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Reduced grid operating costs and renewable energy curtailment with electric vehicle charge management

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ABSTRACT

Widespread adoption of plug-in electric vehicles (PEVs) and renewable energy (RE) can help to jointly decarbonize the transportation and electricity sectors. Previous studies indicate strategies to manage PEV charging facilitate integration of RE into electricity grids, but the value of such strategies at scale is unclear because electricity markets and PEV charging have been inadequately represented together. This analysis focuses on the state of California in 2025, and improves on prior work by linking high-resolution mobility and grid dispatch models to quantify the value of managed charging under a 50% RE grid and PEV adoption scenarios up to California's 5 million vehicle target. Even after accounting for practical charging and grid constraints, 0.95 to 5 million "smart" charging PEVs avoid $120 to $690 million in California grid operating costs annually (up to 10% of total costs) and reduce RE curtailment up to 40% relative to unmanaged PEVs. Overnight time-of-use (TOU) charging provides similar cost savings but increases curtailment. Both of these managed strategies defer system infrastructure expansion at the 5 million PEV deployment. The results suggest residential smart charging complemented by TOU tariffs with added daytime periods are policies with most potential to advance California's dual PEV and RE goals.

1. Introduction

The number of plug-in electric vehicles (PEVs) on the road, including both fully battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs), has surpassed 3 million worldwide and is growing steadily (International Energy Agency, 2018). Widespread PEV adoption can enable oil independence (Kintner-Meyer et al., 2007), save on fuel costs for drivers (Dumortier et al., 2015), and lower greenhouse gas (GHG) emissions (Ramachandran and Stimming, 2015), among other benefits. Increasing the share of renewable energy (RE) on the power grid in parallel with vehicle electrification generates a cleaner PEV fuel source and thus accelerates GHG emissions reductions (Williams et al., 2012).

However, shifts to a PEV-dominant vehicle fleet and decarbonized generation mix can challenge grid operations. PEV charging typically begins as soon as a driver arrives home from their evening commute and plugs in the vehicle (Muratori, 2018; Sheppard et al., 2017). This charging load often coincides with the power system's peak demand (Muratori, 2018) and increases ramping needs and costs through the dispatch of inefficient and expensive fossil generators. High penetrations of intermittent wind and solar photovoltaic (PV) sources may also increase the need for curtailment or require other strategies to mitigate imbalances between energy supply and demand (Nelson and Wisland, 2015; California Independent System Operator, 2016; Bird et al., 2014).

California is an ideal region to study impacts of and interactions between an electrified fleet and a high-RE grid because both transitions are already underway and will likely accelerate in the next decade. In 2012, the Governor set a state goal of 1.5 million zero emission vehicles (ZEVs)—which include hydrogen fuel cell electric vehicles (FCEVs)[2] and PEVs—by 2025, and the goal has since been extended to 5 million vehicles by 2030 (Brown, 2012; Governor Brown Takes Action to Increase Zero-Emission Vehicles). With about 500,000 PEVs currently on the

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[2] We do not evaluate the impact of FCEVs in this analysis, because they comprise a much smaller share of ZEVs in California (Advanced Technology Vehicle Sales Dashboard, 2018).

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road, California has about half of the U.S.'s PEVs and about 15% of the world's PEVs (International Energy Agency, 2018; Advanced Technology Vehicle Sales Dashboard). The state has charging infrastructure investments (Merchant, 2018; Volkswagen California ZEV, 2017; Mulkern, 2016), growing vehicle model options (Vlasic and Boudette, 2017; BBC News 2017; EV Showroom), and other policy support (CVRP Rebate Statistics, 2016; Zero Emission Vehicle (ZEV) Program; Carpool Stickers) to help achieve the vehicle targets. For the power sector, through a Renewable Portfolio Standard (RPS), California mandated in 2015 that 50% of electricity consumption come from RE sources by 2030 (De León, 2015). In 2018, the 50% RPS requirement was accelerated to 2026, on the way to 60% RPS by 2030 and an ultimate goal of 100% zero-carbon resources by 2045 (De León, 2018).

Prior research suggests that if PEV charging is managed, the vehicles could both alleviate peak loads and serve as a complementary grid resource to integrate more RE (Richardson, 2013). Time-of-use (TOU) charging and "smart" charging are two such managed charging strategies that have been commonly studied and piloted (Richardson, 2013; Load Research Report, 2017; Kaluza et al., 2017).[3] Under TOU charging, drivers are incentivized by a lower electricity rate to charge during off-peak hours, often pre-programming the start time through the charger or PEV. With smart charging, PEVs usually participate in a demand response program whereby an aggregator (utility or third-party) remotely controls active charging to be on or off through the charger or vehicle software. The aggregator shifts charging to times that provide most grid benefit, when prices are low and/or RE is abundant, bidding the total flexible load of many PEVs into the wholesale electricity market.

To plan for high adoption rates of both PEVs and RE, policymakers need an understanding of the impacts and benefits that managed charging, also known as Vehicle-Grid Integration (VGI), can realistically provide at scale. However, California's related policy guidance lacks consensus on the systemwide value of VGI, calling for improved quantification to inform program design, investments, and business models (California Independent System Operator, 2014). Accordingly, the purpose of this research is to assess the impacts on California's planned 2025 power system, including operating cost and RE curtailment, resulting from unmanaged, TOU, and smart charging at various PEV adoption levels. Because utilities are ahead of schedule to meet their 2030 RPS goal (California Energy Commission, 2018), and the targets have been since been expedited, we evaluate the California grid in 2025 with a 50% RPS.

Bulk power system impacts have been studied in numerous contexts, varying in results depending on a system's generation portfolio, PEV adoption level, and charging schemes (Richardson, 2013). For example, in several geographies studies including (Foley et al., 2013; Calnan et al., 2013; Weis et al., 2014; Madzharov et al., 2014; Loisel et al., 2014; Coignard et al., 2018; Babrowski et al., 2014; Dallinger et al., 2013; Forrest et al., 2016; Wolinetz et al., 2018; Dallinger and Wietschel, 2012) compare various outcomes of unmanaged and managed charging strategies, finding that overall, managed charging leads to lower costs, reduced emissions, and higher utilization of RE. Some studies (Foley et al., 2013; Loisel et al., 2014; Babrowski et al., 2014; Forrest et al., 2016) use dispatch models to estimate generation with PEVs while others (Kiviluoma and Meibom, 2011; Calnan et al., 2013; Weis et al., 2014; Wolinetz et al., 2018) also plan generation portfolios with consideration of PEV charging load profiles. Prior analyses (Lund and Kempton, 2008; Foley et al., 2013; Calnan et al., 2013; Weis et al., 2014; Dallinger et al., 2013; Forrest et al., 2016; Dallinger and Wietschel, 2012; Eser et al., 2018) examine the interaction between PEV charging and RE resources, showing that PEV charging schemes can lower RE curtailment. Other examples (Coignard et al., 2018; Forrest et al., 2016) compare PEV flexibility value with that of stationary storage.

Although VGI has been analyzed widely, much of the existing literature has either simplified the representation of charging strategies or grid dispatch. Without first robustly accounting for mobility (i.e. drivers' travel demands), charging infrastructure, and drivers' preferences, the availability of grid services provided by managed PEVs could be overestimated (Sheppard et al., 2017; Wolinetz et al., 2018; Dallinger and Wietschel, 2012; Sovacool et al., 2018; Xu et al., 2018). For example, some analyses (Kiviluoma and Meibom, 2011; Lyon et al., 2012; Weis et al., 2014; Forrest et al., 2016) aggregate travel patterns inferred from travel surveys to characterize PEV charging. Because this approach cannot account for individuals' mobility constraints and assumes unlimited chargers, charging demands could be misrepresented. Previous work (Sheppard et al., 2017) demonstrates significant differences in timing and magnitude of loads when PEVs have access to unlimited chargers versus to the actual limited number of installed chargers; when chargers are abundant, charging is evenly distributed between morning and evening peaks, whereas charging occurs primarily in the evening with limited chargers. Studies including (Lund and Kempton, 2008; Kiviluoma and Meibom, 2011; Forrest et al., 2016) assume PEVs park at certain locations and times, presuming they are plugged into a VGI-enabled charger (Eser et al., 2018), thereby potentially overestimating availability by ignoring actual charger scarcity. Secondly, neglecting to model PEV loads endogenously within the dispatch of a RE-dominated wholesale electricity market may skew the demand for, and therefore the value of their grid services. (Lund and Kempton, 2008) uses an input-output method to model the system, (Lyon et al., 2012) conducts a macro-level supply-demand matching analysis, and (Coignard et al., 2018) uses non-PEV loads and RE profiles as the only grid-related model inputs. These approaches may inflate VGI value by ignoring electricity market dynamics and competing sources of flexibility in the dispatch such as stationary storage and gas generation.

As a result, the existing literature lacks realistic estimates of managed charging services, and their value in a power system such as California's with a high share of RE. Building on other studies, we compare grid impacts from managed and unmanaged PEVs, while representing constrained infrastructure, mobility, and the dynamic electricity market. We first use a novel agent-based travel behavior model—Behavior, Energy, Autonomy, Mobility (BEAM) (Sheppard et al., 2017; BEAM)—that represents PEV drivers' charging choices given constrained infrastructure. Agent-based models are seen as best to capture neglected traveler behaviors (Daina et al., 2017), and are distinguished by: 1) simulating individual drivers (agents) in a virtual transportation system with a detailed road network and 2) dynamically representing agents' behavior contingent on the virtual environment and each other. Agents' choices are based on empirical studies of human behavior. We then link the outputs of BEAM with PLEXOS, a unit commitment and economic dispatch model, to simulate PEV charging within the grid at an hourly resolution. PLEXOS is an industry-standard software developed by Energy Exemplar and used by system operators worldwide (Energy Market Modelling) for simulating grid operations, including to model VGI (Foley et al., 2013; Calnan et al., 2013; Gopal et al., 2015; Wagner and Reedman, 2010). PLEXOS uses mixed integer optimization to minimize the cost of meeting load given physical (e.g. generator capacities, transmission limits) and economic (e.g. fuel prices, start-up costs) parameters. Through this integration of BEAM and PLEXOS, we compare unmanaged charging to smart and TOU charging under four scenarios of California PEV adoption ranging from 0.95 million (4% of the current California automobile fleet (Top 10 DMV Facts)) to 5 million PEVs (20% of the current fleet).

[3] Vehicle-to-grid (V2G) charging is also a managed charging strategy. V2G allows for bi-directional power flow between the vehicle and grid such that the vehicle can both discharge energy to the grid and charge from the grid. We do not model bi-directional power flow from the vehicle to the grid (V2G) or participation in ancillary services (Kempton and Tomić, 2005), because of the low marginal benefits and greater complexity and transaction cost of these strategies relative to just one-directional charging (Peterson et al., 2010), (Alstone et al., 2017).

Section 2 describes the two models and their linkage, and the methodology and data for each PEV charging scenario. Sections 3 and 4 discuss the 2025 California hourly and annual results, conclusions, and policy implications.

2. Methodology, data, and scenarios

Fig. 1 illustrates our VGI methodology, beginning with the BEAM mobility model, continuing with the scaling of individual PEVs' charging sessions to 2025 California-wide, and ending with the PLEXOS grid simulation with scenarios of PEV charging strategies and adoption.

2.1. BEAM: agent-based PEV mobility and charging model

BEAM is an extension of the open source transportation systems modeling framework Multi-Agent Transportation Simulation (MATSim), which simulates individuals and their detailed interactions with the transportation system. Prior work describes MATSim and BEAM in depth (Sheppard et al., 2017; BEAM; Daina et al., 2017). BEAM simulates the daily travel patterns of individual drivers (where and when people drive between home, work, shopping mall, etc.) in their personal vehicles. These agents make their trips in a PEV and make charging-related decisions to maximize their utility by considering their battery's state of charge (SOC), their remaining mobility needs for the day, their location, the number of accessible chargers at a site, the level of chargers, the cost, and the distance to their next activity (Sheppard et al., 2017). BEAM's charging behavior model contains terms that simulate the difference between PHEVs and BEVs; charging away from home provides less utility to PHEV drivers, reflecting a lower sense of urgency to top off their battery. The BEAM simulation outputs data from each PEV's charging sessions including: charging session start and end time, end time of active power delivery, charging location, charger level, energy delivered (kWh), and maximum power of the charger and vehicle's charge controller (kW). With these outputs we construct PEV charging scenarios (Section 2.3) for PLEXOS.

BEAM simulates mobility and charging behaviors for the approximately 68,000 BEVs and PHEVs registered in the San Francisco Bay Area in 2016. The number of vehicles and their spatial distribution are based on ownership estimates from the Scenario Evaluation, Regionalization & Analysis (SERA) model developed by the National Renewable Energy Laboratory (NREL) (Scenario Evaluation and Reg). PEV attributes are based on Original Equipment Manufacturer (OEM) specifications and the U.S. Department of Energy (DOE) fuel economy website (FuelEconomy.gov, 2016). Driver mobility is from the San Francisco Bay Area Metropolitan Transportation Commission's (MTC) activity-based travel demand model (Metropolitan Transportation Commission and Parsons Brinckerhoff, Inc., 2012; Horni et al., 2016). The drivers' charging preferences are calibrated to observed 2016 charging session data received from ChargePoint, the largest charging infrastructure provider in the United States (Supplementary Table D1). We assume San Francisco Bay Area driving behavior is representative of other parts of California. According to the MTC, the daily per capita vehicle miles traveled (VMT) in the San Francisco Bay Area (24.8) are almost equivalent to that of Los Angeles (23.7) (Daily Miles Traveled, 2017). Congestion levels are also very similar; in 2017, drivers in both metropolitan areas spent 12% of total driving time in congestion (Inrix Research, 2018). More explicitly modeling driving behavior across California is an area for future refinement.

The charging infrastructure is modeled in detail in BEAM to include the number of parking spaces with physical access to chargers, resulting in the formation of queues at occupied chargers. We assume all drivers have a charger at home (Charging Plug-In Electri) and include a relatively small share of other chargers based on Alternative Fuels Data Center and ChargePoint data; we model about 5400 workplace chargers (Level 1, Level 2, and DC Fast chargers), 1200 public chargers (Level 1, Level 2, and DC Fast chargers), and 68,000 residential chargers (Level 2) for the San Francisco Bay Area (Table 1) (Electric Vehicle Chargin). In two infrastructure sensitivity analyses, we assess potential impacts on our results of additional workplace chargers (Appendix A), and different DC Fast charging assumptions (Appendix B).

To reflect anticipated technology improvements and subsequently higher PEV utilization by our 2025 study year, we assume the PEV fleet has battery capacities—and therefore a driving range—1.5 times greater than that of the original 2016 fleet. For example, the Nissan Leaf's second-generation model (2017-present) has a range of 1.5 times the range of a 2016 Leaf. Evidence suggests that the electric vehicle miles traveled (eVMT) is strongly correlated to battery capacity and vehicle range (California's Advanced Cl, 2017; Carlson, 2015) and we therefore also scale the resulting charging load of the aggregated fleet to correspond to the larger batteries. While proportional scaling of aggregated load does not completely account for the timing and charging power associated with increased travel demand, this approximation maintains the temporal distribution of individual vehicle loads developed within BEAM. This adjustment corresponds to BEVs driving 11,000 electric-miles and PHEVs driving 7600 electric-miles on average per vehicle owner, annually. Given the rapidly evolving PEV market, we evaluate the implications of an even greater share of high-range PEVs (Appendix B).

There are several limitations of the BEAM version used in this analysis. BEAM is calibrated to charging behavior from 2016 ChargePoint data, which may differ by 2025. The calibration data also excludes Teslas, and therefore BEAM may over-represent the behavior of lower range vehicles, especially in the frequency of residential charging (although 961 residential chargers were included in the data). Additionally, PEV energy consumption in BEAM is derived from a simple calculation based on the average fuel economy of the vehicle and BEAM does not consider other forms of mobility, such as electrified ride-hailing.

2.2. PLEXOS: power sector dispatch model

PLEXOS performs a unit-commitment and economic-dispatch simulation using mixed-integer programming and the Xpress-MP 28.01.13 mathematical solver (Xpress Solver, 2018) to minimize an objective function of operating costs, subject to constraints including imports, generator capacities, and a linearized DC optimal power flow (Energy Market Modelling) (Appendix C). We populate PLEXOS with the scaled PEV loads and constraints from BEAM and data from a California stakeholder-validated database originally created by the California Independent System Operator (CAISO) for the state's 2024 grid planning process (Liu, 2014; Liu, 2016; ISO Transmission Plan, 2016). We use a version released in November 2016 that CAISO updated with a 50% RPS RE portfolio and 2025 loads (Liu, 2016; ISO Transmission Plan, 2016). Additional information on the CAISO database is described in regulatory documents (Liu, 2014; Liu, 2016; ISO Transmission Plan, 2016; Picker, 2016). Several studies have been conducted with variants of the same database (Nelson and Wisland, 2015; Eichman et al., 2015; Jorgenson et al., 2014; Fioravanti et al., 2013).

The PLEXOS simulation covers the Western U.S. grid, or Western Electricity Coordinating Council (WECC) geography, and is a zonal model such that the transmission network is broadly represented as paths between utility zones and not as individual lines. There are 25 utility zones, including eight in California (Liu, 2014). California loads and distributed rooftop solar PV estimates come from a California

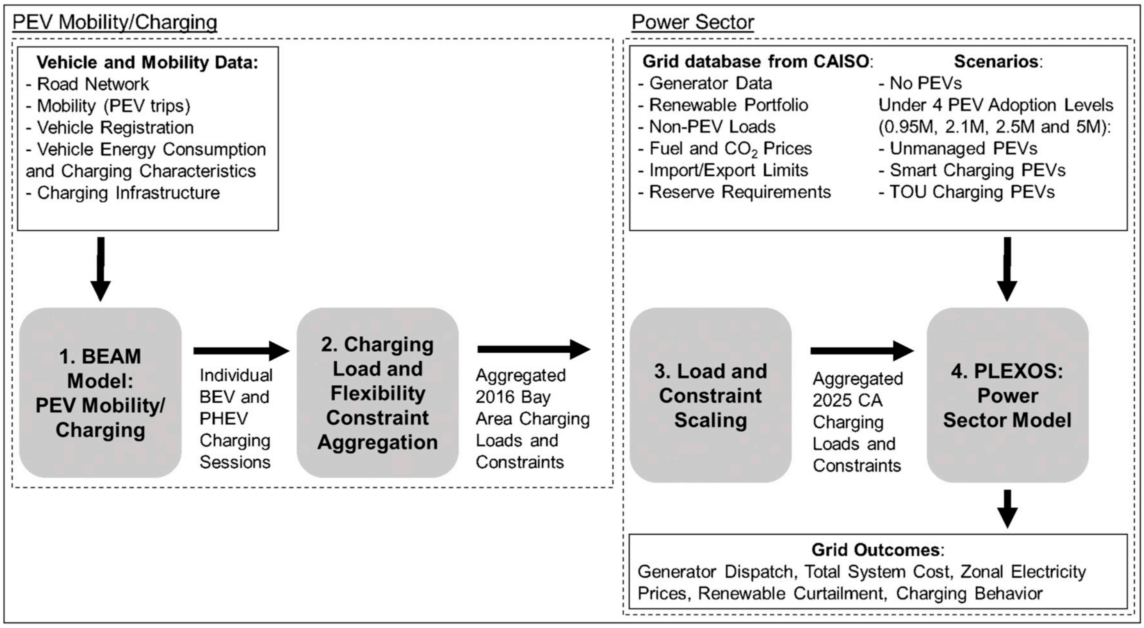

Fig. 1. Vehicle-grid integration modeling framework and methodology. The approach links an agent-based mobility model (BEAM) with a unit commitment and economic dispatch model (PLEXOS) to evaluate grid outcomes of PEV charging.

Table 1
Key assumptions used in BEAM modeling for the San Francisco Bay Area.

PEV Vehicles and Characteristics [A]						
Make/Model	Type	Battery capacity (kWh)	Fuel economy (kWh/mi)	L2 Charging limit (kW)	DCFC Charging limit (kW)	# Vehicles
NISSAN LEAF	BEV	45	0.30	7.0	50.0	16,598
CHEVROLET VOLT	PHEV	28	0.31	7.0	50.0	10,804
TESLA MODEL S	BEV	113	0.33	20.0	120.0	10,102
TOYOTA PRIUS PLUG-IN	PHEV	12	0.29	7.0	20.0	8599
FIAT 500e	BEV	37	0.29	7.0	50.0	3989
FORD FUSION	PHEV	11	0.34	3.3	–	4168
FORD C-MAX	PHEV	11	0.35	7.0	–	3490
BMW I3	BEV	50	0.27	7.4	50.0	2721
GEM - Various Models	BEV	19	0.20	–	–	1806
VOLKSWAGEN E-GOLF	BEV	36	0.29	7.2	50.0	1516
FORD FOCUS	BEV	50	0.32	6.6	–	1265
CHEVROLET SPARK EV	BEV	30	0.28	3.3	50.0	921
TOYOTA RAV4 EV	BEV	63	0.44	10.0	50.0	764
All other BEVs	BEV	*41*	*0.37*	varied	varied	888
All other PHEVs	PHEV	*17*	*0.47*	varied	varied	858

Electric Vehicle Miles Traveled [B]		
Vehicle Type	**eVMT**	**Comments**
BEVs	11,000	Average annual electric vehicle miles traveled per vehicle. Used to scale electricity demand for aggregated fleet for whole year, and based on assumption that all batteries are 50% higher capacity in 2025 than they are in 2016.
PHEVs	7600	

Charging Infrastructure [C]			
Market Sector	**Level**	**# Chargers**	**Charging limit (kW)**
Residential	L2	68,489	Typically 7 kW, up to 20 kW for some vehicles (see [A])
Workplace	L1	330	1.92 kW
Workplace	L2	4900	Typically 7 kW, up to 20 kW for some vehicles (see [A])
Workplace	DCFC	210	Typically 50 kW, up to 120 kW for some vehicles (see [A])
Public	L1	130	1.92 kW
Public	L2	900	Typically 7 kW, up to 20 kW for some vehicles (see [A])
Public	DCFC	160	Typically 50 kW, up to 120 kW for some vehicles (see [A])

Battery capacities are for 2025 (scaled 50% larger than 2016 levels). "All other BEVs" and "All other PHEVs" values represent weighted averages. **Sources: A.** Scenario Evaluation, Regionalization & Analysis model by National Renewable Energy Laboratory, Original Equipment Manufacturer specifications, and U.S. Department of Energy fuel economy website; **B.** San Francisco Bay Area Metropolitan Transportation Commission and California Air Resources Board; **C.** U.S. Department of Energy Alternative Fuels Data Center and ChargePoint data.

Energy Commission (CEC) forecast (Liu, 2016; California Energy Demand,). The total annual 2025 load for the California utility zones, net of distributed solar PV and energy efficiency, is 298 TWh. We remove

6.1 TWh of PEV load[4] included in the original load forecast to avoid double-counting when adding the PEV loads from BEAM (California Energy Demand). Non-California loads come from the WECC Transmission Expansion Planning Policy Committee (TEPPC).

The 125 TWh RE portfolio (Table 2) in this analysis is forecasted by CAISO to meet a 50% RPS mandate (based on (Liu, 2014; Liu, 2016; California Energy Demand; RPS Calculator Home Page)). We set PLEXOS to curtail California in-state solar PV, wind, and solar thermal generation if electricity prices reach a -$150/MWh floor price, the lower limit for economic bids in the CAISO market (Liu, 2014; Golden and Paulos, 2015).

We model the conventional thermal and hydro generators as specified in the CAISO database, including several generic fossil generators that represent authorized new plants expected to be built by 2025 in California (Liu, 2014; Liu, 2016; California Public Utilities Commission Rulemaking, 2013), and excluding California's remaining nuclear plant whose license expires by 2025 (Penn and Masunaga, 2016). Generators are characterized in PLEXOS by start-up and shut-down times and costs, operations and maintenance (O&M) costs, heat rates, emissions rates, and energy limits for hydropower. Fuel prices vary by generator location, using natural gas price forecasts from the CEC for California and natural gas and coal prices from TEPPC for the rest of WECC (Liu, 2014; Liu, 2016). The GHG price we include from CAISO is $20.75/metric ton CO_2-eq, which is added to California fossil generators' variable generation cost (Liu, 2014). Per the CAISO's methodology, for resources imported from outside California, except dedicated imports, a CO_2 cost adder is added to the transmission wheeling charge (Liu, 2014). We also include 1300 MW of stationary storage mandated in California (Liu, 2014; California Public Utilities Commission, 2013), and non-PEV demand response (Liu, 2014).

California's hourly net exports are constrained such that exports minus imports cannot exceed 2000 MW (Picker, 2016). We also model dedicated imports to California entities, including from certain fossil and large hydropower resources, and 70% of out-of-state RPS-eligible RE (Liu, 2014). Regulation and load-following reserve requirements are calculated by CAISO based on variability and forecast error in load and RE (Integration of Renewable Resources, 2010). Renewable generators can provide up to half of their energy as downward load-following reserves, satisfying up to half the downward load-following requirement (Liu, 2016).

For each PEV scenario (Section 2.3), we run PLEXOS deterministically, 1 month at a time for a full year. Each run first optimizes over a month-long time horizon to accommodate generators with monthly energy limits, and then conducts daily chronological optimizations to balance load by dispatching generation for each hour. PLEXOS co-optimizes for energy and reserves provision to achieve a minimum cost result. The optimization is run to globally minimize costs across all generators in the WECC area, but our analysis focuses on results for California.

The PLEXOS solution for 2025 for each scenario includes hourly generator dispatch, RE curtailment, zonal prices, and California imports/exports. We calculate the California total system cost, often referred to as production cost, by summing costs of generation (from fuel, startup/shutdown, and variable O&M) and emissions (for CO_2) for all generators in California. Because the state is a net electricity importer from neighboring regions (Liu, 2014), we include the hourly import costs and export revenue (negative costs) by adding the product of net interstate power flows and the electricity price in the utility zone receiving the power (Brinkman et al., 2016). Finally, we add the total system costs from out-of-state generators serving as dedicated exporters to California. Since our focus is on operational impacts of PEVs and we hold infrastructure fixed, our California total system cost calculation does not include capital costs, such as for building new generators. We also do not include distribution system costs. Even at higher PEV penetrations, distribution system upgrades are forecasted to contribute only a small component of California utilities' costs (California Transportation Electrification Assessment, 2014). Lastly, our study's hourly resolution is standard for dispatch models, but could slightly underestimate ramping costs (Deane et al., 2014) and prevents study of intra-hour impacts of PEV charging for which more research is warranted.

[4] The CEC generated this PEV load forecast based on their 2025 mid-case vehicle adoption scenario, assuming 75% of charging occurs 10pm to 6am (Kavalec et al.,2014).

2.3. PEV adoption and charging strategy scenarios

We run the PLEXOS optimization with constant grid parameters (Section 2.2) under 1 base case scenario with no PEVs included and under 12 PEV scenarios (Table 3) that each test a charging strategy at a range of California PEV adoption from a CEC forecast (Kavalec et al., 2016). "Low" (0.95 million) and "High" (2.5 million) scenarios represent CEC's estimate if PEV prices remain more or less expensive than gasoline vehicles, and "Mid" (2.1 million) scenarios are CEC's estimate of "most likely compliance" with California's ZEV Program[5] (Kavalec et al., 2016; Bahreinian et al., 2016). We add "Reach" scenarios (5 million) to estimate impacts of very aggressive PEV market transformation, which would achieve the Governor's extended target.

Scenarios

- **Base case scenario:** No PEVs included in California load.
- **Unmanaged charging scenarios**: Low (0.95 million), Mid (2.1 million), High (2.5 million), Reach (5 million) PEV adoption, all PEVs charging unmanaged.
- **Smart charging scenarios**: Low (0.95 million), Mid (2.1 million), High (2.5 million), Reach (5 million) PEV adoption, all PEVs participating in an aggregator-based smart charging program.
- **TOU charging scenarios**: Low (0.95 million), Mid (2.1 million), High (2.5 million), Reach (5 million) PEV adoption, all PEVs responding to a residential overnight off-peak TOU rate.

We do not forecast customer participation rates for any charging strategy because the scenarios are meant to characterize the maximum potential wholesale market value—under more realistic mobility, charging infrastructure, and grid assumptions—if all California PEVs participated in a given charging strategy. Therefore, our results are the foundation for future work to assess benefits of specific smart charging or TOU tariff designs. Sections 2.3.1 and 2.3.2 describe how the scenarios are constructed with BEAM and PLEXOS.

2.3.1. Modeling PEV charging strategy scenarios in BEAM

2.3.1.1. Unmanaged charging. Charging sessions are first simulated for individual vehicles in BEAM as unmanaged, such that a PEV starts charging as soon as it is plugged in, and we record the energy delivered during each session as the unmanaged load for an individual PEV.

2.3.1.2. Smart charging. We use outputs from the BEAM unmanaged charging simulation to construct individual vehicle energy and power constraints for smart charging, similar to the methodology of (Wolinetz

[5] The California ZEV Program regulation (in place in some form since 1990) requires that each automaker hold a certain number of ZEV credits, which reflects the share of ZEVs produced out of the total number of cars the manufacturer sold in California each year. Each ZEV vehicle produced receives a number of credits based on its range, and automakers with surplus credits can bank or trade credits with other manufacturers (Zero Emission Vehicle (ZEV) Program). The California Governor's executive orders setting 1.5 million and 5 million ZEV targets are complementary policies to accelerate ZEV adoption.

Table 2
RE capacity and available annual generation in 50% RPS scenario.

	Biogas	Biomass	Geothermal	Small Hydro	Large Solar PV	Small Solar PV	Solar Thermal	Wind	Total
Capacity (MW)	228	635	2076	986	19,316	2073	1021	14,649	40,986
Energy (GWh)	1511	4120	15,775	3104	53,611	4995	2412	39,779	125,307
% of RE	1.2%	3.3%	12.6%	2.5%	42.8%	4.0%	1.9%	31.7%	100%

RE generation and capacity values include RPS-eligible out-of-state RE generators. **Source:** California Independent System Operator.

Table 3
Scenarios of 2025 California PEV adoption and energy.

PEV Adoption [A]	Low	Mid	High	Reach
Number of BEVs (60% of PEVs)	570,000	1,260,000	1,500,000	3,000,000
Number of PHEVs (40% of PEVs)	380,000	840,000	1,000,000	2,000,000
Total Number of PEVs	950,000	2,100,000	2,500,000	5,000,000
PEVs % of Current CA Auto Stock	4%	8%	10%	20%
Annual PEV Loads [B]	**Low**	**Mid**	**High**	Reach
Unmanaged charging load (GWh)	2728	6030	7179	14,358
TOU charging load (GWh)	2728	6030	7179	14,358
Smart charging load (GWh)	2744	6062	7215	14,417
PEV Load as % of CA Load	1%	2%	2%	5%

A. "Total Number of PEVs" are from California Energy Commission (CEC) 2015 California Energy Demand Forecast for 2016–2026, assumed split 60% BEVs and 40% PHEVs. The "Current Auto Stock" assumed is 25.5 million registered automobiles from the California Department of Motor Vehicles. **B.** "Annual PEV Loads" are the scaled loads from BEAM. The "PEV Load as % of CA Load" is of 292 TWh of California load in the PLEXOS model, net of solar PV, energy efficiency and PEV loads. Smart charging total loads are <1% more than the unmanaged and TOU loads due to the load shifting efficiencies assumed for the smart charging storage resource in the PLEXOS dispatch.

et al., 2018). These constraints characterize a flexible resource to be dispatched by PLEXOS (Section 2.3.2.2). We assume smart charging PEVs are plugged-in at the same times as if unmanaged, but that the timing of active charging within those periods is flexible as long as the delivered energy is equivalent to that of the unmanaged case. Smart charging flexibility is thereby limited to within individual charging sessions, rather than across different sessions. We assume that 1) drivers' travel needs are too highly valued and their plans too inflexible to charge at entirely different times of the day because chargers are not universally available, 2) drivers do not unplug immediately after active charging ends unless there is a queue, and 3) drivers have sufficient foreknowledge and willingness to indicate their expected departure times for an aggregator to schedule active charging (similar to (Xu et al., 2016)). We do not model drivers leaving earlier than expected, but only 5% of BEV charging events in BEAM start with a critically low remaining range of 20 miles or less; these BEVs would only need to charge on average 36 uninterrupted minutes to reach a 20-mile minimum in case of unexpected early departure.

The cumulative energy delivered for unmanaged charging is the maximum constraint, representing the earliest possible charge, for each smart session. The minimum cumulative energy constraint assumes that active charging is delayed until the last possible moment, while still delivering equivalent energy by the end of the session, as in (Xu et al., 2016). For three representative PEVs, Fig. 2 illustrates an example of the maximum (earliest) and minimum (latest) smart charging cumulative energy constraints for a week of the BEAM simulation. Within the area bounded by these curves, any monotonically increasing trajectory can be achieved with smart charging, subject to the target SOC and the maximum power of the PEV and charger. The curves meet between charging sessions. In BEAM, the probability that drivers charge at home each day is based on a distribution derived from ChargePoint data, in which the average residential charger was used 93% of the days.

2.3.1.3. Overnight time-of-use charging. We represent the response to TOU rates in a second BEAM simulation by forcing the charging sessions to begin at staggered times (to avoid inducing a sudden demand spike)

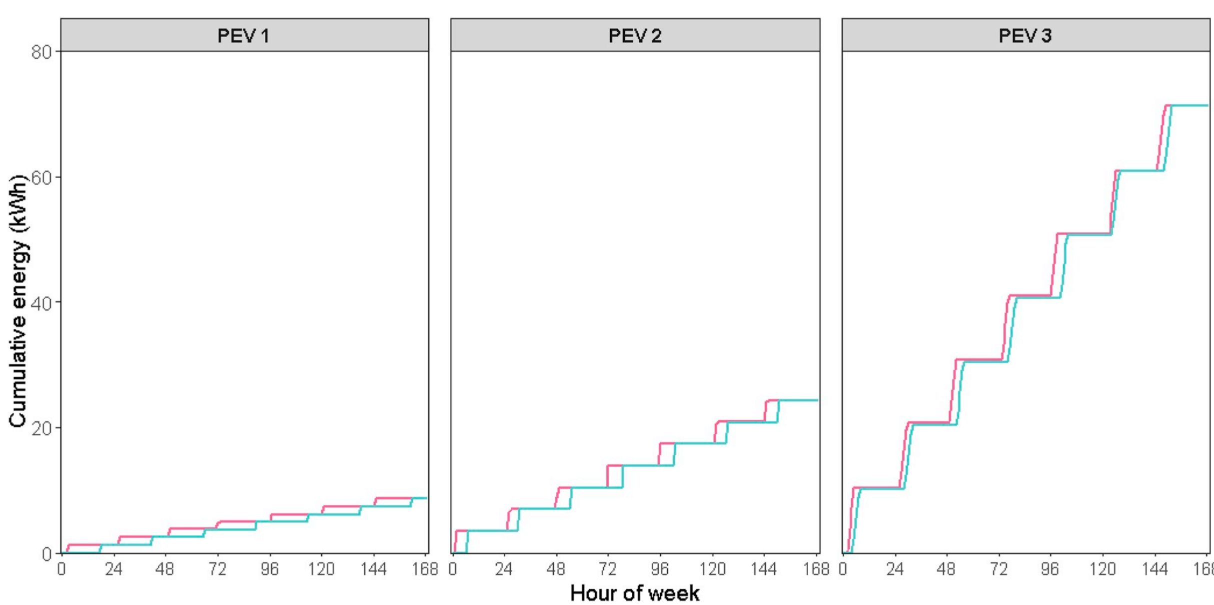

Fig. 2. Illustrative sample smart charging constraints of 3 individual PEVs. Maximum (upper line) and minimum (lower line) cumulative energy constraints bound possible smart charging trajectories for three representative PEVs in the first week of the BEAM simulation.

between 10 p.m. and 2 a.m.—approximately the range of start times of California's current residential off-peak rate periods (Electric Vehicle; EV Rates; Electric Vehicle Rates)—for those PEVs that would already be plugged in overnight at home if unmanaged. Within BEAM, we record the energy delivered during each PEV's TOU session. We do not explicitly model a TOU electric rate but assume the off-peak price would be sufficiently low to incentivize all drivers to pre-program charging for those times. PEV drivers enrolled in current California TOU rates are very responsive to off-peak periods, especially with a large peak/off-peak price differential (Load Research Report, 2017; Cook et al., 2014).

2.3.2. Representing PEV charging scenarios in PLEXOS

2.3.2.1. Aggregation of PEV charging loads and constraints. For the unmanaged and TOU charging scenarios we aggregate the loads, and for the smart charging scenarios we aggregate the constraints, across the individual vehicles in BEAM by summation (Xu et al., 2016). For each scenario, we do this summation separately for BEVs and PHEVs for the San Francisco Bay Area. These aggregated loads and constraints from a typical weekday (the second day of a three-day BEAM run) are used to construct a full week based on observed ChargePoint charging data. This construction occurs by repeating the full day of hourly loads from BEAM seven times to create a week, and then scaling the profiles separately by charger location (residential, workplace, and public) to match the normalized daily average loads from ChargePoint by charger location. Weekend loads are adjusted to mimic the observed ChargePoint weekend load shapes. These weekly loads and constraints are repeated to create an annual data set for San Francisco Bay Area.

These aggregated San Francisco Bay Area loads and flexibility constraints produced by BEAM for the three charging strategies in 2016 are then increased linearly by vehicle type (BEV and PHEV) to represent the eight California utility zones modeled in PLEXOS in 2025. The scaling occurs in two parts: 1) first by the ratio of the current San Francisco Bay Area PEV stock to that of each California utility area from the California Vehicle Rebate Program (CVRP) data (CVRP Rebate Statistics, 2016), and then 2) by the ratio of the current California-wide stock totaled from CVRP data compared to a CEC state forecast ranging from 0.95 million to 2.5 million PEVs for 2025, and a "Reach" adoption level of the Governor's targeted 5 million PEVs (Section 2.3). Because the state forecast is reported for PEVs in aggregate, we assume that 60% of the 2025 stock will be comprised of BEVs and 40% of PHEVs, similar to trends found in the CVRP data (CVRP Rebate Statistics, 2016). Finally, the annual loads for the TOU cases are normalized to equal the annual unmanaged loads for each level of PEV adoption, allowing for results comparison across charging strategies. Implicit in this overall scaling process of PEV loads from the San Francisco Bay Area in 2016 to California in 2025 is that the state's charging infrastructure will continue to grow, such that the proportion of chargers to vehicles is the same as current levels. Given the planned large-scale infrastructure investments (Merchant, 2018; Volkswagen California ZEV, 2017; Mulkern, 2016) and the Governor's goal of installing 250,000 additional chargers by 2025, we think this is a reasonable assumption (Governor Brown Takes Action to Increase Zero-Emission Vehicles). The final loads for each PEV adoption scenario are shown in Table 3.

2.3.2.2. Incorporating PEVs into PLEXOS. For the unmanaged and TOU charging scenarios, for each utility zone we add the aggregated and scaled 2025 PEV load to the non-PEV load as a fixed load profile in PLEXOS. We model smart charging loads in PLEXOS as the sum of a fixed load plus net generation of a dispatchable storage resource. The fixed load is the unmanaged PEV load for each utility. The storage resource for each utility is dispatched as part of the PLEXOS WECC-wide optimization to either discharge energy during high priced times (equivalent to PEVs not charging when unmanaged vehicles would have otherwise charged) or consume energy during low priced times (equivalent to PEVs charging when unmanaged vehicles would not have charged). This represents load shifting a collection of PEVs by an aggregator in a smart charging program. The storage resource starts full at the beginning of each PLEXOS simulation, and if not dispatched by the optimization, the smart load equals the load of the unmanaged scenario.

We constrain the total size (in GWh) of the smart charging storage facility to be the largest difference between the maximum and minimum energy constraints of the aggregated PEVs in each utility zone (from Section 2.3.2.1). We limit the storage resource's SOC to be greater than the hourly difference between the maximum and minimum cumulative energy constraints of the aggregated vehicles. We enforce time-varying maximum power constraints on discharging the storage resource, corresponding to the unmanaged load. The time-varying maximum power constraint for charging the storage resource depends on the capacity of all grid-connected PEVs and available chargers in each hour under unmanaged charging. We set the round-trip efficiency of the storage resource to 99% (instead of 100%) so that PLEXOS first dispatches a zero-marginal-cost generator before the flexible smart charging load. Because the PLEXOS simulation runs 1 month at a time, we account for edge effects by constraining the storage resource to return to the starting SOC by the end of each month.

3. Results and discussion

3.1. Hourly grid impacts

For the same level of PEV adoption, even with PEVs comprising 1%–5% of total California loads (Table 3), the PLEXOS results show the choice of charging strategy noticeably impacts hourly grid operations, in terms of net load shapes, hourly RE curtailment, and wholesale electricity prices.

Fig. 3 illustrates these key system outcomes averaged hourly across three seasonally representative months of grid operation with 2.5 million PEVs; results are similar with other adoption scenarios. The majority of the unmanaged PEV load occurs between 3pm and 11pm (row B), after the predominant commute home. Unmanaged charging yields higher prices (row D) and exacerbates the evening peak of the system's load net of solar PV, solar thermal, and wind generation (row A). TOU charging, by design, is concentrated overnight at home starting at 10pm and lasting until the early morning (row B). TOU charging creates smoother prices (row D), and avoids peak load times (row A) but also most RE curtailment (row C). In contrast, smart PEVs, as dispatched by PLEXOS, charge in the late morning and the late afternoon (row B) to reduce RE curtailment especially in spring (row C), surging again when prices drop around 11pm (row D). This pattern follows the timing of low-priced generation (row D) of solar PV during the day and wind plus baseload plants overnight.

Fig. 3 suggests smart charging is the most favorable strategy for California hourly grid operations because of its flexibility to lower net load peak, smooth prices, and reduce curtailment. Subsequently, this study's linked transportation model can identify when and where PEVs can supply such hourly flexibility to target VGI policies, subject to mobility needs and charger availability. For a typical weekday in the San Francisco Bay Area BEAM simulation (before scaling to California, 2025 levels), Fig. 4 shows the energy demanded in unmanaged charging sessions and the duration of availability flexibility, based on the time between the end of active charging and unplugging. Most charging sessions occur at home in the afternoon and during grid peak hours. These residential sessions have the greatest flexibility (12 + hours) to shift charging and therefore contribute most of the smart charging benefits we see in the hourly outcomes (Fig. 3). In contrast, there are relatively few charging sessions at work or public locations, and those sessions, concentrated in the mid-morning hours, have much less flexibility since drivers are both parked for shorter times and have queues that require unplugging immediately after active charging. A sensitivity

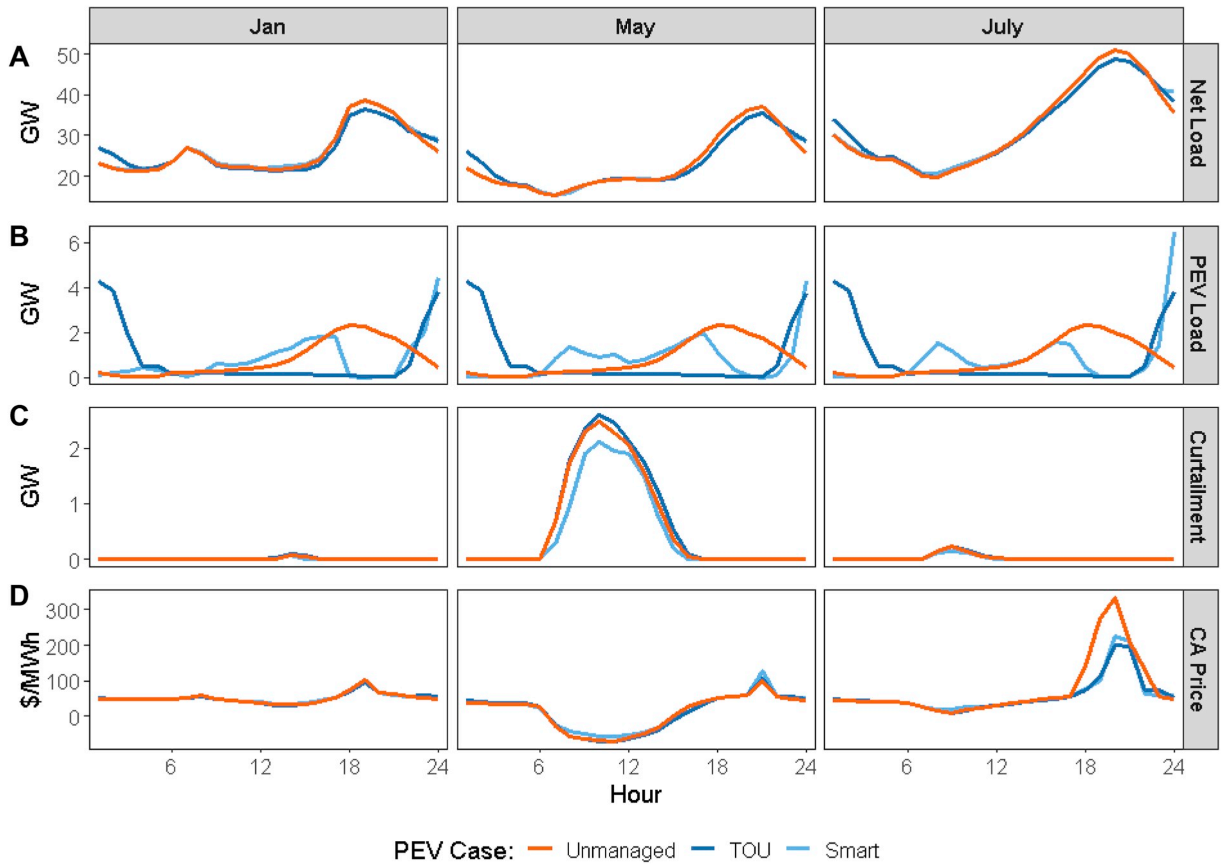

Fig. 3. California net load, PEV charging load, RE curtailment, and average prices with 2.5 M PEVs. These figures are for 2.5 million PEVs and California outcomes averaged hourly across three seasonally representative months of grid operation; results are similar with other PEV scenarios. **A.** "Net Load" is California system load net of solar PV, solar thermal, and wind generation; **B.** "PEV Load" shows Unmanaged, TOU, and smart charging PEV loads; **C.** "Curtailment" is curtailment of California solar PV, solar thermal, and wind generation; **D.** "CA Price" is the Load-weighted average price of California utility regions.

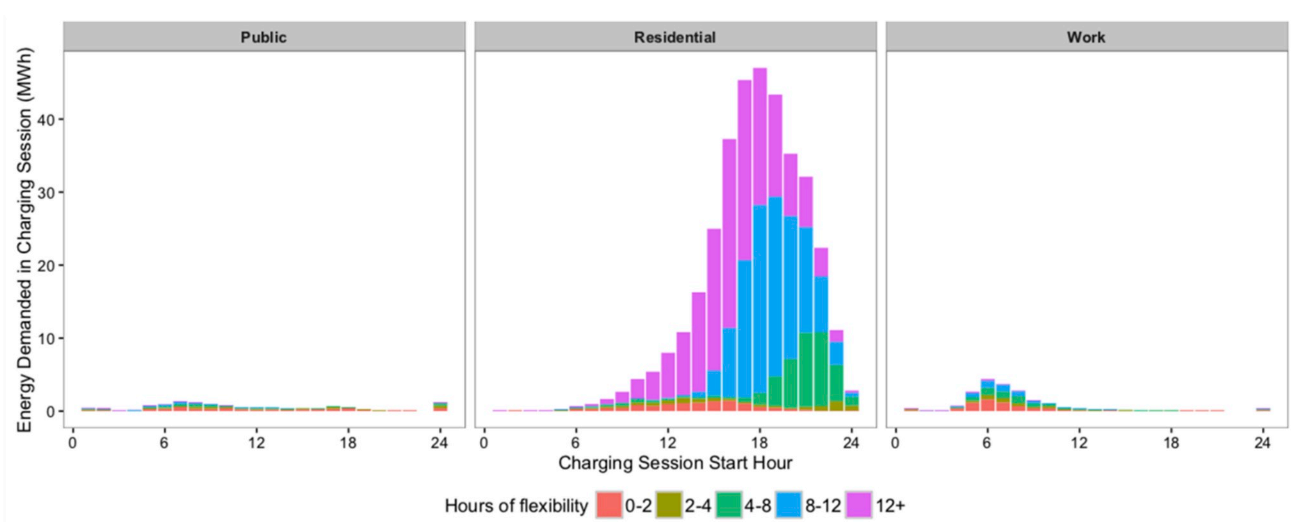

Fig. 4. Weekday charging session flexibility duration and energy demanded, by location and hour. The panels show for a typical weekday in the San Francisco Bay Area BEAM simulation (before scaling to California, 2025 levels), the energy demanded by location and the hours of flexibility to shift load within charging sessions (based on the time between active charging and unplugging).

testing the addition of four and eight times more workplace chargers shows only a minor increase in energy demanded and hours of daytime flexibility (Appendix A).

Together, these results suggest that in terms of location and timing, residential smart charging policies are the most efficient way to capture the majority of hourly grid flexibility. Even when there is remaining RE curtailment and negative pricing in the middle of the day (Fig. 3)—which would be ideal times to shift additional PEV loads—the marginal value from increased smart charging at work or public chargers appears limited. In a sensitivity analysis, these results appear robust to a potentially higher buildout of DC Fast chargers: with a 20-fold increase in public DC Fast charging sessions, the number of charging-hours that can be shifted only decreases 3% and most flexibility still occurs at home (Appendix B). Similarly, if the 2025 PEV fleet includes a greater share of high-range vehicles, based on our sensivity analysis we expect marginally less morning charging and slightly shorter duration evening flexibility but not a significant change to overall grid costs and curtailment (Appendix B).

3.2. Annual grid impacts

The following section compares the annual total system cost and renewable curtailment impacts for California, resulting from hourly charging and grid interactions for each of the PEV scenarios.

3.2.1. Total system cost

When PEVs are added to the grid, California's annual total system costs (grid operating costs described in Section 2.2) increase in all scenarios because of additional generation used to meet load. However, for the same number of vehicles, the charging strategy significantly affects the degree to which costs increase. The difference in total system cost increases from smart or TOU charging compared to unmanaged charging are what we consider the value of a given managed charging strategy.

We find that smart charging provides the greatest annual value among the charging strategies tested. Smart charging avoids $120 to $690 million of California total system cost increases per year with 0.95 million to 5 million PEVs, compared with the same number of unmanaged vehicles (Fig. 5, Table 4). Therefore, by managing PEVs with smart charging, California can save about 50% of the incremental cost of adding the new vehicle loads to the grid. Across the state, these savings are significant, on the order of 2%–10% of California's total system costs with 0.95–5 million smart PEVs, respectively. While smart charging results in lower total system costs than with TOU charging, similar to the findings of (Lyon et al., 2012), the difference in value between the two strategies is not large. Compared to unmanaged charging, TOU charging provides California $90 to $550 million in value per year. Consequently, these cost savings compared to unmanaged charging amount to 1%–8% of California's annual total system cost with 0.95–5 million TOU charging PEVs.

Across PEV adoption levels, smart charging incurs lower system costs relative to unmanaged charging because of lower peak loads (less expensive generators are used) and because more PEV load is served by RE (Supplementary Table D.2). TOU charging decreases system costs relative to unmanaged charging because of reduced load (Fig. 3)—and thus reduced ramping primarily from natural gas generation—during evening peak demand hours. Under both managed charging strategies, the system dispatches less demand response to reduce peak loads and displaces some use of stationary storage (Supplementary Table D.2), increasing the option value, or the opportunity for future use, of these flexible resources for other grid needs.

With both managed strategies, the share of unmanaged charging costs that are avoided and the per PEV value are non-linearly related to increasing levels of PEV adoption. When divided by the number of PEVs assumed for each scenario, the total system cost savings are relatively low, averaging about $120/PEV per year with smart charging and about $90/PEV per year with TOU charging (Fig. 6). We note, however, that this value would be spread more broadly across ratepayers and is not necessarily what would accrue directly to drivers; the driver savings from managed charging would also depend on factors including the enablement cost for demand response aggregators of smart charging and the particular level of TOU rates. Because this analysis takes the societal perspective and focuses on statewide wholesale market value, we do not simulate specific business models or rate designs to determine monetary benefits at the customer level. To fully evaluate the customer impacts, future research must also quantify additional value streams of managed charging, such as from avoided investment in infrastructure upgrades or distributed stationary storage, which also may make managed charging more financially attractive to drivers (Niesten and Alkemade, 2016).

Consistent with (Kiviluoma and Meibom, 2011), our results also show that at very high PEV levels, both smart and TOU charging strategies can defer capital costs for building new generating and transmission capacity. If 5 million PEVs are deployed, unmanaged PEV charging stresses the system peak to the point that about 2500 MWh of load are unserved in California over two days in July, while smart or TOU charging PEVs can still be accommodated by existing generators without any unserved load. In our simulation, when there is not enough generation to meet load (within a utility zone or with imports), a zone's

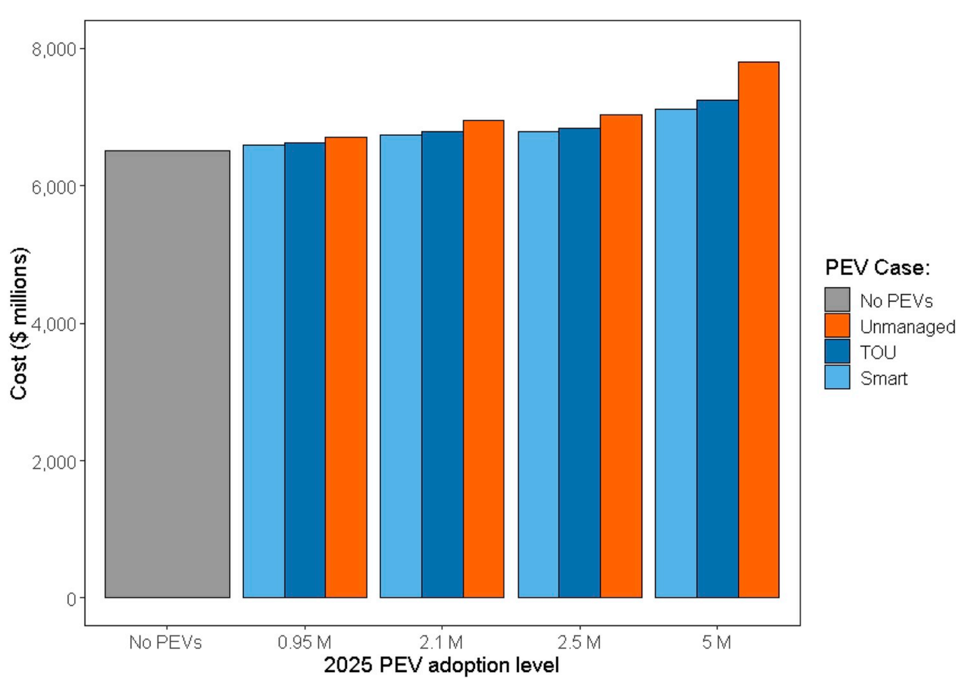

Fig. 5. Annual California total system cost. Annual total system cost for California includes the grid operating cost from generation, emissions, and net imports.

Table 4
California annual total system costs and renewable curtailment results.

California total system costs [A]								
	Total system costs ($ Millions)				Avoided cost relative to Unmanaged ($ Millions)		Share of Incremental Cost Avoided (%)	
PEV Scenario	Base	Unmanaged	Smart	TOU	Smart	TOU	Smart	TOU
No PEVs	6514	–	–	–	–	–	–	–
Low (0.95M PEVs)	–	6711	6592	6620	119	91	60%	46%
Mid (2.1M PEVs)	–	6946	6738	6778	208	168	48%	39%
High (2.5M PEVs)	–	7024	6783	6829	241	195	47%	38%
Reach (5M PEVs)	–	7792	7104	7244	688	548	54%	43%

California renewable energy curtailment [B]								
	Curtailment (GWh)				**Curtailment relative to Unmanaged (GWh)**		**Curtailment relative to Unmanaged (%)**	
PEV Scenario	**Base**	**Unmanaged**	**Smart**	**TOU**	**Smart**	**TOU**	**Smart**	**TOU**
No PEVs	1347	–	–	–	–	–	–	–
Low (0.95M PEVs)	–	1274	1155	1324	-119	50	-9%	4%
Mid (2.1M PEVs)	–	1191	953	1294	-238	103	-20%	9%
High (2.5M PEVs)	–	1164	902	1287	-262	123	-23%	11%
Reach (5M PEVs)	–	1013	608	1230	-405	216	-40%	21%

A. "California Total system costs" reflect the grid operating cost and include the cost of generation and emissions for power plants located within California and the out-of-state import cost and export revenue. "Avoided cost relative to Unmanaged" is the difference in cost between the Unmanaged and Smart (or TOU) cases. "Share of Incremental Cost Avoided" is the "Avoided cost relative to Unmanaged" divided by the cost increase between the Unmanaged and No PEV cases for each PEV adoption scenario. **B.** "California renewable energy Curtailment" is of California's solar PV, solar thermal, and wind generation. "Curtailment relative to Unmanaged (GWh)" is the difference in curtailment between the Unmanaged and Smart (or TOU) cases. "Curtailment relative to Unmanaged (%)" is the avoided curtailment divided by the curtailment under the Unmanaged case for each PEV adoption scenario.

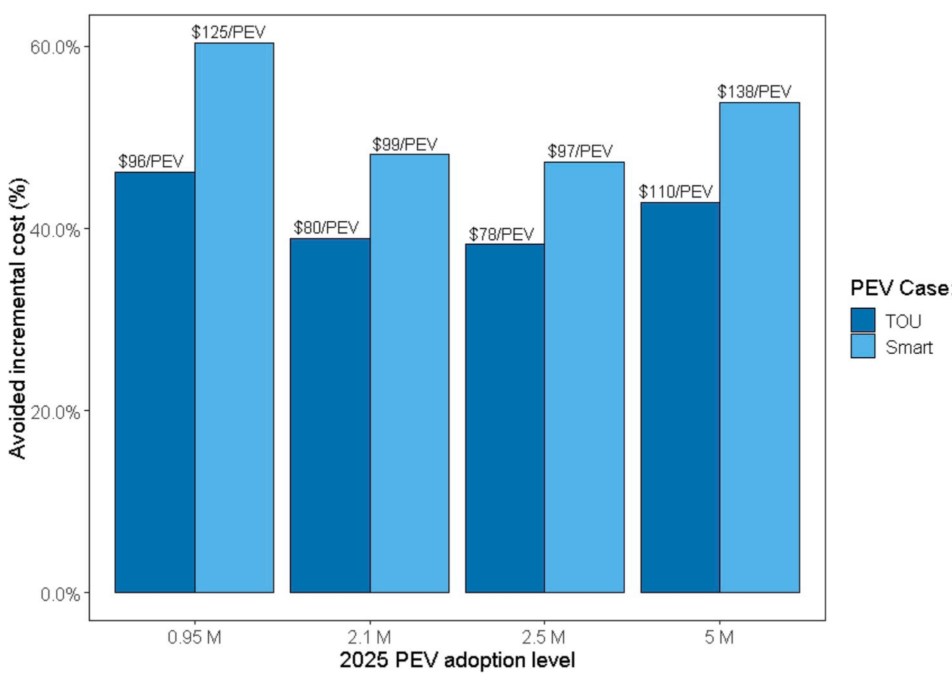

Fig. 6. Avoided total system cost increases relative to Unmanaged PEVs. "Avoided incremental cost (%)" is the difference in incremental California total system cost above the No PEVs case from smart or TOU charging relative to unmanaged charging, divided by the incremental cost of unmanaged charging. The dollar-per-PEV system cost savings from smart charging and TOU charging is the annual avoided incremental cost divided by the number of PEVs for each adoption scenario.

electricity price spikes, up to the level of a market ceiling price set at $2000/MWh. Because we calculate California's total system cost to include price times net imports into the region, the high total system cost for unmanaged charging with 5 million PEVs—and the greatest per PEV value for smart and TOU charging—is driven by the increased imports during spikes of California regional market prices around this price ceiling. These results show that without a charge management policy, California's grid as it is planned for 2025 may reach a saturation point at the state's 5 million PEV goal and require added resources to avoid unserved energy.

3.2.2. RE curtailment

VGI policies that reduce RE curtailment are favorable because curtailment—although a reliable way to maintain grid stability—raises a system's operating cost and is an inefficient use of RE assets (Bird et al., 2014). Curtailment is often invoked because of transmission congestion, but also occurs when must-run inflexible resources and minimal levels of thermal generation exceed load minus exports (Golden and Paulos, 2015). Lowering curtailment can increase investor confidence in developing future RE projects, and enable emissions reductions (Cochran et al., 2014). Our results show that smart charging is best able to shift load to times with excess RE, when power is priced negatively. With 0.95 to 5 million PEVs, compared with unmanaged vehicles, smart charging lowers annual RE curtailment by an additional 9%–40%, or about 120–410 GWh, respectively (Fig. 7, Table 4). Dividing the avoided curtailment by the annual PEV load, it is estimated that with smart charging about 4% of PEV load is served by RE energy that would have otherwise been curtailed if the vehicles were left unmanaged (Supplementary Table D.3). In contrast, across all PEV adoption scenarios TOU charging results in more curtailment than does unmanaged charging, because most of the RE generation, dominated by solar PV, does not coincide with overnight PEV load. For TOU charging to reduce curtailment, off-peak periods may need to be augmented with more hours that overlap with solar generation.

Because utilities consequently deliver less RE to comply with regulations, curtailment also necessitates additional RE capacity or resources such as energy storage, quickly ramping generators, or flexible loads to compensate (California Independent System Operator, 2016; Bird et al., 2014; Golden and Paulos, 2015). The additional monetary value of curtailment reductions therefore depends on the avoided capital cost of overbuilding RE plants and the cost of alternative curtailment-reduction measures. Although we find that annual curtailment even with unmanaged charging is only 1.1%–1.4% of RE generation (Supplementary Table D.3), more study is needed of future higher RE levels when PEV charging may play a much more significant role in reducing curtailment and thus overall costs and emissions in California.

4. Conclusions and policy implications

Previous literature, including (Lund and Kempton, 2008; Kiviluoma and Meibom, 2011; Lyon et al., 2012; Foley et al., 2013; Calnan et al., 2013; Weis et al., 2014; Madzharov et al., 2014; Coignard et al., 2018), shows managed charging can save on grid costs and reduce RE curtailment. However, most prior work does not fully account for constraints on mobility, charging infrastructure, and grid dispatch, thereby estimating benefits which may not be achievable. This study improves on these models through more robust and realistic simulation of both the transportation and power sectors, to represent the hourly impacts and annual wholesale market value and curtailment that California policymakers can expect with large scale PEV and RE adoption. We find unmanaged charging coincides with peak loads and yields higher prices, while smart charging occurs during low-priced times to avoid peaks and lower curtailment; TOU charging also reduces peak impacts. Annually, even with our more realistic assumptions, California can save between $120 to $690 million of grid operating costs by managing PEVs with smart charging, and $90 to $550 million with overnight TOU charging. The introduction of practical limitations further reduces the average per-vehicle value of these managed charging strategies to the order of $100 per PEV annually compared to the $100 to $300 per PEV range seen in previous studies (Richardson, 2013). Nonetheless, the aggregate VGI values still make a significant difference for the California system: comprising up to about 8% or 10% of the state's 2025 expected grid operating costs, making managed charging overall a beneficial policy for the state to pursue. Especially at the 5 million PEV penetration ultimately targeted by state, some form of charge management becomes essential to avoid new generation or transmission investments. Lastly, smart charging lowers the cost of achieving California's RE targets through curtailment reductions. Overnight TOU charging is counterproductive to RE integration efforts because it results in higher annual curtailment than even unmanaged PEVs.

In terms of hourly grid impacts, annual total system cost savings, and RE curtailment reductions, we find that smart charging is overall a more valuable managed charging policy for California. Our detailed mobility model demonstrates most flexibility exists at residential locations rather than at work or public locations. This residential flexibility contributes nearly all the smart charging value by avoiding evening peak times and utilizing solar generation. Therefore, smart charging targeted at residential customers, who typically already have home chargers, appears to be the biggest opportunity and most cost-efficient policy for the state. Many chargers available today can be upgraded for smart charging for about $100, and some PEV models have smart charging software onboard (Coignard et al., 2018; Kaluza et al., 2017). However, for residential smart charging to be implemented at a large scale, careful consideration is needed to design programs that monetize multiple value streams (Niesten and Alkemade, 2016; Kley et al., 2011) to increase driver participation incentives and overcome other consumer adoption barriers including perceived restricted mobility, concerns about data

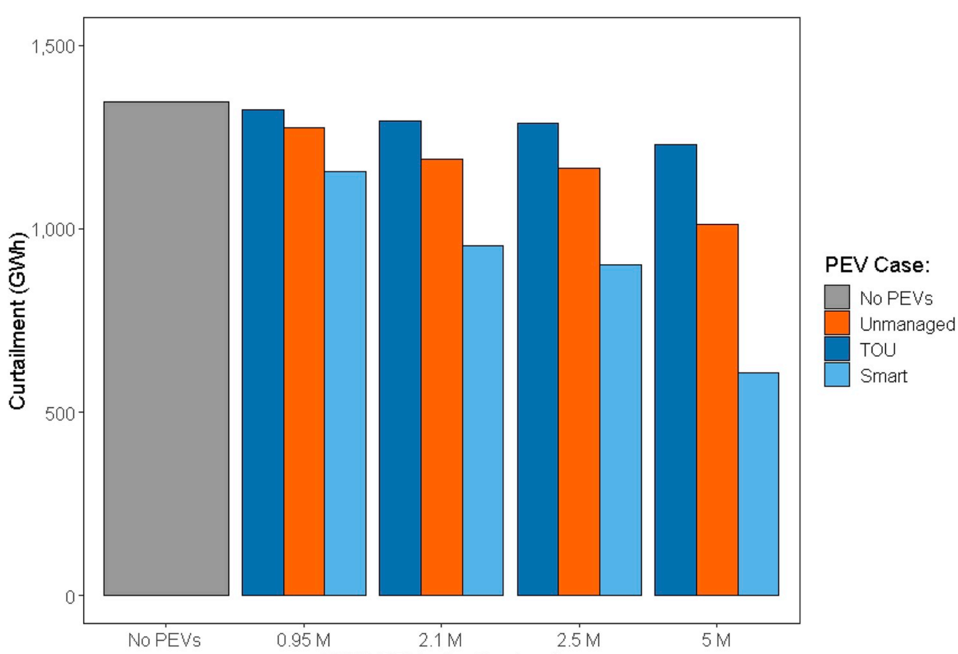

Fig. 7. Annual California renewable energy curtailment. Annual curtailment of California in-state solar PV, solar thermal, and wind generation for each charging strategy and PEV adoption scenario.

privacy, and aversion to new technologies (Wolinetz et al., 2018; Sovacool et al., 2018; Will and Schuller, 2016; Bailey and Axsen, 2015; Axsen et al., 2017). Smart charging pilots have highlighted the importance of customer education on RE benefits, and of guaranteeing minimum charge levels (Kaluza et al., 2017; Will and Schuller, 2016; Schmalfuß et al., 2015).

Overnight TOU rates achieve the majority of smart charging cost savings, have been effective among current adopters (Load Research Report, 2017), and may have fewer customer acceptance barriers (Dütschke and Paetz, 2013), however, our results show they are detrimental for RE integration. Given these tradeoffs, California might additionally consider a policy adjusting residential TOU off-peak periods to include some daytime hours and to establish daytime commercial TOU rates to capture a greater share of RE. Some utilities are moving towards these rates to produce curtailment reductions that cannot be achieved with overnight charging (California Public Utilities Commission, 2017). Further work on impacts of these new TOU rates is needed and on market segmentation for PEV flexibility to account for customer heterogeneity in desired levels of user involvement, financial subsidy, and environmental benefit (Bailey and Axsen, 2015; Curtius et al., 2012; Axsen and Kurani, 2013).

These estimates of VGI value are California-specific and will also depend on the evolution of the generation mix (such as higher RE levels), curtailment-reduction policies (such as better coordination with neighboring areas), distributed energy resources (such as other "smart" loads), and flexible supply-side resources (such as stationary battery storage). However, the relative value of managed compared to unmanaged PEVs is applicable to other systems considering both high PEV and RE deployment. We conclude that regions with dual transportation electrification and grid decarbonization policies can benefit from hybrid smart charging and TOU strategies to avoid grid operating costs, RE curtailment, and capacity expansion.

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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 paper.

Appendix A. Sensitivity analysis of added workplace charging infrastructure

We assess the opportunity for expanding workplace chargers to increase the supply of load shifting flexibility of PEV charging. We do this by simulating BEAM in the San Francisco Bay Area with two workplace charger sensitivities on our base scenario of charging infrastructure (Table 1). The first sensitivity introduces 14,700 additional Level 2 chargers, sited at drivers' workplace locations in the San Francisco Bay Area model. The chargers are sited in proportion to the spatial density of these existing workplace locations. This 4X sensitivity results in four times more Level 2 workplace chargers than in the base scenario. An additional 8X sensitivity is created using the same technique but with 34,300 new chargers, resulting in eight times more Level 2 workplace chargers than in the base scenario.

We then process the charging sessions and analyze the change in charging flexibility from the base scenario (Figure A.1). As in Fig. 4 of the main text, these charging sessions represent a typical weekday in the San Francisco Bay Area and are not shown scaled to California 2025 levels. We find that dramatic increases in workplace charging infrastructure increases the charging load in the workplace sector, but not proportionally with the number of added chargers. The morning peak workplace charging load only increases by 63% and by 99% for the 4X and 8X sensitivities, respectively. For short duration flexibility (0–2 h), the peak morning workplace load increases by 57% from the base to the 8X sensitivity. For longer period flexibility, the peak morning load only increases by 123% with the 8X sensitivity.

With both workplace charging sensitivities, overall, residential charging still dominates the load profile and the opportunity for charging flexibility. Even in the 8X sensitivity, there is still eight times more energy demanded at home than at the workplace, and a much higher fraction of this load is of long-duration flexibility. These sensitivities support a focus on residential smart charging, because of the relatively small marginal increase in daytime load and flexibility from added workplace chargers.

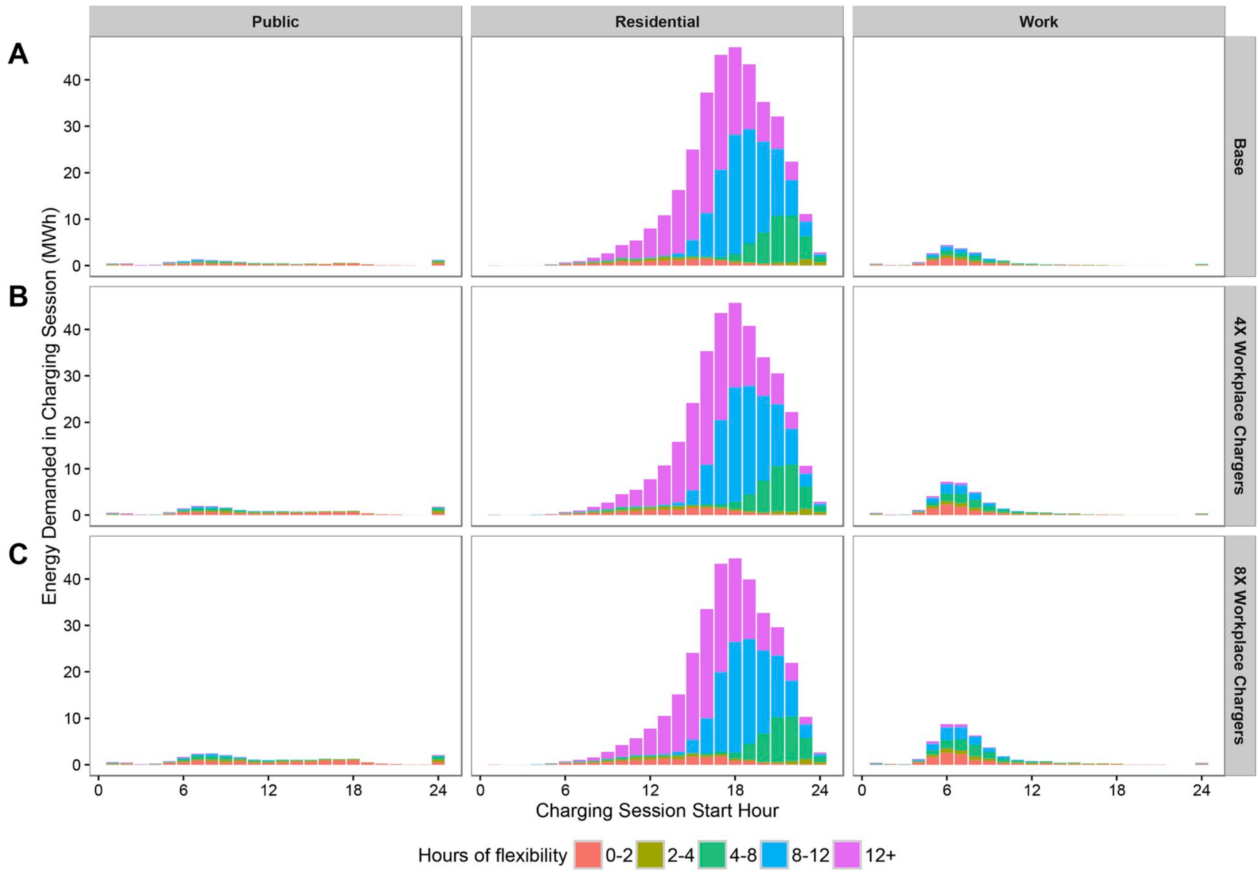

Figure A.1. Weekday charging session flexibility duration and energy demanded, by location and hour for three workplace infrastructure sensitivities. The panels show for a typical weekday in the San Francisco Bay Area BEAM simulation (before scaling to California, 2025 levels), the energy demanded by location and the hours of flexibility to shift load within charging sessions (based on the time between active charging and unplugging). Each row of panels represents a different workplace charging infrastructure sensitivity where progressively more workplace chargers are sited. **A.** Base case with original number of chargers assumed in the analysis. **B.** 4X sensitivity with four times number of workplace chargers as base case. **C.** 8X sensitivity with eight times the number of workplace chargers as base case.

Appendix B. Sensitivity analyses of vehicle range and fast charging infrastructure

The PEV market is quickly evolving and battery capacities in new vehicle models are already much larger than the 2016 fleet (CVRP Rebate Statistics, 2016). While we assume in our baseline analysis that by our 2025 study year every vehicle will have 1.5X larger battery capacity than a 2016 vehicle, even this assumption may be an underestimate. In addition to battery capacity, DC Fast charger technology is also advancing, with chargers rated as high as 350 kW entering the market (Evarts). Furthermore, with increased availability of DC Fast chargers in general (Fehrenbacher, 2018), PEV driver behavior in the future may differ from our assumed behavioral patterns which were based on 2016 utilization of DC Fast chargers in the San Francisco Bay Area. In these sensitivity analyses, we deduce how our flexibility results may potentially change by post-processing the charging sessions from our BEAM baseline scenario (Table 1, Fig. 4) to mimic higher range and faster charging futures.

In Figure B.1 we disaggregate the flexibility result in the baseline BEAM scenario for the San Francisco Bay Area by low- and high-range vehicles using the medians of 126 miles for BEVs and 31 miles for PHEVs, respectively, as the dividing points. We observe subtle differences between low- and high-range vehicles in the time of day and the relative duration of load shift capacity. With BEVs, the low-range vehicles have slightly more of the longest duration flexibility (12 + hours), while the high-range vehicles have more 8 to 10-h duration flexibility. For PHEVs, the low-range vehicles provide more flexibility during the morning hours compared to the high-range PHEVs. Consequently, we deduce that increased numbers of high-range PEVs may result in marginally lower cost savings and curtailment reductions, but not a significant overall change from our baseline results.

In Figure B.2 we present the same flexibility analysis for the San Francisco Bay Area but for several scenarios that vary the amount and rate of DC Fast charging that occurs in the simulation. We replace a share of slow charging (Level 2) sessions in the baseline scenario BEAM output with a representative DC Fast charging session that occurs at approximately the same time and delivers approximately the same amount of energy, but at a higher rate. In these sensitivities, we increase the number of fast charging sessions by a factor of 20, to 6% of all sessions from 0.3% of all sessions originally in the baseline scenario. We also increase the rate of DC Fast charging across the scenarios from 50 kW to 350 kW. We find that including more public DC Fast chargers moves some charging away from home and to the morning (between 6am and 12pm). The added DC Fast chargers also decrease the flexibility in those hours; the overall amount of temporal flexibility (the number of hours into which load can be shifted) decreases by 3% between the baseline and the DC Fast sensitivities. This implies that if DC Fast chargers comprised a greater share of infrastructure, there may be slightly lower curtailment reductions (and cost savings) that could be achieved by smart charging in the morning hours than indicated by our baseline results. However, even with a 20-fold increase in DC Fast chargers, we expect this decrease to be relatively small and overall the bulk of load flexibility to still occur at home with slow chargers in the evening. Our sensitivities also show no difference in flexibility between the three fast charger rates, because in all cases we have assumed that PEVs unplug immediately at the end of active charging during fast charging sessions. Overall, we expect that across increasing rates of DC Fast chargers the shape of the charging load would be different, and a greater installation of faster chargers might allow for more utilization over slow charging, but that the impact of charging rate on total load flexibility (and therefore costs and curtailment) would be marginal.

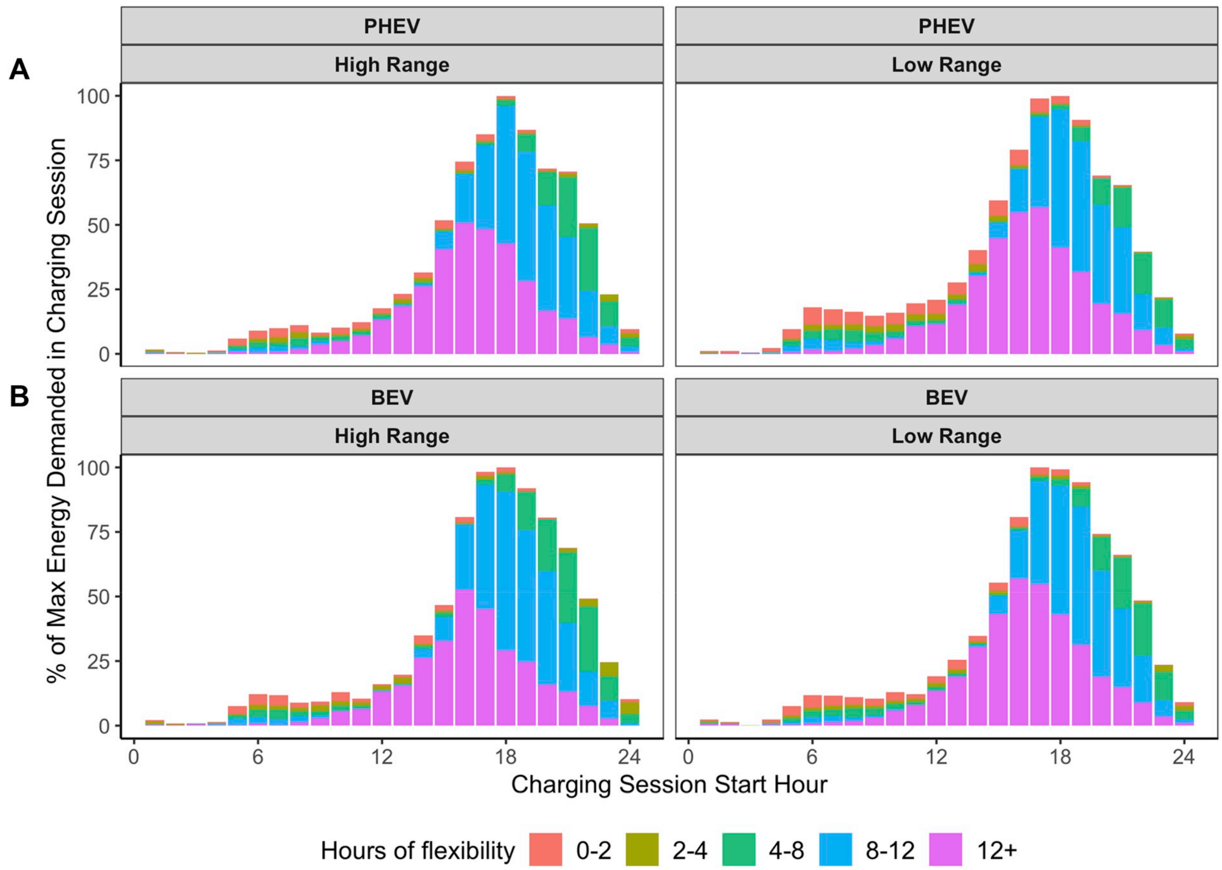

Figure B.1. Weekday charging session flexibility duration and energy demanded, by BEV and PHEV, by high-range and low-range battery sizes. The panels show for a typical weekday in the San Francisco Bay Area BEAM simulation (before scaling to California, 2025 levels), the percent of maximum energy demanded and the hours of flexibility to shift load within charging sessions (based on the time between active charging and unplugging) by high- and low-range battery sizes. Each row of panels represents a vehicle type, either BEV or PHEV. **A.** High- and Low-Range PHEVs, split by the median 31-mile PHEV range in the baseline analysis. **B.** High- and Low-Range BEVs, split by the median 126-mile BEV range in the baseline analysis.

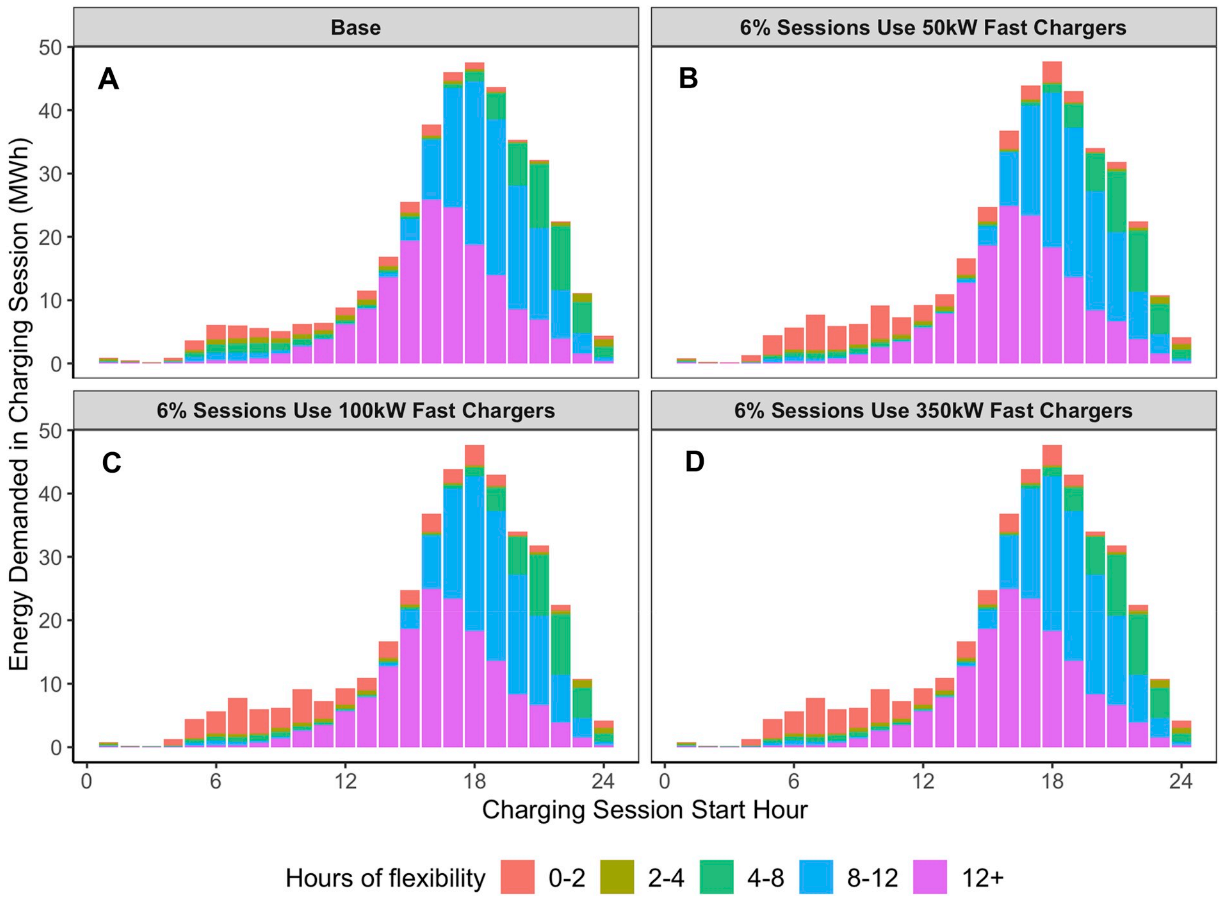

Figure B.2. Weekday charging session flexibility duration and energy demanded in Base case (0.3% DC Fast charging sessions) and sensitivities (6% DC Fast charging sessions) with 50 kW–350 kW DC Fast chargers.

The panels show for a typical weekday in the San Francisco Bay Area BEAM simulation (before scaling to California, 2025 levels), the energy demanded and the hours of flexibility to shift load within charging sessions (based on the time between active charging and unplugging). Each plot represents a different percent of charging sessions by DC Fast chargers, and a particular rate of DC Fast chargers. **A.** Base case with 0.3% of charging sessions at DC Fast chargers, at 50 kW. **B.** Sensitivity with 6% of charging sessions at DC Fast chargers, at 50 kW. **C.** Sensitivity with 6% of charging sessions at DC Fast chargers, at 100 kW. **D.** Sensitivity with 6% of charging sessions at DC Fast chargers, at 350 kW.

Appendix C. PLEXOS Unit Commitment and Economic Dispatch Optimization

In this analysis we use the unit commitment and economic dispatch model PLEXOS, a commercial optimization software created by Energy Exemplar. This Appendix presents the main characteristics and high-level model outline of the optimization used in this analysis, and not a comprehensive mathematical model. More detail on the mathematical model is available in PLEXOS documentation from Energy Exemplar (PLEXOS). Additionally, (Foley et al., 2013; Calnan et al., 2013; Gopal et al., 2015; Wagner and Reedman, 2010) provide examples of other studies which have used PLEXOS for similar types of analyses.

PLEXOS constructs the objective function and constraints based on parameters provided in the input database. The specific PLEXOS database we use in this analysis for the WECC region (containing generator, load, network data, and constraints) was obtained from and originally created by the California Independent System Operator (CAISO) for state grid planning processes, and more information on the database is described in regulatory documents (Liu, 2014; Liu, 2016; ISO Transmission Plan, 2016; Picker, 2016) and prior studies using variants of the same database (Nelson and Wisland, 2015; Eichman et al., 2015; Jorgenson et al., 2014; Fioravanti et al., 2013).

The objective function for each day of the optimization in our WECC-wide analysis can broadly be simplified to:

$$min \sum_{i,t} GenerationCost_{i,t} + \sum_{t} TransmissionCharge_{t} + \sum_{j,t} VoLL_{j} {}^{*} UnservedEnergy_{j,t} - \sum_{j,t} PriceofDumpEnergy_{j} {}^{*} DumpEnergy_{j,t} \tag{C.1}$$

Subject to several types of operational constraints, which are described further below.

The objective function has several main components defined as follows, where:

i indexes each of the generators, which are in specific utility zones (*j*) within the WECC region and could be thermal (natural gas, coal, nuclear, other) or renewable. There are several thousand generators included in WECC.

t indexes each hour in the optimization. The optimization is conducted for hourly intervals, at daily timesteps, 1 month at a time for a complete year.

j indexes each utility zone in the optimization. This analysis has 25 total zones in WECC, including eight in California.

$GenerationCost_{i,t}$ is the operating cost of generator i at hour t, including the fuel costs ($FC_{i,t}$), operations and maintenance costs ($O\&M_{i,t}$), start/shutdown costs of thermal units ($SC_{i,t}$) and the emissions costs of fossil units ($EC_{i,t}$).

$$GenerationCost_{i,t} = FC_{i,t} + O\&M_{i,t} + SC_{i,t} + EC_{i,t} \tag{C.2}$$

Each component of $GenerationCost_{i,t}$ is defined as follows:

$$FC_{i,t} = FuelPrice_i \times HeatValue_i \times HeatRate_i \times Generation_{i,t} \tag{C.3}$$

$FC_{i,t}$ is the fuel cost (applicable only for natural gas, coal, nuclear, and biomass generators).
$FuelPrice_i$ and $HeatValue_i$ are the price and heating value of the fuel used by generator i.
$HeatRate_i$ is the rate of electricity output given a unit of fuel input, and could be modeled as a function (linear or non-linear) depending on the generation level.
$Generation_{i,t}$ is the instantaneous electricity production from generator i in hour t. It is one of the main decision variables of the optimization.

$$O\&M_{i,t} = Generation_{i,t} * VO\&M_i \tag{C.4}$$

$O\&M_{i,t}$ is the cost for operations and maintenance for each generator, based on its variable $VO\&M_i$ cost per unit of $Generation_{i,t}$.

$$SC_{i,t} = StartCost_i \times UnitsStarted_{i,t} + ShutdownCost_i \times UnitsShutdown_{i,t} \tag{C.5}$$

$SC_{i,t}$ is the cost to start and shutdown a generator and is typically applicable only for thermal generators depending on the number of $UnitsStarted_{i,t}$ or $UnitsShutdown_{i,t}$ during the period, which are integer decision values that are part of the unit commitment decision.

$$EC_{i,t} = EmissionsPrice \times EmissionsRate_i \times Generation_{i,t} \tag{C.6}$$

$EC_{i,t}$ is the emissions cost for CO_2 emissions based on each fossil plant's $EmissionsRate_i$ per MWh times its $Generation_{i,t}$ and the exogenously set $EmissionsPrice$ per unit of CO_2. The emissions cost is applied in this way directly to fossil generators within California, and added to the transmission $WheelingCharge_{jk}$ with an assumed $EmissionsRate$ to out-of-state generators which produce "unspecified" imports (not dedicated fossil or RE imports from a known origin).

$$TransmissionCharge_t = \sum_{j,k} WheelingCharge_{jk} \times LineFlow_{jk,t} \tag{C.7}$$

$TransmissionCharge_t$ reflects a Transmission Access Charge (Liu, 2014) for net hourly flow on the transmission paths between each zone j and all the connected utility zones k, based on the $WheelingCharge_{jk}$ per MWh for each set of connected zones j and k and the hourly $LineFlow_{jk,t}$ decision variables in the reference flow direction.

$VoLL_j * UnservedEnergy_{j,t}$ is the cost of load shedding. The $VoLL_j$ sets a maximum price in each zone above which there is $UnservedEnergy_{j,t}$. If there is not enough generation to meet load, the electricity market price will reach the $VoLL$. $PriceofDumpEnergy_j$ is a price below which generators shutoff rather than $DumpEnergy_{j,t}$ or over-generate. If generation exceeds load, the electricity market price reaches the $PriceofDumpEnergy$, which is typically negative.

Generator unit commitment and dispatch is subject to the following selected constraints:

For each utility zone j there is an energy balance constraint such that total generation of all generators within the zone j (minus any over-generation $DumpEnergy_{j,t}$) plus total power $Inflows_{j,t}$ from connected zones minus total power $Outflows_{j,t}$ to connected zones must match the $Load_t$ in zone j, which is the total electricity demanded in hour t (minus any under-generation $UnservedEnergy_{j,t}$):

$$\sum_i Generation_{i,t} - DumpEnergy_{j,t} + Inflows_{j,t} - Outflows_{j,t} = Load_t - UnservedEnergy_{j,t} \tag{C.8}$$

where:

$$Outflows_{j,t} = \sum_k LineFlow_{jk,t} \tag{C.9}$$

$$Inflows_{j,t} = \sum_k LineFlow_{kj,t} \tag{C.10}$$

jk indicates power flow from zone j to zone k, and kj indicates power flowing from zone k to zone. j.

Selected generator constraints:

Instantaneous energy from any generator must be less than or equal to its max capacity:

$$MaxCapacity_i \geq Generation_{i,t} \tag{C.11}$$

All thermal generators must abide by their ramping constraints:

$$|Generation_{i,t} - Generation_{i,t-1}| \leq RampRate_i \tag{C.12}$$

Hydropower generators have monthly energy budgets (based on the amount of water they can allocate that month) as well as minimum and maximum flows. PLEXOS first optimizes for the monthly budget through a monthly scheduling process. There are also particular constraints for other generator types or demand-side resources that are not described here, such as pumped storage, battery storage, and demand response. RE generation is included as a “fixed dispatch” with a $VO\&M_i$ set to -$150/MWh such that generation is curtailed when the market price reaches that level. The method for modeling PEVs and their constraints are described in Section 2.3.2.

Overall, the optimization is a mixed integer program including a unit commitment decision (1 or 0 whether a generator is on or off) and an economic dispatch decision (how much a generator generates). The following are the main unit commitment related constraints:

$$UnitOn_{i,t} = UnitOn_{i,t-1} + UnitStarted_{i,t} - UnitShutdown_{i,t} \tag{C.13}$$

There are also constraints specific to the unit commitment problem for minimum stable levels, minimum up time, and minimum down time:

$$Generation_{i,t} \geq UnitOn_{i,t} * MinStableLevel_i \tag{C.14}$$

when a generator is committed ($UnitOn_{i,t} = 1$), it must operate at or above its $MinStableLevel_i$.

$MinUpTime_i$ is the minimum number of hours a generator unit must be on if committed (primarily applies to thermal generators).

$MinDownTime_i$ is the minimum number of hours a generator unit must be off if shut down (primarily applies to thermal generators).

Selected transmission and reserves constraints:

The optimization solves a linearized DC power flow which follows Kirchhoff’s Laws, and flows between utility zones j and k must not exceed $LineLimits_{jk}$ and $LineLimits_{kj}$.

For California there are some additional import and export constraints that are included in this analysis, per CAISO’s assumptions (Picker, 2016; Liu, 2014). For example, for the set of utility zones j which are part of the CAISO region (PG&E Valley, PG&E Bay, SCE, SDG&E), there is a 2000 MW limit on its total hourly total net exports:

$$\sum_j Outflows_{j,t} - \sum_j Inflows_{j,t} \leq 2000 \; \forall j \in \{PG\&E\ Valley,\ PG\&E\ Bay,\ SCE,\ SDG\&E\} \tag{C.15}$$

There are also hourly reserve requirements (load-following, regulation, spinning, and non-spinning) as estimated by CAISO that must be met for utility zones throughout the WECC. Constraints specify that certain generator types can provision different types of reserves, and the provision of reserves is determined as part of a co-optimization with the unit commitment and dispatch of generators to provide energy.

Solution algorithm:

We set the Mixed Integer Program (MIP) gap, the percentage difference between the best integer solution and the best bound (through the Branch and Bound algorithm) to be 0.01%, and set the optimization to stop solving for each day’s optimum when it reaches this MIP gap or a time limit of 4000 s.

Appendix D. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.enpol.2019.111051.

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