Wind generation's effect on the *ex post* variable profit of compressed air energy storage: Evidence from Texas

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Abstract

We use 1401 daily observations in the 46-month period of 01/01/2011 – 10/31/2014 to estimate wind generation's effect on the daily per MWH arbitrage profits of compressed air energy storage (CAES) in the four regions of Houston, North, South, and West in the Electricity Reliability Council of Texas (ERCOT). We find an increase in wind generation's MWH output in the discharge hours tends to reduce a CAES system's profits. The same MWH increase in the charge hours, however, tends to increase profits. Hence, a wind generation capacity expansion that increases wind MWH in both discharge and charge hours has offsetting profit effects, implying that a CAES unit's profitability is unlikely affected by wind generation development. Sharply contrasting the "gone with the wind" profitability problem faced by natural-gas-fired generation, our findings lend support to the financial attractiveness of CAES, whose development is useful for integrating a rising share of wind generation capacity into an electric grid.

Keywords: Investment incentive, Wind generation, Compressed air energy storage (CAES), Profit effect, Electricity Reliability Council of Texas (ERCOT)

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1 Introduction

Electric energy storage (EES) converts electrical energy input into a storable form for subsequent generation of electrical energy output [1-3]. An example is the Bethel Energy Center compressed energy air storage (CAES) project in Texas, whose 2019 completion will yield 317 MW of fast ramping capacity that helps meet the state's grid operator's need for flexible resources to integrate and manage the intermittent renewable generation [4 and references thereof].[1] This project consumes electricity to compress air for storage and uses natural gas to heat the compressed air to generate electricity.

In a wholesale electricity market such as the Electricity Reliability Council of Texas (ERCOT) with locational marginal pricing (LMP) [5], an installed EES unit can improve economic efficiency by consuming electricity during the low-price hours for later generation during the high-price hours. Since LMP prices track marginal costs, the efficiency gain is the incremental cost saving, which is the positive difference between (a) the unit's incremental revenue from selling the net MWH output (= MWH input – MWH loss due to conversion) and (b) incremental cost of procuring the MWH input and other inputs (e.g., labor and materials for operating and maintaining the unit). As the incremental cost saving is same as the operating profit earned by the unit's owner, construction may occur only when the unit is projected to have sufficiently large operating profits to cover its fixed costs that include the returns on and of investment.

EES is useful for integrating intermittent wind energy into an electric grid because of its operational flexibility in charging and discharging [6-11]. It implements market price arbitrage, offers operation reserve, improves system

[1] See http://www.apexcaes.com/project.

reliability, defers transmission investment, absorbs wind generation during the low-demand hours, and reduces emissions by displacing thermal generation during the high-price hours [3, 8, 10, 12, 13]. Its use in the world will likely expand, thanks to the deep de-carbonization commitments made by the U.S., China and other countries in the 2015 Paris Climate Change Summit [14].

EES has been available since early 20th century. CAES, pumped hydro storage, flow battery, and flywheel are systems that are now commercially available [2, 15]. The performance metrics of a typical EES system are MW size, MWH output, and cycle efficiency (= MWH output ÷ MWH input). Similar to hydro pumped storage that requires the locational availability of reservoirs, CAES may be limited by the presence of low-cost storage sites (e.g., caves and depleted salt mines) [16]. Nevertheless, the commercial viability of CAES is evidenced by the Bethel plant in Texas, as well as the Mclintosh plant in Alabama.[2] When compared to flywheel and flow battery that are relatively costly, CAES is more suitable for large-scale energy management with longer storage duration and life cycle [1-3].

For integrating additional wind energy into the electric grid, CAES can be an attractive alternative to natural-gas-fired generation, whose investment incentive has been found to be “gone with the wind” because of large-scale wind energy development. With zero fuel costs, wind generation displaces thermal generation in a grid operator’s economic dispatch to meet electricity demands [17, 18], resulting in its extensively documented price-reduction (or merit-order) effect [18, 19-21 and references thereof].

The wind-related reduction in electricity prices erodes the per MWH

[2] The 110-MW McIntosh CAES project which has been running for over 20 years, see: http://www.powersouth.com/mcintosh_power_plant.

revenue and therefore operating profit of a thermal generation plant typically fueled by coal and natural gas. Hence, a new thermal plant's construction unlikely occurs when the diminished operating profit from market-based energy sales is projected to fall short of the plant's per MWH fixed costs, including the required returns on and of investments [22-26].

To see how wind generation development may affect a CAES system's investment incentive in Texas,[3] this paper uses a regression-based approach to estimate wind generation's effect on the system's daily *ex post* variable profit ("profit" hereafter) per MWH of electricity input under three charge/discharge durations of 1, 2 and 4 hours. These chosen durations aim to reflect the technical characteristics of CAES described in [3]. Our focus of *ex post* profits reflects our interest in using recorded data that describe actual market conditions, thereby painting a realistic picture of CAES's profit variations in response to wind generation fluctuations.

We define the profit per MWH of electricity input as the difference between the per MWH revenue from on-peak discharge (= average on-peak price) and the per MWH cost of off-peak charge (= average off-peak price):

π = Cycle efficiency × Average on-peak price – Average off-peak price.

Hence, π is a variable profit based on the on- and off-peak price differential, without accounting for the system's non-electric variable O&M costs that tend to be relatively small. To the extent that these variable O&M costs are stable, their inclusion has immaterial effects on how π may vary with market price changes caused by wind generation's as-available random output variations.

For empirical illustration, we choose ERCOT because of Texas' salient

[3] We do not consider other types of renewable generations (e.g., small hydro, solar, and biomass), which are negligible in ERCOT.

electricity characteristics [5, 27, 28]. First, the state is large, with an annual peak demand of 66,454 MW in 2014.[4] Second, the state's installed wind capacity in 2014 is over 12,000 MW, the largest among all the states in the U.S.[5] Third, Texas has highly volatile market prices that can become negative and have large spikes [29]. Finally, Texas faces potential deterioration in its system reliability.[6] It currently sees little construction of new thermal generation plants [30],[7] has experienced substantial plant retirements, encounters delays of newly planned projects [30-32], and likely faces federal environmental regulations that adversely impact the state's large fleet of coal-fired-generation plants.[8]

While wind generation's merit-order effect suppresses the off-peak prices in the charge hours[9] and increases the per MWH profit of an EES like battery and CAES, it also reduces the on-peak prices in the discharge hours and cuts the system's per MWH profit. The profitability of battery EES has been widely investigated, finding that the system's profitability could be greatly improved by implementing a flexible optimal operation within the context of an active-reactive optimal power flow (A-R-OPF) [10, 11, 33, 34].

Turning our attention to CAES with substantial wind penetration, a case study of the 2008 ERCOT zonal market of the Houston region shows that

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[4] See http://www.ercot.com/news/press_releases/show/51654.
[5] See http://www.ercot.com/content/news/presentations/2015/ERCOT_Quick_Facts_52215.pdf.
[6] For example, the 2014 planning reserve margin of 9.8% projected by ERCOT is well below the reserve margin target of 13.75% of peak load [30]. A recent forecast depicts an even worse future of the reserve margin, see http://www.ercot.com/content/meetings/lts/keydocs/2011/0405/Generic_Database_Characteristics.xls.
[7] For the latest plant additions, see http://www.ercot.com/content/gridinfo/resource/2015/adequacy/cdr/CapacityDemandandReserveReport-May2015.pdf.
[8] ERCOT at times experienced generation capacity shortfalls amid soaring demand and plant shortages, see http://www.bloomberg.com/news/articles/2015-07-30/texas-power-hits-21-week-high-as-grid-warns-of-reserve-shortage.
[9] Rising wind generation suppresses the off-peak spot market prices through the merit-order effect by displacing the natural-gas-fired generation units with relatively high marginal fuel cost [18, 26].

operating a CAES system is unprofitable in a wind-rich state like Texas [16]. Nonetheless, wind generation's profit effect on CAES in the ERCOT market since the adoption of a nodal market structure in 2010 has received little attention in the extant literature, unlike the case of natural-gas-fired generation [22-26].

Using a sample of 1401 daily observations for the 46-month period of 01/01/2011 to 10/31/2014, we estimate the relationship between a CAES system's per MWH profit and the fundamental drivers of natural gas price, system demands, nuclear generation and wind generation that tend to move ERCOT's market prices [24-26, 20, 35]. We find that a 1-MWH increase in wind generation in the discharge hours statistically significantly (p-value < 0.01) reduces the per MWH profits.[10] However, the same MWH increase in the charge hours tends to improve the per MWH profits. As the discharge and charge profit effects are offsetting, a wind generation MW capacity expansion's net profit effect is statistically insignificant (p-value > 0.01) at the 1% significance level used throughout this paper, highlighting CAES's natural hedge against the profit risks caused by the wind generation's capacity expansion. This natural hedge characteristic makes CAES attractive in its promotion for integrating wind energy in ERCOT.

Our contributions are as follows. First, our CAES analysis is new. We use historical data to quantify the magnitude and significance of wind generation's effect on investment incentive, thereby complementing the extant studies on the problem of investment incentives of natural-gas-fired generation [22-26].

Second, our regression-based approach uses up-to-date market data to offer an alternative look at EES's financial performance, thus augmenting and

[10] A p-value is the probability used to test the null hypothesis that an estimate is equal to zero. Hence if the p-value < 0.01, the hypothesis is rejected at the 1% significance level. By the same token, if the p-value > 0.01, the null hypothesis cannot be rejected even at the 10% significance level.

complementing the engineering/simulation approaches used in the EES literature [6, 10, 11, 33, 34, 36-38].

Third, not all generation technologies suffer from the “gone with the wind” problem. Our empirical evidence on the insignificant effect of wind generation development on the investment incentives of CAES sharply differs from the findings for natural-gas-fired generation technology in Texas [24, 26], California [25], Germany [19, 23], and Great Britain [22]. This is because for a CAES system, rising wind generation simultaneously reduces the system’s per MWH discharge revenue and charge cost. In contrast, rising wind generation only reduces a natural-gas-fired generation plant owner’s per MWH revenue, without an offsetting effect on the plant owner’s per MWH fuel cost.[11]

Finally, we present an approach for investigating the *ex post* variable profits of other types of EES in a deregulated electricity market. For example, one may adapt the approach to analyze wind generation development’s effect on the investment incentive for pumped storage and batteries in markets such as California, New York, PJM, New England in the U.S., Alberta and Ontario in Canada, as well as Demark, Germany and Spain in Europe.

The rest of this paper proceeds as follows: Section 2 presents our methodology and data construction. Section 3 describes our data sample. Section 4 reports our results. Section 5 concludes.

[11] In a deregulated energy-only market like ERCOT, market-based investment incentive of natural-gas-fired generation is determined by a local distribution company (LDC)’s least-cost dispatch decision. A LDC can choose between dispatching the natural-gas-fired generation capacity and buying from the spot market [26]. The per MMBTU fuel cost of the LDC’s marginal generation faced by the LDC is chiefly the natural-gas price that is unaffected by the LDC’s least-cost decision.

2 Methodology

2.1 Per MWH profit formula

We begin by defining a hypothetical CAES system's daily per MWH profit, the left-hand-side (LHS) variable in our proposed regression analysis:

$$\pi_{nd} = \left[\rho\left(\sum_h P_{1,hd}\right) - \sum_h P_{0,hd}\right]/n; \tag{1}$$

where ρ = cycle efficiency; $P_{0,hd}$ = spot market price ($/MWH) in charge hour h on day d; $P_{1,hd}$ = spot market price ($/MWH) in discharge hour h on day d; and n = duration of charge and discharge.[12]

We use equation (1) to calculate π_{nd} based on: (a) a simple operational rule [39], and (b) perfect price foresight. While π_{nd} under the simple rule may be negative, it is positive under perfect foresight because the CAES operator can decide not to operate the system. The simple rule yields a profit floor readily obtainable in a real-world market environment. The perfect foresight yields a profit ceiling when a CAES operator can accurately forecast electricity prices and operate the system to maximize the system's profit. Thus, the regression results based on (a) and (b) bookend the profit effects of the fundamental drivers.

In addition to on-peak energy, a CAES device may provide ancillary services (AS) [16, 39, 40]. Increasing wind generation tends to the increase the value of AS, since more operating reserves are needed when intermittent wind resources are added to the market. We do not consider AS provision by a CAES system because calculating the profits from AS provision greatly complicates the mode of operations for a CAES device,[13] well beyond the scope of our study.

[12] Technically, ERCOT settles the storage's MWH input and output at nodal prices. Our use of zonal prices reflects that our hypothetical CAES system is located inside a given zone whose price is a weighted average of all the nodal prices within the zone. See http://www.puc.texas.gov/agency/rulesnlaws/subrules/electric/25.501/25.501.pdf.

[13] For example, a CAES device providing both on-peak energy and AS may have at least 9 operation modes under three operation durations because each operation duration can have three

Further, our study's results can be readily compared to those of the regression-based analyses of natural-gas-fired generation's profitability [26], which also do not consider the AS revenue sources.

2.2 Simple rule

To derive the simple rule for operating a hypothetical CAES system in Texas, we first compute the state's hourly price as an equally-weighted hourly average of ERCOT's 15-minute spot prices for the period of 01/01/2011 – 10/31/2014. We then examine the price patterns by hour-of-day and month-of-year, find that price spikes are likely to occur in the morning hours in the winter months and in the afternoon hours in the summer months. Notwithstanding that the charge and discharge operation of CAES is determined by an optimization process involving factors of wind generation, spot market prices, and system load [41, 42],[14] we take the consecutive hours with the most frequent highest (lowest) prices as the discharge (charge) period in a month. Because when wind generation is high, charging should occur to avoid wind curtailment and take advantage of the low prices; whilst when load level is high and wind generation is low, discharge should occur to maximize the gain from the high price hours. To illustrate, we use Figure 1 to set 14:00-18:00 as the 4-hour discharge period and 02:00-06:00 as the 4-hour charge period for Houston region in July.[15]

Table 1 summarizes the simple rule's charge/discharge periods based on the observed price patterns.[16] Assuming a cycle efficiency of $\rho = 0.8$ [3], Table 2

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operation modes (on-peak only, AS only, and mixed mode).

[14] Thanks for an anonymous reviewer's insightful comment, we make further justification for the simple rule charge and discharge strategy in this section.

[15] We have tried the hourly price distributions by month for identifying the monthly hours with high and low prices. The resulting charge and discharge periods can have overlapping hours. To wit, the morning hour of 08:00 – 09:00 may have low and high prices in a given month. Hence, we abandon the price distribution approach.

[16] For brevity, we will not display the tables for the North and South regions (and hereinafter). These tables are available upon request: Liuy050229@gmail.com.

compares the mean per MWH profits under the simple rule with those under perfect foresight. The simple-rule-based profits are 69% to 85% of the perfect-foresight-based profits. Further, notwithstanding the large profit differences between simple rule and perfect foresight, the two profit series are highly correlated ($r \geq 0.78$). Figure 2 aids visual understanding to the correlation between the profits based on the simple rule and perfect foresight.

2.3 Regression model

Our model specification follows those of [20, 24-26]. For region j in ERCOT (j = 1 for Houston, 2 for North, 3 for South, and 4 for West) on day d = 01/01/2011-10/31/2014, equations (2) to (4) below are the per MWH profit regressions corresponding to operation duration of 1, 2, or 4 hours.

$$\pi_{1,jd} = \alpha_{jmd} + \alpha_{jG}\, G_d + \textstyle\sum_{k=1}^{8} \alpha_{jk}\, X_{1,kd} + \varepsilon_{jd}, \qquad (2)$$

$$\pi_{2,jd} = \beta_{jmd} + \beta_{jG}\, G_d + \textstyle\sum_{k=1}^{8} \beta_{jk}\, X_{2,kd} + \epsilon_{jd}, \qquad (3)$$

$$\pi_{4,jd} = \theta_{jmd} + \theta_{jG}\, G_d + \textstyle\sum_{k=1}^{8} \theta_{jk}\, X_{4,kd} + \mu_{jd}. \qquad (4)$$

For clarity, the LHS variables are assumed to be the per MWH profits under the simple rule. As part of our analysis, however, we also perform a similar regression analysis on the profits under perfect foresight, see Section 4 below.

Equations (2) to (4) assume time-varying intercepts to account for the residual profit variations not captured by other right-hand-side (RHS) variables. For example, α_{jmd} is a linear function of the binary indicators for a profit observation's day-of-week (denoted by subscript d) and month-of-year (denoted by subscript m). The objective is to capture the day-of-week and month-of-year effects not accounted for by the other regressors. The intercepts in the other equations are defined analogously.

The remaining right-hand-side (RHS) variables are the fundamental drivers of the simple-rule-based profits. Except for the daily natural gas price that is constant throughout the day, the daily values for the remaining RHS variables vary with the charge and discharge periods:

- G_d = Daily Henry-hub natural-gas price ($/MMBTU). As a natural-gas price increase raises the spot market prices in the charge and discharge periods, we do not know *a priori* its net profit effect given by the coefficients α_{Gjd}, β_{Gjd} and θ_{Gjd}.
- X_{n1d} = Daily average of the region's own hourly load (MWH) in a charge period of n (= 1, 2, 4) hours. Rising load in the charge period tends to raise market prices and reduce profits. Hence, its coefficient estimates are expected to be negative.
- X_{n2d} = Daily average of the other regions' hourly load (MWH) in a charge period of n (= 1, 2, 4) hours. While an increase in region j's load influences a CAES system's profit in the same region, we do not know *a priori* the profit effect of other regions' loads on the system.
- X_{n3d} = Daily average of the state's hourly nuclear generation (MWH) in the charge period. Rising nuclear generation in the charge period tends to reduce market prices and improve profits. Hence, its coefficient estimates are expected to be positive.
- X_{n4d} = Daily average of the state's hourly wind generation (MWH) in the charge period. Rising wind generation in the charge period tends to reduce prices and improve profits. Hence, its coefficient estimates are expected to be positive.
- X_{n5d} = Daily average of the region's own hourly load (MWH) in the discharge period. Rising load in the discharge period tends to raise market

prices and improve profits. Hence, the coefficient estimates are expected to be positive.

- X_{n6d} = Daily average of the other regions' hourly load (MWH) in a discharge period of *n* (= 1, 2, 4) hours. As in the charge period case, we do not know *a priori* its profit effect on a CAES system in region *j*.
- X_{n7d} = Daily average of the state's hourly nuclear generation (MWH) in the discharge period. Rising nuclear generation tends to reduce market prices and cut profits. Hence, its coefficient estimates are expected to be negative.
- X_{n8d} = Daily average of the state's hourly wind generation (MWH) in the discharge period. Rising wind generation tends to reduce market prices and cut profits. Hence, its coefficient estimates are expected to be negative.

Under the assumption that the random errors $\varepsilon_{jd}, \epsilon_{jd}$, and μ_{jd} are serially correlated, we apply the maximum likelihood (ML) method of PROC AUTOREG in [43] to estimate each region-specific regression, yielding the results reported in Section 4.

Four reasons justify our model specification:

- Linear regression. A linear model is a first-order approximation of an unknown nonlinear form. Our preference of a linear model specification over a logarithmic model is due to the presence of negative profits under the simple rule.
- Easy interpretation. Our model specification aids easy interpretation of a profit driver's effect. For example, the coefficient α_{jG} is the marginal profit effect of the natural gas price on the 1-hour profit.
- Serial correlation. Our data firmly reject the null hypothesis of no serial correlation at the 1% significance criterion used throughout this paper.

- Empirical reasonableness. The regression results in Section 4 show statistically significant slope coefficient estimates for wind generation. These estimates have the expected signs, indicating that rising wind generation in the charge (discharge) period tends to increase (reduce) the CAES profit. Further, the coefficient estimates for the remaining RHS variables also have a pattern consistent with our expectations.

2.4 Impact of rising wind generation

We use the ML results to quantify the impact of rising wind generation on the variable profits, entailing the following steps:

- Step 1: Assume wind generation capacity increases by W MW.
- Step 2: Find $\omega = W/K$, the ratio of the new wind capacity W to the installed wind capacity K = Average of the annual installed capacities in the sample period = 10,993 MW.[17]
- Step 3: Find the Y MWH produced by the W MW capacity in the charge period, which is reported in Table 4 and Table 5:

$$Y = \text{Sample mean wind MWH in the charge period} \times \omega.$$

- Step 4: Find the Z MWH produced by the W MW capacity in the discharge period, which is reported in Table 4 and Table 5:

$$Z = \text{Sample mean wind MWH in the discharge period} \times \omega.$$

- Step 5: Estimate the profit effect ($\Delta\pi$) and its variance (V^2). To illustrate, consider equation (2) whose wind coefficient estimates are found to be a_4 and a_8. An unbiased estimate of $\Delta\pi$ is ($a_4\,Y + a_8\,Z$), whose variance is $V^2 = Y^2\,\mathrm{Var}(a_4) + 2\,YZ\,\mathrm{Cov}(a_4, a_8) + Z^2\,\mathrm{Var}(a_8)$. The profit effects based on equations (3) and (4) can be found analogously.

[17] See http://www.ercot.com/gridinfo/resource.

3 Data

3.1 Data construction

We use the sample period of 01/01/2011 to /10/31/2014 available from the ERCOT website. The period's beginning date reflects that while ERCOT adopted its current nodal market structure in December 2010, the data reporting issues in the first month of nodal pricing discourage us from using the December 2010 data. The ending date mirrors the data available at the time of our writing.

To construct the profit in equation (1), we make the following assumptions based on [2, 3, 36, 44, 45]:

- Cycle efficiency. We assume 80% cycle efficiency (ρ = 0.8) for the hypothetical CAES system [45, 46].
- Size. To match the per MWH profit computation, we assume 1-MW CAES ownership. This assumption is reasonable because the typical CAES system has a capacity between 50 and 300 MW [2] and its installation should not impact the market price because the state has more than 74,000 MW to serve its peak demand.[18] Even for the large 317-MW Bethel Energy Center CAES project, the capacity addition is less than 0.5% of the state's total capacity.
- Constant charge and discharge operation. We assume constant charge and discharge durations of 1, 2, and 4 hours, which are within the normal operating duration of a typical CAES [2, 3].[19] The assumption of operating durations makes sure that charge and discharge take place within one day, so as to circumvent the need to use stochastic dynamic programming that is well

[18] See http://www.ercot.com/content/news/presentations/2015/ERCOT_Quick_Facts_52215.pdf.
[19] The average operating duration of the McIntosh CAES plan is less than 3 hours. See http://www.ercot.com/content/gridinfo/etts/compressedair/presentations/Haddington_2nd_ERCOT_CAES_Presentation_100824-a_drm.pdf.

beyond the scope of our paper.

- Spot market price. Although ERCOT website publishes both the day-ahead market (DAM) prices and real-time market (RTM) prices, we choose to use the RTM prices because: (a) they lead to higher per MWH profits; and (b) they circumvent the difficulty of obtaining day-ahead forecasts for the RHS variables to match the DAM prices [47].
- Cycle of operation. The system is assumed to operate within 24 hours a day, 365 days a year. Consistent with the simple rule formation, this assumption keeps our sample size as large as possible.
- Location. As suggested in [16], we assume a load-sited CAES in each region (the Gulf Coast Basin for the Houston region, the aquifers surrounding Dallas for the North region, the South Texas Basin for the South region, and the Delaware and Midland Basins for the West region), so as to achieve higher variable profit with larger transmission capacity.

We make additional assumptions for constructing our RHS variables:

- Daily natural-gas price ($/MMBTU). We use the daily Henry Hub natural-gas price as the local Houston Ship Channel Natural Gas Price may be endogenous, and the two natural gas price series are highly correlated ($r > 0.95$) [26].
- Hourly load. It is the hourly sum of the 15-minute system load data available from the ERCOT website.
- Hourly nuclear generation. It is the hourly sum of the state’s 15-minute nuclear generation data available from the ERCOT website.
- Hourly wind generation. It is hourly sum of the state’s 15-minute wind generation data available from the ERCOT website.

3.2 Descriptive statistics

Panel A and Panel B of Table 3 report the descriptive statistics for the *ex post* variable profit data. Using the Phillips-Perron unit root test [48], we determine that all the series in Panel A and Panel B are stationary at the 1% significance level, thereby obviating the concern of spurious regressions [49].

The daily profit data based on simple rule have means ranging from $19/MWH for the North region under 4 hours' operation, to $45/MWH for the West region under the one-hour operation. These data are highly volatile, as reflected by their standard deviations of $134/MWH to $219/MWH, minimum values of -$160/MWH to -$28/MWH and maximum values of $1972/MWH to $3654/MWH. Relative to the price data based on simple rule, the profit data obtained from perfect foresight have higher means, minimum values and maximum values, and lower standard deviations. This makes sense because perfect price foresight captures extreme price hours and the per MWH profits are non-negative.

Table 4 reports the descriptive statistics for the profit drivers under the simple rule. The natural-gas price data are non-stationary with means of $3.70/MMBTU and standard deviation of $0.81/MMBTU. The remaining series are stationary. For brevity, we focus on the Houston region, the load pocket in Texas,[20] to discuss the descriptive statistics. With standard deviations between 2977 MWH and 3133 MWH, the Houston regional load data for discharge periods are more volatile than those for charge periods. Relative to regional loads, nuclear

[20] Moreover, Houston region will be most likely to be concerned of the proposed environmental regulations on the system. Much of the planned retirement of 10,000 MW natural-gas-fired generation units are located in the Houston region. See: http://www.ercot.com/content/news/presentations/2014/Impacts%20of%20Environmental%20Regulations%20in%20the%20ERCOT%20Region.pdf and http://www.ercot.com/content/news/presentations/2011/ERCOT_Review_EPA_Planning_Final.pdf.

generation is stable, with means ranging from 4440 MWH to 4451 MWH and standard deviations between 819 MWH and 827 MWH. Wind generation series are highly volatile with standard deviations ranging from 2004 MWH to 2103 MWH. The maximum values of wind generation can be 100 times its minimum values. For brevity, we do not report the statistics for the "other regions' load" data, which can be calculated from the daily regional load data.

We omit the discussion of the descriptive statistics displayed in Table 5 for the RHS variables under perfect foresight, because they have comparable statistical characteristics.

4 Results

4.1 Regression results

Table 6 to Table 9 report the regression results for the Houston, North, South, and West regions. These results have been subject to the following checks:

- Order of the AR process. We consider an AR(2) process, finding that the AR(2) parameter estimates are generally insignificant. Thus we retain our AR(1) assumption.
- Nonlinearity. We add squared terms of the profit drivers as additional RHS variables. As 78% of the expanded regressions' coefficient estimates are statistically insignificant, we retain our linear functional form.

These tables suggest that the total R^2 is around 0.20,[21] chiefly because of our sample of noisy daily data. While all AR parameter estimates are statistically significant, they are less than 0.65, indicating that all the AR processes are stationary.[22] Therefore, our regression residuals do not follow a random walk and

[21] The SAS PROC AUTOREG procedure calculates the total R^2 as: 1 – *SSE*/*SST*; where *SST* is the sum of squares for the original response variable corrected for the mean and *SSE* is the final error sum of squares [43].

[22] An AR process is stationary if: (a) its mean and variance are both finite and must not depend on

the regression results are not spurious [51].

We now turn our attention to the wind generation's coefficient estimates that lead to the following findings. Our discussion will focus on the wind effects in all of the load pocket regions (non-West regions) and the West region where most wind farms are housed, leading to:

First, the estimated profit effects of wind generation in the discharge periods under the simple rule for the non-West regions are negative and significant, ranging from -$0.0151/ MWH (North, 1-hour charge and discharge) to -$0.0072/MWH (Houston, 4-hours charge and discharge). While wind generation tends to raise the profit in the charge periods, its estimated effects are mostly insignificant.

Second, the estimated profit effects of wind generation under the simple rule for the West region are significant. A 1-MWH increase in wind generation in the discharge period tends to cut the profit by at least $0.013 but raise the profit by at least $0.007/MWH.

Third, the estimated profit effects of wind generation in the discharge periods under perfect foresight for the non-West regions are insignificant and between -$0.0054/MWH and -$0.0024/MWH. Rising wind generation in the charge periods may increase profit by up to $0.0023. These estimated effects, however, are insignificant.

Finally, the estimated profit effects of wind generation in the discharge periods under perfect foresight for the West region are significant. Increasing wind generation by 1-MWH may reduce the profit by more than $0.0049. The estimated effects for the charge periods are insignificant.

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time; and (b) its covariance between pairs of random values must not depend on the value of time. They require that the coefficient estimates of an AR(1) process be smaller than 1.0 [50].

The remaining non-wind coefficient estimates suggest that an increase in the Henry Hub price tends to raise profits. Rising nuclear generation in the charge (discharge) period tends to increase (reduce) profits. Finally, the estimated profit effects of a regional load increase in the charge (discharge) periods are mostly negative (positive).

4.2 Profit changes

We estimate the profit changes triggered by three possible cases of wind generation development: 1 MW, 313 MW, and 5,000 MW. The first case corresponds to the average size of a wind turbine;[23] the second case signifies the average size of a wind farm in Texas,[24] and the last case reflects the completion of the 5,000-MW Mariah project in Texas.[25] Rather than being predictive, this estimation aims to indicate what may occur for a hypothetical case of wind generation development.

Table 10 describes the estimated profit changes under the *ceteris paribus* assumption. As wind generation increases the spot market prices in the discharge hours, we observe great estimated changes in per MWH profit in the Houston region (e.g., -\$0.0025/MWH under 1-MW wind development). This is because the Houston region imports substantial on-peak wind energy from the wind-rich West region. The estimated profit changes in the West region seem to be smaller, partly due to a "natural hedge" mechanism that reduces the output revenue and the input variable cost at the same time. In particular, for the 1-MW increase in wind capacity, the estimated profit effects range from -\$0.0025/MWH to -\$0.0001/MWH. Increasing wind capacity by 313 MW will suppress the profit by as much as \$0.7885/MWH. The completion of 5000-MW Mariah project may reduce the profit

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[23] See https://renewables.gepower.com/wind-energy/turbines.html.
[24] See http://www.treia.org/pdf_files/Wind%20Plant%20Chart.pdf.
[25] See http://www.scandiawind.com/scandiawindsouthwest.html.

by as high as $12.5962/MWH. Thanks to an insightful referee, we use two compact plots in Figure 3 to aid visual understanding of the profit changes due to wind development.

Table 10, however, also indicates all estimated profit reductions are statistically insignificant. This is understandable because a CAES system uses electricity as its input and the impact of rising wind on the unit's variable cost offsets the unit's revenue from selling the electricity subsequently generated.

5 Conclusion

The profit reduction estimates in Table 10 suggest that raising wind generation by 1 MW tend to reduce the variable profit by at least $0.0001/MWH (4 hours' operation under perfect foresight of the West region); however, it is unlikely to have statistically significant (p-value > 0.01) impact on the investment incentives of a CAES system in Texas. Our finding sharply contrasts the "missing money" problem that plagues the natural-gas-fired generation units of combustion turbine (CT) and combined cycle gas turbine (CCGT) [23-26]. This is because rising wind generation tends to reduce a CAES system's revenue and cost at the same time, unlike the case of CT and CCGT in which rising wind generation only suppresses these natural-gas-fired generation units' revenue.

Our finding documents that the "gone with the wind" phenomenon is not universally true for investment incentive in the power industry, at least not for CAES that uses electricity as an input [46]. This makes a CAES system financially attractive in its development for integrating a larger share of wind energy into the grid, corroborating the evidence found for Germany [39]. This finding complements the studies for the ERCOT market such as [16] after its use of nodal pricing. Our analysis can be well extended to other types of EES such as pumped storage and battery.

We would be remiss had we failed to acknowledge a potential pitfall in this paper. Due to the inevitable use of historical data, our regression-based results may be inappropriate for long-term inferences on the profitability of an EES system in the presence of large and rapid development of wind generation. After updating our data sample in the next few years, however, our regression-based approach can be used to assess the EES system's profitability.

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Table 1: Charge and discharge period definitions under the simple rule by month and ERCOT region in the 46-month sample period of 01/01/2011 – 10/31/2014

Panel A: Houston

Month	Discharge period			Charge period		
	1 hour	2 hours	4 hours	1 hour	2 hours	4 hours
January	6:00-7:00	5:00-7:00	5:00-9:00	2:00-3:00	1:00-3:00	0:00-4:00
February	6:00-7:00	5:00-7:00	5:00-9:00	1:00-2:00	1:00-3:00	23:00-3:00
March	6:00-7:00	5:00-7:00	5:00-7:00, 17:00-19:00	2:00-3:00	1:00-3:00	1:00-5:00
April	15:00-16:00	15:00-17:00	12:00-14:00, 15:00-17:00	2:00-3:00	2:00-4:00	1:00-5:00
May	15:00-16:00	14:00-16:00	12:00-16:00	3:00-4:00	2:00-4:00	1:00-5:00
June	15:00-16:00	14:00-16:00	13:00-17:00	3:00-4:00	3:00-5:00	2:00-6:00
July	15:00-16:00	14:00-16:00	14:00-18:00	3:00-4:00	3:00-5:00	2:00-6:00
August	15:00-16:00	15:00-17:00	14:00-18:00	3:00-4:00	3:00-5:00	2:00-6:00
September	16:00-17:00	15:00-17:00	13:00-17:00	3:00-4:00	2:00-4:00	1:00-5:00
October	15:00-16:00	14:00-16:00	13:00-17:00	2:00-3:00	2:00-4:00	1:00-5:00
November	17:00-18:00	16:00-18:00	15:00-19:00	2:00-3:00	1:00-3:00	0:00-4:00
December	17:00-18:00	16:00-18:00	16:00-20:00	2:00-3:00	1:00-3:00	1:00-5:00

Panel B: West

Month	Discharge period			Charge period		
	1 hour	2 hours	4 hours	1 hour	2 hours	4 hours
January	6:00-7:00	5:00-7:00	5:00-7:00, 17:00-19:00	1:00-2:00	1:00-3:00	0:00-4:00
February	6:00-7:00	5:00-7:00	5:00-9:00	1:00-2:00	1:00-3:00	23:00-3:00
March	6:00-7:00	5:00-7:00	5:00-7:00, 15:00-17:00	1:00-2:00	0:00-2:00	23:00-3:00
April	15:00-16:00	14:00-16:00	13:00-17:00	2:00-3:00	2:00-4:00	1:00-5:00
May	15:00-16:00	14:00-16:00	13:00-17:00	3:00-4:00	2:00-4:00	1:00-5:00
June	15:00-16:00	14:00-16:00	13:00-17:00	3:00-4:00	3:00-5:00	2:00-6:00
July	15:00-16:00	15:00-17:00	14:00-18:00	3:00-4:00	2:00-4:00	1:00-5:00
August	15:00-16:00	15:00-17:00	14:00-18:00	3:00-4:00	2:00-4:00	1:00-5:00
September	15:00-16:00	15:00-17:00	13:00-17:00	3:00-4:00	2:00-4:00	1:00-5:00
October	15:00-16:00	14:00-16:00	13:00-17:00	2:00-3:00	2:00-4:00	1:00-5:00
November	17:00-18:00	16:00-18:00	7:00-9:00, 16:00-18:00	1:00-2:00	0:00-2:00	22:00-2:00
December	17:00-18:00	16:00-18:00	5:00-7:00, 16:00-18:00	1:00-2:00	1:00-3:00	1:00-5:00

Table 2: *Ex post* per MWH profits by charge/discharge duration and ERCOT region for the 46-month sample period of 01/01/2011 – 10/31/2014; simple rule profit = average discharge price – average charge price; perfect foresight profit = average of max(hourly discharge price – hourly charge price, 0)

Region	Charge/discharge duration	Mean profit ($/MWH): simple rule	Mean profit ($/MWH): perfect foresight	Simple rule profit ÷ Perfect foresight profit	Correlation coefficient
Houston	1 hour	37.45	44.21	0.85	0.79
	2 hours	28.89	38.24	0.76	0.87
	4 hours	20.30	28.43	0.71	0.92
North	1 hour	34.47	43.01	0.80	0.80
	2 hours	27.05	34.73	0.78	0.83
	4 hours	19.36	27.30	0.71	0.91
South	1 hour	39.40	47.68	0.83	0.78
	2 hours	30.95	39.15	0.79	0.82
	4 hours	21.95	31.77	0.69	0.92
West	1 hour	45.09	57.70	0.78	0.78
	2 hours	36.13	50.96	0.71	0.84
	4 hours	28.65	41.64	0.69	0.89

Table 3: Descriptive statistics for the daily per MWH profits by charge/discharge duration and ERCOT region for the 46-month sample period of 01/01/2011 – 10/31/2014; unit root test results for data stationarity at the 1% level are based on the Phillips-Perron tests (Phillips and Perron, 1988)

Panel A: Simple rule profit = average discharge price – average charge price

Region	**Duration**	**Mean**	**Standard deviation**	**Minimum**	**Maximum**	**Stationary?**
Houston	1 hour	37.45	215.95	-36.73	2398.07	Yes
	2 hours	28.89	189.57	-41.21	2378.41	Yes
	4 hours	20.30	137.07	-39.30	2105.29	Yes
North	1 hour	34.47	213.01	-37.45	2385.27	Yes
	2 hours	27.05	173.34	-36.51	2378.41	Yes
	4 hours	19.36	134.23	-39.31	1972.75	Yes
South	1 hour	39.40	215.08	-29.62	2379.11	Yes
	2 hours	30.95	175.03	-28.98	2378.41	Yes
	4 hours	21.95	138.41	-29.97	2105.85	Yes
West	1 hour	45.09	219.15	-70.76	3654.42	Yes
	2 hours	36.13	194.76	-160.05	2691.38	Yes
	4 hours	28.65	140.69	-41.05	2117.50	Yes

Panel B: Perfect foresight profit = average of max(hourly discharge price – hourly charge price, 0)

Region	Duration	Mean	Standard deviation	Minimum	Maximum	Stationary?
Houston	1 hour	44.21	205.46	0.00	3310.93	Yes
	2 hours	38.24	179.78	0.00	2462.27	Yes
	4 hours	28.43	132.71	0.00	2213.11	Yes
North	1 hour	43.01	195.99	0.00	3696.40	Yes
	2 hours	34.73	174.67	0.00	2700.18	Yes
	4 hours	27.30	130.43	0.00	2214.27	Yes
South	1 hour	47.68	205.51	0.00	3356.67	Yes
	2 hours	39.15	182.95	0.00	2522.63	Yes
	4 hours	31.77	137.35	0.00	2203.46	Yes
West	1 hour	57.70	199.45	0.00	3654.42	Yes
	2 hours	50.96	177.46	0.00	2691.38	Yes
	4 hours	41.64	133.50	0.00	2210.87	Yes

Table 4: Descriptive statistics for daily profit drivers under simple rule by charge/discharge duration for the 46-month period of 01/01/2011 – 10/31/2014; unit root test results for data stationarity at the 1% level are based on the Phillips-Perron tests (Phillips and Perron, 1988)

Panel A: Charge – Houston

Variable	Duration	Mean	Standard deviation	Minimum	Maximum	Stationary?
Henry Hub natural gas price ($/MMBTU)	All	3.70	0.81	1.82	8.15	No
Houston load (MWH)	1 hour	8133.94	1234.14	3605.00	11263.80	Yes
	2 hours	8155.42	1240.20	3168.09	11185.51	Yes
	4 hours	8253.39	1255.64	4701.24	11339.78	Yes
North load (MWH)	1 hour	11007.24	2248.91	6369.00	20944.47	Yes
	2 hours	11012.40	2211.01	4887.61	21046.35	Yes
	4 hours	11172.91	2237.62	7252.14	20795.55	Yes
South load (MWH)	1 hour	3421.03	654.15	1675.00	6350.10	Yes
	2 hours	3420.26	641.01	1434.75	6118.25	Yes
	4 hours	3462.99	651.32	2142.23	6338.35	Yes
West load (MWH)	1 hour	2604.01	328.44	1565.00	3944.80	Yes
	2 hours	2602.05	326.32	1236.92	3865.85	Yes
	4 hours	2619.73	327.21	1849.04	3918.43	Yes
Nuclear generation (MWH)	1 hour	4442.62	826.87	1347.34	5187.30	Yes
	2 hours	4440.42	827.38	1347.15	5185.10	Yes
	4 hours	4442.25	824.18	1623.94	5186.70	Yes
Wind generation (MWH)	1 hour	4144.62	2103.66	43.86	9693.60	Yes
	2 hours	4113.53	2040.32	51.15	9290.10	Yes
	4 hours	4113.74	2004.72	70.56	9287.90	Yes

Panel B: Discharge – Houston

Variable	Duration	Mean	Standard deviation	Minimum	Maximum	Stationary?
Houston load (MWH)	1 hour	11922.25	3073.26	6363.92	18189.52	Yes
	2 hours	11802.75	3133.96	6398.08	18237.26	Yes
	4 hours	11794.76	2977.33	6466.85	18081.56	Yes
North load (MWH)	1 hour	16857.35	4598.44	8219.33	27847.23	Yes
	2 hours	16596.77	4680.04	8116.18	27873.84	Yes
	4 hours	16587.61	4548.13	8565.05	27712.43	Yes
South load (MWH)	1 hour	5152.88	1344.85	2527.66	8138.00	Yes
	2 hours	5081.83	1377.20	2483.36	8092.00	Yes
	4 hours	5088.86	1296.34	2617.47	8021.25	Yes
West load (MWH)	1 hour	3336.66	607.62	2013.62	4775.00	Yes
	2 hours	3300.40	616.02	1997.76	4774.00	Yes
	4 hours	3296.06	598.49	2042.25	4750.00	Yes
Nuclear generation (MWH)	1 hour	4451.91	819.44	1747.61	5387.70	Yes
	2 hours	4451.90	819.07	1736.37	5384.60	Yes
	4 hours	4450.63	820.28	1732.66	5386.90	Yes
Wind generation (MWH)	1 hour	3232.03	2093.58	131.20	9485.73	Yes
	2 hours	3217.95	2091.21	110.57	9417.72	Yes
	4 hours	3197.27	2025.00	89.31	9351.02	Yes

Panel C: Charge – West

Variable	Duration	Mean	Standard deviation	Minimum	Maximum	Stationary?
Henry Hub natural gas price ($/MMBTU)	All	3.70	0.81	1.82	8.15	No
Houston load (MWH)	1 hour	8138.55	1231.78	1596.14	11258.80	Yes
	2 hours	8163.49	1252.60	3168.09	10988.35	Yes
	4 hours	8297.81	1231.46	4926.85	11314.93	Yes
North load (MWH)	1 hour	10980.69	2236.20	2469.20	20944.47	Yes
	2 hours	11056.48	2263.49	4887.61	21046.35	Yes
	4 hours	11244.58	2232.82	7273.32	20795.55	Yes
South load (MWH)	1 hour	3418.35	649.78	727.52	6350.10	Yes
	2 hours	3439.32	658.10	1434.75	6118.25	Yes
	4 hours	3500.07	643.89	2196.79	6338.35	Yes
West load (MWH)	1 hour	2597.15	330.57	621.14	3944.80	Yes
	2 hours	2610.61	331.27	1236.92	3865.85	Yes
	4 hours	2630.33	326.52	1827.30	3918.43	Yes
Nuclear generation (MWH)	1 hour	4433.45	840.00	947.00	5187.30	Yes
	2 hours	4440.30	827.16	1347.15	5185.85	Yes
	4 hours	4441.73	823.31	1745.60	5184.50	Yes
Wind generation (MWH)	1 hour	4133.97	2105.11	42.70	9639.20	Yes
	2 hours	4167.54	2030.74	51.15	9290.10	Yes
	4 hours	4180.57	1996.24	70.56	9287.90	Yes

Panel D: Discharge – West

Variable	Duration	Mean	Standard deviation	Minimum	Maximum	Stationary?
Houston load (MWH)	1 hour	11929.09	3077.67	6363.92	18189.52	Yes
	2 hours	11798.49	3137.46	6398.08	18237.26	Yes
	4 hours	11782.95	3001.16	6722.62	18081.56	Yes
North load (MWH)	1 hour	16850.82	4595.78	8219.33	27847.23	Yes
	2 hours	16598.37	4710.84	8116.18	27873.84	Yes
	4 hours	16534.96	4547.82	8565.05	27712.43	Yes
South load (MWH)	1 hour	5153.92	1345.59	2527.66	8138.00	Yes
	2 hours	5078.42	1380.92	2483.36	8092.00	Yes
	4 hours	5072.70	1311.29	2780.57	8021.25	Yes
West load (MWH)	1 hour	3335.30	607.50	2013.62	4775.00	Yes
	2 hours	3300.41	621.09	1997.76	4774.00	Yes
	4 hours	3289.03	599.69	2042.25	4750.00	Yes
Nuclear generation (MWH)	1 hour	4451.90	819.44	1747.61	5387.70	Yes
	2 hours	4451.40	819.75	1736.37	5384.60	Yes
	4 hours	4448.61	820.06	1557.33	5374.67	Yes
Wind generation (MWH)	1 hour	3224.68	2095.46	89.94	9485.73	Yes
	2 hours	3217.59	2075.95	110.57	9417.72	Yes
	4 hours	3169.67	1959.05	89.31	9370.61	Yes

Table 5: Descriptive statistics for daily profit drivers under perfect foresight by charge/discharge duration for the 46-month period of 01/01/2011 – 10/31/2014; unit root test results for data stationarity at the 1% level are based on the Phillips-Perron tests (Phillips and Perron, 1988)

Panel A: Charge – Houston

Variable	Duration	Mean	Standard deviation	Minimum	Maximum	Stationary?
Henry Hub natural gas price ($/MMBTU)	All	3.70	0.81	1.82	8.15	No
Houston load (MWH)	1 hour	11033.25	2933.83	1596.14	17817.00	Yes
	2 hours	11021.47	2902.17	4063.73	17706.45	Yes
	4 hours	9915.98	2080.40	5238.22	15795.50	Yes
North load (MWH)	1 hour	15364.16	4401.65	2469.20	26511.48	Yes
	2 hours	15357.97	4363.72	6272.74	26418.63	Yes
	4 hours	13641.18	3187.79	7409.20	22443.75	Yes
South load (MWH)	1 hour	4744.64	1343.47	727.52	8074.00	Yes
	2 hours	4742.49	1331.54	1850.44	8050.50	Yes
	4 hours	4238.06	1033.93	2262.15	7291.25	Yes
West load (MWH)	1 hour	3137.78	655.22	621.14	4775.00	Yes
	2 hours	3136.24	650.60	1567.87	4743.00	Yes
	4 hours	2924.63	514.82	1898.56	4344.00	Yes
Nuclear generation (MWH)	1 hour	4442.14	827.31	947.00	5390.80	Yes
	2 hours	4443.61	823.02	1529.35	5388.40	Yes
	4 hours	4445.51	819.26	1638.33	5277.50	Yes
Wind generation (MWH)	1 hour	3158.19	2016.15	42.70	9415.60	Yes
	2 hours	3122.35	1960.09	63.70	9325.70	Yes
	4 hours	3669.32	1711.27	217.30	9259.30	Yes

Panel B: Discharge – Houston

Variable	Duration	Mean	Standard deviation	Minimum	Maximum	Stationary?
Houston load (MWH)	1 hour	11870.59	2887.62	6477.91	18189.52	Yes
	2 hours	11813.28	2836.88	5960.22	18127.54	Yes
	4 hours	11703.31	2752.74	6551.97	18081.56	Yes
North load (MWH)	1 hour	16673.60	4415.55	9204.50	27900.45	Yes
	2 hours	16588.26	4346.00	9340.98	27873.84	Yes
	4 hours	16409.75	4231.87	9949.50	27712.43	Yes
South load (MWH)	1 hour	5107.31	1244.77	2564.99	8138.00	Yes
	2 hours	5081.03	1212.49	2749.81	7953.50	Yes
	4 hours	5034.38	1175.58	2829.16	7796.25	Yes
West load (MWH)	1 hour	3298.95	580.40	2189.42	4752.00	Yes
	2 hours	3286.28	566.81	2214.61	4726.00	Yes
	4 hours	3263.06	548.40	2200.13	4615.00	Yes
Nuclear generation (MWH)	1 hour	4445.56	824.38	1692.06	5377.00	Yes
	2 hours	4446.51	822.71	1708.59	5386.60	Yes
	4 hours	4445.99	822.59	1634.94	5340.12	Yes
Wind generation (MWH)	1 hour	2828.02	1989.59	18.48	9527.00	Yes
	2 hours	2829.68	1942.31	22.27	9741.90	Yes
	4 hours	2871.06	1923.04	54.77	9652.38	Yes

Panel C: Charge – West

Variable	Duration	Mean	Standard deviation	Minimum	Maximum	Stationary?
Henry Hub natural gas price ($/MMBTU)	All	3.70	0.81	1.82	8.15	No
Houston load (MWH)	1 hour	11004.87	2826.70	1596.14	17817.00	Yes
	2 hours	11008.55	2793.29	4063.73	17675.50	Yes
	4 hours	10043.63	2034.78	5238.22	16031.75	Yes
North load (MWH)	1 hour	15342.99	4226.79	2469.20	26346.08	Yes
	2 hours	15353.32	4193.73	6272.74	26417.41	Yes
	4 hours	13850.66	3101.62	7409.20	22397.75	Yes
South load (MWH)	1 hour	4740.01	1301.69	727.52	8057.00	Yes
	2 hours	4744.91	1291.26	1850.44	8063.00	Yes
	4 hours	4305.44	1011.12	2262.15	7332.50	Yes
West load (MWH)	1 hour	3136.97	630.45	621.14	4727.00	Yes
	2 hours	3136.74	627.39	1567.87	4714.00	Yes
	4 hours	2950.72	496.89	1898.56	4350.75	Yes
Nuclear generation (MWH)	1 hour	4442.34	828.71	947.00	5397.40	Yes
	2 hours	4444.12	824.72	1719.84	5388.40	Yes
	4 hours	4445.17	818.09	1733.71	5273.10	Yes
Wind generation (MWH)	1 hour	3102.81	1990.04	42.70	9483.90	Yes
	2 hours	3090.38	1942.78	73.75	9274.60	Yes
	4 hours	3735.09	1684.52	217.30	9203.82	Yes

Panel D: Discharge – West

Variable	Duration	Mean	Standard deviation	Minimum	Maximum	Stationary?
Houston load (MWH)	1 hour	11690.55	2864.37	4740.03	18189.52	Yes
	2 hours	11646.34	2810.64	5773.95	18127.54	Yes
	4 hours	11542.99	2725.74	6317.23	18081.56	Yes
North load (MWH)	1 hour	16382.38	4408.22	7306.03	27900.45	Yes
	2 hours	16328.31	4322.95	8803.96	27873.84	Yes
	4 hours	16163.75	4201.48	9017.66	27712.43	Yes
South load (MWH)	1 hour	5031.40	1246.34	2141.97	7956.00	Yes
	2 hours	5011.42	1216.60	2688.94	7883.00	Yes
	4 hours	4964.13	1181.89	2797.73	7753.75	Yes
West load (MWH)	1 hour	3263.51	585.71	1852.70	4705.00	Yes
	2 hours	3256.30	570.89	2103.04	4683.50	Yes
	4 hours	3234.46	552.39	2094.28	4590.00	Yes
Nuclear generation (MWH)	1 hour	4447.91	823.94	1725.12	5391.40	Yes
	2 hours	4448.68	821.19	1718.09	5386.60	Yes
	4 hours	4447.88	821.25	1702.59	5340.12	Yes
Wind generation (MWH)	1 hour	2720.76	1948.96	39.61	9527.00	Yes
	2 hours	2754.77	1911.88	54.91	9741.90	Yes
	4 hours	2803.79	1888.55	112.84	9652.38	Yes

Table 6: Houston profit regressions with standard errors in (   ) under the simple-rule by duration for the 46-month period of 01/01/2011 - 12/31/2014

Variables: definition	**Simple rule**			**Perfect foresight**		
	1 hour	2 hours	4 hours	1 hour	2 hours	4 hours
Total R^2	0.1689	0.2287	0.2677	0.3403	0.3806	0.3575
Root mean squared error	201.1560	169.9968	119.7606	170.5179	144.5316	108.6621
AR(1) parameter	**0.2963 (0.0262)**	**0.3753 (0.0255)**	**0.4236 (0.0249)**	**0.4791 (0.0244)**	**0.5331 (0.0235)**	**0.5365 (0.0235)**
G_d: Henry Hub natural gas price ($/MMBTU)	6.6151 (10.1787)	2.4764 (9.5586)	1.4117 (7.2298)	13.5131 (11.1141)	11.3723 (10.3307)	11.3720 (7.7605)
X_{n1d}: Houston load (MWH) in the *charge* hours	0.0043 (0.0151)	-0.0026 (0.0133)	-0.0053 (0.0095)	-0.0083 (0.0061)	-0.0067 (0.0053)	-0.0041 (0.0056)
X_{n2d}: Other regions' load (MWH) in the *charge* hours	0.0041 (0.0057)	0.0090 (0.0051)	0.0078 (0.0037)	-0.0027 (0.0028)	-0.0014 (0.0024)	0.0005 (0.0025)
X_{n3d}: Nuclear generation (MWH) in the *charge* hours	0.0456 (0.0299)	0.0138 (0.0291)	0.0276 (0.0234)	0.0199 (0.0194)	0.0116 (0.0178)	0.0081 (0.0165)
X_{n4d}: Wind generation (MWH) in the *charge* hours	0.0033 (0.0033)	0.0041 (0.0030)	0.0036 (0.0022)	0.0023 (0.0025)	0.0023 (0.0022)	0.0015 (0.0020)
X_{n5d}: Houston load (MWH) in the *discharge* hours	0.0098 (0.0073)	0.0128 (0.0063)	0.0110 (0.0047)	0.0042 (0.0060)	0.0058 (0.0053)	0.0051 (0.0044)
X_{n6d}: Other regions' load (MWH) in the *discharge* hours	0.0069 (0.0036)	0.0040 (0.0032)	0.0022 (0.0024)	0.0056 (0.0027)	0.0046 (0.0024)	0.0027 (0.0021)
X_{n7d}: Nuclear generation (MWH) in the *discharge* hours	-0.0462 (0.0305)	-0.0172 (0.0294)	-0.0301 (0.0234)	-0.0172 (0.0198)	-0.0121 (0.0179)	-0.0085 (0.0162)
X_{n8d}: Wind generation (MWH) in the *discharge* hours	**-0.0128 (0.0033)**	**-0.0107 (0.0028)**	**-0.0072 (0.0021)**	-0.0048 (0.0025)	-0.0032 (0.0021)	-0.0026 (0.0016)

Note: **Bold** font indicates 1% statistical significance. For brevity, this table does not report the time-dependent intercept estimates, which are highly significant (p-value < 0.0001).

Table 7: North profit regressions with standard errors in (   ) under the simple-rule by duration for the 46-month period of 01/01/2011 - 12/31/2014

Variables: definition	**Simple rule**			**Perfect foresight**		
	1 hour	2 hours	4 hours	1 hour	2 hours	4 hours
Total R^2	0.2137	0.2139	0.3091	0.3994	0.4265	0.3950
Root mean squared error	192.8563	156.9350	113.9112	155.2016	135.1232	103.6418
AR(1) parameter	**0.3031** **(0.0261)**	**0.3240** **(0.0260)**	**0.4392** **(0.0247)**	**0.5473** **(0.0233)**	**0.5857** **(0.0225)**	**0.5739** **(0.0227)**
G_d: Henry Hub natural gas price ($/MMBTU)	11.9606 (9.9591)	6.1499 (8.3379)	4.4939 (7.0781)	14.9578 (11.2168)	12.7957 (10.5201)	11.3105 (7.8702)
X_{n1d}: North load (MWH) in the *charge* hours	**0.0471** **(0.0071)**	**0.0210** **(0.0059)**	**0.0246** **(0.0043)**	0.0027 (0.0035)	0.0029 (0.0032)	0.0049 (0.0033)
X_{n2d}: Other regions' load (MWH) in the *charge* hours	**-0.0443** **(0.0086)**	-0.0124 (0.0073)	**-0.0194** **(0.0054)**	-0.0077 (0.0034)	-0.0058 (0.0031)	-0.0038 (0.0032)
X_{n3d}: Nuclear generation (MWH) in the *charge* hours	0.0786 (0.0318)	0.0142 (0.0243)	0.0353 (0.0215)	0.0175 (0.0177)	0.0112 (0.0165)	0.0081 (0.0153)
X_{n4d}: Wind generation (MWH) in the *charge* hours	**0.0099** **(0.0033)**	0.0039 (0.0028)	0.0051 (0.0020)	0.0019 (0.0023)	0.0015 (0.0020)	0.0010 (0.0019)
X_{n5d}: North load (MWH) in the *discharge* hours	0.0015 (0.0046)	0.0086 (0.0037)	0.0023 (0.0028)	**0.0093** **(0.0034)**	0.0066 (0.0031)	0.0051 (0.0026)
X_{n6d}: Other regions' load (MWH) in the *discharge* hours	0.0116 (0.0051)	0.0027 (0.0041)	0.0059 (0.0032)	-0.0007 (0.0036)	0.0003 (0.0034)	-0.0006 (0.0029)
X_{n7d}: Nuclear generation (MWH) in the *discharge* hours	-0.0794 (0.0326)	-0.0158 (0.0245)	-0.0374 (0.0215)	-0.0131 (0.0183)	-0.0108 (0.0168)	-0.0083 (0.0150)
X_{n8d}: Wind generation (MWH) in the *discharge* hours	**-0.0151** **(0.0034)**	**-0.0097** **(0.0026)**	**-0.0076** **(0.0020)**	-0.0050 (0.0022)	-0.0032 (0.0020)	-0.0026 (0.0016)

Note: **Bold** font indicates 1% statistical significance. For brevity, this table does not report the time-dependent intercept estimates, which are highly significant (p-value < 0.0001).

Table 8: South profit regressions with standard errors in ( ) under the simple-rule by duration for the 46-month period of 01/01/2011 - 12/31/2014

Variables: definition	**Simple rule**			**Perfect foresight**		
	1 hour	2 hours	4 hours	1 hour	2 hours	4 hours
Total R^2	0.2372	0.2445	0.3712	0.3935	0.4370	0.4421
Root mean squared error	191.7693	155.0931	111.8135	163.5228	140.2076	104.7782
AR(1) parameter	**0.3776 (0.0255)**	**0.3796 (0.0255)**	**0.5191 (0.0235)**	**0.5521 (0.0233)**	**0.6071 (0.0222)**	**0.6329 (0.0215)**
G_d: Henry Hub natural gas price ($/MMBTU)	3.4564 (11.0360)	13.8373 (8.8728)	7.2146 (7.9762)	19.7803 (12.2029)	17.4524 (11.6052)	12.8002 (9.0948)
X_{n1d}: South load (MWH) in the *charge* hours	**0.0754 (0.0268)**	-0.0105 (0.0201)	**-0.0833 (0.0171)**	0.0032 (0.0135)	-0.0019 (0.0119)	0.0071 (0.0115)
X_{n2d}: Other regions' load (MWH) in the *charge* hours	-0.0031 (0.0048)	-0.0019 (0.0039)	**0.0174 (0.0030)**	-0.0032 (0.0024)	-0.0006 (0.0022)	0.0007 (0.0022)
X_{n3d}: Nuclear generation (MWH) in the *charge* hours	-0.0072 (0.0275)	0.0241 (0.0214)	0.0253 (0.0207)	0.0106 (0.0184)	0.0123 (0.0171)	0.0120 (0.0158)
X_{n4d}: Wind generation (MWH) in the *charge* hours	0.0043 (0.0029)	0.0029 (0.0024)	0.0028 (0.0020)	0.0006 (0.0024)	0.0010 (0.0021)	0.0002 (0.0019)
X_{n5d}: South load (MWH) in the *discharge* hours	-0.0318 (0.0174)	-0.0013 (0.0132)	**0.0414 (0.0119)**	-0.0024 (0.0133)	0.0028 (0.0123)	0.0008 (0.0100)
X_{n6d}: Other regions' load (MWH) in the *discharge* hours	**0.0145 (0.0029)**	**0.0124 (0.0023)**	0.0016 (0.0019)	**0.0068 (0.0024)**	0.0052 (0.0021)	0.0034 (0.0017)
X_{n7d}: Nuclear generation (MWH) in the *discharge* hours	0.0021 (0.0282)	-0.0211 (0.0218)	-0.0247 (0.0208)	-0.0024 (0.0189)	-0.0078 (0.0173)	-0.0087 (0.0155)
X_{n8d}: Wind generation (MWH) in the *discharge* hours	**-0.0137 (0.0030)**	**-0.0100 (0.0023)**	**-0.0072 (0.0020)**	-0.0054 (0.0023)	-0.0035 (0.0020)	-0.0024 (0.0015)

Note: **Bold** font indicates 1% statistical significance. For brevity, this table does not report the time-dependent intercept estimates, which are highly significant (p-value < 0.0001).

Table 9: West profit regressions with standard errors in (   ) under the simple-rule by duration for the 46-month period of 01/01/2011 - 12/31/2014

Variables: definition	**Simple rule**			**Perfect foresight**		
	1 hour	2 hours	4 hours	1 hour	2 hours	4 hours
Total R^2	0.1976	0.2445	0.2852	0.3790	0.4081	0.3703
Root mean squared error	200.2970	172.6897	121.2331	160.5290	139.4003	108.1310
AR(1) parameter	**0.2985 (0.0262)**	**0.3616 (0.0256)**	**0.4087 (0.0250)**	**0.5043 (0.0239)**	**0.5455 (0.0231)**	**0.5201 (0.0235)**
G_d: Henry Hub natural gas price ($/MMBTU)	-0.7182 (10.6114)	-0.1790 (9.9759)	0.5368 (7.5207)	23.4113 (11.1307)	20.0689 (10.4049)	17.7264 (7.6928)
X_{n1d}: West load (MWH) in the *charge* hours	-0.0587 (0.0562)	-0.0875 (0.0518)	-0.0696 (0.0398)	**-0.0858 (0.0287)**	**-0.0823 (0.0261)**	**-0.0827 (0.0267)**
X_{n2d}: Other regions' load (MWH) in the *charge* hours	**0.0135 (0.0049)**	**0.0134 (0.0043)**	**0.0085 (0.0032)**	0.0024 (0.0022)	0.0029 (0.0020)	0.0042 (0.0021)
X_{n3d}: Nuclear generation (MWH) in the *charge* hours	0.0093 (0.0240)	0.0026 (0.0292)	0.0005 (0.0216)	0.0213 (0.0181)	0.0123 (0.0168)	0.0132 (0.0175)
X_{n4d}: Wind generation (MWH) in the *charge* hours	**0.0101 (0.0033)**	**0.0079 (0.0031)**	**0.0075 (0.0022)**	0.0053 (0.0024)	0.0046 (0.0022)	0.0035 (0.0021)
X_{n5d}: West load (MWH) in the *discharge* hours	-0.0035 (0.0429)	0.0083 (0.0385)	0.0014 (0.0298)	-0.0326 (0.0289)	-0.0239 (0.0265)	-0.0237 (0.0233)
X_{n6d}: Other regions' load (MWH) in the *discharge* hours	0.0083 (0.0033)	0.0074 (0.0029)	**0.0065 (0.0023)**	**0.0077 (0.0022)**	**0.0069 (0.0020)**	**0.0058 (0.0017)**
X_{n7d}: Nuclear generation (MWH) in the *discharge* hours	-0.0175 (0.0250)	-0.0090 (0.0295)	-0.0072 (0.0217)	-0.0223 (0.0186)	-0.0158 (0.0171)	-0.0163 (0.0170)
X_{n8d}: Wind generation (MWH) in the *discharge* hours	**-0.0201 (0.0034)**	**-0.0154 (0.0029)**	**-0.0134 (0.0022)**	**-0.0083 (0.0024)**	-0.0050 (0.0021)	**-0.0049 (0.0017)**

Note: **Bold** font indicates 1% statistical significance. For brevity, this table does not report the time-dependent intercept estimates, which are highly significant (p-value < 0.0001).

Table 10: Estimated changes in per MWH profits by region and duration due to wind generation development with standard errors in ( ) for the 46-month period of 01/01/2011 - 12/31/2014

Panel A: Simple rule

New Capacity	**Houston**			**North**			**South**			**West**		
	1 hour	2 hours	4 hours	1 hour	2 hours	4 hours	1 hour	2 hours	4 hours	1 hour	2 hours	4 hours
1 MW	-0.0025 (0.0012)	-0.0016 (0.0010)	-0.0007 (0.0007)	-0.0007 (0.0011)	-0.0014 (0.0010)	-0.0003 (0.0007)	-0.0024 (0.0011)	-0.0018 (0.0010)	-0.0010 (0.0007)	-0.0021 (0.0011)	-0.0015 (0.0019)	-0.0010 (0.0007)
313 MW	-0.7885 (0.3624)	-0.5002 (0.3157)	-0.2338 (0.2234)	-0.2205 (0.3392)	-0.4330 (0.2977)	-0.1054 (0.2073)	-0.7543 (0.3511)	-0.5719 (0.3055)	-0.3243 (0.2054)	-0.6567 (0.3544)	-0.4734 (0.6078)	-0.3166 (0.2324)
5000 MW	-12.5962 (5.7888)	-7.9903 (5.0423)	-3.7348 (3.5682)	-3.5228 (5.4178)	-6.9165 (4.7553)	-1.6843 (3.3117)	-12.0499 (5.6091)	-9.1353 (4.8807)	-5.1798 (3.2816)	-10.4903 (5.6612)	-7.5630 (9.7096)	-5.0577 (3.7117)

Panel B: Perfect foresight

New Capacity	**Houston**			**North**			**South**			**West**		
	1 hour	2 hours	4 hours	1 hour	2 hours	4 hours	1 hour	2 hours	4 hours	1 hour	2 hours	4 hours
1 MW	-0.0005 (0.0012)	-0.0001 (0.0011)	-0.0002 (0.0009)	-0.0008 (0.0011)	-0.0004 (0.0010)	-0.0004 (0.0008)	-0.0014 (0.0012)	-0.0006 (0.0010)	-0.0006 (0.0008)	-0.0004 (0.0012)	0.0003 (0.0011)	-0.0001 (0.0009)
313 MW	-0.1703 (0.3912)	-0.0238 (0.3413)	-0.0610 (0.2695)	-0.2353 (0.3572)	-0.1178 (0.3180)	-0.1232 (0.2560)	-0.4256 (0.3700)	-0.2019 (0.3274)	-0.1940 (0.2559)	-0.1382 (0.3763)	0.0878 (0.3377)	-0.0256 (0.2775)
5000 MW	-2.7205 (6.2488)	-0.3804 (5.4524)	-0.9744 (4.3052)	-3.7593 (5.7061)	-1.8813 (5.0800)	-1.9676 (4.0896)	-6.7980 (5.9101)	-3.2255 (5.2308)	-3.0988 (4.0881)	-2.2082 (6.0119)	1.4022 (5.3949)	-0.4091 (4.4329)

Note: **Bold** font indicates 1% statistical significance.

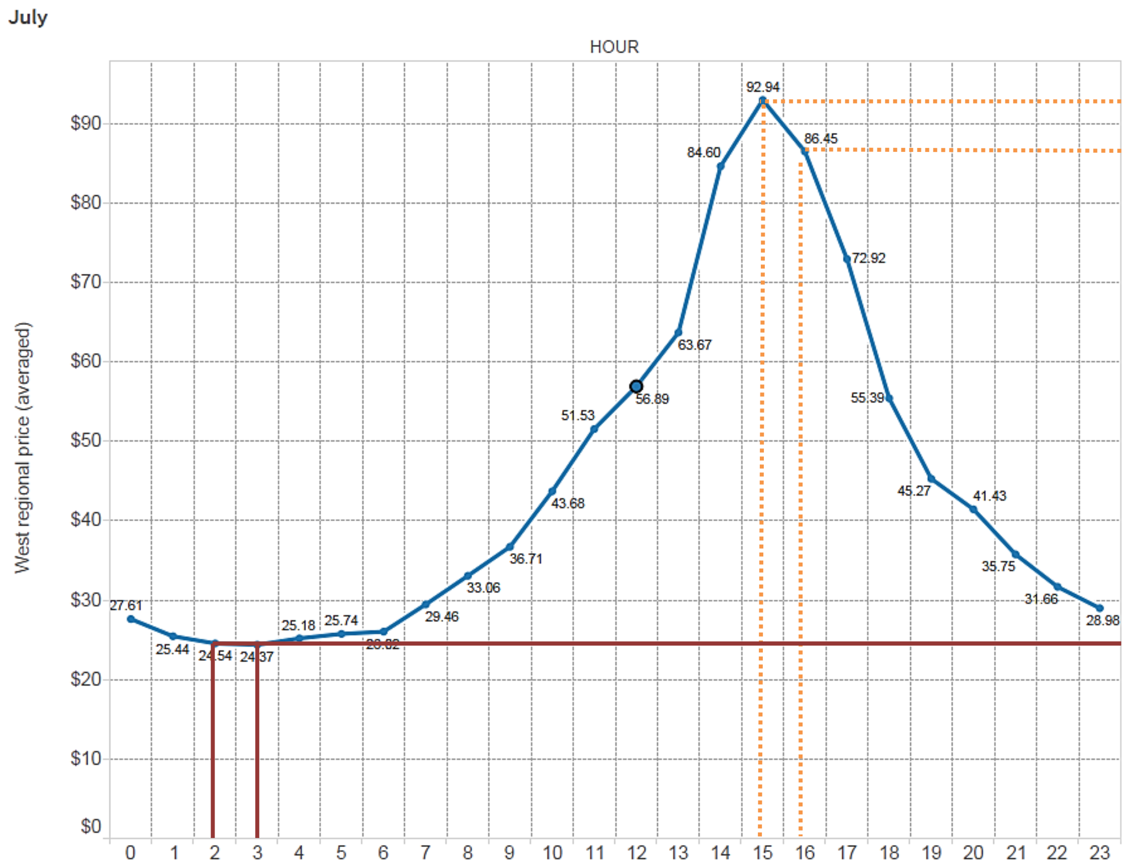

Figure 1: The charge (indicated by the solid lines) and discharge period (indicated by the dotted lines) definitions for the Houston region in July under the simple rule in the 46-month sample period of 01/01/2011 – 10/31/2014

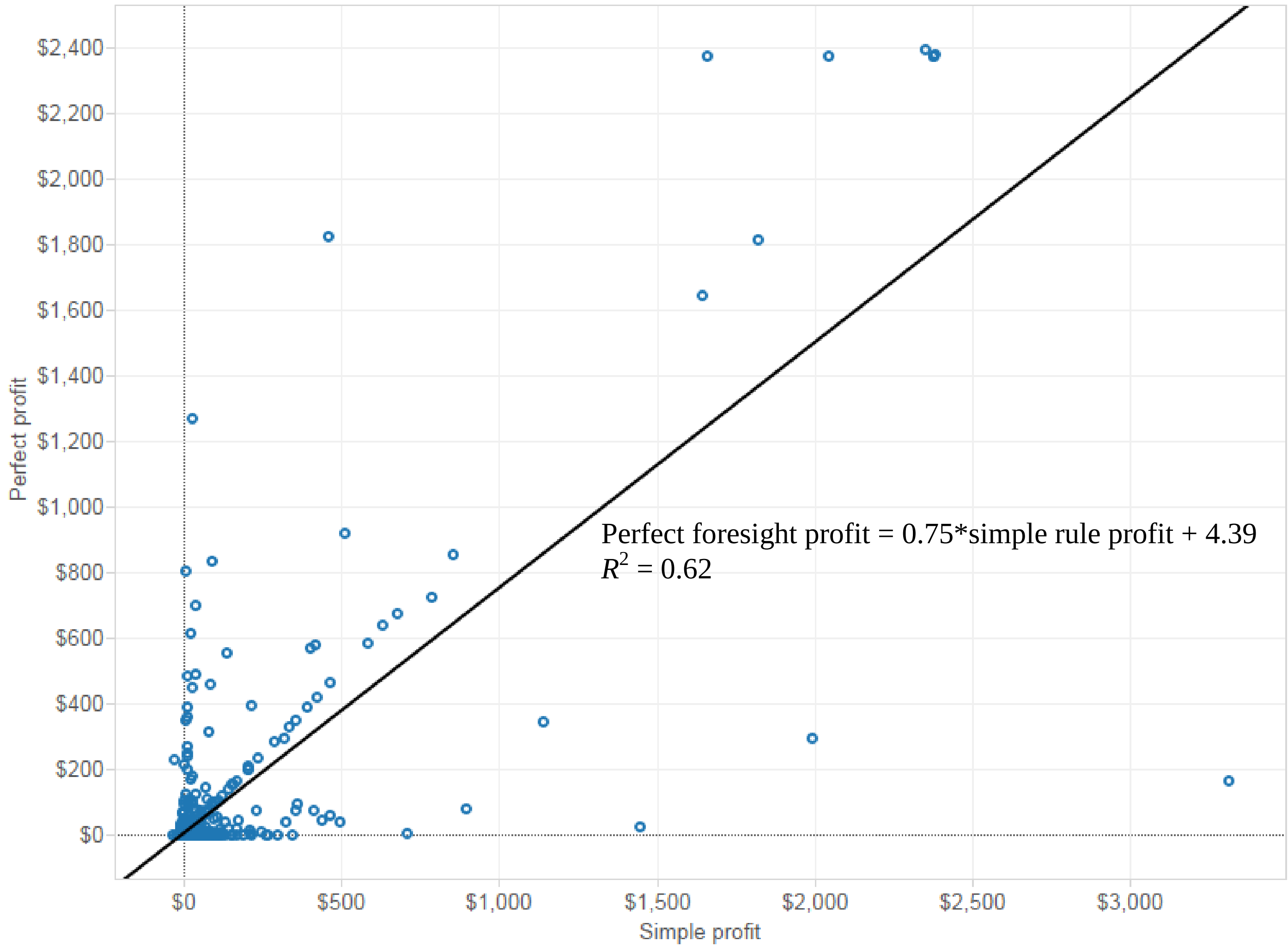

Figure 2: Simple rule profit (horizontal axis) vs. perfect foresight profit (vertical axis) for the Houston region of 1 hour's charge and discharge under the simple rule in the 46-month sample period of 01/01/2011 – 10/31/2014

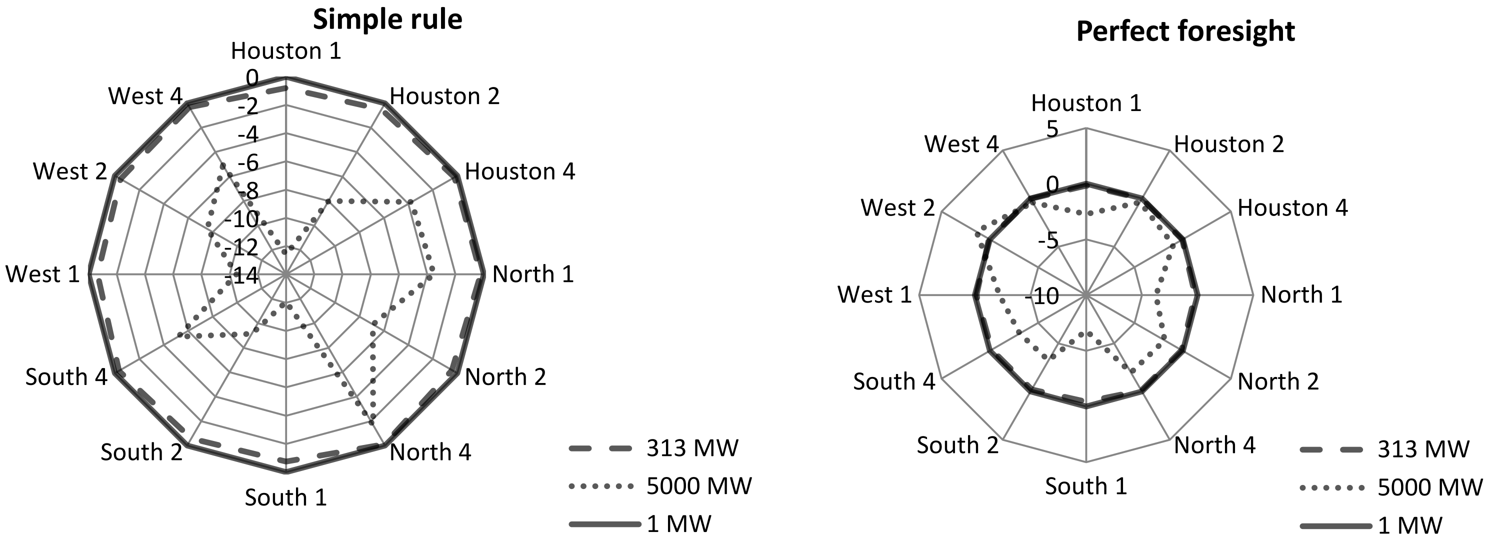

Figure 3: Estimated changes in per MWH profits by region and duration due to wind generation development by region in the 46-month sample period of 01/01/2011 – 10/31/2014