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Charging infrastructure access and operation to reduce the grid impacts of deep electric vehicle adoption

Siobhan Powell[1,8] ✉, Gustavo Vianna Cezar[2], Liang Min[3], Inês M. L. Azevedo[3,4,5] ✉ and Ram Rajagopal[3,6,7] ✉

Electric vehicles will contribute to emissions reductions in the United States, but their charging may challenge electricity grid operations. We present a data-driven, realistic model of charging demand that captures the diverse charging behaviours of future adopters in the US Western Interconnection. We study charging control and infrastructure build-out as critical factors shaping charging load and evaluate grid impact under rapid electric vehicle adoption with a detailed economic dispatch model of 2035 generation. We find that peak net electricity demand increases by up to 25% with forecast adoption and by 50% in a stress test with full electrification. Locally optimized controls and high home charging can strain the grid. Shifting instead to uncontrolled, daytime charging can reduce storage requirements, excess non-fossil fuel generation, ramping and emissions. Our results urge policymakers to reflect generation-level impacts in utility rates and deploy charging infrastructure that promotes a shift from home to daytime charging.

The use of electric vehicles (EVs), coupled with an electricity grid that is decarbonizing, can help the United States achieve emissions reduction targets[1,2]. Industry analysts forecast that the number of light-duty EVs and their charging plugs will multiply to over 300 million and 175 million, respectively, worldwide by 2035, an order of magnitude increase when compared with 2021[3]. EV charging couples transportation to the grid, yet the two sectors' transformations are largely uncoordinated, despite their shared objectives of lowering emissions[4–10]. While the implications of transportation electrification for the grid have been studied at low, near-term levels of adoption, identifying and mitigating system consequences at deep levels of EV adoption has remained a critical challenge as it requires models that capture the diverse behaviours and conditions of future drivers[11].

Charging infrastructure, controls and drivers' behaviour have implications for grid operations, making the long-term planning to support daily charging demand under high electrification scenarios challenging. Driver behaviour is highly heterogeneous and stochastic[12–16]; where, when and how often drivers choose to plug-in determines their load shape and demand on the grid. Adding charging controls and changing the landscape of charging infrastructure by increasing or decreasing the availability of different charging options represent powerful tools to reshape charging to improve grid impacts at future, deep levels of EV adoption. Charging controls, also called smart or managed charging, reshape demand by delaying charging to a preset time or by modulating the power delivered throughout a vehicle's charging session in response to electricity prices. The charging infrastructure network's design and geography, in turn, change the choices available to drivers and reshape system-wide charging demand by changing the charging location and time of day (for example, from overnight if charging at home to midday if charging while at work).

Charging access is key to avoiding charging inconvenience, which can be a barrier to both adoption and continued use of EVs[16–20]. Wealthy residents of single family homes (SFHs) are over-represented among early EV adopters and are likely to have access to home charging[21]. Lower-income households, renters and residents of apartment buildings or multi-unit dwellings (MUDs), meanwhile, are all less likely to have access to home charging[12,13,16,17,22,23] despite targeted subsidies[24]. Assuming the use of charging infrastructure will continue to match early-adopter behaviour would misrepresent future drivers' options and could miss valuable opportunities for households, utilities and the regulator.

Existing approaches to modelling large-scale charging demand impute charging decisions based on early-adopter behaviours or modeller assumptions about driver behaviour[9,10,25–27]. Numerous previous studies have used charging controls to improve the grid impact and costs of EVs[8,9,25,26,28–36]. However, most studies have limited scenarios regarding charging infrastructure access, use centrally optimized controls rather than site by site, rate schedule-driven optimizations or focus on current grid resources and conditions, and few include grid storage and calculate emissions (Supplementary Note 1). Previous studies with different charging infrastructure scenarios have mostly focused on early adopters and do not conceptualize infrastructure as a tool for charging control[9,10,26,34,37,38]. The importance of charging infrastructure for long-distance travel and high-energy days to support EV adoption has been a focus of other recent studies[18,39,40].

[1]Department of Mechanical Engineering, Stanford University, Stanford, CA, USA. [2]Applied Sciences Division, SLAC National Accelerator Laboratory, Menlo Park, CA, USA. [3]Precourt Institute for Energy, Stanford University, Stanford, CA, USA. [4]Department of Energy Resources Engineering, Stanford University, Stanford, CA, USA. [5]Woods Institute for the Environment, Stanford University, Stanford, CA, USA. [6]Department of Civil & Environmental Engineering, Stanford University, Stanford, CA, USA. [7]Department of Electrical Engineering, Stanford University, Stanford, CA, USA. [8]Present address: Department of Management, Technology, and Economics, ETH Zurich, Zurich, Switzerland. ✉e-mail: spowell2@alumni.stanford.edu; iazevedo@stanford.edu; ramr@stanford.edu

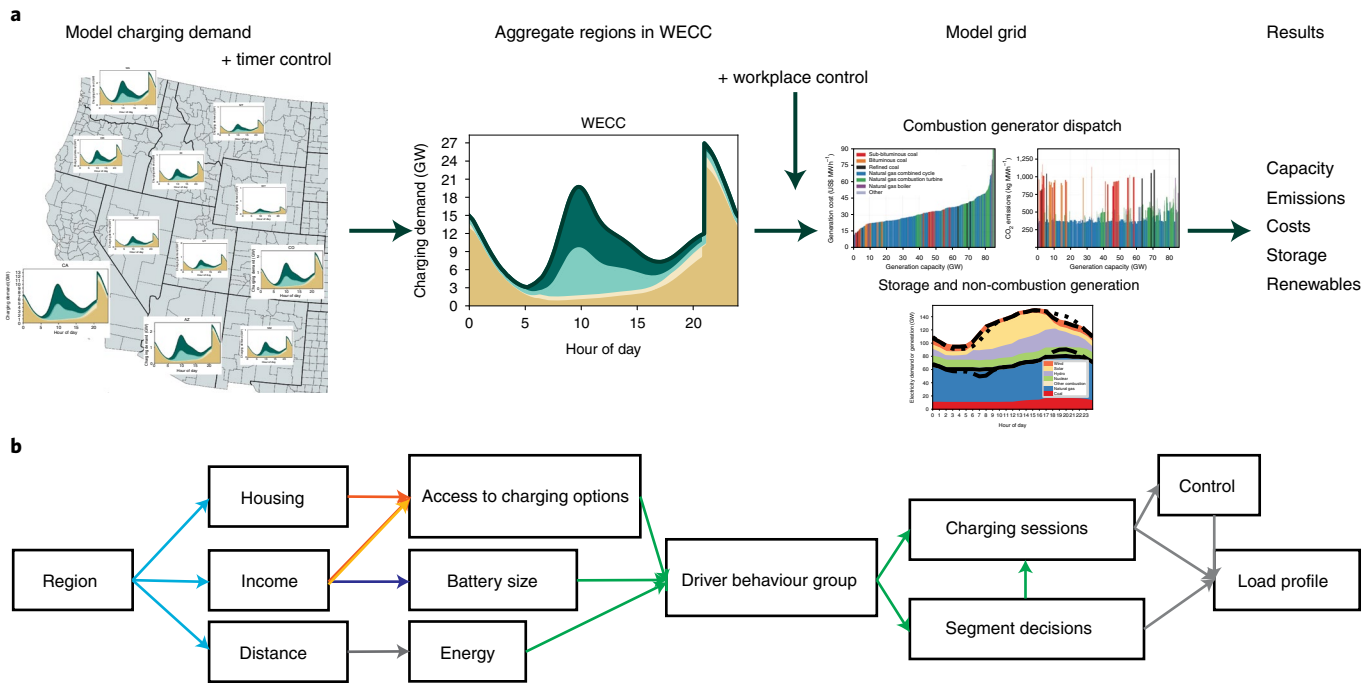

Fig. 1 | Overview of the methods for evaluating grid impacts and modelling EV charging demand. a, An overview of the modelling approach. To study the grid impacts of EV charging scenarios, charging demand was simulated for each region using a model of driver behaviour, regional profiles were aggregated, and grid dynamics were modelled including non-fossil fuel generation, storage and the dispatch of fossil fuel generators. In scenarios with charging control, timer controls in residential charging were applied while generating each county's demand, and load modulation controls in workplace charging were applied to the aggregate uncontrolled workplace profile for WECC. States are identified by postal abbreviation. The hourly dispatch of net demand and total demand across both fossil and non-fossil fuel generation resources is illustrated for a sample day under the "Model grid" step. Original net and total demand profiles are shown with dot-dash and dotted lines, respectively, and the smoother net and total demand profiles achieved through the dispatch of 10 GW of grid storage are shown with solid and dashed lines, respectively. **b**, The model for EV charging demand in each region as a function of neighbourhood characteristics, access to charging and driver behaviours (Methods). The arrows are colour coded according to the data sources: US Census and Community Survey[45] and EASI MRI Consumer Survey[69] (light blue), California Vehicle Rebate Project (purple)[71], California Energy Commission[70] and National Renewable Energy Laboratory survey (red), University of California at Davis study[12] (yellow), set of observed drivers' charging sessions (green) and modelled (grey) as detailed in Methods. EASI MRI stands for Easy Analytic Software Inc. Mediamark Research, a database from which county-level annual mileage data was accessed.

The charging of EVs has consequences for the distribution, transmission and generation of electricity[41]. For example, uncontrolled charging has been shown to increase peak demand and cause transformer overloading[5], force early replacement of equipment[7], overload transmission lines[28], worsen power quality[4,6] or require substation upgrades[42]. Avoiding the high costs of distribution system upgrades is a key value offered by controlled charging. EVs can also provide value to the grid by providing services of frequency regulation and real-time ramping[43,44].

In this study, we model daily charging demand for personal EVs under high electrification scenarios in 2035 for the US portion of the Western Interconnection (WECC) grid, covering 11 states with over 75 million people[45]. We compare a range of future scenarios to understand how charging infrastructure, control and driver behaviour will together affect grid impact. Our study includes two strategies (control and infrastructure build-out) and uses realistic, detailed models of all three elements: driver behaviour, control and grid dispatch. We focus on typical, aggregate charging patterns of personal light-duty vehicles as drivers of generational-level grid impact. Our aim is to identify what scenarios of large-scale EV adoption best mitigate the negative consequences of charging and chart an effective decarbonization pathway via vehicle–grid integration. Our results urge the coupling of charging and grid-planning measures. To make charging controls more effective, policymakers should consider coordinating the management of grid generation and distribution impacts. Most importantly, planning should target build-out of charging infrastructure over the next decade that supports a shift from home to daytime charging in WECC.

Increased electricity consumption

Driver behaviour is highly heterogeneous. We use a probabilistic, data-driven method to capture driver charging preferences based on patterns observed in real charging data (Methods). We calibrate our model using a dataset of 2.8 million sessions recorded for 27.7 thousand battery electric vehicle drivers in the California Bay Area in 2019. We model the connection between charging behaviour clusters and drivers' income, housing, miles travelled and access to charging options as shown in Fig. 1. We implement controlled charging site by site to simulate realistic responses to electricity rates. We focus on the US portion of the WECC grid and simulate charging for the more than 48 million personal vehicles in its 11 main states (Methods).

Recent planning in California finds 50% of the light-duty fleet will need to be electrified by 2035 to reach upcoming decarbonization deadlines and track timelines for the end of internal combustion engine vehicle sales[10,46]. In line with these and other studies of high electrification[47,48], we include results for 50% adoption or 24 million EVs in WECC (electrification of half the personal vehicle fleet) in the year 2035. Industry and policymakers, however, are working to accelerate adoption even faster. We include results for

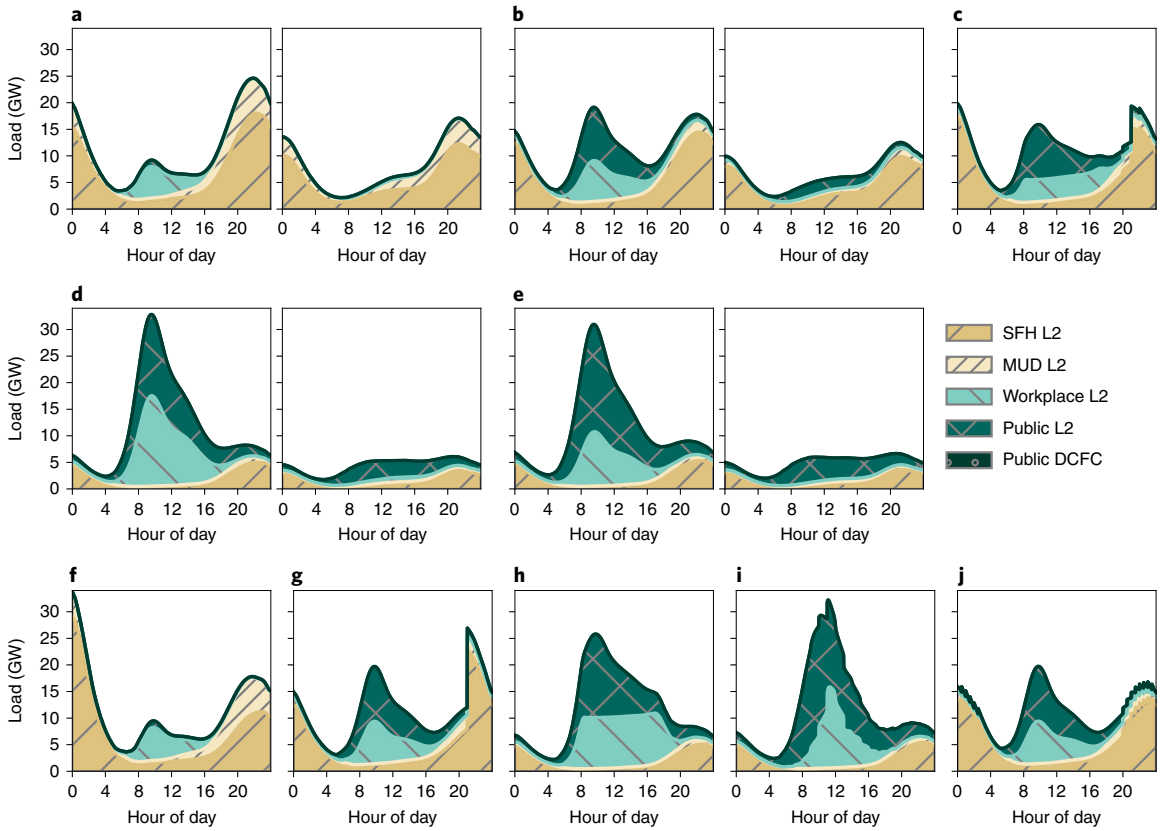

Fig. 2 | Profile of aggregate EV charging demand illustrated for each infrastructure and control scenario. a,**b**,**d**,**e**, The uncontrolled profiles for a typical weekday (left) and weekend (right) are shown for Universal Home access (**a**); High Home access (**b**); Low Home, High Work access (**d**) and Low Home, Low Work access (**e**). **f**–**j**, The weekday profile is shown for one example of each type of control: midnight SFH timers with Universal Home access (**f**); 9 p.m. SFH timers with High Home access (**g**); workplace peak minimization with Low Home, High Work access (**h**); workplace average emissions minimization with Low Home, Low Work access (**i**); and random SFH timers between 8 p.m. and 2:30 a.m. with High Home access (**j**) (Methods). Profiles are illustrated for full electrification for the US states in WECC to show the maximum modelled demand. Demand is aggregated in local time for this illustration, but in the simulation the two time zones are reflected and there is a 1 h delay between the timers set on Pacific and Mountain Time. **c**, Business As Usual is a special case of High Home access with a mixture of residential timers at 8 p.m., 9 p.m., 10 p.m. and midnight and peak minimization workplace control. The weekday and weekend profile for each scenario is repeated to compile the full year's charging demand. L2 stands for Level 2 charging and DCFC stands for Direct Current Fast Charging.

100% adoption (full electrification of the personal vehicle fleet) as a stress test to characterize grid readiness for deep adoption and identify what additional changes will be needed in the grid or in charging. We also present the sensitivity of all key results to higher or lower levels of adoption throughout the paper.

To calculate the grid impact at the generation level under each charging scenario, we dispatch the aggregate electricity demand for an entire year to a model of future grid generation resources that reflects forecast retirements and additions of fossil fuel generators and increased wind, solar and grid storage (Methods). We assume wind and solar generation vary hour by hour throughout the year as they did in 2019.

Baseline annual electricity consumption is assumed to increase by 16% on average by 2035 due to electrification in applications other than transportation, such as heating and cooling[48]. We find that the addition of EV charging at deep adoption further increases annual electricity consumption by the same order of magnitude. Each percent increase in EV adoption increases total consumption by about 0.11% in this system (Supplementary Figure 7). At 50% adoption, this amounts to a 5% increase over the 2035 baseline. Combined, the total increase due to electrification in all sectors is up to 22% over 2019 levels. In the stress test with 100% EV adoption, consumption is increased by 11% by EVs and by up to 28% overall over 2019 levels.

Charging scenarios

The timing of this increase in electricity use is critical, and the grid impacts of charging vary substantially with different demand profiles. Thus, we model four scenarios for future charging infrastructure varying home charging access from universal to low based on recent California survey data (Methods). With Universal Home access, 86% of total electricity consumption occurs at home, compared with 22% in the Low Home access cases (Supplementary Note 5 and Supplementary Table 2). Within each access scenario, we model four types of conventional charging control to represent common implementations in the United States today[49]: SFH timers set for 9 p.m. and 12 a.m. start times based on residential EV rates[50,51] and site-level, uni-directional load modulation control at workplaces responding to demand charges through peak minimization or to time-of-use rates based on average grid emissions (Avg Em). Spikes in demand from synchronous timers are observed in today's charging data and persist in many planning scenarios[10,52], despite their impacts on grid stability[53,54]. For contrast we model a third type of SFH timer control where participating drivers are randomly assigned a start time on the half hour between 8 p.m. and 2:30 a.m. Finally, we model an additional scenario, Business As Usual, as a special case of High Home Access with both workplace control and timers to represent

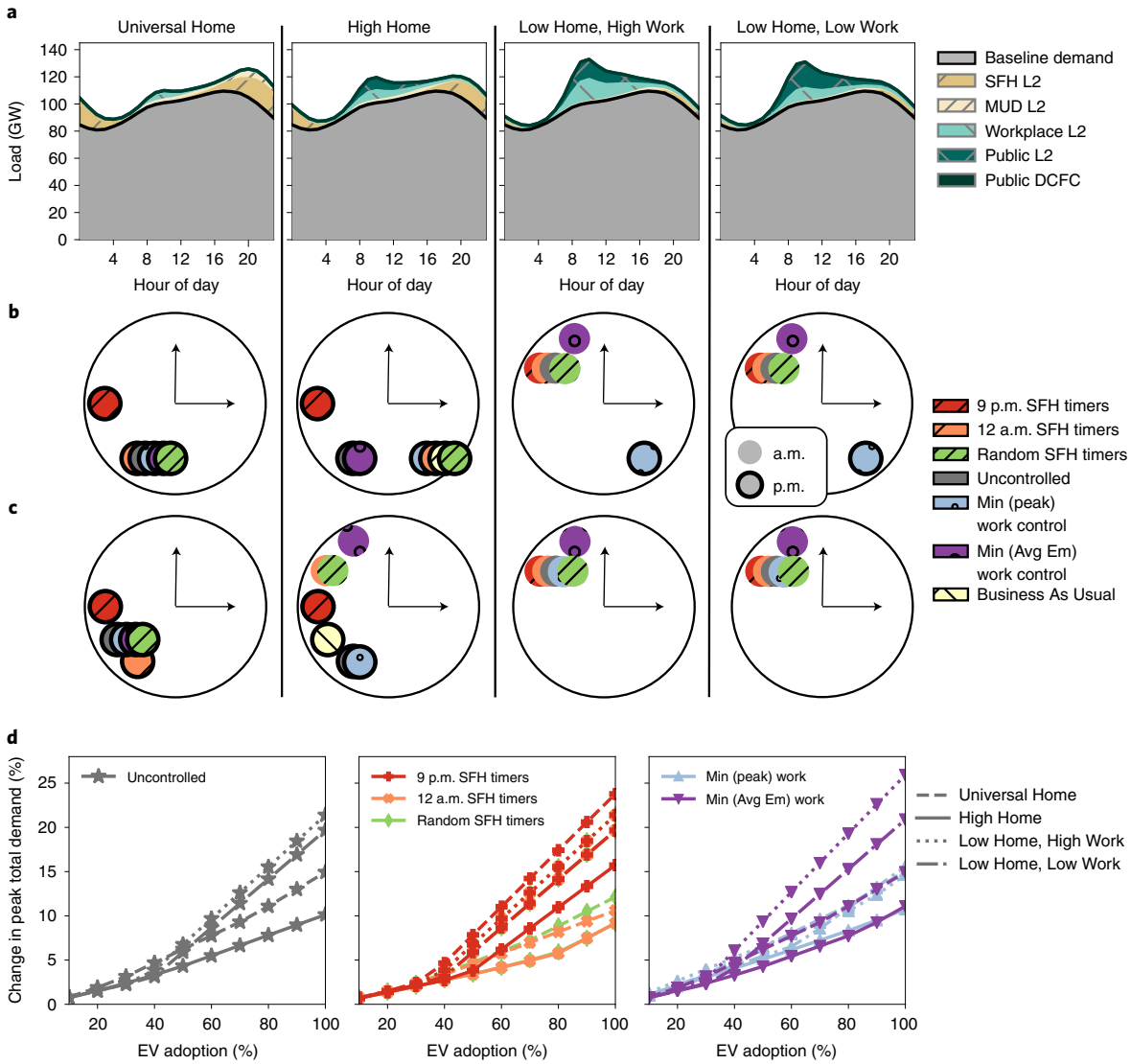

Fig. 3 | Timing and change in peak total demand after the addition of EV charging. The timing of peak total demand depends on the interaction of charging and baseline demand. **a**, The demand profile for each access scenario with uncontrolled charging over baseline non-EV demand for 2035. L2 stands for Level 2 charging and DCFC stands for Direct Current Fast Charging. **b**,**c**, The clock faces below each profile illustrate the timing of peak total demand for that access scenario under all control options for 50% EV adoption (**b**) and 100% EV adoption (**c**). Min(peak) refers to peak minimization workplace control and Min(Avg Em) refers to the workplace control designed to minimize average grid emissions. Thick borders are used to denote p.m. peaks. We observe the timing of the peak shifts from 5 p.m. pre-EVs to late evening in many of the home charging scenarios or to mid-morning in the daytime-charging scenarios. **d**, The percentage change in peak total demand as adoption of EVs is varied from 10% to 100%.

today's dominant mix of control strategies. This results in 25 total scenarios, a subset of which is illustrated in Fig. 2.

Increased peak demand

Baseline demand in WECC is the highest in the late afternoon and early evening. Peak total electricity demand on a typical weekday in 2035 without EVs is modelled to be around 109 GW at 5 p.m. Each charging scenario lines up with this differently, as shown in Fig. 3. High home charging adds demand in the evening and pushes the peak later towards 7 p.m., while daytime charging creates new peaks mid-morning at 10 a.m. and 11 a.m. The value of the peak increases modestly with the addition of EV charging until around 30% adoption, after which there are break points in several scenarios. The steepest increases occur in the charging scenarios with the highest peaks once the timings of the peak total demand and peak charging demand are aligned. With 50% adoption, the increase ranges from 3% to 9% depending on the scenario, as shown in Fig. 4. In the stress test with 100% adoption, charging increases peak total demand by 9–26%. Daytime-charging scenarios increase peak total demand by more than the High Home and Universal Home charging scenarios, except in cases with 9 p.m. timers.

Net demand and coupling with the grid

Total demand, however, does not tell the full story of grid impact, and it is critical to study how this demand is felt across the different sources of electricity generation. Net demand, calculated by removing the contribution of non-fossil fuel generation, drives the dispatch of fossil fuel generators.

To better understand these impacts, we developed a detailed model of the grid in 2035 based on the outputs of recent state- and region-level capacity expansion planning[55,56]. We extended the merit order-based dispatch model presented by Deetjen and

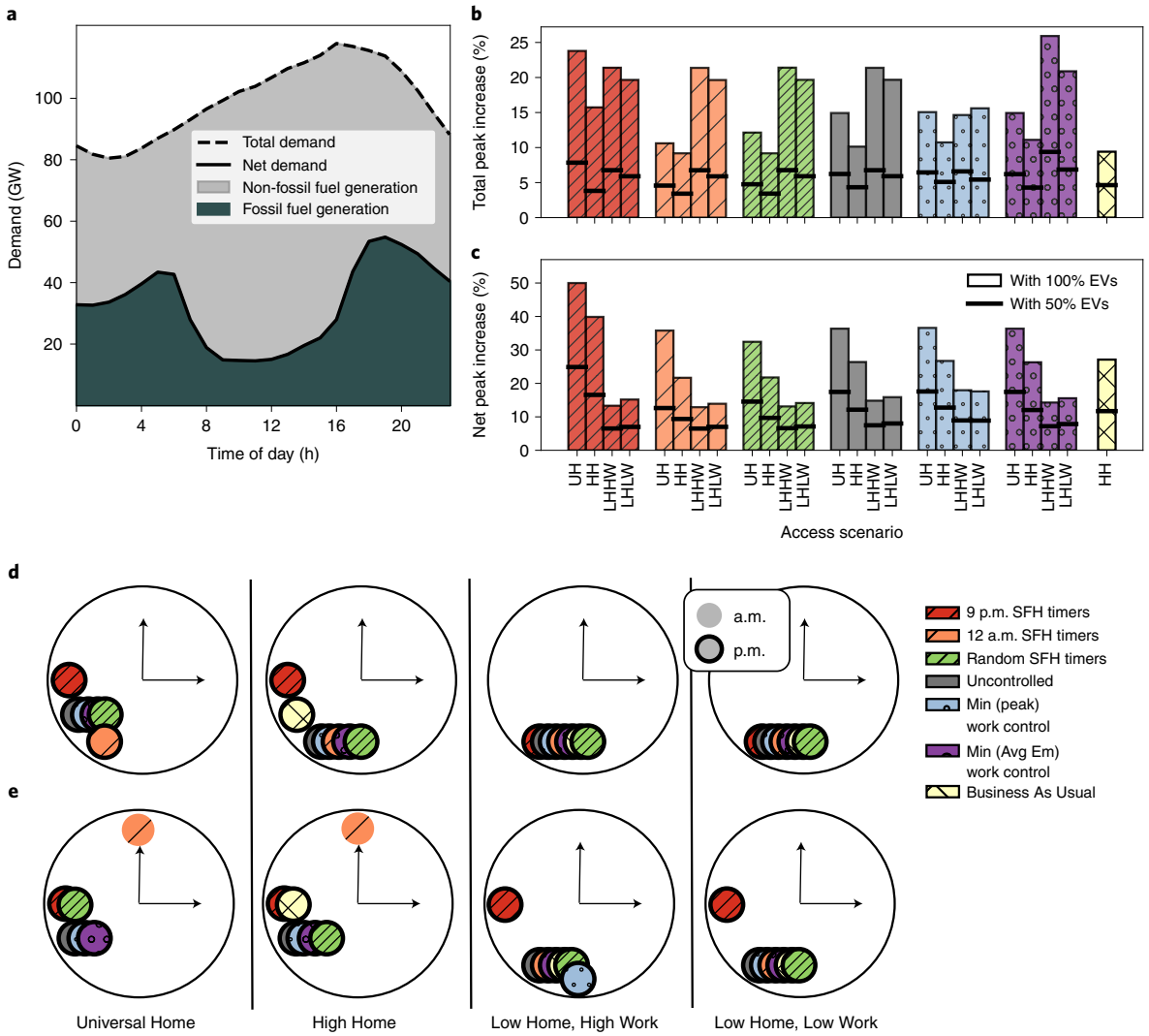

Fig. 4 | Timing and change in peak net demand reveal different impacts thanks to the contribution of non-fossil fuel generation. a, A typical day from the pre-EV dispatch is used to illustrate the calculation of net demand: non-fossil fuel generation is dispatched first; net demand is calculated by subtracting that generation from the total demand. Total demand is shown with a dashed line and net demand is shown with a solid line. **b**,**c**, A comparison of the increase in peak total (**b**) and peak net demand (**c**) when compared with electricity demand pre-EVs. Values for both 50% and 100% EV adoption are shown. We observed that High Home access leads to the lowest increase in peak total demand, but daytime-charging scenarios lead to the lowest increases in peak net demand. The following short forms are used for the access scenarios: UH = Universal Home; HH = High Home; LHLW = Low Home, Low Work; LHHW = Low Home, High Work. **d**,**e**, The timing of peak net demand in each scenario for 50% EV adoption (**d**) and 100% EV adoption (**e**). We find that peak net demand occurs in the evening in every scenario as most daytime charging is covered by non-fossil fuel generation.

Azevedo[57] to reflect announced generator retirements and additions, we increased baseline demand, and we increased solar and wind generation to a base case 3.5× and 3× 2019 levels, respectively. We summed charging demand across fast and slow stations, home, workplace and public charging to study the impacts on the bulk-power system, and we assumed the distribution system could handle the demand (Methods).

Changes in peak net demand, shown in Fig. 4, reveal the opposite impact as total demand. Home charging scenarios, not daytime-charging scenarios, have a worse impact on peak net demand and put more stress on the remaining fleet of fossil fuel generators. Thanks to high solar generation during the day, peak net demand occurs in the evening in every scenario. The Business As Usual scenario increases typical peak net demand by 1.6× more than the Low Home, High Work scenario with 50% EVs or 1.8× with 100%. In the worst case, the Universal Home access scenario with 9 p.m. SFH timers increases it by 3.3× or 3.4×.

Focusing on daytime charging to minimize grid impacts is the first major conclusion of this study. First drawn here, it is supported by all following analyses. The timing of added demand is more important in the future grid with increased renewable generation. Daytime-charging scenarios benefit from their alignment with solar generation while overnight-charging scenarios miss that opportunity.

Grid capacity consequences

To ensure the grid's capacity to support charging under high levels of EV adoption, storage will be needed. A small amount, 0.39 GW, is needed to meet baseline demand. California's recent planning targets 9.7 GW of 4 h duration grid storage by 2030[58], which would be a more than 40× increase over 2019 levels.

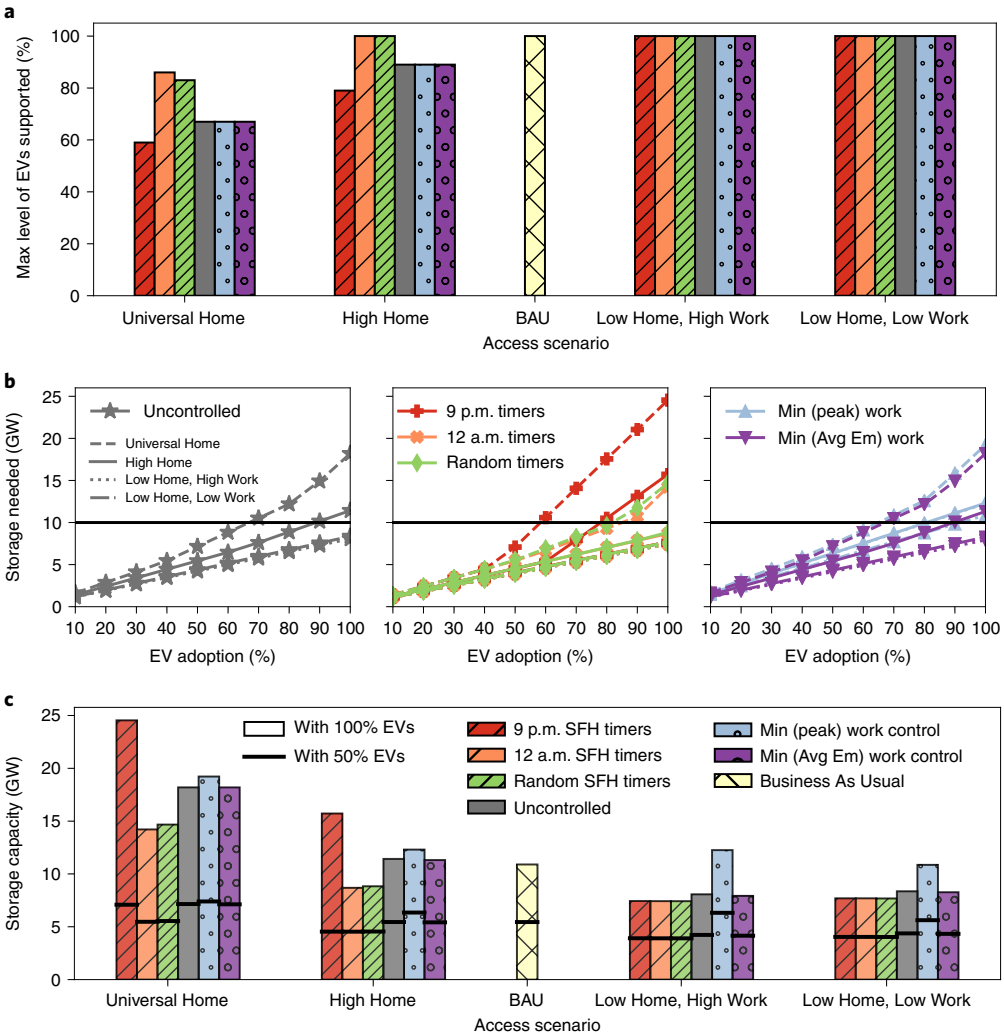

Fig. 5 | Limits to the grid's capacity to support high EV adoption and the impact on grid storage. a, The maximum level of EV adoption for which charging can be supported before there is insufficient generation capacity at least 1 h in the year in the 2035 grid. There is capacity to support more EVs in the Low Home access scenarios, thanks to better alignment of charging with hours of low baseline demand and higher renewable generation. This model of the grid in 2035 includes 10 GW of technology-agnostic 4 h duration storage operated to smooth net demand. BAU stands for Business As Usual. Max stands for Maximum. **b**, The minimum capacity of 4 h duration storage that would enable the grid to support charging for increasing levels of EV adoption. This type of storage is dispatched after all other generation resources to cover unmet demand and we assume additional solar is deployed to charge it (Methods). **c**, A close-up look at the amount of storage required to support 50% or 100% EV adoption in 2035. With uncontrolled charging in the best case, the Low Home, High Work access scenario would require just 4.2 GW or 3.6% of typical weekday peak total demand for that scenario. In our stress test with 100% EV adoption, the grid would need 8.1 GW of storage or 6.1% of typical weekday peak total demand. At 50%, we find the storage requirement varies by a factor of 1.9× from 3.9 GW to 7.4 GW between scenarios. At 100%, we find the requirement varies by 3.3× from 7.4 GW to 24.5 GW between scenarios.

We find that 10 GW of storage installed in WECC is enough for the grid to support at least 50% EV adoption. In WECC in 2035 with Business As Usual EV charging, 10 GW is between 8% and 9% of peak total demand on a typical weekday or between 6% and 7% of peak total demand on an extreme day. The grid can support more EVs in scenarios with more daytime charging and fewer EVs in scenarios with more home charging, as shown in Fig. 5a.

In the best cases, with Low Home access, Business As Usual or High Home access with midnight or random timers, the grid can support charging for 100% EV adoption. In the worst case, with Universal Home access and 9 p.m. timers, the grid can support only 59% EV adoption.

Charging controls are often presented as a solution to grid capacity constraints and, indeed, we find that 12 a.m. SFH timers and randomized SFH timers substantially increase the level of EV adoption that the grid can support. In the Universal Home access scenario, they increase the capacity from 67% to 86% and 83%.

Minimum grid storage requirements

Adding 10 GW of storage, however, is expensive, and thus we compute how much storage is needed in each scenario. In Fig. 5b, we show the minimum amount of 4 h grid storage that would be sufficient to cover all unmet demand. Fortunately, most scenarios require less than 10 GW to reach 50% or even 100% EV adoption, as shown in Fig. 5b,c. Again, we find that scenarios with more daytime charging are better than those with high home charging.

Policies supporting a future with Low Home, High Work access could translate into remarkable storage savings. With uncontrolled charging and 50% EV adoption, that scenario would decrease the storage requirement by 1.3× compared with Business As Usual or 1.7× compared with uncontrolled Universal Home access.

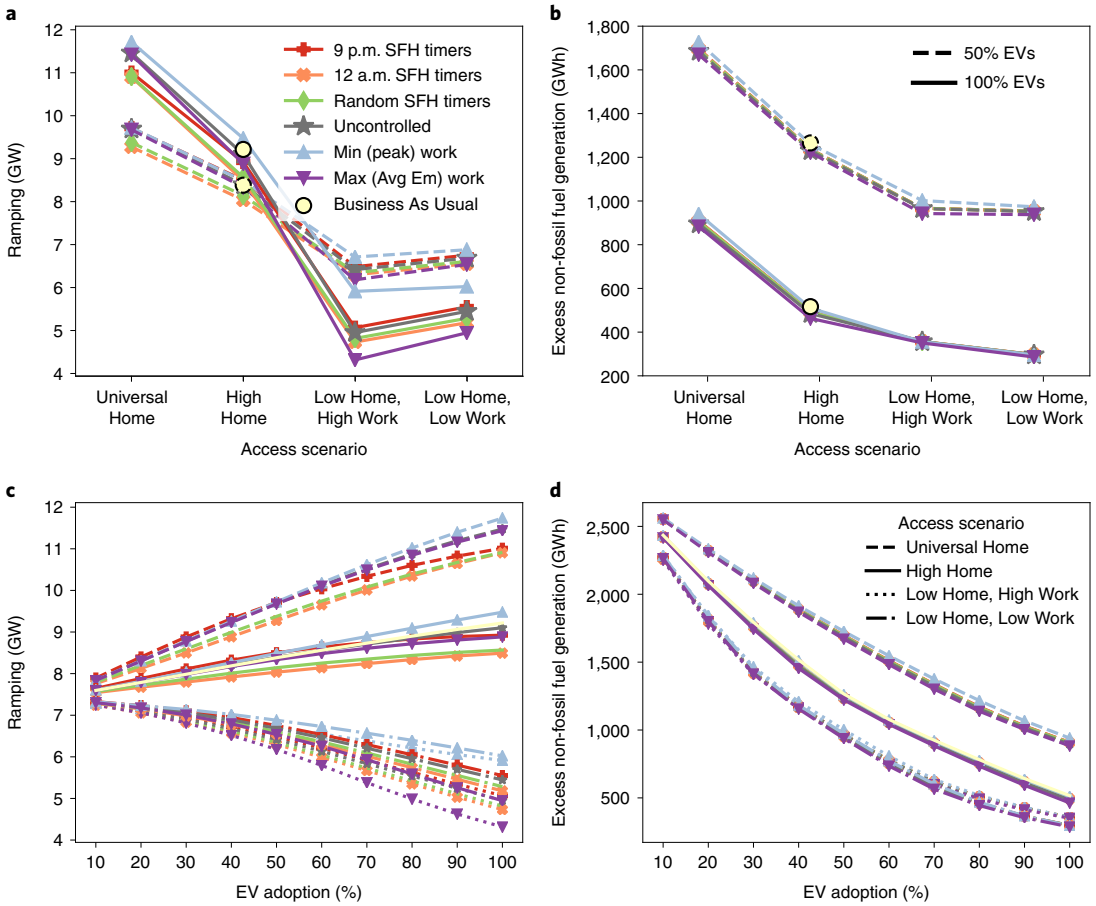

Fig. 6 | Maximum ramping and excess non-fossil fuel generation under each scenario of charging demand. a,**c**, The maximum 1 h ramp in the mean day's profile of demand for fossil fuel generation under each charging scenario for 50% (dashed lines) and 100% EV adoption (solid lines) (**a**) and across all levels of adoption (**c**). **b**,**d**, The values for 50%, 100% (**b**) and other EV adoption levels (**d**) of the total annual amount of excess non-fossil fuel generation. In each scenario, 10 GW of grid storage operated to smooth net demand. We find that both ramping and excess non-fossil fuel generation are lower in scenarios with low home charging and high daytime charging. Ramping increases with the addition of EVs in scenarios with high home charging but decreases in scenarios with high daytime charging; adding EV charging demand decreases the amount of excess non-fossil fuel generation decreases in all scenarios, fastest in those with more daytime charging.

Switching from Business As Usual charging to the Low Home, High Work access charging scenario would reduce the cost of installed storage by US$0.7 billion with an optimistic 143 US$ kWh^{-1} forecast for the cost of storage or US$1.5 billion with a higher forecast cost of 299 US$ kWh^{-1} (refs. [59,60]). These savings are substantial compared with total electricity costs (Supplementary Note 6) and grow substantially as we look at higher levels of EV adoption. In the stress test with 100% EV adoption, the switch to Low Home, High Work access would yield savings of US$1.6 billion or US$3.4 billion with either cost forecast.

Storage can also provide other values to the grid. Policies encouraging daytime charging could translate into better grid reliability by freeing storage capacity to act as reserve for extreme days or provide other grid services, rather than cover the peak demand induced by EV charging.

The second major conclusion of this study is that common charging control implementations can cause severe generation-level impacts at deep adoption. Timer control, in particular, can have substantial negative impacts. Studying the increase in peak net demand in Fig. 4, we saw 9 p.m. SFH timers lead to high increases, up to 25% with 50% EV adoption or up to 50% with 100% EV adoption. The impacts on storage are less severe at 50% adoption, but looking to Fig. 5b, we can see that storage demand grows very quickly at higher levels. Additional generation capacity at 9 p.m. would need to be added before EV adoption reaches 100% in the Universal Home access scenario to avoid demand for storage topping 24 GW, an amount over 18% of typical peak total demand in 2035. With Low Home, High Work access, peak minimization control would increase the storage requirement by 1.5× over the uncontrolled amount by pushing charging into the late afternoon where baseline demand is already high, increasing peak net demand.

Ramping and non-fossil fuel generation impacts

In this section, we assume the planned amount of 10 GW grid storage is added and operated to smooth net demand. Even so, there are substantial 1 h ramps in the final profiles dispatched to the fossil fuel generators, as shown in Fig. 6. This is an important metric for grid reliability, as frequent and fast ramping of fossil fuel generators can shorten plant lifetimes and increase operational costs[43,61]. All scenarios start from a situation where there are no EVs, and adding daytime charging decreases ramping by flattening net demand while adding home charging increases ramping because it aligns with the baseline peak (Fig. 5 and Supplementary Note 7). Random and 12 a.m. SFH timers can decrease ramping in some scenarios, but the effect of adding control is small in comparison with the effect of switching between charging access scenarios.

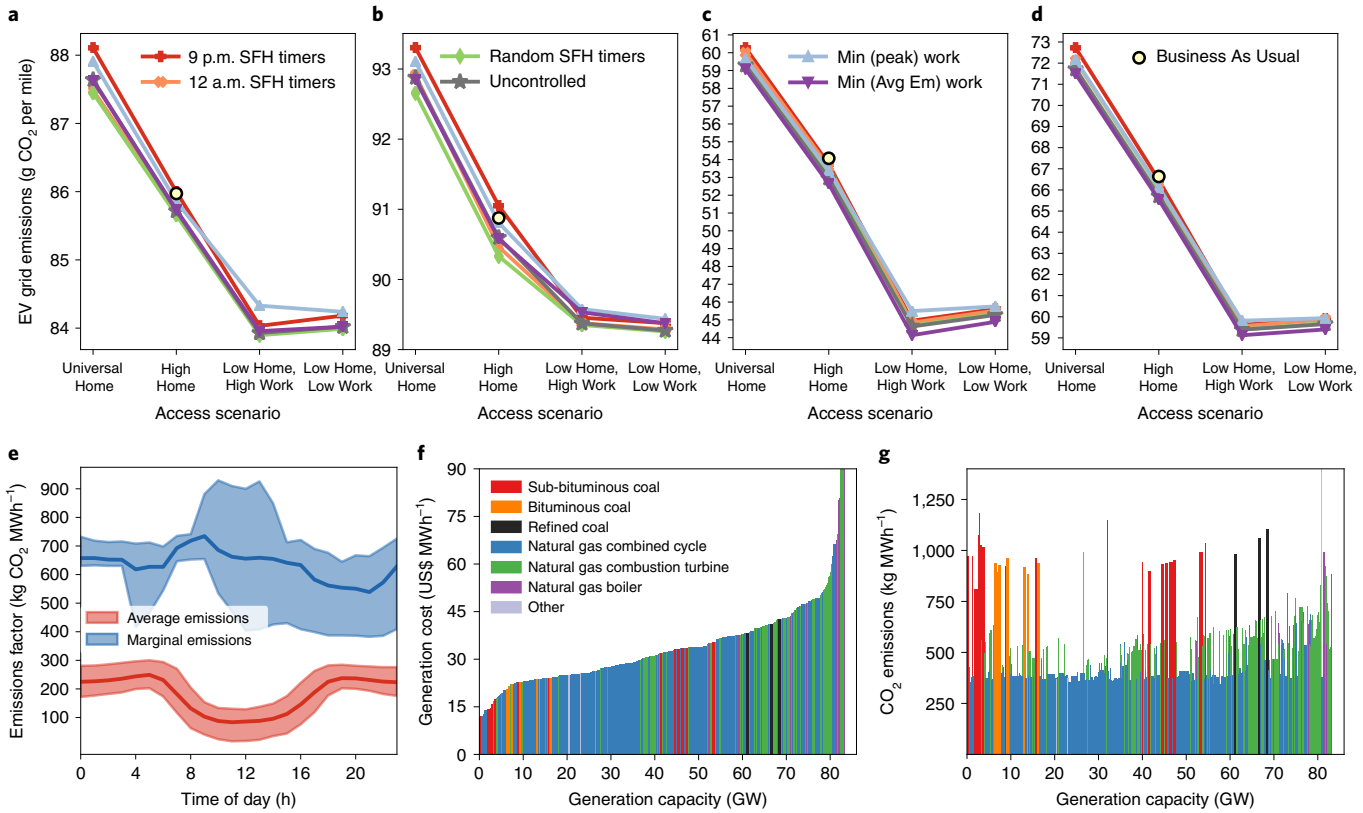

Fig. 7 | Grid emissions and the dispatch of fossil fuel generation. a–d, The additional CO_2 emissions associated with added EV charging demand are shown for two levels of EV adoption—50% (**a**,**c**) and 100% (**b**,**d**)—and two scenarios of renewable generation in 2035: the base case Medium Renewables with 3.5× and 3× the wind and solar of 2019 (**a**,**b**) and High Renewables with 5× 2019 levels of each (**c**,**d**). We find that daytime-charging scenarios have lower emissions than home charging scenarios under both grid conditions. The worst scenario emissions are higher than the best by 5.0% and 36.6%, respectively, in the two grids with 50% EV adoption. We see the same trends with 100% EV adoption, with slightly smaller spreads of 4.5% and 23.0% between the best and worst scenarios. **e**, The median (50th percentile) profile of average and marginal emissions for weekdays in 2035; the shaded bands show the range from the 25th to 75th percentile, highlighting the uncertainty. **f**,**g**, The merit order of generators arranged by cost as used by the dispatch model[77]: generation cost (**f**) and CO_2 emission rate (**g**) for each generator. The width of the bar for each generator shows its capacity. The dispatch order is highly variable throughout the year with variable historical fuel prices and each week's merit order mixes generators in this way. Additional weeks are presented in Supplementary Fig. 12.

For some of our modelled days in the year, non-fossil fuel generation exceeds demand. Without modelling transmission, we cannot determine if this excess generation is curtailed or exported to another region. In either case, it may represent a missed opportunity for WECC to reduce its emissions and increase its use of non-fossil fuel sources. Without EVs, the total annual excess non-fossil fuel generation is around 2.8 TWh. This amount decreases in all scenarios as more EVs are added, most quickly in scenarios with more daytime charging as shown in Fig. 6. Under the Business As Usual scenario with 50% EV adoption, there is 1.3 TWh; this drops to just 0.5 TWh with 100% EV adoption. Scenarios with high daytime charging align better with renewable generation and make use of more of that excess energy (Supplementary Note 7). Again, changing charging access has a bigger effect than adding control.

Grid emissions

Tailpipe emissions for internal combustion engine passenger vehicles sold in the United States vary by type (Supplementary Note 8). As light-duty trucks and sport utility vehicles (SUVs) are the most popular segment, the US Environmental Protection Agency (EPA) estimates that the average passenger vehicle in the United States emits approximately 404 g of CO_2 per mile from its tailpipe[62]. Sedans emit less; the 2019 Honda Civic, for example, emits approximately 276 g of CO_2 per mile (ref. [63]). We find that the added grid emissions of CO_2 per mile of EV charging in WECC are substantially lower, between 84 g and 88 g of CO_2 per mile in a base case scenario for 2035 renewables with 50% EV adoption or between 89 g and 93 g of CO_2 per mile with 100% EV adoption. This represents a more than 4× improvement in operational emissions compared with the average internal combustion engine vehicle or a 3× improvement compared with a sedan, which is comparable in size and style to the EVs modelled here (Methods and Supplementary Note 8). Similar drops in SO_2 and NO_x are also observed (Supplementary Figs. 8 and 9).

Scenarios with less home charging yield lower CO_2 emissions per mile, as shown in Fig. 7. This result is consistent across both grid scenarios and EV adoption levels. Under the base case 'Medium Renewables' scenario with 3.5× and 3× 2019 levels of solar and wind, the spread between the best and worst case is 5% at 50% EV adoption or 4.5% at 100% EV adoption. With High Renewables at 5× 2019 levels, we see a larger difference in emissions between scenarios. Universal Home has up to 36% higher emissions per mile than Low Home, High Work access with 50% EVs, or up to 23% higher emissions with 100% EVs.

Different charging control strategies do not change our result by more than 2%. Uncontrolled workplace charging is well aligned with solar generation, and we see that average emissions minimization control does not meaningfully reduce emissions relative to uncontrolled. This occurs, in part, because average and marginal

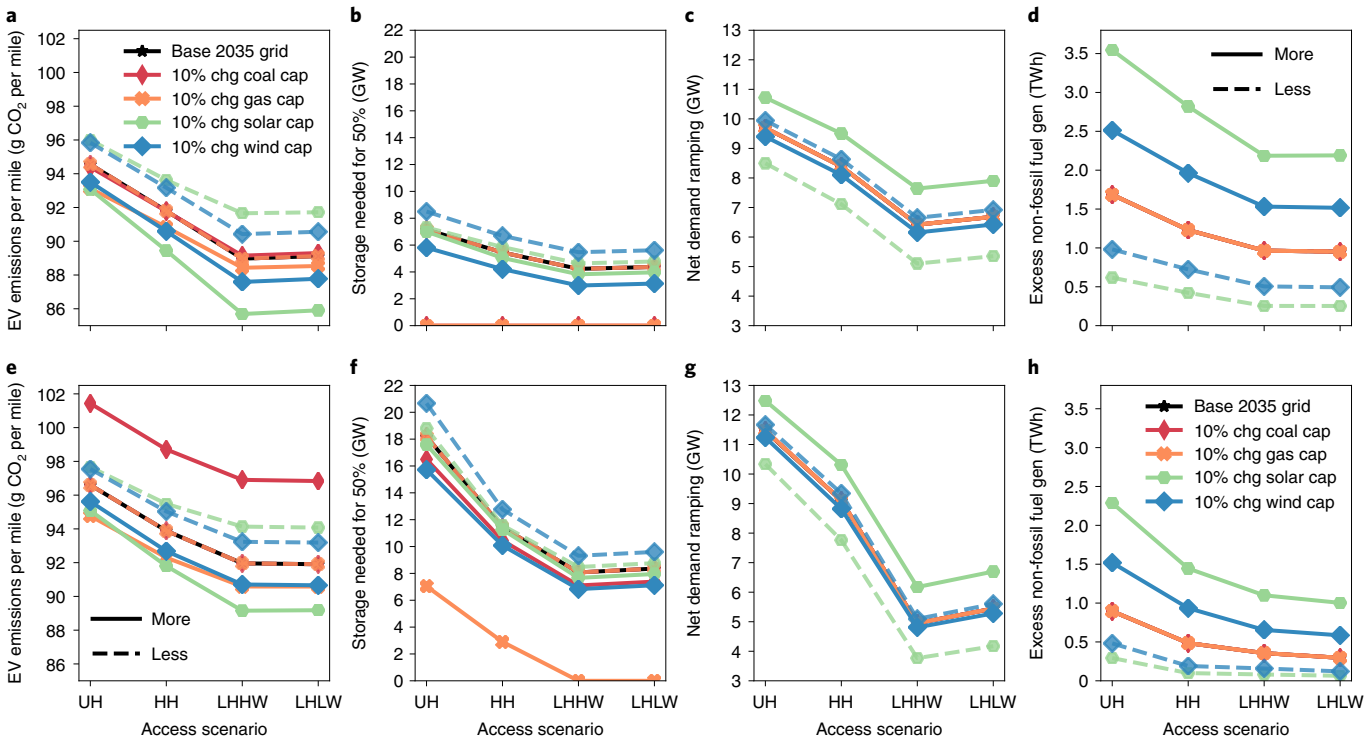

Fig. 8 | Sensitivity of key results to changes in grid capacity. We test 10% increases (solid lines) and 10% decreases (dashed lines) in the capacity of solar, wind, gas and coal generation. We show the results only for uncontrolled charging scenarios to make them easier to read. **a**–**h**, The result for 50% EV adoption (**a**–**d**) and the result for 100% EV adoption (**e**–**h**). In every case, we find that the main conclusion holds: daytime-charging scenarios reduce grid impacts relative to scenarios with high home charging. Adding capacity of wind and solar improves grid emissions, especially with daytime charging. Increasing the capacity of gas and coal by 10% is sufficient to eliminate the need for grid storage to cover charging for 50% EV adoption, as both the added capacity and the grid storage act like peakers. Only solar and wind change ramping or the amount of excess non-fossil fuel generation as both those results depend on the profile of net demand. Here the following short forms for the access scenarios are used: UH = Universal Home; HH = High Home; LHLW = Low Home, Low Work; LHHW = Low Home, High Work. The following abbreviations are used in the labeling: chg = change; cap = capacity; and gen = generation.

emissions are misaligned. Average emissions are low during the day thanks to high solar generation, but marginal emissions are often higher during the day than at other times (Supplementary Figs. 10 and 11). Though average emissions have been decreasing, marginal emissions have been increasing in the United States over the past decade[64]. The control used average emissions as a fixed objective throughout the year. This led to marginally better use of excess non-fossil fuel generation, as we saw in Fig. 7, but there were only up to 100 days in the year with excess non-fossil fuel generation to target. On the other days, this control increased daytime demand for fossil fuel generators with often high marginal emissions.

Improving this control design, however, would be difficult because the profile of marginal emissions and the dispatch order of generators changes throughout the year. Fig. 7b shows the high uncertainty in marginal emission factors, often higher at midday, and average emission factors, which are lowest at midday. Fig. 7c shows the merit order of fossil fuel generators from one week in the middle of the year. Both high- and low-emitting generators are present throughout the merit order, the daily profile of marginal emission factors is highly variable, and shifting demand for these generators has an inconsistent, small impact on total emissions.

Changing the grid

Current grid planning depends on models of future charging demand. This study has tested the sensitivity of those plans to different realizations of charging based on scenarios of driver behaviour, infrastructure and control. In Fig. 8, we test the sensitivity of our results to updates in grid planning. In each case, we draw the same conclusion: Low Home charging access reduces EV grid emissions, storage requirements, ramping and excess non-fossil fuel generation when compared with scenarios of High or Universal Home charging access. The costs and emissions benefits of each charging scenario are discussed in Supplementary Note 9.

We provide a sensitivity analysis to natural gas prices, vehicle battery capacity and the prevalence of fast charging in Supplementary Figs. 17–19.

Discussion

Our results show the potential for charging infrastructure to improve the grid integration of EVs in WECC at deep levels of adoption. In the future grid with higher renewable generation, timing is more important and net demand tells a very different story than total demand. Shifting drivers from home to daytime charging improves all metrics of grid impact including ramping, use of non-fossil fuel generation, storage requirements and emissions. This insight is robust across varying levels of EV adoption.

Our results demand expanded daytime-charging access; simply limiting home charging could negatively impact adoption and contribute to inequitable access to EV ownership. Policymakers should ensure daytime-charging options are convenient, inexpensive, widespread and open access to the public.

While the emissions reductions unlocked by switching between charging scenarios are modest with medium levels of renewables, the needed grid storage requirements are substantial. Storage is

expensive, current grid penetration is low and the industry is already under pressure to scale up in the face of other grid challenges. By avoiding the evening peak and better aligning with renewables, daytime-charging scenarios reduce the amount of storage required to support EV charging and free it to provide other services.

Our results also reveal challenges with charging controls based on existing and proposed rate schedules. Grid operator centralized controls can change this situation to guarantee smooth grid operations.

We reveal a conflict between system- and site-level benefits. Peak minimization control is widely implemented at commercial sites based on equipment capacity limits and electricity rates designed to protect distribution system infrastructure[7]. However, spreading workplace charging throughout the day increases demand in the late afternoon when high baseline demand and decreasing solar generation already strain the grid at the generation level, leading to higher storage requirements. Given the high costs of both grid storage and distribution system upgrades, further research is needed to evaluate the trade-off between these objectives.

A similar conflict was recently identified with valley-filling control of home charging in the United Kingdom[28]. This also represents a tension between near-term concerns about infrastructure upgrades and long-term concerns about grid decarbonization. Utilities in California are moving away from demand charges at commercial EV sites to improve the economic case for station operators and encourage adoption[65]. A similar issue arises in residential rate design between simple and complex structures, which have better impacts on the grid[54], but introduce practical, regulatory and ethical challenges involved in assigning different rates to neighbouring customers.

We find that workplace control designed to align charging with low average grid emissions does not realize meaningful reductions when implemented. High variability in the dispatch order of generators and the profile of marginal emissions makes designing emissions-reducing rate schedules challenging. In addition to balancing distribution- and generation-level impacts, future electricity rates should better harmonize with wholesale electricity prices and could vary day by day with grid generation conditions.

Different assumptions regarding future baseline demand and generation resources could lead to different results, possibly inverting the dynamics of daytime and nighttime charging. For example, controlled home charging could be best in systems with low overnight demand and high dependence on overnight wind generation. Similarly, seasonal effects caused by changing outdoor temperature could impact the results in some regions. Coupling should also be explored with different scenarios of electrification in other sectors than transportation and with different pathways for grid decarbonization. In any case, the time of day of charging matters.

The build-out of new charging stations represents a powerful multi-year timescale form of charging control to improve the impacts of EV charging, support equitable widespread adoption, reduce emissions, support renewable integration and smooth the transition to a decarbonized future.

Methods

Overview. We develop a model of EV charging and the electricity grid to study the consequences of charging demand on emissions, grid capacity, costs, storage and renewable integration in 2035 (Fig. 1a). First, we develop scenarios for the future minute-by-minute EV charging demand, modelling drivers' charging behaviour across the WECC states using a probabilistic, data-driven model of driver behaviour and charging. We then explore a range of scenarios for controlled charging or for changing drivers' access to charging at home and at work. We model controlled charging in both residential and workplace settings based on existing electricity rates. We repeat the typical weekday and weekend day profile for each charging scenario to represent a full year of charging demand. Second, we extend an existing model of the electricity grid to represent conditions and operation in 2035, using a reduced-order dispatch model to simulate the use of fossil fuel generators and considering future levels of renewable generation and grid storage. Then, combining the two elements, we calculate the grid dispatch over all 8,760 hours of the year and the emissions associated with the added demand from EV charging to study the impacts of each scenario.

EV charging demand. EV charging demand is driven by driver behaviour and vehicle type: where, when, how, how often and how much each driver charges. To model charging demand in WECC, we build on and substantially extend our earlier model of charging, which clustered drivers into distinct groups by their observed charging behaviours[52]. The complete modelling approach is detailed here.

Here we model only personal, light-duty vehicles and do not model scenarios for commercial medium- and heavy-duty vehicles. Commercial vehicles will follow very different charging patterns, dictated more by scheduling than individual driver behaviour or preferences. Medium- and heavy-duty vehicles will also experience different adoption timelines[66].

A driver's charging profile is influenced by mobility needs, by the characteristics of the vehicle and, critically, by access to charging in different locations. The data used for this study captures a wide range of behaviours for drivers of different makes and models of EVs.

To model the charging behaviour of drivers of lower-income groups, future adopters and other drivers under-represented in historical charging data, we used those three factors as an intermediate: we parameterize current drivers' observed behaviour groups on their energy needs, vehicle battery capacity and access to charging and model how those factors would change to represent future drivers of different income or housing in different regions of the United States. The probabilistic model of charging demand connecting these features is depicted in Fig. 1b.

Each connection in Fig. 1b represents a conditional dependency: given the driver's region, we model the probability they would have a particular type of housing, level of income and annual distance to travel; given the driver's income and housing type, we model the probability they would have a large- or small-battery capacity vehicle and their probability of having access to different types of home or workplace charging; and given the driver's annual mileage, we model their total annual demand for charging energy. The links were fit using a range of inputs and datasets described below.

Modelling the full range of early-, mid- and late-stage adopters is a key challenge to long-term planning for EVs. Late adopters are best represented in today's data among residents of MUDs, drivers without access to home charging and drivers with small-battery vehicles. With this method, the unique behaviour patterns of drivers in each of those segments are captured and rescaled to build future charging scenarios.

The driver behaviour groups are identified by clustering drivers from a large dataset of real charging sessions[52]; each cluster represented a unique type of driver with a pattern of charging across different segments, charging at different times of day and charging with different frequencies. We design the feature vector for each driver to include their vehicle battery capacity and statistics describing their use of each charging segment: their number of sessions, their frequency of charging on weekends rather than weekdays and their mean session start time, energy and duration within each segment. We model the daily charging decisions and session parameters separately for the drivers in each group. The data do not reveal any clear direct connections between drivers' behaviour groups and socioeconomic indicators after accounting for access, energy use and vehicle battery capacity. The behaviours observed and captured by these clusters represent revealed preferences of real drivers. Several behaviours identified in other studies are confirmed in this data including, for example, the presence of more and less risk-averse drivers, strong habits of regular charging and mixed use of different infrastructure[13,67]. These revealed behaviours are different from those identified through stated preference surveys[17]. The arrival times were further validated using data from the 2016-2017 National Household Transportation Survey[68] across different household income levels for respondents in the Bay Area (Supplementary Note 4).

To generate the scenarios presented in the paper, we model the charging demand for each county in the main 11 states in WECC separately and aggregate the regional profiles. WECC refers to the Western Interconnection, overseen by the Western Electricity Coordinating Council. In this study we excluded the Canadian and Mexican portions of the territory. We shift all charging demand onto Pacific time when creating the aggregate demand.

By concatenating the weekday and weekend profiles to compile one year of charging, we assume seasonal effects caused by changes in outdoor temperature can be neglected.

Data used to model charging demand. We accessed the number of passenger vehicles and the county-level distributions of housing types, household incomes and travel demand from census, community and consumer survey data[45,69]. We model the dependence of access to residential charging on income and housing type using data from a 2021 survey of Californians jointly conducted by the California Energy Commission and the National Renewable Energy Laboratory[70]. The survey defines three bins for annual household income: up to $60,000, between $60,000 and $100,000 and greater than $100,000. We match the survey housing types to five bins in the census data: SFH detached, SFH attached, low- and mid-rise apartments, high-rise apartments and mobile homes. We model

access to workplace charging based on a 2018 survey of California commuters[12]. We model the dependence of battery capacity on driver income using data from the California Clean Vehicle Rebate Project on over 400,000 purchases of electric vehicles in California between 2010 and 2020[71].

To model driver behaviour, we use a dataset of over 2.8 million charging sessions from 27.7 thousand battery electric vehicle drivers recorded by a large charging station provider in 2019 in the California San Francisco Bay Area. Each session is associated with a unique driver ID and the start time, end time, energy, charging rate and location category are known. The sessions cover five segments: workplace level 2 (L2) charging, public L2 charging, public fast charging (DCFC), SFH residential L2 charging and MUD residential L2 charging. L2 charging occurred at 6.6 kW and DCFC occurred at 150 kW.

Data cleaning is described in further detail in Supplementary Note 2 and Supplementary Methods, and statistics about the drivers and sessions are presented in Supplementary Figs. 1–3. Seventy-five percent of the sessions occur at workplaces, followed by 17% in public, 8% at SFHs and less than 1% (3,592 sessions) at MUDs. Of the vehicles, 53% have large battery capacities (greater than 50 kWh) and 47% have smaller battery capacities. The most common make is Tesla, followed by Chevrolet and Nissan. This dataset serves as revealed preference data and contains a rich set of behaviours.

Fitting model of charging demand. We assume that all drivers have access to public charging. We label home or workplace charging access for drivers in the dataset based on their charging history in 2019. We model free and paid workplace charging as separate categories of access and assign free access to drivers whose median session fee in 2019 was below US$0.05. We define four scenarios by varying drivers' access to charging. For 'Universal Home access', we assume every driver of every housing and income level would have access to charging at home. For 'High Home access', we model access to home charging based on the 'potential access with parking modification' scenario from the survey[70], assuming that L2 charging would be installed for all drivers who responded that they could install some type of charging at their residence. In both 'Universal Home access' and 'High Home access', we that assume 50% of high-income drivers would have access to workplace charging based on the 2018 study[12], and lower-income drivers would be less likely to have access. For 'Low Home, Low Work', we modelled access to home charging based on the 'existing access' scenario from the survey[70], assuming that only drivers who already park beside Level 1 (L1) charging equipment would be able to install L2 home chargers. For 'Low Home, High Work', we used the same model of low access to home charging but increased the probability of access to workplace charging, bounded by the fraction of Californians who drive to commute to work[45]. In all cases we assume workplace charging was free for 75% of those with access. The scenarios are illustrated in Fig. 1 and Supplementary Fig. 28.

We model the vehicle purchase decisions in the Clean Vehicle Rebate Project data with logistic regression, representing each driver's income with their zip code's median household income and using high-end vehicle makes to represent larger battery vehicles. The mean probability of a driver purchasing a large battery vehicle is 30.6%, 33.2% and 37.9% for drivers in the low-, middle- and high-income bins, respectively. We model the distribution of drivers' total annual energy use by assuming a high mean efficiency in future EVs of 5 miles per kWh (ref. [72]) with negligible losses to charging efficiency and define seven bins aligned with the annual mileage distributions: (0, 600), (600, 1,000), (1,000, 1,600), (1,600, 2,000), (2,000, 3,000), (3,000, 4,000), (4,000, +) kWh. We assume that the distribution of EVs over counties will match the current distribution of passenger vehicles at the high levels of EV adoption studied in this paper.

We cluster the drivers using agglomerative clustering with Ward's method. The clustering algorithm is initialized with each driver as a separate cluster. Let x^d represent the normalized feature vector describing driver d. At each step the algorithm chooses two clusters to combine such that the total within-cluster variance[73] is minimized. Where C_l denotes the set of drivers in cluster l and x^{C_l} represents the centroid of the feature vectors of drivers in C_l, this can be expressed as

$$\min \sum_{l=1}^{L} \sum_{d \in C_l} ||x^d - x^{C_l}||_2. \quad (1)$$

This creates a hierarchy of clusters; the elbow plot showing the marginal benefit of each increase in the number of clusters is used to select the optimal cut-off. We cluster the drivers in each bin of annual charging energy separately and found a total of 136 groups. The typical weekday load profile for drivers in each group is illustrated in Supplementary Fig. 26.

We model the dependence of driver group on access, battery capacity and energy by calculating the distribution of cluster labels for drivers within each bin. Specifically, where $N_{A,B,E}$ denotes the number of drivers with access A in battery capacity bin B and energy bin E and where N^G denotes the number of drivers in group G, the probability is calculated as $P(G|A, B, E) = N_{A,B,E}{}^G / N_{A,B,E}$.

The probability of a driver in a given group charging in each segment on a weekday or weekend day is modelled using the charging histories of drivers in the group. For each driver group G and charging segment z, we model the joint distribution of session parameters, start time and energy, s, using a Gaussian mixture model with up to $K = 10$ components ref. [74]). The probability density function of the mixture can therefore be expressed as

$$P(s) = \sum_{k=1}^{K} P(s|k)P(k), \;\; P(s|k) = \mathcal{N}(s|\mu_k, \sigma_k). \quad (2)$$

Each component, k, in the mixture model is a Gaussian distribution and its weight in the mixture is $P(k)$. Each component represents a distinct pattern of charging behaviour that occurs in the sessions observed in segment z for drivers in group G. In this notation, component k has mean μ_k and standard deviation σ_k, and $\mathcal{N}$ is short-hand for the standard Gaussian distribution formula.

We tested the sensitivity of charging behaviours to US states using the National Household Travel Survey[68] and found that any differences in behaviour beyond those captured by our model of energy needs were small.

For a small number of battery and energy bins, there are no drivers with MUD access: we model the behaviour group distribution for those bins by using other bins in the MUD access category, matching as well as possible first by access, then energy and then battery capacity, based on observations of the relative impact of each on a group's profile. Modelling home charging access, we assume charging for residents of mobile homes could be represented by our data on MUDs and we derate the results of the survey by 50% to reflect the specific difficulty of installing L2 instead of L1 charging at a mobile home.

Because of the probabilistic, open-loop structure and the size of the census mileage bins, the total annual energy varies slightly between uncontrolled scenarios, from 8.654×10^7 MWh for the 'Low Home High Work' scenario to 8.994×10^7 MWh for the 'Universal Home' scenario, a less than 5% difference.

Application of model of charging demand. To generate the daily charging demand in each scenario, we use this model to sample each charging session, repeating to simulate charging for the total number of vehicles in each region. The total set of sessions, their start times, energies and segment charging rates, were used to define the uncontrolled charging load profiles with 1 min time resolution. With this approach, we were able to generate the typical weekday and weekend demand profiles representing 48.6 million drivers for each scenario in under 9 min on a laptop computer. Controlled or smart charging is applied to the output of this module, using either the set of session parameters or the uncontrolled profiles.

Controlled EV charging. We model two types of controlled charging: load-shifting control at single family residences, where an uncontrolled session is delayed to a preset start time; and load modulation control at workplaces, where each vehicle at a site's charging rate is modulated throughout its session to optimize the aggregate load profile. We focus on uni-directional charging because of its widespread implementation. Considerable regulatory, social and technical barriers remain to widespread deployment of bi-directional or vehicle-to-everything (V2X) charging, despite growing academic research on the topic. These challenges include the impact of V2X on battery health, drivers' acceptance of V2X programs, taxation and warranty implications and the development of sufficient charging protocol, regulations and standards[41,75].

Workplace charging control. To estimate the effect of load modulation control at large scale, we fit a data-driven model of control results for smaller-scale sites, following our method proposed by Powell et al.[76]. The complete approach is detailed here. In each case the driver receives the same amount of energy as without control. We implement peak minimization and average emissions minimization.

We simulate 1,000 workplace site-days with 150 vehicles in each by randomly sampling from the workplace charging sessions in the dataset. The optimization problem for each day's charging is subject to constraints limiting the charging rate, charging time interval and ensuring each vehicle receives the same amount of energy as in the uncontrolled session. We assume the session parameters are known in advance. Written as functions of the total site load L at each time of day t, the controlled site load after peak minimization is $L^* = \text{argmin} \;\; \max_t L^t$. Given the daily average emission factor profile, e^t, simulated by the dispatch model for a scenario without EV charging demand, the controlled site load after emissions minimization is $L^* = \text{argmin} \sum_t e^t L^t$.

We use the results to learn a data-driven model of the mapping from the uncontrolled to controlled site profiles, $f: L \rightarrow L^*$. We model f with ridge regression, normalize and divide the 1,000 site profiles into training, development and testing sets and train the model with cross-validation and a grid search over the ridge parameter. The model root mean squared errors on the development set for the peak minimization and emission minimization optimizations respectively were 2.06% and 3.34% of the peak load.

In the optimization formulation for workplace charging emissions minimization, we added a small regularization term proportional to the slope of the aggregate profile to encourage a smoother, more realistic charging dispatch.

To model the final profiles for the workplace control scenarios, we apply the trained model for each optimization objective to the total WECC uncontrolled workplace charging profile.

Residential timer control. Over 31% of the residential charging sessions in our charging dataset demonstrate the use of timers to delay evening start times until the local utility's lowest price period. We assume the same response rate in all future scenarios with timers.

We model load-shifting timer control by identifying the components in the Gaussian mixture models of session behaviours which represent those behaviours and shifting their start times. The 'Random Timers' scenario represents a theoretical case where residents using timers were randomly assigned rate schedules with lowest price periods starting at 8:30 p.m., 9 p.m., 9:30 p.m., 10 p.m., ..., 2 a.m. and 2:30 a.m. To model uncontrolled residential charging, we remove those components of the mixture models and add their weight to other components with evening start times.

On weekends, the energy distributions for components of residential charging demand are more variable: modelling uncontrolled residential charging, we specifically target non-timer components with the closest energies to the timer components being removed.

Grid model. We model the US portion of WECC, building on the reduced-order generator dispatch model proposed by Deetjen and Azevedo[57,77] and extending the model to consider both non-fossil fuel generation and grid storage.

The dispatch model constructs a merit order of generators for each week in the year using historical cost data and dispatches generators by lowest cost to meet each hour of demand. Costs and generator availability are updated weekly or monthly, depending on the available data, resulting in 52 different merit orders throughout the year. We construct the model using the latest available data from 2019 and we add several extensions to represent the future grid: we remove or add generating units based on announced retirements and additions through 2035; we increase the baseline demand to represent electrification in other sectors; we include two scenarios for increased renewable generation; we model the behaviour of projected grid-scale storage additions and we add the demand from our EV charging scenarios.

As historical data on fuel price and production are used to calculate the generation cost for each plant, factors including efficiency, contract difference, and location lead plants of the same type to have different generation costs. As a result, the generators are not well ordered by their emission rates.

A range of grid models are used in the literature on EV charging impact, including models of transmission[9,28], unit commitment[25,34] and others[29,32]. The reduced-order dispatch model proposed by Deetjen and Azevedo[57] is fast and computationally inexpensive, allowing us to compute and compare many scenarios. It is also open-source, highly customizable and based on publicly available data, allowing us to share our model of the future grid open-source, as well. A more detailed literature review is included in Supplementary Note 1.

Data used in grid model. Data collected by the EPA through its Continuous Emissions Monitoring Systems give the hourly operation, fuel consumption, capacity and emissions for each fossil fuel generating unit in WECC[78]. Data collected by the EPA in its Emissions and Generation Integrated Resource database give the construction date, fuel type and location of each plant[79]. Data collected by the US Energy Information Administration Form 923 dataset give the fuel purchases and prices for coal, natural gas and oil plants[80]. Hourly generation from non-fossil fuel sources including nuclear, hydro, wind, and solar was accessed through the US Energy Information Administration Electric System Operating Data website[81].

Modelling the future grid. Planned and announced generation changes for 2035 are the result of capacity expansion planning models which include a Business As Usual base case forecast of EV charging demand. We use the results of these models and announcements to update our model of grid generation, then change the portion of demand from EVs to test the sensitivity of grid impacts to different charging scenarios.

Plants or units with announced retirements through 2035 are removed from the set of generators[56]: 7,644 MW of natural gas and 17,175 MW of coal capacity. Announced additions are included by duplicating the most similar existing plants, prioritizing those most recently online and in the same region as the additions[56]: 14,283 MW of natural gas and no coal.

Baseline demand is scaled by a factor of 1.16 to represent electrification based on the Electrification Futures Study's Reference electrification and Moderate technology advancement scenario load profile[48,82]. This factor was calculated as the average percent increase in consumption over 2018 levels across all states in WECC, excluding that associated with transportation electrification, using data made available by Mai et al.[48] and interpolating between the years 2030 and 2040. This estimate represents the effect of a growing population, business-as-usual forecast increases in the use of electric technologies for heating, cooling, cooking and other end uses[48] and moderate improvements in technology and efficiency[83].

We develop two scenarios for the expansion of renewable generation based on recent projections spurred by California's Senate Bill 100, 'The 100 Percent Clean Energy Act of 2018'[58]. We assume the increases in capacity projected for California could be mirrored across the WECC region. Our 'Medium Renewables' scenario based on the 2035 projections puts wind and solar capacity 3× and 3.5× 2019 levels respectively; and our 'High Renewables' scenario based on the 2045 projections puts wind and solar capacity each at 5× 2019 levels. We model a baseline amount of battery storage in WECC of 10 GW capacity and 4 h duration based on the same report[58,84].

We calculate the future demand faced by fossil fuel generators, D_{ff}, by subtracting the adjusted non-fossil fuel based generation, $G_{\mathrm{non\text{-}ff}}$, from the total demand, D_{total}, adjusted for electrification by the factor α_{elect}, and adjusted to include the added demand from EV charging, D_{EVs}. The calculation can be expressed as

$$D_{\mathrm{total}} = \alpha_{\mathrm{elect}} \left({D_{\mathrm{comb}}}^{2019} + {G_{\mathrm{non\text{-}comb}}}^{2019} \right), \tag{3}$$

$$D_{\mathrm{comb}} = D_{\mathrm{total}} - {G_{\mathrm{hydro,\,nuclear}}}^{2019} - \alpha_{\mathrm{wind}} {G_{\mathrm{wind}}}^{2019} - \alpha_{\mathrm{solar}} {G_{\mathrm{solar}}}^{2019} + D_{\mathrm{EVs}}. \tag{4}$$

We use multipliers, α_{solar} and α_{wind}, to adjust the renewable generation and in so assume that future installations will have the same capacity factors and operations as those in the 2019. We operated the 10 GW of baseline storage with charging schedule r_1 before dispatch for peak-shaving, optimizing the operation to minimize the norm of the demand faced by combustion generators, $r_1^* = \mathrm{argmin}\ ||D_{\mathrm{comb}} - r_1||_2$. Any overgeneration is curtailed at this point to ensure a non-negative $D_{\mathrm{ff,\,dispatched}}$. The final amount dispatched to the generators was

$$D_{\mathrm{comb,\,dispatched}} = |D_{\mathrm{comb}} - r_1^*|. \tag{5}$$

We also apply a second type of storage, after the generator dispatch, using additional storage to cover any unmet demand and optimizing to find the minimum additional capacity of 4 h storage needed.

The capacity of the grid to support EVs is limited by the maximum total capacity of the generators in each week of the year.

To test capacity and study impacts at lower adoption levels, we scale the output of the model for EV charging demand at 100%, assuming a constant distribution of adoption.

The capacity limit is the first percent EV adoption when the total load including EVs could not be supported. This measure is more sensitive to extreme days than studying the peak on an average day, but it represents a real limitation and important grid impact. It also represents an important threshold for grid reliability; operating near this limit, the grid is likely to fall short on days of lower-than-average generation or higher-than-average demand.

The dispatch model uses a heuristic to implement minimum downtime constraints for coal plants[57]. We assume these constraints would be active for the same time periods in the future grid. The dispatch model updates each week based on historical data on periods certain generators were offline in 2019, so the maximum generation capacity varies each week. When the window for which a minimum downtime constraint is triggered crossed the division between one week and the next, the capacity in that period is limited by the lower of the two weeks' capacities. Meanwhile, the storage requirement is calculated not based on weekly limits but with an hourly time series of the demand that could not be met when running the dispatch model.

Projections of storage capacity in 2035 are highly uncertain and cover a wide range of values. Announced additions in WECC yield an approximate 8× increase over 2020 levels[56]. Though California already has more than three times the grid-scale storage capacity of any other state[85], the Senate Bill 100 report requirement of 10 GW by 2030 would represent an increase of 50× the 2019 level of 0.2 GW (ref. [58]). We assume this value would represent a fair base case projection for the total installation in WECC by 2035.

In the second type of storage implementation when adding additional storage capacity to cover unmet demand, we include a small regularization term in the objective to smooth operation of the battery. The additional storage is needed to meet evening capacity constraints. We assume it would be charged using additional solar and we do not iterate or re-dispatch with the added demand for charging the additional storage.

Grid model outputs. We calculate the total emissions at each hour as the sum of emissions from each generator that was dispatched. The last generator dispatched for each hour of demand is identified as the marginal generator, and its emission rate in $\mathrm{kgCO_2\,kWh^{-1}}$ determines the marginal emissions factor. To attribute the emissions caused by adding EVs in each scenario, we subtract the total emissions from the dispatch of a parallel scenario without EV charging demand.

We calculate the excess non-fossil fuel generation by summing the excess generation on hours where non-fossil fuel generation exceeds demand. The model does not represent transmission, interconnection or congestion; therefore, we do not model whether excess generation is curtailed or exported to another region.

Data availability

The charging data used in this study cannot be made publicly available due to privacy concerns for the individual drivers, but the model objects and charging profiles that were calibrated with that data and used in this study have been

made available at https://data.mendeley.com/datasets/y872vhtfrc/2with https://doi.org/10.17632/y872vhtfrc.2. This minimum dataset makes it possible to run the charging model and simulate new future charging scenarios to test. G.V.C. (gcezar@stanford.edu) can be contacted with questions about access. The grid model was run using publicly available data. Instructions for its collection and processing are included with the code at https://github.com/Stanford-Sustainable-Systems-Lab/speech-grid-impact. Please contact S.P., I.A. or R.R. with any questions.

Code availability

The code used for the analysis presented in this paper has been made available at https://github.com/Stanford-Sustainable-Systems-Lab/speech-grid-impact with DOI 10.5281/zenodo.7031008. Please contact S.P. with any questions.

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Author contributions

S.P., G.V.C., L.M., I.M.L.A. and R.R. conceived the research. S.P., R.R. and I.M.L.A. designed the modelling framework. S.P. implemented the framework, processed the data and analysed the results. S.P. and R.R. prepared the first draft of the manuscript. S.P., G.V.C., L.M., I.M.L.A. and R.R. edited and revised the manuscript. G.V.C., L.M., I.M.L.A. and R.R. provided institutional and material support for the research.

Competing interests

The authors declare no competing interests.

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Correspondence and requests for materials should be addressed to Siobhan Powell, Inês M. L. Azevedo or Ram Rajagopal.

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