The Relationship between Wind Power, Electric Vehicles and Charger Infrastructure in a Two-Settlement Energy Market

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Abstract

This study investigates the technological and economic relationships of integrating wind power, plug-in electric vehicles (PEVs) and mixtures of Level 1/Level 2 charger infrastructures in New York Independent System Operator’s (NYISO’s) two-settlement wholesale electric energy market. Using 7,560 scenarios constructed from various PEV penetrations, Level 2 charging and wind dispatch policies, this study reports findings that substantiate and challenge aspects of the previously envisioned synergy between wind power, PEVs and charging infrastructure. An econometric model based on historical market data, including system-level costs of load ramps, was used to study resource integration and to avoid data fidelity issues that plague traditional fundamentals-based models. Results show: (1) the existence of time-series correlation between PEV charging and wind dispatch depends on curtailment policy, (2) PEV charging with wind over-forecast nearly triples the rate of reduction in curtailed wind energy compared to under-forecast, (3) using wholesale energy cost as metric, PEVs can be adversely coupled to curtailable wind, and decoupled with must-take wind, and (4) PEV penetration, Level 2 charging and wind power may be economic substitutes in the energy market.

1. Introduction

As both renewable energy and PEV market penetrations increase, there is a growing intent of using the flexible charging of PEVs as a demand-side resource to improve the integration of intermittent generation resources into power systems [1, 2]. In terms of wind energy, areas of improvement include reducing wind curtailment and diminishing the effects of wind variability and unpredictability on generation-load balancing. Consequently, traditional wisdom suggests the coupled benefit of these two resources, i.e. wind and PEVs mutually benefit their individual integration into electricity markets and that they both benefit the markets as system-level resources. However, given the complexity of the electricity markets, wind dispatch policies and charging infrastructure, whether this traditional wisdom holds has not been thoroughly investigated.

There is a growing body of literature on the charging of an aggregated number of PEVs and the dispatch of regional wind generation. Several charging control mechanisms and aggregation methods have been investigated in direct coupling wind energy and PEVs [3-6], and many of them involve ancillary services enabled by vehicle-to-grid (V2G) technologies [7-9]. A single-settlement approach was adopted to model energy markets [10, 11], which reported decreases in wind power curtailment with flexibly charged PEVs. A yearly generation planning algorithm was applied to assess the impact of PEVs on the mixture of Ireland's energy and capacity needs based on the island's existing units and potential new builds [12]. Another study optimized PEV charging and dispatch of renewable assets using a non-market approach based on thermal generator costs and emissions to report decreases in system costs and pollutant emissions [13].

This study adds to the body of literature on electric vehicles and wind integration by examining the dispatch linkage between PEVs and wind units with forecasted and realized wind profiles. By doing so, we aim to examine the transitional wisdom that wind and PEVs are coupled resources. A unique aspect of our study is to model the dispatch of PEVs and wind generators with various charging infrastructures in a two-settlement energy market—the common structure of U.S. energy markets. We quantify the validity of commonly assumed coupled benefit of the two resources. Specifically, (1) we substantiate previous claims of more PEV penetration decreases wind energy curtailment, and (2) we find that PEV charging and wind power injection are not correlated in time by cause-and-effect, rather by coincidence. Moreover, we reveal the existence of an economic substitution effect between EVs, level of charging infrastructure and wind power in minimizing wholesale energy cost.

We expand the two-settlement, econometrics-based market model previously developed, to be described in Section 2. The market model incorporates the steady-state production cost and system-level ramping cost of generators. Flexible PEV charging and wind power dispatch subject to curtailment and must-take regulations are optimized in the market model where the objective is to minimize total wholesale market cost. Level 1/Level 2 charger infrastructures at 95/5, 85/15, 70/30, 50/50 and 30/70 mixtures are incorporated based on a commuter transportation model [14]. The study spans 21 days in June, July and August of 2006—a summer of record breaking peak loads—with 0%, 2%, 5%, 10%, 15% and 25% wind power penetrations and the same six market penetrations for PEVs for a total of 7,560 scenarios.

2. Modeling of a Two-Settlement Energy Market, Wind Power and PEVs

The New York bulk power system serves 19 million people and NYISO administers trades of power products worth \$7 billion annually. In 2006, the average generation mixture was 30% natural gas, 30% nuclear, 18% conventional hydro, 15% coal, 5% petroleum and 2% renewables. This was a much cleaner and diverse mixture compared to the then national average of 49% coal, 21% natural gas, 19% nuclear, 7% conventional hydro, 2% petroleum and 2% renewables. For the 3 summer weeks studied, the average load was 22 GW, average locational marginal price (LMP) was \$71/MWh and highest LMPs were well over \$500/MWh.

The day-ahead market (DAM) dispatches generators and settles LMPs in advance of the actual system operation. On a 5-minute basis, the real-time market (RTM) adjusts generation and LMPs according to actual system conditions. The commitment cost from the DAM and adjustment cost from the RTM form the total wholesale energy market cost.

2.1. A Wholesale Energy Market Model and Cost of Generator Cycling

2.1.1. Statistical Versus Fundamentals-Based Modeling Approaches

Flexibility in the power system is critical to better integrate renewable energy. Consequently, energy markets need to better describe the cost of load ramps. However, modeling renewables integration and ramping costs in the energy market are difficult tasks. Many power industry modelers use a fundamentals-based approach of incorporating unit-level cost information, fuels data, transmission topologies, interface limits, demand response levels, etc. They then use security-constrained unit-commitment and optimal power flow (SCUC-OPF) solvers to determine resource dispatch and market prices.

However, we did not choose this type of fundamentals-based model for the following reasons: (1) the fundamentals-based approach currently does not capture cost of generator ramping, (2) ramping costs of individual generators are not publicly available if they are reported at all, (3) actual unit-level cost of steady-state production are not publicly available, (4) lack of publicly available high-fidelity transmission models, (5) lack of publicly available network and unit contingency lists—potentially making security-constrained solvers inaccurate, (6) bid adders are usually used to calibrate fundamentals-based models to historical data. In essence, these bid adders are blunt instruments used to correct inaccuracies in the fundamentals-based approach, data- and method-wise, and (7) even in well-structured U.S. wholesale markets, significant market uplift payments are paid to suppliers in addition to market settlements—limiting the confidence of market fundamentals-based models.

Consequently, we explicitly modeled system-level generator ramping costs along with steady-state production costs in this and a previous study [15]. This econometrics-based two-settlement market model is regressed and calibrated to the historical loads, load ramps and LMPs in the day-ahead and real-time markets as administered by the New York Independent System Operator (NYISO) in 2006. This “top-down” approach avoids the aforementioned problems in the fundamentals-based approach in order to produce system-level outcomes of wind and PEVs, e.g., aggregate dispatch and economics benefits. The disadvantage of this statistical approach is the loss of unit-level information. Hence, this model is suitable for system-level assessments such as this study.

2.1.2. Statistical Model Details

The two-settlement energy market model was first published in a previous study and relevant aspects are explained here [15]. The wholesale energy cost is the sum of the DAM cost and adjustment cost in the RTM, where cost is the product of LMP and load served, i.e. net load [16]. This relationship is given in Equation 1.

Daily Total System Cost =

$$\sum_{t=0}^{T_1} LMP_{DAM,t}(P_{DAM,t}, |\Delta P_{DAM,t}|) * P_{DAM,t} + \sum_{t=0}^{T_2} LMP_{RTM,t}(P_{RTM,t}, |\Delta P_{RTM,t}|) * (P_{RTM,t} - P_{DAM,t}) \quad (1)$$

LMP at time t is a function of steady-state net load, P , and modulus of load ramp, $|\Delta P|$. T_1 is the 23rd dispatch hour in the DAM and T_2 is the 143rd ten-minute dispatch period in the RTM.

In order to capture the trend of market prices for the 21 selected summer days and to ensure accuracy from the use of Taylor Series expansion, weighted average values of these regression variables were used to construct the energy model. This averaging method also preserves the cost sensitivity due to changes in net load and load ramps while dampening the instability of real-time prices. Equation 2 expresses the averaging process, while Equation 3 expresses the energy costs in terms of averaged variables.

$$\sum_{t \in T} LMP_t(P_t, |\Delta P_t|) * P_t \approx \overline{LMP}(\bar{P}, \overline{|\Delta P|}) * \bar{P}_{sys} \quad (2)$$

where weighted averaging is indicated by the accent bar and $\bar{P}_{sys}$ is the equivalent average net load of the system.

Daily Total System Cost $\approx$

$$\overline{LMP}_{DAM}(\bar{P}_{DAM}, \overline{|\Delta P_{DAM}|}) * \bar{P}_{sys,DAM} + \overline{LMP}_{RTM}(\bar{P}_{RTM}, \overline{|\Delta P_{RTM}|}) * (\bar{P}_{sys,RTM} - \bar{P}_{sys,DAM}) \quad (3)$$

Econometric analyses showed that:

$$\overline{LMP}(\bar{P}, |\Delta P|) \approx a_0 + a_1 \bar{P} + a_2 \bar{P}^2 + a_3 \bar{P} |\Delta P| \quad (4)$$

Equation 4 shows that NYISO's LMP is approximately second-order in weighted average net load with a mixed term of the net load and load-ramp modulus.

To evaluate the impact of integrating wind power and PEVs, $\bar{P}$ is carefully calculated for each day selected. Within a given day, $\bar{P}$ is a weighted average of three types of load: peak (p), shoulder (s) and valley (v), shown in Equation 5 for DAM.

$$\bar{P} = \sum_{i=1}^{I_1} C_p W_p P_{p,i} + \sum_{i=1}^{I_2} C_v W_v P_{v,i} + \sum_{i=1}^{12} \frac{1}{2} P_{s,i} \quad (5)$$

where P is net load from hourly data, $I_1 + I_2 + 12 = 24$, W is the load-type weight and C is the user-defined tuning parameter used to calibrate this statistical model to match historical prices. Load weighting for RTM is similar.

Finally, a similar benchmarking analysis is done to determine Equation 6 for the NYCA region.

$$\bar{P}_{sys} \approx \bar{P} + |\Delta P| \quad (6)$$

Thus, the energy cost as expressed in Equation 3 is fully described by the inputs of daily net loads and load ramps. Moreover, wind power and PEV charging directly influence these input variables and therefore wholesale energy cost. Consequently, cost optimization determines best aggregate wind dispatch and PEV charging.

2.1.3. Model Comparison

The statistical model was calibrated for accuracy and stability across various input scenarios in a previous study [15]. A well-published fundamentals-based model, MATPOWER, was one of the comparisons [17]. It is paired with a 36-bus reduced NPCC transmission network and generation set [18]. In summary, the comparison showed <1% price difference between the statistical model and MATPOWER.

2.2. Wind Power Inputs to the Statistical Market Model

Inaccurate forecast and variable production of wind power are two of the primary drivers that add to the cost of wind integration [19]. This study uses geographically and temporally varying land-based wind power data provided by the National Renewable Energy Laboratory (NREL) to build a large selection of wind scenarios based on production predictability and variability [20]. These scenarios include realized wind power in 10-minute increments and forecasted wind power with day-ahead and four-hour-ahead horizons in hourly increments.

Wind power from 66 potential wind farms in New York State with a total capacity of 14,860 MW are used for 2%, 5% and 10% wind penetration scenarios. A hundred-and-seventy potential wind farms with a total capacity of 20,580 MW are added to support 15% and 25% wind penetration scenarios. Figure 1 shows the average realized wind power, four-hour-ahead and day-ahead wind power forecasts for the selected 21 summer days.

Figure 1 also shows that the average wind power realizations range from approximately 1,200 MW to 15,600 MW. The narrative is for a highly variable wind resource across days. In addition, the average wind power supply varies from 3% to 45% of the total nameplate capacity. There is a small mean and spread of the difference between the averages of the forecasts (mean

of 7%, standard deviation of 7%) and a large mean and spread for that between the averages of the forecast and realized wind power (mean of 47%, standard deviation of 60%). As a consequence of the different wind data sets, wind production inputs in the DAM use a day-ahead forecast. The RTM use a persistence scheme based on realized production for the hour-ahead, a four-hour-ahead forecast for hours two to four ahead, and a day-ahead forecast for hours five to twenty-four ahead.

There is also a variety of intraday production variability exemplified in Figure 2. The two time-series of normalized wind production on June 25th and August 18th showcase high production and high volatility in the morning and midday, respectively, while July 10th showcases relatively steady wind production.

Sixteen types of wind power categories from four selection criteria are used in the 7,560 scenarios. The first three criteria assess wind resource and the fourth criterion is based on regulatory policy.

1. Under- or over-forecast (between day-ahead forecasted and realized wind power)
2. High or low predictability (between day-ahead forecasted and realized wind power)
3. High or low variability (within realized wind power)
4. Must-take or curtailable wind

A “must-take wind” policy is a requirement on the power system to absorb all available wind production. This type of policy enforces wind participation—overriding merit-based dispatches, where cost of system ramps due to wind variability and forecast error can curtail some wind. A “curtailable wind” policy adheres to market-based dispatches, where wind can be curtailed to reduce total system cost. (See Section 2.1 for system cost explanation and Section 2.4 for details on dispatch formulation.)

2.3. The Charge Flexibility Constraint in the Market Model

The Charge Flexibility Constraint (CFC) and Level 1/Level 2 charging infrastructure are critical in deriving the optimal PEV charging profiles [15]. The CFC is a time-varying profile that provides an upper bound on the aggregated charging power for commuters to charge at home. The CFC is derived from the ratio of Level 1 and Level 2 charger infrastructure in the NYCA and a commuter transportation model built from several data sources [14]. The maximum charging available to commuters places limits on the PEV's power withdraw from the grid. A Level 1 charger delivers 1.44 kW at 120V/12A and a Level 2 charger delivers 7.68 kW at 240V/32A. Analysis of PEV charging at the distribution system level is beyond the scope of this study. It is reported that charging above 7.68 kW may have adverse impacts on distribution feeders and is not studied here [21-23]. However, the concept of a CFC is expandable to incorporate distribution constraints as such limitations directly impact charging flexibility.

The data needed to build the transportation model include the 2000 US Census survey containing the 4.6 million commuters in New York State, categories of drivers in "center city", "suburban" and "rural", and the electricity used per mile for a range of vehicle types [24]. The transportation model also used the Regional Travel Household Interview Survey (RTHIS), the 2000 Census Transportation Planning Package (CTPP), and different Travel Time Indexes to formulate traffic and profiles of commuters at home [14].

2.4. Optimal PEV Charging and Wind Power Dispatch

Optimal PEV charging utilizes the concept of an aggregator or operator that actively manages charging in its service territory and minimizes the daily wholesale energy cost. In contrast to optimal charging, unregulated charging schemes allow commuters to charge whenever they are home, which should exacerbate peak loads and prices. Grid-scale wind farms are bulk power suppliers directly dispatched by a system operator. Under the must-take policy, wind power is an exogenous input directly modifying system loads. This policy enforces the injection of all available wind power with the risk of increased ramping cost. A curtailable policy maintains system optimality with the risk of less wind. The curtailment policy bounds wind dispatch between 0 MW and the maximum available wind power.

A metaheuristic solver adapted from Simulated Annealing (SA) and Dynamically Dimensioned Search (DDS) optimizes the market model via controlling PEV charging and wind dispatch given a curtailable policy. Such solver is used due to the non-convexity of the objective function with the ramping costs. SA is guaranteed to converge to global optimality and DDS quickly searches high-dimensional spaces. Visual inspection of solution can be equally important, such as PEVs charge and wind curtails mostly at night, the early morning, and to smooth costly ramp events.

As this study is an assessment using historical data, DAM and RTM data are both known. All firms seeking to participate in energy markets have expectations of bidding in the DAM (hourly settlements) and RTM (10-minute settlements). RTM information is speculative in forward settlements. However in this data-based assessment, there is RTM information—making expected RTM settlements part of the DAM settlement process (Equations 7-13). Due to use of the 2006 market data, historical RTM is the expected RTM. Moreover, DAM settlements

are deterministic inputs in the RTM settlement stage (Equations 14-17). In both market optimizations, total energy costs are DAM costs plus RTM adjustment costs.

DAM Settlements:

$$\min_{\substack{\text{PEV}_{\text{DAM},t}, \text{PEV}_{\text{RTM},t} \\ \text{Wind}_{\text{DAM},t}, \text{Wind}_{\text{RTM},t}}} \left\{ \overline{\text{LMP}}_{\text{DAM}}(\bar{P}_{\text{DAM}}, |\overline{\Delta P}_{\text{DAM}}|) \times \bar{P}_{\text{sys,DAM}} + E[\overline{\text{LMP}}_{\text{RTM}}(\bar{P}_{\text{RTM}}, |\overline{\Delta P}_{\text{RTM}}|) \times (\bar{P}_{\text{sys,RTM}} - \bar{P}_{\text{sys,DAM}})] \right\} \quad (7)$$

s.t.

$$0 \leq \text{Wind}_{\text{DAM},t} \leq \text{Wind}_{\text{Max},t} \quad \forall t \in \{0, \dots, T_1\} \quad (8)$$

$$0 \leq \text{Wind}_{\text{RTM},t} \leq \text{Wind}_{\text{Max},t} \quad \forall t \in \{0, \dots, T_1\} \quad (9)$$

$$0 \leq \text{PEV}_{\text{DAM},t} \leq \text{CFC}_t \quad \forall t \in \{0, \dots, T_1\} \quad (10)$$

$$0 \leq \text{PEV}_{\text{RTM},t} \leq \text{CFC}_t \quad \forall t \in (0, \dots, T_1) \quad (11)$$

$$0 \leq \sum_{t=0}^{T_1} \text{PEV}_{\text{DAM},t} \leq \sum_{i=1}^{19} M_{\text{PEV}} N_i D_i E_i \quad (12)$$

$$\sum_{t=0}^{T_1} \text{PEV}_{\text{RTM},t} = \sum_{i=1}^{19} M_{\text{PEV}} N_i D_i E_i \quad (13)$$

RTM Settlements:

$$\min_{\text{PEV}_{\text{RTM},t}, \text{Wind}_{\text{RTM},t}} \left\{ \overline{\text{LMP}}_{\text{DAM}}(\bar{P}_{\text{DAM}}, |\overline{\Delta P}_{\text{DAM}}|) \times \bar{P}_{\text{sys,DAM}} + [\overline{\text{LMP}}_{\text{RTM}}(\bar{P}_{\text{RTM}}, |\overline{\Delta P}_{\text{RTM}}|) \times (\bar{P}_{\text{sys,RTM}} - \bar{P}_{\text{sys,DAM}})] \right\} \quad (14)$$

s.t.

$$0 \leq \text{Wind}_{\text{RTM},t} \leq \text{Wind}_{\text{Max},t} \quad \forall t \in \{0, \dots, T_2\} \quad (15)$$

$$0 \leq \text{PEV}_{\text{RTM},t} \leq \text{CFC}_t \quad \forall t \in \{0, \dots, T_2\} \quad (16)$$

$$\sum_{t=0}^{T_2} \text{PEV}_{\text{RTM},t} = \sum_{i=1}^{19} M_{\text{PEV}} N_i D_i E_i \quad (17)$$

The optimizations described above assume a curtailable wind policy. A must-take policy would have equivalent constraints for Equations 8, 9 and 15. Equations 12, 13 and 17 are reproduced from a previous study to model the daily PEV energy requirement [14]. DAM energy bidding is not a requirement as physical energy delivery must be satisfied in the RTM only (Equation 12). A forecasted wind supply constrains wind dispatch in the DAM and expected RTM (Equations 8, 9). A different wind power forecast based on rolling horizons constrains the RTM (Equation 15, See Section 2.2). The Charge Flexibility Constraint (CFC) limits PEV charging. Algorithmically, decision variables change the daily load, $\bar{P}$, and load ramp, $|\overline{\Delta P}|$, and thereby change the cost function.

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322 3. Results and Discussion

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324 3.1. Time-Series Wind and PEV Dispatch

325 We examine the claim of the time-based correlation: “PEVs charge at night when there is
326 more wind power.” Figure 3 reveals the time-varying power dispatch relationships between
327 wind power, optimal PEV charging, CFC and base case load. Figures 3a, 3b and 3c showcase
328 the original loads and net loads (with 10% wind, 15% PEV and 95/5 Level 1/Level 2 charging)
329 for July 15th and August 13th. System cost is minimized via a combination of lowering and
330 flattening the net load as shown in the three graphs. Figure 3f displays the Charge Flexibility
331 Constraint, whose limit on PEVs’ maximum aggregate power withdraw is clearly present.

332 July 15th is a typical example with excess wind power supply in the early morning where a
333 “curtail if economic” policy is followed. Excess wind is defined as the wind generation under a
334 must-take policy that increases system cost.

335 Furthermore, PEVs are optimally charged in the early morning to take advantage of low
336 prices and also to reduce generator cycling (minor amount of charging and curtailment at 8 PM
337 to reduce ramping of peaking units). In contrast to the morning, the large availability of wind
338 power in the afternoon and nighttime is almost completely utilized to reduce peak load as seen in
339 Figure 3a. Thus, wind curtailment and PEV charging are observed to occur at the same time as
340 they are both strategies facilitated by system operators to reduce thermal generator cycling in
341 energy markets with excess wind.

In contrast, August 13th is a typical case with a relatively flat and low load valley and low wind power supply in the early morning where “curtail if economic” policy is adopted. In Figure 3e, PEV largely charges in the early morning when it is the cheapest to purchase electricity. However, there is only minor amount of wind curtailed at the same hours, because the net load with optimal PEV charging is already relatively flat at that time period. Therefore, PEV charging is not correlated in time with wind curtailment for energy markets with minimal excess wind power.

It is also observed that PEV charging is not correlated in time with wind dispatch under a must-take policy over the horizon of a day. Furthermore, PEV charging is not correlated in time with wind power variability over the horizon of a day. These two conclusions are seen in Figure 3e and 3f. The cause is the same for both conclusions—original load, not wind power, is the primary contributor to a net load profile before optimizing PEV charging, shown in Figure 3b and 3c. On July 15th for example, the percentage difference between the average original load and the average net load less PEV charging is -5.2%. The difference between the standard deviations of the two loads is 8.7%. As the original and net loads are largely sinusoidal and PEVs must charge in a 24-hour horizon to fulfill the driving needs of the commuter, aggregators managing the PEVs will charge most vehicles during a load valley for the low prices, and charge the remaining PEVs to reduce any uneconomic ramping of thermal generators. On the other hand, the time-series profile for must-take wind power is dependent on the physical wind resource and its capture by the wind farms. Consequently, the PEV charging and wind resource in the morning of July 15th in Figure 3f is coincidental. This happenstance disappears in the afternoon and nighttime. This reasoning is valid up to a moderate amount of wind power

penetration. However, when net load is dominated by wind power via extreme wind penetrations, it is likely that PEV charging will correlate in time with wind variability and wind resource.

3.2. Wind Curtailment and PEVs

Contrary to the lack of time-based dispatch correlation between PEV charging and wind power in the power market, results show increased PEV penetrations reduce daily wind curtailment in terms of energy. Figure 4 reveals the relationship between reductions in wind energy curtailment and PEV penetration, where energy is the sum of dispatched power over a 24-hour horizon. Results are averaged and classified into four categories based on wind uncertainty and variability. Uncertainty refers to the difference between the mean forecast and mean realization, where over-forecast is with mean forecast larger than mean realization and under-forecast is the opposite. Figure 4 presents wind uncertainty in three categories: significant over-forecast, significant under-forecast and minimal. Wind variability is shown in two categories: significant and minimal. The six combined categories are reduced to four due to the marginal effects of variability. The category with minimal uncertainty and variability provides a base case for comparison.

Since wind bids into the market lower than generation that burns fuel, it is contracted at higher levels to balance the added PEV load. On average, curtailed energy is reduced 1% for every 1% increase in PEV penetration. Curtailment reduction results are very close between the two cases with minimal forecast uncertainty but vastly different variability. This shows wind variability have only a minimally effect on the relationship between PEV penetration and

curtailed wind energy. This result compliments the observation in Section 3.1 on the lack of time-wise correlation between PEV charging and wind power variability. The reason is the same: wind power variability is a minor contributor to net load variability when compared to original load, based on the penetration cases studied.

Figure 4 also shows that wind uncertainty affects the magnitude of the positive relationship between PEV penetration and reduction in curtailed wind energy. Specifically, over-forecast amplifies and under-forecast diminishes this relationship. The principle cause of this conclusion lies in that the best available forecast is still different than realized wind power. Over-forecast presents the inaccurate information that there is more wind generation than in reality. Therefore, the magnitude of a wind curtailment based on the over-forecast is lessened when it is compared to realized wind. The opposite is true for under-forecasted wind. For example, a 100 MWh curtailment decision made with a 1,000 MWh forecast injects 900 MWh of wind energy into the market. If the realized wind resource is 950 MWh, the resultant wind curtailment is 50 MWh or 5%. However, if the realized wind is 1,050 MWh, the resultant wind curtailment is 150 MWh or 14%. For the scenarios examined, wind power over-forecast shows an average increase of 1.4% in wind curtailment reduction for every 1% increase in PEV penetration while that for under-forecast is at 0.5% with the base case at 1.1%.

3.3. Energy Market Cost Reductions

It is clear that for the penetrations studied, optimal PEV charging, increased Level 2 charging and higher wind penetration (both curtailable and must-take) all reduce wholesale

energy costs. However, economic coupling of PEV charging and wind power injection as the claimed “synergistic” resources is a more complicated dynamic.

At the system level, Figure 5 reveals the influence of PEV charging, wind dispatch, and Level 1/Level 2 charging mixture on wholesale energy costs. (Reductions are calculated from the base case without PEVs and wind.) Even though PEV penetration increases net load, optimal charging is observed to reduce energy cost via a flattened load profile and decreased ramping of the system. On the other hand, must-take wind reduces energy cost by lowering the overall net load while potentially increasing system ramping. Curtailable wind performs better than must-take wind by allowing the market to economically reject any amount of wind that creates a cost increase from cycling generators over the savings from reducing the net load. Lastly, aggregators that use more Level 2 chargers have more dispatchable power from PEVs to reduce market costs. However, as the PEV penetration increases beyond the scope of this study at 25%, it is likely that the increased cost to charge PEVs will outweigh any savings from a smoothed system load—netting an overall cost increase for PEV participation.

Economic coupling among PEVs, wind power and charger mixtures can be defined from their cost-based interactions. In this study, two resources are considered economically coupled when one influences the other’s effect on energy market costs. The degree to which they are coupled is based on the magnitude of such influence. Quantitatively for this study, decoupling occurs when a wholesale cost reduction from a nonzero PEV penetration and a nonzero wind power penetration is equal to the sum of the cost reduction from the same PEV penetration and zero wind power penetration, and the cost reduction from the same wind power penetration and zero PEV penetration. Adverse coupling occurs when the cost reduction is less than the sum. Conversely, favorable coupling occurs when the cost reduction is more than the sum.

Figure 5a and c illustrate: (1) optimally dispatched wind power and charged PEVs are adversely coupled for all mixtures of Level 1 and Level 2 charging, and (2) higher mixtures of Level 2 charging increases the degree of adverse coupling. Figure 5b and 5d reveal: (1) must-take wind power and optimally charged PEVs are decoupled.

Dispatchable wind and high ratio of Level 2 PEV charging lower energy market cost more than any other scenario category. This is due to their unsurpassed flexibility in dispatch compared to the more constrained scenarios of a must-take wind policy or low penetrations of Level 2 charging. Ironically, it is this high resource flexibility that forces wind and PEV to compete for the same opportunities in reducing system cost and ramping through optimal curtailment and charging. Consequently, as low penetrations of Level 2 charging reduce resource flexibility, system cost reductions are lower, and the adverse coupling between wind and PEVs is also weaker. Must-take wind and PEVs are largely decoupled as resource flexibility only exists with PEV charging with wind power as an exogenous source of power injection.

Lastly, superimposing Figure 5a onto b, c and d shows various combinations of optimal PEV charging, wind dispatch and Level 1/Level 2 charging infrastructures may be economically equivalent—potentially making the three resources mutual substitutes in the wholesale energy market. This is due to flexible resources participating in the same platform create competition and substitution. There are other factors outside the scope of this study to consider when fully evaluating this observation, e.g. long term variability of wind resources versus commuter driving patterns, transmission congestion and implementation costs. Nevertheless, it is more likely for the resource substitutions to vary from system to system than for there to be no substitutions that achieve economic equivalency.

3.4. Study Limitations

The limitations in this study should be investigated to tailor the results to specific systems. For example, scenario selections can be expanded to include not only load and wind power supply in the summer, but also in other seasons and years. Nonzero wind production costs and penalties accrued from actual versus contracted production will diminish the idealized market for wind integration studied here. Transmission reliability considerations, such as line flow limits and reserve allocation, can constrain system operation and market equilibrium [25, 26]. Distribution system constraints can exacerbate the Charge Flexibility Constraint. The severity of the CFC can be lessened by charging at places other than home, e.g. at work and parking lots. Lastly, transportation inputs can include commercial and fleet vehicles with characteristically different driving patterns compared to residential commuters.

4. Conclusion

This study assesses the relationship between electric vehicle charging and wind power dispatch in two-settlement electric energy markets. Based on modeled results for NYISO and by incorporating transportation constraints, Level 1/Level 2 charger infrastructure and wind power forecasts and realizations, the following conclusions are presented.

From the dispatch perspective, optimal PEV charging occurs at the same time as wind curtailment for an energy market with excess wind power; optimal PEV charging is not generally correlated with must-take wind power (wind resource) or with wind power variability.

From the wind curtailment perspective, an increase in optimally-charged PEVs reduces curtailment in wind energy; uncertainty in wind power forecast affects the magnitude of the base

case relationship between PEV charging and wind energy utilization. In particular, over-forecast amplifies and under-forecast diminishes this relationship; variability in wind power does not significantly affect the base case relationship.

From the energy cost perspective, high PEV, curtailable wind power and Level 2 charger penetrations have the lowest wholesale market costs; PEVs and curtailable wind power are adversely coupled; PEVs and must-take wind power are decoupled; levels of PEV penetration, wind power integration and Level 2 charging may be economically equivalent in the wholesale energy market.

These conclusions are accompanied by the understanding that there are limitations with the model (See Section 3.4). Future work to generalize the model to multiple markets and to allow for additional inputs can further support or add layers of complexity on top of current findings.

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Figure Captions

Fig. 1. Average of simulated wind power realizations and forecasts from four-hour-ahead and day-ahead horizons for 21 summer days in 2006. The scenarios show a wide range of under- and over-forecasts of wind power [18].

Fig. 2. Time-series of diverse intraday variability in normalized wind production in summer 2006. The spectrum of wind forecast accuracy and production variability in the case studies provides a comprehensive analysis on the relationships between wind, PEV and charger infrastructure in energy markets.

Fig. 3. Optimal PEV charging and wind power dispatch under curtailable and must-take policies to minimize wholesale energy market cost. Principle time-based influences are revealed between wind power, PEV charging and net load from a dispatch perspective. Figures (a) and (d), (b) and (e), (c) and (f) showcase typical results with significant wind curtailment, minimal wind curtailment and must-take wind, respectively.

Fig. 4. PEV penetration and reduction in wind curtailment are positively correlated under various categories of wind power uncertainty and variability.

Fig. 5. Reductions in wholesale energy costs are derived from PEV penetrations with optimal charging, wind power penetrations under curtailable and must-take policies and various mixtures

of Level 1/Level 2 charger infrastructures. System cost reductions range from approximately 1% to 25% depending on resource penetration. Results reveal adverse coupling or competition between wind power and PEVs as system-level resources in reducing energy cost.

Nomenclature

–	Weighted Average Value
a	Regression Constants
C	User Defined Load Weight
CFC	Charge Flexibility Constraint
ΔP	Load Ramp
D	Daily Average Distance Per Vehicle At Load Center i
DAM	Day-Ahead Market
E	Average Electricity Used Per Distance at Load Center i
I_1	Peak Load Interval
I_2	Valley Load Interval
LMP	Locational Marginal Price
M_{PEV}	PEV Market Penetration
N	Number of Commuting Vehicles At Load Center i
P	Net Load
p	Peak Load Interval
PEV	Plug-In Electric Vehicle
RTM	Real-Time Market
s	Shoulder Load Interval
T	Last Market Settlement
T_1	Last Settlement In DAM
T_2	Last Settlement In RTM
v	Valley Load Interval
W	Type-Based Load Weight

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Figure 1

FIGURES

Figure 2

Figure 3

Figure 4

Figure 5