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Future-proof rates for controlled electric vehicle charging: Comparing multi-year impacts of different emission factor signals

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ABSTRACT

Electricity pricing can be used to shift the timing of electricity demand, but the choice of price signals is highly constrained. Consumer rates are updated every few years and limited to simple daily profiles, yet must capture the complex dynamics of a changing electricity system. Emission factors (EFs) were developed as an evaluation tool, but are increasingly used as demand response (DR) signals. Given these constraints, can they be effective? We evaluate the emissions impact of EF-based electricity rates with and without supply-side emissions pricing. We study controlled electric vehicle (EV) charging in the Western U.S. up to 2037 by coupling an electricity system dispatch model and a data-driven EV charging model. We compare average and short-run marginal EFs with a new medium-run marginal EF that better matches the timeline of electricity rate updates. We find that a stable supply-side signal makes DR more valuable: DR reduces emissions by up to 6% with supply-side carbon pricing or just 2% without it. Medium-run marginal EFs yield the most consistent emission reductions, but constraints on charging flexibility limit their impact. We recommend policymakers base rates for DR on medium-run marginal emission factors and implement supply-side carbon pricing to facilitate greater emission reductions.

1. Introduction

Reducing emissions from the electricity sector is central to global plans to tackle climate change (IPCC, 2023). Electricity generation is undergoing a major transformation to reduce emissions, including transitioning from high-emitting sources like coal and gas to low-emitting sources like wind and solar (IEA, 2022; Callaway et al., 2018). Supply-side interventions like carbon pricing can reduce generation emissions further (Levin et al., 2019). Demand-side interventions can reduce emissions by shifting consumption to times when it will be met by lower-emitting generation sources (Xu et al., 2020). The implementation of these demand-side interventions, however, is challenging, especially for small-scale, distributed electricity customers.

Utilities often use prices to attain shifts in demand among small-scale customers: low or high prices signal when or when not to consume electricity. While this can motivate small behavioural changes (Fischer et al., 2016), a growing portion of distributed demand responds to price signals in an automated way. Electric vehicles (EVs) in particular are a rapidly growing new load, as electrification is used to reduce emissions from personal transportation (Bistline et al., 2022), and passenger EVs represent a valuable source of automated, distributed demand response (Muratori et al., 2021; Anwar et al., 2022). EVs typically remain plugged in for longer than it takes to recharge (Sadeghianpourhamami et al., 2018) and many individuals or charging aggregators leverage the flexibility that this provides to shift their demand and minimise their electricity bills (Kara et al., 2015).

The possibility of control raises the question: what electricity rates could utilities use to shift EV demand in a way that reduces emissions? In this work, we are not searching for the optimal pricing scheme but instead will evaluate the merits of a few simple approaches suited to the way rates are currently set.

An important assumption of our work is that we constrain ourselves to current implementations and we do not consider dynamic pricing or

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centrally-managed control. Many previous studies have explored the potential of centrally-managed control to reduce emissions from EV charging (van Triel and Lipman, 2020; Tarroja et al., 2015; Bellocchi et al., 2019; Hanemann et al., 2017). For example, different studies found fully managed charging could reduce added CO_2 emissions for EV charging by up to 75% in California (Zhang et al., 2018) (Table IX) and up to 67% in Europe (Xu et al., 2020) (Figure 6) compared with uncontrolled. However, these results depended on idealised implementations with centralised, direct dispatch of EV demand. In this study, we consider the highly constrained case faced by most utilities today: decentralised, rate-based control, with charging flexibility limited by low charger availability and stochastic charging behaviours.

In practice, the problem utilities face setting rates is highly constrained in terms of timing and complexity. Consumer-facing electricity rates only undergo major updates every three to ten years (RAP, 2011), but the grid itself is constantly changing. In the time between when a rate is set and when it is next updated, there may be substantial structural changes to the generation fleet. Are rates related to emissions 'future proof' to last until the next update? Further, consumer-facing electricity rates are constrained to very simple forms.

Many utilities in the United States have rolled out EV-specific rates, but most are time-of-use (TOU) rates with a small number of different price periods per day, typically limited to a single weekday and weekend schedule (Cappers et al., 2023). We recognise that TOU tariffs are an imperfect reflection of the time-varying nature of wholesale energy costs and may even lead to bunching of electricity consumption near the start and end of off-peak periods (Muratori and Rizzoni, 2015). Our study is not intended to advocate for TOU pricing but rather to investigate the flexibility of EV charging in response to current financial incentives.

Emission factors (EFs) are one tool used to test and reduce the emissions from charging. Hourly EFs are calculations that condense the complex dynamics of grid emissions into a simple signal. The three relevant EFs are: Average Emission Factors (AEFs), the ratio between total emissions and total demand (Elenes et al., 2022); Short-Run Marginal Emission Factors (SR-MEFs), the immediate marginal change in emissions caused by a marginal change in demand (Hawkes, 2010; Siler-Evans et al., 2012); and Long-Run Marginal Emission Factors (LR-MEFs), the marginal change in emissions caused by a persistent change in demand or supply over a longer period of time (Hawkes, 2014). The SR-MEF we use in this paper has also been called the Costliest Plant MEF (Elenes et al., 2022): assuming that the last plant dispatched in the generation merit order is the one to respond to a small increase in demand, that plant's emission rate sets the SR-MEF.

EFs were originally created—and are still most commonly used—as a tool to evaluate the emissions impact of an intervention. The AEF and SR-MEF are both based on snapshots of the system and describe short-term emissions. Both the AEF and SR-MEF have been widely used to assess the emissions from EV charging (e.g. AEF (Li and Jenn, 2022; Lin, 2021; Linn and McConnell, 2019; McLaren et al., 2016), SR-MEF (Zivin et al., 2014; Yuksel et al., 2016; Tong et al., 2021), or both AEF and SR-MEF (Chen et al., 2022; Mehlig et al., 2022; Brinkel et al., 2020; Jochem et al., 2015; Holland et al., 2022; Gagnon and Cole, 2022)). Elenes et al. showed that short-term changes can be evaluated more accurately with SR-MEFs than AEFs, in most cases (Elenes et al., 2022). The gap between evaluations made by AEFs or SR-MEFs has been widening over the past decade in the U.S. (Holland et al., 2022). As the AEF and SR-MEF capture only snapshots of the grid, the LR-MEF was introduced to capture the long-term impacts of persistent changes (Hawkes, 2014). Gagnon and Cole showed that the LR-MEF provides better estimates of the long-run emissions impact of various demand interventions than the AEF or SR-MEF when the impact of investment in new generation capacity is considered (Gagnon and Cole, 2022).

Recently EFs have been used for a new purpose: guiding an intervention as the objective for demand optimisation. Researchers have used both the AEF and SR-MEF as signals for optimised EV charging (e.g. AEF (Mehlig et al., 2022; Cheng et al., 2022; Powell et al., 2022b; Daneshzand et al., 2023), SR-MEF (Kang et al., 2023; Gai et al., 2019; Hoehne and Chester, 2016), or both (Huber et al., 2021; Brinkel et al., 2020)). Many report very positive results. For example, SR-MEF control was reported to reduce emissions by 23.6% (Brinkel et al., 2020) or over 18% (Kang et al., 2023) in California (different years and methods), and up to 31% in other U.S. regions (Hoehne and Chester, 2016). Li and Jenn find that real-time pricing could yield better emission reductions than static time-of-use prices in a system with high carbon prices (Li and Jenn, 2022). However, these studies use the same EFs to evaluate the impact on emissions as they do to guide the control, rather than testing total emissions with a simulation. As a result, the signals' success at reducing emissions remains unclear (Elenes et al., 2022).

To the best of our knowledge, the LR-MEF has not been used for charging control. That may be because charging control is typically considered a short-term problem, but in practice rates are fixed for multiple years. The interpretation of the LR-MEF suggests it could be a successful signal: when the LR-MEF is lowest, added demand causes the smallest long-term increase in total emissions.

However, the time horizon of rate design for EV charging falls between those of the SR-MEF and LR-MEF. The SR-MEF does not capture structural changes in the grid that will occur in the five years between rate updates, including planned additions and retirements of power plants and the deployment of new renewable generation (Gagnon and Cole, 2022). On the other hand, five years is much shorter than the planning horizon for most new generation (WECC, 2022) and the 20+ year timelines modelled by Hawkes (2014), and Gagnon and Cole (2022).

Here we define a new EF, the Medium-Run Marginal Emission Factor (MR-MEF), specific to the time horizon of rate design. The MR-MEF calculates the 5-year change in emissions from a unit change in demand. Planned and projected changes to the generation fleet in that time are reflected in the simulation, but we assume that any additional investments in new generation induced by the change in demand are negligible. This assumption differs from the methods used by Hawkes, and Gagnon and Cole. We believe the assumption is justified in this use-case for three reasons: investments in new generation are typically planned on longer time scales, the changes in demand from EV charging control are relatively small, and the change in demand only persists for 5 years until the next rate change.

In this study, we compare the use of the AEF, SR-MEF, and MR-MEF as control signals for EV demand to test which most reduces total emissions, under which conditions. Our main contribution is the use of a highly detailed, realistic model to offer a comprehensive evaluation of these signals. While previous research has compared these control signals for snapshots in time, we are not aware of any that has evaluated the use of fixed EF rates as the electricity system changes over time. We analyse the resulting emissions reductions along three key axes to draw a range of insights: different EFs, different levels of constraint on EV charging demand, and different scenarios of supply-side carbon pricing.

We compare the three signal types over three 5-year periods from 2023 to 2037 in two scenarios: with and without a supply-side carbon price influencing the grid dispatch. We conduct a "what-if" analysis using a model of future EV demand and electricity generation. Our aim is not to provide forecasts, but to evaluate these signal designs in a realistic setting with a changing electricity system. We focus on the case of EV charging demand in the Western U.S. Interconnection (WECC) and use an open-source, reduced-order model of dispatch in WECC where each future year is modelled with planned changes to the generation fleet and baseline electricity demand (Deetjen and Azevedo, 2019b). We combine the grid model with an open-source, data-driven model of EV charging behaviour and control (Powell et al., 2022b); the model simulates charging for battery electric vehicles or fully electric vehicles only, with a range of battery capacities, charging behaviours, driving distances, and charging options. We compare the

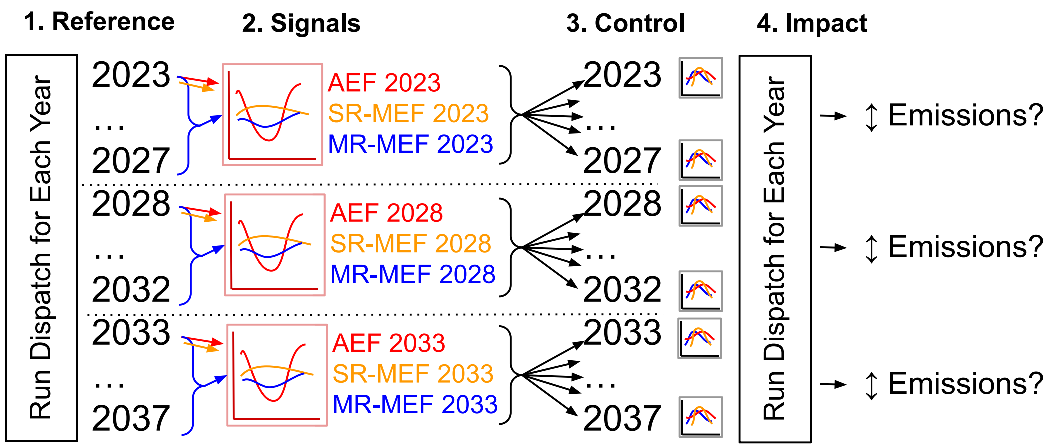

Fig. 1. Overview of modelling steps. We re-calculate the signals every five years: in 2023, 2028, and 2033.

fully constrained model of EV demand with a minimally constrained counterpart to reveal the reduced flexibility imposed by realistic EV modelling.

Our results reveal an important synergy between supply-side and demand-side efforts to reduce emissions: adding a carbon price to the electricity dispatch makes the EF signals more stable and the demand response more successful. In the short-term we find the MR-MEF gives the best signal and that AEF signals may increase emissions. In the medium-term, the best signal is less clear. In the long-term, changes to the electricity system make the AEF and MR-MEF converge, but cause the SR-MEF to increase emissions. In the carbon price scenarios, all signal types converge to similar shapes and impacts. Our results offer critical insights to policymakers and utilities as they approach rate design and set rates in the medium-term to reduce grid emissions.

The body of this paper is organised as follows: in Section 2 we present the modelling framework and methods used; in Section 3 we present the signals, demand profiles, and impacts on grid emissions; in Section 4 we discuss limitations of this study; and in Section 5 we summarise the conclusions and policy implications of our findings.

2. Methodology

The sequence of modelling steps is depicted in Fig. 1. The four major steps in the analysis are: (1) run reference simulations for each year without any added EV demand; (2) calculate signals; (3) simulate uncontrolled and controlled EV demand; (4) re-run the grid simulation with the added EV demand, and compare with the uncontrolled demand results to assess whether control caused an increase or decrease in emissions. The AEF and SR-MEF signals are calculated using one-year snapshots in 2023, 2028, and 2033. The MR-MEF signals are calculated using five year intervals: for example, the MR-MEF signal in 2023 is calculated using the simulation results from 2023 through 2027. The grid dispatch model and the model of EV charging demand are described in detail in the following subsections.

To simulate the process of rate design, we update the rates in each scenario every 5 years: the rates calculated in 2023 are used as control signals from 2023 through 2027, the rates calculated in 2028 are used as control signals from 2028 through 2032, and the rates calculated in 2033 are used from 2033 on. Major rate changes are only possible when a utility files a General Rate Case (GRC) with the regulator. Most utilities file every two to five years, but in some states utilities have waited up to 10 years between filings (RAP, 2011). The California Public Utilities Commission, for example, requires utilities to file a GRC every four years (Electric, 2023).

The time period from 2023 to 2037 was chosen to align with the planning horizon for large-scale power systems in the U.S. 2019 was used as a base year for all data to avoid including any short-term effects caused by the COVID-19 pandemic in 2020 and 2021 or the global gas crisis in 2022 driven by the Ukraine war. Gas prices have since returned to pre-crisis levels (Ricker and Comstock, 2024), but more recent data required for the model is not yet available. We test and discuss the sensitivity to 2022's extremely high natural gas prices in Section 3.4.

We use only open-source models; the code for this analysis has been published open-source on Github (Powell et al., 2024).

2.1. Grid model

The grid model consists of four parts: demand, non-fossil fuel generation, fossil fuel or combustion-based generation, and storage.

First, we model the increase in baseline non-EV electricity demand due to electrification in other sectors (Mai et al., 2018).

Second, we model the increase in renewable generation based on planned, announced, and forecast installations. We obtain hourly generation totals for each resource, and we assume the timing of fluctuations in solar and wind generation are the same as in the base year. We assume the timing of hydro and nuclear generation are unchanged. We assume all non-fossil fuel and non-combustion generation is dispatched first; the remaining demand, referred to as net demand or residual demand, is then adjusted by the use of storage. We assume planned grid-scale storage is operated to smooth net demand. The smoothed net demand is then dispatched to the fossil fuel generators.

We simulate the dispatch of fossil fuel and biomass generators using an economic dispatch model (Deetjen and Azevedo, 2019b). The model dispatches generators in order of lowest cost to serve the net demand at each hour of the year, including both operating costs and costs imposed by emission pricing. Costs and emission rates are calculated from historical data reported for each generating unit. Generators are removed from the fleet based on their announced retirement years (WECC, 2022). To reflect generator additions (WECC, 2022), we duplicate existing generators matching as closely as possible by type and capacity. We model the region with one node and do not represent transmission or losses within the region.

In some hours of the year during peak evening demand, there is insufficient generation capacity to cover demand even after the operation of the storage planned above. We assume additional battery storage will be added to cover those events. We calculate the smallest 4-hour storage that would be sufficient and we assume it is operated in a simple way: it is discharged only to cover that excess demand and its charging is spread evenly over other hours with available capacity.

The application of this model to our case study region is described in detail in Section 2.4.1.

2.2. Emission factors

We calculate the AEF and SR-MEF using the results of a reference dispatch where the grid model is run without any added EV demand.

Let e^t represent the total emissions produced at hour t to serve the total demand, d^t. Let e^t_m represent the emission rate of the marginal generator, i.e. the most expensive generator dispatched at time t. Then, the AEF and SR-MEF are calculated as:

$$\mathrm{AEF}^t = \frac{e^t}{d^t} \tag{1}$$

$$\text{SR-MEF}^t = e^t_m. \tag{2}$$

We calculate this profile for each day in the year, then calculate the weekday and weekend profiles as the mean over all weekdays and weekend days, respectively. The AEF and SR-MEF are recalculated every 5 years in 2023, 2028, and 2033.

We calculate the MR-MEF as a 24 h profile. To calculate the MR-MEF at hour, $h_0 \in [0, 23]$, for starting year, y_0, $\text{MR-MEF}^{h_0}_{y_0}$, we take the following steps:

1. We simulate a reference scenario with demand, d^t_y, where no EV demand is added.
2. We calculate the reference scenario emissions, $e_y(d^t_y)$ for every time in each of the five years from the starting year, y_0 to y_0+4.
3. We simulate a scenario where Δ demand has been added to d^t_y at hour h_0 every weekday (or weekend). Where t covers the whole year from 1 to 8760, let $h(t)$ return the hour of day for time t.
4. We calculate the emissions after this intervention, $e_y(d^t_y + \Delta\mathbb{1}_{h(t)=h_0})$, for each of the same five years.
5. We calculate the MR-MEF from the difference between the delta and reference scenario results.

The dispatch model, $e_y(.)$, and the baseline demand, d_y, both change each year as described in the previous section. The final calculation is:

$$\text{MR-MEF}^{h_0}_{y_0} = \frac{\sum_{y=y_0}^{y_0+4}\sum_{t=1}^{8760} e_y(d^t_y + \Delta\mathbb{1}_{h(t)=h_0}) - e_y(d^t_y)}{\sum_{y=y_0}^{y_0+4}\sum_{t=1}^{8760}(d^t_y + \Delta\mathbb{1}_{h(t)=h_0}) - d^t_y} \tag{3}$$

We test cases with Δ equal to 5 GW, 10 GW, and 20 GW. We choose these values similar to the magnitude of EV demand to make the signal more relevant to the problem.

This formula is most similar to the LR-MEF formula used by Gagnon and Cole (2022), though for simplicity we do not discount future emissions. The dispatch model we use to simulate emissions, $e(.)_y$, does not model optimal investments in additional generation. The original formula proposed by Hawkes also does not discount future emissions (Hawkes, 2014). Where Hawkes calculated one LR-MEF for a multi-hour intervention, we use the Gagnon and Cole method of hourly demand changes to calculate an hourly profile. We call this the MR-MEF to differentiate from the LR-MEF, which takes a longer time horizon and includes the possibility that long-lasting changes in demand can induce additional investments in new generation. The MR-MEF is defined to match the timeline of electricity rate updates.

2.3. EV model

To model uncontrolled charging we use SPEECh (Scalable Probabilistic Estimates of EV Charging), a data-driven model of large-scale EV demand (Powell et al., 2022c,b). The model takes a data-driven approach: it requires a large dataset of charging sessions across charging segments for a diverse set of EV drivers.

First, agglomerative clustering with Ward's method is applied to cluster the drivers by their charging histories into 136 behaviour groups. Each group has a different pattern of when, how often, and for how long they charge at home, the workplace, or public charging stations. For example, some behaviour groups with larger battery capacity vehicles charge infrequently and prefer public charging, while others with smaller battery capacities and access to workplace chargers prefer to top-up every day.

We use a probabilistic graphical model to connect the drivers' behaviour groups to: (1) their vehicle battery capacity, access to charging options, household income, housing type, and annual mileage; and (2) their daily charging decisions and load profiles. Daily charging decisions and session parameters, including start time, session energy, and end time, are fit with Gaussian Mixture Models. We calculate the number of drivers from each behaviour group in a given county based on the distribution of household income, housing type, and annual mileage in that county, combined with survey data on access to different charging options. Then, we use the probabilistic model of decisions and sessions to simulate daily charging sessions for all drivers in the county. The weekday and weekend profiles are concatenated to create one year's EV demand. The reader is referred to Powell et al. (2022b) for more details and validation of the methodology.

We simulate only fully-electric EVs, also called battery electric vehicles. We assume that charging patterns and constraints of plug-in hybrid EVs can be represented by the data in our sample with small vehicle battery capacities or with preferences for more frequent charging. Plug-in hybrid EVs are a fraction of current plug-in EV sales in the U.S. today (IEA, 2022) and recent policy support targets all-electric models to align with long-term emission targets (Dawson, 2023). Conventional hybrid vehicles do not interact with the electricity system.

In Sections 2.3.1 and 2.3.2, respectively, we explain the difference between the minimally constrained and fully constrained EV control cases. The application of this model to our case study region is described in detail in Section 2.4.2.

2.3.1. Minimally constrained

To separate the effect of the control signals from limitations related to the driving profiles, we first implement a minimally-constrained version of EV control.

Let $C_{w,y}$ be the total daily EV electricity consumption on a weekday/weekend w in year y, measured in GWh. Let s^t be the control signal and d^t be the demand at hour t. We implement the following optimisation for one weekday and weekend day for each year:

$$\begin{aligned} \min_{d} \quad & s^T d \\ \text{s.t.} \quad & \sum_{t=1}^{24} d^t = C_{w,y} \\ & 0 \leq d \leq 20 \text{ GW}. \end{aligned} \tag{4}$$

We include the constraint limiting demand to less than 20 GW to make it more similar to the EV demand profiles, but we do not include any constraints related to timing.

2.3.2. Fully constrained

Real-world constraints on driver mobility, behaviour, and the availability of charging stations add important constraints to this control problem.

We use three scenarios of future charging behaviour (Powell et al., 2022b): Universal Home Access, where all drivers have access to home charging either at their single family home (SFH) or multi-unit dwelling (MUD); High Home Access, where 72% of drivers have access to home charging; and Low Home High Work Access, where 27% of drivers have access to home charging. These scenarios are derived from the California Energy Commission's 2022 survey on potential home charger installation (Alexander, 2022). In all cases we simulate driver behaviour using the SPEECh model; drivers with home or workplace access are not forced to use those stations, and we observe that many use a combination of two or more charging options (Powell et al., 2022b).

Based on large-scale implementations in the U.S. today, we assume that charging control is only implemented within sessions at workplaces and single-family homes in a distributed way. We only include automated control, we do not assume changes in behaviour, and we do not include any shifting across locations.

Consider charging at a workplace where N drivers will charge throughout the day. Let a_i and b_i be the arrival and departure times of vehicle i, and let c_i be the total energy consumed with uncontrolled charging for vehicle i. Let r_i^t be the charging rate of vehicle i at time t. Then the workplace aggregator executes the following optimisation problem:

$$\min_{r} \quad \sum_t s^t \left(\sum_{i=1}^{N} r_i^t \right) \tag{5}$$

$$\text{s.t.} \quad \sum_t r_i^t = c_i \quad \forall i \in \{1, \dots, N\} \tag{6}$$

$$r_i^t = 0 \quad \forall i \in \{1, \dots, N\},\ \forall t < a_i \tag{7}$$

$$r_i^t = 0 \quad \forall i \in \{1, \dots, N\},\ \forall t \geq b_i \tag{8}$$

$$0 \leq r \leq r_{max}. \tag{9}$$

The constraints can be read as: Eq. (6), each vehicle must receive the same amount of energy as in the uncontrolled case; Eqs. (7) and (8), the vehicle cannot charge before arrival or after departure; and Eq. (9), the maximum charging rate for L2 charging of 6.6 kW is imposed and there is no bi-directional charging allowed.

We implement this optimisation for aggregators of workplaces and SFH residential charging.

Each day is discretised into 1440 one-minute time steps in the model of uncontrolled demand and aggregated into 15-minute intervals for the control calculation.

It is too computationally expensive to run the full optimisation problem for all vehicles in a large region, so we instead apply a scaling method (Powell et al., 2022a) to model the large-scale effect of this control. The scaling method trains a machine learning model of the mapping from uncontrolled to controlled site load shape. First, we sample from the uncontrolled simulated sessions to create 100 sites with 200 vehicles in each. Second, we run the full optimisation problem for each site, for each signal being tested. This creates a set of 100 input–output profile pairs. Third, we split this data into training, development, and testing sets. We train a ridge regression model for each signal on the mapping from uncontrolled to controlled, using a grid search over the alpha parameter and 5-fold cross validation using the Python package scikit-learn (Pedregosa et al., 2011). The root-mean-squared error of the test prediction ranged from 5.5% to 6.5% for home charging and from 2.9% to 3.3% for workplace charging across the different control signals. Finally, the trained models were used to estimate the aggregate controlled charging profiles.

2.4. Case study details

We detail the application of this methodology to our case study region: the U.S.-portion of the Western Interconnection, or the Western Electricity Coordinating Council (WECC).

2.4.1. Case study grid model

To model the U.S. WECC grid, we use a baseline year of 2019 and extend the model presented by Powell et al. (2022b). The model includes four main components: changes in demand, non-fossil fuel generation, fossil fuel and combustion-based generation, and battery storage.

WECC's latest resource planning from 2022 lays out the planned changes to the WECC generation fleet to at least the year 2032 (WECC, 2022). It includes lists of particular plant retirements and new projects (WECC, 2022) including plans up to 2037. This is a period of major change. Nearly 26 GW of resources, mostly coal and natural gas, will be retired between 2022 and 2032, and nearly 80 GW of new generation and storage is planned (WECC, 2022). We use these plans in our modelling unchanged and assume that short-term changes in EV demand, a small portion of total load, will not cause large changes to these plans.

We model an increase in non-EV electricity consumption of 14% from 2019 to 2037 due to electrification in other sectors like heating and cooking (Mai et al., 2018).

The 2022 WECC resource document includes new utility-scale generation projects in all stages of the planning pipeline (WECC, 2022). Planned total capacity for each non-fossil fuel resource follows an approximately linear trend until 2032; beyond 2032, few projects have been announced yet. To project beyond 2032 to the end of our model horizon, we fit a linear trend to total capacity for each technology. We assume small variations year-to-year are random, given the many uncertainties in the timeline of large new constructions (Gumber et al., 2024). Behind-the-meter rooftop solar is not included in the announced projects; we use available historical data on the growth of rooftop solar capacity in WECC, which grew approximately linearly from 11 GW in 2019 to 18 GW in 2022, and assume it continues to grow linearly through our model time period (WECC, 2024). This results in 2037 capacity of 4.1 × 2019 for solar, 1.8 × 2019 for wind, and 1.07 × 2019 for hydro.

We use hourly data for non-fossil fuel generation from the U.S. Energy Information Administration Electric System Operating Data website (EIA, 2019a). We implement the retirement of the Diablo Canyon nuclear plant after the year 2030 (CEC, 2023). We do not include the two new advanced nuclear plants planned for 2028 and 2029 due to high uncertainty around their operation and construction.

WECC has plans to install nearly 25 GW of battery storage by 2035, compared with just 200 MW in the region in 2020 (WECC, 2022). As not all projects have been announced or included in the planning documents, we fit a linear trend to the values of planned capacity to estimate a total of 26.6 GW in 2037 at the end of our model horizon. We implement this as 4-hour storage.

To simulate the dispatch of fossil fuel and biomass generators in WECC we extend the open-source, reduced-order economic dispatch model presented by Deetjen and Azevedo (2019b). We use data from the U.S. Environmental Protection Agency (EPA) Continuous Emissions Monitoring System (CEMS) and Emissions and Generation Integrated Resource database (eGRID), as well as the U.S. Energy Information Administration (EIA) Form 923 (EPA, 2019a,b; EIA, 2019b). We obtain the list of generators for retirements and additions from WECC resource planning documents (WECC, 2022). We do not include the two non-emitting peaker plants planned for 2033 due to uncertainty around their operation and construction (WECC, 2022).

2.4.2. Case study EV model

The SPEECh model of EV charging was trained on a large data set of over 2.8 million real battery EV charging sessions from 27.7 thousand drivers in the Bay Area in California, U.S., in 2019. We use the model to simulate the load profile for each county in the 11 main states in WECC, totalling 48.6 million personal vehicles.

We assume a high electrification scenario where 50% of light-duty vehicles in WECC are electrified by 2035; this is consistent with recent planning in California to meet timelines for the end of the sale of internal combustion engine vehicles (Fideldy, 2020; CEC, 2021). This is an optimistic scenario as not all states in WECC have implemented the same policies as California. Recent support from the Inflation Reduction Act and other policies will increase EV adoption (Bistline et al., 2022), but further policy support may be needed to achieve these targets across WECC (Woody et al., 2023). We assume the fraction of EVs scales linearly to that level from the base year of 2019. We simulate the demand profiles for 100% electrification in each county and scale linearly to lower levels of EV penetration. Due to the model's open-loop structure, the final load profiles vary slightly in terms of total energy.

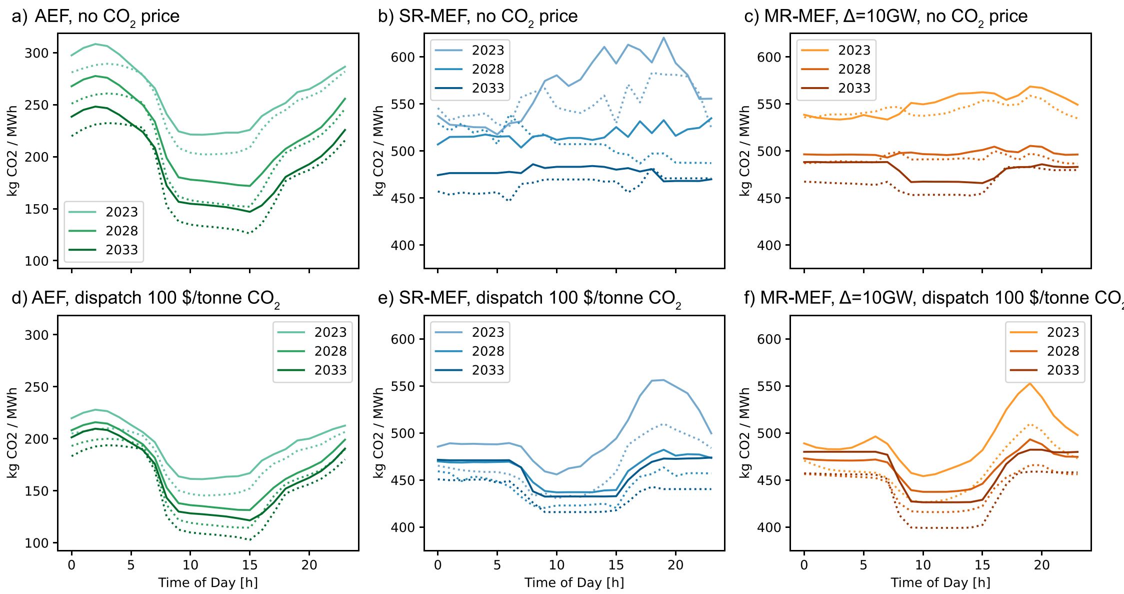

Fig. 2. Emission Factors (EFs) used as signals for demand optimisation: the Average Emission Factor (AEF), the Short-Run Marginal Emission Factor (SR-MEF), and the Medium-Run Marginal Emission Factor (MR-MEF) for a 10 GW demand delta and five-year period.
Note: the SR-MEF and MR-MEF subplots have a different *y*-axis scale than the AEF subplots.

All emissions results are normalised and reported as kg CO_2/MWh to avoid confusion.

At 50% electrification in 2035, EVs consume 44 TWh of electricity per year or approximately 5 GWh per hour if spread evenly throughout the year. That represents 5.15% of total electricity consumption from all sources.

3. Results

In Section 3, we discuss the shapes of the EF signals over the simulation period, we analyse the impacts on emissions with both minimally constrained and fully constrained EV control, and lastly we examine the sensitivity of the model to extreme fossil fuel prices.

3.1. Signals

In all cases, the emission factors decrease in absolute terms from 2023 to 2037. As shown in Fig. 2, the EFs give different signals earlier in the study period, but the AEF and MR-MEF converge to a similar shape by 2033 with the lowest emission rate during the day.

The AEF and SR-MEF are calculated based on a snapshot reference scenario with no EV demand. The MR-MEF at hour h is calculated based on the increase in emissions caused by adding the demand delta, here 10 GW, at that hour for a five year period. We compare results with and without a carbon price affecting the dispatch of generators. We chose a high carbon price of \$100/tonne CO_2 to isolate its effect and ensure the resulting merit order is largely by emission rate.

With no CO_2 price in the dispatch, the AEF is between 202 and 308 kg CO_2/MWh in 2023 and between 126 and 248 kg CO_2/MWh in 2033. The AEF has a consistent shape throughout the study period: lowest in the middle of the day during periods of high solar. The mid-day trough would be lower if there were no battery storage; the battery operates to shift demand from the evening to the middle of the day, smoothing net demand, which reduces the spread in average emissions.

Adding a CO_2 price to the dispatch does little to change the AEF shape but decreases the AEF in absolute terms. With a CO_2 price, the AEF is between 145 and 228 kg CO_2/MWh in 2023 and between 103 and 210 kg CO_2/MWh in 2033. This is a reflection of how the CO_2 price re-orders the dispatch merit order, as shown in part (b) of Fig. 3 (Deetjen and Azevedo, 2019a). To meet the same level of demand, lower emitting generators are used with the CO_2 price than without, reducing the average emissions intensity.

With no CO_2 price in the dispatch, the highest SR-MEFs occur in the evening in 2023 and 2028, and during the day in 2033. Notably, the SR-MEF is very noisy in the earlier periods and does not give a strong indication that short-run marginal emissions depend on the time of day. This is caused by the disorder in the dispatch merit order, as shown in part (a) of Fig. 3, where a small change in demand can easily put either a coal or gas generator on the margin.

Adding a CO_2 price to the dispatch, the SR-MEF gives a much clearer signal: marginal emissions are highest in the evening, especially in 2023. This occurs because the order of generators in the dispatch better aligns with their emission rates, as shown in part (b) of Fig. 3, so adding demand during peak hours in the evening uses generators with higher marginal emission rates from higher up the merit order.

With no CO_2 price in the dispatch, the MR-MEF shape changes from 2023 to 2033. In 2023, there is no benefit to adding demand in the middle of the day, principally because there is little to no excess solar and there are many high-emitting coal plants operating during periods of low net demand. By 2033, after the addition of large amounts of solar, adding demand in the middle of the day can reduce emissions by targeting curtailment. The retirement of many low-cost coal generators also plays a key role and changes the emission dynamics of periods with low net demand. With a CO_2 price in the dispatch, the reordering of generators has the same effect as for the SR-MEF: adding demand at peak times uses generators with higher emissions.

The demand profiles for all types of charging scenario are shown in Fig. 4 for the year 2028. Each row presents one of the charging scenarios: (a) and (b) minimally constrained EV demand; (c) and (d) Universal Home Access where all drivers have home charging; (e) and (f) High Home Access similar to today's home charging levels; and (g) and (h) Low Home High Work Access where more drivers depend on work and public charging. Each column presents one example control signal: (i) Uncontrolled; (ii) the AEF signal from 2033; (iii) the SR-MEF signal from 2033; and (iv) the MR-MEF signal from 2033 with 10 GW delta demand. We consider only automated control occurring within single family home and workplace sessions; no behaviour changes or shifts between locations. The signals were calculated with (a, c, e, g) and without (b, d, f, h) a carbon price in the dispatch.

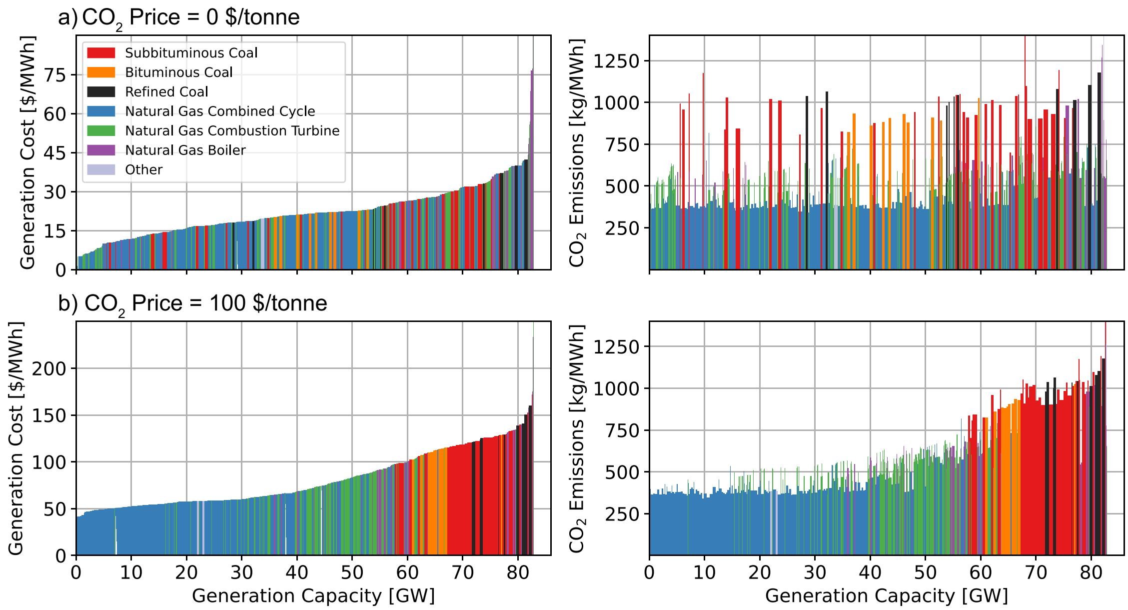

Fig. 3. Merit order of generators. The merit order used for generator dispatch in a summer week in 2023: without any carbon pricing (a) and with a high carbon price of 100 USD per tonne (1000 kg) of CO_2 (b); costs (left) and emissions (right). Each bar represents one generator.
Note: the *y*-axis for generation costs is different between the cases with and without a CO_2 price.

The minimally constrained case shows that, without charging constraints, the optimal charging strategy for the AEF and MR-MEF in 2033 is to concentrate charging during the middle of the day, and the optimal demand for the SR-MEF without a carbon price is to concentrate charging overnight (Fig. 4.a and 4.b).

Comparing Universal Home Access with Low Home High Work Access, the latter scenario has more flexibility to shift demand to the optimal charging hours in middle of the day because more drivers in that scenario have access to workplace charging, as seen in Figs. 4.c.iv and 4.g.iv. Lastly, while the Low Home High Work Access scenario has significant daytime charging even in the uncontrolled case (i.e. Figs. 4.g.i and 4.h.i), its peak demand occurs earlier in the morning than is optimal under these signals.

3.2. Impact on emissions with minimally constrained demand

Fig. 5 shows the annual added emissions per unit of added demand from 2023 to 2037 (left), normalised by the value for flat or uncontrolled demand (right) to compare the control signals. Each row presents a different set of constraints on demand: (a) minimally constrained EV demand, (b) the Universal Home Access charging scenario, (c) the High Home Access charging scenario, and (d) the Low Home High Work Access charging scenario.

For the emissions results for the minimally constrained case we use flat demand as a comparison point; more complex uncontrolled demand profiles are considered in the fully constrained EV scenarios.

In the minimally constrained case, the AEF performs poorly in the first half of the time horizon, actually causing a small increase in added emissions relative to uncontrolled. The MR-MEF performs best in this period, particularly for the case with 20 GW test demand. The second period is most challenging as many retirements occur, a very large nuclear plant retires in 2030, and storage is still scaling up. In 2031, the first year following the nuclear plant retirement, the MR-MEF signals perform worse than the others. The 5 GW test-demand signal performs worse than the 10 GW and 20 GW MR-MEF signals because it is farthest from the real value of added demand (see Fig. 4). The performance of the 10 GW and 20 GW MR-MEF signals (overlapping in the 2031 result) likely represents a simple trade-off: the signal is calculated based on total added emissions from the full five-year period between 2028 and 2032, so the optimal signal prioritises reductions in the first three years at the cost of slight increases in the last two year years of the period. We expect that increasing the frequency of the signal updates would improve these results.

By the final period, the AEF and MR-MEF are better aligned and both yield emission reductions, while the SR-MEF causes large increases. The worst increase is caused by the SR-MEF signal in 2037: more than 5% above emissions from flat demand. The best decrease is caused by the MR-MEF 20 GW signal in the early period, with 1.9% below emissions from flat demand in 2023, and by the AEF, MR-MEF 5 GW, MR-MEF 10 GW, and MR-MEF 20 GW signals at the end of the period, with 2.1–2.2% below emissions from flat demand in 2037.

In a system with a supply-side carbon price of 100 $/tonne CO_2, absolute emissions are lower. The lowest value occurs in 2030 for the MR-MEF signals with 444 kg CO_2/MWh, just 89% of the value there without the CO_2 tax. There is again a small step increase in emissions after 2030 associated with the retirement of the large Diablo Canyon nuclear plant.

The control performs notably better in the carbon price case, especially in the later periods. By 2037, all four signals achieve a reduction of 5.8–5.9%. This reflects the benefit of a simpler supply-side: with carbon pricing, shifting demand away from peak hours will consistently shift away from higher emitting generators.

These small improvements show the challenge of reducing emissions in such a highly constrained set-up. There are two ways to reduce emissions: use less fossil fuel generation by reducing curtailment or use cleaner fossil fuel generators. Unfortunately there is little curtailment to target in this system. There is no curtailment (defined as unused non-fossil fuel generation) until 2033, then a small amount increasing to 0.5 TWh in 2037 without EV demand. 0.5 TWh is only 1.1% of annual EV electricity consumption, and it is completely used until 2035 in all of the EV scenarios. Nearly all of the emission reductions are achieved through the second option, despite the noisiness of the signals and system.

There is sufficient capacity to meet demand at all hours in the AEF, MR-MEF 5 GW, and MR-MEF 10 GW minimally constrained cases. In the SR-MEF case, extra storage is needed from 2033 onward, with a maximum value of 13.7 GW in 2037. In the minimally constrained scenarios with a supply-side carbon price, no extra storage is needed.

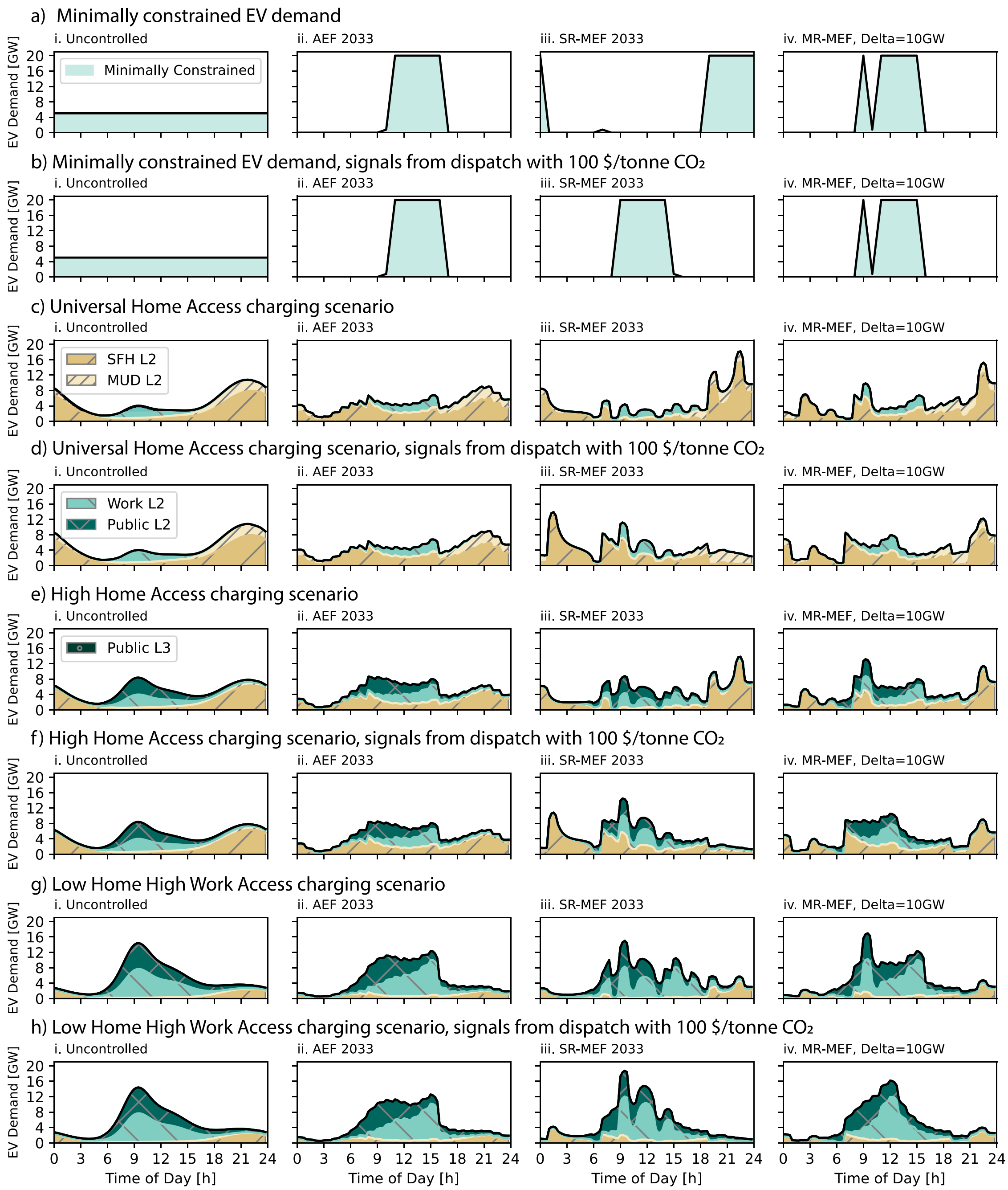

Fig. 4. Electric vehicle charging demand is illustrated for the year 2033. SFH stands for single family home; MUD stands for multi-unit dwelling; L2 stands for Level 2 charging at 6.6 kW; and L3 stands for Level 3 charging at 150 kW.

3.3. Impact on emissions with fully constrained demand

Fig. 5 parts (b–d) show the emissions results for the fully constrained charging scenarios. The Low Home High Work Access scenario has the lowest absolute emissions but is affected very little by the control. In this scenario, most demand is constrained to occur during the day: this increases emissions in all cases in the near-term, relative to flat demand, and decreases emissions in all cases in the long term. With supply-side carbon pricing there is some benefit from AEF and MR-MEF control, but only up to 0.7%.

The Universal Home Access scenario has the highest emissions and sees larger benefits from control: without supply-side carbon pricing, the maximum reduction is 1.0–1.2% relative to uncontrolled demand, with the SR-MEF in the early period, with the AEF in the later period, and with the MR-MEF signals in both. With supply-side carbon pricing, control can decrease emissions by 2.3–2.8% relative to uncontrolled and the AEF is the most consistent signal.

The results for the High Home Access scenario fall between the other two: reductions of up to 0.9% without and 1.8% with carbon pricing.

Relative to flat demand, these reductions across EV scenarios of up to 1.8% without and 4.1% with carbon pricing are smaller than the 2.2% and 5.9% possible with the minimally constrained demand.

The additional constraints from realistic EV modelling include constraints on charging infrastructure availability, where charging is controllable, and when vehicles are plugged-in. Our results show that these constraints reduce the flexibility of EV demand and can reduce emissions-savings potential completely in some cases.

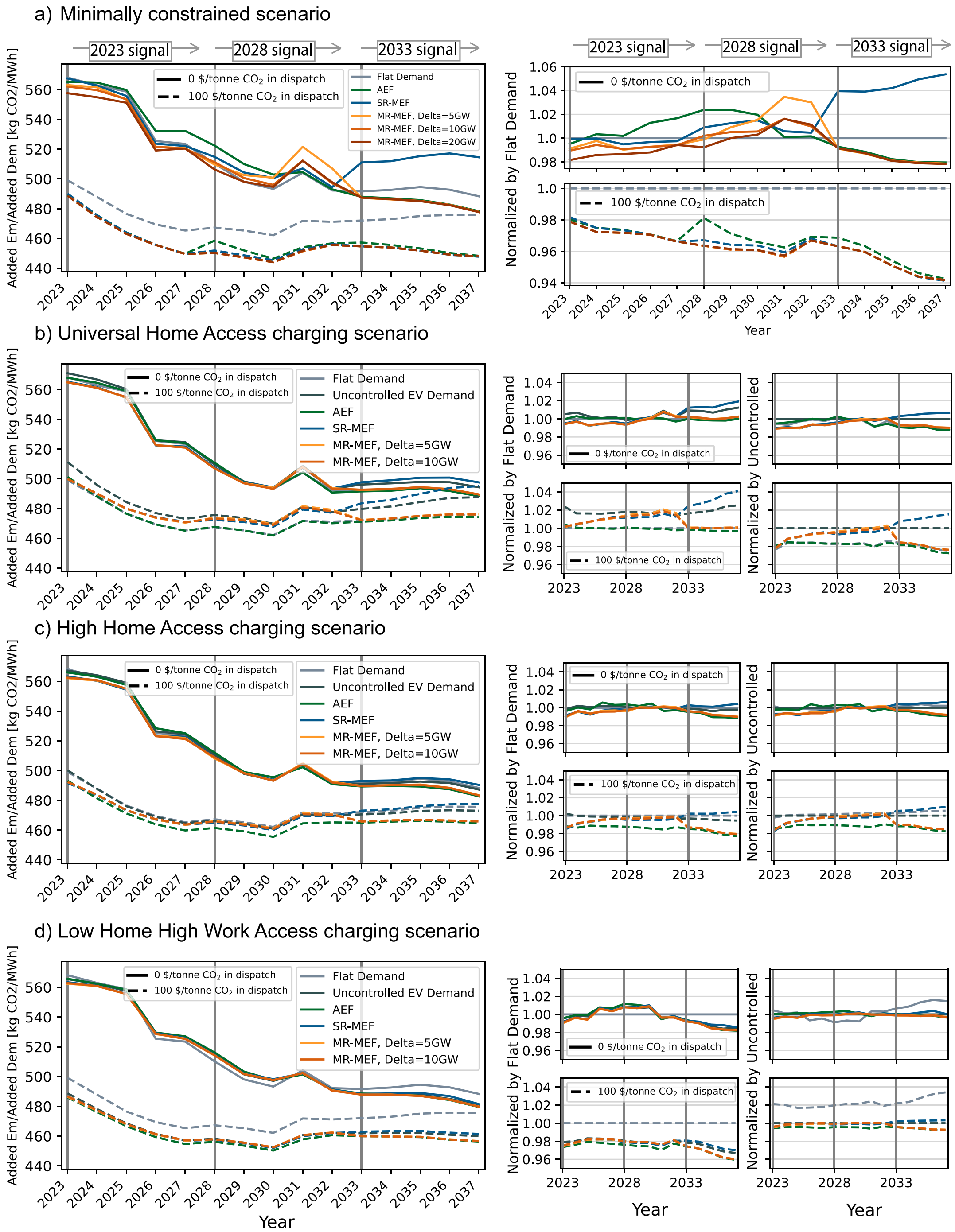

Fig. 5. Added emissions in each control scenario. Vertical lines at the years 2023, 2028, and 2033 indicate when the control signals were updated. Scenarios are shown with (dashed lines) and without (solid lines) the carbon price in the grid dispatch.

Starting in 2036, there is insufficient capacity to meet peak demand in the uncontrolled Universal Home EV cases: up to 4.8 GW of extra storage is needed by 2037 to cover a small set of hours. The SR-MEF control increases the need for storage to 6.2 GW in 2037; the MR-MEF controls reduce the need for storage to 0.9 and 0.05 GW in 2037; and the AEF control avoids the need for extra storage completely. No storage is required in any of the other EV cases.

3.4. Sensitivity to extreme prices

Finally, we assess how extreme prices from the recent energy system crisis affect these signals and results. We test only the minimally constrained case; based on the results in Section 3.3, we expect the fully constrained EV scenarios would show similar but muted results.

We emphasise that this scenario is separate from the current situation for WECC, as gas prices have already returned to pre-crisis levels, but the comparison to 2022 can offer interesting insights into the dynamics of the merit order and emission reductions.

In 2022, natural gas prices spiked in many countries around the world, including the Western U.S. Fig. 6 parts (a–b) illustrate the impact of 2022 prices on the dispatch of generators: in 2022, the merit order was reordered by high gas prices, visible also when comparing the y-axis of generation costs between 2019 and 2022. The three columns correspond to the merit order under three price scenarios: (left) in 2022

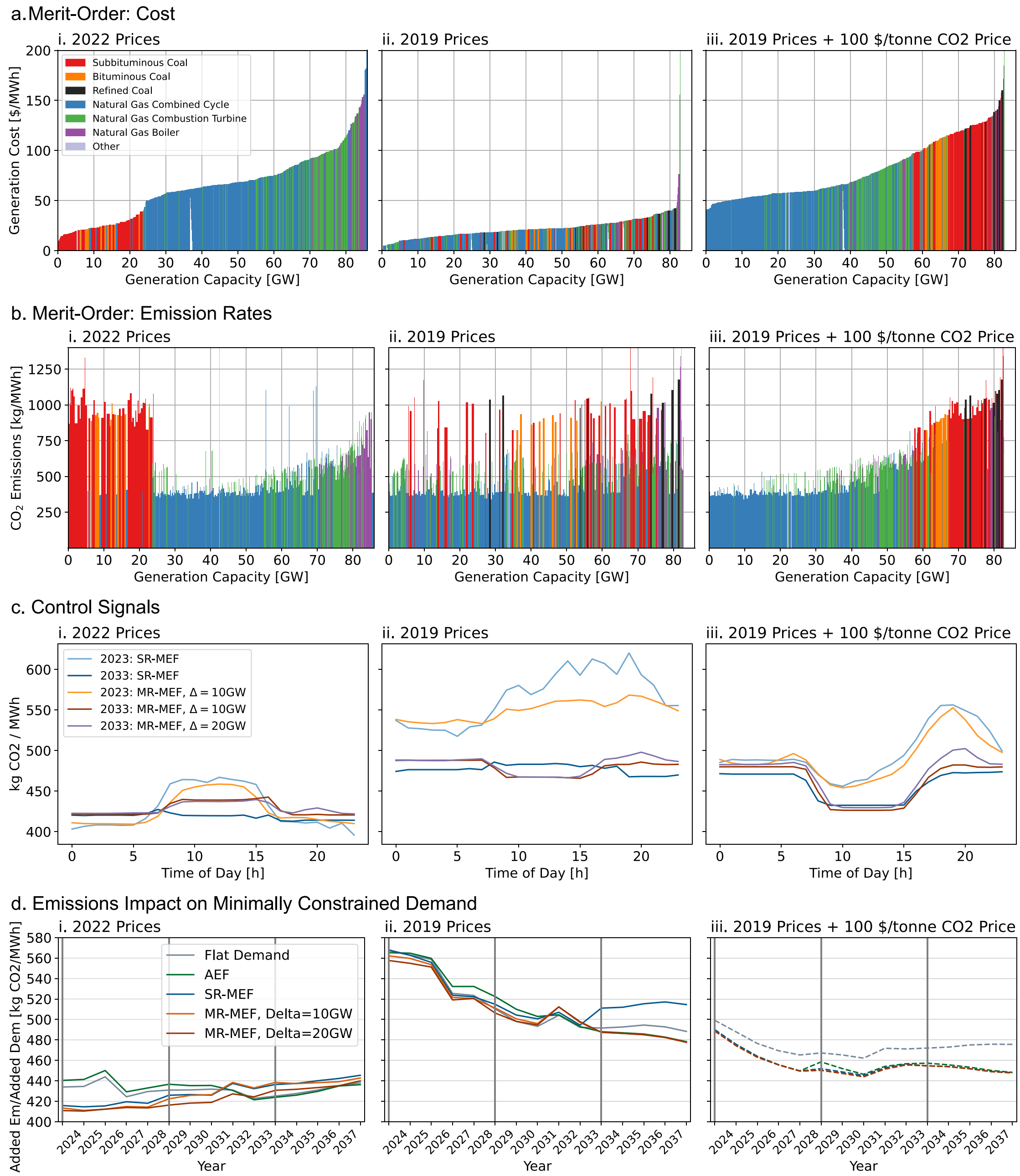

Fig. 6. Sensitivity of results to extreme gas prices. The merit order is shown for a summer week in 2023 using (i) 2022 base fuel prices, (ii) 2019 base fuel prices, and (iii) 2019 base fuel prices with the carbon tax. Emissions impacts are shown for only the case of minimally constrained demand.

coal was consistently the least expensive resource; (middle) in 2019 the order of gas and coal generators was mixed; and (right) under a \$100 per tonne carbon price and 2019 fuel prices scenario, coal is consistently the most expensive resource. This reordering also affected the SR-MEF and MR-MEF signals, shown in Fig. 6 part (c). The AEF was not affected.

The two extreme scenarios on the left and right have opposite system dynamics: when coal is less expensive than gas, as in 2022, charging added in periods of low net demand has higher emissions; when gas is less expensive than coal (carbon price case), charging added in periods of low net demand has lower emissions. In the later periods, low net demand aligns with peak solar hours.

As a result, the MR-MEF in 2033 has opposite shapes in the 2022 price and 2019 price cases: in the 2022 price case, the MR-MEF is highest during the day; in the 2019 carbon-price case, the MR-MEF is lowest during the day. The non-crisis, no-carbon-price case falls in the middle.

In absolute terms, the SR-MEFs are lower in the 2022 case, as lower-emitting gas is almost always on the margin. The MR-MEFs and the added emissions are also lower in the 2022 case, as added demand is also mostly met with gas.

In the early period in the 2022 case, the MR-MEF is most effective at reducing emissions relative to flat demand. In the middle and later periods, the 10 GW and 20 GW MR-MEF signals diverge: in this scenario, it is important that the MR-MEF signal is calculated using a test demand value that aligns well with the final added demand.

The performance over time of the AEF and SR-MEF is consistent across the scenarios: in the first period, the SR-MEF decreases emissions while the AEF increases emissions; in the last period, vice versa. This reflects the timeline of increasing renewable generation. The best signal choice depends whether the generation mix is dominated by fossil fuels or renewables. In all cases, the MR-MEF signals yield the best or near-best reductions.

As gas prices have since returned to pre-crisis levels, the 2022 case does not inform future operations in the Western U.S. However, this sensitivity analysis offers an important conclusion for transfer to other regions, as understanding real generation costs and dispatch conditions is critical to choosing the right signal for EV charging to achieve emission reductions.

4. Discussion of model limitations

Limitations related to the model and case may affect the results of this study. Specifically, we make assumptions about EV driver behaviour in the future and transmission congestion in the grid, and we recognise that the effects of EF-based rates shown in this paper are tested only on the WECC region.

We use a data-driven model to avoid reliance on modeller assumptions when representing EV charging behaviour. We make adjustments to increase or decrease the weight of driver behaviours to match the future population of drivers, but we must assume that all future behaviours are represented by at least a sub-sample of today's drivers. We also assume that charging patterns of future plug-in hybrid EV drivers can be represented by the charging patterns of today's small-battery EV drivers. Large changes to behaviour are not represented. For example, our results would change if autonomous or shared mobility were to see widespread adoption during the study period.

We also assume there is no change in individual behaviour due to changes in electricity pricing; all control occurs within existing charging sessions. In the future, if drivers were to become more responsive to price signals and more aware of their charging patterns, that could increase the flexibility of their charging demand. We use the minimally constrained case in our analysis to estimate the best case of controllable demand.

We assume a base scenario of high vehicle electrification. With a range of state and federal goals and policy supports, there is debate over when the passenger vehicle fleet will reach 50% EVs. We do not expect this assumption to affect the trends and conclusions in our results, and we have reported all normalised emission impacts to reduce sensitivity to the level of demand.

We focus on the dispatch of generators and do not represent constraints introduced by transmission or the distribution system. Congestion and local limits on peak demand could influence our results. Future work should extend this analysis using models of transmission and distribution constraints to understand the full impact of EF-based rates.

Finally, our results may change for another system with different characteristics than the Western U.S. We use the WECC model to provide realistic conditions for our "what-if" analysis of signals, not to develop forecasts of future WECC operation, but features specific to the WECC system may affect the results. The large amount of solar generation planned in WECC plays an important role in emissions and EFs, especially in the later periods of our study. In another system more dependent on hydro or wind, for example, intra-day demand response may play an even smaller role. Further, as our model of the WECC merit order depends on reported operating cost data, another system with more difference between coal and gas operating costs may have smoother signals and more valuable demand response.

5. Conclusion and policy implications

Our findings reveal an important synergy between these two demand-side and supply-side interventions: controlling EV charging to reduce emissions and adding a carbon price to the generator dispatch. The signal is much clearer in the system with a carbon price, and this can make the demand response more valuable by a factor of 3× in 2037. Further, all three EF types take similar shapes and signal similar responses in the system with a carbon price, making the choice between them less important.

Without a carbon price, there is limited room for improvement. Between 2023 and 2028, the MR-MEF and SR-MEF signals decrease emissions; after 2033, the MR-MEF and AEF signals decrease emissions; and in the transition, the best signal is less clear. Notably, we also observe emission increases caused by control when the signals misrepresent the impact of added demand.

These dynamics over time follow changes in the generation portfolio. For example, we observe a step increase in added emissions after 2030 following the retirement of large nuclear plants in California. The system also benefits from the retirement of low-cost coal generators, making the cost-based merit order align better with the ordering of generators by emissions rate, which causes the AEF and MR-MEF to align in the later period as the best signals.

In terms of absolute emission reductions, our results are smaller than many others published in recent research. Without a supply-side carbon price, the maximum emission reduction relative to flat demand was just 2.2%. Previous studies have found much higher potential reductions in the range of 70% using centralised control, or in the range of 20%–30% using EF-based control without testing the results with a dispatch model. Our much smaller reduction reflects the limitations of a simpler rate- or tariff-based implementation.

Finally, our model of EV charging demand revealed the limitations caused by driving patterns and charging infrastructure availability. The emissions reductions relative to flat demand were smaller when all EV constraints were considered, compared with the minimally constrained EV test. Reductions relative to uncontrolled EV demand were slightly greater in some cases, reflecting the poor timing of uncontrolled charging with respect to grid emissions. The scenario with more daytime charging options and less dependence on home charging had lower absolute emissions, which confirms earlier results that daytime charging should be pursued to reduce emissions in the Western U.S. (Powell et al., 2022b).

We recommend that research on rates for EV charging reflect constraints on charging infrastructure and the availability of vehicles for control. Critically, we recommend careful implementation of rate-based control models to reflect the simplicity of signals and multi-year periods between rate updates. Our findings show this has a large impact on results, and simplifying these constraints on signal implementation may lead to overestimation of possible emission reductions. We also advise that the AEF and SR-MEF be used with great caution. Our results revealed that AEF and SR-MEF-based electricity rates can inadvertently increase emissions, especially in a complex system without curtailment and with large amounts of coal and gas. We recommend using the MR-MEF to best capture multi-year, near-term emission dynamics.

Finally, we recommend that policymakers use supply-side interventions to make demand-side changes easier and more valuable. Adding a carbon price on the supply-side affects the order by which generators are dispatched: then, avoiding times of high demand consistently avoids the use of higher emitting generators, making the design of simple electricity rates for emissions reduction much easier.

CRediT authorship contribution statement

Siobhan Powell: Conceptualization, Investigation, Methodology, Software, Visualization, Writing – original draft. **Sonia Martin:** Investigation, Writing – review & editing. **Ram Rajagopal:** Methodology, Supervision. **Inês M.L. Azevedo:** Conceptualization, Methodology, Supervision. **Jacques de Chalendar:** Conceptualization, Investigation, Writing – review & editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Jacques de Chalendar reports a relationship with TotalEnergies SE that includes: consulting or advisory.

Data availability

Data will be made available on request.

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