The Use of Statistically Based Rolling Supply Curves for Electricity Market Analysis: A Preliminary Look

Thomas Jenkin, Andrew Larson, and Mark Ruth
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List of Acronyms

CCGT	combined-cycle gas turbine
CT	combustion turbine
ERCOT	Electric Reliability Council of Texas
ISO	independent system operator
LMP	locational marginal price
LSE	load-serving entity
MISO	Midcontinent Independent System Operator
NREL	National Renewable Energy Laboratory
O&M	operation and maintenance
PJM	PJM Interconnection
PV	photovoltaic
RSC	rolling supply curve
RTO	regional transmission organization variable
VRE	renewable energy

Executive Summary

In light of the changing electricity resource mixes across the United States, an important question in electricity modeling is how additions and retirements of generation, including additions in variable renewable energy (VRE) generation, could impact markets and generators by changing hourly wholesale energy prices. Estimating hourly electricity prices over time for any given load in a regional transmission organization (RTO) or independent system operator (ISO) is challenging and frequently resource-intensive, because many factors that may affect electricity supply in any given hour change in ways that are hard to estimate and interact with each other in nuanced ways over time.

One common way to estimate the impact of such supply changes on wholesale electricity prices is to use a production cost model, which tends to be data-intensive, time-consuming, and expensive. A less resource-intensive alternative is to build simple generator supply curves that can be modified to reflect additions or retirements, but such representations tend to be fairly simple, because they do not address many of the constraints addressed by production cost models.

In contrast to those "bottom-up" methods, the analysis reported here uses a "top-down" approach based on regression analysis of hourly historical energy and load data that allows for analysis of the impact of supply changes to the system on wholesale energy prices to be estimated, provided the changes are not so substantial that they fundamentally alter the market and dispatch-order driven behavior of non-retiring units. This rolling supply curve (RSC) approach first estimates the shape of the supply curve that fits historical hourly price and load data for given time intervals and then repeats this process on a rolling basis through the year. These supply curves can then be modified to account for the impact of generation retirements or additions on wholesale electricity prices and then reapplied to the same load data to estimate the changes in prices. Using multiple years of data enables exploration of the impact of year-to-year variations in demand and supply that are due to weather, fuel prices, and other factors.

We illustrate the potential use and value of the RSC method by first developing 26 rolling two-week supply curves based on 2015 hourly price and load data from the PJM Interconnect (PJM). The choice of duration over which these curves are estimated has a significant impact on goodness of fit. For example, in PJM in 2015, moving from fitting a curve for 1 period per year (i.e., an annual fit) to the 26 rolling two-week supply curves shown in Figure ES-1 (next page), improves the standard error of the regression by over 60% (from $16/MWh to $6/MWh) and improves the R-squared value of the estimate from 0.48 to 0.76.

We use the RSC approach to illustrate the price impacts of the following retirement and addition scenarios, based on the initial 2015 PJM supply curves: retirement of 500 MW of capacity without any replacement; retirement and replacement with combined-cycle gas turbine (CCGT) capacity; and retirement and replacement with combustion turbine (CT) capacity. Under the conditions of the modeled system, the retirement-only scenario results in an increase in wholesale energy prices and a reduction in reserve margin. The addition of CCGT capacity to restore the original reserve margin is more effective at mitigating the increase in wholesale energy prices resulting from the retirement than the addition of CT capacity, as seen in

Figure ES-2. We also use the RSC approach to estimate the price impacts of adding VRE, which shifts the hourly fitted RSCs to the right on a variable basis depending on resource availability.

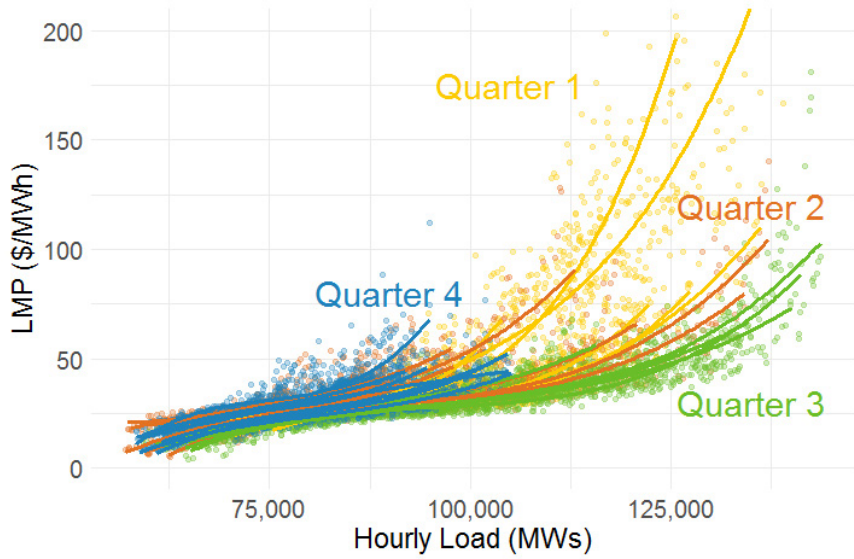

Figure ES-1. 2015 hourly PJM price and load data with cubic regression estimates for 26 two-week periods (split by quarter)

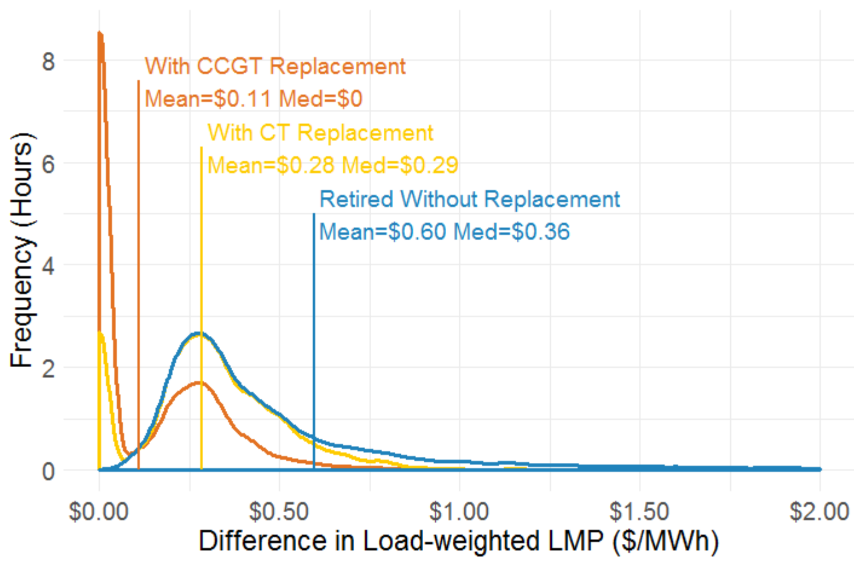

Figure ES-2. Distribution of price increase in PJM due to 500 MW of plant retirement for each hour in 2015 with no replacement, replacement with CT, and replacement with CCGT

In addition, we demonstrate the use of an RSC backcasting approach to estimate near-term future price-load relationships that could be used to estimate revenue for new generation without relying on perfect foresight of future supply curves. Backcasting could also be used to better inform short-term decision-making by generators deciding when to take generation offline for maintenance. Although the backcast estimates increase variation in the results on an hourly basis for any given two-week period, the offsetting positive and negative effects of the errors in different periods can significantly mitigate the errors over a complete year. In our example, the cumulative average cost of energy backcast estimate is within about 5% of the estimate from a curve fitted with actual data for the entire year.

The RSC approach has several limitations. While the approach might be used to compare the effect of using various types of new generation to mitigate wholesale price impacts that are due to generator retirement, it cannot determine where to place that new generation capacity geographically within an RTO. The simple regression analysis used here, in common with production cost models and other methodologies, also has difficulties estimating price spikes, because at high loads the realized price can be highly variable. Some of these issues and uncertainties are hard to address, either because they are inherent limitations of the technique or because they may require tradeoffs associated with greater analytical complexity.

That said, the top-down nature of the RSC approach offers an implicit way to incorporate the effects of a vast array of underlying factors interacting in complex and difficult-to-foresee ways when investigating the impact of changes in system retirements or additions. This type of analysis may be of interest to a wide variety of market participants and other stakeholders given the rapidly evolving generation mix of today's electric sector. This type of analysis may also have a role in complementing or calibrating production cost models, where some transmission constraints and other factors may be difficult or labor intensive to replicate, or when analysts do not have access to these types of models.

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1 Introduction

An important question in electricity modeling is how additions and retirements of generation capacity, including additions of variable renewable energy (VRE) generation, may impact wholesale energy prices. This is of interest in the context of market design questions, particularly under scenarios or futures that include high penetrations of VRE and low-marginal-cost technologies (Traber and Kemfert 2011; Borenstein and Bushnell 2015; Jenkin et al. 2016; Woo et al. 2016). This research is also motivated by broader trends in the actual or potential retirement of existing generation, which may reflect short-term market conditions that do not compensate generators for the full set of benefits they provide (e.g., reliability, resilience, and environmental benefits) (PJM 2017a).

One common way to estimate the impact of such supply changes on wholesale energy prices is to use a production cost model (e.g., Denholm et al. 2013a, 2013b). Such models, while very useful, can be expensive to use in terms of both the cost of maintaining the modeling capability and the scale of effort needed to populate data accurately in the production cost model system at a sufficient level of detail to perform the analysis properly. Even then, the correct treatment of transmission constraints and the effects of imports and exports can be technically challenging given the complex nature of the real system being modeled and its interaction with the non-modeled surroundings.

A less resource-intensive approach is to build simple supply curves for different regions that can be modified to determine the impact of additions or retirements as well as changes in fuel prices. This approach was recently used by Wiser et al. (2017) based on a simple merit order of generation from lowest marginal cost to highest marginal cost. Both production cost models and simple supply curves are “bottom-up” methods, because they involve building supply curves on a unit-by-unit basis.

In contrast, the analysis reported here employs a “top-down” econometric technique that uses historical price and load data to estimate wholesale electricity prices over various timescales and to assess the price impacts of system-wide changes. This rolling supply curve (RSC) approach is based on regression analysis of hourly historical energy and load data that allows the impact of supply changes on wholesale energy prices to be estimated, provided the changes are not so substantial that they fundamentally alter the market behavior of non-retiring units. The RSC approach first estimates the shape of the supply curve by fitting historical hourly prices to loads for given time intervals and then repeats this process on a rolling basis through an entire year. These supply curves can then be modified to account for the impact of generation retirements or additions on wholesale prices and then be reapplied to the same hourly load data to estimate the changes in wholesale electricity prices.

These RSCs can be used to investigate the impact of generation retirements or additions on wholesale energy prices in a historical year without using a production cost model. The RSC method does not forecast prices for future years but rather yields a counterfactual case for the historical year examined. The approach is simple and quick and—because it is based on real price-load behavior—implicitly incorporates many factors, including transmission constraints and imports and exports, that would otherwise be difficult to estimate or model. It may be useful as an alternative or complement to production cost models.

The U.S. electric system is a mixture of regulated and restructured markets. Restructured markets consist of regional transmission organizations (RTOs) and independent system operators (ISOs), and their operation has been widely discussed (e.g., Spees et al. 2013; Borenstein and Bushnell 2015). In restructured markets, generation dispatch is coordinated by the RTO, and the wholesale energy price paid to all generators running in any hour is set by the marginal cost of the last generator needed to match supply to demand. Because of transmission constraints, the locational marginal price (LMP) for any given hour may vary widely by location within an RTO.
In contrast, regulated markets consist of vertically integrated utilities, municipalities, and cooperatives that earn a cost-plus regulated rate of return. In this report, we focus on restructured markets and other markets organized and run by RTOs/ISOs. Figure 1 shows the nine RTOs and ISOs in the United States and Canada. The remaining areas, such as Florida or most of the West, provide electricity under traditional cost-of-service regulation; the RSC approach is not applicable in such regions.

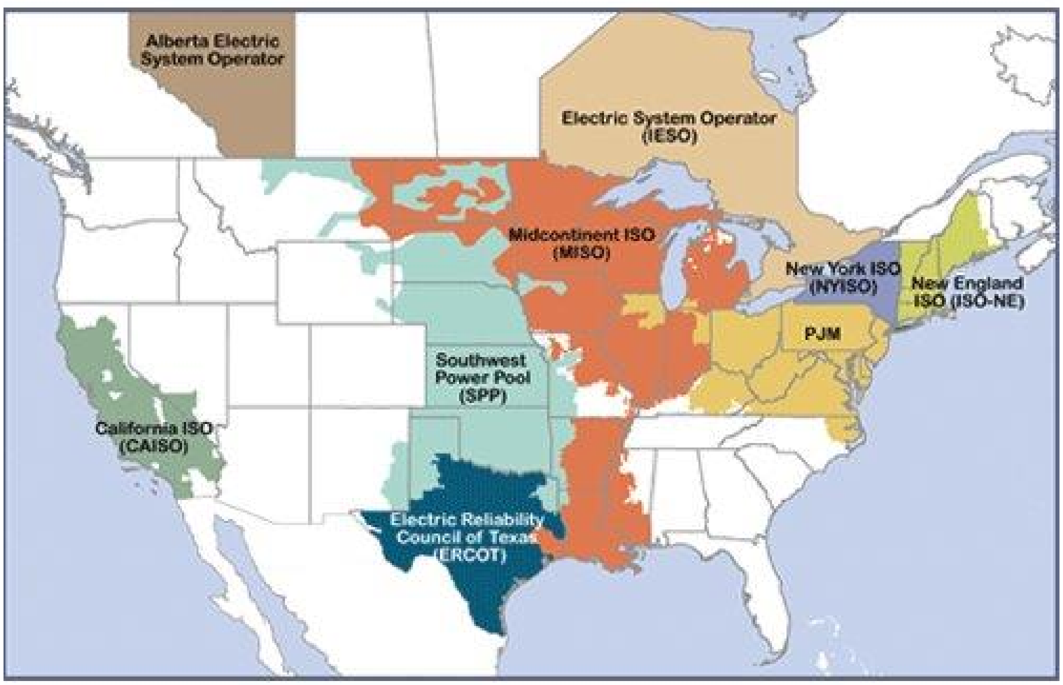

Figure 1. North American RTOs and ISOs (FERC 2017)

Most of our analysis focuses on the PJM Interconnection (PJM),[1] because it is one of the largest, oldest, and most developed U.S. RTOs, and its low wind and solar penetration reduces the complexity of net load adjustments required by the RSC approach.[2] We analyze PJM's hourly price-load behavior over time, and we also briefly compare PJM in 2015 with the Electric Reliability Council of Texas (ERCOT). The PJM RTO has both energy and capacity markets,

[1] PJM is an RTO that coordinates the movement of wholesale electricity in all or parts of 13 states and the District of Columbia (http://www.pjm.com/).
[2] Penetration refers to the fraction of annual generation provided by VRE. In PJM, wind and solar generation represented 2.1% and less than 0.1% of generation, respectively, in 2015 (Monitoring Analytics 2016). Net load in any given hour is defined as the load less VRE generation in that hour.

whereas ERCOT is an ISO with an energy-only market and a much higher fraction of wind and natural gas generation (IMM 2016a).[3]

The ability to analyze the impact of supply changes on wholesale energy prices relatively quickly and easily may be useful to a wide range of stakeholders, including market participants like generators and load-serving entities (LSEs); local, state, and federal policymakers; advocacy organizations and trade associations; and others. Such analysis can inform ongoing debates with rough estimates of the potential impact on wholesale energy prices of retirement of existing generation and replacement with a variety of generation types.

The remainder of this report is structured as follows. Section 2 outlines our methodology. Section 3 illustrates how RSCs can be applied to study the impacts on wholesale electricity prices and costs to LSEs of generation retirements and additions. Retirements are considered without replacement and with replacement by different generation technologies with different marginal costs. The effect of adding wind and solar generation on wholesale prices is also shown illustratively for different solar-wind combinations. We also consider how well-backcasted supply curves can be used for forward-looking operational analysis that does not rely on perfect foresight assumptions. Section 4 discusses some temporal and geographic considerations, including year-to-year variation of short-duration supply curves that is due to variation in natural gas prices and other factors, the structural differences of such curves, and differences in their ability to estimate prices across RTOs. Section 5 highlights our key findings and proposes areas for future research.

[3] Capacity markets are intended to solve the "missing money problem" by providing market-determined payments for new generation in order to satisfy future demand and maintain a desired reserve margin. As opposed to markets with capacity payments, energy-only markets, such as ERCOT, assume that energy prices will spike to very high values at times of scarcity, and that these infrequent price spikes should incentivize future generation buildout.

2 Methodology

Various studies have examined techniques to estimate electricity prices. Electric price forecasting approaches include multi-agent, fundamental, reduced-form, statistical, and computational intelligence. Weron (2014) provides a meta-analysis of existing and potential future electricity price forecasting methods. Our approach extends an approach used by Sioshansi et al. (2009), who use a monthly linear fit of hourly price and load data in PJM to investigate the impact of adding energy storage on wholesale prices and subsequent shifts in consumer and producer surpluses. More recently, Navigant (2011) fits hourly price load data in PJM to exponential curves, using log-linear functions to better capture the upward-curving nature of the supply curve, although this analysis is on a seasonal rather than monthly basis.

On a much shorter timescale, Brijs et al. (2016) apply a piece-wise linear approach for which, in any given hour, a dispatch model is run not only for the realized load, but also assuming incremental load is greater or less than actual (in 50-, 250-, and 500-MW increments), enabling construction of a partial supply curve relevant to each hour in a piece-wise linear manner. Although our RSC approach may be inherently less accurate than the Brijs et al. approach, it may be widely applicable and require less analytic effort because of the widespread availability of historical U.S. RTO/ISO hourly price and load data. Kanamura and Ohashi (2007) explore the impact of using different econometric fits applied in a piece-wise manner including stochastic analysis to mimic price jumps based on daily rather than hourly price and load data.

A related approach is to perform regression-based analysis on the underlying drivers of wholesale electricity prices using one or more years of data. A series of studies by Woo et al. (2011, 2014, 2016) examines hourly day-ahead or real-time prices in terms of demand, VRE generation, and natural gas prices, with some consideration of outages and hydroelectric flow conditions and other factors. Woo et al. (2014, 2016) use this multi-factor regression model to investigate the impact on wholesale prices of the retirement of nuclear plants and the addition of VRE.

In this study, we explore the impact of a rolling time horizon on fitting estimated supply curves to hourly price and load data, and we show how the fit improves as the timescale is reduced from annual to seasonal to biweekly to weekly. We also replace the linear supply curve fit with fits determined via multiple types of regressions to better match historical hourly price and load data on a rolling basis. These RSCs can be used to estimate hourly electricity prices at given load quantities or be shifted to assess the impact of supply changes on electricity prices. This includes the impact of retirement or additions of generation capacity, including VRE.

2.1 Generating Rolling Supply Curves Using PJM Hourly Price and Load Data

Our RSC approach uses regression analysis to estimate the shape of the supply curve that best fits historical hourly price and load data for given time intervals, such as two weeks, with this analysis repeated on a rolling basis through time. Once each time interval curve's optimal fit is determined, the resulting fitted supply curve can then be modified to estimate the impact of retirement or addition of generation, including addition of VRE generation, on electricity prices and consumer costs for any given load.

The hourly electricity price for a load varies widely during the year for many reasons, including the effects of changing fossil fuel prices, transmission constraints, imports and exports, planned and unplanned outages, the addition of new generating capacity or retirements, and the effects of VRE (e.g., Monitoring Analytics 2015, 2016, 2017; Weron 2014; Woo et al. 2014, 2016). Figure 2 shows the hourly load and hourly load-weighted average day-ahead LMP for the full PJM transmission zone in 2015.[4] The LMP is made up of three components: an energy price and two adders for losses and transmission constraints. Hourly LMP for a given load varies considerably throughout the year, and this variance tends to increase with increasing load. The curve in Figure 2 shows our fit of a cubic equation to these data to estimate price for a given load:

$$LMP_i = \alpha + \beta L_i + \gamma L_i^2 + \delta L_i^3$$

where the hourly (*i*) locational marginal price (LMP_i) is fitted to load (L_i), and α, β, γ, and δ are the coefficients determined by the fit. The R-squared value of this fit ($R^2 = 0.48$) is low and consistent with a high variation in price for a given load.[5] Moreover, while the entire fit's standard error of the regression (S)[6] is $16/MWh, the standard error of the upper 10th percentile of price points is $46/MWh, suggesting such a curve is of less use for estimating prices at high loads. (For comparison, a linear fitted equation is also shown in Figure 2, which has an R-squared value of 0.42.)

[4] Day-ahead hourly price and load for PJM used in this report were sourced from the PJM website (PJM 2017b, 2017c).

[5] R-squared is a commonly used goodness-of-fit measure in regression analysis that represents the amount of variation explained by the fit. A fit with no variation explained would have an R-squared value of 0; a perfect fit would have an R-squared value of 1 (Wooldridge 2009).

[6] Standard error of the regression, also called root mean squared error, is a common measure of accuracy in econometric electricity price forecasting (Weron 2014). Standard error of the regression is calculated as the square root of the mean squared residuals (i.e., differences between each predicted and actual price) (Wooldridge 2009).

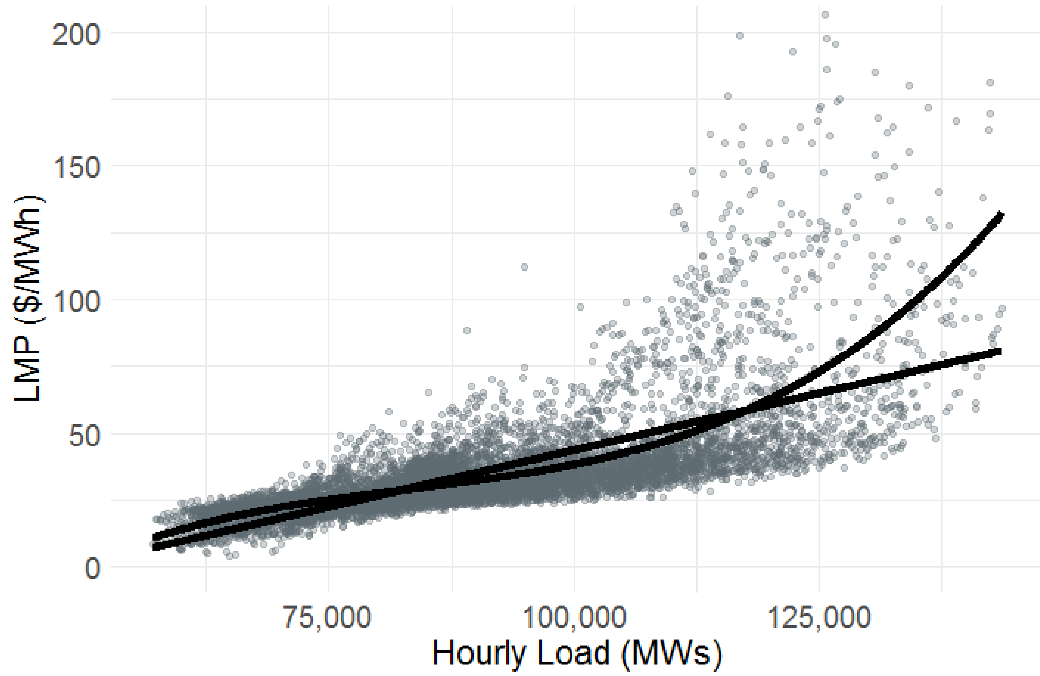

Figure 2. 2015 PJM price and load data with linear and cubic regression estimates

Although the hourly price and load data for the entire year in Figure 2 produce a poor cubic fit, such a curve produces about the same annual load-weighted energy price as reported by PJM. However, such a curve would be much worse at estimating the price for any given hour than would a curve fit to a set of price-load data for a shorter period. Thus, we consider breaking down the hourly price and load data into various shorter periods. For instance, Figure 3 breaks the hourly price-load data into 26 successive two-week periods and fits the data for each period to a cubic curve, divided by quarter.

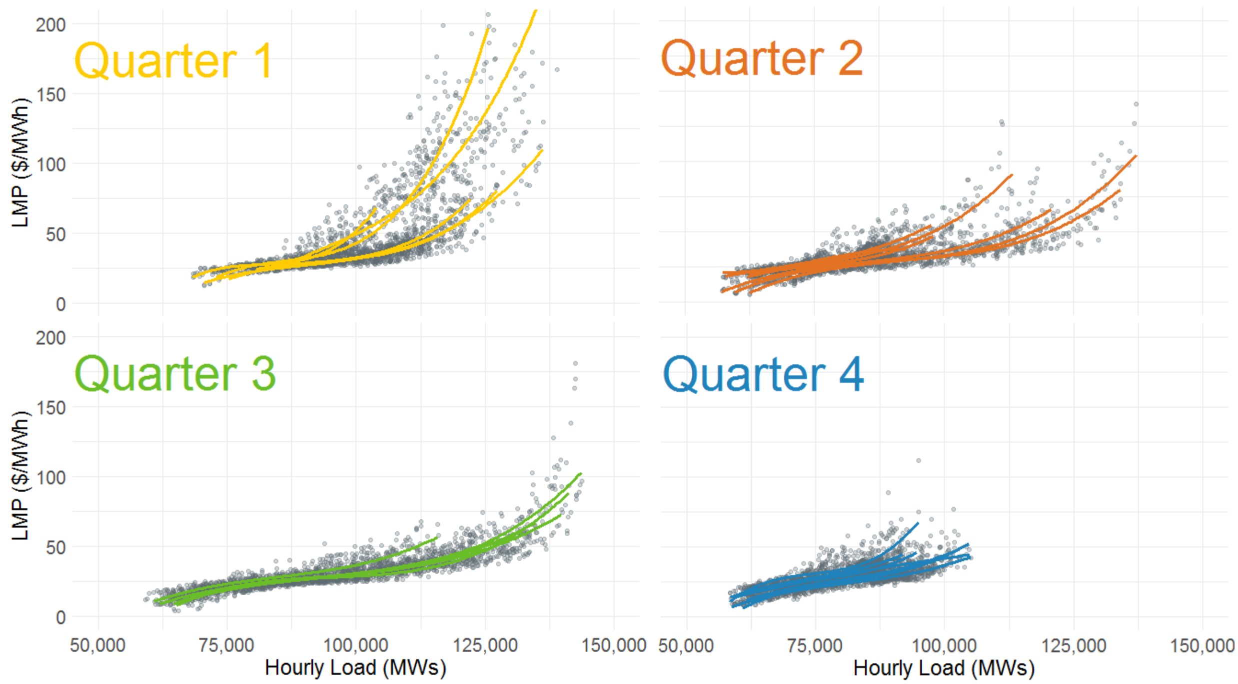

Figure 3. 2015 PJM price and load data with cubic fits for 26 two-week periods, by quarter

Table 1 shows the R-squared values for fitted estimated supply curves based on various period durations. The fit of the curves improves substantially when moving from annual (R^2 = 0.48, S = \$16.37/MWh) to quarterly (R^2 = 0.63, S = \$10.95/MWh) to biweekly durations (R^2 = 0.76, S = \$6.94/MWh), but it shows little additional improvement when moving to weekly durations (R^2 = 0.79, S = \$6.11/MWh). For this reason, we use two-week periods in our analysis.[7]

Table 1. R-squared Fits for RSCs Estimated Using PJM 2015 Hourly Price and Load Data over Various Periods

Periodicity	Annual Average R^2	Minimum Period R^2	Maximum Period R^2
Annual	0.48	—	—
Quarterly	0.63	0.48	0.76
Biweekly	0.76	0.60	0.88
Weekly	0.79	0.60	0.95

[7] Running this analysis using equivalent data in PJM for 2014 and 2016 yielded average biweekly R-squared values of 0.78 and 0.80, respectively. Thus, we conclude this approach is robust across multiple years.

Figure 4 shows the 2015 PJM price-load data for weeks 1 and 2 (period 1) in winter and weeks 23 and 24 (period 12) in summer, along with how well these data fit to linear and cubic-power curves. The improvement in moving from a linear fit to a cubic fit is very substantial, with the R-squared value increasing by over 20% for winter (R^2 from 0.71 linear to 0.87 cubic) and over 10% for summer (R^2 from 0.73 linear to 0.82 cubic). Moving from a linear to a cubic fit also reduces the standard error of the price estimate for a given load by over 30% in winter (from $9.93 to $6.69/MWh) and over 15% in summer (from $7.64 to $6.24/MWh).[8] Because of this improved fit, we use a cubic fit for the analysis in the rest of the report.

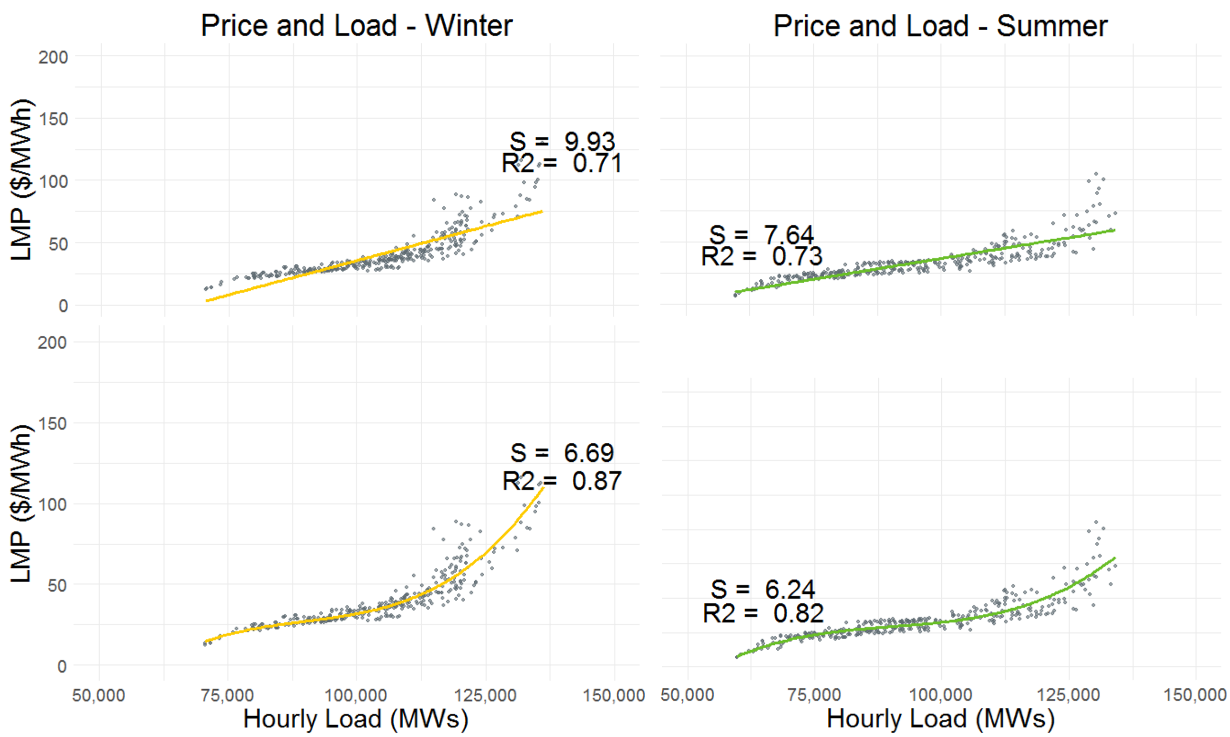

Figure 4. Hourly price-load data in PJM in 2015 for two-week periods in winter (period 1, left) and summer (period 12, right) with linear fits (top) and cubic fits (bottom)

Figure 5 shows the improvement in standard error of the difference in the estimated versus actual prices over an entire year produced by fitting curves to shorter analysis periods. Because, for each different duration, the annual average prices (blue bars) are calculated based on one year of data, these averages are very similar for each estimate, around $38.40/MWh. These estimates are only 6% higher than the actual PJM load-weighted average energy cost in 2015 (as reported by the Market Monitor) of $36.16/MWh. However, using two-week fits rather than an annual fit reduces the hourly standard error of the wholesale price from about $16/MWh to $7/MWh, which leads to improved price estimates for a given load when applying this technique.

[8] In contrast, the improvements in R-squared value and standard error when moving from the cubic to the fifth-power fit are less than 1% and produce no material impact on price spikes.

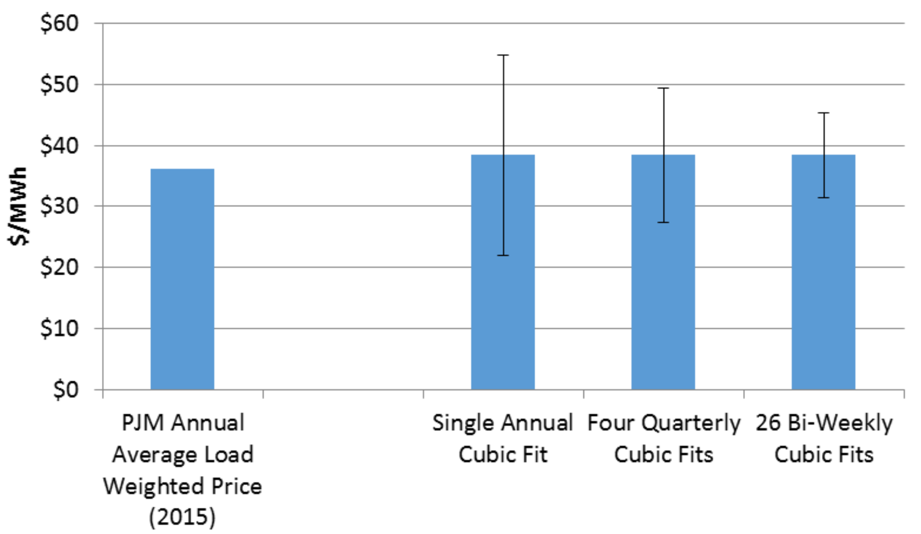

Figure 5. Actual vs. estimated load-weighted annual average price of electricity (LMP) from using estimated RSCs with cubic fit for different durations; standard errors of fits shown as error bars

This methodology can easily be adjusted if significant VRE is present in the market being examined, because VRE generation is typically at zero or near-zero marginal cost. Ideally, the RSCs would be fitted to hourly net load data rather than overall load data to remove the impact of variable zero-marginal-cost renewable energy. Estimating net load adjustments for existing VRE can be challenging given the need for actual data as well as choices that must be made about aggregation of both resources and VRE nameplate capacities across geographic areas. Because VRE penetration was low in PJM in 2015, we do not make this VRE net load adjustment in our PJM analysis. However, we do consider net load effects in Section 4, which briefly explores some differences between PJM and ERCOT, where wind penetration is much higher.

2.2 Limitations

This section discusses several limitations of the RSC method.

2.2.1 Estimating Price during High-Load Periods

Although the RSC methodology using two-week durations estimates the hourly price as a function of load reasonably well, its predictive accuracy is lower in hours with particularly high load. Figure 6 provides the cubic fit and actual hourly day-ahead LMP compared with load for weeks 23 and 24, showing the difference between the fit and actual hourly prices, which can be significant, especially at high load. These differences may be hard to fit even with a modified curve, because the curve is not capturing significant changes that might be due to other variables. For example, although the peak demands for the 8th and 12th days are similar, the accuracies of the hourly price estimates are substantially different. On day 8 the RSC underestimates the actual wholesale hourly energy prices by up to $35/MWh, whereas on day 12 the RSC slightly overestimates the price. A number of factors may affect this, including forced and unforced outages, existing VRE variation, imports and exports, and transmission issues. Some of these may be partly captured (e.g., VRE and imports and exports) within the current approach, at least on a historical basis, and this is discussed in Section 4.

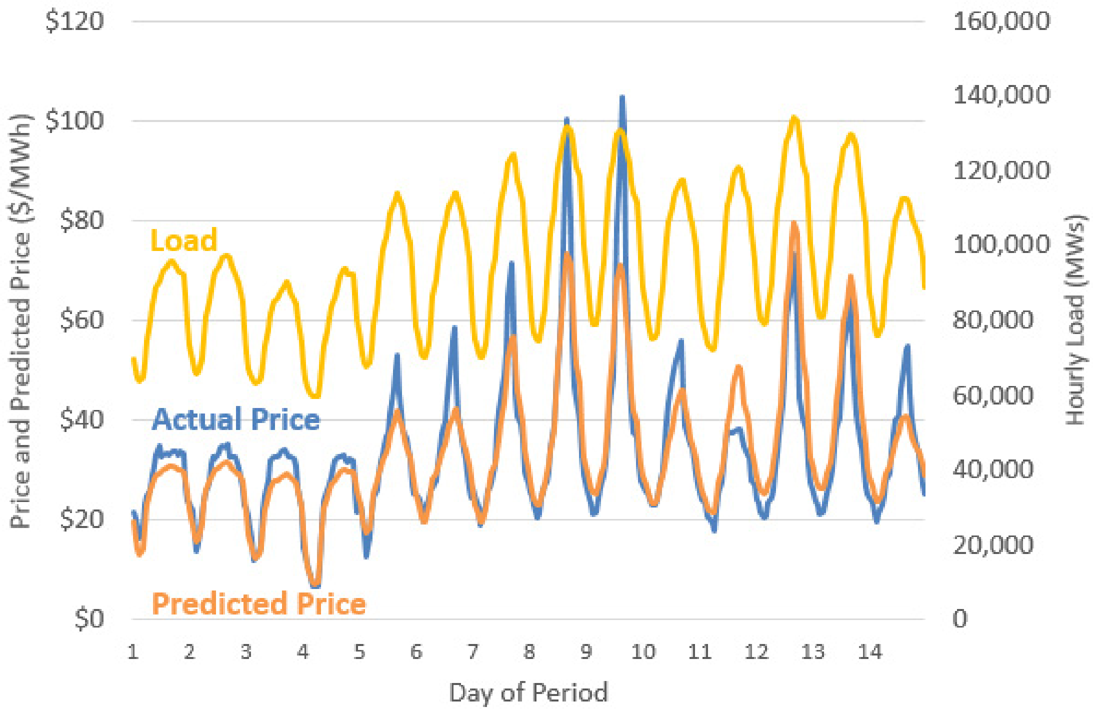

Figure 6. Comparison of actual hourly prices vs. estimated hourly prices for load in PJM over a two-week period (weeks 23 and 24 in summer 2015) using cubic fit

Figure 7 shows hourly congestion charges, which represent a key driver of the differences between the actual LMP and estimated LMP in any given hour. The energy price can be determined by simply removing the congestion and loss charges from the LMP. However, although congestion charges may be a contributing factor, they do not completely explain the variation between estimated and actual LMPs (because similar congestion charge profiles for different days may have very different errors in fit). Further research is needed in this area (see Section 5), but there likely are significant inherent limits on estimation accuracy due to the complicated and changing way the transmission system network constraints interact over time, even if adjustments are also made for congestion charges, because of imports and exports, forced and unforced outages, bidding behaviors, and other factors.

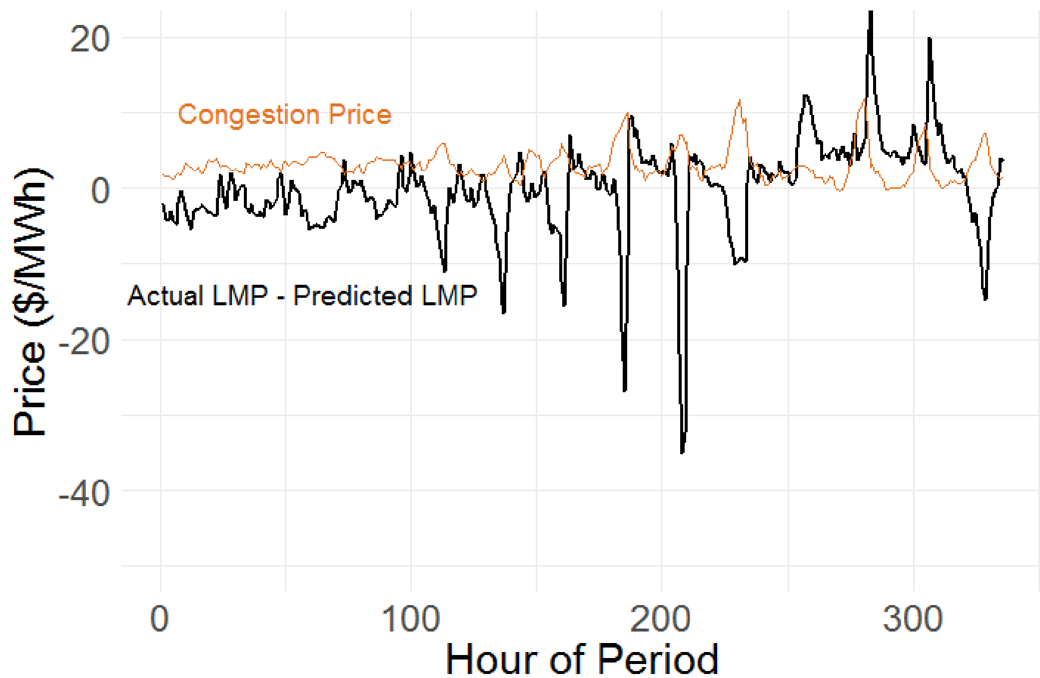

Figure 7. Estimate of differences between hourly LMP estimates and actual LMPs in PJM (for cubic fit), and comparison with hourly congestion charges over the same two-week period (weeks 23 and 24 in summer 2015)

2.2.2 Tying Revenue Estimates to Underlying Generation

Beyond estimating the impact on wholesale prices of adding or retiring generation, the RSC approach can also estimate the net revenue of new generation (although with uncertainty due to errors in estimating utilization). The approach can also estimate the overall revenue for the system, and hence costs to LSEs. However, it is more challenging to tie these net revenue estimates to individual existing generation plants, because other variables—such as transmission constraints, outages, and imports and exports[9]—are constantly changing and affecting system and plant-level utilization and economics.

Additionally, estimating impacts on LSEs and generators using RSCs is further complicated by the presence of bilateral and self-supply contracts. In PJM and many other RTO territories, many consumers are served by LSEs that may purchase some electricity via bilateral contracts and/or through self-supply rather than from the wholesale energy market. This may include vertically integrated utilities, even in restructured markets. Such arrangements may partly mitigate the effects of additions or retirement in capacity on the impact of changes in wholesale prices to an LSE—at least in the short term. This is because, under bilateral contracts and self-supply, the LSE is both a seller and buyer of electricity, and therefore largely hedged from any near-term changes in the wholesale price.

[9] The RSC approach also does not estimate the impacts of payments for ancillary services, although capacity payment estimates can be added in a straightforward manner based on recent capacity auction estimates and capacity credits for different technologies (PJM 2017a).

More generally, in restructured markets the expected net revenue for new generation is modified in most RTOs—including PJM and the Midcontinent Independent System Operator (MISO) but excluding ERCOT—through capacity payments whose future value is adjusted (imperfectly) to reflect future estimates of many factors including expected changes to energy prices, reserve margins, and ancillary services.[10]

[10] The net cost of new entry is the gap (or "missing money") between the estimated energy payments and ancillary service revenue and the total revenue necessary to cover expenses and earn a fair rate of return at the target reserve margin. This gap determines the capacity payments, which are scaled up or down depending on whether the system is short or long in capacity relative to the desired reserve margin. In this way, lower energy revenues due to retirement can in part be replaced—at least in the longer term—by higher capacity payments. How well this system provides the right incentives for capital investments to new and existing generation is, however, an open question (see, e.g., Spees et al. 2013, Bowring 2013, Borenstein and Bushnell 2015, Jenkin et al. 2016).

3 Applications of the Rolling Supply Curve Methodology

This section demonstrates the use of RSCs to assess the wholesale electricity price changes caused by generation retirements and additions (including the addition of VRE). Section 3.1 estimates the impact of retiring 500 MW of dispatchable generation, both without replacement and with replacement by two different types of natural gas generation technologies: combustion turbine (CT) and combined-cycle gas turbine (CCGT). Section 3.2 shows how the technique works for estimating the change in wholesale energy prices when VRE is added owing to well-known merit order effects (Traber and Kemfert 2011).[11] Finally, Section 3.3 assesses how backcasting may be used to generate future RSCs to estimate future wholesale electricity prices and operational net revenues for specific generators and the aggregate market.

3.1 Estimating Impacts on Wholesale Energy Prices of Retirements, with or without Replacement

Our RSC methodology can estimate wholesale price effects under various retirement scenarios. Here we demonstrate a use of this methodology by showing the wholesale price effects of retiring 500 MW of generating capacity without replacement, and then we consider how the observed price increases may be partly mitigated if the reserve margin is restored by adding back 500 MW of capacity with CTs or CCGTs.[12]

The impact of this retirement is estimated as follows. First, we calculate hourly LMPs in each two-week period as described in Section 2.1, and we use these curves to generate a load-weighted average wholesale price for each period. We then shift each of the 26 estimated RSCs toward the origin of the MW capacity x-axis by 500 MW and calculate new hourly and biweekly wholesale prices based on the original hourly demand over that period. This can be seen in Figure 8 in the shift from the original supply curve to the retired supply curve. The effect on wholesale price of the retirement without replacement in any given hour is the difference between these new and original wholesale prices for any given demand. In this case, we directly shift the full curve toward the origin, because we assume the retiring capacity has a marginal cost of $0/MWh, which we use to illustrate the maximum mitigation effect for a replacement technology.[13] More generally, for the retirement of a plant with non-zero marginal cost, the impact can be estimated by only shifting the original RSC that lies between the marginal costs of the retired and replacement units, as we show later.

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[11] A supply curve in any hour is built up of generator capacity in order of increasing marginal costs. This is sometimes known as the "merit order." Because VRE has close to zero variable operations and maintenance (O&M) cost, VRE generation changes the merit order as it pushes generators that are making up the supply curve to the right (along the load x-axis).

[12] Under this approximation, we assume the capacities being retired and replaced are equal, and we do not adjust for any differences in availability.

[13] The $0/MWh value may be relevant for baseload technologies where it may be costly to reduce output, or for technologies with no fuel costs. For example, while nuclear plant fuel costs are about $7/MWh, their all-in variable and fixed O&M costs are closer to $35/MWh (with variation by unit). In the long run, energy and capacity prices below $30/MWh may lead to plant closure, but in the short run (relevant to these RSCs) the nuclear plants are likely to bid in at close to $0/MWh to ensure they run even at energy prices below their near-term marginal cost. Hydroelectric generation also has very low variable costs (about $2 to $3/MWh for variable O&M) (EIA 2017).

To estimate the price increase in scenarios in which the reserve margin is restored with CT or CCGT capacity, we use the procedure illustrated in Figure 8. The yellow arrow represents the retirement of Q MW at $0/MWh. The green arrow represents the replacement capacity with a marginal cost of $X/MWh. The hourly price for any given load is then given by the left-shifted (i.e., retired) supply curve until the price estimate for a given load equals the marginal price of the replacement capacity ($X/MWh in this case). For prices below this load, the price has shifted up compared with the pre-retirement case; that is, at Q_a, the price has increased from P_a to $P_{a'}$. For the next Q MW, the price remains flat as new generation bridges or switches from the left-hand supply curve to the right-hand supply curve. Thereafter, at higher loads, the price estimate is given by the pre-retirement supply curve and so is unchanged.

For the CT calculation, we assume a marginal cost of $43/MWh for replacement capacity.[14] The retired RSC is used whenever load predicts a price less than $43/MWh. Above that load, the price is kept at $43/MWh for the next 500 MW, corresponding to the effect of the inserted CT, which at that point connects back to the original RSC. The original pre-retirement RSC is used to estimate prices for higher loads. We employ the same process for the CCGT impact, but now the crossover takes place at the CCGT's lower marginal cost of $30/MWh.

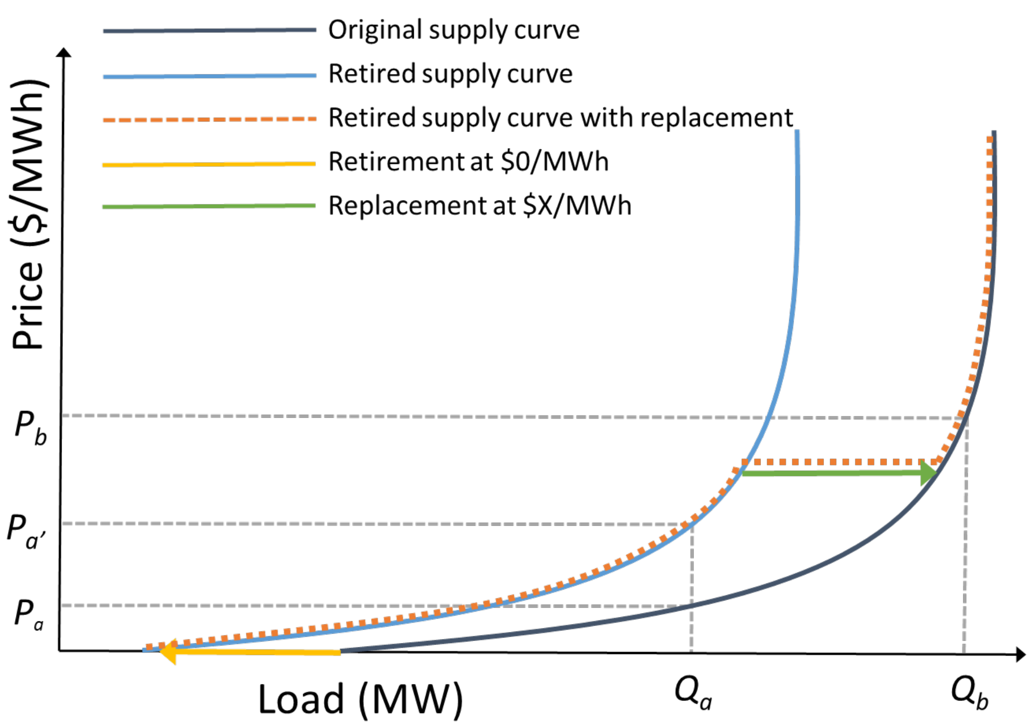

Figure 8. Schematic illustration of impact of retiring Q MW at $0/MWh (yellow arrow) and replacing with similar amount of generation with a marginal cost of $X/MWh (green arrow)

Figure 9 shows the distribution of the hourly price increases in 2015 for three scenarios: 500 MW of $0/MWh capacity retired without replacement capacity, 500 MW of capacity retired and replaced with CT capacity, and 500 MW of capacity retired and replaced with CCGT capacity.

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[14] The estimated total variable costs for a CT and CCGT are $43/MWh and $30/MWh, respectively (assuming $4/MMBtu natural gas prices and heat rates consistent with Lazard 2016).

Assuming no replacement of lost capacity, the distribution of hourly LMP price increases during the year is asymmetric with a long positive tail, a mean of $0.60/MWh, and a median of $0.36/MWh. The effect of replacement capacity is to lower the mean and median price increases in both cases. While both technologies mitigate the price increase relative to the retirement case, the CCGT is much more effective; it reduces the average price increase by 80%, to $0.11/MWh. In contrast, the CT reduces the average price increase by 50%, to $0.28/MWh. In addition, the variation in price increases is smaller for the CCGT than for the CT. The CCGT gives a better outcome in this case because its marginal cost is lower, so the switch back to the original “lower” supply curve takes place at lower load, and hence, more frequently. In addition, because the point at which the marginal cost of CCGT plants intersects the existing supply curve has a flatter slope than it does for a CT, this contributes to the observed variance reduction in the estimated prices during the entire year.

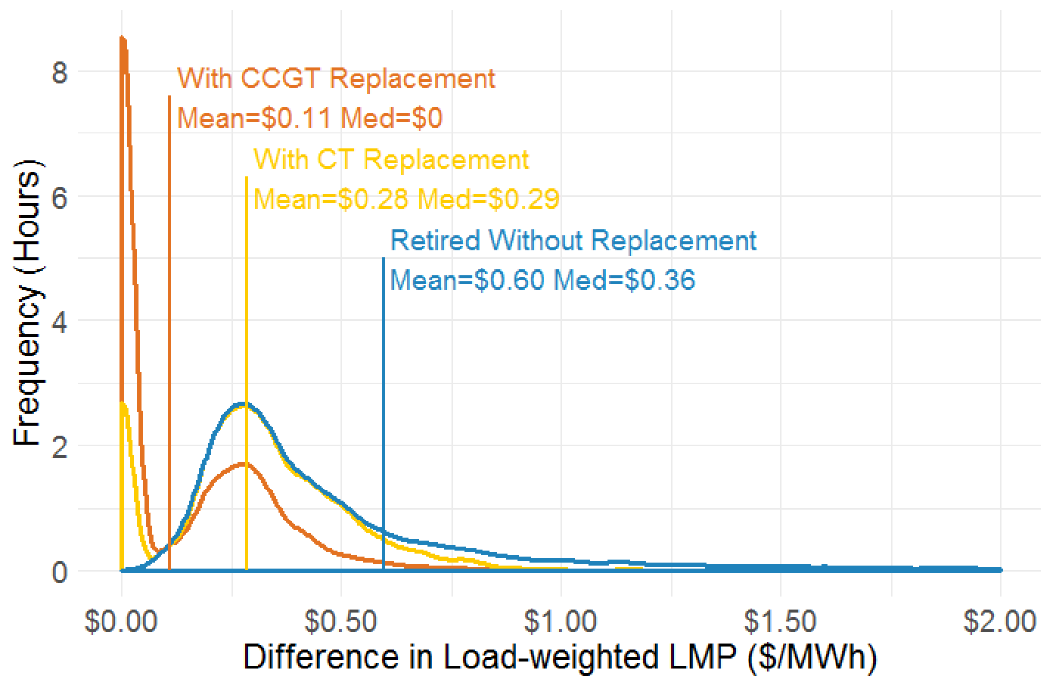

Figure 9. Distribution of price increase due to 500 MW of plant retirement for each hour in 2015 with no replacement, replacement with CT, and replacement with CCGT

Figure 10 aggregates hourly price changes into biweekly load-weighted average LMP increases and shows the impact for each of the 26 different RSCs. Although the broad conclusion is similar to what is observed in Figure 9, examining the data at a less granular timescale yields several further insights. The retired without replacement scenario clearly has a long right tail in Figure 9, but Figure 10 shows that many of these hours fall in two biweekly periods with substantially higher average increases (i.e., periods 4 and 5, discussed in greater detail below). Additionally, although the modal hourly price increase for both the CT and CCGT replacement scenarios is $0 (as seen in Figure 9), Figure 10 shows that these instances are sufficiently distributed such that few single biweekly periods have an average price increase of $0–$0.05.

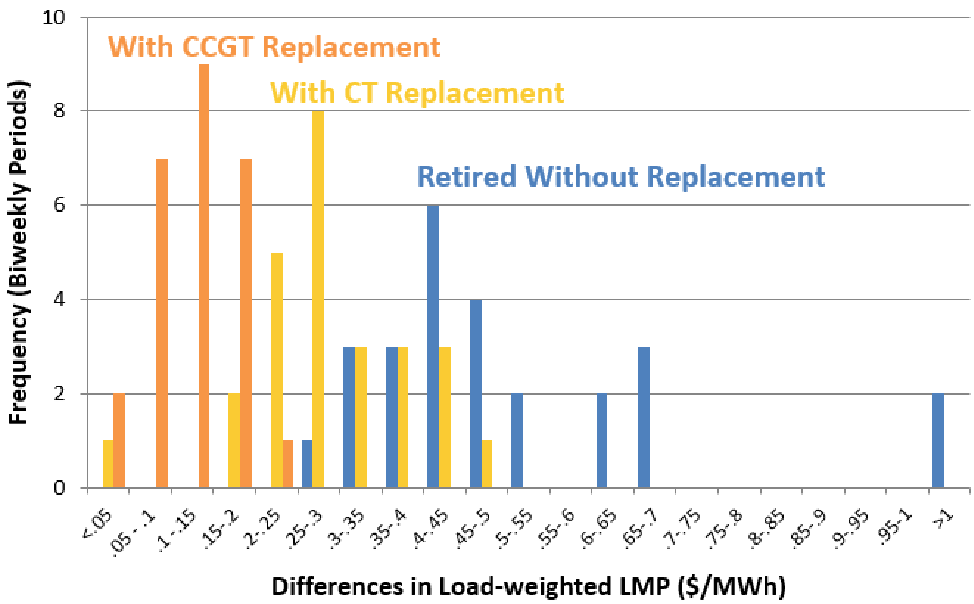

Figure 10. Distribution of price increase due to 500 MW of plant retirement for each two-week period in 2015 with no replacement, replacement with CT, and replacement with CCGT

Overall, this analysis shows that changes in price and revenue for a given reserve margin depend closely on choices about the marginal cost of the retiring generator as well as what technology is used for replacement, if any. This type of analysis suggests the potential importance of market design and incentives, because different generation mixes—for the same level of reliability—can affect revenue for the generating fleet.

The effects shown in this analysis are short term, and the analysis says little about longer-term system evolution. The longer-term effects on producers vary for at least two reasons. First, higher energy prices are expected if the reserve margin is reduced, as in the no replacement case; in turn, these higher energy prices may reasonably be expected to incentivize the building of new capacity, reestablishing a market equilibrium closer to the existing (i.e., lower) price. Second, net revenue depends not only on energy revenue, but also on ancillary services revenues and capacity payments, which are not independent of energy prices (at least in the longer term). The impact of these effects may also be reduced in the short and longer terms owing to the presence of substantial generation used by LSEs coming from bilateral contracts or self-supply arrangements in restructured markets, including in some cases vertically integrated utilities. Under these arrangements, the price of electricity is essentially (at least in the near term) independent of the wholesale energy price (although this may vary by contract). Further analysis in this area is suggested in Section 5.

Assuming a marginal cost of $0/MWh for the retired 500 MW simplifies the analysis. However, the RSC approach can be applied more generally to consider retirement of generation with any marginal cost. Figure 11 shows a more general case in which the retired capacity has some marginal cost $X/MWh. If the marginal costs of the retired and replacement capacity are identical, the yellow and green arrows in Figure 11 cancel each other out, and there is no change in wholesale prices.

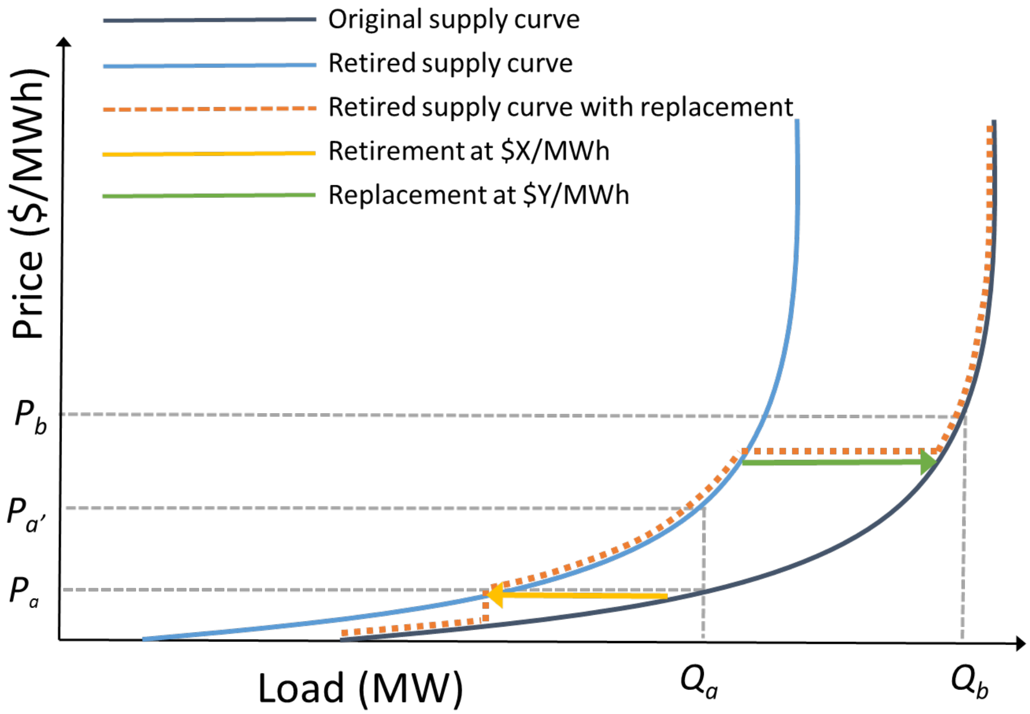

Figure 11. Schematic illustration of impact of retiring Q MW at $X/MWh and replacing with similar amount of generation with a marginal cost of $Y/MWh

3.2 Estimating Impacts on Wholesale Energy Prices of Adding VRE

The RSC approach can be extended to estimate the price impacts of adding VRE in addition to dispatchable capacity. Because VRE capacity has a $0/MWh marginal cost, adding VRE capacity to the market simply shifts the hourly supply curves to the right on a variable basis depending on the amount of VRE generation available at any given time. To estimate the impacts of adding a set amount of VRE capacity, we shift the hourly supply curve (represented as each of the 336 price-load data points used to generate our RSCs) by an amount equal to the sum of the wind and solar photovoltaic (PV) generation in that hour.

To determine the amount of wind and PV generation by which to shift each hourly curve, hourly wind and PV generation must be determined based on real-world data or data modeled to reflect real-world variations. The wind and PV profiles are based on simulated data in 2012 for Ohio, which was chosen as representative because it is part of PJM. The wind output was simulated using the National Renewable Energy Laboratory's (NREL's) Wind Integration National Dataset Toolkit (NREL 2015) based on 40 wind sites (between 12 and 16 MW in size) with an overall capacity factor of 32.8%. PV was based on 10 sites of 4-MW utility-scale PV with no tracking and an overall capacity factor of 16.0%.[15] The PV output was then estimated using NREL's National Solar Radiation Database (NREL n.d.). The use of multiple sites allowed for aggregation effects to be included when estimating hourly capacity factors for wind and PV.

[15] This is intended to be illustrative. Tracking PV or the use of a lower latitude may increase PV's capacity factor significantly.

These capacity factors were then used to determine how much wind and PV nameplate capacity was needed for the two scenarios studied below.

We illustrate this technique with two simple scenarios: a) an 80:20 wind-PV generation split (the high-wind scenario), and b) a 50:50 wind-PV generation split (the equal wind-PV scenario). To make the analysis broadly comparable with the analysis in Section 3.1, we add sufficient VRE capacity to generate the equivalent of the 500 MW of retiring generation capacity. For the high-wind scenario, this corresponds to 1,219 MW of wind and 625 MW of PV nameplate capacity. For the equal wind-PV scenario, it corresponds to 762 MW of wind and 1,562 MW of PV.[16]

3.2.1 High-Wind Scenario

The top part of Figure 12 (next page) shows the wind and PV generation for each of the 26 two-week periods; in these data, wind generation peaks in late winter and again in late summer, while PV generation increases in spring and summer compared to winter. Also shown in Figure 12 is the load-weighted average LMP for each of the 26 two-week periods before and after adding VRE; the bottom graph in Figure 12 plots the difference between these two prices.

Biweekly periods with higher amounts of wind generation are fairly strongly correlated with larger declines in price (correlation coefficient = -0.70). The estimated price in the four biweekly periods with the highest levels of wind generation is, on average, nearly three times lower (compared to the prices prior to adding the VRE generation) than the four biweekly periods with the lowest levels of wind generation. However, the difference in electricity price is also heavily impacted by underlying market dynamics; indeed, the period with the third-highest price difference (period 4) also has some of the lowest levels of wind generation. The high wholesale energy prices in this period occurred owing to a number of factors, including a spike in natural gas prices (discussed in more detail in Section 4), and the ability of wind to provide even a small amount of generation during this period of high prices had a substantial impact on the price.

[16] These values are based on our illustrative annual average capacity factors of 32.8% for wind and 16.0% for PV.

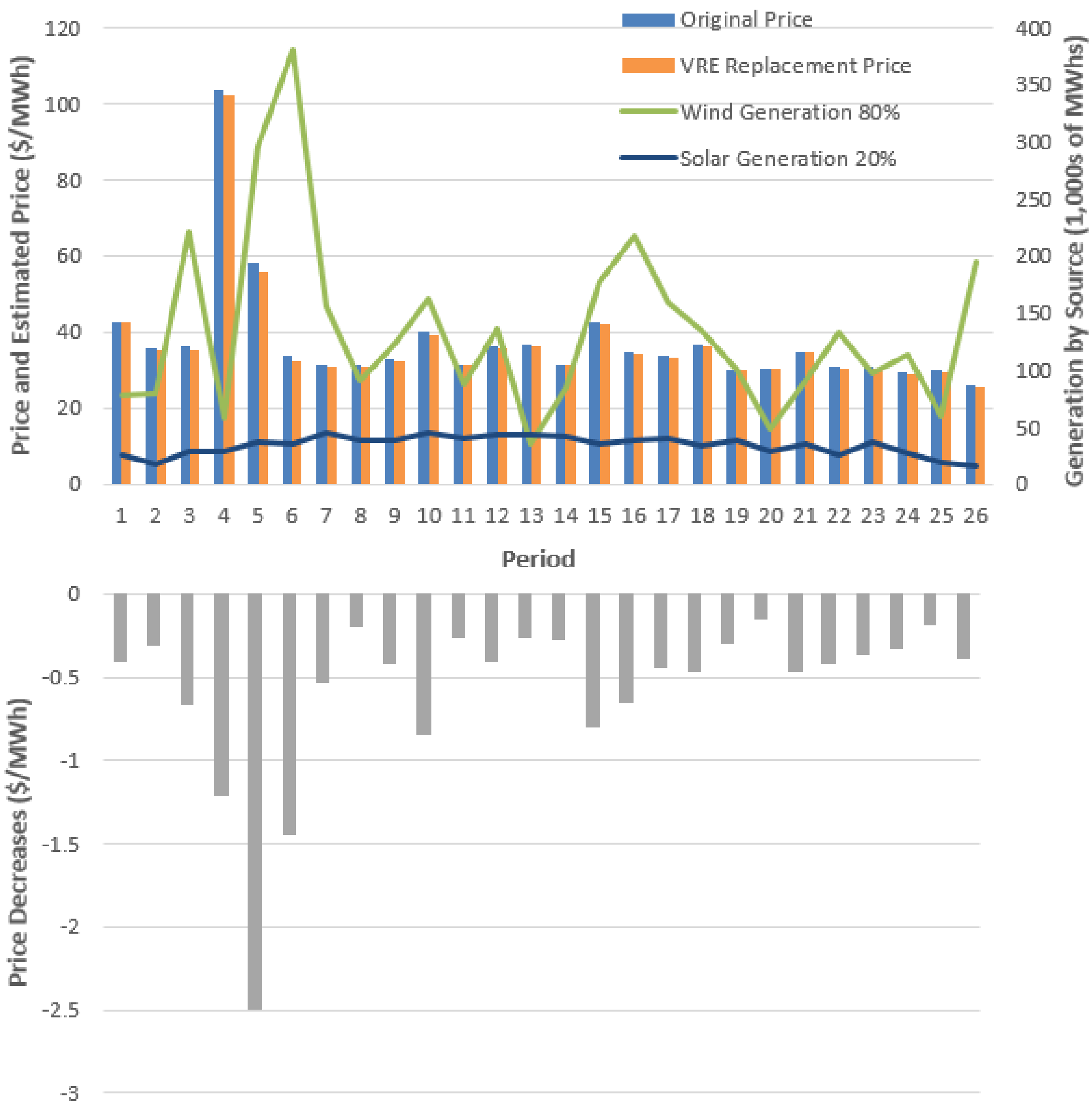

Figure 12. Generation for each of 26 two-week periods due to adding VRE for 80:20 wind-PV case plus load-weighted average wholesale price before and after added VRE (top) and difference between wholesale price with VRE and without VRE for each period (bottom)

3.2.2 Equal Wind-PV Scenario

The results of the 50:50 wind-PV scenario (Figure 13) are similar to the results of the 80:20 wind-PV scenario. The main differences are a somewhat less strong correlation between wind generation and price decreases (correlation = -0.56) and slightly less volatility in prices (despite a slightly larger average price decrease across the year). Periods 4, 5, and 6 still have the largest price decreases and, in the case of periods 5 and 6, the highest amount of cumulative wind and PV generation.

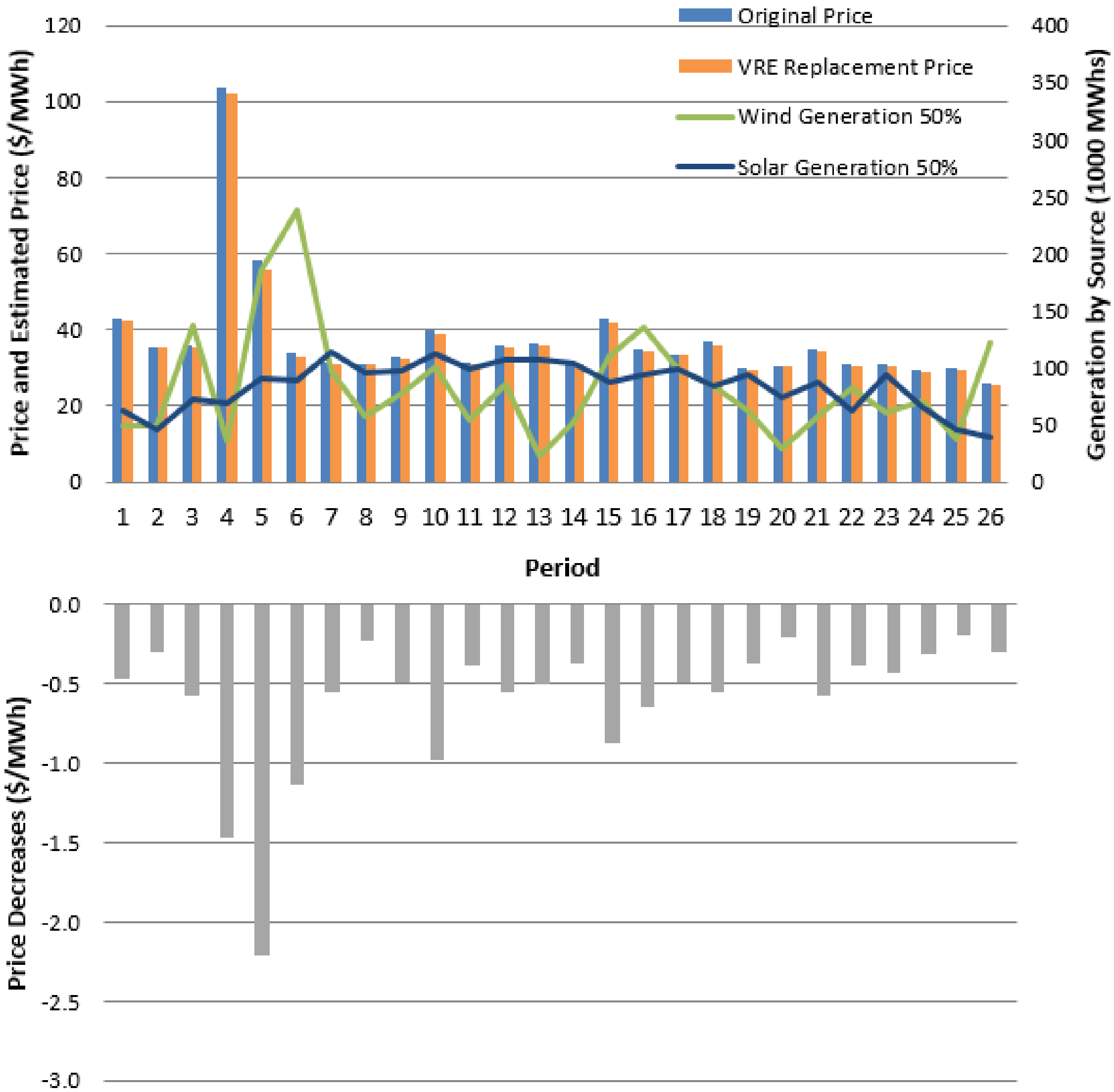

Figure 13. Generation for each of 26 two-week periods due to adding VRE for 50:50 wind-PV case plus load-weighted average wholesale price before and after added VRE (top) and difference between wholesale price with VRE and without VRE for each period (bottom)

3.3 Rolling Backcast Supply Curves and their Potential for Operational and Net Revenue Analysis

For the operation of an individual plant within an existing system, it is often desirable to estimate future prices for a given load without relying on knowing future price-load curves—that is, to make operational decisions without perfect foresight. One partial solution is to use recent historical data and regression techniques (backcasting) to build RSCs for use in projecting near-term future price-load relationships. In Figure 14, the actual RSC (solid line, which would not be known in advance) is compared with an estimated (backcast) two-week RSC (dashed line) generated based on the prior two weeks' data. Because the backcast RSC estimate is similar to the current period RSC estimate (i.e., the cubic fit of the actual hourly price-load data), RSCs based on backcast data are sometimes reasonably good predictors of RSCs for the next two weeks, although this is not always true as seen in Figure 14.

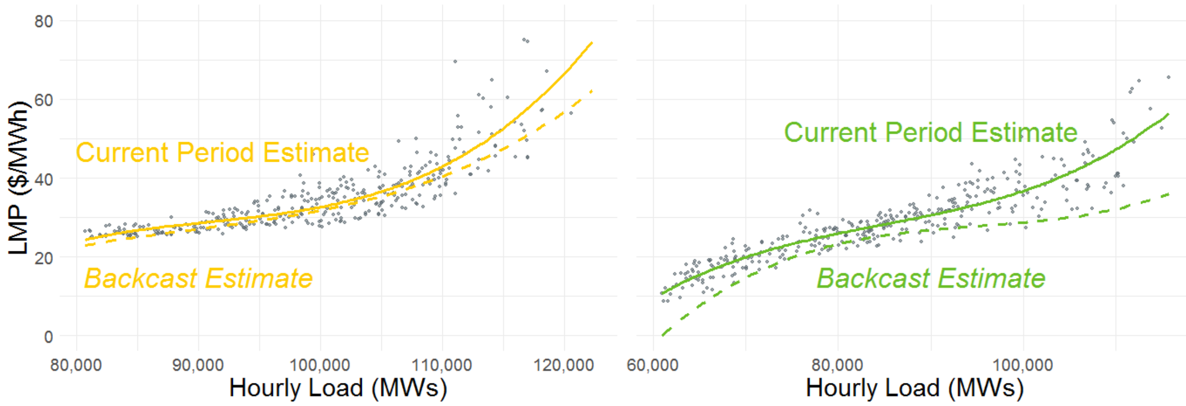

Figure 14. Actual (solid) versus backcast (dashed) two-week RSCs in PJM for 2015 for periods in winter (left) and summer (right)

Backcasting introduces significant additional variation in the price results. Figure 15 shows the average difference between the estimated and actual prices for each of the 26 two-week periods based on the actual data RSC and the backcast RSC. The average variation increases from +/- $7.0/MWh using actual data to +/- $10.0/MWh using backcasting, for the same two-week period, although with very significant variation across the year. As expected, the average error for the backcast supply curve is always worse than for the best-fit curve based on actual data.

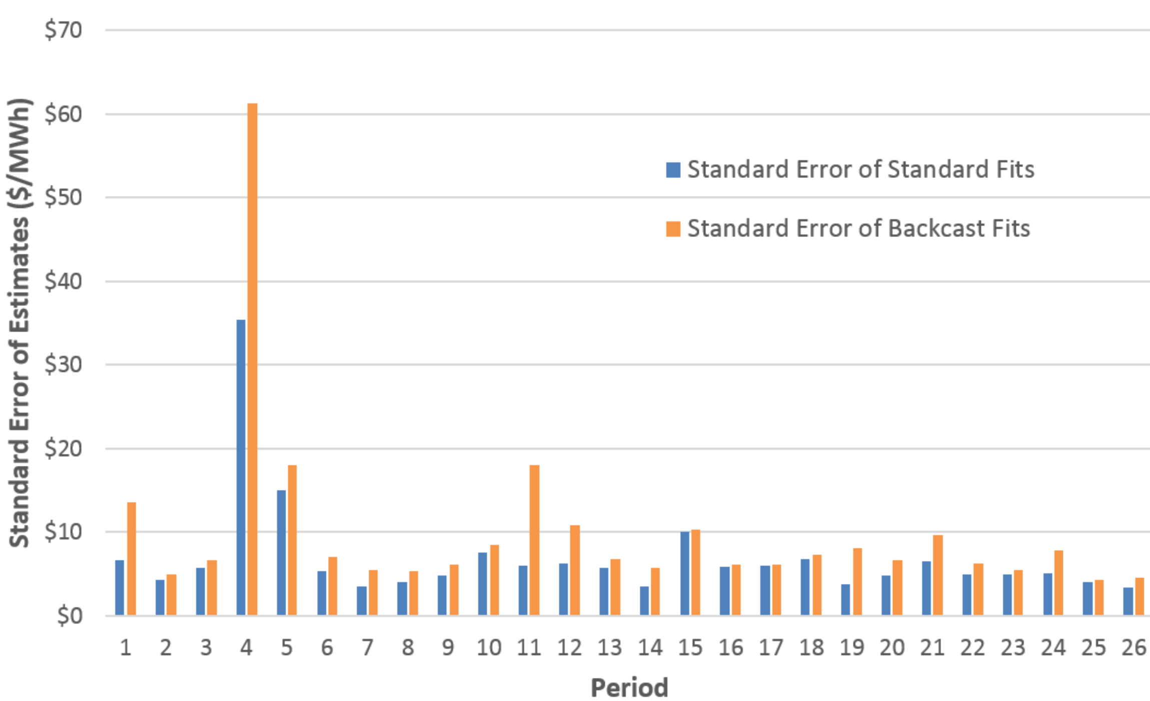

Figure 15. Standard error of difference between actual hourly price and estimated hourly price for each of 26 two-week periods using the fitted (normal) RSC and backcast-fitted RSC

Despite this increase in variance for backcast estimates, the error between estimates using a backcast-fitted RSC and a fitted RSC tend to offset each other over the longer term, because the differences commonly change sign over this period. These offsetting effects to a significant degree mitigate the errors in the estimate of the overall wholesale costs to LSEs[17] or net revenue to generation over the complete year. Figure 16 compares the variation in the average cost of energy during the 26 two-week periods and the backcast-fitted results. The backcast fit can vary significantly from week to week, e.g., being 42% and 19% greater in two-week periods 11 and 12 but 45% and 21% lower in periods 4 and 19, respectively. Because the differences may be positive or negative, the cumulative average cost of energy estimate is within about 5% for the entire year, provided the load in any given hour is known. This is seen in Figure 16 where the cumulative revenue lines intersect with the right axis: $30.4 billion for actual versus $29.4 billion for backcast. This analysis suggests that the backcasting technique could be used to estimate the future net revenue of new generation accurately without knowledge of actual supply conditions, using only the known conditions from two weeks prior on a rolling basis. Backcasting may also be used to better inform short-term decision-making by generators such as deciding when to take generation offline for maintenance

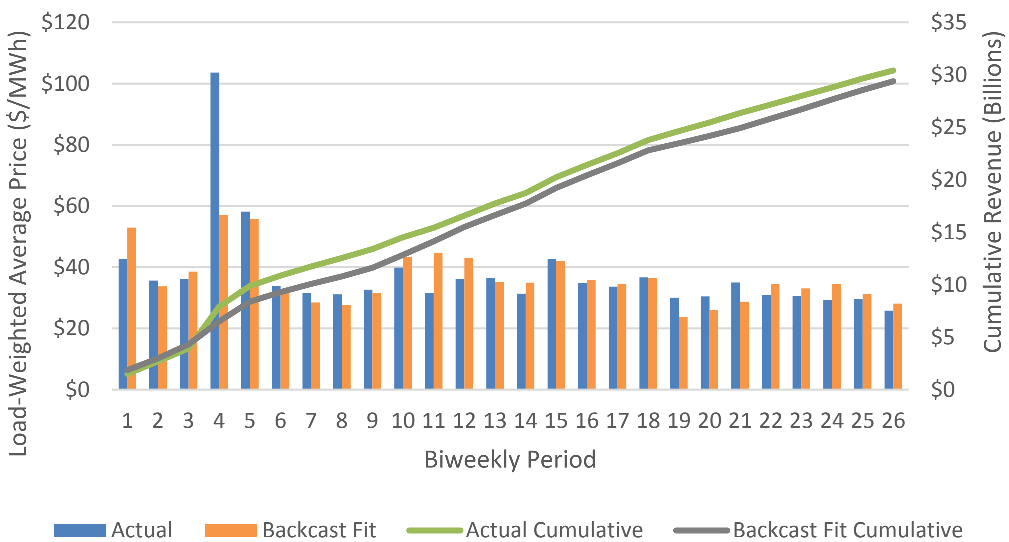

Figure 16. Weighted-average price of energy vs. estimated price of energy using backcast RSC (left axis), with lines showing cumulative impact on revenue using actual prices vs. backcast estimates (right axis)

[17] With all the caveats of mitigating effects of bilateral contracts and self-supply, including vertical integration, discussed earlier.

4 Uses and Limits

There are a number of potential issues or limits that need to be better understood about the use of this RSC approach to estimate the impact of retirements or additions on wholesale costs, including:

1. Size of the region chosen, e.g., RTO versus state versus utility level, and number of consumers affected
2. Natural gas and other fuel price changes
3. Forced and unforced outages
4. Hourly imports or exports
5. Hourly transmission constraints and their complex relationship to the region
6. Net load adjustment—actual and forecast (for VRE, potentially for imports and exports)
7. Fit for higher prices, including difficulty estimating price spikes

Although some of these issues—such as numbers 2, 4, and 6—may be mitigated by refining the approach or gaining access to additional data, others likely reflect inherent limitations of the technique or are otherwise difficult to estimate. However, one attraction of the RSC approach is its simplicity and speed, and therefore there is an inherent tradeoff between accounting for more of these factors in estimates and how easily the estimates can be calculated. This section illustrates some of the issues raised above by analyzing PJM across multiple years and comparing the price-load behavior of PJM in 2015 with results from ERCOT.

4.1 Variation of Statistically Generated Rolling Supply Curves across Multiple Years: Impact of Natural Gas Prices and other Factors

The analysis in Section 3 focuses on PJM in 2015. However, the shape of the estimated RSCs changes over time owing to factors that affect the availability or cost of generation units in any given hour. In particular, increases or decreases in natural gas prices shift parts of the supply curve up or down where the underlying generators are CCGT or CT units that run on natural gas. Depending on the relative and absolute prices of other fuels, such as coal, this may change the generation dispatch order. The effects of natural gas price changes may be significant, as suggested in Figure **17**. For example, a $1/MMBtu increase in natural gas prices may produce a $10/MWh increase in the marginal cost for a CT with an efficiency of 34% (or heat rate of 10,000 Btu/kWh), or a $6.50/MWh increase for a CCGT with an efficiency of 53% (or heat rate of 6,500 Btu/kWh).[18]

Figure 17 shows natural gas delivery prices at various locations across PJM as well as the average biweekly electricity prices during the same period (EIA 2017). The highest variability in electricity prices is in 2014; the lowest is in 2016.[19] The figure suggests that, while natural gas prices may be important, they are not the sole contributor to such variation. The high electricity prices and corresponding steep supply curves in early winter 2014 were driven by a polar vortex,

[18] These heat rates are consistent with ranges given in Lazard (2016).
[19] The day-ahead hourly price and load for PJM for 2014, 2015, and 2016 were sourced from the PJM website (PJM 2017b, 2017c).

which led to record lows across much of the United States, including all of PJM (NERC 2014, Reed Smith 2015). During this time, natural gas prices were higher owing to increased demand (for electricity and natural gas for heating) and natural gas delivery constraints. However, other important contributing factors likely included increased forced outages, which grew in early January from an average of 7% to 22% (Reed Smith 2015). The combined effects of these and other factors had a significant impact on the shape of the fitted supply curves, and they likely limit the ability to backcast supply curves—at least for some weeks—to estimate future electricity prices for a given load.

Overall, Figure 17 shows the relationship between electricity prices and one key external factor—natural gas prices. Such external factors can be expected to affect the impact on wholesale prices of additions or retirements. To illustrate this point, Figure 18 shows the distribution of average hourly electricity price increases over two-week periods when 500 MW is retired at $0/MWh over this 3-year period. The differences within and between years are substantial in terms of mean and median electricity prices as well as the variance and skewness of the distributions, and they are the result of a variety of factors external to the price-load relationship.

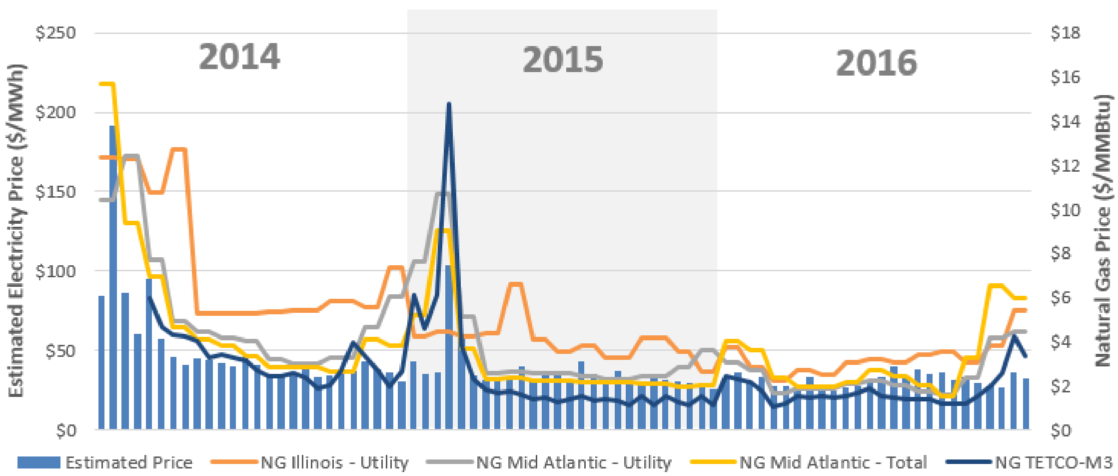

Figure 17. Natural gas and estimated load-weighted average electricity prices for each two-week period for PJM in 2014, 2015, and 2016

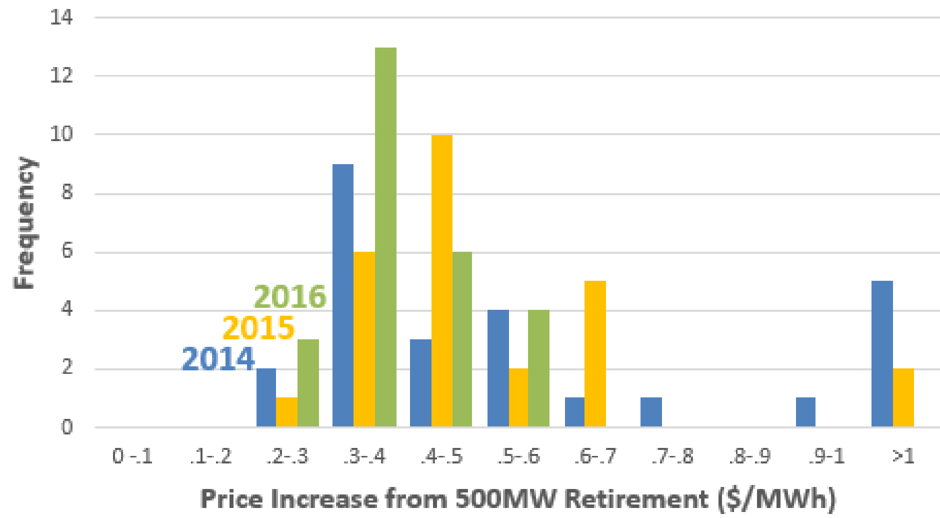

Figure 18. Distribution of average hourly price increase for 26 two-week periods due to 500 MW of plant retirement (at $0/MWh) without replacement for 2014, 2015, and 2016

4.2 Differences Between PJM and ERCOT

In this section, we compare the application of the RSC methodology in a different RTO/ISO. ERCOT was chosen due to two factors that differentiate it from PJM. First, ERCOT has much more VRE than PJM does: 12% wind generation in ERCOT in 2015 versus 2% in PJM for the same period (IMM 2016a, Monitoring Analytics. 2016). Additionally, it is an energy-only market, whereas PJM has energy and capacity markets. Figure 19 shows a number of comparisons between PJM and ERCOT.[20] The upper right figure replicates Figure 2 for PJM, and the upper left figure shows the corresponding 26 two-week RSC estimates for ERCOT. One difference between the two figures is that the ERCOT figure uses a form of net load, calculated as the original load less any load met by wind generation in an hour, whereas the PJM figure uses actual load.

The average biweekly R-squared value for ERCOT (0.57) in 2015 is lower than for PJM (0.76), and these R-squared values in ERCOT range from less than 0.11 to about 0.8 versus PJM's much narrower range of about 0.6 to 0.9. ERCOT's higher wind penetration might seem like a major cause of this higher variability, but adjusting for net load has little effect on the results. Rather, the large variation in R-squared values seems to stem from the difficulty accounting for price spikes using the current RSC method. This is evident from the bottom curves in Figure 19, which compare for PJM and ERCOT the actual prices with the estimated cubic fits for two weeks in winter and summer. Although the two-week periods in summer for PJM and ERCOT both have a reasonable fit (with R-squared values of 0.82 and 0.72, respectively), the fit for the winter two-week period is much worse for ERCOT compared to PJM (with R-squared values of 0.39 and 0.87, respectively). The worse fit in ERCOT is largely driven by several price spikes above $100/MWh during that period. It appears the RSC approach—at least as currently implemented—has difficulty estimating the magnitude and frequency of prices spikes.

[20] Day-ahead hourly price and load for ERCOT used in this report were sourced from the ERCOT website (ERCOT 2017a, 2017b).

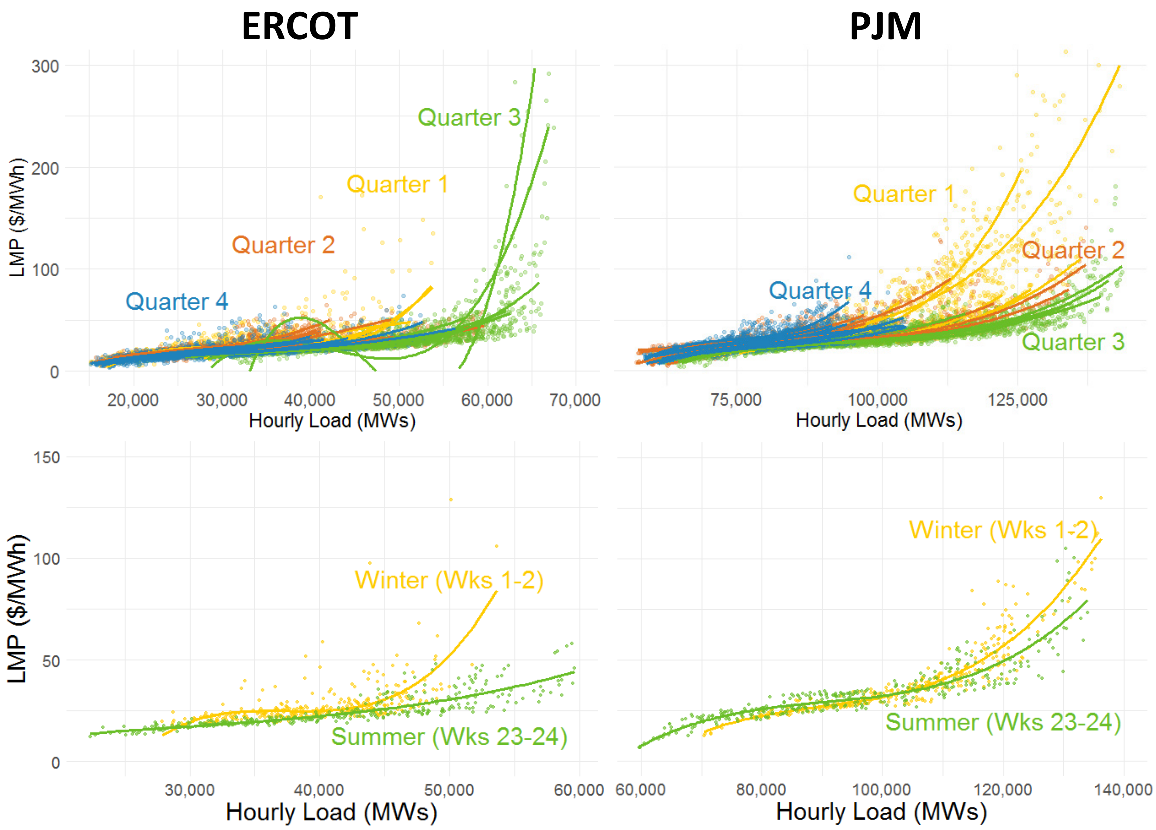

Figure 19. Comparison of price-load data and cubic fits for ERCOT (left, using net load) and PJM (right, using actual load) on an annual basis (top) and for selected weeks (bottom)

5 Main Findings and Next Steps

The RSC approach used in this report uses regression analysis to estimate the shape of the supply curve that best fits historical hourly price and load data for given time intervals, repeating this on a rolling basis through time. These supply curves can then be modified to estimate the impact of generation retirements or additions, including adding VRE, on wholesale electricity prices over a variety of time horizons.

The supply curve fit to hourly price and load data improves as the timeframe is reduced, and RSCs with durations of two weeks (or less) can provide a fast simple method for estimating hourly prices over the course of a year. In our example of PJM in 2015, fitting hourly price-load data to 26 rolling two-week cubic curves yields an average R-squared value of 0.76. The shorter-duration rolling curves provide a better fit by naturally incorporating significant seasonal effects such as variations in fuel prices, outages, and imports. Using rolling periods shorter than two weeks may improve the fit marginally but may also increase computational requirements.

We illustrate the potential use and value of the RSC method by estimating the impact on wholesale prices under various generator retirement and addition scenarios. Such estimates can be made quickly via simple supply-curve modifications that depend on the size and marginal cost of the retired and added capacity—allowing users to avoid more complex analyses that rely on production cost models or other more analytically intensive techniques.

Our illustrative analysis shows how the impact on wholesale energy prices of the restoration of a given reserve margin following the retirement of other generation will depend significantly on the choice of replacement technology, which may have implications for market design. We also use the RSC approach to estimate the price impacts of adding VRE, which could then be combined with retirements and additions of more conventional generation. We also use an RSC backcasting approach to estimate near-term future price-load relationships that could be used to estimate revenue for new generation without relying on perfect foresight of future supply curves. Although the backcast estimates increase variation in the results on an hourly basis, the offsetting positive and negative effects of these differences can significantly mitigate the errors over a complete year. In our example, the cumulative average cost of energy backcast estimate is within about 5% of the estimate from a curve fitted with actual data for the entire year.

The RSC approach has several limitations, and this affects the applications for which it is appropriate. For example, while the approach might be used to compare the effect of using a CT versus a CCGT (or other types of generation or storage) to mitigate wholesale price impacts that are due to generator retirement, it cannot determine where to place that new generation capacity within an RTO.

Like other methods such as production cost models, the simple regression analysis used here also has difficulties predicting price spikes, because at high loads, the realized price can be highly variable for a given load. Some of these issues and uncertainties are hard to address, either because they are inherent limitations of the technique or because they may require tradeoffs associated with greater analytical complexity.

That said, the top-down nature of the RSC approach offers a natural way to incorporate the effects of an array of underlying factors that interact in complex and difficult-to-foresee ways when investigating the impact of system retirements or additions.

The ability to do such analysis is important to a wide range of market participants and other interested stakeholders given the ongoing shifting dynamics of the economic and operational characteristics of the grid. This type of analysis may also have a role in complementing or calibrating production cost models, where some of these transmission constraints and other factors may be difficult or labor intensive to replicate, or when analysts do not have access to these types of models.

Several next steps might be useful to better understanding the potential use and limits of the RSC approach and how it might complement other analyses, including production cost modeling.

Improving Curve Fit Estimates

RSCs are poor estimators of hourly price extremes. Our approach might be improved with an alternative way of fitting data for high loads and better treatment of sources of variation, including multi-part (or piece-wise) data analysis or exponential and/or trigonometric adjustments; improved adjustments for changes in natural gas prices, imports and exports, VRE impacts, and congestion; development of implicit heat rate curves; and comparison of results using real-time prices versus day-ahead hourly prices. However, because the RSC approach is intended to be simple, quick, and a potential complement to production cost analysis, care should be taken to avoid refining it to the point of creating a top-down variant of the production cost approach—or at least to be aware of the tradeoffs.

Comparing Results with Production Cost Approaches, Including Calibration

Comparing results by analyzing a similar problem for the same geographic area with the RSC approach and with a production cost model like PLEXOS might benefit both techniques—for example, providing insight into better calibration of the production cost model. On a smaller scale, it would be useful to examine the structure of the two-week or other-duration RSCs generated from real historical data over one year to those generated by a production cost model for a similar area over the same period. There are also some open questions about the geographic area over which such analysis is valid, the number of LSEs affected, and the related potential impact of imports and exports outside the region. For example, in this study we chose the entire PJM region. A smaller region within PJM, such as parts of Illinois, would likely have yielded a different effect, and also not fully accounted for imports and exports within PJM, which might be particularly important for Illinois, given its direct interconnection to MISO. Working with a production cost model may help better understand and resolve such issues.

Performing Operational Analysis on Wholesale Energy Prices under Alternative Retirement and Addition Scenarios

The use of RSCs could be expanded to investigate the impact on wholesale prices and costs to LSEs of a wide range of investment choices and market designs. This might include, for example, comparing the differences in the impact on costs to LSEs and consumers of replacing retired generation with a variety of alternatives—such as CTs, CCGTs, and storage for a specified reserve margin—including capacity payment and other ancillary services considerations. This might also account for VRE additions, including the impact of ramping constraints on generator net revenues.

Expanding Approach to Market Structure Analysis

Market structure analysis using the RSC approach might include examining the impact on wholesale energy prices (as experienced by LSEs) and the rate of return of new and existing generation in regulated versus restructured markets with varying rules, including variable resource requirement curves for capacity payments with a given reserve margin. This would entail careful consideration of limitations to the expanded approach, because some changes might change the dispatch in a way that is not well reflected as a simple perturbation to an RSC based on the existing fleet. In addition, ancillary services and capacity payments may change with lower energy payments, so the degree to which this can be modeled and how the results vary with reserve margin would be important.

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