10%** | **15%** | **20%** |
| **Avg. Response Time (min)** | 5.2 | 4.9 | 5.8 | 4.9 | 4.4 | 4.3 | 4.7 | 4.3 | 4.3 | 4.2 | 4.4 | 4.3 |
| **Avg Person-Trips/ SAV/day** | 24.6 | 24.9 | 21.4 | 23.9 | 26.9 | 26.7 | 26.9 | 26.1 | 27.2 | 26.8 | 26.5 | 25.4 |
| **Avg. SAV VMT/day** | 298 | 311 | 286 | 310 | 296 | 305 | 284 | 279 | 294 | 301 | 302 | 304 |
| **%eVMT** | 44.0% | 40.8% | 41.9% | 40.0% | 41.3% | 41.3% | 37.5% | 37.5% | 40.6% | 37.6% | 37.0% | 36.2% |
| **Charging (kWh/SAV/day)** | 88.5 | 89.0 | 76.4 | 100.3 | 85.3 | 91.0 | 82.2 | 76.4 | 82.6 | 85.2 | 102.2 | 99.4 |
| **AVO** | 2.50 | 2.50 | 2.50 | 2.50 | 2.70 | 2.75 | 2.79 | 2.80 | 2.69 | 2.74 | 2.78 | 2.81 |

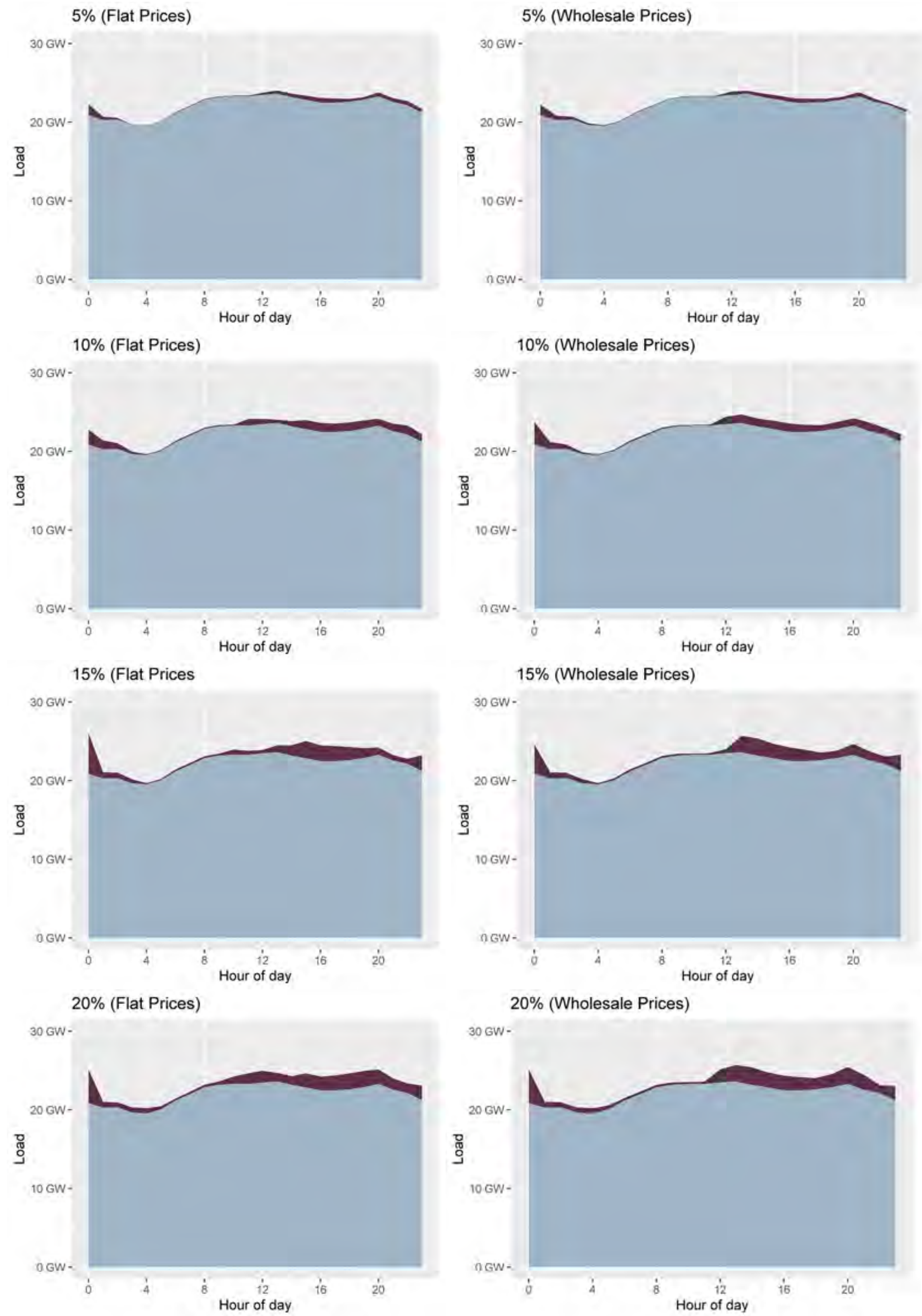
Note: Fleet size does not linearly scale with mode share within the geofence. The ratio of 1 SAEV to residents from 5% to 20% mode share is 1:300, 1:140, 1:105, and 1:75, respectively. Abbreviations: AVO = revenue-miles weighted average vehicle occupancy (accounting for party size), DRS = dynamic ride-sharing (or pooling).

**Table 3**: SAEV Mobility and Vehicle Statistics by Mode Share, DRS Acceptance, and Electricity Price for a Winter Day

| **Metrics** | **Unmanaged Charging: Flat Electricity Prices (Winter)** | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **SAEV (No DRS)** | | | | **SAEV + DRS Acceptance Model** | | | | **SAEV + 100% DRS Acceptance** | | | |
| **Mode Share** | **5%** | **10%** | **15%** | **20%** | **5%** | **10%** | **15%** | **20%** | **5%** | **10%** | **15%** | **20%** |
| **Avg. Response Time (min)** | 6.2 | 5.8 | 6.1 | 5.6 | 5.1 | 4.6 | 4.6 | 4.4 | 5.1 | 4.6 | 4.6 | 6.4 |
| **Avg Person-Trips/ SAV/day** | 22.2 | 22.8 | 21.9 | 22.3 | 24.8 | 25.6 | 26.1 | 25.6 | 24.7 | 25.5 | 26.1 | 19.6 |
| **Avg. SAV VMT/day** | 288 | 305 | 303 | 310 | 284 | 299 | 305 | 306 | 285 | 299 | 304 | 261 |
| **%eVMT** | 46.9% | 44.3% | 43.4% | 43.8% | 43.5% | 40.2% | 38.5% | 39.3% | 43.6% | 40.2% | 38.4% | 42.4% |
| **Charging (kWh/SAV/day)** | 97.9 | 105.7 | 107.0 | 121.6 | 98.1 | 108.3 | 109.6 | 121.8 | 99.4 | 108.4 | 113.5 | 93.2 |
| **AVO** | 2.50 | 2.50 | 2.50 | 2.50 | 2.70 | 2.75 | 2.78 | 2.80 | 2.70 | 2.75 | 2.78 | 2.82 |
| **Metrics** | **Managed Charging: Time-of-Use (TOU) Electricity Prices (Winter)** | | | | | | | | | | | |
| | **SAEV (No DRS)** | | | | **SAEV + DRS Acceptance Model** | | | | **SAEV + 100% DRS Acceptance** | | | |
| **Mode Share** | **5%** | **10%** | **15%** | **20%** | **5%** | **10%** | **15%** | **20%** | **5%** | **10%** | **15%** | **20%** |
| **Avg. Response Time (min)** | 6.2 | 6.1 | 6.2 | 6.0 | 5.3 | 5.1 | 4.7 | 4.8 | 5.1 | 4.6 | 4.6 | 4.9 |
| **Avg Person-Trips/ SAV/day** | 22.6 | 22.4 | 22.8 | 21.9 | 24.8 | 25.0 | 25.3 | 25.2 | 24.7 | 25.5 | 26.1 | 25.1 |
| **Avg. SAV VMT/day** | 291 | 304 | 311 | 310 | 287 | 299 | 299 | 305 | 285 | 299 | 304 | 305 |
| **%eVMT** | 46.7% | 44.6% | 43.7% | 44.4% | 43.8% | 41.2% | 38.9% | 40.3% | 43.6% | 40.2% | 38.4% | 40.4% |
| **Charging (kWh/SAV/day)** | 96.3 | 103.9 | 114.7 | 119.8 | 95.8 | 104.3 | 113.8 | 120.2 | 98.2 | 108.4 | 113.5 | 119.7 |
| **AVO** | 2.50 | 2.50 | 2.50 | 2.50 | 2.70 | 2.75 | 2.78 | 2.82 | 2.70 | 2.75 | 2.78 | 2.82 |
| **Metrics** | **Managed Charging: Wholesale-Indexed Electricity Prices, Endogenously Derived (Winter)** | | | | | | | | | | | |
| | **SAEV (No DRS)** | | | | **SAEV + DRS Acceptance Model** | | | | **SAEV + 100% DRS Acceptance** | | | |

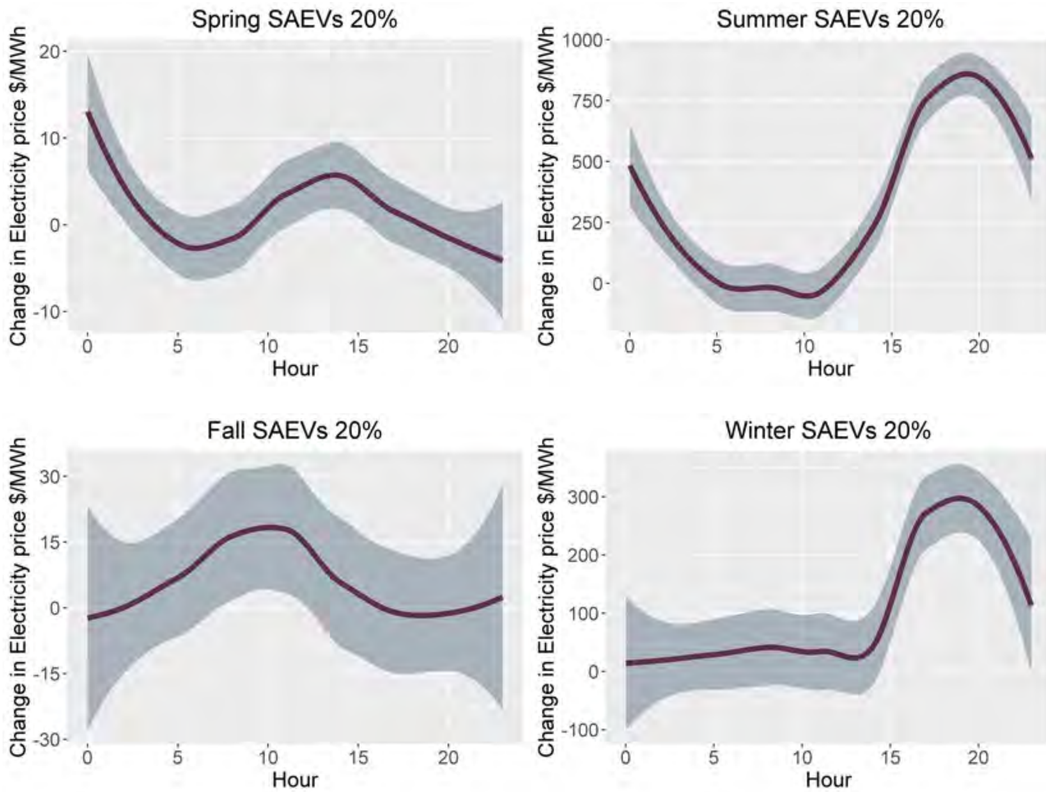
| Mode Share | 5% | 10% | 15% | 20% | 5% | 10% | 15% | 20% | 5% | 10% | 15% | 20% |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Avg. Response Time (min)** | 6.3 | 6.5 | 6.4 | 5.9 | 5.2 | 5.1 | 4.9 | 5.0 | 5.2 | 5.3 | 4.9 | 4.9 |
| **Avg Person-Trips/ SAV/day** | 22.0 | 22.0 | 22.9 | 22.2 | 24.8 | 25.1 | 24.6 | 18.9 | 24.4 | 24.1 | 25.4 | 23.8 |
| **Avg. SAV VMT/day** | 291 | 293 | 300 | 304 | 284 | 293 | 318 | 280 | 285 | 288 | 298 | 283 |
| **%eVMT** | 47.0% | 44.6% | 44.5% | 43.0% | 44.0% | 40.9% | 41.2% | 39.3% | 44.1% | 41.2% | 39.2% | 39.4% |
| **Charging (kWh/SAV/day)** | 106.0 | 100.4 | 107.2 | 117.5 | 102.9 | 105.8 | 125.8 | 111.3 | 103.5 | 103.7 | 112.4 | 103.7 |
| **AVO** | 2.50 | 2.50 | 2.50 | 2.50 | 2.70 | 2.76 | 2.79 | 2.81 | 2.70 | 2.76 | 2.79 | 2.81 |

Note: Fleet size does not linearly scale with mode share within the geofence. The ratio of 1 SAEV to residents from 5% to 20% mode share is 1:300, 1:140, 1:105, and 1:75, respectively. Abbreviations: AVO = revenue-miles weighted average vehicle occupancy (accounting for party size), DRS = dynamic ride-sharing (or pooling).




Note: EV demand (purple) is added to the non-transportation demand (blue). Assuming 100% DRS acceptance.

**Fig. 6**: Change in Illinois' projected 2035 springtime power demand profile due to Chicago SAEVs charging, with and without wholesale prices (right and left panels), across different SAV mode splits.




Note: Y-axis scale differs for each subfigure. LOESS regression-generated mean line in purpose with 95% confidence interval band captures wide estimate from 12 data points for each hour (3 DRS scenarios x 4 feedback-loops per scenario).

**Fig. 7**: Average change in Illinois' projected 2035 hourly wholesale electricity prices due to a fleet of Chicago SAEVs charging by season, assuming 20% mode share.

## 4. DISCUSSION

### 4.1 Load Shape Impacts

The study finds that even at low EV ownership levels, like when 8% and 17% of personal LDVs are EVs in 2035, the unmanaged charging demand from the 20-county Chicago metro can increase the peak demand for the state by up to 2.2%. The added electricity demand depends on weather conditions, with winter having the highest relative increase in peak demand and does not consider EVs outside of this metro. If personal EVs charge between activities or immediately when the driver returns home, assuming chargers are available, the power grid must ramp up generation by 410–760 MW in the winter and 320–580 MW in the summer during the maximum 1-hour peak in electricity demand.

At 20% mode share, a fleet of Chicago SAEVs can increase a spring day's peak hour (at 1 PM) electricity demand by 2,100 MW. However, this additional increase in demand is met with existing energy resources since the grid is designed around the annual peak (usually in winter or summer). In winter, the 20% fleet scenario could increase peak hour demand (at 6 PM) by 1,800 MW (with DRS) to 2,400 MW (without DRS). Since the fleet expects higher energy consumption during winter months and higher energy prices at peak hours, the magnitude of the increase in energy demand during peak hours may be less in winter than during more temperate months. On the other hand, higher non-transportation demand for electricity and the additional demand from SAEVs may lead to a higher marginal increase in wholesale prices than in the spring or fall (Fig. 7). This study finds the marginal increase during temperate months may be as high as +$25/MWh, but summer and winter months may see price increases of $250–$750/MWh for about five hours in the evening (adjusting down in price to forecast transmission expansion).

The new peak from EVs in temperate months could be supplied by existing power plants, as indicated by the negligible increases in hourly wholesale prices **(**Fig. 5). During summer and winter months, smart charging reduces the additional EV demand during expected peak hours, which can defer grid capacity expansion in the short term (see Figs. A.11 and A.12). However, if other sectors increase their electricity demand and there are additional retirements of dispatchable fossil fuel-powered generators, capacity expansion may be warranted, especially within the Chicago region if import/export remains constant. The extent to which smart charging and other electricity efficiency measures defer grid capacity and affect long-term reliability planning is outside the scope of this study.

### 4.2 Effects of Vehicle- and Ride-sharing

The introduction of on-demand urban passenger mobility may motivate some households to give up some or all of their personal vehicles. The household vehicle discontinuance model by Menon et al. (2019) was adopted for the Chicago region and suggests that up to a quarter of its personal vehicle fleet may be retired because of this new mobility option. Encouraging households to scrap old and less efficient vehicles can greatly improve the personal vehicle fleet's efficiency. Governments could encourage households to scrap their oldest and least efficient vehicle, based on registration data at each address, and give usable credits for mobility options like SAEVs, public transit, and micromobility. Although some households receiving this credit will likely have scrapped their vehicle anyway (i.e., the free-rider effect), they still contribute to an important reduction in on-road emissions.

The 8% and 17% personal EV fleet adoption levels would replace over 500 thousand to a million internal combustion engine vehicles with electric vehicles. In contrast, serving 20% of trips in the sprawling 2,360 sq-mile region (see Fig. 3a) is handled with a fleet of 198 thousand SAEVs. As a result of reliable and fast vehicle assignment and dispatch (< 5 min. response times), households let go of over 300–800 thousand personal vehicles. The embodied vehicle emissions savings are equal to the avoided production emissions of personal EVs. Production emissions depend on the carbon intensity of the grid where the battery materials were processed, assembled, and packaged into the battery pack and the vehicle, as well as supply chain transportation emissions. Dillman et al. (2020) found that an average BEV produces 10.8 tons of $CO_2$ equivalent ($CO_{2e}$) during the production phase, while an average gasoline-fueled vehicle produces 6.6 tons of $CO_{2e}$. At 20% mode share, the embodied emissions saved due to shared fleet vehicles relative to 20% personal EV fleet adoption is 11.4 million tons of $CO_{2e}$. Relying on shared vehicles instead of private vehicles in the Chicago metropolitan area is the equivalent of avoiding over a quarter of a million U.S. households' annual carbon footprint (Jones and Kammen, 2011). Shifting people away from personal vehicles to shared vehicles by providing reliable and convenient alternatives is a decarbonization strategy that provides immediate benefits.

And while charging infrastructure has a negligible climate impact relative to in-use emissions (Mulrow and Grubert, 2023), shifting to shared vehicles reduces the number of public (and private) chargers that are needed. This study used a ratio of 5.87 SAEVs per 120 kW fast charger (or port) and assumed a high supply of public chargers to achieve a ratio of 6.22 personal EVs per 50 kW fast charger (at 17% personal EV fleet adoption). At 20% mode share, shared vehicles could avoid adding about 200 thousand public ports across 6–15 thousand public charging stations (depending on station density). The emissions reductions come from installing the cables, wiring, and digital equipment and create other co-benefits, like reducing impervious pavement across communities and the environmental damages from sourcing metallic components in charging equipment.

The study compared the benefits of ride-sharing at two acceptance levels—all customers versus some customers who were willing to share rides—relative to no sharing. Offering a ride-sharing option decreased the average daily VMT for each SAEV by 7 to 15 miles, with only a small difference in benefits between 100% ride-share acceptance and a choice model by Gurumurthy and Kockelman (2020). This reduction in daily VMT per vehicle is significant at scale, since 20% mode share is served with a fleet of 105,000 vehicles. Assuming a BEV emits 190 g $CO_{2eq}$ per mile in Illinois from in-use activity, a fleet offering ride-sharing trips could avoid 40–86 tons of $CO_{2eq}$ every weekday when serving 5% of the region's trips (Energy Systems 2023). Energy consumption on a per-trip basis also declined with DRS (Fig. A.9). If all customers were willing to share rides and the fleet used a directionality-based matching heuristic (Gurumurthy and Kockelman, 2022), the per-trip energy savings may range from 0.27 to 0.52 kWh. At 20% mode share, Chicago's fleetwide energy savings from a single day due to DRS may be as high as 54.6 MWh[10]. Applying long-run marginal emission rates from Cambium scenarios (121.4–301 kg $CO_{2eq}$/MWh), the emissions savings from DRS are on the order of 3.3–8.2 tons of $CO_{2eq}$ per day.

### 4.3 Limitations and Future Research

The unit commitment and economic dispatch power system model, called A-LEAF, was developed from 2015 data. This paper adjusted generator information to simulate 2035 feedstocks, based on NREL's Cambium model with an assumed business-as-usual scenario with no phase-out of production or investment tax credits and no nascent technology. Adjustments included retiring coal and oil-gas steam power plants, but due to modeling limitations the paper did not add utility-scale battery storage, which constitutes 6.1% of the state's projected generation capacity (or 6.28 GW). Despite these limitations, the paper estimated that a 17% Chicago personal EV fleet scenario would increase winter peak demand by at most 760 MW, which could be met by a new gas-fired peaker power plant or utility-scale battery storage systems. Since batteries can shape "intermittent resources into desired output profiles" (Ziegler et al., 2019), fossil-fuel peaker plants may be displaced by short-term battery storage systems bidding lower prices because they stored excess renewable generation. However, the model predicted that electricity demand growth (even absent EV demand) in the summer and winter months would lead to high prices and possibly curtailed

[10] This is equal to the average daily electricity consumption of 1,900 U.S. residential customers, according to 2021 data from the U.S. Energy Information Administration (EIA).

demand, highlighting the need for transmission system expansion, beyond 2015 capacity, to meet decarbonization goals.

Battery storage systems may also be used behind the meter at large charging stations to reduce peak power demand from the local electrical grid, reducing demand charges on the electric bill and potentially even power sharing across chargers. The optimal location and operations of site-specific batteries for SAEVs is a pressing research need. Future research can explore how this technology improves grid reliability by reducing SAEVs' contribution to peak demand at the distribution and bulk power system level.

This paper did not consider energy imports from other states or transmission expansion. The results indicate that these limitations underscore the importance of investing in transmission system expansion and reducing barriers to upgrading or building new transmission infrastructure. To provide insight into projected price changes in the state's wholesale market from Chicago EVs, the paper uses LOESS regression, which can mimic price changes under a limited build-out of transmission capacity because the modeling technique uses a weight function to smooth out large differences in data.

There are several challenges of modeling into 2035, namely estimating the energy increase from the electrification of transportation, building, and industrial sectors. For example, the adoption of heat pumps and electrification of space heating will further increase the region’s winter baseline demand curve, which may overlap with a higher EV load due to battery performance issues in colder weather. Although wind generation performance is above the yearly median in the winter months in Illinois, solar generation capacity is lower. Potential shifts in peak demand from summer to winter will require power grid expansion planning that considers the region’s seasonally adjusted VRE generation capacity, which is not within the scope of this paper.

This paper acknowledges the difficulty of fully capturing the variability in VRE output by hour and across days, as well as the variability in non-transportation load across days within the season. Future work could use more characteristic days, as well as extreme winter and summer days, to develop a more comprehensive view of the transition to a clean transportation and power system. Nonetheless, the paper concludes that the results indicate the value of using EVs to solve problems caused by EVs (via smart charging), especially during summer and winter peak hours.

Finally, there are several other assumptions in this study that may impact results, including uniform plug density at fleet-owned charging stations and the assumption of 50 kW public chargers. Future work could use optimization-based charging station siting algorithms and include heterogeneity in public chargers to develop more behaviorally realistic models for charging station selection based on one's value of travel time, trip purpose, and flexibility in the next activity.

## 5. CONCLUSION

This study aimed to investigate the impacts of vehicle electrification and new mobility technology, like shared autonomous electric vehicles (SAEVs), on the power grid using an integrated transportation-power system model. The power system model examined shifts in energy demand and wholesale power prices in Chicago due to adoption levels of EVs, seasonal effects on energy consumption, and electricity price rates. The results showed that at relatively low EV penetration levels (8% to 17%), an increase in demand may require at most 1 GW of additional generation capacity, and the state's transition to intermittent VREs and phase-out of coal power plants will likely not substantially increase wholesale power prices due to unmanaged personal EV charging at peak hours.

However, the simulation results found that wholesale power prices will increase during winter (+$100/MWh) and summer (+$300/MWh) peak hours due to higher energy fees and steep congestion fees on the 2015-era transmission system. Even without this new demand for electricity from EVs, the model results indicate that prices would still spike due to inadequate transmission capacity to send power from VRE sources to demand centers like Chicago.

Additionally, a fleet of SAEVs serving 20% of Chicago's regional trips is more energy efficient and avoids several hundred thousand vehicles' embodied emissions, but the higher daily use of fleet vehicles and reliance on fast charging equipment increases electricity demand and thus energy prices. Although a fleet paying wholesale prices uses these price signals to reduce electricity demand during peak hours, spreading charging demand in hours before and after the baseline peak creates new "ridges" in energy demand, which raises prices for all.

The modeling framework and relative scale of the findings are relevant to both transportation and power system audiences. The results reveal the pathways that result in expected emission and cost reductions, indicating that investing in transmission lines can reduce congestion fees in wholesale markets and address spatiotemporal imbalances in energy supply and demand. At the same time, some energy customers, like EV fleets, could alter their charging behavior to avoid adding to peak demand. Finally, ride-sharing with electric vehicles avoids new embodied emissions from personal vehicles and charging equipment and can reduce energy consumption on a per-trip basis, even with high empty travel between passengers and fleet-owned maintenance and charging depots.

## 6. CRediT AUTHORSHIP STATEMENT

**Matthew D. Dean:** Conceptualization, Methodology, Software, Formal Analysis, Writing – original draft, Visualization. **Krishna Murthy Gurumurthy:** Conceptualization, Methodology. **Zhi Zhou:** Conceptualization, Software. **Omer Verbas:** Software. **Taner Cokyasar:** Software. **Kara M. Kockelman:** Supervision. All authors reviewed and approved the final version of the manuscript.

## 7. DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this study.

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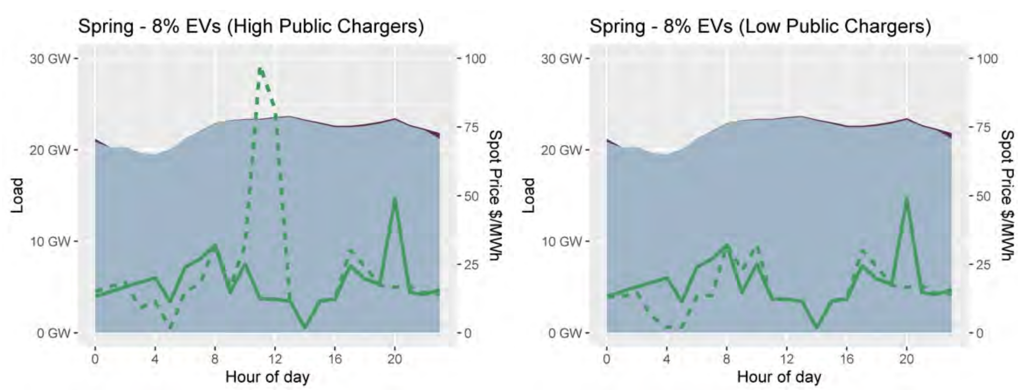
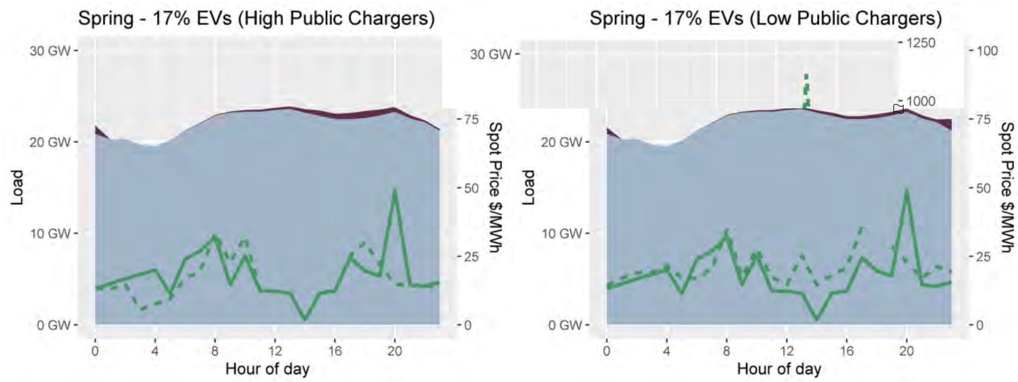
## 9. APPENDIX

### 9.1 Personal Light-duty Vehicle Electrification

Personal light-duty EV adoption levels and charging infrastructure are projected using estimates from the National Renewable Energy Laboratory tool, Electric Vehicle Infrastructure – Projection (EVI-Pro).

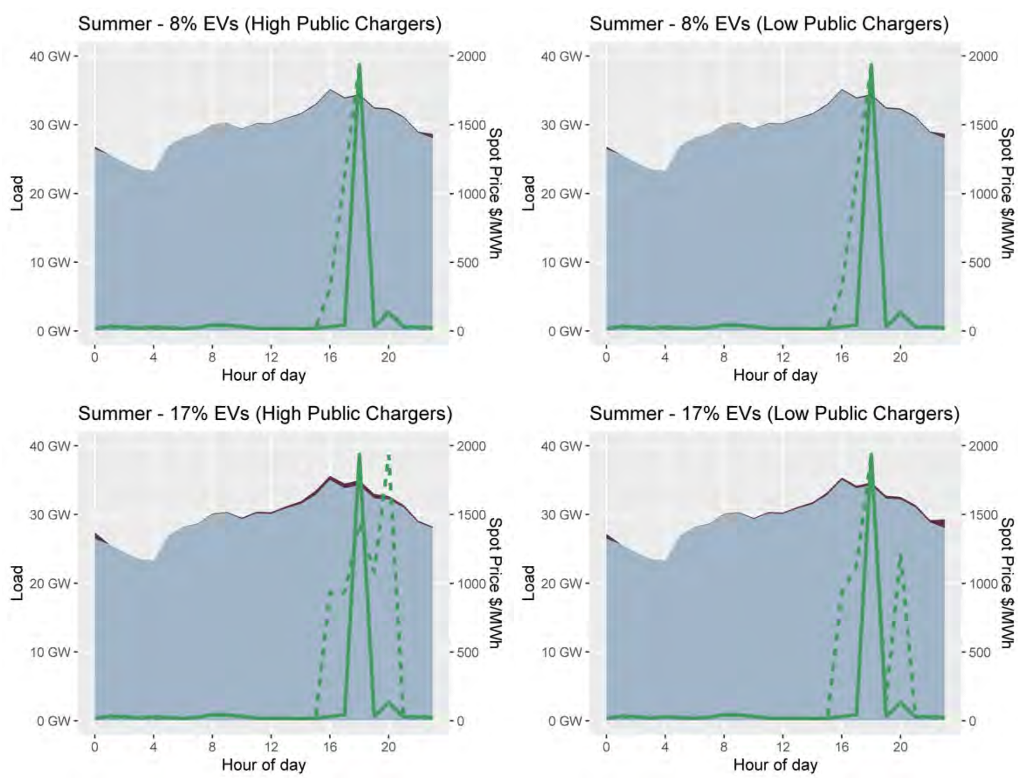
The effect of personal EV charging demand is studied across the four seasons at two fleet share adoption levels and public charging infrastructure scenarios. Fig. A.1 adds the change in market clearing price at the state level due to this shift in demand to the plots in Fig. 4 for a characteristic spring day. The previous, or “baseline,” price line is in solid green while the new prices are shown with a dotted green line. Figs. A.2 to A.4 show similar plots for summer, fall, and winter seasons, respectively.





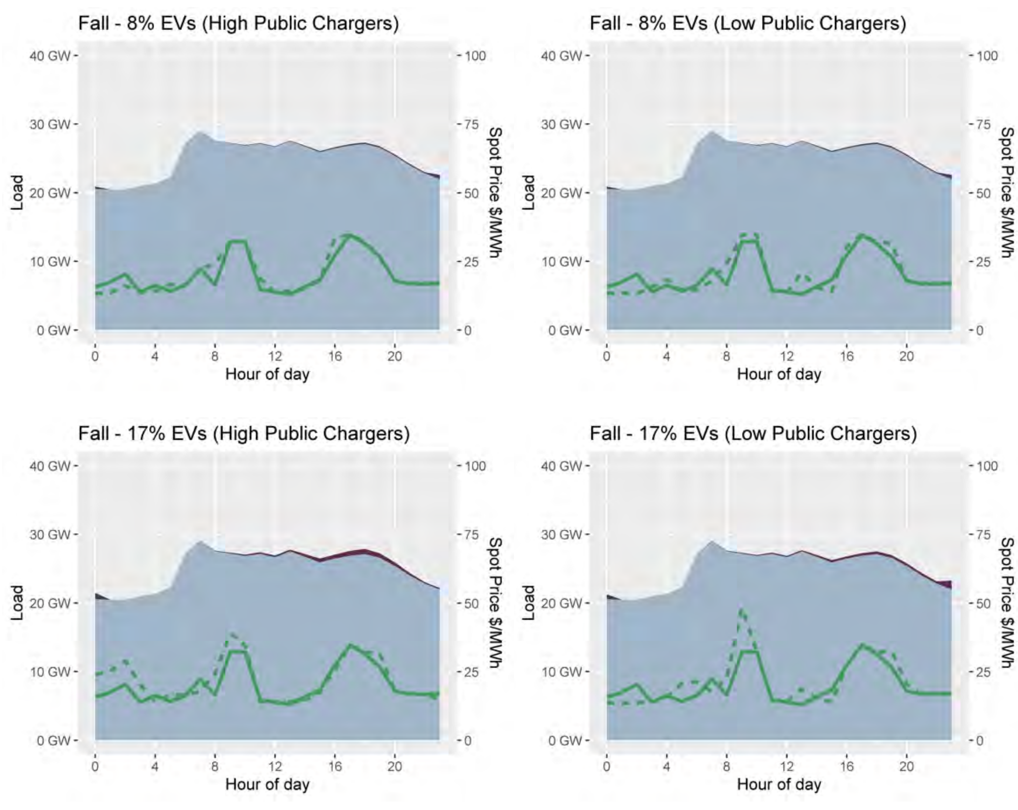

Note: EV demand (purple) is added to the baseload demand (blue) in the area plot. The market clearing price from the baseload demand (solid green) is compared to the price with the additional EV demand (dashed green) in the line plot.

**Fig. A.1**: Change in Illinois' projected spring 2035 power demand curve overlaid with the change in the market clearing price due to Chicago's unmanaged personal EVs charging at 8% vs 17% household-EV fleet adoption and charging station density levels.



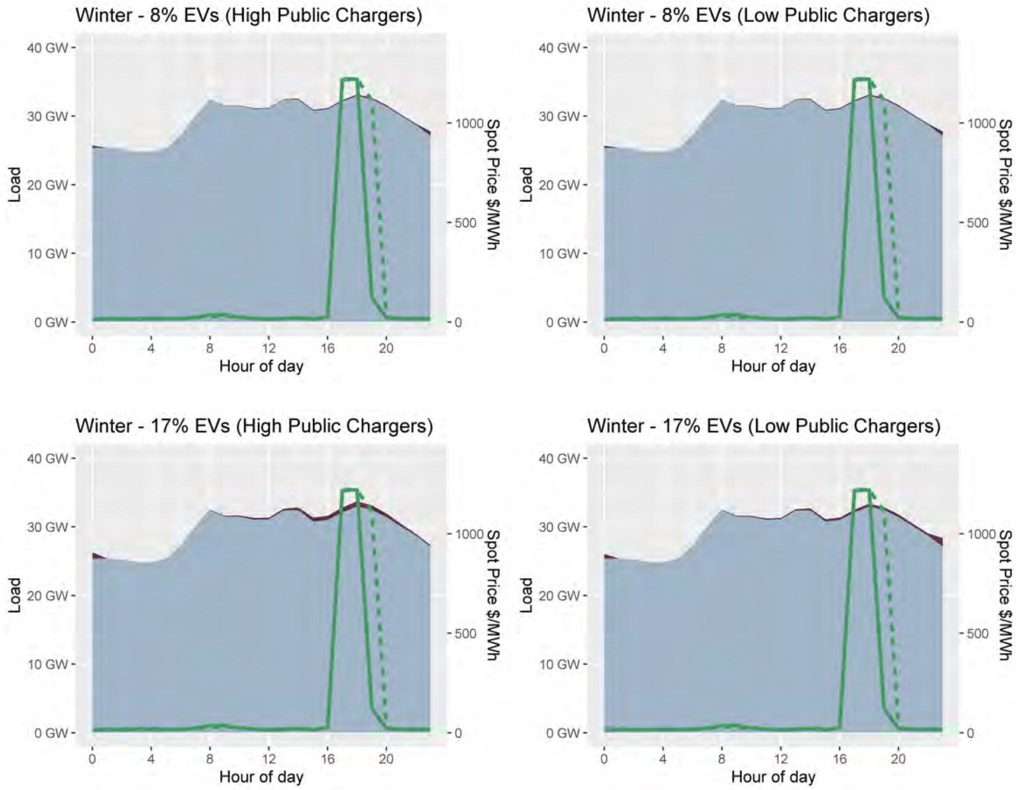

Note: EV demand (purple) is added to the baseload demand (blue) in the area plot. The market clearing price from the baseload demand (solid green) is compared to the price with the additional EV demand (dashed green) in the line plot.

**Fig. A.2**: Change in Illinois' projected summer 2035 power demand curve overlaid with the change in the market clearing price due to Chicago's unmanaged personal EVs charging at different EV fleet adoption and charging station density levels.




Note: EV demand (purple) is added to the baseload demand (blue) in the area plot. The market clearing price from the baseload demand (solid green) is compared to the price with the additional EV demand (dashed green) in the line plot.

**Fig. A.3**: Change in Illinois' projected fall 2035 power demand curve overlaid with the change in the market clearing price due to Chicago's unmanaged personal EVs charging at different EV fleet adoption and charging station density levels.




Note: EV demand (purple) is added to the baseload demand (blue) in the area plot. The market clearing price from the baseload demand (solid green) is compared to the price with the additional EV demand (dashed green) in the line plot.

**Fig. A.4**: Change in Illinois' projected winter 2035 power demand curve overlaid with the change in the market clearing price due to Chicago's unmanaged personal EVs charging at different EV fleet adoption and charging station density levels.

### 9.2 Power System Projections for Future-Year 2035

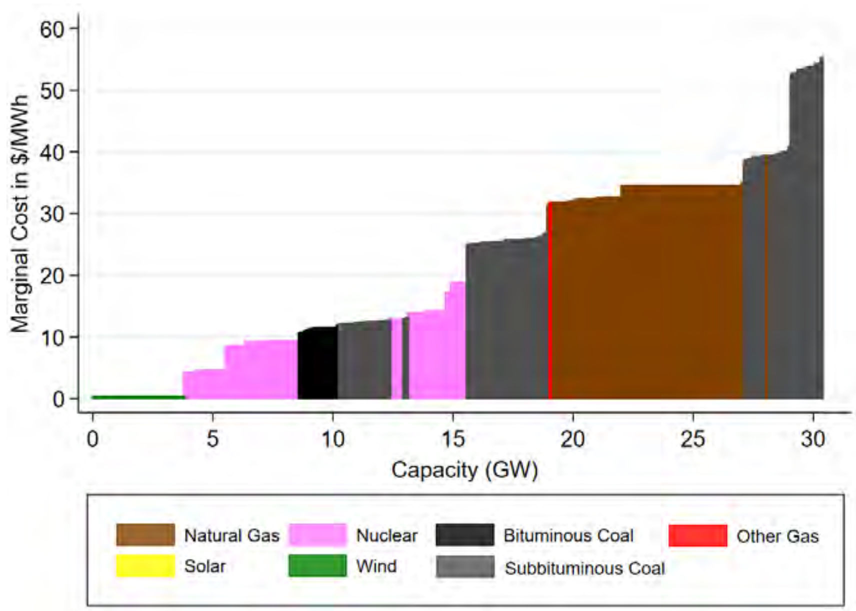
The demand for electricity is set to rise given population growth, economic outlooks, and the electrification of end-uses (e.g., transportation vehicles, heating and cooling equipment, and appliances). Instead of applying a uniform growth factor that does not account for additional heating or cooling demands by season, the authors opted to use estimated generation data from NREL's Cambium tool. The estimated annual growth rate between 2015 and 2035 was obtained and averaged by month and hour for all 8,760 hours of the year (Fig. A.5). Since electricity generation must match demand at all hours, the growth factors are appropriate even if transmission losses overestimate demand. While total demand is higher in the evening hours in the summer months, the growth factor is higher in the morning hours, which might capture the pre-cooling load-shifting behavior that is increasingly common with programmable air conditioning systems.

Hour of the Day

| Month of the Year | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1.17 | 1.19 | 1.19 | 1.17 | 1.15 | 1.12 | 1.12 | 1.15 | 1.22 | 1.22 | 1.19 | 1.19 | 1.21 | 1.26 | 1.26 | 1.21 | 1.20 | 1.19 | 1.17 | 1.16 | 1.15 | 1.14 | 1.15 | 1.15 |
| 2 | 1.14 | 1.14 | 1.13 | 1.13 | 1.12 | 1.11 | 1.12 | 1.14 | 1.17 | 1.20 | 1.19 | 1.22 | 1.29 | 1.34 | 1.32 | 1.23 | 1.20 | 1.18 | 1.16 | 1.15 | 1.14 | 1.14 | 1.15 | 1.14 |
| 3 | 1.23 | 1.23 | 1.22 | 1.17 | 1.13 | 1.11 | 1.12 | 1.19 | 1.23 | 1.24 | 1.24 | 1.25 | 1.28 | 1.32 | 1.32 | 1.28 | 1.23 | 1.22 | 1.18 | 1.15 | 1.14 | 1.15 | 1.18 | 1.21 |
| 4 | 1.19 | 1.19 | 1.18 | 1.14 | 1.12 | 1.13 | 1.21 | 1.23 | 1.25 | 1.26 | 1.28 | 1.29 | 1.32 | 1.33 | 1.33 | 1.29 | 1.24 | 1.22 | 1.19 | 1.16 | 1.15 | 1.15 | 1.17 | 1.17 |
| 5 | 1.16 | 1.16 | 1.16 | 1.13 | 1.13 | 1.18 | 1.26 | 1.28 | 1.29 | 1.28 | 1.26 | 1.24 | 1.24 | 1.25 | 1.25 | 1.23 | 1.23 | 1.21 | 1.17 | 1.15 | 1.13 | 1.13 | 1.15 | 1.14 |
| 6 | 1.15 | 1.16 | 1.16 | 1.15 | 1.18 | 1.29 | 1.32 | 1.31 | 1.30 | 1.23 | 1.18 | 1.17 | 1.17 | 1.17 | 1.18 | 1.19 | 1.20 | 1.19 | 1.16 | 1.14 | 1.12 | 1.12 | 1.13 | 1.13 |
| 7 | 1.14 | 1.15 | 1.14 | 1.12 | 1.12 | 1.30 | 1.35 | 1.33 | 1.30 | 1.22 | 1.14 | 1.14 | 1.14 | 1.14 | 1.15 | 1.17 | 1.18 | 1.17 | 1.15 | 1.13 | 1.12 | 1.11 | 1.11 | 1.12 |
| 8 | 1.12 | 1.12 | 1.12 | 1.11 | 1.10 | 1.19 | 1.39 | 1.38 | 1.38 | 1.33 | 1.23 | 1.16 | 1.15 | 1.15 | 1.16 | 1.18 | 1.20 | 1.19 | 1.16 | 1.13 | 1.12 | 1.11 | 1.12 | 1.11 |
| 9 | 1.15 | 1.15 | 1.13 | 1.11 | 1.10 | 1.11 | 1.30 | 1.38 | 1.36 | 1.30 | 1.24 | 1.21 | 1.20 | 1.21 | 1.19 | 1.20 | 1.21 | 1.20 | 1.17 | 1.15 | 1.13 | 1.13 | 1.13 | 1.14 |
| 10 | 1.19 | 1.20 | 1.20 | 1.21 | 1.17 | 1.12 | 1.24 | 1.31 | 1.24 | 1.22 | 1.21 | 1.24 | 1.24 | 1.29 | 1.27 | 1.21 | 1.23 | 1.22 | 1.18 | 1.16 | 1.15 | 1.15 | 1.15 | 1.17 |
| 11 | 1.20 | 1.19 | 1.19 | 1.17 | 1.14 | 1.12 | 1.13 | 1.28 | 1.34 | 1.26 | 1.23 | 1.25 | 1.32 | 1.34 | 1.24 | 1.20 | 1.21 | 1.20 | 1.17 | 1.15 | 1.14 | 1.14 | 1.15 | 1.18 |
| 12 | 1.21 | 1.21 | 1.21 | 1.18 | 1.16 | 1.13 | 1.13 | 1.15 | 1.20 | 1.17 | 1.15 | 1.17 | 1.18 | 1.20 | 1.19 | 1.19 | 1.21 | 1.20 | 1.17 | 1.15 | 1.14 | 1.13 | 1.15 | 1.18 |

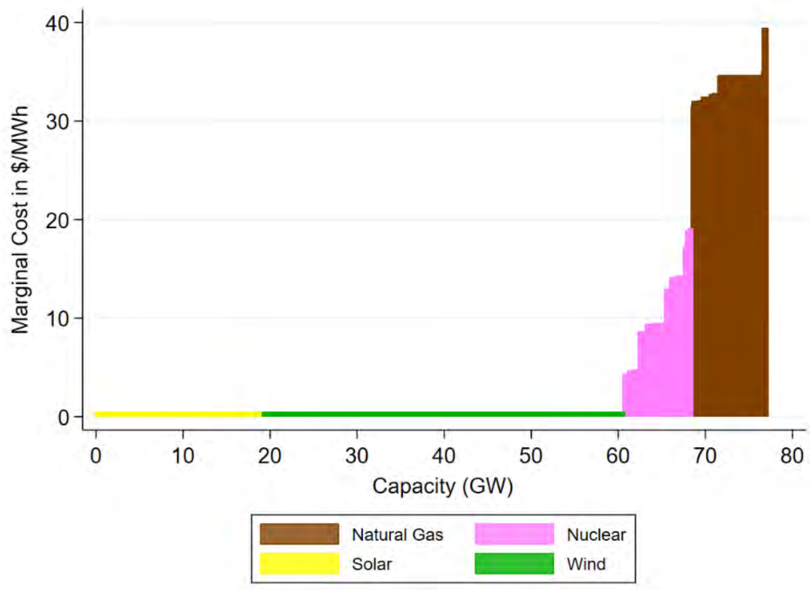
**Fig. A.5**: Predicted electricity demand growth factors year-over-year for Illinois (by hour of day and month of year, from NREL's Cambium tool).

Power plants are dispatched in order of the marginal cost of producing power (i.e., merit order). The baseline power system in 2015 is plotted in Fig. A.6, and the estimated 2035 system is plotted in Fig. A.7. To account for a decarbonizing grid, where renewable resources provide a higher share of electricity and coal is retired, solar and wind capacity was uniformly increased across all generation nodes to achieve future-year generation mixes, rather than a region-specific basis to simulate additions based on land availability and land use regulations. Annual long-run marginal emission rates were obtained for 2035 from Cambium's 95% decarbonization by 2050 scenario (301 kg $CO_{2e}$/MWh) and for 2030 from Cambium's 100% decarbonization by 2035 scenario (121.4 kg $CO_{2e}$/MWh) to obtain an upper and low bound, respectively, on estimating electric-sector emission savings from SAEVs versus personal EVs (Gagnon et al., 2023).




Note: Solar is not plotted due to its small generation capacity in 2015 but should appear to the left of wind.

**Fig. A.6**: Merit order curve for Illinois power grid in 2015.




Note: This plot ignores distributed rooftop solar, biofuel, and battery storage resources.

**Fig. A.7**: Predicted merit order curve for Illinois power grid in 2035.

The seasonal capacity factors for utility-scale wind and solar in Illinois are shown in Table A.1 (U.S. EIA, 2022b).

**Table A.1:** Capacity Factors for Utility-Scale Wind and Solar.

| | Month of the Year | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Source | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
| Wind | 33.8 | 39.7 | 46.8 | 39.6 | 34.0 | 24.2 | 15.0 | 17.1 | 31.5 | 33.2 | 46.0 | 45.9 |
| Solar | 7.3 | 11.7 | 20.3 | 24.5 | 23.5 | 27.5 | 24.4 | 26.6 | 24.5 | 15.0 | 14.2 | 10.0 |

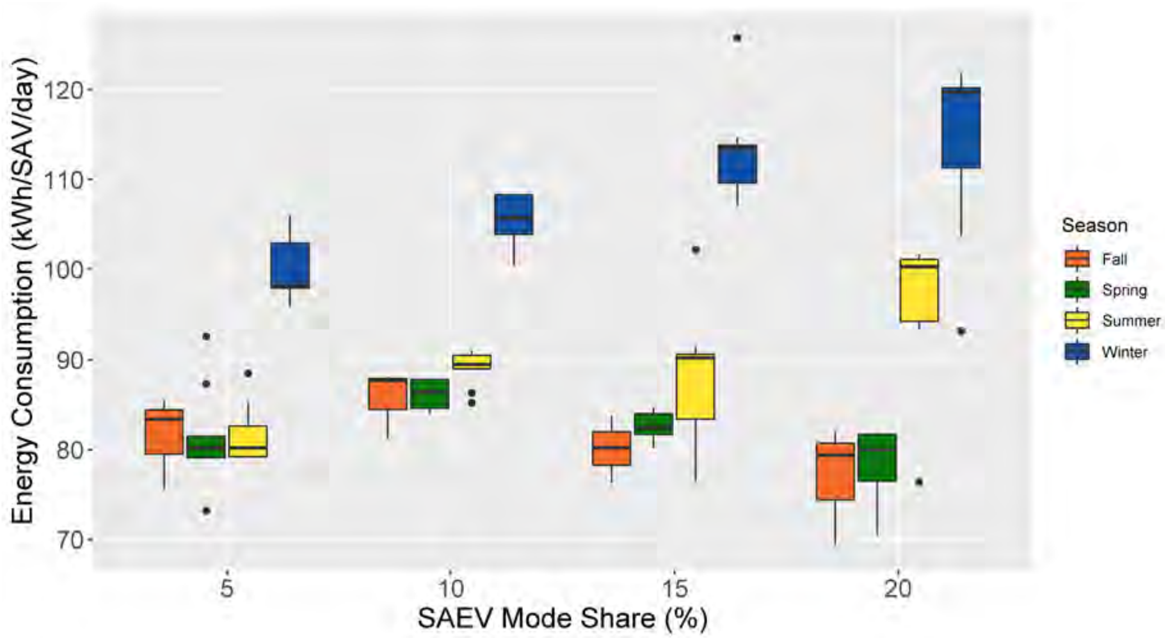
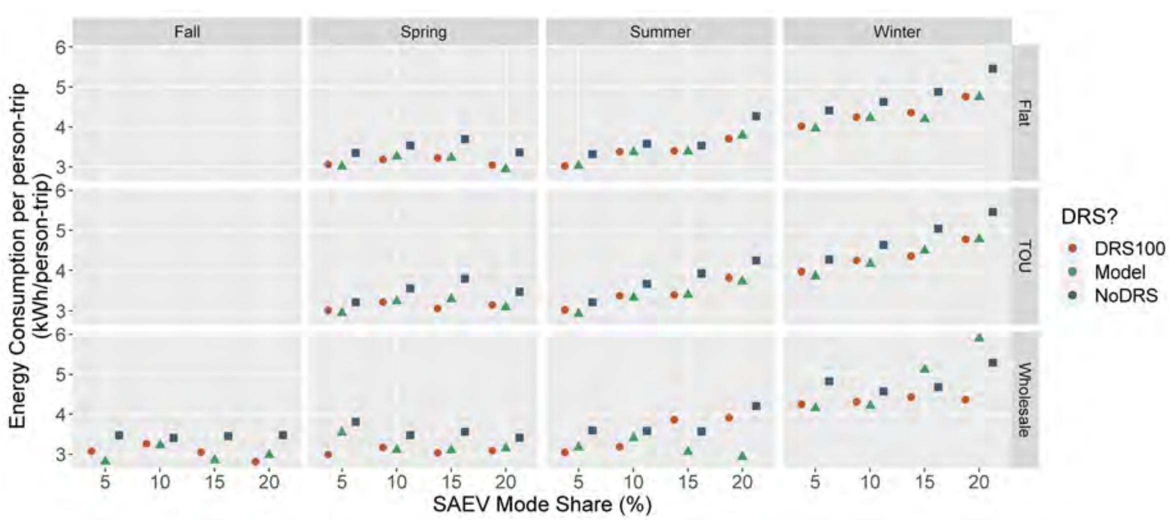



**Fig. A.8**: Daily energy consumption per SAEV by mode share and season.




Note: Spring and fall have no energy consumption multiplier due to auxiliary loads and normal battery performance in temperate weather, thus flat and TOU rates show no variability in fall.

**Fig. A.9**: Energy consumption per person-trip by season, energy price, and DRS scenario.

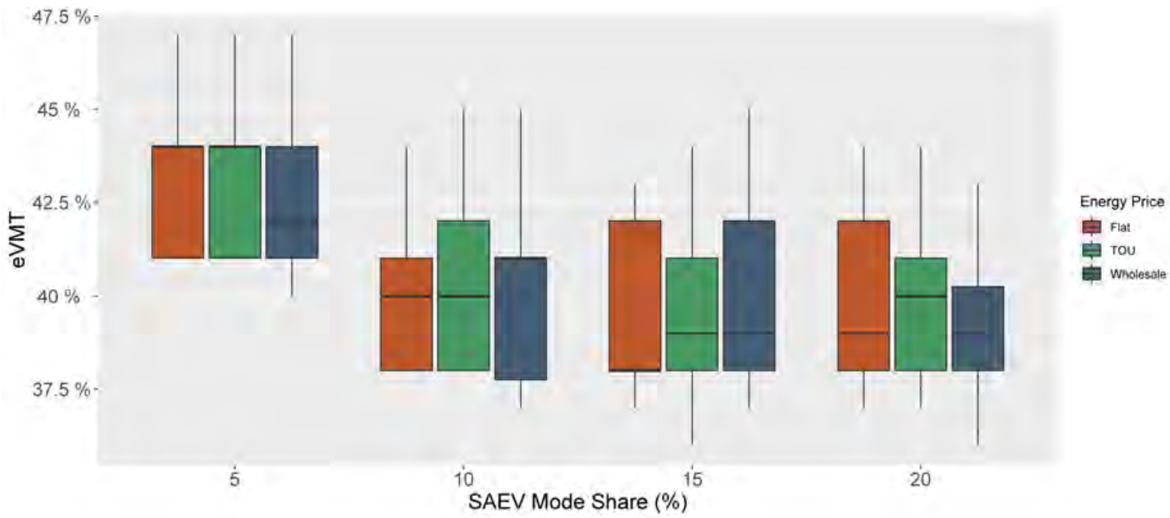



**Fig. A.10**: Empty travel by mode share and energy price.

Smart charging using price signals is most effective when fleets pay wholesale-indexed energy rates. Fig. A.11 displays the expected change in statewide electricity prices in 2035 due to a fleet of SAEVs in Chicago serving 20% of daily trips. The existing rise in prices is already accounted for and any large increase reflects an extension of already high prices. Wholesale-indexed rates can avoid an extra $50/MWh increase in the evening peak. Although TOU rates can lead to a decrease in prices in the morning hours the fleet's charging behavior with this structure leads to higher increases in state electricity prices than flat rates.

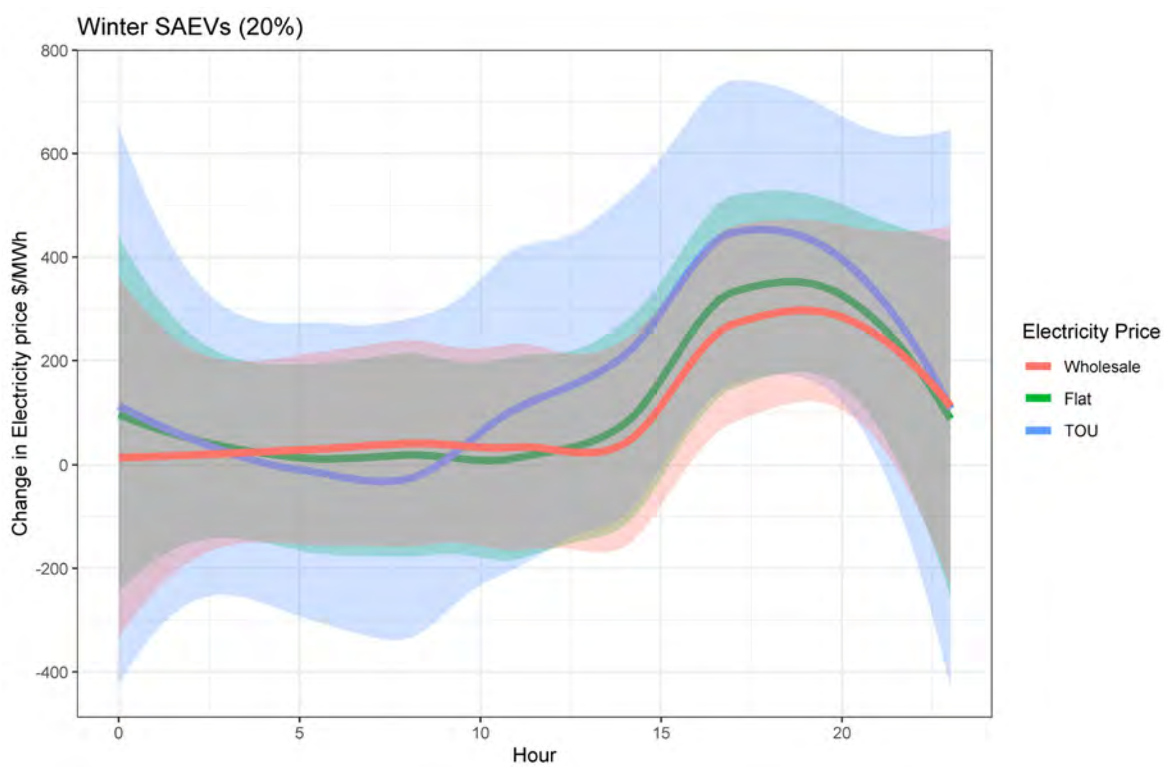


**Fig. A.11**: Change in state electricity prices due to additional electricity demand from a Chicago SAEV serving 20% of daily trips in the winter.

Similarly, Fig. A.12 displays the change in state electricity prices for the summer months. Wholesale-indexed rates are only marginally better than TOU or flat rates during the afternoon through evening hours. If fleets ignore energy prices they may end up charging more of their fleet vehicles overnight when trip demand is lower. However, unmanaged charging at scale may lead to higher increases for all energy customers (+$300/MWh).

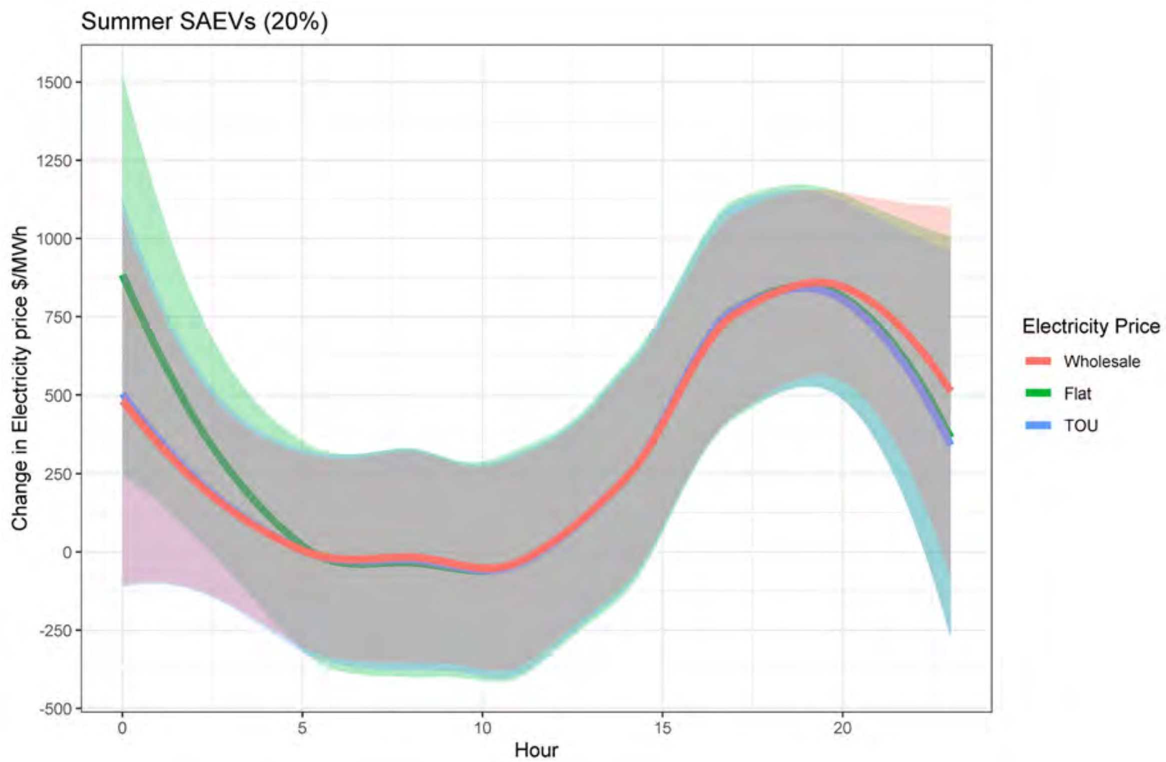



**Fig. A.12**: Change in state electricity prices due to additional electricity demand from a Chicago SAEV serving 20% of daily trips in the summer.

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