Using ICT-Controlled Plug-in Electric Vehicles to Supply Grid Regulation in California at Different Renewable Integration Levels

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Abstract—The purpose of this paper is to quantify the potential for plug-in electric vehicles (PEVs) to meet operating reserve requirements associated with increased deployment of wind and solar generation. The paper advances prior PEV estimates in three key ways. First, we employ easily implementable scheduling strategies with very low centralized computing requirements. Second, we estimate PEV availability based on data sampled from the National Household Travel Survey (NHTS). Third, we predict regulation demand on a per minute basis using published models from the California ISO for 20% and 33% renewable electricity supply. Our key results are as follows: First, the amount of regulation up and regulation down energy delivered by PEVs can be balanced by using a hybrid of two scheduling strategies. Second, the percentage of regulation energy that can be delivered with PEVs is always significantly higher than the percentage of conventional regulation power capacity that is deferred by PEVs. Third, regulation up is harder to satisfy with PEVs than regulation down. Fourth, the scheduling strategies we employ here have a limited impact on load following requirements. Our results indicate that 3 million PEVs could satisfy a significant portion - but not all - of the regulation energy and capacity requirements that are anticipated in California in 2020.

Index Terms—Plug-in Electric Vehicles, renewable integration, regulation, capacity, load following, scheduling

I. INTRODUCTION

This paper examines the future potential for plug-in electric vehicles (PEVs) to balance variability and uncertainty from wind and solar generators. We focus specifically on approaches to leverage emerging Information and Communication Technologies (ICT, i.e. the “smart grid”) to coordinate PEVs to provide ancillary services in the regulation (secondary frequency control) time frame. As a first step into this direction, we analyze in this paper how the charging demand of a large population of PEVs can be sculpted such that the demand for regulation in California is reduced as much as possible. From an institutional point of view, the scenario we are investigating could be realized by concentrating the control over PEV charging at the system operator. Since the system operator already has full control over generators providing load following and regulation, we believe that this is a realistic scenario. We model the relevant market operations of the California Independent System Operator (CAISO) and evaluate the performance of a basic greedy algorithm for load shifting.

The approach in this paper requires the ICT-based communication between the system operator and the controllable PEVs to be two-way. Specifically, the system operator (or an intermediate aggregator) will collect information from the PEVs including: arrival and anticipated departure from the grid, battery state of charge, maximum charge rate and battery capacity. The system operator then sends the charging schedules to the PEVs. We will assume the ICT is capable of this information exchange at a minimum frequency of once per minute.

The PEVs let the aggregator know when they connect to or disconnect from a charging station. Upon connection they reveal their battery’s state of charge. If the PEV owner does not specify the starting time of the next trip, the system operator predicts it. We do not address the details of how this might be done in this paper. In addition to the start time of the next trip and the connection period, the system operator would need to know the charging rate and battery capacity of each PEV. Based on this information, it can devise a charging schedule and send it back to the PEV for execution. Our evaluation is based on one minute time intervals, therefore the ICT infrastructure should make it possible to send one schedule per minute to each controllable PEV. We show how the regulation potential provided by our charging algorithm changes depending on a number of basic parameters such as PEV fleet size and charging job scheduling method.

The goal of this article is to evaluate the regulation potential of PEVs, not their overall economic implementability. Neither do we consider vehicle-to-grid (V2G), i.e. PEVs providing power to the grid, nor exceptionally high charging rates. The charging algorithm we propose does not increase the number of charging cycles, the depth of discharge, or the power put in or taken out of the PEV batteries compared to uncontrolled charging. Therefore its impact on battery life time should not be significantly more negative than the impact of uncontrolled charging.

II. RELATED WORK

The authors of [1] were among the first to investigate how the U.S. light vehicle fleet could serve as grid resource. They argue that, in the short term, PEVs should be tapped for delivering high-value, time critical services, in particular regulation and spinning reserve. The main difference between [1] and our work is that we are able to simulate the impact of controlled PEVs charging based on actual grid and driving data.

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over longer time periods. This allows us to consider dynamics which static, back-of-the-envelope type of models as the one used in [1] cannot.

Recent efforts to integrate more intermittent power from wind and solar have revived the interest in demand response from a different angle. The authors of [2] explore the conceptual requirements and opportunities of developing load control schemes that are competitive with conventional generation-based approaches. One of the major goals they identify is “full responsiveness” defined as enabling high-resolution system-level control across multiple time scales. A second goal is “non-disruptive” control, meaning that control should have an imperceptible effect on end-use performance. The PEV charging control infrastructure outlined in this article achieves both goals. Similar to previous work in the area of demand response, e.g., [3] or [4], the goal of the coordination schemes investigated in [2] is to fill valleys of aggregated electricity demand rather than providing regulation as discussed in this paper. The authors of [5] present new methods to model and control thermistically controlled electric loads which can also be applied to deliver load following and regulation services for the grid. The authors of [6] use a basic economic model to investigate the formation of valley-filling Nash equilibria if charging control is decentralized and agents behave rationally minimizing their operation cost.

The authors of [7] describes a similar vision as put forward in [2], namely fully responsive loads. They demonstrate the concept by providing details on a prototype smart PEV charging system developed by Google. Their system also allows for dispatching PEV charging load to provide regulation services for the grid. In contrast to us, they use a simplistic vehicle usage model. They focus on demonstrating the functionality of their prototype using non-representative data of regulation demand and PEV usage.

The authors of [8] compare the impact of controlled and uncontrolled PEV charging on emissions and generation costs in the state of Ohio. They use a unit commitment model to simulate the cost-minimal scheduling of fossil-fueled generators assuming that PEVs and generation dispatch are co-optimized. Our model has not yet been extended to capture emission and generation cost. In contrast to the authors of [8], we focus on regulation and load following and thus use a per minute instead of an hourly model.

The authors of [9] describe the outcome of a research project which investigated the revenues that could be generated from providing regulation services to the Californian grid. They used a prototypical PEV outfitted with all necessary upgrades for controlling charging and discharging to analyze the impact of regulation services provision on battery wear out costs. In contrast to us, they used a historical grid regulation signal as input to their charging control algorithm and focus on comparing the benefit obtained from selling regulation capacity to the cost caused by battery wear out.

The authors of [10] present the most comprehensive modeling framework we could find in the literature. It consists of groups of V2G-capable PEVs, thermal household loads, and combined heat and power (CHP) turbines. Their goal is also to evaluate the possible contribution of deferrable loads to supplying regulation, in their case referred to as secondary control. Without doubt, the authors of [10] have done an excellent job integrating different models and considering as much detail as possible. However, it is a challenging task to obtain the data required to parametrize these models. For their case study, they use an invented 4 hub transmission network covering a residential area with 160,000 households. Instead of simulating the demand for regulation by modeling ISO operations like us, they use the swissgrid pre-qualification profile and an actual one day long regulation signal in the range of up to 40 MW.

In contrast to all other models presented so far, our model is capable of predicting the consequences of using PEVs for supplying regulation over an entire year and in different renewable integration scenarios. Considering longer time horizons for this kind of analysis is important, since load (including the additional one caused by PEV charging), as well as wind and solar energy supply, exhibit significant seasonalities. The chosen level of abstraction allows us to leverage actual data made available by the CAISO via [11]. Thus, our results can be used for deriving concrete policy recommendations for the CAISO control area. Our method could also be applied for other control areas, provided that the relevant operational characteristics are captured and corresponding data is available.

### III. The Model

In the following Section III-A, we present a model used by the CAISO for deriving the demand for load following and regulation [12], [13]. We modified this model to include the charging demand of PEVs as a separate variable. In Section III-B, we explain our innovative approach to derive PEV charging jobs from NHTS data. Section III-C outlines how we integrate the CAISO model and the PEV model into a simulation tool that can quantify the impact of continuously arriving PEV charging jobs and load shifting on regulation and load following.

![Flow chart of simulation procedure.](image)

Figure 1 provides an overview of the complete simulation procedure. It indicates the cyclical relationship of regulation demand and generation scheduling which our tool simulates: A change of the PEV load at the current time step influences future PEV demand and therefore the load forecast (cf., Equations 3 and 9). The load forecast, in turn, influences the
regulation demand and to the extent the demand is served by PEVs, it also influences future PEV charging schedules (cf., Equation 2). The generation schedules are updated in regular time intervals according to CAISO operation procedures and thus do not reflect all changes of the PEV charging schedule at every given time.

A. Regulation and Load Following Demand

The CAISO is responsible for balancing supply of and demand for electricity within its control territory. It also runs the corresponding wholesale markets on which participants can trade electricity. At the end of each trading interval, the CAISO determines a market clearing price based on the submitted bids and the constraints of the transmission grid.

The final aggregated power generation schedules for the hourly scheduling processes have 20 minute long ramps between the output levels of subsequent operating hours and are available 75 minutes before the start of the corresponding operating hour [14], [15]. The generation schedules for the real-time scheduling process contain 5 minute ramps and are available 7.5 minutes before the corresponding operating interval [16], [15]. Updated forecasts of demand and supply from renewable resources that become available within the time interval between dispatch instructions and energy delivery/consumption cannot be considered in the corresponding schedules. Demand and supply forecasts can be inaccurate, especially the forecasts of wind and solar output. This has a negative impact on the economic efficiency of the mentioned energy markets.

In addition to the markets for electric energy, the CAISO also runs markets for capacity products or ancillary services (AS). We do not consider the market for regulation in further detail in this work, although one could imagine that PEV aggregators will participate in the AS markets. Recent work in this direction includes [9], [17] and [18]. Instead, we investigate the theoretical situation in which the system operator can directly control the charging behavior of PEVs. Regulation up and down is the most demanding AS: It has to be available within one minute and is the most expensive AS on a $/MW-hr basis [19]. In this work, we infer the demand for up and down regulation using the model described in [15], [13]. We provide all relevant details and the parametrization of our model in the following.

Table I provides an overview of the different variables used in the following.

The modelling approach described in this section takes advantage of the fact that the actual power generation must be equal to the total load minus the non-dispatchable generation, i.e., \( L_t^{non-PEV} + L_t^{PEV} - WG_t - SG_t \), and that the total generation committed hour-ahead can be obtained from the different hour-ahead forecasts, i.e., \( LF_t^{HA}, WGF_t^{HA}, \) and \( SGF_t^{HA} \), load following demand \( LFD_t \), and regulation demand \( RD_t \). Equation (1) summarizes this coherence.

\[
L_t^{non-PEV} + L_t^{PEV} - WG_t - SG_t = LF_t^{HA} - WGF_t^{HA} - SGF_t^{HA} + LFD_t + RD_t \quad (1)
\]

In the following, we make two further simplifying assumptions:

- The aggregated hour-ahead and real-time schedules are followed perfectly, i.e. generators do not deviate from their individual schedules.
- The ISO has sufficient load following resources at its disposal to meet the ramping requirements.

The demand for regulation, \( RD_t \), is then equal to the difference between the generation according to the real-time schedule, i.e., \( LF_t^{RT} - WGF_t^{RT} - SGF_t^{RT} \), and the actual load minus the non-dispatchable generation, i.e., \( L_t^{non-PEV} + L_t^{PEV} - WG_t - SG_t \). Equation (2) provides a formal expression of the regulation requirement \( RD_t \) at time \( t \) based on the assumptions stated above.

\[
RD_t = L_t^{non-PEV} + L_t^{PEV} - WG_t - SG_t - LF_t^{RT} + WGF_t^{RT} + SGF_t^{RT} \quad (2)
\]

Historical values for the total load as well as the total output generated by wind and solar power generation resources are available for download from the CAISO website [20]. The downloadable data file contains projections of expected values in 2020 based on 2005 measurements. The CAISO has provided technical details on the generation of this dataset in [13]. Regarding the non-PEV electricity demand, we follow the CAISO’s assumption that it grows exponentially according to the following equation with \( \alpha = 1.5\% \) [15], [13]:

\[
L_{2005+i}^{non-PEV} = (1 + \alpha)^i L_{2005}^{non-PEV}
\]

The wind and solar traces are scaled to reflect different installed capacities. The capacities we use in this article are shown in Table II. They are adopted from the CAISO’s 20% and 33% renewable resources studies (cf., [12], [21]). According to California’s regulatory targets, 20% renewable electricity production has to be reached in 2012 and 33% in 2020.

As in [15], [13], we approximate the real time market’s forecast of wind output \( WGF_t^{RT} \) by the observed wind output 8 minutes before, i.e. we assume that \( WGF_t^{RT} = WG_{t-8} \).

The computation of the demand resulting from PEV charging, \( L_t^{PEV} \), is described in Section III-B. The computation

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description (at minute ( t ))</th>
</tr>
</thead>
<tbody>
<tr>
<td>( LF_t^{HA} )</td>
<td>Load according to hour-ahead forecast</td>
</tr>
<tr>
<td>( LF_t^{RT} )</td>
<td>Load according to real-time forecast</td>
</tr>
<tr>
<td>( LFD_t )</td>
<td>Load following demand</td>
</tr>
<tr>
<td>( L_t^{non-PEV} )</td>
<td>Actual non-PEV load</td>
</tr>
<tr>
<td>( L_t^{PEV} )</td>
<td>Actual PEV load</td>
</tr>
<tr>
<td>( RD_t )</td>
<td>Regulation demand</td>
</tr>
<tr>
<td>( SG_t )</td>
<td>Actual solar output</td>
</tr>
<tr>
<td>( SGF_t^{HA} )</td>
<td>Solar power output according to hour-ahead forecast</td>
</tr>
<tr>
<td>( SGF_t^{RT} )</td>
<td>Solar power output according to real-time forecast</td>
</tr>
<tr>
<td>( WG_t )</td>
<td>Actual wind output</td>
</tr>
<tr>
<td>( WGF_t^{HA} )</td>
<td>Wind power output according to hour-ahead forecast</td>
</tr>
<tr>
<td>( WGF_t^{RT} )</td>
<td>Wind power output according to real-time forecast</td>
</tr>
</tbody>
</table>

TABLE I

VARIABLE DESCRIPTIONS.
of the remaining values, i.e., $LF_{t}^{RT}$ and $SGF_{t}^{RT}$ will be described in the following. We obtain the real-time load forecast $LF_{t}^{RT}$ by adding forecast errors to 5 minute averages of the non-PEV load $L_{t}^{non-PEV}$ and connecting the resulting values with 5 minute long ramps. The forecast errors are generated using the following auto-regressive process:

$$
\epsilon_{t}^{RTload} = \epsilon_{s}^{RTload}(t-1) + x_{s}(t)_{RTload}
$$

The random numbers $x_{s}(t)_{RTload}$ are drawn from a truncated normal distribution $N_{x}^{RTload}$ with zero mean and standard deviation $\sigma_{x}^{RTload}$ during season $s$. The distribution $N_{x}^{RTload}$ is truncated such that $\epsilon_{s}^{RTload}$ lies in the interval $[(-3)\sigma_{x}^{RTload}, (+3)\sigma_{x}^{RTload}]$. [15] is based on only one estimate of $\gamma$ and $\sigma$ for the entire year 2006. The most recent source for the required parameter estimates is [12]. The values in [12] are season-specific and thus more accurate, which is why we also use these values. They are denoted by $\gamma_{s}^{RTload}$ and $\sigma_{x}^{RTload}$. We report the values in Table III to facilitate the reproduction of the results presented in this article.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Symbol</th>
<th>Winter</th>
<th>Spring</th>
<th>Summer</th>
<th>Fall</th>
</tr>
</thead>
<tbody>
<tr>
<td>Auto-correlation $\gamma$</td>
<td>$\gamma_{s}^{RTload}$</td>
<td>0.85</td>
<td>0.86</td>
<td>0.92</td>
<td>0.90</td>
</tr>
<tr>
<td></td>
<td>$\gamma_{s}^{HAload}$</td>
<td>0.54</td>
<td>0.61</td>
<td>0.70</td>
<td>0.65</td>
</tr>
<tr>
<td></td>
<td>$\gamma_{s}^{HAwind}$</td>
<td>0.3867</td>
<td>0.5421</td>
<td>0.6987</td>
<td>0.5034</td>
</tr>
</tbody>
</table>

| Standard deviation         | $\sigma_{s}^{RTload}$ | 230.96 | 216.05 | 288.93 | 277.38|
|                           | $\sigma_{s}^{HAload}$ | 681.86 | 545.18 | 636.03 | 559.69|
|                           | $\sigma_{s}^{HAwind}$ | 0.031  | 0.040  | 0.038  | 0.032 |

TABLE III
AUTO-CORRELATION AND STANDARD DEVIATION OF LOAD AND WIND FORECAST ERRORS ACCORDING TO [22], [21].

Equation (3) describes the method we use to derive the real-time load forecast formally. The ramp generation is denoted by the function $AR_{5min}$.

$$
LF_{t}^{RT} = AR_{5min} \left( \frac{1}{5} \sum_{i=t_{stop}(I_{5min}(t))}^{t_{start}(I_{5min}(t))} (L_{t}^{non-PEV} + L_{t}^{PEV}) + \epsilon_{I_{5min}(t)} \right)
$$

In Equation (3), $I_{5min}(t)$ returns the 5 minute interval that minute $t$ belongs to, $t_{start}$ and $t_{stop}$ return the start and stop minute of a 5 minute interval.

The real-time solar generation forecast $SGF_{t}^{RT}$ is computed according to the method described in [13]. For each type $r$ of solar resource, we obtain one forecast value for each 5 minute long time interval in the simulated year using the following equation:

$$
SGF_{t}^{RT} = CI'(t-8)\frac{1}{5} \sum_{i=1}^{t+5} \max(SG^r, i)
$$

$CI'(t) \in [0,1]$ denotes the “clearness factor” regarding a solar resource type $r$ at time $t$. The higher this factor, the more sunlight penetrates the cloud cover on average at time $t$. It is obtained from our data set using the following equation:

$$
CI'(t) = \frac{\sigma}{\max(SG^r, t)}
$$

The expression $\max_{day}(SG^r, t)$ denotes the maximum solar output at time $t$. It is obtained by selecting the maximum value found in the corresponding year long solar output trace at the corresponding minute of the day.

To generate the final real-time solar generation forecast, we add 5 minute long ramps to the sum of solar resource forecasts (cf., Equation (4)).

$$
SGF_{t}^{RT} = AR_{5min} \left( \sum_{r} SGF_{t}^{r} \right)
$$

We obtain all hour-ahead dispatchable generation and wind schedules by adding forecast errors to the hourly averages of the measured quantities. Similar to the real-time load forecasting error, we compute the hour-ahead forecast errors based on auto-regressive stochastic processes. Equation (6) provides the description of the stochastic process of the hour-ahead load forecast error.

$$
\epsilon_{t}^{Hload} = \gamma_{s}^{Hload}(t) \epsilon_{t-1} + x_{s}(t)_{Hload}
$$

The random variable $x_{s}(t)_{Hload}$ is drawn from a season-specific truncated normal distribution $N_{x}^{Hload}$ with zero mean and standard deviation $\sigma_{x}^{Hload}$. The truncation makes sure that $\epsilon_{s}^{Hload}$ lies in the interval $[(-3)\sigma_{x}^{Hload}, (+3)\sigma_{x}^{Hload}]$. The measured season-specific auto-correlation and standard deviation we use to generate the hour-ahead load forecast is reported in Table III.

Equation (7) shows the corresponding formula for the hour-ahead wind forecasting error.

$$
\epsilon_{t}^{Hwind} = \gamma_{s}^{Hwind}(t) \epsilon_{t-1} + x_{s}(t)_{Hwind} WGC_{Y}
$$

The random variables $x_{s}(t)_{Hwind}$ are drawn from a truncated normal distribution $N_{x}^{Hwind}$ with zero mean and standard deviation $\sigma_{x}^{Hwind}$. The random variable $X_{s}(t)$ describes the forecast error as the fraction of total wind generation capacity in the year $Y$, $WGC_{Y}$ (cf., Table II).
The truncation makes sure that $\epsilon^H_{t, t} \in \{-(3)\sigma_{\text{WGC}_Y}, (3)\sigma_{\text{WGC}_Y}\}$ and that $\frac{1}{60} \sum_{i=t_{\text{start}}(1)_{\text{hour}}(t)}^{t_{\text{stop}}(1)_{\text{hour}}(t)} \text{WGC}_i + \epsilon_{t, t}^H \text{remains in the capacity interval } [0, \text{WGC}_Y]$. The measured season-specific autocorrelation and standard deviation parameters for the hour-ahead load forecast is reported in Table III.

We obtain the hour-ahead solar forecast using the following procedure described in [13]. For each hour of the simulated year, we compute a clearness fraction $C^I(I_{t, \text{hour}}(t))$ using the following equation:

$$C^I(I_{t, \text{hour}}(t)) = \frac{1}{60} \sum_{i=t_{\text{start}}(1)_{\text{hour}}(t)}^{t_{\text{stop}}(1)_{\text{hour}}(t)} \text{SG}_{r, i} \max_{\text{day}}(\text{SG}_{r, i})$$

Based on the hourly clearness fractions, we can derive the standard deviation of the solar forecast error using the correlation of sky clearness and the variability of solar output. Table IV provides the mapping of clearness fractions to standard deviations from [13].

<table>
<thead>
<tr>
<th>Clearness fraction $C^I(I_{t, \text{hour}}(t))$</th>
<th>Standard deviation $(\sigma_{H\text{Asolar}, r, t})$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$0.0 \leq C^I(I_{t, \text{hour}}(t)) \leq 0.2$</td>
<td>0.05</td>
</tr>
<tr>
<td>$0.2 \leq C^I(I_{t, \text{hour}}(t)) \leq 0.5$</td>
<td>0.20</td>
</tr>
<tr>
<td>$0.5 \leq C^I(I_{t, \text{hour}}(t)) \leq 0.8$</td>
<td>0.15</td>
</tr>
<tr>
<td>$0.8 \leq C^I(I_{t, \text{hour}}(t)) \leq 1.0$</td>
<td>0.05</td>
</tr>
</tbody>
</table>

**TABLE IV**

**STANDARD DEVIATIONS OF SOLAR FORECAST ERRORS BASED ON CLEARNESS FRACTION LEVELS ACCORDING TO [13]**

To generate the hourly solar forecast error, we use a corresponding truncated normal distribution $N^{\text{HAsolar}, r, t}_{2}$ (cf., Equation (8)).

$$\epsilon^H_{t, t} = x^H_{\text{Asolar}, r, t} \text{SC}_Y$$

(8)

The truncation makes sure that the forecast error does not exceed 3 times the standard deviation, i.e. each $x^H_{\text{Asolar}, r, t}$ must lie in the interval $\{-(3)\sigma_{\text{HAsolar}, r, t}, (3)\sigma_{\text{HAsolar}, r, t}\}$ and must not exceed installed capacity, i.e. $x^H_{\text{Asolar}, r, t} \in [0, \text{SC}_Y]$ is fulfilled for all solar resource types $r$ at all times $t$.

We compute the final hour-ahead load and wind/solar generation forecasts by adding 20 minute long ramps to the sum of the corresponding hourly averages and forecast errors. The ramp function is denoted with $AR_{t, \text{hour}}$. Equation (9) describes the hour-ahead load forecast. Equations (10) and (11) provide the power production from wind and solar at time $t$ according to the hour-ahead generation forecast.

$$WGF^H_{t, t} = AR_{t, \text{hour}} \left( \frac{1}{60} \sum_{i=t_{\text{start}}(1)_{\text{hour}}(t)}^{t_{\text{stop}}(1)_{\text{hour}}(t)} \text{WGC}_i + \epsilon_{t, t}^H \right)$$

(10)

$$SGF^H_{t, t} = AR_{t, \text{hour}} \left( \frac{1}{60} \sum_{i=t_{\text{start}}(1)_{\text{hour}}(t)}^{t_{\text{stop}}(1)_{\text{hour}}(t)} \sum_r (\text{SG}_{r, i} + \epsilon^H_{t, t}) \right)$$

(11)

**B. PEV Charging Demand**

In this section we describe our approach to obtain representative driving patterns from the National Household Travel Survey (NHTS) data. The collected dataset is publicly available and contains trip data reported by more than 150,000 U.S. households [23]. The survey asked household members for all trips they completed on a particular day in 2009. The allocation of reporting days to households was done such that a roughly equal share of data was collected for each weekday/month type. In addition to the trips, households provided information about vehicles in use. Trips are provided in DAYV2PUB.csv, vehicles in VEHV2PUB.csv, all downloadable from the NHTS web site [23].

To obtain the subset of the NHTS data we are interested in, we applied a number of selection criteria outlined in the following. We selected all trips completed by car of equal size as the PEV model considered in this study. Daily driving profiles are assembled by collecting the trips of individual vehicles completed on one day. We do not use any daily driving profiles that either begin at other locations than home or end at such locations.

To ensure a sufficient level of data quality, we applied a number of plausibility rules. Redundant trips resulting from the reports of several household members who shared the same vehicle were deleted. If trips in a daily driving profile overlapped, the entire profile was removed from the database. Some trip reports implied unrealistically high speeds. We therefore deleted entire daily profiles if the average speed of one of its trips exceeded 80 mph.

After all selection criteria and quality assurance had been applied, we obtained a total of number of 140,707 daily driving profiles from an initial set of 178,070 profiles.

We created a software tool that uses randomly sampled daily driving profiles from this database to generate one year long driving profiles. To produce a realistic set of such yearly driving profiles with characteristics corresponding to the database of daily driving profiles, we subdivided the latter into weekday/work ($n_{w/w} = 43,933$ profiles), weekday/non-work ($n_{w/nw} = 61,199$ profiles), and weekend profiles ($n_{w} = 35,575$ profiles).

The NHTS driving profile generator concatenates daily driving profiles based on the assumption that vehicle usage can be distinguished into two types: commuting to work and other purposes from Monday to Friday (work vehicles) and usage for other purposes only (non-work vehicles). We assume
that no vehicle is used for commuting to work on weekends. The fraction of weekend daily driving profiles that included at least one work-related trip is less than 10%.

For this study, we generated a total number of 5,000 yearly driving profiles. To accurately reflect the characteristics of the NHTS dataset, we generated \( n_{w/w} / (n_{w/w} + n_{w/nw}) \times 100\% = 41.79\% \) of these yearly profiles as work vehicle profiles. Before starting the actual generation of these yearly driving profiles, each work vehicle is assigned a commute distance drawn from an empirical probability distribution. We derive this distance distribution directly from the set of all weekday/work daily driving profiles in the database. We assume that the distance to work remains the same during the target year. The weekday parts of the yearly driving profiles of the work vehicles are composed of randomly chosen daily driving profiles of the weekday/work type with the same work distance. The weekday parts of the non-work vehicle yearly driving profiles are generated by concatenating daily profiles of the weekday/non-work type. For the weekend parts of both the work and non-work vehicle driving profiles, the tool appends randomly chosen daily driving profiles of the weekend type.

Many vehicles that could be replaced by PEVs were not used on the day that NHTS asked for. We computed the corresponding non-usage fractions on weekdays and weekends by taking the number of deleted profiles in each category into account. The non-usage fractions are 0.4936 and 0.4138, respectively. For the weekday/work profiles we assume that the non-usage fraction is zero since the corresponding vehicles are used for commuting on every weekday. During the generation of the yearly driving profiles, the profile generator randomly inserts idle days (instead of weekday/non-work and weekend daily driving profiles from the database) based on the corresponding non-usage fractions.

Based on the vehicle usage data, we inferred PEV charging jobs by assuming the relevant characteristics of the first mass market PEV equipped with a range extender: the Chevrolet Volt. According to [24], the Volt has an average electrical range of 35 miles and requires 240 minutes to recharge using a level 2 charging device. Each charging job has a start time, range of 35 miles and requires 240 minutes to recharge using a level 2 charging device available for purchase today [18]. Its average power draw is 3.3 kW (240 Volts, 14 Amperes).

C. Simulation Framework

Our simulation framework combines the models for regulation and load following demand described in Section III-A with the PEV charging model described in Section III-B. Formally, the two models are connected by the term \( L^{PEV} \) in Equation (2) and the consideration of \( L^{PEV} \) in the real-time and hour-ahead generation scheduling processes (Equations (3) and (9)). It allows for simulating the impact of a population of PEVs and the way they are charged on the regulation and load following demand in California.

The simulation is based on a number of assumptions:

- (i) At each time step, the system operator can adjust the PEV load only at the current time step.
- (ii) The system operator can use the entire slack of the charging job, i.e. we assume that the system operator knows the time of departure upon the start of each parking interval. However, we restrict the look-ahead to 24 hours.
- (iii) The system operator only considers charging jobs for load shifting if their start times have been reached, i.e. the system operator does not predict future charging jobs.
- (iv) Aside from PEV charging control, the system operator’s current operating procedures remain unchanged.

Assumption (iv), implies that the real-time generation schedule is updated every 5 minutes based on the real-time load, wind and solar generation forecasts. These forecasts are available 8 minutes before the start of the corresponding operating interval. The load-following instructions are sent to the available generators 5 minutes before the start of each interval. The units begin to move to the instructed output level 2.5 minutes after the instructions are sent. Thus, each update of the real-time generation schedule caused by changes to the real-time load, wind, or PEV load forecast shows effect after 2.5 minutes already. We refer to the time period between the receipt of fresh data on future load, wind and solar and the time that the corresponding adjustment begins to show as the “no impact period”. Furthermore, we call the time between the end of the no impact period and the start of the part of the schedule that reflects all information “partial impact period”. Figure 2(a) provides a schematic overview of the real-time generation scheduling process of the CAISO.

The effect of the delayed availability of new forecasting data on the hour-ahead generation schedule is similar to the effect on the real-time generation schedule. The hour-ahead schedule is updated hourly based on 2 hours old data on
non-PEV load, wind and solar as well as the PEV charging schedule known at this time. The corresponding generation instructions are sent to the generators 75 minutes before the start of the corresponding operating hour. This results in a 65 minutes long no impact period and a 20 minutes long partial impact period. Changes to the PEV charging schedule that concern these periods are not or only partially reflected by the generation schedule. Figure 2(b) provides a graphical view of the hour-ahead scheduling time line.

D. PEV Charging Algorithm

Charging schedules are initialized when PEVs connect to the grid (cf., Section I). PEV charging jobs can be initialized differently, i.e. the actual charging time of a job can be distributed in many different ways over the available time slots in the parking interval at first. To evaluate the impact of different ways of upfront charging job initialization, we consider two extreme cases: In the first case, charging is scheduled to start at the beginning of the parking interval and continues until either the battery is fully loaded or the parking interval ends. In the second case, all required charging is scheduled as late as possible. We refer to these two types of charging initialization as “early” and “late”, respectively.

The two considered charging job initialization methods provide complementary opportunities for load shifting. Early initialization gives the algorithm the ability to instantaneously decrease demand by deferring charging jobs to later intervals. Late initialization provides capacity to instantaneously increase demand by moving charging jobs originally scheduled for later intervals to earlier intervals. We assume the system operator maintains a searchable database of currently parked vehicles. For each vehicle, the database contains the vehicle’s power capacity and the charging intentions (idle/charging) during each minute of the time that the PEV is parked.

The PEV charging control algorithm we evaluate works as follows: At every time step, the system operator determines the amount of regulation demand required in the current period. For each currently parked PEV, the algorithm checks whether it is available, i.e. it can contribute to the required service (regulation up or regulation down). A PEV is available if it has not yet reached its maximum state of charge and will still be able to meet its targeted state of charge if charging is deferred for one time step. From the pool of available PEVs, the algorithm engages enough PEVs to satisfy the amount of regulation demand (unless the available pool is too small, in which case the algorithm uses as much of the pool as possible).

At the vehicle level, regulation up is provided by deferring charging in the current time step to the next time step in which the vehicle is not currently scheduled to charge. This reduces the load at the current time step and is thus equivalent to a corresponding increase of generation. Regulation down is achieved by moving load from the last time step in which the vehicle is scheduled to charge to the current time step.

In [25], the authors explore several types of scheduling policies for managing deferrable loads like PEVs. They show that the well-known Earliest Deadline First (EDF) scheduling algorithm performs well in this context. Using this knowledge as starting point, we propose a similar selection criterion that reflects the specialties of our setting: For regulation down, those PEVs with the earliest deadlines but are not yet charging are instructed to begin charging. For regulation up, those PEVs that are currently charging with the latest deadlines are instructed to stop charging for one time step.

In summary, the scheduling algorithm advances or defers demand from the early and late charge initialization baselines. Its goal is to reduce the demand for regulation from the supply side by as much as possible. The constraints of this algorithm are imposed by the properties of the charging jobs and the requirement of non-disruptive use. Decisions are made without predicting demand for regulation or changes of the constraints.

IV. NUMERICAL STUDY

In the following, we present the results of a numerical study which we conducted based on the simulation model described in Sections III-A and III-B.
A. Setup

We simulate one entire year of grid and vehicle fleet operation based on scaled grid data collected in 2005 [11] and artificial driving profiles generated from data collected in 2009 [23]. To consider the impact of wind and solar penetration on regulation demand, we used the scaling of the corresponding capacities suggested in [12] and [21] as provided in Table II. This allows us to analyze the impact of higher renewables penetration in California on the simulation results and thus provides further insights regarding the prospect of integrating more intermittent renewables by leveraging PEVs as distributed energy storage.

Our simulation framework has three scaling parameters for PEV population size. The first parameter, $a$, specifies how many times each vehicle trace is used to instantiate a controllable group of PEVs. The second parameter, $b$, denotes the number of yearly driving profiles we generated using the approach described in Section III-B. The third parameter, $c$, denotes the number of actual PEVs in each of the controllable groups. Thus, the total number $n$ of simulated PEVs is the product of the number of the three scaling parameters $a$, $b$, and $c$. The minimum change of PEV charging power draw is equal to 3.3$c$ kW. The accuracy of the matching of regulation demand and supply from the PEVs therefore negatively correlates with $c$. Increasing $a$ or $b$ to be able to reduce $c$ increases the computational cost of the simulation, since every PEV group is controlled independently and memory requirements increase with the number of driving profiles used in the simulation.

By using this kind of setup for creating a controllable PEV population, we make sure that the information contained in our sample of vehicle traces is used entirely and the different traces are weighted equally. In our simulation experiments, we keep $b$ constant at 5,000, $c$ at 100, and vary $a$ in a computationally acceptable range, namely between 1 and 6. This allows us to simulate the impact of 0.5 up to 3 million Chevrolet Volts in steps of 0.5 million cars.

Since the objective of the load shifting approach is to provide both up and down regulation, we initialize the charging jobs derived from $kn$ driving profiles using “early” and $(1 - k)n$ using “late” charging initialization.

Table V provides an overview of the parameter configurations we use in the numerical study.

B. Results

1) Effect of Controlled PEV Charging: In this section we demonstrate the effect of the PEV load shifting approach described above. Figure 3 shows the impact of load shifting. The figure depicts different metrics collected during two subsequent days of simulation (Jan 24–26, 2020).

Figures 3(a) and 3(b) give an impression of the regulation capacity up and down that the CAISO could command if one million PEVs were controlled. It was generated by summing up the corresponding capacities at each minute of the simulated day with load shifting deactivated. Especially in the morning and early evening hours, when most PEVs are expected to recharge after trips to and from the workplace of their drivers, the PEV regulation capacity is relatively high. During the night, the available regulation capacity is rather low: On the one hand, many charging jobs prescribing “early” recharging cannot be used to provide regulation up anymore since even a full recharge takes at most 4 hours. On the other hand, most charging jobs that prescribe “late” recharging cannot be rescheduled to deliver regulation down since the time step from which onward the corresponding PEVs have to start recharging their batteries anyways in order to fulfill the service level has been reached. Figures 3(a) and 3(b) also reveal how changing $k$ from 0.5 to 0.8 increases the regulation up capacity, but at the same time decreases the regulation down capacity of the PEV fleet. The change is more dramatic in the case of regulation down which indicates that more PEVs are required to provide regulation up than regulation down.

Figure 3(c) shows the demand for regulation if the charging rate of PEVs is not controlled. The demand strongly fluctuates and can increase from maximum demand for up regulation to maximum demand for down regulation in just a few minutes. Figure 3(d) shows the demand for regulation if the PEVs are controlled to reduce regulation demand. Load shifting leads to a clearly observable reduction of the regulation down demand, especially during times of high regulation capacity in the morning between 8 and 10 A.M., as well as during the evening hours between 5 and 10 P.M.. The figures also show that, at least at a fleet size of 1 million PEVs, there remain times when the demand for regulation cannot be significantly reduced by load shifting; particularly in the middle of the night.

Figures 3(e) and 3(f) depict the additional load resulting from PEV charging. One can clearly distinguish the deep valleys in the aggregated load pattern that are caused by deferring the corresponding load to later time periods. The maximum PEV load during the observed time interval without load shifting is approximately 500 MW, whereas the PEV load with load shifting peaks at 1,000 MW.

2) Performance of Controlled PEV Charging: We present our results regarding the performance of the PEV load shifting approach in this section. Performance is measured by the reduction of regulation capacity that is necessary to balance supply and demand of electric power in the grid.

The provision of regulation capacity mainly depends on the highest demand for regulation up and the lowest demand for regulation down that can be expected under reasonable conditions. We calculate these maximal requirements using the method proposed in [12]. For each parameter configuration, our simulation runs 10 times through all hours of the year. In each hour, the maximal regulation up and minimal regulation down requirement across all 60 minutes of the hour are selected. These are called the hourly up and down capacity requirements. Sometimes only one of them exists. Hence, we obtain at most 10 hourly up and 10 hourly down capacity requirements for each hour of each day in the year. From each of these sets, we again select the maximum/minimum value. The overall procedure thus results in 365 up and 365 down capacity requirements of which we report the corresponding
Fig. 3. Effects of controlled PEV charging. $k$ is the fraction of vehicles charged according to “early” charge initialization; the remaining fraction follow the “late” initialization protocol.
TABLE V
MODEL SENSITIVITY PARAMETERS (* INDICATES DEFAULT VALUE)

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Values</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>k</td>
<td>0.5*, 0.6, ..., 0.8</td>
<td>Fraction of PEVs with “early” charging initialization</td>
</tr>
<tr>
<td>n</td>
<td>0.5 m; 1 m*, ..., 3 m</td>
<td>Total number of PEVs</td>
</tr>
<tr>
<td>S</td>
<td>0 (no PEVs); 1 (PEVs without control); 2 (PEVs with control)</td>
<td>PEV scenario</td>
</tr>
<tr>
<td>Y</td>
<td>2012, 2020*</td>
<td>Simulated year</td>
</tr>
</tbody>
</table>

Fig. 4. Percentage change of required regulation energy (a & c) and capacity (b & d). k denotes the fraction of PEVs with “early” charging initialization.

95th percentiles. This means that we identify the highest regulation up and the lowest regulation down value after eliminating the 2.5% highest regulation up values and the 2.5% lowest regulation down values.

The mean amount of regulation up and down can be interpreted as a measure of the regulation energy that is actually required to balance the grid in different scenarios. When the activation of regulation capacity causes additional costs, in particular when regulation up is needed, a higher level of regulation energy delivered by PEVs is of additional importance.

Figure 4 shows how the percentage reduction of the mean and high/low regulation capacity requirements evolve as the total number of PEVs is scaled up from 0.5 to 3 million. The percentage change metrics are calculated according to Equation (12), where \( d(S) \) denotes the corresponding regulation demand metric in scenario \( S \), e.g. the 95th percentile of the maximal regulation up capacity:

\[
p = \frac{d(2) - d(1)}{|d(1)|} \times 100\% \quad (12)
\]

If the percentage change metrics approach +/- 100%, the PEV fleet is able to supply all regulation in the corresponding case.

The percentage mean regulation energy demand that can be satisfied using controlled PEV recharging is always higher than the corresponding percentage capacity demand. For instance, with 1 million controlled PEVs, between 60 and 75% of the regulation up energy can be supplied, whereas only between 25 and 35% of the capacity can be covered.

Regulation up appears to be harder to satisfy using PEVs: At a penetration of 2 million PEVs and \( k = 0.5 \), all regulation down capacity could be supplied, but only 35% of regulation up capacity.

As already indicated in Figures 3(a) and 3(b), higher levels
of $k$ increase the regulation up capacity at the expense of regulation down capacity. Interestingly, the results shown in Figure 4 indicate that a small increase of the mean or high regulation up supply has to be traded against a high reduction of the regulation down supply. For example, with 1 million controllable PEVs, a 10% increase of the regulation up energy supply by changing $k$ from 0.5 to 0.8 causes a reduction of the regulation down energy supply by 40%.

Figure 4 also reveals the difference in the regulation supplied in 2010 and 2020: In terms of percentage of required regulation energy, the same number of PEVs will be able to contribute less in 2020 compared to 2012. For instance, the contribution of 1 million controllable PEVs to regulation down energy will decrease by approximately 5%. This is due to the fact that both the capacity of intermittent renewables and the load is expected to grow which also increases the absolute amount of regulation required (cf., the assumptions described in Section III-A).

Surprisingly, the same number of PEVs will be able to satisfy more of the actual bottleneck resource in 2020 compared to 2012: regulation up capacity. Although this difference does not exceed 5%, it is remarkable: It indicates that the patterns of peak regulation up demand evolve in a way that is advantageous to supply it with PEVs.

3) Effect of Controlled PEV Charging on Load Following: Shifting PEV load will not only have an effect on regulation, but also on load following. It is important to consider this impact since, in order to reduce generation cost, a reduction of the regulation demand should not be bought by a significant increase of the load following requirements.

The CAISO updates the hour-ahead generation schedule only every hour. Therefore the arrival of load shifting activity affect it on much longer time scales (cf., the “no impact period” in Figure 2). Using our simulation model, we are able to quantify the change of load following requirements caused by load shifting in the same way as the regulation requirements (cf., Section IV-B2). Instead of calculating the mean and 95th percentile values of $R_{Di}$ for $S = \{1, 2\}$, we calculate these values for $L_{FDi}$ (cf., (5)). Afterwards, we apply the percentage change formula (12) accordingly.

Our results show that load shifting increases the demand for load following up, both in terms of energy and capacity, in the range between 0.5 and 3% depending on $n$ and $k$. At the same time, it reduces the demand for load following down in the range between 0.5 and 1.5%. In the light of the substantial residual load following resources controlled by the CAISO [12], the negative impact of PEV load shifting on its average cost of supplying load following up should be limited. One could also argue, that the negative impact of increased load-following up capacity is compensated by a reduction of load following down requirements.

V. CONCLUSIONS

In this article, we have proposed a model-based approach to assess the potential of ICT-controlled PEVs as suppliers of regulation in California. Our model considers the actual generation scheduling processes of the CAISO in use today and evaluates our proposed PEV load shifting approach based on representative data.

The evaluated approach for PEV charging control greedily satisfies the grid’s demand for regulation up and down using the slack in current PEV charging without reducing the electric mileage of PEVs (cf., “non-disruptive” control mentioned in [2]). It has only limited computational and communication requirements and could thus scale to large PEV populations.

The regulation capacity depends on the way that charging time slots are distributed across the PEVs’ parking intervals upon arrival time. We evaluate a simple scenario in which a randomly chosen fraction $k$ of the controlled PEVs uses “early” and the remaining fraction $1 - k$ uses “late” charging initialization. Although many more initialization methods are conceivable, this approach should effectively reveal the maximum potential of PEV load shifting under the given restrictions, in particular no V2G capability, non-disruptive control, no forecasting of driving behavior, and no informed selection of PEVs. Relaxing the restrictions could lead to an improved capability of PEVs to satisfy the demand for regulation.

Our results indicate that roughly 3 million PEVs with the operational characteristics of a Chevrolet Volt would suffice to supply a large part of the regulation up and down demand in California. Interestingly, [1] also use California as an example to quantify the number of vehicles needed to provide regulation capacity. Based on their assumptions (V2G capability, half of the fleet available anytime, 15 kW power draw and feed-in, 1,200 MW of regulation capacity), this number would be $(1,200 \text{ MW} / 15 \text{ kW}) 	imes 2 = 160,000$. Our numbers are significantly higher, mainly since we assume a charging rate of 3.3 kW and no V2G capability. Moreover, due to our more advanced approach, we are able to consider the dynamics of regulation demand as well as the PEVs’ actual availability for charging (which is lower than the one assumed in [1]).

We were also able to show how this result changes if more intermittent renewables are used to generate electricity in the near future. Moreover, we evaluate the impact of PEV load shifting for supplying regulation on load following requirements concluding that it is limited.

Another major result of this work is that providing regulation up necessitates significantly more controlled PEVs than regulation down and thus represents a bottleneck. The gap in the supply of regulation up could be efficiently closed by making a subset of the PEV fleet V2G capable. A relevant research question that could be answered by extending our model is, for instance, how many V2G-capable PEVs are needed to close the identified gap in the regulation up supply and based on which properties the corresponding V2G-capable PEVs can be determined.

Our results have significant implications for policy making in California. To our knowledge, this is the first work that integrates two policy dimensions, namely renewable integration and electric mobility, at a per minute level of detail. Based on the changes of regulation and load following capacity we present, a policy maker could compute a realistic financial return on investment of PEV grid integration.
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REFERENCES


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