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FLEXIBLE RESERVE MARKETS FOR WIND INTEGRATION

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by

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ABSTRACT

The increased interconnection of variable generation has motivated the use of improved forecasting to more accurately predict future production with the purpose to lower total system costs for balancing when the expected output exceeds or falls short of the actual output. Forecasts are imperfect, and the forecast errors associated with utility-scale generation from variable generators need new balancing capabilities that cannot be handled by existing ancillary services. Our work focuses on strategies for integrating large amounts of wind generation under the flex reserve market, a market that would called upon for short-term energy services during an under or oversupply of wind generation to maintain electric grid reliability. The flex reserve market would be utilized for time intervals that fall in-between the current ancillary services markets that would be longer than second-to-second energy services for maintaining system frequency and shorter than reserve capacity services that are called upon for several minutes up to an hour during an unexpected contingency on the grid. In our work, the wind operator would access the flex reserve market as an energy service to correct for unanticipated forecast errors, akin to paying the generators participating in the market to increase generation during a shortfall or paying the other generators to decrease generation during an excess of wind generation. Such a market does not currently exist in the Mid-Atlantic United States. The Pennsylvania-New Jersey-Maryland Interconnection (PJM) is the Mid-Atlantic electric grid case study that was used to examine if a flex reserve market can be utilized for integrating large capacities of wind generation in a low-cost manner for those providing, purchasing and dispatching these short-term balancing services.

The following work consists of three studies. The first examines the ability of a hydroelectric facility to provide short-term forecast error balancing services via a flex reserve market, identifying the operational constraints that inhibit a multi-purpose dam facility to meet
the desired flexible energy demand. The second study transitions from the hydroelectric facility as the decision maker providing flex reserve services to the wind plant as the decision maker purchasing these services. In this second study, methods for allocating the costs of flex reserve services under different wind policy scenarios are explored that aggregate farms into different groupings to identify the least-cost strategy for balancing the costs of hourly day-ahead forecast errors. The least-cost strategy may be different for an individual wind plant and for the system operator, noting that the least-cost strategy is highly sensitive to cost allocation and aggregation schemes. The latter may also cause cross-subsidies in the cost for balancing wind forecast errors among the different wind farms. The third study builds from the second, with the objective to quantify the amount of flex reserves needed for balancing future forecast errors using a probabilistic approach (quantile regression) to estimating future forecast errors. The results further examine the usefulness of separate flexible markets PJM could use for balancing oversupply and undersupply events, similar to the regulation up and down markets used in Europe. These three studies provide the following results and insights to large-scale wind integration using actual PJM wind farm data that describe the markets and generators within PJM.

- Chapter 2 provides an in-depth analysis of the valuable, yet highly-constrained, energy services multi-purpose hydroelectric facilities can provide, though the opportunity cost for providing these services can result in large deviations from the reservoir policies with minimal revenue gain in comparison to dedicating the whole of dam capacity to providing day-ahead, baseload generation.

- Chapter 3 quantifies the system-wide efficiency gains and the distributive effects of PJM’s decision to act as a single balancing authority, which means that it procures
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- Chapter 4 uses probabilistic methods to estimate the uncertainty in the forecast errors and the quantity of energy needed to balance these forecast errors at a certain percentile. Current practice is to use a point forecast that describes the conditional expectation of the dependent variable at each time step. The approach here uses quantile regression to describe the relationship between independent variable and the conditional quantiles (equivalently the percentiles) of the dependent variable. An estimate of the conditional density is performed, which contains information about the covariate relationship of the sign of the forecast errors (negative for too much wind generation and positive for too little wind generation) and the wind power forecast. This additional knowledge may be implemented in the decision process to more accurately schedule day-ahead wind generation bids and provide an example for using separate markets for balancing an oversupply and undersupply of generation. Such methods are currently used for coordinating large footprints of wind generation in Europe.
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Table 4. This table lists quantile regression and ordinary least squares regression coefficients as labeled in the top column for distinct quantiles at tau = 0.10, 0.30, 0.60 and 0.90. An asterisk denotes whether the value of the coefficient is significantly different that zero at the 5% significance level with an asterisk. The plus sign is used to denote when the quantile regression coefficient value is significantly different than the OLS regression coefficient at the 5% significance level. If the confidence interval for the quantile regression coefficient lies outside of the OLS regression coefficient, or equivalently, if the OLS regression confidence interval does not contain the quantile regression coefficient value, then there is significant difference between the quantile regression and OLS regression coefficients at the 5% significance level. Results are for farm 1 in the Appalachia region (see Figure 25 for a visual representation). 105

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Chapter 1

Introduction

Utility-scale wind capacity installation in the United States now reaches 50 gigawatts, totaling more than 20% of the world’s installed wind capacity [1]. Variability from a large quantity of wind capacity will require larger amounts of reserve energy to balance supply and demand mismatches. Forecasts of expected wind power output help to alleviate the impact of shortfalls or over generation of actual generation from expected generation [2]. The imperfect nature of forecasts will become a crucial factor as forecasts will be implemented to improve the coordination of conventional generation units and wind turbines [3]. An incorrect wind power forecast can lead to imbalance costs [4], motivating wind utilities to seek strategies that will reduce imbalance costs and increase potential revenue. Errors in a forecast predicting the output from a growing amount of wind capacity will inevitably require larger amounts of reserve-type services. These reserve-type services will need to be provided by operationally flexible generation units that are often control area specific [5].

1.1 Review of imbalance deviation practices

In 2007, two types of imbalance charges were applied to wind operators under Federal Energy Regulatory Commission (FERC) Order 890. If the imbalances (over or under) are less than 1.5% of the scheduled energy or 2 MW, whichever is larger, it will be netted out on a monthly basis and settled at incremental or decremental cost [6]. If the imbalance is due to an oversupply of wind generation, the operator would receive a payment and if the imbalance occurs due to an undersupply the operator is charged depending upon the sign of the netted energy.
When the hourly imbalance is outside the 1.5% band, the wind operators will receive an additional payment equal to the amount of the imbalance over 1.5% multiplied by 90% of the energy price for the hour for oversupply. During undersupply periods, wind operators will be charged an amount equal to the imbalance outside the deviation band multiplied by 110% of the energy price for the hour [6]. However, FERC states that the typical charge amount is the greater of $100/MWh or the control area’s incremental cost of dispatching supplemental energy to compensate for the undersupply (110% rule). Since the charge amount based on the 110% rule is usually smaller than $100/MWh, operators pay the latter [4]. Imbalance charges based on the actual costs of the generation imbalance or market price provide incentives for accurate forecasting [5]. The wind forecast in our model however is exogenous.

Depending on the control area, wind operators may incur imbalance charges based on the differential of expected generation to actual generation, similar to the FERC order rules (see [7] for further explanation for imbalance settlement protocols in the US control areas). As of 2011, imbalance differentials greater than the 5% or 5W bandwidth from the scheduled and actual energy delivery mean a charge to the operator in PJM [7]. Higher imbalance charges (at times as high as $20/MWh) may greatly reduce profits for wind operators as larger amounts of wind capacity enter in the supply side. One strategy PJM is exploring would be to base the imbalance charges on the deviation from the forecast of wind power output. Wind operators can adjust their bid up to one hour before dispatch and if they commit to that adjusted bid they can avoid any penalty charge [3].

The Pacific Northwest possesses a large capacity of hydro and wind capacity, and has implemented wind integration policies to better co-manage these generation assets. As of 2011, BPA lowered its imbalance fee from $12/MWh to $5.70/MWh after legal discussion of the rate,
though BPA remained skeptical if the original rate would hinder wind operator profits and challenge the state’s capability of maintaining their renewable portfolio standards [8]. I will be applying the $5.70/MWh imbalance charge as the flat rate for expected costs from the uncertain forecast error portion of our model. The imbalance charge will be assessed if the differential is greater than 5% or 5MW. Future work may test the FERC-based rules for imbalance charges less than 1.5% and between 1.5% to 7.5% to evaluate how the FERC and the PJM penalty bandwidth structure differently impact operators’ decisions to provide or purchase flex reserves from a portfolio of other revenue-generating or cost-minimizing options. I hypothesize that the wind operator will likely take the penalty of $5.70 per MWh because the marginal cost for a gas plant alone would be at least ten times as large. I will perform a sensitivity analysis of a range of imbalance charge prices to observe changes in the decision to buy flex reserve capacity.

The Midwest Independent System Operator (MISO) in 2011 implemented a Dispatchable Intermittent Resource (DIR) program where wind can fully participate in the five-minute real-time dispatch market[5], [9]. The DIR program will use the forecasted maximum output of the wind generator at ten-min-ahead intervals to dispatch wind [10]. Thus, the wind operator can adjust its maximum available output forecast up to 10 minutes prior to each interval. The DIR is expected to provide its own forecast, and if it is not submitted in time the five-minute interval MISO forecast will be used [10]. The intent is, by 2013, that all wind resources (more than 1,000 MW) will be covered under the DIR program [9].

1.2 Flex reserve market concept

Installing low-carbon resources such as solar and wind facilities provide emissions-free electricity, but the intrinsic variability in generation coupled with the uncertainty in forecasts
require available, fast-ramping generators to balance the supply to meet electricity demand. The rules surrounding the integration of variable energy resources (VERs) varies globally, and many countries have made significant strides to accommodate large-scale deployment of VERs. Given that the focus of this dissertation is wind generation, a majority of the dissertation will discuss market mechanisms used for integrating utility-scale wind capacity. This section will discuss the concept of a flex reserve energy product, and how other balancing authorities in the United States are currently implementing sophisticated programs designed around the variability of wind and solar assets.

Anti-correlation in the general peak patterns between wind power and electricity demand prompt the need for alternative market designs that are used for following the variability structure that is unique to wind generators. Load or electricity demand generally has a diurnal pattern with a morning and early evening peak, while wind speeds typically peak in the late evening hours (see [11] for further discussion of the mismatch in wind power and load peaks). In a balancing authority area such as PJM, real-time markets can be used to follow load fluctuations, which would not coincide with wind variability peaks.

In addition to the different load-following and wind-following markets, wind power can fluctuate rapidly at short timescales, which motivates the need for electricity markets that recognize the short-term variability. Wind power output can change sub-hourly, which would mean a real-time market that is cleared hourly may not be able to compensate for sub-hourly deviations. The system operator may need a different market designed for dispatching generators sub-hourly to smooth these short-term deviations as well as a market that utilizes forecast tools for anticipating uncertainty in variable generation. Deviating from the forecasted schedule in real-time could result in penalties for exceeding or falling short, so accurate forecasts in combination
with determining the economic dispatch at shorter time intervals than an hour may benefit variable generators and the system operator.

As mentioned in section 1.1, balancing authorities are launching new markets to incorporate large footprints of wind generation. The Midwest ISO is implementing a five-minute real-time market for variable resources like wind and solar that requires forecast of production ten minutes in advance, which differs from the standard real-time energy market for controllable assets [12]. These dispatchable intermittent resources (DIRs) provide 12 five-minute forecasts, and will be paid based on the maximum limit of its forecasted generation in real time. This market differs from the traditional MISO real-time market that dispatches conventional generators hourly and requires an hourly forecast of generation a half hour in advance of the operating hour. Since a wind plant is not considered controllable or dispatchable by MISO’s standards, it cannot bid into the real-time market but it can participate in the day-ahead market [12].

In the Mid-Atlantic region of the United States, PJM uses a combination of the real-time and ancillary service markets for smoothing supply deviations. The PJM footprint includes far less wind capacity than MISO, however electricity generated by variable assets is projected to increase [13]. Wind generators may participate in the real-time and day-ahead markets, and no variable generator market exists similar to that for DIRs in MISO. Currently, PJM would rely on the real-time approach for balancing deviations hour to hour, which may result in high prices during peak-load periods. Markets for ancillary services in PJM were originally designed to provide backup services (1) in the event that an unexpected power outage or transmission line congestion in the electrical grid occurs (synchronized reserves), and (2) to maintain the system frequency at 60 hertz (frequency regulation). A flex-reserve market is a market that does not exist in PJM.
In 2011, the California Independent System Operator (CAISO) has implemented a flexible ramping constraint that utilizes fast-ramping generators at the five-minute interval, and participating resources are paid based on the opportunity cost of the marginal unit that is dispatched to resolve the ramping constraint [14]. Generators may allocate the remaining portion of their capacity for this flexible ramping service that is not already allocated to regulation and reserve services. Capacity dedicated to the flexible-ramping service is designed for generators with the ramping capability that can smooth any imbalances that occur after the fifteen-minute unit commitment process or pre-dispatch and before the real-time unit commitment, targeting this vulnerable five-minute interval [15]. Current plans are to use the flexible-ramping constraint for providing upward-ramping capacity, though downward-ramping capability could be committed. This flexible-ramping constraint, when applied to the context of a hydroelectric facility as the marginal unit, could result in high opportunity costs if dedicating capacity for this service requires substantial deviations from the release schedule (see Chapter 2 for further discussion). Upward flexible-ramping capacity may be used for correcting for intra-hourly imbalances from wind power forecast errors, similar to our problem that utilizes the flex reserve market for balancing wind power forecast errors.

The flex-reserve market is a mechanism that can be used to access short-term reserves energy at a time interval longer than the existing ancillary services regulation market and for a shorter duration than the ancillary services synchronized reserves market in PJM. Since this market does not currently exist, there are no precise rules if generators would be required to submit a forecast of production or at what time interval this would need to be submitted, in contrast to MISO’s five-minute DIR market forecast rules.

Since day-ahead forecast data are used for the PJM wind farm case study, the wind plant would access the flex-reserve market to correct for forecast errors that occur based on the
difference between the actual supply and the day-ahead schedule. Thus, the wind operator would use a day-ahead forecast of generation and correct for day-ahead forecast errors (see section 1.3 for a description of the forecast data used in our case study). The existing PJM frequency regulation prices ($/MWh) are used as a proxy for the price a flex-reserve provider would be paid, and, equivalently, the price a wind plant would pay for purchasing flex-reserve energy services. During an unexpected undersupply of generation, the wind plant would pay for short-term flex-reserve energy services to fill-in by increasing generation to balance the portion of the day-ahead forecast that was unmet. The undersupply flex-reserve services are similar to the upward flexible-ramping capacity product in the California ISO, though price is not based on the marginal unit’s opportunity cost. When an oversupply of generation occurs, the wind plant would be paid by the flex-reserve participants to decrease generation, provided it is operating at a set point greater than zero to be able to decrease by the amount of the energy that exceeded the forecast. Again, the downward flexible-ramping capacity product would be similar to using flex reserves during an oversupply event. Each chapter implements the flex-reserve market to examine the impact of large-scale wind integration in the PJM territory.

1.3 Description of hydrological, price and load data for Chapter 2

The following sections will provide an overview of the subset of the data implemented in each chapter for analyzing the flexible-ramping service in the PJM context. A description of the hydrological data that the revenue-maximizing model used for simulating flex-reserve decisions at a hydroelectric facility is provided (Chapter 2). A description of the PJM price and load data follows. Section 1.4 provides a deeper discussion of the wind data in section 1.4.
In chapter 2, the hydropower operations model uses historical data for price, electricity load, and hydrological conditions for determining the day-ahead and flex-reserve generation decisions. Chapters 3 and 4 also use the same record of hourly regulation prices as a proxy for flex-reserve market prices. The following chapters use price, hydrologic and wind data reflecting the physical system being tested within the PJM markets, namely the day-ahead, ancillary services synchronous reserves and ancillary services frequency regulation markets.

### 1.3.1 Hydrological data

USACE hydrological data records from 2006 to 2008 are used for hourly power production from the turbines, reservoir elevation, and release targets based on [16] to construct the ecosystem services guide curve at Kerr. Ecosystem services guide curve was developed by [16] that pertains to a proposed release schedule at Kerr Dam that more closely mimics the natural regime for the downstream floodplain in the Roanoke River Basin. A detailed description of the guide curves at Kerr can be found in Table 5 in the Appendix. Additionally, the year 2006 represents a hydrologic wet year, 2007 represents a dry hydrologic year and 2008 represents a sustained dry year. Typically, hotter years see higher price peaks during the summer, which may increase revenues for balancing forecast errors for a reservoir like Kerr. A statistical description of the mean, maximum and minimum properties of the PJM price and hydrological data can be found in Table 6 in the Appendix. Chapter 2 section 2.2 also provides some insights into the physical system being modeled in the multi-purpose hydroelectric facility case study.
1.3.2 Price and load data

All hourly day-ahead and regulation price data come from PJM archives from years 2006 to 2008. Hydropower scheduling decisions for committing to the next operating day use hourly PJM day-ahead prices for this three-year period. The hydroelectric facility uses electricity load data to represent local electricity demand. The load data are the aggregate of the electricity demand from the Dominion Zone of PJM and the seventy-size preference customers with low-cost water rights to Kerr generated electricity. Hourly ancillary services regulation prices ($/MWh) from 2006 to 2008 are used as a proxy for the market price the hydroelectric facility would receive for providing flex reserves. The wind plant would pay to purchase flex reserves at this price.

Monthly gas prices reported to the Energy Information Administration (EIA) were used for an alternative flex-reserve price scenario other than the regulation prices. The 2012 monthly gas prices are extracted as a proxy for hourly gas prices, where year 2012 represents the year with the lowest prices from 2002 to 2013. By using gas prices from this year, the lowest-cost gas flex-reserve scenario is estimated. Each hour in a given month has the same price as determined by the reported monthly price. Again, January through June is the representative ‘year’ in the analysis and figures to match the available forecast data.

1.4 Description of data used in Chapters 3 and 4: wind data for existing PJM farms

The next sections describe the wind data that is used for the flex-reserve market analysis in Chapters 3 and 4. Since data consist of existing farms in the PJM region, this section discusses the different attributes of the data at these farms as well as the techniques employed to determine
which data to use for the separate analyses in Chapters 3 and 4. Also briefly mentioned are the
type of wind data used in Chapter 2 initially, since the hydroelectric facility required
deterministic wind data to determine how much capacity would be dedicated for a flex-reserve service.

1.4.1 Overview of wind farm data

The full wind data set spans twenty-eight existing wind farms across six states in the PJM territory, though only twenty-four were used in this analysis (Figure 1). These data come from a PJM proprietary data set from an internal forecast model and come from actual recorded observations for these twenty-four farms. Ten farms lie in Pennsylvania, one in Maryland, one in West Virginia, two in Indiana, one in Wisconsin and nine in Illinois (Figure 1). Four farms were removed for this analysis due to an insufficient number of reported observations (two in Pennsylvania, one in Indiana and one in Illinois). The original full set for this analysis includes 51,357 five-minute sample points for twenty-four existing wind farms. The forecast intervals extend from one-hour ahead to seventy-two hours ahead. This analysis principally focuses on the twenty-four-hour-ahead forecast interval.
The analysis in chapters 2 and 3 use the aggregate hourly average actual production (MWh), day-ahead forecast of production (MW) and the forecast error (MWh) from all twenty-four farms to coincide with the time length of the hydrological and price data. The five-minute data for the actual production and day-ahead forecast of production are used to calculate the hourly average production and hourly average day-ahead forecast of production. These data are then summed to calculate the twenty-four farm aggregate. In a similar fashion, the five-minute day-ahead forecast of production and actual production data are differenced to find the five-minute forecast error, which is then averaged at the hourly time step. Later chapters may refer to the aggregate wind forecast error, which is the sum of the wind forecast error among the grouped farms at the specified time step (i.e. five minute or hourly level). In any context throughout this dissertation, the wind forecast error is the forecast of production minus the actual power at the
given time step. Actual wind power production and wind forecast data previously described at five-minute intervals are from a PJM propriety forecast and observational dataset from January to June 2010. Due to limited wind data, model simulations focus on hydroelectric operations from January to June, capturing the spawning season in the Roanoke River Basin and seasonal electricity price peaks and lows from winter to early summer.

In Chapter 4, the data include the same six-month proprietary archive of PJM historical data of the forecast of production and actual production data, but these data are used to derive the five-minute forecast error values. The forecast errors are the differences between the five-minute forecast of production and the actual production. The five-minute reported data at the twenty-four forecast time horizon are used to examine the day-in-advance forecast errors that a wind operator may see when operating based on a day-ahead schedule in PJM. Using five-minute forecast data as an input to the quantile regression in Chapter 4 provides an even finer time resolution of possible future forecast errors than at the hourly level that captures the more extreme ranges of the forecast errors at this time interval. The next sections will discuss how the twenty-four forecast interval still provides a fairly accurate prediction in comparison to the one-hour forecast using kernel density estimation at distinct forecast intervals.

1.4.2 Heteroskedasticity in the wind data

The wind forecast data used in the quantile regression in Chapter 4 possesses a range in the maximum power production output. In this work, each wind farm’s capacity is equal to its maximum power production at each time step (i.e. five-minute interval), since no capacity description was reported for each farm. The capacity of a farm is also referred to as the size of the farm. A further statistical analysis of the forecast of production and forecast error relationship
was required because there was a change in the variance of the forecast errors with the forecast of production.

The fan shape of the spread of forecast errors versus the magnitude of the forecast values in Figure 2 resembles the shape of heteroskedastic errors. Figure 2 illustrates the hourly-average data, though the same relationship persists at the five-minute level. Heteroskedasticity in the forecast errors implies that the variance of the forecast error is not constant across all ranges of the forecast.

![Figure 2](image.png)

Figure 2. This plot shows the hourly average day-ahead forecast of the wind power output (MW) and the associated hourly average day-ahead forecast error (MW) from a PJM forecast model (see section 1.4 for further description of wind data). The wind forecast errors describe positive errors when the actual generation exceeds the forecast, termed an oversupply. Negative forecast errors describe an undersupply period where the actual generation is less than the forecast. The characteristic fan shape suggests that the variance structure of the positive errors is not equal to the variance structure of the negative errors. The trend line from a linear fit differs for the positive and negative errors.

An F-test of the vector of positive and negative errors was performed under the null hypothesis that positive and negative errors have equal variance. A two-sample F-statistic is calculated to test for equal variance of the two samples of positive and negative forecast errors. The F-statistic was 1.02 for 2,751 degrees of freedom in the numerator and 1,525 degrees of freedom in the denominator. At the 5% significance level, the critical value is 1.00. In order to
reject the null hypothesis the F-statistic needed to exceed the critical value, which in this case the test statistic value failed to reject the null hypothesis. The F-test however only tests for the equality of variances between the two samples of data and does not suggest that the two data subsets have an identical distribution shape.

Additional heteroskedasticity tests were performed to further examine the heteroskedastic nature of the hourly average positive and negative forecast errors, where the average is the average across the twenty-four wind farms in the wind forecast data set (see Section 1.4.1). A chi-squared critical value of 0.103 at a significance level alpha equal to 0.05 with two degrees of freedom was used to determine if the White test statistic value was greater than critical value, which would result in rejecting the null hypothesis of homoscedasticity. The positive wind forecast error White test statistic was 0.004, and the negative wind forecast error White statistic was 0.590, indicating that the positive forecast errors result would not reject the null hypothesis but the negative forecast errors would. The number of observations for the positive forecast errors was 2,752 with the remaining 1,526 comprising the negative forecast errors. The Breusch-Pagan test results were consistent with the White test, resulting in a test statistic of 0.003 for the positive forecast errors that was not greater than the critical value and 0.547 for the negative forecast errors that was. The same number of observations and critical value were used. Further analysis will be needed to better determine the different in these test statistic results. The distributions of the positive and negative forecast errors were further examined to better understand the characteristics of the set of positive and negative forecast errors.

The historical day-ahead forecast errors were divided into positive and negative groups to examine if the distributions were symmetric (Figure 3). A histogram for the negative forecast errors is shown on the top panel with a histogram of the positive forecast errors in the bottom panel. The forecast error observations were placed into twenty equally spaced bins with the
number of observations or frequency shown as the height of each bin. The more observations in each bin the higher the bin. The vertical height of the bins in the negative forecast error histogram do not reach the same vertical height in the positive forecast error histogram, indicating there are more positive forecast error observations than negative forecast error observations. The histograms were not shown with a global vertical axis to further illustrate this point. The bins in the positive forecast error histogram also reach larger forecast error values along the horizontal axis (35 MWh is greater than the 30 MWh maximum negative forecast error associated with the left most bin). Although similar, the shapes of the distributions reflected by the positive and negative histograms do not look symmetrical. The difference in the forecast error distribution nicely compliments the motivation behind using quantile regression to examine the conditional relationship between the forecast of production and forecast errors, since quantile regression is a robust regression method with outliers and heteroskedastic data [17].
Figure 3. The top panel shows the histogram of the hourly average day-ahead negative forecast errors and the bottom panel displays the histogram for positive forecast errors. The distribution shape is somewhat similar but not the same. There are 20 bins, noting that the peak of the positive forecast error distribution reaches a taller height than the peak of the negative forecast error distribution. There are more positive observations than negative observations in this historical forecast error data set, which can impact the peak height and the width of the distribution.
1.4.3 Kernel density estimation of wind data

The non-parametric kernel density estimation technique is used to demonstrate that there is not a significant loss in the accuracy of estimating the future forecast error density as the forecast interval increases from one-hour to twenty-four hours ahead (Figure 5).

1.4.3.1 Definition of kernel density estimation

Kernel density estimation (KDE) performs a non-parametric estimation of the probability density function. The KDE technique was chosen since it limits assumptions about the distribution family and the estimated errors from the assumed distribution type. A large sample of data is needed to create the probability density, since no moments and distribution type are used. A large data set of forecast and forecast errors at the five-minute level were available that resolves the disadvantage of requiring a large data set when implementing KDE. The simplest representation of the kernel density estimation begins with a univariate kernel density estimation for a single variable. The multivariate expansion from the univariate case would include a matrix $X$ with each column $x$ representing a vector of evaluation data for the multiple variables. Equation 1.1 defines the d-dimensional multivariate estimation function $\hat{f}$ with a specified kernel function $K$ and bandwidth $H$ ($d \times d$ matrix) for sample size $N$ of data values $x_1, x_2, \ldots, x_N$, where $x$ is the evaluation point used to estimate the distribution of similarities between it and the data [18].

\[
\hat{f}(x) = \frac{1}{N|H|} \sum_{i=1}^{N} K(H^{-1}(x - x_i))
\]
The histogram represents a simple non-parametric density estimation that divides the sample space of the data into bins, requiring a starting position of the first bin and bin bandwidth to estimate the density within each bin [19]. The kernel and bandwidth analogously represent the two parameters for estimating the probability density function, where the kernel is a weighting function and the bandwidth determines the binning or smoothing of the curve that is more appropriate for estimating an unknown, continuous random variable. The weighting function described by the kernel determines the volume it contributes within the density and the sum of these volumes determines the shape of the distribution. The size of the bandwidth parameter controls over- and under-smoothing, affecting the accuracy of the estimated distribution [18].

The kernel type plays a less significant role than the bandwidth for determining the desirable smoothing. In univariate KDE, the bandwidth affects the width of the distribution, and it additionally affects the orientation of the distribution in the sample space for multivariate KDE. Determining a desirable bandwidth to avoid over- or under-smoothing the density function to more accurately capture features of the density surface such as a local maximum and a local minimum that are crucial when predicting wind power production and speed [20], [21].

For our problem, \( \hat{f} \) would be estimating the probability of the day-ahead forecast error distribution using the forecast of production as the evaluation point data, \( x \). This work uses a Gaussian kernel, though a quartic kernel was chosen to reduce computational time in [18]. Estimation of the look-ahead forecast errors using the Gaussian and quartic (biweight) kernel type showed no difference for this analysis. For the bandwidth, the cross-validation bandwidth type was chosen to better estimate possible multimodal features in the wind data, noting that this bandwidth type typically avoids over-fitting that affects the quality of the density estimation [18]. Additionally, the cross-validation bandwidth is useful for estimating multiple explanatory
variables, which would be applicable for performing future density estimations that utilize more than one explanatory variable [22].

1.4.3.2 Kernel density estimation applied to look-ahead forecast errors

This section begins by visualizing the univariate kernel density estimation of the forecast of production for distinct prediction intervals, since this research is interested in the probability of certain forecast of production levels as well as the shape and surface of the distribution as the forecast interval changes. Kernel density estimations are used to observe if there is a significant trade-off in forecast interval and accuracy. Wind production typically varies from the morning to night-time hours with wind speeds commonly stronger in the late-evening hours, though this diurnal pattern varies depending upon geography. The univariate density curves show the probability of a forecast of the production level for distinct look-ahead periods across twenty-four hours in a day, capturing wind power production variability. Figure 4 shows the univariate density of the look-ahead day-ahead forecast error using the five-minute data for a single Pennsylvania farm within the eastern half of the PJM territory. Figure 5 represents the same univariate KDE curve but for a single Illinois farm in the western portion of the PJM territory.
Figure 4. A univariate kernel density estimation for a single farm located in the Appalachia region of PJM showing the non-parametric estimation of the look-ahead forecast errors at the one, two, four, sixteen and twenty-four hour ahead intervals. Note that the structure of the distribution from the one-hour to twenty-four hour ahead estimated densities remain fairly consistent. These distributions possess a singular peak with some multi-modal variation in the ‘tail’ of the right portion of the distribution. Data used here are at the five-minute level.

In Figure 4, the mass of the estimated density curve is between zero and ten MW, with an additional smaller peak near a forecast of 40 MW of power output. For the forecast interval at sixteen hours ahead (blue) the density curve shows more varied peaks and lows in comparison to the hour-ahead density curve (red), confirming that predicting forecasts of production for later evening hours may involve higher levels of wind output variability. The sixteen-hour-ahead curve more closely resembles the twenty-four-hour ahead density shape than the one-hour-ahead density curve, though the differences in the multi-modal features of the curves are quite small for this farm in the eastern portion of PJM.

Figure 5 shows that the univariate density estimation curves are better-behaved with far less multi-modal features between the look-ahead forecast periods. These density curves do exhibit a different feature with a second peak occurring at a forecasted production level of
approximately 50 MW. The shape of the estimated density curves along different forecast look-ahead periods for this farm and the other farm shown in Figure 4 are similar but not identical.

![Kernel Density Estimation Comparison of Forecasts](image)

Figure 5. A univariate kernel density estimation for a single farm located in the Midwest region of PJM showing the non-parametric estimation of the look-ahead forecast errors at the one, two, four, sixteen and twenty-four hour ahead intervals. Note that the structure of the distribution from the one-hour to twenty-four hour ahead estimated densities remain fairly consistent. These distributions possess a singular peak with some multi-modal variation in the ‘tail’ of the right portion of the distribution. Data used here are at the five-minute level.

Each farm will possess a distinct density structure; however, from these two farms in different geographic locations the density curves during the one (red), two (green) and four (dark blue) forecast intervals possess a similar shape, with the most concentrated mass of the distribution just above zero MW. However, the overall shapes coincide quite similarly as the forecast interval increases from one to twenty-four hours ahead. The height and placement of the peaks and lows as well as the full range of the estimated density curves is similar preserved as the forecast interval changes not the density curves do not perfectly align. The day-ahead forecast is
used in this study because it is fairly similar to the hour-ahead forecast but more importantly it aligns with the day-ahead scheduling the wind farm would operate within the flex reserve market.

1.4.4 Examination of the statistical properties of the wind data at different forecast look-ahead intervals

The univariate kernel density estimation in section 1.4.3 provides a probabilistic estimation of the forecast of production across all observations for a given wind farm. As illustrated, a single wind farm can have peaks in the forecast of production level. Box plots are used to calculate the inter-quantiles of the forecasts of production along with any large forecast of production values not considered outliers. For the following plots, no outliers are shown, but some wind farms not displayed here do have outlier values of forecast production.

The twenty-four wind farm sample within PJM represents a range of different capacities or sizes as well as different levels of production. Naturally, a single farm may possess different statistical properties than another. The box plots shown below describe the forecast of the production structure as the forecast interval increases from one-hour ahead to twenty-four-hours ahead using five-minute forecast data using the same single Appalachia and Midwest farms analyzed in the kernel density estimation section. Each box plot denotes the median (red line) and the inter-quantiles that describe up to the $25^{th}$ percentile as displayed at the bottom box edge and up to the $75^{th}$ percentile seen in the upper box edge of the forecast of production data. For the $25^{th}$ percentile, 75% of the forecast of production is greater than the value at the 0.25 quantile. The box plots display the forecast of production values at these inter-quantiles along with the extreme values denoted by the whiskers change with each forecast interval.
Figure 6. The figure displays the median (red line), 75th percentile (top edge), 25th percentile (bottom edge), and extreme forecast production values not deemed outliers but beyond the 25th/75th percentile are shown as black whiskers at the lower/upper edge for distinct forecast intervals on the horizontal axis. The following distributions show no significant outliers, where an outlier is a value that is greater than +/- 2.7 times the standard deviation. Notches delineate the median forecast of production. Forecasts are given at the five minute level for an existing farm in Pennsylvania.

The median forecast of production for both the Appalachia wind farm (Figure 6) and the Midwest wind farm (Figure 7) slightly increases from the one- to twenty-four-hour-ahead forecast, while the lower and upper percentiles pertain to generally the same forecast of production value. The single Appalachia farm for the inter-quantiles show that the 25th and 75th percentile of the predicted production output are at approximately 5 and 78 MW, respectively, for the one-, two-, and four-hour look-ahead periods. There is a noticeable increase in the forecast of production level at the inter-quantiles for the sixteen- and twenty-four-hour-ahead forecast period, though the upward movement of these predicted power output values is still small in magnitude. Notice that the extreme values beyond the 25th and 75th percentile of the forecasted production (0 to 60 MW) does not extend as large as the extreme values of the forecasts of production at the Pennsylvania farm site (0 to 80 MW). The single Midwest farm does similarly
show that the 25th and 75th percentiles of the forecast of production do not strongly deviate as the look-ahead period increases in time. Using the twenty-four-hour-ahead forecast data will provide an accurate description of the statistical properties quite similar to the one-hour-ahead forecast data.

**Figure 7.** The figure displays the median (red line), 75th percentile (top edge), 25th percentile (bottom edge), and predictions outside the middle fifty percent of the forecast of production (MW) are shown as black whiskers at the upper/lower edge for distinct forecast intervals. The following distributions show no outliers, where an outlier corresponds to +/- 2.7 times the standard deviation. The height of the extreme forecast values, denoted as whiskers, reduces as the forecast interval increases. Forecasts are given at the five minute level for an existing farm in Illinois.

1.4.5 Data for cost analysis

In order to quantify the effectiveness of different farm groups for balancing forecast errors, the flex-reserve market costs are calculated in Chapter 3. Hourly PJM ancillary services frequency regulation prices are used to represent the realized prices in the flex-reserve market. Cost includes the hourly regulation price ($/MWh) multiplied by the hourly averaged forecast
error (MWh). The timeframe for the hourly regulation prices spans the full year from 2006 to 2008, though only use the hours during the months of January to June during this three-year period are used to coincide with the available forecast data. Figures from the cost analysis use only the 2006 prices as they have the smallest price peaks, quantifying the best-case scenario of the flex-reserve costs. The results from 2007 to 2008 with the more extreme price structures can be found in the Appendix. These years were selected for the regulation price data because they were used in previous, published work evaluating the impact of providing flex reserves from a single, multi-purpose dam, which allows us to have greater depth of knowledge about how pricing from this period impacts farm clustering strategies for lowering flex-reserve costs as well [11], [23].

1.5 Description of chapters

1.5.1 Chapter 2

Chapter 2 introduces the first of three studies. This first study incorporates forecast errors in a revenue-maximizing model for a single reservoir. This model simulates hydroelectric operational decisions when the electric facility is able to provide wind integration services at a sub-hourly time step through a mechanism called ‘flex reserves’ (see section 1.2 for further description of the flex-reserve market). Kerr Dam in North Carolina is the a case study, simulating operations under two alternative reservoir policies, one reflecting current policies and the other regulating flow levels to promote downstream ecosystem conservation. Even under perfect information and significant pricing incentives, Kerr Dam faces operational conflicts when providing any substantial levels of ‘flex reserves’ while also maintaining releases consistent with other river-
management requirements. These operational conflicts are severely exacerbated during periods of drought. Increasing payments for flex reserves does not resolve these operational and policy conflicts.

1.5.2 Chapter 3

Chapter 3 discusses the second study that examines different grouping scenarios of the twenty-four wind farm data set in the PJM footprint with the intent to minimize the average cost of balancing aggregate forecast errors. This analysis quantifies the flex-reserve costs of each grouping scenario to determine the advantages and disadvantages to aggregating forecast errors using alternative methods. The clustering involves three wind policy scenarios for quantifying the total cost and average cost of correcting for errors in the wind forecast when farms are evaluated (1) individually, (2) regionally, or (3) as one total collective. The costs analysis uses ancillary services regulation and natural gas prices for estimating how different pricing affects the average cost for balancing forecast errors in a year. A switching model was developed to allow the farms to select among the three wind policy scenarios with the objective to lower the average cost for reserve services. Three different cost allocation schemes are incorporated that divide the average of reserve services equally, based on the size of the farm and based on the level of total production to further evaluate how the physical arrangement of the plants impacts the percentage of cost a farm would incur for smoothing excess and shortfalls of expected wind power output.
1.5.3 Chapter 4

Chapter 4 focuses on probabilistic representations of forecast errors to better inform wind plant owners of the probability of the quantity of reserve energy needed to balance distinct proportions of the estimated wind forecast error distribution. Data input include the five-minute forecast errors from the day-ahead forecast of production for the quantile regression. The same wind policy scenario described in Chapter 3 is applied here for examining the wind forecast error distribution structure (multi-modal features) and quantity of flex reserves at the median and inter-quantiles. The distinct quantiles are examined to better interpret the quantity of reserve energy needed to balance smaller proportions (quantiles below the median) and larger proportions (quantiles above the median) of the look-ahead forecast errors, where these quantities may vary depending upon whether the farm balances its individual wind forecast errors, a regional aggregate, or the aggregate of all the farms within PJM.
Chapter 2
Operational Constraints and Hydrological Variability Can Limit Hydropower in Supporting Wind Integration

2.1 Introduction

As a growing percentage of electric energy demand is served by wind energy, wind integration strategies are being developed to better predict expected wind supply and use of existing generators to balance errors in the wind power forecast. Uncertain wind forecasts pose a considerable challenge for energy system operators. The significant variability of large-scale intermittent renewables has motivated focus on energy storage as a potentially important technological pathway to enable wind and solar energy integration. Existing hydroelectric dams represent a vital energy storage option as they are the largest source of renewable electrical generation [24]. Although hydroelectricity itself may exhibit significant variability over annual time scales, short-time scale storage and release decisions can be used to offset errors in wind forecasts (i.e., oversupply or undersupply). Pumped-hydro storage (PHS), batteries, and compressed energy air storage (CAES) are other commonly proposed storage technologies to aid wind integration (see [25], [26], [27]). Storage via new pumped hydro represents a limited option due to construction costs, property right difficulties, and limited plans for large-scale development in the U.S. since 1995 [28]. This work investigates the decision of a moderately-sized multi-purpose dam to compensate for errors in forecasts of wind energy production as a type of reserve service to electric system operators. Successful implementation of this wind integration service requires adequate price incentives and an understanding of how this new

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operational demand for multi-purpose dams conflicts with existing water management policies or priorities (i.e., federal or state regulations, local allocation agreements, etc).

Particularly relevant to our analysis is a recent report from the National Renewable Energy Laboratory (NREL) focusing on market integration for renewable electric generation. While technology exists to facilitate large-scale renewables integration, NREL finds that non-competitive market prices to generators offering supplemental power from storage or electrical generation are the main barrier to seamlessly integrating large capacities of renewables. This work recognizes that competitive pricing is an important factor for inducing participation in market constructs, but the results here find that multi-use dams face more intricate policy constraints of a nature that pricing alone cannot resolve, at least in the current regulatory environment. Our focus is to illustrate how institutional and policy-making change would be required to facilitate wider utilization of hydroelectric facilities in the provision of wind integration services.

A growing body of research has examined the impact of large-scale wind penetration (examples are in [29], [30], [31], [32]), and regional electric system operators in the U.S. have implemented a variety of wind integration programs. In the U.S. Pacific Northwest, the Bonneville Power Administration (BPA) has initiated a pilot program for a twice-an-hour, versus the traditional once-an-hour, wind scheduling market to reduce the system costs associated with excessive wind or under-producing wind periods in the Pacific Northwest [33]. Five Northwest states in partnership with BPA, the California Independent System Operator and the Department of Energy have launched the Pacific Northwest Smart Grid Initiative, a demand response program with the proposal of storing surplus wind energy by turning hot water heaters on and off to maintain low electricity prices [34]. In 2011, the Federal Energy Regulatory Commission
approved the definition of wind as a Dispatchable Intermittent Resource (DIR) that can fully participate in the Midwest Independent System Operator five-minute real-time dispatch market; the intent is that all wind resources will be covered under the DIR program by 2013 [9]. Wind in the New York Independent System Operator electrical territory must also operate as a dispatchable resource, so it is not a price taker and is not subject to manual curtailment to balance system supply, demand or transmission congestion costs [5]. In the PJM Interconnection, which covers the Mid-Atlantic area of the U.S., wind may operate as a non-dispatchable unit or participate in the real-time market as a dispatchable unit, incurring penalties for supply deviations greater than 5% of the forecast [35].

Operational conflicts will emerge when existing multi-purpose dams are used to integrate utility-scale wind capacity under current regulatory regimes. To illustrate these conflicts, the model implemented for this study simulates the decision of a hydropower operator in the U.S. Southeast (within the PJM Regional Transmission Organization) to provide a type of reserve capacity that balances unexpected changes in wind power output. Our analysis considers the allocation challenges that emerge during droughts and when reservoir operations are altered to improve downstream ecological conditions. This study focuses on the U.S. Southeast due to hydroelectric data availability, as well as the region’s population pressures and growing uncertainties associated with hydrological extremes [36]).

Following [28], this reserves-type service is referred to as ‘flex reserves’ that call for short-term supplemental electricity at time intervals longer than the frequency-based ancillary services regulation market but shorter than the synchronized reserve market (i.e., response times longer than seconds but shorter than hourly or half-hourly; see the Model Description for further details). Current PJM regulation energy prices ($/MWh) are used as a base-case proxy for prices.
that would prevail in the flex-reserve market, although perform a sensitivity analysis on the level of the flex-reserve price is performed. If prices in a flex-reserve market were similar to regulation prices, then multi-purpose dams would have limited incentives to supply substantial amounts of flex-reserve capacity. Allocation decisions to the flex-reserve market are further reduced during periods of drought. More importantly, water and environmental-related institutional constraints, rather than the level of compensation for providing flex-reserve services, limit the operational and policy changes that would be necessary for multi-purpose hydroelectric dams to offer substantial quantities of flex-reserve capacity.

The following discussion is organized as follows. Section 2 describes the model, including the case study and problem formulation. Section 3 follows with the results, and Section 4 ends with policy suggestions and conclusion.

2.2 Case Study: Roanoke River Basin and PJM

Chapter 2 features a single hydroelectric facility case study for examining properties of a flex-reserves product in centralized electricity markets. This study examines a small hydroelectric power producer in the Roanoke River Basin (RRB), located in the Southeastern U.S, providing reserve-type products in a centralized electricity market Mid-Atlantic electrical territory of the PJM Interconnection. The RRB possesses three dams that lie in series: Kerr, Gaston and Roanoke Rapids, ultimately controlling outflow to the downstream Hardwood Bottomland Forest ecosystem. This forestland houses protected aquatic and terrestrial wildlife and plant species that have been the subject of extensive conservation efforts [16]. Preserving
downstream environmental quality in the face of hydrologic fluctuations is an additional regulatory objective in the operations of dams on the Roanoke River.

The focus of this study is on the operation of Kerr Dam, owned by the U.S. Army Corps of Engineers but operated by Dominion Energy. Kerr Dam sells electricity into the PJM market, and Dominion also wheels energy from Kerr or the broader PJM market to local electric distribution companies in North Carolina known as “preference utilities.” The preference utilities lie outside PJM’s territory and have been allocated property rights to the output of Kerr Dam at low rates. Kerr is responsible for flood control, recreation, municipal supply, hydroelectricity generation, and ecosystem services; the last two operational objectives are the main focus.

Ecosystem services guide curve was defined within the scope of [16] that pertains to a proposed release schedule at Kerr Dam that more closely mimics the natural regime for the downstream floodplain in the Roanoke River Basin. This natural regime features high flow flood events at a short duration. This study does not quantify ecosystem services but seeks to estimate the implications of adjusting the river management policy with the intent of improving downstream ecology for purposes such as fish migration [16].

Power production decisions at Kerr Dam are made on a weekly basis. Each Wednesday, the United States Corps of Engineers (USACE) determines a weekly volume of water to be released from the Kerr reservoir, which is sent to the Southeastern Power Administration (SEPA). The water-release target can also be expressed in a weekly energy target (MWh). In parallel, the preference utilities submit a delivery schedule to SEPA that specifies when they are to receive electricity wheeled from Dominion at the subsidized rate. Dominion is responsible for wheeling power to the preference utilities according to their declared schedules, but can draw either on Kerr Dam or the PJM spot market to fill the preference utilities requests. Thus, the operation of Kerr Dam does not always physically follow the schedules set by the preference utilities.
As will be discussed, Kerr Dam follows strict federal environmental regulations and reservoir laws. Altering reservoir policies for this case study would require changes to the guide curve, likely involving lengthy, complex federal court cases. To suggest changing the operating policies at a dam like Kerr would require both federal and local policy review.

2.3 Model description

2.3.1 Case Study: Roanoke River Basin

Our model simulates reservoir allocation decisions at Kerr Dam, a multi-purpose hydroelectric dam located at the headwaters of the Roanoke River Basin (see Case Study in section 2.2 for further explanation of the Kerr Dam in the Roanoke River Basin). The U.S. Corps of Engineers (USACE) develops policies governing operations at Kerr Dam. Dominion Power manages Kerr and two downstream dams, Gaston and Roanoke Rapids. Releases from this dam system feed into the federally protected floodplains of the Hardwood Bottomland Forest, which has recently had over $40 million of conservation funds invested to improve its long-term viability [16]. Releases at Kerr are influenced by a large number of factors. The energy declaration sets a weekly schedule for the upper bound on total allowable power generation, while the dam’s guide curve sets a lower bound rule for reservoir elevation and operational controls on releases. Kerr Dam’s operations are influenced by federally mandated policies (flood control, municipal water, low-flow protocol) enforced by the USACE. Dominion has wide discretion for controlling intra-weekly reservoir releases and storage. While Dominion’s service territory is a part of PJM, Kerr Dam also provides lost-cost energy to local electric distribution
companies (collectively known as “preference customers”) that lie outside PJM’s electrical
territory, in coordination with the Southeastern Power Administration (SEPA) [11].

The model includes two water policy scenarios. The first is based on the historical
practices at Kerr Dam, while the second is an alternative water control plan seeking to enhance
the downstream environment, which in this work is termed the “ecosystem services” scenario
[37]. The policies define two distinct guide curve constraints, which is defined as business-as-usual (BAU) and ecosystem services (see Appendix). Historical practice at Kerr Dam has been
for Dominion to schedule operations during times of peak electricity demand, effectively chasing
peak spot-market electricity prices (15). The ecosystem services scenario requires a high-volume,
short-duration release schedule that more closely follows natural flow levels to enhance the
spawning season of nearly fifty fish species, in particular striped bass (March-June) [16]. The
ecosystem services releases pose a conflict when they do not coincide with peak generation
patterns. Under both the BAU and ecosystem services guide curves, Dominion faces the decision
to sell electricity in the PJM spot market2 or allocate capacity for compensating for errors in
PJM’s wind power forecast via the flex-reserves market.

The model developed within this study simulates hydropower production decisions across
a hydro-climatic gradient that captures the region’s transition from a wet year to a 1-in-100-year
drought over the period from 2006-2008 [36]. This hydro-climatic gradient provides insight into
how rapid changes in inter-annual water supplies affect dam operations, especially as population
pressures and droughts are growing concerns in the Northern Coastal Plain area of North Carolina
[36], [37], [38]. One assumption that is made is that Dominion has perfect knowledge of wind
forecast errors in PJM and can thus make perfectly-informed decisions to allocate capacity to the

\footnote{2 Note that the “spot” market in PJM is actually a one-day-ahead forward market. The distinction between spot and day-ahead is not important for the purposes of our analysis.}
flex-reserve market or to spot market sales. Incorporating uncertainty in Dominion’s expectation of the wind forecast error is a topic of ongoing research, but the assumptions used here reflect the best possible case for a multi-purpose dam offering capacity for wind integration services while managing a suite of water management policies (flood protocol, ecosystem services, drought releases, and hydroelectricity). The policy conflict arises when the flex-reserve provision is introduced into Kerr Dam’s decision-making because it would be exacerbated in the absence of perfect information. This is particularly true during drought years and suggests the increasing difficulty of balancing operational objectives, particularly with additional stresses induced by climate change [36].

2.3.2 Problem formulation

Within the model, Kerr Dam acts as a revenue-maximizing producer of hydroelectric power that makes hourly capacity allocation decisions between two electricity markets: the day-ahead spot “energy” market and the flex-reserve market (Equation 2.1). An additional assumption is that Kerr Dam is a price-taker in the day-ahead energy market and that any capacity allocated to the energy market will be fully utilized by PJM, thus committing \( y_{\text{CAP}} \) MW of capacity into the day-ahead market during hour \( t \) would result in Kerr Dam generating \( y \) MWh of electrical energy during hour \( t \). Dominion receives the day-ahead spot market price \( p_t \) for energy sales into the PJM spot market. Operational costs are ignored in this model, but do include the opportunity cost of wheeling power to preference customers since this is an important determinant of revenues at Kerr Dam. The quantity sold to preference customers at a regulated price \( p_{\text{SEPA}} \) is denoted as \( y_{\text{SEPA}} \). As noted in [11], the price at which sales to preference customers are made is typically lower than the prevailing spot market price in the Dominion zone of PJM.
The second decision variable is the amount of capacity offered into the flex-reserve market for balancing the wind forecast error \( e_t \). The wind forecast error could be either a positive or a negative number (i.e., the forecast wind output could be larger or smaller than the actual wind output). The following sign convention and terminology are used. If actual wind output exceeds the forecast, this is as an ‘oversupply’ event and \( e_t \) takes on positive values. If actual wind output falls short of the forecast, this is as an ‘undersupply’ event and \( e_t \) takes on negative values. During each period, Kerr Dam can allocate capacity to balance an oversupply or undersupply event. The capacity allocated to balance oversupply events is denoted \( y_{O,t} \) and the capacity allocated to balance undersupply events is denoted \( y_{U,t} \). The implied reservoir management strategies for balancing oversupply and undersupply events are quite different. Balancing an oversupply event would involve a reduction in water released through the turbine; thus Kerr would need to be storing water equivalent to at least the amount of oversupply capacity offered \((y_{O,t})\). Balancing an undersupply event would require Kerr to release water equivalent to at least the amount of undersupply capacity offered \((y_{U,t})\). The flex-reserve price is denoted as \( p_{FR,t} \) as discussed below, and prices from the PJM regulation market are used as a base-case proxy for \( p_{FR} \) and perform a sensitivity analysis to simulate the effects of higher prices. This formulation assumes that \( p_{FR,t} \) is identical for providing both oversupply capacity and undersupply capacity. This assumption reflects current convention in PJM’s ancillary services markets (unlike in the Electric Reliability Council of Texas market, which has distinct prices for “regulation up” and “regulation down”).

Consistent with current market rules for ancillary services in the PJM system [39], the model assumes that Dominion needs to offer into the day-ahead spot market in order to be eligible to provide flex reserves. The model further assumes that Kerr Dam is a price-taker in the flex-reserve market. Allocating \( y_{UCAP} \) MW of capacity to balance undersupply events will yield
energy production from the dam equal to \( y_{U,t} = \min(-e_t, y_{UCAP,t}) \) MWh (the minus sign in front of \( e_t \) appears because \( e_t \) is a negative number in the case of undersupply events). Allocating \( y_{OCAP} \) MW of capacity to balance oversupply events will yield a reduction in energy production from the dam equal to \( y_{O,t} = \min(e_t, y_{OCAP,t}) \) MWh (i.e., the change in total energy production to balance an oversupply event would be \( \Delta y_{O,t} = \max(-e_t, -y_{OCAP,t}) \) since \( e_t \) is a positive number in the case of oversupply events).

Mathematically, Kerr Dam maximizes revenues according to the following formulation:

\[
\begin{align*}
\text{(2.1)} & \quad \max_{y_{CAP,t}, y_{OCAP,t}, y_{UCAP,t}} \sum_{t=1}^{T_{cap}} p_t y_t + p_{FR,t} (y_{OCAP,t} + y_{UCAP,t}) - (p_{SEP,t} - p_t) y_{SEP,t} \\
& \text{Such that:} \\
\text{(2.2)} & \quad y_{CAP,t} + y_{OCAP,t} + y_{UCAP,t} \leq y_{\max} \\
\text{(2.3)} & \quad y_t \leq y_{\max} - y_{O,t} \\
\text{(2.4)} & \quad \sum_{t=1}^{T_{cap}} y_t + y_{O,t} + y_{U,t} \leq Declaration_{\ guide} 
\end{align*}
\]
In our model, Kerr makes decisions between the energy spot market and the flex-reserves market on a daily basis, and each day’s decision is a sequence of scheduled energy and capacity allocations for each hour, defined by $T_{\text{cap}}$ ($t=1, 2, \ldots T_{\text{cap}} = 24$ hours). Again, Kerr Dam is assumed to be a price taker in both the energy and flex-reserves market and that Kerr Dam can predict errors in PJM’s wind forecast with perfect accuracy. Equation 2.2 indicates that the sum of the scheduled energy and the capacity allocation for flex reserves at each hour can be no larger than the turbine capacity. Remaining capacity that has not been stored for oversupply flex reserves is available to be sold in the scheduled energy market as defined in equation 2.3. Since daily energy and allocation decisions are simulated, total hourly output each day is bounded by the allowable generation for that day’s share of the weekly energy declaration (Equation 2.4; here the same energy declaration framework as in [11] is used).

### 2.3.3 Data and Modeling Scenarios

The model uses historical data for price, load, wind forecast errors and hydrological conditions. All price data come from PJM archives from years 2006 to 2008. Scheduled market prices use hourly day-ahead prices, and the flex-reserve market uses hourly regulation prices. For the same-year timeframe, USACE hydrological data records are used for hourly power production from the turbines, reservoir elevation, and release targets based on [16] to construct the ecosystem services guide curve at Kerr (see Appendix for further details on the guide curve). Actual wind power production and wind forecast data at five-minute intervals was obtained from PJM for the period January to June 2010. The five-minute actual wind power output data and day-ahead forecast data from all twenty-four wind farms are used to calculate aggregate hourly averages to coincide with the time length of the hydrological and price data. Wind error data are
the differences from the hourly average actual and hourly average day forecast data that are also aggregated. Due to limited wind data, model simulations focus on hydroelectric operations from January to June, capturing the spawning season in the Roanoke River Basin and seasonal electricity price peaks and lows from winter to early summer.

2.4 Results

Our model assesses Kerr Dam’s incentives and barriers for diverting capacity away from the spot energy market to the flex-reserve market, under the assumption that Kerr Dam possesses perfect information regarding prices in both markets and the errors in PJM’s forecast of wind energy output (i.e., oversupply and undersupply). While our assumption of perfect information is not realistic in this context, these assumptions provide a best-case bounding scenario for the decision of a multi-purpose hydroelectric facility to provide a wind integration service. Our modeling results, detailed in this section, suggest that even under this best-case information scenario, the incentives for multi-purpose dams to provide substantial participation in the flex-reserve market would require flexibility in storage and release policies that can create conflicts with other operational objectives.

2.4.1 Willingness to offer capacity for flex reserves is constrained by non-economic factors

The decision framework presented in Section 2.3.2 allows us to assess the conflicting incentives faced by multi-purpose dams given the demands for providing flex reserves in addition to other services. This section presents the results of our base-case decision analysis under the BAU and ecosystem services guide curves, under the assumption that prices in the flex-reserves
market are similar to those prevailing in the regulation market in PJM. Figure 8 shows the cumulative distribution function (CDF) of hourly capacity allocations in the flex-reserve market during oversupply events under the business-as-usual (BAU) and ecosystem services guide curves during peak and off-peak hours from 2006 to 2008. Undersupply results can be found in the Appendix. Thus, Figure 8 shows bounds on Kerr’s willingness to provide flex reserves to the market under different operational constraints (guide curves) and during different market conditions. The guide curves constrain Kerr’s ability to provide oversupply flex reserves, where these amounts vary depending upon the type of guide curve, the hydrological conditions, magnitude of the forecast error, as well as the time of day where flex reserves are requested. Results for providing flex reserves during undersupply events are shown in the Appendix.

Since multi-purpose dams typically store large volumes of water and have the capability to ramp output up or down rapidly, Kerr may be hypothetically more willing to offer capacity into the flex-reserve market under the BAU guide curve, which is generally less constraining (i.e., it permits more flexible releases throughout the year, as discussed in the Appendix). Based on our data, the timing and magnitude of releases required under the ecosystem services guide curve correspond more closely with the timing and magnitude of flex reserves that PJM would demand. The capacity allocated for flex reserves under the ecosystem services guide curve exceeds allocations under the BAU guide curve, except during the severe drought year in 2008. During off-peak hours over the transition from a wet to a drought year (2006-2007), Kerr is willing to provide 58% (2006) and 73% (2007) of total capacity needed to balance the oversupply wind forecast errors under the ecosystem services guide curve, but less than 20% (2006) and 60% (2007) under the BAU guide curve. This suggests that storage and releases for the downstream environment are complementary with storage and release requirements to balance the oversupply of wind energy. Our findings in Figure 8 are different than in [11], which found that opportunity
costs associated with smoothing the level of wind energy output (as opposed to compensating for deviations between forecasted and actual output) are substantially larger under the ecosystems guide curve. Our results in Figure 8 highlight how water scarcity influences the decision to offer flex-reserve fill-in power in both peak and off-peak hours. Moreover, Figure 8 shows that based on prevailing regulation prices, the requested flex-reserves capacity is never met at 100%. A key question is whether this is an effect of our pricing assumptions or from the operational conflicts faced by Kerr Dam.
Figure 8. This figure shows the cumulative distribution function (CDF) of the percentage of the capacity allocated for balancing wind forecast errors during an oversupply of wind power during peak hours (left) and off-peak hours (right) under the BAU (solid) and the ecosystem services (dashed) guide curves.
NREL [28] argues that pricing of new ancillary services products to facilitate renewables integration is crucial; model simulations from [11] have made similar arguments based on the notion of pricing ancillary services based on opportunity costs. While this study agrees that price is an important component of a well-functioning market, the results in Figure 8 are primarily due to policy constraints embodied in the operational constraints posed by Kerr Dam’s guide curve and not due to inefficient pricing of ancillary services. A sensitivity analysis was performed on flex-reserve prices to highlight our finding that resolving policy constraints for multi-purpose dams through price alone seems unlikely to be successful. The results here focus on the ecosystem services guide curve because it better illustrates the operational complexities involved with integrating wind generation using hydropower. Figure 9 displays the results of a sensitivity analysis in which the price for flex reserves is increased (up to the current PJM price cap of $1,000 per MWh) and the optimization problem presented in Section 2.3.2 was solved for each price level. In no month can Kerr provide 100% of the requested flex-reserves to balance wind forecast errors without violating the guide curve. In most cases Kerr Dam is willing to provide less than 20% of the overall quantity of flex reserves demanded by PJM. Willingness to provide flex reserves is highest during off-peak hours in the spring of 2007 but drops substantially during these same months when transitioning to a sustained drought in 2008. Spring is an interesting indicator of environmentally-related policy constraints since the spawning season falls during these months, indicating that enhancing river conditions supports releases for flex reserves outside peak hours and severe drought conditions. (See Appendix for further price sensitivity analysis and description of data.) Our results suggest that even if prices for flex reserves properly reflect opportunity cost, multi-use hydroelectric dams may not be the lowest-cost option to provide wind integration services.
Figure 9. Displays the capacity allocation for balancing an oversupply of wind power during hourly average monthly peak (left) and off-peak hours (right) from 2006 (top), 2007 (middle) and 2008 (bottom). All results are under the ecosystem services guide curve. Only results up to a 50% price increase of the prevailing regulation prices within the market price cap are shown. Darker regions indicate a higher allocation and white a lower allocation. (See Appendix for further analysis.)
2.4.2 Policy changes to promote the provision of flex reserves

Operational constraints on how storage and release policies meet multiple services play a pivotal role at Kerr Dam. The ecosystem services guide curve cannot accommodate the timing and amount of the total wind power forecast errors at any realistic price. Kerr would have to deviate from the guide curve and violate the energy declaration as shown in Figure 10 for the ecosystem services case. Results for the BAU guide curve are shown in the Appendix. While an electric system operator would likely have a portfolio of potential suppliers in a market for flex reserves, it is useful as a bounding analysis to consider how the guide curve for Kerr dam would have to change in order for Kerr to provide 100% of the total flex reserves demanded by PJM. A violation occurs when the combined daily magnitude of oversupply and undersupply events exceeds the daily energy declaration; the magnitude of the violation is defined as the difference between the daily energy declaration and the combined daily magnitude of oversupply and undersupply events. While an oversupply event would result in Kerr storing more water by reducing energy output, in order for Kerr to provide some quantity of this service it would have to be producing at least that quantity of energy when the oversupply event occurred (even if it would have not otherwise been producing due to low energy market prices or some other operational constraint). Violations become more frequent and larger in magnitude from 2006 to 2008, but are generally lower in 2007. With a larger water supply in 2006, spot market sales dominate the Kerr Dam’s capacity allocation decision (see Figure 8 and Figure 9) and supplying substantial shares of flex reserves would require significant changes to the ecosystem services guide curve. Smaller, less-frequent violations occur in 2007, and during the spring months (days 90-120) multi-purpose dam policies more easily accommodate flex reserves. Water scarcity due to drought causes the largest violations (see Figure 10); the policy conflicts arising from the provision of flex reserves
(in terms of magnitude and timing of releases) are most evident here.

Figure 10. The panels feature the days where the total daily capacity requested to balance 100% of the forecast error exceeds the daily energy declaration (MWh) for the ecosystem services guide curve.

Figure 11 provides a daily illustration of the violations to the ecosystem services guide curve expressed in terms of the energy declaration that occur as the amount of flex-reserve capacity offered by Kerr Dam varies, assuming that flex-reserve prices are similar to historical regulation prices in PJM (results for the BAU guide curve are shown in the Appendix). In the figure, darker shading denotes larger violations of the daily energy declaration. Spring and early summer days exhibit the least conflict with the ecosystem services guide curve. Extreme dry conditions in 2008 impose more constraints on operations not embodied in the guide curve; the policy conflicts appear to worsen during the transition from spring to summer.
Figure 11. This figure shows the timing and amount the ecosystem services guide curve expressed in terms of the energy declaration is exceeded by the total daily energy output required to balance the wind forecast error from 10% up to 100%. Black signifies a large quantity exceeding the guide curve, as seen in the early summer of 2008, with minimal violations to the guide curve in white, such as the winter months in 2006 and 2007.

An additional analysis was performed by calculating the opportunity cost, energy and volumetric flow adjustments arising from providing increasing quantities of flex-reserve capacity.
to PJM under the ecosystem services guide curve. The results of this analysis are shown in Figure 12 (see Appendix for results under the BAU guide curve). The total wind forecast error, as defined in the figure, combines under and oversupply events. Similar to Figures 3.3 and 3.4, the daily energy declaration is compared to the amount of flex reserve required during each day, based on our historical wind forecast error data. If the requested flex reserves are larger than the energy declaration, the model calculates adjustments to the guide curve necessary for Kerr to feasibly provide various proportions of the total requested flex-reserves capacity (hence the use of percentage units in Figure 12).

Opportunity cost represents the potential flex-reserves revenue that Kerr forgoes due to release limitations set by the ecosystem services guide curve (panel a in Figure 12). Wet-year conditions show a reduced inter-annual opportunity cost increase from $8,646 when providing 10 percent of requested flex reserves to $159,506 when providing 100 percent of requested flex reserves (panel b). In 2008, the opportunity costs when providing 10 percent of requested flex reserves increases from $28,983 per year to $303,428 per year when providing 100 percent of requested flex reserves. To provide 100 percent of the requested flex reserves in 2008, the weekly energy declaration would need to be nearly double the 2006 declaration. Kerr would then need to exceed the total volume of water released under the ecosystem services guide curve (2.92×10^{15} cubic feet) by nearly 20 percent (panel c), an infeasible adjustment under current water management policies. From January to June 2008, BAU guide curve annual releases at Kerr historically reached 3.25×10^{14} cubic feet (nearly 800 percent below what would be required to support all flex reserves demanded by PJM), and ecosystem services guide curve annual releases would have reached 9.44×10^{11} cubic feet (four orders of magnitude smaller than what would be required to support all flex reserves demanded by PJM) if that policy were in place in 2008. Opportunity costs increase along with the quantities of flex-reserve capacity offered, but these
opportunity costs represent just over 2% of historical revenues from selling into PJM’s day-ahead energy market (assuming that PJM regulation prices are a suitable proxy for prices that would prevail in the flex-reserve market).

Figure 12. Results here show the (a) opportunity cost, (b) energy adjustments, (c) and percentage of the total volume used to smooth increments of the total wind forecast error from 2006 through 2008 under ecosystem services. Panel (a) describes the annual opportunity costs representing the revenues that could have been realized from selling flex reserves at current regulation market prices. Panel (b) describes the quantity of the energy adjustments needed annually to balance increasing percentages of the forecast error (MWh). Panel (c) describes the volumetric deviation from the guide curve as a percentage of the total volume of water released when complying with the guide curve. The additional volume of water is used to compensate for varying percentages of the wind forecast error across all hours in the simulation period.

2.5 Policy suggestions and conclusion

Large-scale wind integration requires supplemental energy reserves. Hydroelectric dams have a combination of ramping and storage characteristics, combined with low marginal
operating costs, making them appealing candidates to provide these reserves. Our analysis, however, suggests that the magnitude and timing of releases needed to compensate for errors in the wind power forecasts may require substantial changes in multi-purpose reservoirs’ operations, especially in regions with significant hydro-climatic variability and increased electricity and water demands. Our conclusions differ from those of NREL [28] by suggesting that fundamental water management policy changes for reservoir releases, in addition to pricing reform in ancillary services markets will be necessary to successfully integrate wind and hydroelectric power (see also [11]). Current regulation prices appear to provide little incentive for Kerr Dam to accommodate a large amount of the wind power supply forecast errors (see Figure 8, Figure 9, Figure 10, Figure 11, and Figure 12). Even if prices are increased substantially, the greater challenge of managing conflicts between energy and water management policies for multi-purpose dams will not be resolved.

The combination of severe drought conditions and strict water management policies based on the BAU and ecosystem services guide curves highly constrain Kerr’s ability to provide substantial amounts of flex-reserves type of capacity to correct for the wind forecast error (see Figure 12). Adjustments to either guide curve will likely need cooperative policy making to reach a compromise policy solution that benefits the multiple constituents involved with Kerr Dam. A flex-reserve type of market construct may provide some revenue for Kerr, but would require guide curve adjustments that are infeasible given current operating policies. Whether Kerr’s operators would be willing to go through the complex and lengthy legal process required for guide-curve alteration is not clear. Higher prices for flex-reserve services would improve the cost-benefit calculation but, as our results in Figure 9 suggest, they would not necessarily increase the quantities that Kerr would be willing to offer in the flex-reserve market. Improving the willingness of Kerr Dam to provide flex-reserve services would require both economic incentives
(in the form of higher flex-reserve prices) and more fundamental policy reforms in how the Roanoke River system is managed.

Results from this study provide the best-case scenario for similar multi-purpose dams balancing distinct water and energy policy goals while operating within federal laws that control a reservoir’s operations and services. This study suggests that the energy sector should consider the future uncertainty of surface water supplies because it will likely impact the long-term ability for hydropower to provide both base load and supplemental energy (such as flex reserves). It is likely that the historic water management policies will need to be revised for individual reservoirs to compensate for the variability of wind generation across the electrical grid. Cooperative policy-making that carefully considers both the energy and the water sectors’ operational management practices for dealing with growing hydrological uncertainties and rising demands for electricity and water is needed.
Chapter 3
Cost and Distributive Effects of Wind Energy Balancing in PJM

3.1 Introduction

Utility-scale wind developments have increased in number in the United States. In certain wind farm instances, spatially dispersed wind plants can help lower variability in output (see [40] as an example). The degree to which imbalance costs decline is a function of the correlation structure between the aggregated farms. Revenue from wind-generated electricity relies on fixed payment from a power purchase agreement or in some cases energy sales in a real-time or day-ahead market structure (see section 1.2 for a discussion of distinct variable generation integration programs in the United States). In the latter case, selling generation into a Regional Transmission Organization (RTO) or Independent System Operator (ISO) spot market as merchant generation means uncertainty in prices and uncertainty in revenue, which motivates the need for accurate forecasts of expected generation. With more accurate information regarding wind forecast errors, the wind plant can better anticipate the financial impacts from an incorrect forecast and better plan their generation bids. If the system operator had improved knowledge of predicted imbalances such as forecast errors, it could better coordinate the dispatch of the generators providing energy and capacity services with the goal to maintain a reliable electrical grid in the face of unexpected short-term imbalances.

Balancing authorities such as PJM require a mechanism for correcting for short-term imbalances like prediction errors in the wind forecast that would be needed at different timescales which the existing ancillary services markets. The system operator goal is to maintain electric grid reliability in the short- and long-term. This study explores the use of a market designed to
manage power fluctuations in variable energy generation that in effect would help maintain short-term grid reliability. The objective of this study is to determine cost-minimizing strategies for balancing unexpected deviations in the actual wind power supply from the forecast. These strategies may vary from the context of an individual wind power plant and from the system operator perspective.

In current practice, the PJM system operator determines the needed energy and reserves services for smoothing mismatches in supply and demand from a total sum of power supply imbalances for all fuel types. These imbalances may occur second to second or over several minutes. Minimizing total cost for the whole electrical territory by summing all power supply imbalances may or may not be the least-cost strategy at the individual operator level. The following research focuses on the imbalances from incorrect wind forecasts. The wind forecast error is used as a proxy for unanticipated supply-and-demand mismatches, under the assumption of a system with highly reliable conventional generation, predictable demands and little to no solar capacity.

As wind generation transitions from providing electricity ‘when available’ to a ‘dispatchable intermittent resource’, policies governing ancillary services will need to be fine-tuned to explore other options. In hydro systems specifically, previous work [11] demonstrated that a load-following-based ancillary services market does not meet the timing of the backup electricity needed to follow the variability in wind production. Capacity payments to hydro operators are lower than the opportunity costs, discouraging participation from hydroelectric operators to balancing wind production oversupply or shortfall. Additionally, hydro operators incur opportunity costs that exceed the payments for backup energy needed for compensating for errors in the wind production forecast, which is largely exacerbated by inflexible operating constraints that conflict with the rapidly fluctuating timing and magnitude of wind forecast errors.
The cost analysis uses gas prices that are representative of flex-reserve prices, given that PJM possesses a large percentage of natural-gas capacity and this technology has the operational flexibility to provide such backup service.

The first component in this work addresses the question of whether balancing the aggregate of the wind forecast errors is the least-cost strategy for an individual wind plant operator. Current practice in PJM aggregates the wind forecast errors from all the farms in its territory and uses ancillary service markets as the backup source to fill in when the expected wind production deviates from the actual wind production. Whether balancing the collective forecast errors based on ancillary-services market prices is the least-cost strategy for the individual operators is examined.

To address the least-cost strategy question, three alternative scenarios for wind aggregation in the PJM territory are explored. The first scenario would be if each wind farm balanced its own forecast errors. An assumption is that individual wind farm operators self-supply balancing services through bilateral contracts; self-supply (for example, co-location of gas turbines with wind plants); or individually purchase balancing services from PJM through the flex-reserves market. The size of the farm and the variance of the forecast errors affect the magnitude of the forecast errors and therefore the costs, which plays a role in the wind operators’ decisions to self-supply balancing services or utilize the flex reserve market.

The second scenario is a regional approach of aggregating wind farms into two groups – which referred to as Appalachian and Midwestern – and basing balancing requirements on the aggregate forecast error in each group. The third scenario collectively sums the forecast errors from all farms within PJM into a single system-wide balancing requirement. By comparing scenarios one through three, the extent to which average balancing costs decline with aggregation
is examined. Also examined is how aggregation affects individual wind farms – identifying who the winners and losers are.

Three cost analyses are performed to highlight the differences between the regional-aggregate and PJM-aggregate scenarios. The first component of the cost analysis determines the total cost ($) for the local farms to form regional collectives based on the sum of the regional forecast errors and regulation prices as a proxy for the prevailing flex-reserve prices and the PJM-aggregated wind forecast errors. Similarly, the average cost ($/MWh), a function of the total cost divided by the produced output, is outlined for the regional- and whole-PJM aggregate cases. Lastly, three different schemes to allocate balancing costs in the Appalachian, Midwest and PJM-wide wind farm aggregations are examined. Specifically, allocating costs equally among all wind farms in an aggregated group is examined, as are allocating costs based on production capacity and allocating costs based on actual production. Each of these cost-allocation schemes are compared to what an individual wind farm would have paid if it procured balancing services individually.

For each individual farm, the cost percentage for flex reserve varies depending upon the allocation scheme and wind policy scenario. Highlighted are three price scenarios that have increasingly higher price peaks, which influence the total and average cost of purchasing flex reserves. The regulation prices in 2006 possess the least-variable price peaks and lows, with years 2007 and 2008 having more pronounced peaks and lows in the prices, primarily during the summer months.

A decision framework is developed where each individual wind operator can decide among the three schemes for procuring balancing services:

- Aggregation with the whole of PJM;
• Aggregation with the Appalachian or Midwest group, depending on the wind farm’s location; or
• Procurement of balancing services depending on only that wind farm’s forecast errors.

Farms iteratively switch between the PJM aggregate, two regional aggregates (Appalachia or Midwest depending upon physical location) or self-supply, where each farm actively seeks an option that results in the lowest cost for purchasing flex reserves. Thus, the option may be to partner with nearby farms or switch to another regional collective or leave all groups. Switching among these aggregation options showed that farms prefer to join the PJM aggregate or self-supply. Although the model did not reach a steady state where no farm preferred to switch into another aggregation, it is concluded that at best only four of the twenty-four farms switched. The situation where only a small number of farms chose to switch where no other farms desired to is called a pseudo-equilibrium. Future work would be to use evolutionary algorithms to identify whether an optimal arrangement of the wind farms exists that satisfies the least-cost strategy for these wind farms simultaneously.

The culminating policy question for this work concerns how to adjust the current strategy for grouping wind farms and balancing the large-scale wind forecast errors using existing backup assets that address the system operator’s approach for aggregating all farms to maintain system reliability and determine the individual least-cost aggregate strategy for each wind plant.
3.2 Background

The extreme growth of wind installation has prompted an evolution of how wind operators evaluate the financial risks of selling their electricity and how system operators manage renewable energy within their respective territory. As a whole, wind operators largely sell the electricity when available and must pay a penalty when the forecast in production varies from actual output, though the implementation of new wind integration programs within the balancing authority areas in the United States have substantially grown [5], [9], [33], [34], [35]. As more wind capacity comes online, balancing authorities like PJM will have to rely on a greater amount of backup provisions to compensate when the forecast of variable generation is wrong. The volume of back-up capacity and energy provisions constitutes one challenge and the second challenge involves the timing of providing these services, which remains an immense hurdle for some technologies such as hydroelectric dams [11], [23]. Depending upon the generation mix, the costs for these ancillary services will vary.

The focus here is on the flex-reserve market as a mechanism for a wind plant to purchase back-up energy to compensate for wind forecast errors, though the flex-reserve market can be used to balance forecast errors for solar generation as well [41]. Although not modeled in our cost analysis, the alternative would be to incur a penalty, where the penalty price varies depending upon the bandwidth or magnitude of the imbalance deviation and the market rules exercised by the balancing authority. Note that PJM currently balances the total volume of small-scale fluctuations in supply, such as unexpected fluctuations in wind production output, using a combination of ancillary service provisions. The question proposed here is: will utilizing a flex-reserve market, either under the banner of an individual wind farm or some collective group, align with the system operator’s current practice to balance the aggregate amount of forecast
Thus, if wind farms are allowed to behave as single entities, whether the least-cost option leads to all farms forming a single collective and balancing the aggregate of the forecast errors or not is investigated.

System operators have in the past gained greater reliability by joining with other electrical territories, creating a new, larger territory [42], where the more open-market structures form larger balancing areas to allow for more-flexible accommodation and smoothing of the unpredictable variability from wind generation [43]. Investigated here is whether PJM’s decision to treat its entire footprint as a single balancing authority is likely to increase or decrease the costs associated with wind integration. Existing forecast data is used from twenty-four farms within the PJM territory to examine the cost differences these individual wind operators would pay to balance the forecast errors through a variety of flex-reserve policy options (see section 1.3.3 for wind farm forecast data description). These policy options consist of different ways to aggregate wind farms within the existing PJM territory into regional groups, or view it as a contiguous group, as currently done, or opt out of any group and in theory use bi-lateral contracts for supplying flex reserves. Examined are various PJM divisions using the wind policy scenarios to test whether an alternative formation of the wind farms results in lower average costs to the wind plant.

The proceeding work considers distinct wind aggregation scenarios for purchasing flex reserves within the PJM territory.

- First, all farms belong to the collective and flex reserves are needed to balance the aggregate of the forecast errors for all farms.
- Second includes an aggregation of wind farms within the PJM territory into the Appalachian group in the east and/or the Midwest group in the west.
Third, wind operators may choose to leave both the collective group and the regional aggregates and purchase the amount of flex reserves to compensate for the forecast errors from only their respective farm.

Relatively fifty percent of the forecast errors come from the east and the other fifty percent from the west, so the sum of the regional errors is equivalent to balancing the sum of the errors for all farms in this PJM test case. From the system operator’s viewpoint, it is indifferent to aggregating or not because the total cost of balancing the forecast errors does not change. However, the cost of flex reserves for the individual wind operators reflects a much different cost scenario depending upon which aggregation it joins, if it procures flex reserves alone (self-supply) or does not leave the collective group.

### 3.3 Wind policy scenarios

The following wind policy scenarios are used in Chapters 3 and 4. Each scenario features different aggregate groupings of the twenty-four farms a case study is used for examining the distributive effects of balancing forecast errors under these aggregated scenarios.

The first scenario represents a single farm balancing its own forecast errors. The second scenario divides the PJM footprint into the eastern Midwest portion and the western Appalachia portion, with the aggregated forecast errors calculated based on the local farms. The Appalachian farm group consists of twelve farms located in Pennsylvania, Maryland and West Virginia. The remaining twelve farms comprise the Midwest farm group that is collectively located in Illinois, Indiana and Wisconsin. The third scenario groups all twenty-four farms together throughout the PJM territory into one aggregate for the PJM whole forecast error aggregate.
In the first wind policy scenario, a quantile regression is performed for each of the twenty-four wind farms to display the flex-reserve quantity that balances look-ahead forecast errors at defined proportions of the distribution. The second wind policy scenario performs a quantile regression for the twelve farm regional forecast error aggregates, which helps examine any changes in the quantity of flex reserves at the same quantiles for balancing individual- versus regional-aggregated forecast errors. The third wind policy scenario provides a macroscopic grouping of all farms, where the range in flex reserves may dramatically shift when procuring flex reserves as a single entity as opposed to a regional or whole territory collective. The scenario analysis of farm groupings examines whether a wind operator may desire to be penalized for the magnitude of its individual farm forecast errors (individual flex-reserve scenario) or form an intra-balancing or whole-area group to minimize the additive forecast errors and associated financial uncertainty for balancing the forecast errors.

3.4 Cost analysis

3.4.1 Flex reserve costs for wind farm aggregations within PJM

The cost of balancing the forecast errors is analyzed in a variety of wind policy scenarios to better understand how the formation of the farms impacts individual operations. First, this analysis calculates how the regional total cost and regional average cost vary per aggregation for purchasing flex reserves for the year. The total cost of flex reserves purchases at each hour $t$ over the course of the year$^3$ equals the sum of the hourly price $p_t$ multiplied by the sum of the forecast

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$^3$ Note that this study uses data from January to June in 2010 so the ‘year’ consists of approximately six months. The total number of hours $T$ is 4,279.
errors \( f_e \), of all farms belonging to that region aggregate. Total costs are calculated in Equation 3.1 and results are shown in Figure 13 (panel (a)) shows three aggregates, Appalachia (blue) and Midwest (green), and then the PJM collective as one group.

\[
\sum_{t=1}^{T} (\text{price}_t \times \sum_{t=1}^{T} \text{forecast error}_{\text{Region},t})
\]

The average cost per MWh (Figure 13 panel (c)) is then calculated as a function of the total cost (panel (a)) divided by the aggregate production (MWh) (panel (b)) of the farms within each type of aggregate (Equation 3.2).

\[
\frac{\sum_{t=1}^{T} (\text{price}_t \times \sum_{t=1}^{T} \text{forecast error}_{\text{Region},t})}{\sum_{t=1}^{T} \text{production}_{\text{Region},t}}
\]

Regional total and average costs are the costs associated with the twelve farms originally located in each geographic region (twelve in the eastern Appalachia region and twelve in the Midwest region). The PJM aggregate is irrespective of geography and is the collective of all farms from the twenty-four farm data set. In Figure 13, farms located in the Appalachia group (blue, panel (c)) pay on average more than the Midwestern group (green panel (c)). If all farms formed the PJM collective (red, panel (c)), farms would pay less than if they created within-region flex-reserve balancing areas. Panel (c) reflects the costs that farms would pay if regional balancing areas were allowed (blue, green) as compared to maintaining current practices (red). Production levels can highly impact the average cost when aggregating wind farms, as seen by the higher total production for the Midwest aggregate and thus lower average cost in comparison.
to the Appalachia aggregate in 2006. In 2007, the PJM aggregate annual costs were slightly larger than the Midwest aggregate costs, and although the total production reaches higher MWh levels for the PJM aggregate, the Midwest aggregate has just slightly lower average costs in comparison. Recall that 2008 represents the year with the most pronounced peaks and lows in regulation price, so the average costs are highest for each aggregate. The regulation price levels and total production directly impact average costs when aggregating wind farms for this representative PJM case study.

Figure 13. Total costs for the Appalachia (blue) and Midwest (green) regions as compared to the entire PJM (red) region are shown in dollars. Yearly total production within these three regional designs is shown in panel (b) in MWh. The yearly average cost ($/MWh) are function of the total costs divided by the total production for each region. Farms belonging to the Appalachia region would may more on average for flex reserve provisions than farms located within the Midwest region, and the average costs based on the aggregate of the farms in PJM is slightly higher than the Midwest region from 2006-2008. These results are based on historical PJM regulation prices, which become more variable with higher price peaks from 2006 to 2008.

Later sections build from this cost analysis by examining how the regional costs change depending upon distinct cost allocations. As a next step, a model is developed that simulates the
decision to switch among a variety of wind aggregation scenarios for each wind farm, observing how the combination of the cost allocation scheme and selection of the wind aggregation impacts least-cost decision-making for individual wind farms aimed at balancing wind forecast errors (see Equation 3.1).

3.4.2 Costs for self-supplying flex reserves

Purchasing flex reserves to compensate for an individual wind operator’s forecast errors allows the operator to self-supply the desired volume of back-up energy by utilizing a bilateral contract in the context of this work. Total costs for self-supplying for an individual operator varies depending upon the size of the farm, the variability of its output and the magnitude of its forecast errors. The wind forecast error data is heteroskedastic (see section 1.4.2), so forecasting for a larger production amount may result in a larger forecast error and consequently higher flex-reserve costs. The heteroskedastic nature of the forecast error data implies that the variance is not consistent from one hour to the next. The cost to purchase back-up provisions for the forecast errors associated only with the operator’s farm may provide a less costly option than the other aggregate options, specifically for farms with smaller capacities.

Hourly average costs ($) shown in Figure 14 illustrate the cumulative distribution function of the hourly total costs for farms located within the Appalachia region (left) and Midwest region (right) using existing regulation prices as a realistic proxy for prices a farm operator may see. Hourly average cost is defined in Equation 3.2. The steeper, more vertical cumulative distribution functions with shorter tails do not reach as extreme cost values as those with flatter, longer tails. More s-shaped curves illustrate that an incremental change in the cost for balancing forecast errors results in a larger change in the probability of that cost value occurring.
The full range of costs are not shown here, though the PJM market price cap of $1,000/MWh is exceeded at the tails of the hourly cost distributions. However, a large percentage of the costs for balancing the forecast errors during oversupply (negative values) and undersupply (positive values) fall within this price cap. A majority of the hourly cost values are near zero, signaling that the likelihood of a cost near zero is derived from a forecast error embedded in the cost calculation that is near zero as well.

Figure 14 A cumulative distribution of the hourly total cost ($) for farms in the Appalachia region (panel (a)) and the Midwest (panel (b)) to balance individual farm forecast errors. Most farms show that the hourly costs are near zero except at the tails. Positive costs denote the costs for purchasing flex reserves during an undersupply event and negative costs are incurred to balance an oversupply event.
### 3.4.3 Cost allocation methods

This section explores three cost-allocation schemes where individual farms pay to join a wind aggregation. At the start of each switching turn, the farm operator calculates its individual or self-supply costs, which are a function of the sum of the hourly regulation price $price_t$ multiplied by the hourly forecast error $forecast\ error_{farm,t}$ across all hours (Equation 3.3). Self-supplying obviously involves no cost allocation scheme since each member acts as a single agent procuring flex reserves as a separate entity. Regional Appalachia and Midwest costs are calculated, which change depending upon who has left or joined the regional aggregation. The farm cost allocation represents the ratio of the individual cost (Equation 3.3) to the regional cost (Equation 3.4). The allocation variable $A$ is in fact a percentage from zero to one (one being one hundred percent) that applies any of the three cost-allocation schemes (equal, size or output) that are based on attributes of that single farm (Equation 3.6 and 3.7). The allocation percentage is inserted into Equation 3.5 to find the flex-reserve cost percentage each farm would pay for balancing the forecast errors associated various wind policy scenarios. Each percentage $P$ reflects the absolute value of the percentage, since the net forecast errors may be negative. A separate market structure or pricing for negative and positive forecast errors are not included, so only the magnitude is evaluated.

\[
\sum_{t=1}^{T} price_t \times error_{farm,t}
\]
The first allocation method equally divides the cost of the aggregates among the members within the regional grouping. For the Appalachian and Midwest aggregations with \( A \) equal to one twelfth, each of the twelve farms are responsible for one twelfth of the sum of the regional cost shown in Equation 3.4. When all twenty-four farms are grouped, one twenty-fourth of the costs based on the aggregate sum of forecast errors is divided amongst the members (\( A \) equal to one twenty-fourth). In the second allocation scheme, farms pay for flex reserves based on the ratio of their individual farm size or capacity to the aggregate capacity of the grouping (Appalachia,
Midwest, of PJM aggregate) (Equation 3.6). The third cost allocation scheme divides cost based on the ratio of the sum of the farm’s output to the sum of the output from all the members belonging to the regional aggregations (Equation 3.7). The value for A varies per farm for each of the capacity size and production-based allocation schemes. The percentages defined in Equation 3.5 are used for quantifying an increase or decrease in flex-reserve cost. The following section discusses the percentage of flex-reserve cost results under the distinct allocation schemes.

3.5 Results

The results from the cost analysis and allocations previously described show that the allocation of cost highly impacts which aggregation a farm joins when seeking the least-cost flex-reserve policy option. The switching model provides further insight about which group individual farms with differing capacity sizes and production levels prefer to join depending upon which farms have entered and left (See Table 1 and Table 2 for a description of the forecast errors from the observational data for each farm within the Appalachia and Midwest regions for a further explanation of the magnitude and range of the errors across each geographic region).

Under all cost-allocation schemes, the model did not reach equilibrium where no farm switched. This suggests there is no formation of the farms that satisfies all farms without at least one farm wanting to switch to a lower-cost policy option. A pseudo-equilibrium criterion was applied for examining if there existed a small subset of farms that, when allowed to switch, no further switches occurred. The end result showed that a minimum of four farms must switch in order for no further switches to occur.

4 The maximum capacity of size for the farms is not reported with the forecast data. Farm size is calculated as the maximum production across all hourly periods from the individual farms. The regional sizes are then the sums of the maximum production from all farms belonging to the group.
Table 1. This table contains the minimum, maximum, mean and variance of the five-minute forecast errors at the twenty-four hour ahead forecast interval for the twelve farms that compose the Appalachia region in eastern PJM. The units are MWh. A negative forecast error value denotes an oversupply event where the actual generation exceeded the forecasted generation. A positive forecast error value denotes an undersupply even where the actual generation fell short of the forecasted generation.

<table>
<thead>
<tr>
<th>Statistics of Appalachia Wind Farm Forecast Errors (MWh)</th>
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<tbody>
<tr>
<td>Farm</td>
</tr>
<tr>
<td>Max</td>
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<td>Mean</td>
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<td>Var</td>
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Table 2. This table contains the minimum, maximum, mean and variance of the five-minute forecast errors at the twenty-four hour ahead forecast interval for the twelve farms that compose the Midwest region in western PJM. The units are MWh. A negative forecast error value denotes an oversupply event where the actual generation exceeded the forecasted generation. A positive forecast error value denotes an undersupply even where the actual generation fell short of the forecasted generation.

<table>
<thead>
<tr>
<th>Statistics of Midwest Wind Farm Forecast Errors (MWh)</th>
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<tr>
<td>Farm</td>
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<td>Min</td>
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The following results illustrate the total and average cost analysis for individual and aggregate farms based on their original geographic location. This analysis uses the 2006 prevailing PJM regulation prices as this year possessed the lowest regulation prices from the 2006 to 2008 data period as a plausible flex-reserve market price scenario. As an alternative price scenario, this analysis uses 2012 monthly gas prices as a proxy for hourly gas prices, where year 2012 represents the year with the lowest prices from 2002-2013. The distinct cost allocation schemes (equally, based on size and based on production output) are applied to the cost analysis as well to further investigate if the manner of dividing the cost impacts the percentage each wind farm would pay under the three wind policy scenarios (Appalachia aggregate, Midwest aggregate and PJM aggregate).

The next section discusses the switching model results that simulate how the decision-making to join or leave an aggregation or self-supply changes depending upon the cost allocation scheme and the price reflecting the source of the short-term backup energy to fill-in for the forecast errors.

**3.5.1 Cost allocation affects operators’ decision to form within-region flex reserve markets**

The following results here within describe the cost percentage individual operators pay if the current PJM territory is divided geographically or remains whole where no switching among regions has occurred (Figure 16, Figure 18, Figure 20). These cost percentages $P$ are the final mathematical results derived from Equation 3.5 using different allocation schemes represented by variable $A$. This analysis tested if aggregating wind farms in PJM into two regions, Appalachia region to the east and the Midwest region for wind farms in the west, yields lower flex-reserve
costs to the individual operators as opposed to purchasing supplemental energy to balance the aggregate forecast errors from all farms in our PJM case study. Operators can elect to pay costs with respect to their geographic location (top panel) or pay as a collective member of the PJM region (bottom panel), where costs are allocated equally among the farms, allocated based on the rated capacity of the farm or allocated based on the total production of electricity. A price comparison between PJM existing regulation prices and gas prices as the prevailing flex-reserve prices is also examined. The range of the percentage individual farms pay for flex reserves with respect to the different aggregation varies amongst cost allocation types. The range in percentage results derives from how the ratios from variable $A$ are calculated.

Figure 15 and Figure 16 focus on the equal cost allocation scheme. The aggregate forecast errors across all twenty-four farms in the PJM collective case is typically smaller than the aggregate of the intra-regional group. However, in the case of the PJM collective, the equal allocation ratio divides by $A$ equal to one twenty-fourth, which typically yields large numbers as opposed to dividing by $A$ equal to one twelfth in the intra-regional case. The equal cost allocation may also delegate a larger percentage of the cost to small and average-sized farms or farms with low levels of output than the size or output cost allocations. Figure 15 and Figure 16 show that in both the Appalachia and Midwest regions, when farms share equal proportions of cost, the percentage of cost an individual operator pays varies depending upon whether it belongs to the regional group or the PJM collective. Implementing the gas prices in place of the regulation prices does not alter the average cost results.
Figure 15. Percentage of the flex-reserve cost based on equal cost allocation each farm within their respective geographic region pays (vertical axis) with twelve farms in the Appalachia region and twenty-four farms in the PJM collective. The horizontal axis features the percentage the twelve local individual wind farm operators pay under three flex-reserve markets based on PJM regulation prices and natural gas prices. No switching has occurred, so farms would be charged these cost percentages based on their original geography.
Figure 16. Percentage of the flex-reserve cost based on equal cost allocation each farm within their respective geographic region pays (vertical axis) with twelve farms in the Midwest region and twenty-four farms in the PJM collective. The horizontal axis features the percentage the twelve local individual wind farm operators pay under three flex-reserve markets based on PJM regulation prices and natural gas prices. No switching has occurred, so farms would be charged these cost percentages based on their original geography.

Size and output-cost allocation schemes reference the same twelve-farm regional and twenty-four farm collective groups, but with a different percentage of cost due to different allocation methods. Results under the capacity size allocation scheme are shown in Figure 17 and Figure 18, and Figure 19 and Figure 20 display the production-based allocation results. Similar to the equal-cost allocation scheme, belonging to the PJM collective results in a much lower percentage than belonging to their local geographic group in the size and production-based
allocation schemes. Additionally, smaller-sized farms and farms with lower levels of electricity production result in a smaller allocation value and cost-percentage value, and are by consequence paying lower costs for flex reserves than their larger farm counterparts. Thus, operators of smaller-capacity farms may favor a flex-reserve policy based on their installed capacity (or size as derived by the maximum production value reported in the data set for that individual farm) of production levels, while larger farms may prefer equal-allocation methods. Using gas prices does not result in different average cost percentages under these two cost-allocation schemes. A natural gas unit is a likely candidate to be the marginal unit that sets the market clearing price for flex reserves since it has flexible, fast-ramping capabilities. Variable generators may be indifferent to paying at the regulation or gas prices.
Figure 17. Percentage of the flex-reserve cost based on size cost allocation each farm within their respective geographic region pays (vertical axis) with twelve farms in the Appalachia and twenty-four farms in the PJM collective under the size allocation scheme. Note that the range in percentages is smaller, suggesting that farms with smaller size pay less and larger farms are responsible for a larger share of the costs. The horizontal axis features the percentage individual wind farm operators pay under three flex-reserve markets based on PJM regulation prices and natural gas prices.
Figure 18. Percentage of the flex-reserve cost based on size cost allocation each farm within their respective geographic region pays (vertical axis) with twelve farms in the Midwest region and twenty-four farms in the PJM collective under the size allocation scheme. Note that the range in percentages is smaller, suggesting that farms with smaller size pay less and larger farms are responsible for a larger share of the costs. The horizontal axis features the percentage individual wind farm operators pay under three flex-reserve markets based on PJM regulation prices and natural gas prices.
Figure 19. Percentage of the flex-reserve cost based on output cost allocation each farm within their respective geographic region pays (vertical axis) with twelve farms in the Appalachia region and twenty-four farms in the PJM collective under the production-based allocation scheme. Note that the range in percentages is smaller, suggesting that farms with smaller power output pay less and larger farms with larger production levels. The horizontal axis features the percentage individual wind farm operators pay under three flex-reserve markets based on PJM regulation prices and natural gas prices.
Figure 20. Percentage of the flex-reserve cost based on output cost allocation each farm within their respective geographic region pays (vertical axis) with twelve farms in the Midwest region and twenty-four farms in the PJM collective under the production-based allocation scheme. Note that the range in percentages is smaller, suggesting that farms with smaller power output pay less and larger farms with larger production levels. The horizontal axis features the percentage individual wind farm operators pay under three flex-reserve markets based on PJM regulation prices and natural gas prices.
3.5.2 Switching model description

The switching model represents a decision-making tree with various cost options for procuring flex reserves across the wind aggregate options. Figure 21 depicts the switching model used for examining if there is a formation of farms that when grouped provide the lowest cost for all farms in the system. The decision tree within this flow diagram describes how each farm cross-comparing flex-reserve costs under each allocation scheme to arrive at a final decision regarding which aggregation it will join based on a least-cost strategy.

Each farm seeks the least-cost option. All farms begin as a collective and have the option to switch to a regional group that matches their real-world geographic location, the other regional group or self-supply. Switches are made in sequential order, beginning with the first to the last twenty-fourth farms. A full iteration means the initiating farm switches (or decides to stay) first, and then the other twenty-three farms in numerical order make their switching decisions, where all previous switches or non-switches are permanent for that iteration and known to all members. For example, the first farm in the data set selects one of the wind-aggregation options or self-supply option. The second farm chooses its least-cost flex-reserve strategy once costs are recalculated given farm one’s move, and the sequencing continues until the twenty-fourth farm cost compares. For the next iteration, the second farm becomes the initial mover, the third farm is the second, and this continues until the first mover from the previous iteration, now the last member, compares costs given farms two through twenty-four have already moved (or not). Selecting the least-cost option for procuring flex reserves motivates each farm; therefore, the allocation of cost highly influences the decision-making in this model.

A more detailed description of the switching decisions is provided with reference to the steps in Figure 21. All farms first compare their self-supply costs (SS) to their original placement (R1-Appalachia region, R2-Midwest region), then to the opposing region, and finally to the PJM
aggregate. Once switching has occurred, the farm compares costs based on the current regional/PJM grouping it resides within. The flow diagram of the decision tree is shown from the perspective of a farm originally located in the Appalachia region where the main difference begins with the region $R$ changing to the second ($R_2$) as opposed to being the first ($R_1$). The red-dotted rectangle denotes the iterative process for each farm switching in succession and then repeating this process until a pseudo-optimal farm formation has been reached.

<table>
<thead>
<tr>
<th>Initial:</th>
<th>Cost allocation scheme:</th>
<th>Begin:</th>
</tr>
</thead>
<tbody>
<tr>
<td>- Cost regional (R)</td>
<td>- Equal</td>
<td>Each farm moves in numerical succession</td>
</tr>
<tr>
<td>- Cost PJM</td>
<td>- Size</td>
<td></td>
</tr>
<tr>
<td>- Cost self-supply (SS)</td>
<td>- Production</td>
<td></td>
</tr>
<tr>
<td>- Position*</td>
<td></td>
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</table>

**Figure 21.** A flow diagram of decisions is used to compare the self-supply costs (SS) to the intra-balancing regional costs ($R_1$ for Appalachia region and $R_2$ for the Midwest region) and the PJM collective costs. Each farm compares its self-supply costs to the original or current grouping it may have switched to, and then to the PJM aggregate costs. The following decisions in the diagram are from the perspective of a farm originally located in the Appalachia region, though the decision steps for a farm originally located in the Midwest aggregate would the mirror opposite, beginning in the Midwest, then comparing to the Appalachia and PJM costs. The red line denotes the switching iterations that occur in succession until pseudo-equilibrium of final farm arrangements has been reached for no other farms to desire a switch.
At the start of the switching model, either of the three cost allocation scenarios may be selected. A farm can only belong to one switching policy option at any one time, though it may continue to switch when seeking to minimize its flex-reserve costs. The stopping criterion for the switching model involves at most 50,000 iterations for each farm acting as a first mover and all farms switching afterwards in succession. The cost comparison reflects the yearly costs, though further application of this switching model may be to shorten the time horizon to monthly or weekly, allowing the switching tree to begin anew at the end of each month or week. Such future applications will likely need to consider computational time and implement flexible stopping criteria to arrive at meaningful results.

3.5.3 Summarizing gains and losses from cost allocation and flex-reserve policy scenarios

To better understand if the regional aggregations result in an improvement by lowering costs, this work created definitions for *winners* and *losers*. In general, a winner is a farm that pays less for flex reserves if it remains with the twenty-four farm collective and is a loser if its local regional aggregate is more expensive. The difference in the flex-reserve cost percentages between the PJM aggregate and regional aggregate determines the more costly aggregate. Thus, the first step involves evaluating the sign and magnitude of the percentage difference between the regional percentage (example, top panel in Figure 15) and the PJM percentage (example, bottom panel in Figure 15) for each farm. A negative difference indicates the PJM aggregate is more costly, while a positive difference indicates the opposite. Examining the difference in cost percentages categorizes each farm as winner or loser, but this study was additionally interested in
the degree of the percentage difference. Small differences in the percentage of cost will categorize each farm but may not reveal to what extent the farm would see a substantial advantage or disadvantage from switching.

A user-defined percentage-difference threshold was used to further evaluate if a farm is indifferent to the percentage of cost it is allocated between the PJM and regional aggregate. Indifference describes the situation where a farm sees no advantage to switching since the difference in flex-reserve cost percentage is similar enough to not define a clear cost reduction or increase. The threshold was set at ten, five and one percent. Applying the indifference threshold to the sign of the cost percentage differences, winners and losers are further categorized.

If the difference between the percentages an individual farm pays in the regional aggregate context and the PJM percentage it would pay is positive, then the farm would see an increase in the flex-reserve cost percentage if it left the PJM collective for the regional intra-balancing area. If this positive-percentage difference is less than the threshold, i.e. less than ten percent, the farm would be indifferent to paying at the regional or PJM aggregate percentage cost. Conversely, if the individual farm’s cost-percentage difference between its regional cost percentage and the PJM cost percentage is negative, it would advantageous for the farm to leave the twenty-four farm PJM collective. In similar form, if the magnitude of negative difference is within the threshold percentage bandwidth, i.e. less than ten percent, this farm would be indifferent to either the regional or the PJM aggregate policy; otherwise, any negative difference larger than the threshold percentage bandwidth would constitute as a loss for this farm.

The cost percentages displayed in section 3.5.3 for all cost allocation schemes show the absolute value of the percentage. Some farms’ individual aggregate forecast errors are negative, meaning flex-reserve cost percentages pay for smoothing an oversupply of wind (see numerator in Equation 3.5 for further details). Positive percentages originate from undersupply or shortfalls
of the actual production from the anticipated generation. The cost percentages can be both positive and negative depending upon the implicit sign of percentage of cost before it is differenced as well as after percentages are differenced.

Across the scenarios, the PJM aggregate formation performs the best, yielding the lowest-cost percentages for individual operators. The definition of best in this context is all farms would be losers if they opted for their local regional aggregate as opposed to staying in the PJM aggregate. Based on the winning and losing criteria, no farm’s regional aggregate average cost under the three cost-allocation schemes using regulation and gas prices won.

The next section illustrates how switching among wind policy scenarios impacts average costs, since the intra-balancing regions based on the fixed, original locations did not reduce the flex-reserve costs for the individual farms. Within the switching model, a farm can enter into a bilateral contract to self-supply flex reserves, join the local or other regional group or the PJM collective. These switching options ultimately test whether an optimal formation of the farms will yield a lower cost for all farms simultaneously.

### 3.5.4 Analyzing decision-making to switch among flex-reserve policy scenarios

Farms preferred to either self-supply or not leave the PJM collective where all other farms that are not self-supplying were present. The switching model does not randomly select the first mover, which may impact whether the same farm selects to self-supply or remain as a member of the PJM collective. From the percentage of flex-reserve cost allocated to the wind farms under distinct aggregation scenarios shown in section 3.5.1, the percentage of flex-reserve cost that each individual farms must pay for flex reserves within regional markets typically
exceeds the percentage allocated to each in the PJM grouping. As described, a pseudo-equilibrium criterion was introduced where a minimum number of farms were allowed to move to reach a steady state of no farms switching. Up to four farms chose to switch. Typically, the additive sum of forecast errors from highly anti-correlated farms is near zero, which yields much lower flex-reserves costs. The aggregate forecast error likely highly affects farms’ decisions to either group with certain farms to have a lower aggregate forecast error, and subsequently lower flex-reserve costs, or procure cheaper flex reserves by going alone.

3.6 Conclusions

Utility-scale wind integration in the deregulated market context of PJM allows for a unique analysis of how the system operator may choose to correct for any future imbalances from wind generation and how that decision may or may not favor the individual wind plants within the electrical territory. In certain instances, spatially-dispersed wind farms can lower variability in the power supply. Lower wind power variability could then lower the total costs of balancing excess or shortfalls of expected supply. In this work, the degree of declining costs varies depending upon a combination of factors, such as the capacity of farms, anti-correlation of the forecast errors, the variability in power output, and how the cost of balancing power output fluctuates from an incorrect forecast is allocated. This study examined the cost variation from forming large-scale aggregates of wind farms against intra-regional aggregates of wind farms to determine the lowest-cost options for individual wind farms selling generation using day-ahead scheduling. The focus of this study was on the PJM region using data from twenty-four existing wind plants and current ancillary services regulation and gas prices as proxies for possible market prices for energy required to balance smaller, fluctuating imbalances.
This work focused on a cost analysis of the total and average costs from the individual wind farm perspective to quantify the least-cost methods for smoothing the wind forecast errors annually under three wind policy scenarios. The first scenario represents the farm as an individual entity that would select energy services to cover the forecast errors from its farm alone. The second scenario looked at grouping the farms based on their original location within PJM’s footprint to examine if an intra-balancing region would yield lower costs from clustering the forecast errors from the local farms. Lastly, the third scenario groups all farms into on PJM collective to determine if, from the system perspective, the aggregates of all the forecast errors yields the smallest forecast errors and thus the lowest costs to balance deviations in supply.

Regarding data, PJM regulation prices spanning three years, 2006 to 2008, to examine how fluctuations in price affect the total and average costs for short-term energy services that would correct for errors in the wind power forecast, a market termed in this study as flex reserves.

The total costs ($) each farm would spend varies depending upon if its fixed original regional grouping, Appalachia region to the east and the Midwest grouping to the west, in comparison to the PJM collective costs. Inter-annual variations that are likely due to the difference in price peaks from 2006 to 2008, where 2006 has lower peaks with 2008 possessing more variable low- and high-price peaks. Since total cost is a function of the aggregate prices multiplied by the forecast error, this suggests that the forecast errors when summed are slightly larger for the western farms in the Midwest region than the eastern farms in the Appalachia region (Equation 3.1). Since farms would pay for flex-reserves energy on an hourly basis, this work is interested in the average cost of electricity.

The average cost ($/MWh) reflects the cost for flex reserves based on the total production from the fixed regional groups and the PJM collective. From the average cost perspective, the Midwest farms see a significant reduction likely in part for the large amounts of electricity
produced (see Equation 3.2). Across the three years, the Appalachia regional average costs are the highest, which can be a factor of lower total production yielding a larger average cost, with the PJM average costs being the second most expensive.

Allocating average cost based on the size or production of the farm demonstrates lower percentages than the equal-allocation method, and between the two the percentages vary depending upon the region and individual aspects of the farm. Farms with a smaller capacity, as measured by the maximum production within the dataset, would inherently pay less for flex reserves when considered alone, but when considered in a regional setting, some farms incur higher costs. Overall, farms with a smaller capacity or production level are allocated smaller percentages of the average cost for these two allocation methods. For farms with a larger annual production level, the percentage of the average cost is higher (see Equations 3.3-3.7 for further derivation of the costs). The analysis introduced a winning and losing criterion to flesh out how each individual farm performed when comparing their regional percentage of costs given their original location to the PJM collective. All farms would see a reduction of the cost of flex reserves if they did not form intra-balancing groups.

If these farms were able to switch their location to other regions or leave any grouping, a lower-cost solution may benefit the individual wind farm and possibly the system operator. For this question, switching model is used that allowed each of the farms in succession to iteratively change among the three wind policy groupings (Appalachia, Midwest and PJM collective) based on average costs. A farm can belong to one group at a time and switches after the preceding farm has completed its turn. A stopping criterion was instituted for this model where at most four farms could switch to arrive at a pseudo-optimal formation of farms where no other farm could improve its cost reduction. All farms chose to either self-supply or belong to the PJM collective.
Aggregating wind farms within the PJM footprint into eastern and western halves would not likely yield an improvement in reduced costs for balancing utility-scale wind forecast errors in this case study. As other balancing authorities implement variable-generation programs for improving planning and integration of variable generators, the results here suggest that the aggregate coupling of balancing all imbalances maintains the lowest system cost and may even outperform the costs a wind plant would pay if it purchased back-up energy alone (self-supplier).

The next chapter investigates a statistical method for analyzing the quantity of flex reserve desired for balancing different oversupply and undersupply forecast errors using probabilistic methods.
Chapter 4

Quantile Regression

The Pennsylvania-New Jersey-Maryland (PJM) Interconnection represents the largest balancing area in the United States with a continued installation of variable generation, such as wind and solar. As of 2012, low-carbon-generated electricity from wind and solar represents more than half (59%) of the millions of megawatt hours of renewable energy provided to the PJM territory [44]. Wind capacity in 2009 represented a smaller yet significant 1.5% of the total capacity portfolio in PJM (2,500 MW of wind with a total of 165,000 MW available), and there is a strong, continued investment in interconnecting more renewables (see the PJM Generation Queues for active and withdrawn projects by fuel type) [44], [45]. The Midwest Independent System Operator (ISO) and Electric Reliability Council of Texas (ERCOT) have a larger fraction of their total portfolio capacity dedicated to wind [45].

Since 2009, PJM has used centralized wind forecasting tools for coordinating its wind assets at various forecast interval lengths from five minutes to forty-eight hours in advance. Forecasting instantaneous power and forecasted power at the five-minute level are currently being implemented for improving the dispatch of the existing wind assets [13]. As more renewable assets come online, forecast tools will be crucial, prompting the need for a better understanding of possible errors in the forecasts and exploring strategies for managing financial uncertainty from forecast errors.

With the intention that increasing percentages of the U.S. electricity demand be met by renewables, innovative strategies will be needed to enable operators of variable-generation assets to provide the electricity in a reliable and profitable manner. This analysis uses data from twenty-

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5 Wind represents 5.5% of the total capacity in MISO and 11.25% of the total capacity in ERCOT [45].
four wind farms within PJM as a case study for examining a prospective market for a flexible ramping service. The wind owner operating a wind plant is the decision maker, selling wind generation using a day-ahead schedule. Market prices, penalty rules for deviations from the anticipated supply offer and natural variability of wind speeds impact the revenue stream for wind independent power producers (IPPs) and utilities operating wind power plants. Committing to a day-ahead schedule like conventional generators such as gas and coal presents a certain margin of financial uncertainty from the time the schedule is submitted to the day and hour of production.

Given the inherent variable and uncontrollable characteristics of wind generation, a flexible-ramping service may help balance the unexpected changes in actual supply through use of forecasting tools for planning the future generation schedule. This work applies the flex-reserve market also used in operating reserve-market applications from the National Renewable Energy Lab, called flex reserves [41]. For this case study, the wind operator would access the flex-reserve market in the event of an excess or shortfall of expected generation; essentially, utilizing the flex-reserve market for balancing the look-ahead forecast errors. This research introduces a wind policy scenario analysis with quantile regression to illustrate possible quantities of energy needed to balance varying proportions of forecast errors.

4.1 Background

The decision process for operating wind plants is changing as wind forecasting becomes a mandated scheduling tool [29], [38]. Currently in PJM, wind operators are assessed a penalty based on operating reserve charges when the energy delivered in real time differs from the day-
ahead submitted schedule \[35\].\(^6\) A wind operator will then need to anticipate the financial and operational impacts of incorrect forecasts of production. A quantile regression is utilized as a mathematical representation of the probability of the day-ahead forecast errors. Quantile regression is currently implemented in coordinating large footprints of wind capacity in Western Europe and several studies use Nord Pool as a case study for implementing non-parametric, probabilistic forecasting methods for predicting wind production output \[47\], \[48\], \[49\], \[50\]. These forecasting methods are not applied in the U.S. balancing areas.

The authors in \[47\] examine the optimal quantile using the time-adaptive quantile-regression approach with the Nord Pool case study where the optimal quantile is a function of the wind production cost function for up-and-down regulation services. No one quantile is consistently used when operating wind plants since cost can change, as do the forecasts of production. Cost functions for the wind plants are not calculated, though the distinct quantiles can be used to outline optimal paths for balancing different error types. \[42\] develops an algorithm that uses time-adaptive quantile regression for modeling prediction errors from a forecast model, the Wind Power Prediction Tool, using data from an existing wind farm in Denmark. \[50\] uses local quantile regression for improving probabilistic forecasting for wind power, which closely relates to our work in exploring future wind power forecast errors.

A quantile \(\tau\) describes the flex-reserve quantity of energy found at the \(\tau^{th}\)-percentile of the conditional density of the response variable, day-ahead forecast errors, and the explanatory variable, forecasts of production. Quantile regression used in this analysis is based upon a linear conditional quantile function that assumes the conditional density of the response variable exists and is positive in the quantile tau for all values of the explanatory variable \[51\]. Examining the

\(^6\) Deviations less than 5% or 5MW do not result in any charge \[35\]. These charges on average cost $2-3/MWh \[46\].
quantiles below and above the median will help inform the wind plant owner of the probability of the type of look-ahead forecast errors (undersupply and oversupply) and the magnitude of these look-ahead forecast errors that translate into the volume/quantity of flex reserves. The wind plant owner can further compare how the quantity of flex reserves changes at the same quantile in the three distinct wind policy scenarios that were previously considered in section 1.6.

This work demonstrates how a collection of twenty-four PJM farms can use quantile regression to examine potential uncertainty in the type and magnitude of future wind forecast errors from varying proportions of day-ahead forecast errors as defined by the quantile \( \tau \). Data for this chapter utilizes forecasts of production and forecast errors for twenty-four existing farms across six different states in PJM (see section 1.3 for further information). Five-minute data is also used, as opposed to hourly data to incorporate a larger sample size, to better analyze the range in forecast errors that occur sub-hourly and to match the five-minute forecast timeframes currently used in PJM [13]. As a guideline for the following results from the wind operator perspective, a single farm would likely desire to procure flex reserves individually if the quantity of flex reserves is less than the aggregate policy, either regional or for the entire PJM, for the same forecast quantile. The system operator perspective is depicted as the PJM aggregate.

### 4.2 Summary of PJM flex reserve intra-balancing area cost analysis and quantile regression

The previous chapter provides an in-depth calculation of the total and average cost for flex reserves using different cost-allocation schemes at the hourly level under the same three wind policy scenarios, and this chapter builds from the previous by examining the quantity of flex reserves needed to balance various wind policy scenarios. The term intra-balancing group refers to the two regional aggregates of the wind farms, the Appalachia group in the East and the
Midwest group to the West, formed within the PJM territory. The last chapter showed the total-cost and average-cost calculations summed across all forecast errors for the complete year (January to June) at the hourly level using twenty-four-hour-ahead forecast data. This analysis does not directly estimate flex-reserve costs at the five-minute level since regulation prices for PJM are reported hourly. This study follows the logic that purchasing a large volume of flex reserves as opposed to a smaller quantity is more costly in total cost at the same five-minute segment in time.

The allocation scheme affects the fraction of cost each farm would pay if it elected to join a regional aggregate or the whole PJM aggregate. The equal-allocation scheme yielded cost percentages of at most 5% of the average cost for the individual farms in the regional aggregates and the whole PJM aggregate in contrast to the size and production allocation schemes. The size-and-production-based allocation schemes showed higher percentages of the average cost for the western farms in the Midwest regional aggregate in comparison to the Appalachia farms. The PJM aggregate scenario demonstrated consistently a low-average-cost percentage for all farms in the size-and-production allocation cases. Gas prices are introduced along with the regulation prices as possible prices for flex reserves. There is little difference in the percentages across the equal size and production cost-allocation schemes and the three wind policy scenarios when using PJM regulation and natural gas prices as the representative price in the flex-reserve market.

The equal allocation scheme may not accurately allocate the costs to all farms intra-regionally since not all farms are sized similarly and they possess different power production levels. Further variation in the cost percentages allocated to the individual farms for the size-and-

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7 Prices for PJM regulation market are reported hourly, so the same hourly price would be applied to each five minute segment within the hour. The approximate flex reserve cost would be the flex reserve quantity multiplied by the regulation price ($/MWh).
production-based allocation schemes occurs when the farms join a regional aggregate or remain in the whole PJM collective. A switching analysis is performed to allow each individual farm to change the flex-reserve grouping to find the least-cost flex-reserve option, concluding that farms prefer to either individually balance their forecast errors (self-supplier) or pay for flex reserves based on the PJM collective. In a similar fashion, the wind policy scenario affects the reduction or increase in the quantity of flex reserves required for balancing forecast errors at the day-ahead forecast interval.

The absolute value of the look-ahead forecast errors was not used when training and evaluating the quantile regression model because one objective was to see what type of forecast error may be predicted for the varying quantile levels that result in different real-world operational decisions to decrease, generate at negative prices or increase generation. Apart from the sign of the forecast error, the magnitude of the look-ahead forecast error is important because it impacts the wind plants willingness to pay for the volume of flex reserves based on the probability of the magnitude of a day-ahead forecast error that inherently may be an over- or under-estimate. The decision to purchase flex reserves in this work reflects the magnitude of the look-ahead forecast error that represents the $\tau$–th percentile of the conditional distribution. The following results describe the different volumes of flex reserves that individual farms may purchase to balance over- and under-supply forecast errors.
4.3 Methods

4.3.1 Quantile regression formulation

This chapter extends the wind aggregation work previously explored from the perspective of the individual wind operator, but with a renewed focus in understanding the financial uncertainty for errors in a wind forecast for plants participating in a deregulated electricity market. Quantile regression can provide advantages to the ordinary least squares (OLS) regression approach in the presence of heteroskedasticity and outliers in the data. The conditional mean from a least-squares approach requires homoscedasticity in the variance of the error terms [17], which may not be a property of all data. Quantile regression has been developed to test for heteroskedasticity, and the median regression estimation can be more robust than the mean regression estimators [17]. Recall, in section 1.4.2 the discussion about the heteroskedastic nature of our forecast data (see Figure 2). Quantile regression is used to more robustly represent the covariate relationship between the look-ahead forecast errors and the previous forecast of production, which outperforms the OLS regression for most all quantiles (see Figure 24 and Figure 25 as representative examples of two farms in the PJM region).

Using quantile regression, an individual wind operator can have deeper knowledge of the type of forecast error events and the associated quantity of flex reserves for balancing distinct proportions of the conditional density of the wind forecast errors and the previous forecast of production. The magnitude of the forecast error at a specified quantile is the quantity of flex reserves that is needed to balance the forecast error at the tau\textsuperscript{th} percentile. Depending upon the wind policy scenario, the individual wind plant can further examine the flex-reserve quantities at the same quantile levels to calculate which policy scenario yields the least quantity and therefore
the lower cost of purchasing flex reserves. Later sections discuss how quantile regression explores distinct forecast error types, which may influence flex reserve decision-making when planning for an anticipated over- or under-supply of generation.

Analyzing the quantile regression results at different values of $\tau$ under three wind policy scenarios (individual, regional aggregates, and PJM whole aggregation) helps describe the strategies for wind operators selling merchant wind generation. Merchant generation means the generation is sold directly to the electricity market rather than through a long-term power-purchase agreement, but sellers of merchant generation are most exposed to uncertainty in revenue [47]. A majority of wind-generated electricity is sold via a PPA where future revenue gain and losses for the wind operator are buffered by the fixed generation price from the PPA [52], [53]. The percentage of new, installed wind power capacity sold as merchant generation in an electricity market reached a peak of 38% in 2009 and has recently decreased to 19% in 2012. If a wind farm operator transitions to selling generation as a merchant generator in a day-ahead market structure, managing potential financial risk from forecast errors and the associated penalty costs will become increasingly important.

The *flex reserve market* serves as the context for buying energy at the regulation price to balance a forecast deviation, as opposed to incurring a penalty. The magnitude of these deviations varies depending upon the forecast quantile of predicted forecast errors. Quantile regression for look-ahead forecast errors helps present trade-offs between over purchasing flex reserve to smooth more extreme potential forecast errors and hedging that the forecast is not significantly wrong. Results from the quantile regressions show the quantity of flex reserves that may be

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8 As of 2012, the cumulative wind power capacity breakdown shows that utilities own 15% or buy 54% of its power from 69% of all the wind power capacity in the United States. For newly installed wind power capacity Independent Power Producers (IPPs) own 88% in the United States in 2012. Directly selling merchant generation or owning wind capacity that is sold as merchant generation in a portfolio may have some financial risks since revenue is coming solely from market-based prices [52], [54].
required for balancing forecast errors at distinct quantiles. These quantities reflect the proportion of the look-ahead forecast error distribution that results from under or over predicting future production.

The quantile regression formulation for this work borrows from the work developed originally by [51]. For this problem formulation, the response variable \( y \) is a vector of the look-ahead forecast error for the next time period \( \text{p}+1 \), which is the difference between the five-minute forecast of production twenty-four hours in advance and the actual production for all observations in the data set. The independent variable, \( x \), is a vector of the five-minute forecast of production twenty-four hours ahead from the previous time period \( p-1 \). In a general context, \( x \) can be one of many input variables that form a multivariate matrix \( X \). Quantile regression is used to understand the present conditional relationship between the look-ahead day-ahead forecast errors \( (p+1) \) and the previous forecast of production \( (p-1) \). Quantile regression can relate to ordinary least squares to understand a basic regression model, and then proceed with what a quantile is and what information a quantile can provide.

In ordinary least squares minimization, the conditional mean of a random sample of data \( \{y_1, y_2, ..., y_n\} \) is found with a minimization function using a parametric function \( \mu \) of the regression coefficients \( \beta \) and explanatory variable(s) \( x \) given a sample size \( n \) (Equation 4.1) [55]. Equation 4.1 yields the conditional expectation function \( E(Y|x) \).

\[
\min_{\beta \in \mathbb{R}} \sum_{i=1}^{n} (y_i - \mu(x_i, \beta))^2
\]

---

\(^9\) Quantile regressions are performed using the QuantReg package in the R software developed by Roger Koenker.
Quantile regression estimates the conditional relationship between the response and explanatory variables at a specified proportion of the conditional density. The quantile regression equation for a given quantile $\tau$ is linear, and assumes that the conditional density of the response variable exists [51], [55]. In our case, a quantile would pertain to the look-ahead forecast error at the $\tau$-th portion of the conditional density of the look-ahead forecast error and previous forecast of production. The quantile equivalently describes the probability of a forecast error being less than or equal to the day-ahead forecast error that corresponds to the quantile $\tau$, in decimal form from zero to one (or the $\tau$-th percentile), of the conditional density. Equation 4.1 can be re-written as a minimization function that estimates the conditional quantile functions using a parametric function $\xi(x, \beta)$ as done in equation 4.2.

(4.2)

$$
\min_{\beta \in \mathcal{R}} \sum_{i=1}^{n} \rho_{\tau}(y_i - \xi(x_i, \beta))^2
$$

Where $\tau \in [0,1]$

A loss function is introduced here with $\rho_{\tau}$ defined in equation 4.3. The $\rho_{\tau}$ component of minimization function is sometimes referred to as a loss function, which finds the solution at which all values of $x$ lie below the $\tau$th quantile and lie above the $1 - \tau$th quantile space. A specific quantile is defined by a linear loss function that minimizes the loss of function below for estimating the values that fall within the $\tau$th quantile (Equation 4.3).

(4.3)

$$
p_{\tau}(r) = \begin{cases} 
\tau r, & r < 0 \\
(\tau - 1)r, & r \geq 0
\end{cases}
$$
The conditional quantile function \( \hat{Q} \) of the \( \tau^{th} \) quantile is based on the conditional distribution function \( F_{y|x}(y|x) \). A quantile expresses the conditional relationship between the dependent variable \( y \) given the explanatory variable \( x \) at distinct segments of the conditional density, such as the median. The conditional median can be found by setting \( \tau = 0.5 \). This analysis focuses on the \( \tau^{th} \) quantile in increments of 0.10 from 0.10 to 0.90 (also referred to as deciles). One can interpret the \( \tau \)-quantile as the \( \tau \)th percentile, where the percentile is the likelihood of a value in the density being equal to or below the percent on a scale of one hundred percent. If a forecast error falls within the 80\(^{th} \) percentile or 0.80 quantile, then 20\% of the forecast errors are greater than it and 80\% of the forecast errors are equal to or smaller than it. Quantile regression allows us to visualize the look-ahead errors conditional upon the previous forecast of production values at distinct values of \( \tau \).

### 4.3.2 Application of quantile regression for understanding look-ahead forecast errors

The quantile regression is performed using the past time period forecast of power production as the independent variable and the look-ahead time-period forecast error as the dependent variable. Seventy-percent of the five-minute look-ahead forecast errors at the day-ahead forecast interval and the five-minute previous forecast of production at the day-ahead forecast interval were used to train the quantile regression model for each farm in the twenty-four farm dataset. The remaining thirty percent of the same data were used as evaluation data, all at the five-minute time resolution. The coefficients from the regression function describe the conditional relationship between the future day-ahead forecast error regressed upon the past day-ahead forecast of power production at the five-minute time horizon. This work shows the
regression coefficient values $\beta_0$ (intercept) and $\beta_1$ (response variable, previous day-ahead forecast of production) and the standard errors for the quantile regressions for values of $\tau$ at 0.10 to 0.90. The full statistical results can be found in the Appendix, Table 7.

The next step explored is to examine the $\beta_1$ coefficient values for the response variable for each farm of the twenty-four farms at the distinct $\tau$-quantiles and the standard errors to understand the covariate relationship between the previous forecast of production and the look-ahead forecast error in the conditional quantile regressions (Figure 22 and Figure 23). The $\beta_1$ coefficient values describe the covariate relationship between the previous day-ahead forecast of production value (explanatory variable) and the look-ahead forecast error (response variable). The standard errors help describe the precision of the conditional estimates of the look-ahead forecast errors at each quantile at the 5% significance level, which means 95% of the predictions should fall within plus or minus 1.96 multiplied by the standard error at each quantile. The latter is how the confidence interval at the 5% significance level is determined, which is later used to compare the ordinary least squares (OLS) regression approach to the quantile regression. Recall our regional division of PJM, farms one through twelve belong within the original Appalachia group in the east and the last twelve farms would be found in the western Midwest group. Each farm is denoted by a specific color labeled in the legend in Figure 22 and Figure 23.
Figure 22. The left panel displays the coefficient $\beta_1$ for the explanatory variable, forecast of production from the previous time step, for each quantile (tau) in increments of 0.10 from 0.10 to 0.90 for the farms in the Appalachia grouping. Each of these twelve Appalachia farms are denoted by the color legend, and the standard errors for each incremental quantile regression is denoted in the the same color in the right panel.

The $\beta_1$ coefficient values of the previous forecast of production for the individual farms within the Appalachia group range between -0.2 and 1, with farm 2 (blue) and 11 (medium red) displaying larger coefficients than the other Appalachia farms at higher quantile values (Figure 22). At the 0.10 quantile, the interpretation of the $\beta_1$ coefficient for farm 11 is for each additional previous forecast of production the look-ahead forecast error would result in a change of 0.10 MW in the downward direction as an expected oversupply event (i.e. -0.1). At the 0.90 quantile, for one more previous forecast of production, farm 11 would result in a change of approximately 1 MW in the upward direction for an expected undersupply event (i.e. 0.99). The standard errors at each quantile for most all farms in the Appalachia region are tightly clustered, exhibiting an overall range between near 0.002 and 0.008 along the quantiles. Again, the standard errors for farms 2 and 11 typically exceed those of the other farms at the same quantile. The confidence
interval, for example, at the median quantile (0.50) for farm 11 is +/- 1.96 multiplied by 0.006, which means the $\beta_1$ coefficient at 0.096 has a confidence interval of 0.08 to 0.10. Larger standard errors would translate to a larger confidence interval, and what this study focuses on next is whether the quantile regression confidence interval contains the OLS regression coefficient at the $\tau$th quantile. If this occurs, then the quantile regression performs no better than the OLS regression.

Figure 23. The left panel displays the coefficient $\beta_1$ for the explanatory variable, forecast of production from the previous time step, for each quantile ($\tau$) in increments of 0.10 from 0.10 to 0.90 for the farms in the Midwest grouping. Each of these twelve Midwest farms are denoted by the color legend, and the standard errors for each incremental quantile regression is denoted in the the same color in the right panel.

In the Midwest portion of PJM (Figure 23), the $\beta_1$ coefficient values of the previous forecast of production for the individual farms show values that are within the same range as the Appalachia farms, as shown in the right panel of Figure 22. Farm 4 (light green) in the Midwest region has larger coefficient values, which also show a more variable standard error value at each quantile in comparison to the other eleven farms. The confidence interval is calculated with the
same method as before, noting that the Midwest farm standard errors are all non-zero with higher values than the Appalachia farms.

As previously mentioned, this work verified that quantile regression provides coefficient estimations that are significantly different than using the OLS regression coefficients at most all quantiles, which means using the probabilistic quantile approach provides an estimation of forecast errors that is not captured using the conditional mean. The previous discussion showed the OLS regression coefficient (red solid line) and its confidence interval (red dashed line), as well as the quantile regression coefficients (black dots), $\beta_0$ and $\beta_1$, with the confidence interval shaded in grey at each quantile in increments of 0.10. Figure 24 features one farm in the Appalachia region, and Figure 25 features one farm in the Midwest region of PJM. The coefficient for the previous forecast of production $\beta_1$ is the primary discussion point, as it is the independent variable in the quantile regression formula.
Figure 24. The top panel shows the quantile regression intercept coefficient $\beta_0$ value for each quantile $\tau$ (tau) from tau in increments of 0.10 from 0.10 to 0.90 (horizontal axis). The bottom panel shows the quantile regression coefficient for the previous forecast of production $\beta_1$ for each quantile $\tau$ (tau) from tau in increments of 0.10 from 0.10 to 0.90. The gray shaded region is the confidence interval for each quantile regression coefficient. The red dashed lines denote the ordinary least squares (OLS) confidence interval for the OLS regression coefficient. If the OLS confidence interval contains the quantile regression coefficient value, then there is no statistical advantage to using quantile regression over OLS regression. These results feature farm 1 in the Appalachia region.

Using the results above and a further analysis of the coefficient values, this study determines if the coefficients from both regression approaches are significantly different from zero and if the quantile regression coefficients are significantly different from the OLS regression coefficients at the 5% significance level. A snapshot of these coefficient values at quantiles 0.10, 0.30, 0.60 and 0.90 is provided in Table 3 and Table 4 to demonstrate significant difference from zero with an asterisk and significant difference in the OLS regression coefficient along distinct percentiles of the conditional density of the look-ahead forecast errors with a plus sign. If a quantile regression and OLS regression coefficients are significantly different from zero at the 5% significance level that means that the p-value for the variable is less than 0.005. The variable is deemed significant and should remain in the regression. If the confidence interval denoted by the shaded grey region for the $\beta_1$ at each quantile does not contain the OLS regression coefficient,
then the quantile regression coefficient is significantly different from the OLS regression coefficient at a 5% significance interval.

Table 3. This table lists the quantile regression and ordinary least squares regression coefficients as labeled in the top column for distinct quantiles at \( \tau = 0.10, 0.30, 0.60 \) and \( 0.90 \). An asterisk denotes whether the value of the coefficient is significantly different that zero at the 5% significance level with an asterisk. The plus sign is used to denote when the quantile regression coefficient value is significantly different than the OLS regression coefficient at the 5% significance level. If the confidence interval for the quantile regression coefficient lies outside of the OLS regression coefficient, or equivalently, if the OLS regression confidence interval does not contain the quantile regression coefficient value, then there is significant difference between the quantile regression and OLS regression coefficients at the 5% significance level. Results are for farm 1 in the Appalachia region (see Figure 24 for visual representation).

<table>
<thead>
<tr>
<th>Coefficients</th>
<th>OLS Regression Coefficient</th>
<th>Quantile Regression at ( \tau = 0.10 )</th>
<th>Quantile Regression at ( \tau = 0.30 )</th>
<th>Quantile Regression at ( \tau = 0.60 )</th>
<th>Quantile Regression at ( \tau = 0.90 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Previous forecast of production (MWh) ( \beta_1 ) Coefficient</td>
<td>0.24*</td>
<td>0.142**</td>
<td>0.09**</td>
<td>0.19**</td>
<td>0.59**</td>
</tr>
<tr>
<td>Intercept ( \beta_0 ) Coefficient</td>
<td>-1.17*</td>
<td>-12.65**</td>
<td>-2.30**</td>
<td>1.56**</td>
<td>2.65**</td>
</tr>
</tbody>
</table>

*Significantly different quantile regression coefficient from zero at the 5% significance level  
+Significantly different quantile regression coefficients from the OLS coefficients at the 5% significance level as defined by the OLS coefficient being outside the quantile regression coefficient confidence interval.  
**See the standard errors for farm 1 in Table 5 in the Appendix for the standard errors. The confidence interval is +/- 1.96 multiplied by the standard error.

The two farms selected here show that the OLS regression and quantile regression coefficients are significantly different from zero and the difference between the regression approaches is generally significant. The Midwest farm example in Table 4 at the 0.60 quantile, the \( \beta_0 \) coefficient value of 0.04 is contained within the OLS regression confidence interval of the OLS regression coefficient value 0.4 (0.035, 0.045) at the 5% significance level. The quantile regression at this quantile did not produce a coefficient that is significantly different from the conditional mean. However, the quantile regression provides significantly different coefficient
estimates to describe look-ahead forecast errors than the OLS regression estimates, as seen numerically in the tabled data and by visualizing the coefficient plots (note + signs in Tables 3 and 4).

![Figure 25](image)

**Figure 25.** The top panel shows the quantile regression intercept coefficient $\beta_0$ value for each quantile $\tau$ (tau) from tau in increments of 0.10 from 0.10 to 0.90 (horizontal axis). The bottom panel shows the quantile regression coefficient for the previous forecast of production $\beta_1$ for each quantile $\tau$ (tau) from tau in increments of 0.10 from 0.10 to 0.90. The gray shaded region is the confidence interval for each quantile regression coefficient. The red dashed lines denote the ordinary least squares (OLS) confidence interval for the OLS regression coefficient. If the OLS confidence interval contains the quantile regression coefficient value, then there is no statistical advantage to using quantile regression over OLS regression. These results feature farm 10 in the Midwest region.
Table 4. This table lists quantile regression and ordinary least squares regression coefficients as labeled in the top column for distinct quantiles at \( \tau = 0.10, 0.30, 0.60 \) and 0.90. An asterisk denotes whether the value of the coefficient is significantly different that zero at the 5% significance level with an asterisk. The plus sign is used to denote when the quantile regression coefficient value is significantly different than the OLS regression coefficient at the 5% significance level. If the confidence interval for the quantile regression coefficient lies outside of the OLS regression coefficient, or equivalently, if the OLS regression confidence interval does not contain the quantile regression coefficient value, then there is significant difference between the quantile regression and OLS regression coefficients at the 5% significance level. Results are for farm 1 in the Appalachian region (see Figure 25 for a visual representation).

<table>
<thead>
<tr>
<th>Coefficients</th>
<th>OLS Regression Coefficient</th>
<th>Quantile Regression at ( \tau = 0.10 )</th>
<th>Quantile Regression at ( \tau = 0.30 )</th>
<th>Quantile Regression at ( \tau = 0.60 )</th>
<th>Quantile Regression at ( \tau = 0.90 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Previous forecast of production (MWh) ( \beta_1 ) Coefficient</td>
<td>0.04*</td>
<td>-0.19*</td>
<td>-0.06**</td>
<td>0.04**</td>
<td>0.37**</td>
</tr>
<tr>
<td>Intercept ( \beta_0 ) Coefficient</td>
<td>-7.03*</td>
<td>-52.25**</td>
<td>-8.45**</td>
<td>6.44**</td>
<td>17.51**</td>
</tr>
</tbody>
</table>

*Significantly different quantile regression coefficient from zero at the 5% significance level
+Significantly different quantile regression coefficients from the OLS coefficients at the 5% significance level as defined by the OLS coefficient being outside the quantile regression coefficient confidence interval.

**See the standard errors for farm 22 in Table 5 in the Appendix for the standard errors. The confidence interval is +/- 1.96 multiplied by the standard error.

The regressions are performed as if operating the wind turbine at the present time period \( t \) using the look-ahead day-ahead forecast error (\( p+1 \)) and previous time period forecast of production (\( p-1 \)) historical data to understand potential financial uncertainty for different types of forecast errors. Since the data are heteroskedastic, the predicted look-ahead forecast error values that lie within the proportion of the conditional density as defined by \( \tau \) do not have a constant slope, as shown by the varying slopes in the linear lines in Figure 26. For example, the median quantile or 50th percentile for the individual Appalachia farms does not have a constant slope, so no one fixed look-ahead forecast error is associated with all previous forecasts of production values. For this reason, all the look-ahead forecast error values that are less than or equal to the
\( \tau^{th} \)-percentile of the density are averaged to find a fixed average look-ahead value at the quantile \( \tau \). Quantile regressions were performed at distinct increments of nine deciles (0.10 to 0.90) for describing ten segments of the conditional density of the look-ahead forecast errors and previous forecasts of production that would give the wind plant operator ten distinct quantity levels of flex reserves that would balance distinct, cumulative proportions of the conditional density. In short, these mean fixed look-ahead forecast errors represent the quantity of flex reserves needed to balance a specific \( \tau^{th} \)-percentile or \( \tau \)-quantile of the look-ahead forecast errors.

Figure 26. This plot shows the quantile regressions in increments of 0.10 from 0.10 to 0.90 for a single wind farm (same shown in Figure 4) in PJM overlaid against a scatter plot of the forecast errors (positive and negative black dots) with respect to the forecast of production (MW). The \( \tau \)-quantile regression denoted in a spectrum from red to yellow partitions the distribution of look-ahead forecast errors to find the forecast error value that corresponds a certain forecast of production. The \( \tau \)-quantile can be interpreted as the \( \tau \)-th percentile. Lower quantiles describe negative forecast errors or oversupply events while the upper quantiles describe positive forecast errors or undersupply events. Notice the quantile regression lines are not perfectly linear, which prompted an averaging of the corresponding look-ahead forecast errors at the \( \tau \)-th percentile for interpreting the quantity of flex reserve at the \( \tau \)-quantile.

In practice, the wind plant would purchase the absolute value or magnitude of look-ahead forecast error, though the type of forecast error the wind plant anticipates can describe different ramping operations and revenue possibilities. The volume of flex reserves at the \( \tau \)-quantile (tau)
represents the volume necessary to balance up to \( \tau \) percentile of forecast errors but will not balance the proportion belong to 1-\( \tau \) area of the forecast error distribution.

The lower value quantiles (0.10 to median 0.40) are categorized as the oversupply forecast error scenario, since these quantiles refer to proportions of the negative look-ahead forecast errors in the conditional density, while higher value quantiles (0.60 to 0.90) correspond to the undersupply forecast error scenario, as these look-ahead forecast errors are positive. The median (0.50) represents a sign-neutral forecast error benchmark for the quantity of flex reserves needed to cover half of the total quantity of flex reserves that would correspond to the average look-ahead forecast error at the lower half segment in the conditional density. The median quantile commits the wind plant to no one specific type of forecast error flex-reserve product, which assumes the flex-reserve buyer is buying a volume of energy products for balancing up to fifty percent of forecast errors, be it for undersupply or oversupply events. The results from the quantiles inform the wind operator about the type and magnitude of possible forecast errors within the conditional density. Recall that for oversupply events, the wind plant in practice would either curtail generation or continue to sell electricity at negative prices (i.e. at a financial loss). Undersupply events would require fill-in energy since the wind plant fell short of the day-ahead scheduled output. For wind merchant generators in PJM participating in this proposed flex-reserve option, it would have to consider the cost differential between a penalty that varies depending upon operating reserve charges for operating differently than the day-ahead schedule and the cost for purchasing flex reserve [35]. Operating reserve charges are not publicly available, though this financial risk is important to note.
4. 4 Results

This section displays the quantile regression analysis results for the three wind policy scenarios (for example, see Figure 27 and Figure 28 for the individual farm regression results). The individual quantile regression analysis illustrates the varying range in the volume of flex reserves at single farms needed to balance distinct quantile ranges of forecast errors that may reflect an oversupply or undersupply, depending upon the sign of the forecast error. The forecast of production and forecast errors are additively summed for the regional and PJM groups for determining the quantile regression for the collective regional farm groupings (Figure 29).

5.4.1 Procuring flex reserves at the individual farm level

Individual farm quantile regression by region shows an overall trend with the volume of flex reserves corresponding to the lower quantiles that describe oversupply events where the actual production was greater than the forecast of production (negative forecast error). In real-world practice, an oversupply event may require the wind operator to reduce or curtail generation equivalent to the magnitude of the forecast error or they can continue to provide electricity to the grid but bid at negative prices. A negative price thus indicates the wind operator is paying to generate electricity. There exists an inherent opportunity cost in this instance between bidding at negative prices while continuing to generate electricity versus stopping generation altogether (assuming no operational challenges to do so on short notice), though decision-making based on a price signal is not considered in this work. The decision maker considers purchasing flex reserves as a mechanism to balance the predicted magnitude of unforeseen generation, either in excess or deficit, via a flex-reserve market similar to the existing PJM ancillary services.

Figures displaying individual farms are shown in no particular numerical order.
regulation market. The flex reserves market behaves as a quasi ‘back-up electricity bank’ where operators may pay for future balancing services at prices seen in a regulation market, as a first proxy. Although not analyzed in this work, a possible extension would be for wind operators to pay other generators to increase or decrease generation, depending upon the sign of the predicted forecast error for flex reserves.

5.4.2 Appalachia individual farms

Appalachia farms are typically smaller in size than the Midwest farms\(^{11}\), and the lower forecast quantile ranges (0.10 to 0.30) suggest that to balance the look-ahead forecast error the operator would pay for *oversupply* flex reserves (Figure 2). As the quantile increases closer to the median (0.50), the proportion of the look-ahead forecast errors change from oversupply events (negative forecast error) to *undersupply* events (positive forecast error) for all farms in the Appalachian region. The magnitude of the forecast errors close to the median quantile are near zero. As the proportion of the forecast errors within the distribution increases to the higher quantile ranges (0.60 up to 0.90), the operator, if it chooses to purchase flex reserves to balance a larger mass of the distribution, would balance larger undersupply events as indicated by the positive forecast error values upwards of 60 MW.

The look-ahead forecast error value increases as the forecast quantile increases from the median (0.50 quantile) up to the 0.90 quantile (Figure 27 upper range quantiles). For the Appalachia farms located in rather remote, mountainous locations, committing to a quantile from 0.70 to 0.90 corresponds to balancing a greater proportion of the distribution and anticipating

\(^{11}\) The minimum and maximum production output for the Appalachian aggregate from the historical five-minute data is (-57, 249) MW and the Midwest aggregate shows an production output range of (-32, 585) MW.
undersupply (positive forecast errors) events at a fairly high magnitude. The higher quantile regressions at 0.70 to 0.90 would translate to not balancing the 0.30 to 0.10 upper proportions. The upper proportion includes more extreme undersupply or shortfall events where a farm may desire to balance a larger amount of the undersupply predicted forecast errors to minimize the likelihood of falling short of meeting the day-ahead schedule. Larger quantities of total flex reserves naturally come at greater costs.

The farm size can impact the predicted forecast error ranges, variability and quantity of flex reserves to manage possible forecast error risks. Recall the size of a farm plant for this case...
study is the maximum production output rather than nameplate capacity since the nameplate capacity data for the twenty-four farms were unavailable. There is no hard-and-fast rule that a larger wind plant will have more variability and thus more extreme forecast errors in the future, but there is the possibility for substantial forecast errors with larger installed capacities. One particular farm denoted as the fifth farm in the Appalachia group has a large power production range and variance in forecast errors and consequently a larger range in the probabilistic look-ahead forecast errors as seen in the quantiles from 0.10 to 0.90. Smaller capacity Appalachia farms, such as farms 3 and 10, present a smaller, more clustered range near zero MW in the magnitude of the day-ahead forecast errors for the varying quantiles; thus, a smaller farm will likely require a smaller quantity of flex reserves in comparison to a larger-sized wind farm. Farm’s with a smaller range of look-ahead forecast errors required to balance the quantiles for flex reserves quantities may not be as concerned with the type of forecast error as the flex-reserve quantities for lower and upper quantiles are near zero (see Farms 3, 4, 7, 9, and 10 in Figure 27). A larger farm as opposed to a smaller farm may need to be more critical of the quantity of flex reserves it purchases since the range of look-ahead forecast errors can be larger and pertain to a different forecast error type (see Figure 27quantile 0.10 (red) and quantile 0.90 (purple)).

5.4.3 Midwest individual farms

Individual Midwest farm quantile regression results exhibit similar structural features as the Appalachia farms with lower quantiles corresponding to oversupply (negative) day-ahead forecast error events and higher quantiles including undersupply (positive) day-ahead forecast error events (Figure 28). The range in the positive and negative look-ahead forecast errors reaches greater values, which is likely due to a combination of factors (larger size of the farms, greater
range in power production and possible larger forecast errors). Larger output levels are associated with higher variance of output.

Apart from farms 4 and 10 of the Midwest farms, the majority of the Midwest farms show a range of 50 MW for both negative and positive error types, which is within the minimum and maximum range of the Appalachia farm look-ahead forecast errors. For the farms exhibiting a broader range in look-ahead forecast errors, both in type and magnitude, decision-making regarding the quantity of flex reserves is likely quite complex. As mentioned, the flex reserves balance the magnitude of a forecast error, though the flexible-energy service may be called for different motivations depending upon the sign for the error at the selected quantile.

The vertical shape of the look-ahead forecast errors at each quantile in Figure 28 possesses a more symmetric spread at zero MW not seen in Figure 27. Certain Midwest farms, 4 and 10, possess a particularly large range upwards of a 150 MW forecast error for undersupply and oversupply events. Farm 10 shows a particularly unique forecast error structure where the quantile covering the smallest portion of the distribution (0.10) indicates a large oversupply event (large negative forecast error at approximately 100 MW) and the 0.90 quantile covering the largest portion of the distribution reaches undersupply forecast errors as large as 130 MW. A large farm with higher variability will likely need to purchase larger volumes of flex reserves to hedge against a particularly large shortfall or excess event. Farms with smaller ranges in the look-ahead forecast errors will likely need to purchase smaller volumes of flex reserve to balance 50% of the oversupply forecast errors and undersupply forecast errors. This study concludes the latter by observing that the look-ahead forecast errors at the 0.90 quantile are not significantly larger than the median (see farms 2, 3, 5, 7, 8, and 9 in Figure 28).
5.4.4 Intra-regional and whole PJM aggregation impact on the quantity of flex reserves

A regional aggregate farm analysis was implemented to determine if individual farms would observe a reduction in the quantity of flex-reserve purchases if flex reserves were purchased based on the regional additive aggregate of the local eastern and western farm forecast errors as opposed to the individual site forecast errors. The following results focus on the Appalachian aggregate and the Midwest aggregate. The additive sum of lead-time forecast errors
and forecast of production from the previous time period for the regional aggregates consisting of twelve farms are used for the quantile regressions. 12

Figure 29 illustrates the quantity of flex reserves each farm would face if forecast errors were balanced based on the regional aggregate or not, which will help illustrate from the wind plant perspective when an improvement (reduced quantity) or a degradation (increased quantity) may occur. The aggregation results use an equal-allocation scheme where each farm would purchase one-twelfth of the aggregated flex reserves (Chapter 3 examined different allocation schemes with respect to the average flex-reserve cost ($/MWh) each farm would pay using an equal size- and power production-based allocation scheme). Certain farms may benefit from a flex-reserve market based on the regional forecast error aggregate if the individual flex-reserve quantity exceeds that of the regional aggregate at the same quantile level. Later, this work highlights the differences in the flex-reserve quantities between the individual farms, the regional aggregates and the whole PJM aggregate. Forming these intra-balancing areas may or may not conflict with a system operator’s (PJM aggregate) objective for seeking the lowest-cost strategy for balancing the total sum of the wind forecast errors for all farms in PJM’s territory. 13 The maximum and minimum of the oversupply and undersupply look-ahead forecast errors, as seen in the vertical axis in Figure 29, is less than the range for the Midwest individual farm results (Figure 28) and the Appalachia individual farm results (Figure 27).

12 The additive sum in this instance is the sum of the positive and negative forecast errors and not the additive sum of the magnitude of the forecast error data.
13 For this research, the system operator’s perspective would look to balancing the total additive sum of the forecast errors as it is currently done when clearing the frequency regulation market in PJM.
Figure 29. Quantile regressions shown here are for the aggregate farms in Appalachian and Midwest region of PJM. The Appalachian region includes twelve wind sites in Pennsylvania, Maryland and West Virginia, and the Midwest region includes Illinois, Indiana and Wisconsin. Quantiles are listed in increasing order in increments of 0.10 from 0.10 to 0.90. The 12 farms in each region are allocated one-twelfth of the quantity of flex reserves at each quantile proportion, so the quantity value is the same for each farm. The quantity of flex reserves to balance the look-ahead forecast errors are shown (vertical axis) and are a function of the previous time step forecast of production. All data used for the regressions use five-minute data for the twenty-four hour ahead forecast interval. Legend shows the differing quantities of flex reserves for each region, Appalachia (blue) and Midwest (red).

5.4.4.1 Aggregate for the Appalachian region

Farms within the Appalachian regional aggregate, as an intra-balancing group, show a general improvement (decrease) in the quantity of flex reserves that would be required to balance various proportions of the look-ahead forecast error distribution (Figure 29). The range in look-ahead forecast errors is smaller in the Appalachia-aggregate scenario (-5MW to approximately 9 MW) than the individual quantile regressions for the same individual Appalachia farms (-60, 60 MW). In Figure 27, the farm 2 quantile of 0.90 reaches 30 MW of undersupply flex reserves demanded, where at the same quantile it decreases to 9 MW of undersupply provisions (Figure 29). The look-ahead forecast errors in Figure 27 for Appalachia farm 5 also show a prominent
spread of look-ahead forecast errors across the varying quantiles, and to purchase flex reserves at
the 0.90 quantile individually (55 MW) the operator at farm 5 would have to overpay by 45 MW
in the Appalachia-aggregate scenario at the 0.90 quantile (9 MW). Farm 5 has a large variance in
the raw forecast error data values. The maximum magnitude of the quantity of flex reserves in the
aggregate-Appalachian group (9 MW) in Figure 29 is upwards of 6 times smaller than in the
individual results (60 MW) shown in Figure 27. This difference may indicate that a local intra-
balancing division for the Appalachia farms could lower the quantity of balancing energy for
future forecast errors from some individual farms. From the system operator perspective,
aggregating all twenty-four farms yielded flex-reserve quantities which at each quantile were
smaller than those of the Appalachia aggregate.

5.4.4.2 Aggregate for the Midwest region

For the Midwest region, flex reserve purchases show some distinct advantages for
individual farms to form a regional aggregate or intra-balancing group. The Midwest aggregate
flex-reserve quantities are typically larger than the Appalachia-aggregate quantities largely due to
greater capacities at the Midwest farms (Figure 29 and Figure 28). The range in the oversupply
and undersupply events (-13, 20 MW) for the aggregate Midwest farms is up to an order of
magnitude less than for the individual Midwest farms flex-reserve purchases in Figure 28 at the
varying quantile levels (-150, 135 MW). At the 0.90 quantile, which reflects the 90th percentile of
look-ahead forecast errors, a Midwest farm would only need to purchase near 20 MW of flex
reserves for undersupply forecast errors, which would be a significant improvement for farms
with large forecast errors (i.e. farm 4 and 10 in Figure 28).
Both the aggregate Appalachia and Midwest flex-reserve quantile regressions show a rather symmetric pattern for the same quantiles as the quantile tau increases from 0.10 to 0.90. The magnitude of the look-ahead forecast error is nearly the same about the median (0.50). For example, the difference in the oversupply look-ahead forecast error flex-reserve purchase for the two aggregations is approximately 6 MW at the lower quantile at 0.20, and is approximately 7 MW at the 0.80 quantile for the undersupply look-ahead forecast errors. Thus, a farm in the Midwest may have to purchase upwards of seven times more in terms of quantity than a farm located in the eastern portion of PJM to balance the likelihood of a shortfall at the 80th percentile of the look-ahead forecast errors.

5.4.4.3 PJM aggregation and system operator perspective

Within a specific geographic location possessing utility-scale, dispersed wind farms, wind power variability can be reduced by interconnecting more farms regionally or increasing the distance between farms, noting that the anti-correlation of wind power variability (and similarly anti-correlation in forecast errors) influences the reduction in variability across large-scale wind farm areas. [40] find that the correlation of power output between moderately spatially dispersed farms (more than 500 kilometers) decreases with an increase in distance for an example case study of 20 Texas wind plants located in the ERCOT territory. [56] demonstrate the decrease in variability for a German wind plant. [57] analyzes a U.S. wind plant site and wind plants in Western Europe. A follow-up study by [52] finds that at short distances high-frequency fluctuations balance one another more than low-frequency fluctuations at short distances, and that interconnection of aggregated wind power across multiple regions in the United States would not further reduce the ratio of high- to low-frequency fluctuations relative to more wind plants being
connected within a region. [52] concludes that interconnecting aggregate regional wind plants
does reduce variability and at multiple frequencies examined. The precise change in cost of the
distributive effects of interconnection of more farms is not captured in these studies. This study
aims to examine how forming different aggregations of wind plants impacts the aggregated
forecast errors and the distributive effects of cost to these wind plants from the various aggregate
scenarios. Current practice in PJM aggregates all short-term imbalances across the whole
electrical territory as opposed to intra-regional aggregates.

One would ideally have an anti-correlated nature in the forecast errors from spatially
separated farms, which when aggregated would result in lower net forecast errors. The smaller the
aggregated forecast errors, the lower the total costs for balancing deviations for the system
operator. Thus, the system operator could hypothesize that forecast errors from the Appalachia
farms would be anti-correlated with the Midwest farms and result in a net aggregated forecast
error that minimized total balancing costs (net aggregated forecast errors would ideally be close
to zero). Following the argument that having utility-scale wind assets over a large geographic
area is more cost effective, the following analysis examines the quantity of flex reserves at the
various forecast quantiles seen previously for all farms aggregated as a PJM collective.

The PJM-aggregate results represent the current, traditional method that aggregates all
positive and negative forecast errors. Figure 29 displays the PJM-aggregate results for the twenty-
four-farm sample. This sub-sample of existing farms is used to examine whether the traditional
methods for balancing utility-scale forecast errors results in the lowest quantity of flex reserves
with respect to the regional aggregations and individual farm scenarios.

In Figure 29, the lower quantile regressions (0.10 and 0.20) for the look-ahead forecast
errors describe an oversupply in predicted wind production (negative error), similar to the
regional-aggregate results and individual-farm results, the PJM-aggregate quantity for flex reserves shows a much smaller volume (MW). Although the system operator will balance the magnitude of the look-ahead forecast error value, because the sign is irrelevant in practice, the 0.30 and 0.40 quantile show an interesting relationship where the sign and quantity for the PJM-aggregate scenario differ from the Appalachia and Midwest scenarios. From the quantiles from the median and beyond, the PJM-aggregate marker consistently shows smaller look-ahead forecast errors. Risk-averse management decisions for balancing larger proportions of future forecast errors may require less flex reserves in the PJM aggregate as opposed to the intra-balancing regions.

5.4.4.4 Summary of quantile regressions under grouping scenarios

Figure 30 and Figure 31 reflect the reduction or increase in flex reserves from the individual-plant perspective when participating in the other aggregation policy scenarios. The previous results provide a broader representation of the magnitude of the look-ahead forecast errors as the flex-reserve policy changes between single-merchant generators to coupling co-located farms in an effort to find the least-cost operator flex-reserve strategy. This section specifically examines how the ratio of the individual flex-reserve costs to the regional- and PJM-aggregate changes as the quantile increases from smaller to larger proportions of the distribution in order to visually observe possible reductions or increases each farm may experience.

In order to quantify the ratio changes, the first step involves differencing the individual flex-reserve quantity (the quantity of the look-ahead forecast error at the specified quantile) and the regional flex-reserve quantity to balance either the Appalachia or Midwest aggregates,
respectively. Differenced values near zero indicate a negligible change in flex-reserve quantity if the farm joined a regional flex-reserve policy or not. Since the data include positive and negative forecast errors, the flex-reserve quantities were scaled and normalized to be in a positive range to have positive ratios. The Appalachia-farm flex-reserve quantities were scaled by 45, the maximum quantity (MW) of flex reserves at all quantiles for the twelve local farms, and normalized by 90, given the positive and negative error structure, to calculate the ratios shown in Figure 30. Similarly, the Midwest farms were scaled by 105 and normalized by 210 to find the positive-valued ratios that are also plotted in Figure 30. To calculate the flex-reserve quantity changes under the PJM policy, all farms were scaled by 120 and normalized by 240 (Figure 31).

If the individual-farm quantity was greater than its regional-aggregate quantity when scaled and normalized, this farm was assigned a red shade to signify an increase in the flex-reserve quantity. If the individual quantity was less than the flex-reserve quantity for the regional aggregate when scaled and normalized, it was assigned a blue shade. Although our results do not show a difference value of zero, a zero difference value results in a ratio value of 0.50 (light green). More neutral shading (yellow- slightly larger and light blue- slightly smaller) indicate smaller ratio differences near 0.50 to more effectively illustrate the slight flex-reserve quantity changes between the individual-farm and regional (or PJM) aggregate policy scenarios.

The mass of the distribution (up to quantile 0.6) for many of the individual farms face minimal trade-offs to procuring flex reserves as an individual entity or forming a regional collective. Figure 30 displays the ratio of individual-farm flex-reserve quantities to the respective regional aggregate flex reserves. A majority of the individual farms see only slight reductions or augmentation in the quantity of flex reserves along the distinct quantile levels, seen by numerous

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14 Farms 1 to 12 represent the Appalachia region, and farms 13 to 24 represent the Midwest region.
lightly shaded green boxes. Farms 3 and 4 in the Appalachia region consistently show that there are no significant quantity reductions in either the individual or regional aggregate scenarios for small up to moderate amounts of back-up energy (quantiles 0.10 to 0.60). Farms 19 to 21 in the Midwest region possess similar flex-reserve quantity patterns. As the quantile reflects a growing proportion of the look-ahead forecast errors, these farms would not see a significant increase or decrease in the flex-reserve quantities in the individual- and regional-aggregate scenarios as denoted by the same light green shading up into the 60th percentile. A later discussion focuses on the upper-quantile region of the look-ahead errors in the regional- and PJM-aggregate scenarios.

A few of the individual farms experience larger trade-offs in flex-reserve quantities, balancing individual versus regionally aggregated forecast errors. Farm 16 is a great example of a farm that if it were to behave as a risk taker, by balancing a smaller portion of the expected forecast errors (quantiles 0.10 to 0.30), the individual flex-reserve quantity far exceeds that of the regional aggregate (red). The individual flex-reserve quantity for farm 16 would become far less than the regional-aggregate quantity as the wind operator seeks balancing an increasing portion of the distribution (quantiles 0.60 to 0.90) (note the shade transition from yellow to green). Farm 22 closely follows the trend of Farm 16, but it exhibits more intense flex-reserve quantity increases (dark red) at the initial 10th percentile (quantile 0.10) of the distribution to a significant reduction as the quantile level dominates the upper portion of the distribution (0.90) (dark blue). These farm operators could utilize the quantile regression shading here to better interpret how they should manage future risk below and above the median of the imbalances from the day-ahead forecast.
Figure 30. Evaluation of the single farm flex reserve quantities to the regional aggregates. Farms 1-12 are located within the Appalachia aggregate and farms 13-24 are located within the Midwest aggregate. For a fixed quantile from 0.1 to 0.9, each single farm compares its individual flex reserve quantity to the regional aggregate. Red spectrum colors denote that the individual farm flex reserve quantity was larger than the regional aggregate flex reserve quantity, and the blue shades denote that the individual flex reserve quantity was less than the regional aggregate flex reserve quantity.

If a system operator were to balance forecast errors in PJM, it would balance the whole territory as an aggregate (Figure 31). The shading for each farm in the PJM collective does not strongly deviate from the regional-aggregate scenario. Farms 1, 2, 5, 18 and 24 still face higher individual flex-reserve quantities (yellow-marked boxes) at the 10th and 20th quantile, and the ratios from farms 16 and 22 suggest strong flex-reserve quantity trade-offs between the lower and upper quantiles (Figure 30 and Figure 31). A majority of the farms from the regional-aggregate scenario would see a subtle improvement in the flex-reserve quantity as indicated by the change.
from near-negligible quantity differences (light green) to a reduction in the quantity (light blue) for the upper quantile levels.

Figure 31 Evaluation of the single farm flex reserve quantities to the PJM aggregate. For a fixed quantile from 0.1 to 0.9, each single farm compares its individual flex reserve quantity to the regional aggregate. Red spectrum colors denote that the individual farm flex reserve quantity was larger than the regional aggregate flex reserve quantity, and the blue shades denote that the individual flex reserve quantity was less than the regional aggregate flex reserve quantity.

The upper quantiles reflect the more extreme region of the look-ahead forecast errors, which, from the merchant generator perspective, may be of great concern to carefully choose how to pay for future imbalances. The difference values at quantiles 0.70 to 0.90 in the regional-
aggregate level, although not explicitly displayed here, are both negative and positive, with a greater number of the individual flex-reserve quantities exceeding the respective regional-aggregate quantity (labeled as a positive value). In the PJM scenario, all differences in the upper quantiles are positive and all of these positive differences are larger than the positive differences in the regional-aggregate scenario. This relationship indicates that the individual flex-reserve quantities far exceed the PJM-collective flex-reserve quantities as compared to the regional-aggregate quantities. A few of the Appalachia and Midwest farms individual quantity was less than their respective regional flex-reserve quantity, but this instance did not occur in the PJM-collective scenario. A farm would likely benefit from operating under the PJM collective as a more cost-effective approach when purchasing flex reserves to balance both positive and negative look-ahead forecast error values denoted at the distinct quantiles describing segments of oversupply and undersupply forecast error distribution.

15 Farms 3, 4, 7, 9, 10, 12, 13, 14, 15, 17, 19, 20, and 21 showed at least one negative difference between the individual and local regional aggregate flex reserve quantity at the 70th to the 90th quantile.
Chapter 5

Discussion of flex energy markets for balancing wind forecast errors

Incorrect forecast errors present an ever-growing concern as larger percentages of electricity demand are met using variable generation. Wind generation fluctuates at short timescales (second to second) and typically presents a diurnal shift for less variability during the day to increased variability during the night with stronger wind speeds. Planning for and managing variability in the expected output for wind generation motivates the need for accurate forecasts to minimize the amount of reserves to smooth these rapid, unexpected fluctuations. Hydropower possesses the ramping flexibility to provide these services, though the reservoir policies in conjunction with meeting environmental downstream objectives may conflict with the timing and the amount of energy desired by the system operator to maintain grid reliability. This dissertation examined the costs and quantity of energy that wind plants would have to incur if they were to purchase flexible energy services in the event the actual output differed from the expected output schedule, a service that could likely be provided by a hydroelectric dam. This discussion explains how flexible-energy markets used for correcting for forecast errors can be implemented in the context of a multi-purpose hydroelectric facility and for individual wind plants within the PJM Interconnection of the Mid-Atlantic U.S.

Hydropower can provide relatively inexpensive, flexible fill-in power to compensate for intermittent renewable generation, with minimal environmental effects compared to competing generation sources. Water management policies for hydropower dams maintain multiple services beyond electric generation, such as flood control, recreation, ecosystem services, and municipal water supply. Managing these multiple services involves various, sometimes conflicting policy objectives. A scenario analysis is performed that models the profit-maximizing behavior of
Dominion, a small-scale dam owner, when providing multiple services that include flow management for downstream ecosystem maintenance; utility profit-maximization in a day-ahead (DA) market; and a “flex-reserve service” similar to ancillary services frequency regulation. Our specific case study uses the Kerr Dam, located on the Roanoke River in North Carolina. Flex-reserve service that Kerr provides allows the wind turbine to behave as a controllable or dispatchable generator, providing energy into the day-ahead market much like a hydroelectric dam does. The analysis focuses on the potential conflicts and trade-offs that arise from the formulation of energy policy, separate from river-management policy decisions.

Our analysis suggests that reservoir operational policies governing the release schedules for the existing services it already provides (flood control, ecosystem services, power generation) do not compliment the release schedule to compensate for the forecast errors. Even under perfect information and significant pricing incentives, Kerr Dam faces operational conflicts when providing any substantial levels of flex reserves while also maintaining releases consistent with other river-management requirements. These operational conflicts are severely exacerbated during periods of drought. Increasing payments for flex reserves does not resolve these operational and policy conflicts.

The next study shifts perspective from the hydroelectric facility being faced with providing flex-reserve services for correcting for forecast errors to the wind plant determining at what price and volume of energy it would desire when purchasing flex reserves. Power purchase agreements (PPAs) provide a revenue buffer to secure a fixed price and buyer of the wind generation. Without a PPA, wind plants would sell merchant energy to the day-ahead market with a certain level of uncertainty in the expected revenue, due to not only changes in price but deviations in real-time generation. This study begins by analyzing the cost of a wind plant to
purchase flex reserves under the assumption that a PPA is in effect and the wind plant would be procuring flex reserves to correct for any forecast errors. The final analysis examines the quantity of flex reserves a wind facility would decide upon when selling merchant generation and looking to maximize revenue while minimizing the quantity (and therefore cost) of flex-reserve services. These two studies feature twenty-four existing wind plants in the PJM footprint.

By altering the cost-allocation scheme and implementing different wind-farm grouping scenarios, this work analyzed if forming regional aggregates within PJM would yield lower costs to the individual wind plant as well as the system operator. The wind-grouping scenarios include dividing PJM into two groups, the eastern Appalachia region and the western Midwest region, and the original base case where all farms form the PJM whole-territory aggregate. A few of the farms’ least-cost strategy resulted in purchasing flex reserves individually, i.e. forming no collective grouping with the other farms and electing to be a self-supplier that purchases flex reserves based on the single farm’s forecast errors. This study hypothesized that forming local groups within PJM or intra-area balancing groups may yield lower costs for the nearby individual farms if their regional grouping showed a smaller aggregate of forecast errors as compared to aggregating across all farms in PJM. A smaller aggregate would cost less to balance. The analysis revealed that local-regional aggregates of forecast errors typically yielded higher costs than the PJM aggregate of all the forecast errors.

Allowing the farms to switch from their original regional aggregate to another region or remain as one PJM aggregate collective showed that farms either preferred leaving the one PJM aggregate as a self-supplier or joined as one PJM aggregate to lower to costs of flex reserves. These results suggest as wind capacity increases in a deregulated market like PJM, the individual wind plant strategy may be in alignment with the system operator to balance the aggregate of
variable-generation fluctuations, particularly for large wind farms with highly variable output that could benefit from grouping with farms from other geographic locations with high anti-correlated forecast errors.

Understanding the type of forecast errors at future look-ahead periods becomes increasingly crucial for the system operator as well as the individual wind plant when scheduling wind generation a day ahead. Our previous work held the assumption that the wind plant revenue was supported by a PPA, but this work uses probabilistic methods for estimated future forecast errors for wind plants selling merchant generation without a PPA within PJM. Anticipating a shortfall (positive error where forecast is larger than the actual output) or an excess (negative error where the forecast is less than the actual output) translates to different operating modes for the wind plant. Although prices for regulation services are the same in the United States, regulation services have different pricing schemes in Western Europe, which can highly influence scheduling decisions for wind owners looking to maximize revenue and minimize cost impacts. Quantile regression can be used to examine the type of forecast error and magnitude of future forecast errors.

Quantile regression is used for examining the covariate relationship between the forecast of production and the forecast error for these twenty-four wind plants in PJM. The quantile describes the proportion of the conditional density that translates to the quantity of flex reserves that would balance the probability of a random future forecast error being less than or equal to the look-ahead forecast error at the quantile $\tau$ or $\tau^{th}$ percentile. The same wind policy scenarios are applied for aggregating farms into regional groups. With respect to magnitude, aggregating all 24 farms into the PJM aggregate may benefit large farms in the Midwest group, since their regional flex-reserve quantities are likely larger than those for the PJM aggregate. Investing in spatially
distributed, utility-scale wind farms may benefit larger, more-variable wind farms but smaller farms may be bearing the cost burden of the geographic spread since the flex-reserve cost and quantity may be lower if they were to be self-suppliers.

Our results in the context of PJM suggest that forecast errors from larger and/or more variable farms may place an externality on the smaller-sized and/or less-variable farms. Since the PJM flex-reserve quantities were smaller than a majority of the individual-farm quantities (Figure 30 and Figure 31), balancing the aggregate for the larger and more dispersed wind footprint would benefit both the individual wind plant and system operator perspectives.

The Electric Reliability Council of Texas (ERCOT) implements an 80%-exceedance rule for the wind power forecasts [52]. The 80%-exceedance rule means that there is an 80% chance the actual wind power generation will exceed the forecast, which translates to the 20th percentile (0.20 quantile). According to the Utility Variable-Generation Integration Group (UVIG) [29] and a report by Argonne National Lab [52], this is the current practice in day-ahead resource planning in ERCOT. If this 80%-exceedance rule was applied for the twenty-four PJM wind farms, the following conclusions could be made. Under the regional-aggregate scenario, some wind farms saw an increase in the quantity of flex reserves at the 0.2 quantile (yellow-shaded boxes in Figure 30). Under the PJM-aggregate scenario, the same farms saw an increase in the quantity of flex reserves at the 0.2 quantile when grouped as one collective (Figure 31). Thus, a system operator like ERCOT may benefit from clearing the day-ahead market by planning according to the 0.2 quantile, which in our case would reflect the percentage of look-ahead forecast errors that are less than or equal to the value corresponding to 20% of the distribution. This exceedance rule however may not benefit individual wind farms in a flex-reserve market context if the individual wind plant’s strategy would be to purchase flex reserves at a quantile less than 0.2.
The flexible market design studies conducted in Chapters 2-4 demonstrate that uncontrollable, variable generation prompts a careful look at how the wind-integration programs affect the system operator and individual wind plants. The flex-reserve market can be used as a mechanism for correcting for forecast errors, though such a market is not currently operating in PJM. Further policy reform may be required as the wind capacity percentage increases to utilize flexible markets designed around the diurnal pattern of wind variability and at timescales that differ from the existing ancillary-services markets that manage longer-term outages or extremely short-frequency deviations. As wind plant owners are tasked with providing a forecast of expected generation and incur penalties when supply varies, similar to the cost of flex reserves, estimating future forecast errors using probabilistic methods may ease scheduling and financial costs.
References


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Table 5. Reservoir elevation and releases at Kerr under current BAU operations and the ecosystem services management plan [8].

<table>
<thead>
<tr>
<th>Kerr reservoir level (ft-msl)</th>
<th>Current BAU Operations</th>
<th>Ecosystem Services **</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Below 300</strong></td>
<td>Up to 8,000</td>
<td>Below 302</td>
</tr>
<tr>
<td><strong>300-312</strong></td>
<td>Up to 20,000</td>
<td>302-303</td>
</tr>
<tr>
<td><strong>312-315</strong></td>
<td>Up to 25,000</td>
<td>303-315</td>
</tr>
<tr>
<td><strong>315-320</strong></td>
<td>Up to 35,000</td>
<td>Above 315</td>
</tr>
<tr>
<td><strong>320-321</strong></td>
<td>85% of inflow or up to 35,000 (choose highest)</td>
<td>-</td>
</tr>
<tr>
<td><strong>Above 321</strong></td>
<td>Reservoir inflow</td>
<td>-</td>
</tr>
</tbody>
</table>

* Occurs during April 1 - June 30
** From Jan. 1-March 31, release up to 20,000 cfs to a reservoir level of 303 feet. Above 303 feet, follow the ecosystem services release schedule, and all other times follow BAU operations.
Table 6. This table describes the historical data mean and standard deviation beginning with the day-ahead spot market prices, regulation prices, power production at Kerr Dam, volumetric releases at Kerr Dam, and the normalized wind forecast error.

<table>
<thead>
<tr>
<th>Year</th>
<th>Mean</th>
<th>Standard deviation</th>
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</thead>
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<tr>
<td>Day-ahead price ($/MWh)$^1$</td>
<td>55.01</td>
<td>60.46</td>
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<tr>
<td>Regulation price ($/MWh)$^1$</td>
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<td>34.13</td>
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<tr>
<td>Power (MWh)$^2$</td>
<td>26.79</td>
<td>56.36</td>
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<tr>
<td>Volume Released (cubic feet)$^2$</td>
<td>6.81×10$^{10}$</td>
<td>1.39×10$^{11}$</td>
</tr>
<tr>
<td>Normalized Wind forecast error (MWh)$^3$</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

$^1$ Price data for the Dominion Zone in PJM from 2006 to 2008.

$^2$ Power production data are from the Kerr Dam turbines provided by United States Army Corps of Engineers (USACE). Volume release data are from the Kerr Dam turbines also provided by USACE. All hydrological data include 2006 to 2008.

$^3$ Wind forecast data provided by PJM proprietary forecast model. All statistics represent normalized data values. The original data include the day ahead forecast and actual power supply at five minute intervals. These data were average hourly to coincide with the hourly price, power, and volumetric flow data. The forecast error is the difference between the forecast and the actual hourly value.
Table 7. This table contains the coefficient results from the quantile regression for distinct values of $\tau$-quantile in 0.10 increments from 0.10 to 0.90. Farms are denoted as 1 to 24, with the first twelve belonging to the eastern half of PJM (Appalachia group), and the last twelve farms belonging to the western half of PJM (Midwest group). The first coefficient pertains to the constant $\beta_0$ in the linear quantile regression and $\beta_1$ is the coefficient for the explanatory variable, the forecast of production from the previous time step. These coefficients describe the covariate relationship of the explanatory variable to the response variable, the look-ahead forecast error in the next time step, using five-minute forecast data at each individual farm. The standard error is displayed for each coefficient.

<table>
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<tr>
<th>Farm</th>
<th>Tau</th>
<th>$\beta_0$ Coefficient</th>
<th>$\beta_0$ Standard error</th>
<th>$\beta_1$ Coefficient</th>
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<td>10.27345</td>
<td>0.16723</td>
<td>0.17867</td>
<td>0.00452</td>
</tr>
<tr>
<td>24</td>
<td>0.9</td>
<td>13.3595</td>
<td>0.15277</td>
<td>0.33286</td>
<td>0.00571</td>
</tr>
</tbody>
</table>
Figure 32. Displays the percentage of capacity allocation for balancing an oversupply of wind power during hourly average monthly peak (left) and off-peak hours (right) from 2006 (top), 2007 (middle) and 2008 (bottom). The percentage allocations during peak hours are also shown in lower panel for the same years, moving from the wettest year (2006-top) to the sustained dry year (2008-bottom). All results are under the ECO guide curve. Darker regions indicate near 100 percent of the requested flex-reserve balancing services were provided. White indicates negligible allocations were provided (closer to 0 percent).
Figure 33. Displays the percentage of capacity allocation for balancing an oversupply of wind power during hourly average monthly peak (left) and off-peak hours (right) from 2006 (top), 2007 (middle) and 2008 (bottom). The percentage allocations during peak hours are also shown in lower panel for the same years, moving from the wettest year (2006-top) to the sustained dry year (2008-bottom). All results are under the BAU guide curve. Darker regions indicate near 100 percent of the requested flex-reserve balancing services were provided. White indicates negligible allocations were provided (closer to 0 percent).
Figure 34. Displays the percentage of capacity allocation for balancing an undersupply of wind power during hourly average monthly peak (left) and off-peak hours (right) from 2006 (top), 2007 (middle) and 2008 (bottom). The percentage allocations during peak hours are also shown in lower panel for the same years, moving from the wettest year (2006-top) to the sustained dry year (2008-bottom). All results are under the BAU guide curve. Darker regions indicate near 100 percent of the requested flex-reserve balancing services were provided. White indicates negligible allocations were provided (closer to 0 percent).
Figure 35. Displays the percentage of capacity allocation for balancing an undersupply of wind power during hourly average monthly peak (left) and off-peak hours (right) from 2006 (top), 2007 (middle) and 2008 (bottom). The percentage allocations during peak hours are also shown in lower panel for the same years, moving from the wettest year (2006-top) to the sustained dry year (2008-bottom). All results are under the ECO guide curve. Darker regions indicate near 100 percent of the requested flex-reserve balancing services were provided. White indicates negligible allocations were provided (closer to 0 percent).
Figure 36. The panels feature the days where the total daily capacity requested to balance 100 percent of the forecast error exceeds the daily energy declaration (MWh) for the BAU guide curve.
Figure 37. The panels feature the days where the total daily capacity requested to balance 100 percent of the forecast error exceeds the daily energy declaration (MWh) for the ECO guide curve.
Figure 38. This figure shows how the timing and amount of the BAU guide curve expressed in terms of the energy declaration is exceeded by the total daily capacity required to balance the wind forecast error from 10 percent up to 100 percent. Black signifies a large quantity exceeding the guide curve, as seen in the early summer of 2008, with minimal violations to the guide curve in white, such as the winter months in 2006 and 2007. The daily time series for the BAU case closely mirrors the ECO violations (Figure 39).
Figure 39. This figure shows the timing and amount the ECO guide curve expressed in terms of the energy declaration is exceeded by the total daily energy output required to balance the wind forecast error from 10 percent up to 100 percent. Black signifies a large quantity exceeding the guide curve, as seen in the early summer of 2008, with minimal violations to the guide curve in white, such as the winter months in 2006 and 2007. Darker shading denotes larger violations of the daily energy declaration. Spring and early summer days exhibit the least conflict with the ECO guide curve. Extreme dry conditions in 2008 impose more constraints on operations not embodied in the guide curve; the policy conflicts appear to worsen during the transition from spring to summer.
Figure 40. Results here show the (a) opportunity cost, (b) energy adjustments, (c) and percentage of the total volume used to smooth increments of the total wind forecast error from 2006 through 2008 under BAU practices. Panel (a) describes the annual opportunity cost or foregone revenue from selling flex reserve energy at current regulation market prices. Panel (b) describes the quantity of the energy adjustments needed annually to balance increasing percentages of the forecast error (MWh). Panel (c) describes the volumetric deviation from the guide curve as a percentage of the total volume of water released when complying with the guide curve, where this additional volume of water is used to compensate for varying percentages of the wind forecast error across all hours in the simulation period.
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Education
Doctorate of Philosophy, Energy and Management Policy
The Pennsylvania State University, PA, August 2014
Bachelor of Arts, Mathematics, University of Colorado-Boulder, May 2007

Awards and Fellowships
Alfred P. Sloan Foundation Fellow, 2012-2013
National Science Foundation Graduate Research Fellow, 2009-2012
Gates Millennium/Hispanic Scholarship Fund Scholar, 2002-2013
USAEE Best Student Paper Award for top oral presentation and paper, Washington D.C., 2011

Technical Skills
Operating Systems: MacOS, Windows, Unix
Programming Languages, Software: Matlab, R, C++, Microsoft Office

Professional Experience
U.S. Department of Energy, WWPTO, February 2014- present
- Provided technical consulting to industry constituents and national laboratories on market valuation of and strategies for improving grid reliability using pumped hydro storage
- Managed optimization and modeling projects focused on hydropower operations in support of national strategic planning for implementing improved decision-making tools and data analysis
- Facilitated projects that identify market barriers for hydropower deployment

American Meteorological Society (AMS) Summer Policy Colloquium Fellow, June 2010
- Completed professional development colloquium aimed at educating scientists and policy makers about domestic and international environmental science policies in Washington, D.C.

Research Experience
The Pennsylvania State University (PSU), Cornell University, August 2008-May 2014
- Analyzed flexible market designs and wind forecasting techniques for integrating grid-scale wind
- Developed energy-economic models for evaluating the impact of large-scale wind integration on hydro-electric dams and ecosystem services in Mid-Atlantic US *
- Conducted policy analysis of regulatory and economic opportunities for distributed generation*
- Financial and life-cycle analysis of the profitability of energy storage technologies with an emphasis on Compressed Air Energy Storage (CAES)

*Publication available upon request.