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Abstract Flexibility in plug-in electric vehicle (PEV) charging can reduce the ancillary cost effects of wind variability and uncertainty on electric power systems. In this paper, we study these benefits of PEV charging, demonstrating that controlled PEV charging can reduce costs associated with wind uncertainty and variability. Interestingly, we show that the system does not require complete control of PEV-charging loads to mitigate the negative cost impacts of wind variability and uncertainty. Rather, PEV owners giving the system a two-hour window of flexibility in which to recharge their vehicles provides much of the benefits that giving full charging control does.

Keywords Plug-in electric vehicle · controlled charging · wind integration · demand response · unit commitment and dispatch

1 Introduction

Concerns surrounding growing energy demand, climate change, and finite fossil-fuel supplies have increased interest in the use of renewable energy reto operate ine□ciently in a partially loaded fashion [18,16]. Empirical numerical studies of the Belgian [

Our case study examines PEV charging and power system operations over a one-year period. We assume about 7 GW of wind is added to a system with a peak non-PEV load of about 60 GW. We further assume that a fleet of about 50000 PEVs, which require a total of about 470 MWh of energy to be recharged into their batteries each day, is added to the system.

We demonstrate that without the PEVs, wind uncertainty and variability impose an ancillary cost of about \$0.23/MWh of wind. This cost increases to \$0.46/MWh of wind if PEV charging is not controlled (*i.e.*, PEVs charge

non-spinning reserves that generator i can provide. Non-spinning reserves can be provided by generators regardless of whether they are online or offline. In addition to the limits, ρ and ρ, any reserves provided by a generator must satisfy its ramping and capacity constraints.

Wind generators are modeled as having zero operating cost. Moreover, we let $\bar{W}_t$ denote total wind generation available in hour t.

We let l_t denote the hour-t non-PEV load. In addition to a load-balance constraint, we also impose load-based reserve restrictions. We require that, at a minimum, a fraction, η, of the hourly load be held as spinning reserves. We similarly require that, at a minimum, a fraction, η, of the hourly load be held as non-spinning reserves.

3) PEV Parameters and Data

$$1 - \sum_{= \, -}^{} h_{i}^{i} \geq u \, ; \quad \forall t = m, \ldots, T + m; i \in I; \tag{13}$$

$$u - u_{-1} = s - h \, ; \quad \forall t = m, \ldots, T + m; i \in I; \tag{14}$$

$$u, s, h \in \{0, 1\}; \quad \forall t = m, \ldots, T + m; i \in I; \tag{15}$$

$$0 \leq w \leq \bar{W}; \quad \forall t = m, \ldots, T + m; \tag{16}$$

$$0 \leq z \leq \bar{H}; \quad \forall t = m, \ldots, T + m; v \in V; \tag{17}$$

$$z = 0; \quad \forall v \in V; t \notin [\varphi^{A}, \varphi^{D}]; \tag{18}$$

$$\sum_{=}^{+} z = \zeta \, ; \quad \forall v \in V. \tag{19}$$

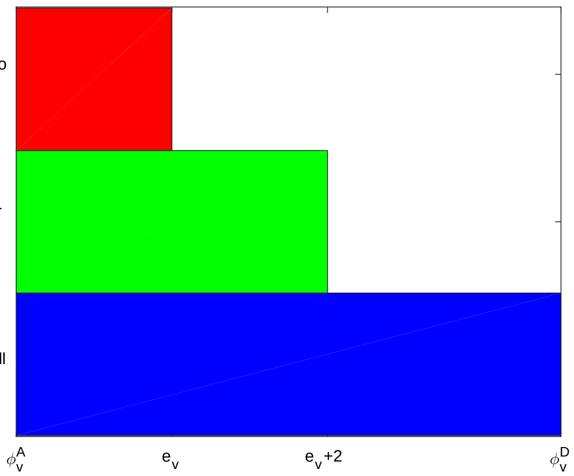


Illustration of Charging Window in No-, Two-Hour-, and Full-Control Cases

to the no-control case. If a PEV is parked for less than two hours beyond e , then it is assumed to charge as in the uncontrolled case (i.e., immediately) in the two-hour-control case.

Constraints (22), defining the two-hour control case, fix v over the year one hour at a time, by rolling forward through the hours of the year.

Algorithm 1 Rolling-Horizon Solution Algorithm

1: fix starting values for $h_{i,0}$, $q_{i,0}$, $s_{i,0}$, $u_{i,0}$
2: $m = 1, \ldots, 8760$
3: update $\bar{W}_m, \ldots, \bar{W}_{m+T}$
4: $(h, q, r, s, u, w, z) \leftarrow \arg\min$ (1) s.t. (2)–(19)
5: fix $h_{i,m}, q_{i,m}, r^N_{i,m}, r^S_{i,m}, s_{i,m}, u_{i,m}; \forall i \in I; w_m; z_{v,m}; \forall v \in V$; to values found in Step 4
6: $K_t \leftarrow \sum_{i \in I} \left[c^V_i(q_{i,m}) + c^N_i u_{i,m} + c^S_i s_{i,m}\right]$
7: $\zeta_v \leftarrow \zeta_v - z_{v,m}; \forall v \in V$ such that $\varphi^A_v \leq m$ and $\varphi^D_v \geq m + 1$
8:

The algorithm works by first fixing the starting state in hour 0 of all of the generators in Step 1. This is needed to set hour-1 ramping and minimum up- and down-time constraints for the generators. We assume that all of the generators are online and producing at their minimum operating points (i.e., that $q_{\ 0} = Q^{-}; \forall i \in I$) and that each generator has been online a sufficient number of hours that it could be immediately switched off in hour 1, if the

We detail all of the data sources that are used in our analysis in the following subsections.

3.1 Conventional-Generator Data

Cost data for conventional generators are modeled using heat rates and historical fuel and SO_2-permit prices. These data are obtained from proprietary databases maintained by Platts Energy and Global Energy Decisions. Conventional-generator-constraint data are obtained from Global Energy Decisions. The two nuclear plants in ERCOT are modeled as must-run units that constantly operate at their nameplate capacity. In total we model 375 dispatchable generators that were installed and operational in the ERCOT system in the year 2005.

3.2 Non-PEV-Load Data

Non-PEV loads are modeled using 15-minute metered historical ERCOT load data from the year 2005, obtained from the Public Utility Commission of Texas. Because our scheduling model is formulated using hourly time steps, each of the four 15-minute measurements corresponding to each hour are averaged together to obtain an hourly-average load.

3.3 Wind Data

Our case study assumes that there is 7 GW of wind installed in the system, which is approximately 10% of the peak non-PEV load of about 60 GW. Thus, we study a high-penetration scenario (relative to the year 2005), considering ERCOT did not achieve 7 GW of wind until 2008. We simulate real-time wind availability and generate wind forecasts using a vector autoregression

3.4 PEV Data

PEV driving patterns are modeled using a Monte Carlo-based method to generate typical daily driving patterns. We use statistical properties of light-duty vehicle driving patterns within the United States [

As noted in Section 2.1, the scheduling model represents each driving profile as having a single arrival and departure time to a charging station. Because each of the simulated driving profiles can have multiple daily trips, each driving profile is subdivided into a separate profile in the scheduling model. As such, there are 4410 PEV driving profiles in the scheduling model, corresponding to these subdivisions.

4 Case Study Results

Table 3 summarizes the total annual generation costs incurred in the eight different cases (cf. Table 1) examined. These costs are computed as:

$$\sum_{t=1}^{8760} K_t;$$

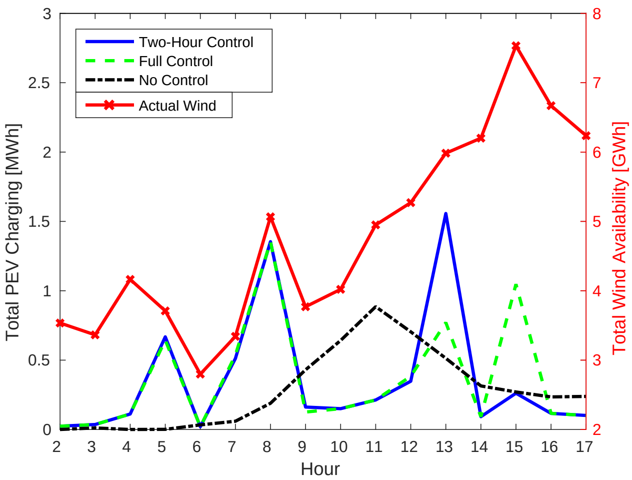
where the K_t's are defined in Step 6 of Algorithm 1. The first two columns of the table show that without PEVs and in the three different PEV-charging control cases, costs are higher when the system must be scheduled using wind forecasts as opposed to having perfect foresight of wind. This is to be expected, and the cost difference between each pair of forecast and perfect-foresight cases measures the value of perfect wind-availability information.

Annual Generation Costs

PEVs	Total Generation Cost [$ Million]		Wind-Integration Cost
	Perfect Foresight	Forecast	[$/MWh of Wind]
None	10934.34	10940.67	0.23
No Control	10928.22	10940.84	0.46
Two-Hour Control	10926.64	10930.86	0.15
Full Control	10928.16	10930.68	0.09

The last column of Table 3 reports the cost difference between the forecast and perfect-foresight cases divided by total wind generation over the course of the year. The values in this column represent the cost of wind uncertainty and variability (which we term 'wind-integration cost' in the table) on a per-MWh basis. We find that when PEVs are added to the system but their charging cannot be controlled, they double the ancillary cost impacts of wind uncertainty. However, if PEV charging can be fully controlled, wind-integration costs are reduced by close to 61%. Interestingly, having only two-hours of flexibility within which to control PEV charging reduces wind-integration costs by close to 35%. This means that two hours of charging control delivers close to 60% of the benefits of complete control over PEV charging.

We note that with perfect foresight of wind, the two-hour-control case achieves lower total cost than the full-control case. This is not unexpected, because by default CPLEX does not solve the scheduling model to complete optimality. Rather, the branch-and-cut algorithm terminates once the optimality gap of the incumbent solution is sufficiently small. In essence, the objective function of the scheduling model is extremely 'flat' around the optimum, and there are many near-optimal solutions that are virtually identical in terms



Aggregate PEV-Charging Profiles with Two-Hour, Full, and No Control with Wind Forecasts Used in Scheduling on 24 July

that if the scheduling model has full flexibility to schedule PEV charging, it would be optimal to delay some of the vehicles to recharge in hour 15. Doing so would, however, violate the two-hours of flexibility available in the two-hour-control case. As such, there is a larger peak in the PEV-charging profile in hour 13, relative to the full-control case.

Although there are days, such as that shown in Figure 4, on which the two-hour limitation on control hinders the ability to properly coordinate PEV charging with power system operations, the limitation from two-hour control is relatively small. This is because the two-hour-control case achieves much of the benefits in mitigating wind-integration costs, as shown in Table 3.

5 Conclusions

This paper presents an analysis of the synergies between wind and PEV charging [30]. We show that if PEV charging is not coordinated with power system operations, PEV-charging loads can exacerbate the ancillary costs of wind uncertainty and variability. This is because PEV-charging loads tend to add to peaks in the non-PEV-load profile midday and in the early ev87(n)0.95.89115()-2i63(63(4.BT 29372.375(o)4.0311