94867 project writeup

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1 Introduction and motivation

Operating reserves are crucial for maintaining power system reliability: they are used to maintain constant balance between electricity supply and demand despite forecast errors (e.g. of load and variable generation resources) and sudden failure of generators and transmission lines. Traditionally, system operators use heuristics for determining the level of operating reserves to procure. A common heuristic is to hold sufficient reserves to guard against the largest single contingency (termed the N-1 contingency). Under this approach, the system must remain stable under instantaneous failure of the largest single online generator or transmission line.

The PJM Interconnection (PJM) is the largest system operator by load in North America, serving 65 million customers in 13 mid-Atlantic U.S. states (Figure 1). PJM has a competitive two-settlement wholesale electricity market, with the two settlements at day-ahead and real-time (5 minutes ahead) timescales. In these settlements, generation offers are selected to meet expected load at least cost, subject to relevant physical constraints. To ensure system stability, PJM maintains 150% of its real-time N-1 contingency in operating reserves in real-time (generally 2.1 GW of capacity, the size of two large nuclear reactors), with additional heuristics for checking reserve sufficiency in the more uncertain day-ahead market (which clears before uncertain on solar, wind, and load forecasts is realized). Recent empirical evidence suggests holding constant levels of reserves may not be an optimal strategy, as PJM's conventional generators[1] are much more likely to fail during extreme temperature events [2].

Additional analysis using the same data as [2] identified that generation losses greater than PJM's operating reserve procurement have occurred in approximately 1% of hours since 1995. While these large losses typically occur only in a single hour per day, some very bad historical days have occurred. For example, during the Polar Vortex of 2014, 15 hours experienced generation losses of greater than the operating reserve procurement target. A barplot of these large-loss hours are presented against the prevailing ambient temperature in Figure 2.

[1]Conventional generator types include simple-cycle and combined-cycle gas, diesel, hydroelectric and pumped storage, nuclear, and coal.

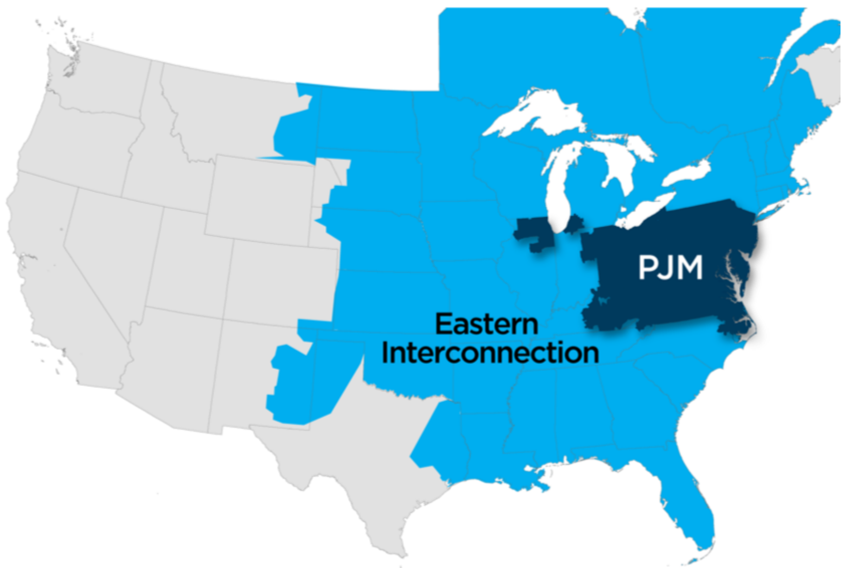

Figure 1: Map of the PJM control area (dark blue), part of the Eastern Interconnection (light blue). Image source: PJM.

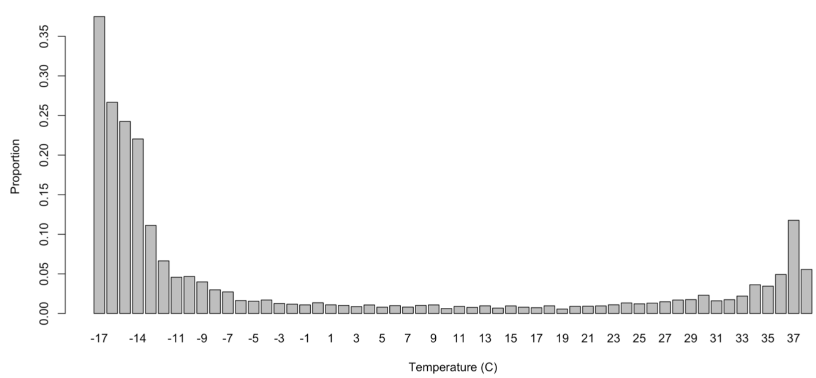

Figure 2: The proportion of hours at a given ambient temperature where generator losses greater than PJM's operating reserve target occurred. Data period: 1995-2018.

Recognizing the operational challenges posed by the Polar Vortex of 2014 and extreme weather events in other recent years, PJM is currently considering enhancements to its reserves procurement approach through scarcity pricing reform [3], and has submitted an active proposal for this reform to the Federal Energy Regulatory Commission (FERC)[2] [4]. PJM is proposing a stepped, rather than vertical, demand curve for operating reserve procurement. This operating reserve demand curve (ORDC) will provide additional monetary incentive for the provision of operating reserves in excess of the current heuristics during scarcity conditions. We seek to contribute to this discussion by demonstrating the benefits that could be obtained by using the real-time probability of generator failures when setting operating reserve requirements in a given hour, rather than simply using an updated average heuristic. While we employ PJM as a test case given data availability and its ongoing discussions of reserve pricing reform, we expect results to be broadly relevant to independent system operators (ISOs) with similar two-settlement market designs and conventional generation fleets.

2 Methods

We employ a zonal unit commitment and economic dispatch (UC/ED) optimization model to simulate generation, reserves, and prices in PJM. Temporal resolution is hourly, with prices interpreted as the dual variable of the model's load-balance constraint when relaxed to a linear program for the pricing run.[3] The main distinction between our approach and UC/ED models used for dispatch and pricing by system operators (including PJM) in the United States is our dynamic estimation of an operating reserve demand curve (ORDC) based on hourly ambient conditions and online generators, described in more detail below. Because energy and reserves are co-optimized in commitment and dispatch, the ORDC has effects on the simulated zonal market clearing prices.

Our approach is broadly similar to that employed in [6], but with a focus on generator forced outage rates instead of wind power variability for estimation of the ORDC.

2.1 Articulation of Operating Reserve Demand Curve

Operating reserves represent the ability of generators to maintain system stability and served load in the face of temporal uncertainty in the availability of generation and load. Power system operators procure or maintain multiple types of reserves associated with different uncertainties and timescales, with some of these services procured using market mechanisms in jurisdictions with competitive wholesale markets.

As evidenced by current practice in the Electricity Reliability Council of Texas, Inc. (ERCOT) [5] and proposals in PJM [4], an increasingly popular market approach to reserve procurement in a competitive market context is a

[2]FERC regulates interstate wholesale power markets in the United States.

[3]This approach to price formation is consistent with current practice in PJM, though PJM's models have more detailed representation of the transmission system for determining locational marginal prices (LMPs) and constraints around ability of certain generators to set price. Alternative approaches to price formation within an optimization market clearing price framework are possible and have been recently discussed by PJM [3].

so-called "operating reserve demand curve" (ORDC). An ORDC accounts for the incremental utility of operating reserves as a function of the incremental probability of lost load the reserve mitigates, co-optimizing with energy prices to allow for trade-offs between the utility of serving load with its cost. ORDCs function as something of a stand-in for demand side bidding of loads given the difficulty of representing granular demand-side bidding on operational timescales in electricity markets and the physical importance of maintaining instantaneous demand and supply balance.

The crucial parameter for determining the shape of the operating reserve demand curve is thus the probability of lost load, which is itself a function of the uncertainty in the availability of generators and amount of load at some time t in the future. Current practice generally employs administratively determined average values for articulation of this demand curve on market-clearing (often day-ahead and real-time) timescales. However, average values necessarily make simplified assumptions about generator failures ("forced outage rates"), often assuming these failures are uncorrelated and invariant to ambient conditions. However, [1] demonstrates conventional generator failures are correlated, and often correlated with ambient conditions–such as low and high temperatures– which are also correlated with high loads and system stress. We therefore draw on [2] to dynamically estimate hourly generation margins and implied loss-of-load-probabilities to construct an ORDC.

We model loss-of-load-probability (LOLP) solely as a function of conventional generator forced outages since they are the focus of the paper and largest reason for unexpected insufficiency of the ability of generation to serve load, though inclusion of additional uncertainties associated with load, wind, and solar forecast error are also possible. The expected generation margin for the upcoming day forms the basis of our day-ahead ORDC. The generation margin is determined by the below steps:

(1) Estimating the expected online generators based on the load, their availability, and a merit-order of their marginal costs (see Figure 3).

(2) Creating a capacity outage probability table (COPT) for expected online generators in each hour. Outage probabilities for generators are estimated at hourly resolution using [2] based on ambient conditions. Generator-level ambient conditions are based on a geographic match against the closest weather station for which we obtain data.

(3) The COPT is converted into a hourly probability distribution of generation margins (see Figure 4).

(4) Finally, this cumulative probability distribution of generation margins is translated into a ten-segment step-wise operating reserve demand curve, where the probability of generation availability being less than that at the midpoint of each segment determines the LOLP on the segment. Segment-wise LOLPs are multiplied by the VOLL to determine the utility of reserves on the segment. Each of the ten segments are equivalent in length (number of megawatts, MW) and the cutoff point for the final segment is determined as the point where the LOLP is ≤ 0.00001 (i.e., less than 0.001% chance that this amount of expected online generators are unavailable) (see Figure 5).

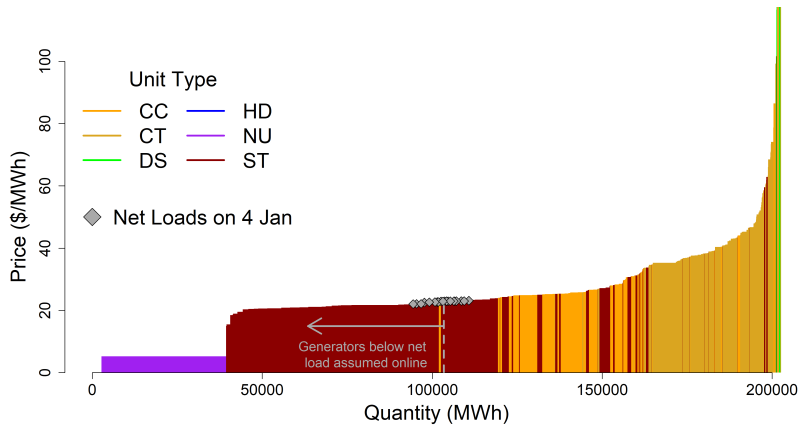

Figure 3: Example of Step (1), estimation of online generators based on marginal cost merit order. CC is combined cycle (natural gas-fired), CT combustion turbine (natural gas-fired), ST is steam turbine (coal), HD is hydro, NU is nuclear, and DS is diesel. Hydro units are assumed to have zero marginal cost and make up the far left portion of the merit order.

As noted, this ORDC is then parameterized in the model, and generation is dispatched to co-optimize energy and reserves. Provision of operating reserves is modelled as a single type of reserves—online hourly spinning reserves—based on the delta between the generator operating point and its ramping capability within the hour.

2.2 Electricity Market Model

We formulate a unit commitment and economic dispatch (UC/ED) model of PJM as a mixed-integer linear program in Pyomo, solved using IBM's CPLEX solver. Generator commitments are binary in the day-ahead unit commitment run, with relaxation to a linear program after fixing commitment decisions for determination of prices. The model co-optimizes energy and reserves simultaneously, where the utility of reserves is articulated as a stepwise ORDC as described above. Market clearing prices are reported as the dual variable of the zonal load balance constraint. Additional prices may be reported for reserves and transmission congestion on lines linking the zones.

The objective function of the model is to minimize the negative utility of provisioning electricity to load-serving entities (and by association, their end-use customers). The (negative) utility of held operating reserves is the (negative) value of lost load (VOLL) times the probability of a lost load event the held operating reserves would mitigate, as articulated by the ORDC. Utility of served load is represented in the objective by cost of starting and operating generators, which is mathematically equivalent to the negative utility of served energy

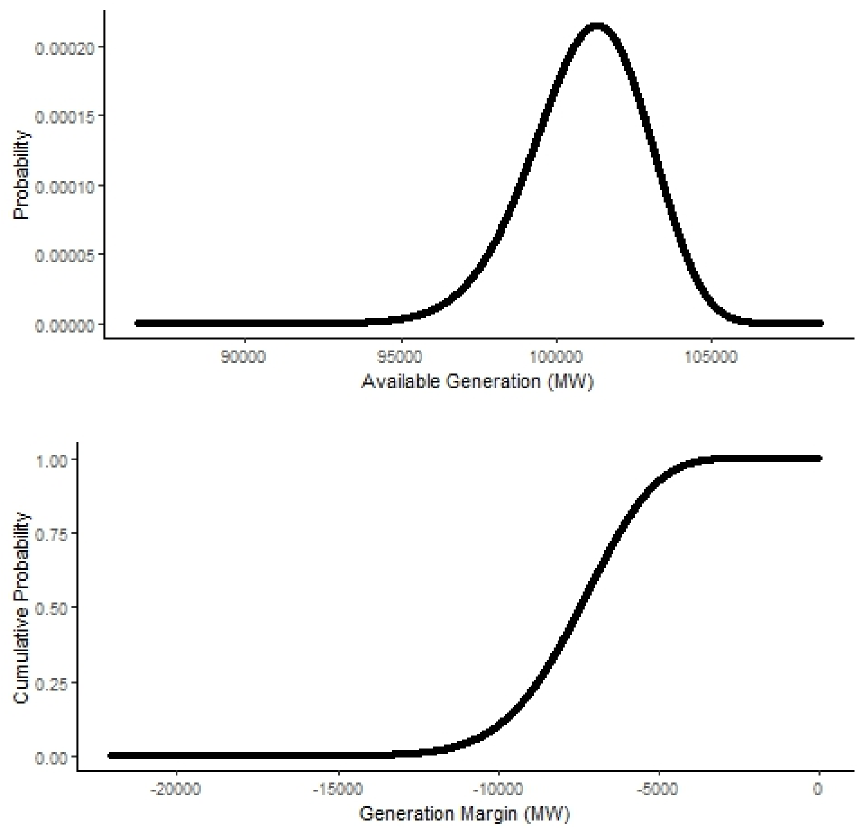

Figure 4: Example of Steps (2-3). The first panel is the available generation probability distribution in 1 MW increments for an example hour with 108,538 MW of net load after accounting for forced outages. The second panel shows the cumulative probability that the generation margin is below the corresponding amount.

assuming a constant VOLL (i.e., the consumer surplus). A mathematical formulation of the objective function is provided below:

$$MIN \sum_{t,g,z}[FC_{t,g,z} + SC_{t,g,z} + UE_{t,z}] - \sum_{t,s}[PR_{t,s}] \tag{1}$$

Where $t \in T$ is the set of timepoints, $g \in G$ is the set of generators, $z \in Z$ is the set of zones used to represent the balancing area. FC are generator cost of burning fuel, SC are generator start-up costs when they come online, UE is the cost of unserved energy, and PR is the utility of held operating reserves on each segment $s \in S$ of the ORDC.

Constraints in the model enforce serving of zonal load (with penalties for un-

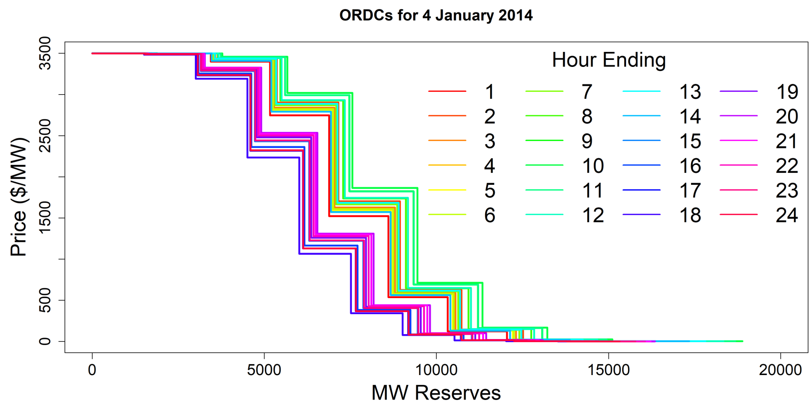

Figure 5: Example of Step (4), ten-segment ORDCs for 4 January, 2014. Hours with higher loads and lower ambient temperatures have rightward and upward shifted ORDCs due to larger quantities and higher probabilities of generator failures, respectively.

served energy at the input VOLL), generator scheduled availability, generator commitment parameters (minimum up/down time, minimum generation level, ramp rate, etc.), generator ability to provide operating reserves, and inter-zonal transmission flows. Wind and solar connected to the bulk power system are modelled as zero marginal cost variable resources without commitment parameters or ability to provision reserves, though they can be curtailed.

A full mathematical formulation of the UC/ED model will be provided in the Appendix[4]

2.3 Data Development

We draw on numerous public data sources to realistically parameterize the model as a zonal representation of PJM's footprint. Results are compared for historical hours and events for preliminary validation of the model in the Results section. Additional detail on inputs are provided in the Appendix.[5]

3 Initial Results

3.1 Selection of Validation Weeks

To validate and explore the behavior of our model, we elect to run an analysis of the PJM system over the period of Jan. 4-10, 2014. This period corresponds to the "polar vortex", a period in which the electric grid was stressed due to

[4]To be completed.

[5]We will add this in full report later

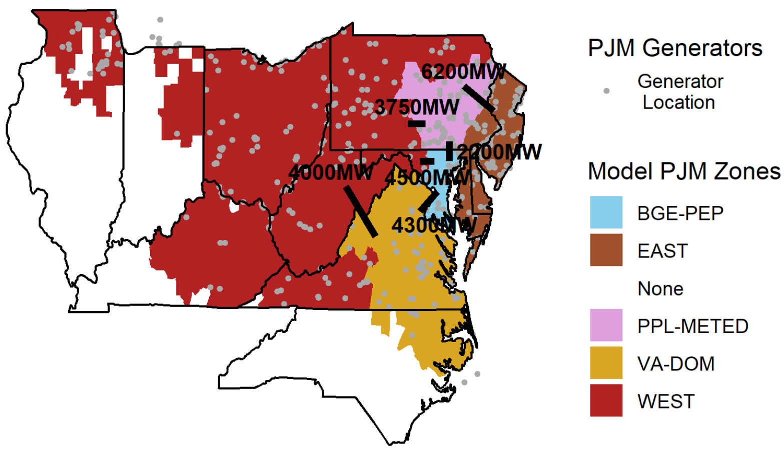

Figure 6: PJM zones, generator locations, and average transmission flow limits between zones. Generators are assigned to the zone they are physically located in. Generators physically outside the PJM footprint but contracted to provide capacity in PJM are assigned to the geographically closest zone. Transmission flow limits may change hourly based on PJM data inputs.

generator outages and high electricity loads. Accordingly, this period represents a time of particular importance in terms of reserve procurement since these stresses may result in the operator making a trade-off between reserves supplied and load served.

We present initial results for this period, focusing primarily on Jan. 4, with the aim of modeling the entire week for the final project deadline. Once validated in historical cases, our full paper will explore a range of potential future scenarios and compare the effects of our dynamic ORDC on price formation with current PJM practice and their proposed reforms. We expect our proposal will better value the utility of operating reserves, increasing both generation revenues and end-use customer utility by decreasing the probability of unserved energy and increasing incentive for long-run new entry of resources that better provision operating reserves during extreme events.

3.2 Model performance: generation and LMPs

Figure 7 illustrates total generation by fuel type dispatched by the model for the 24 hours of Jan. 4, 2014 to meet electricity demand. The model utilizes steady output from hydro and nuclear plants, and responds to variability in load and in wind and solar resource availability by changing the output of coal and gas generation over time. In times of stress, the model also call upon demand response (DR) resources to reduce load at lower cost than increasing generation.

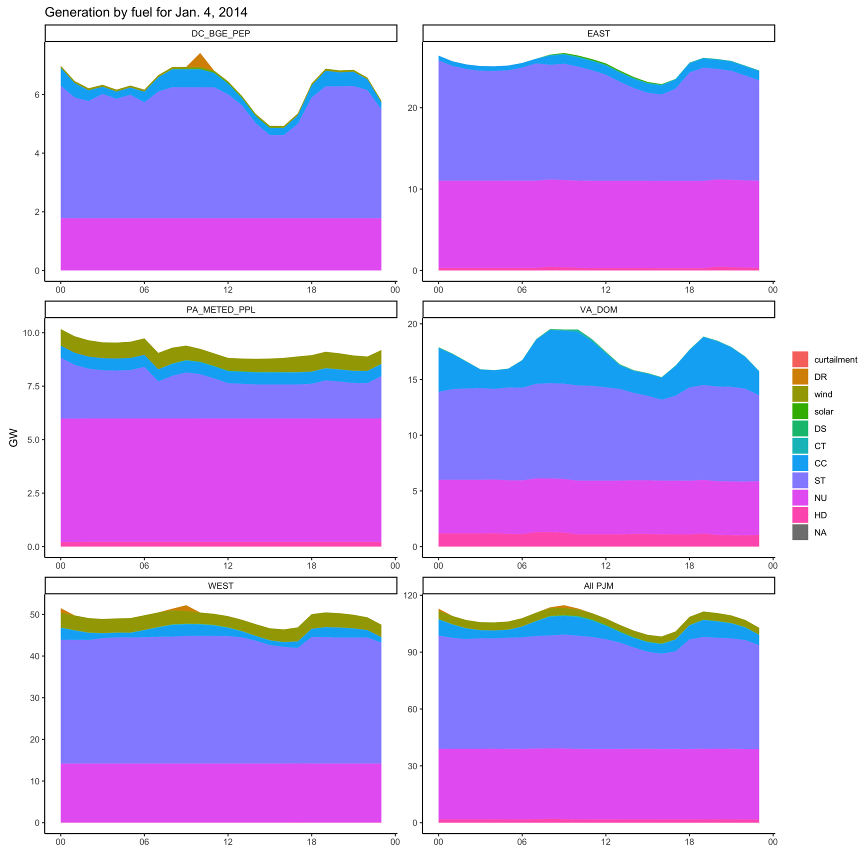

Figure 7: Generation by zone and fuel type for Jan. 4, 2014, in GW.

One way to validate the performance of our model is to compare its performance to historical data. Figure 8 shows the zonal LMPs associated with the above dispatch profile. These LMP values are the dual variables of the load-balance constraint and thus reflect the cost of needing 1 MWh of additional generation to serve load in each zone. The figure compares LMPs as calculated from our optimization (modeled) with actual prices reported by PJM for the historical date.

The figure illustrates that our LMP values are consistently lower than those that actually occurred on Jan. 4; in addition, the order of prices by zone is inconsistent with what was observed in reality. Still, our model roughly approximates the shape of the curves over the course of the day, which price spikes at consistent times. Currently, our model reaches several shortage pricing events in which generation and reserves are insufficient to meet load, leading to high spikes in hours 0 and 10.[6]

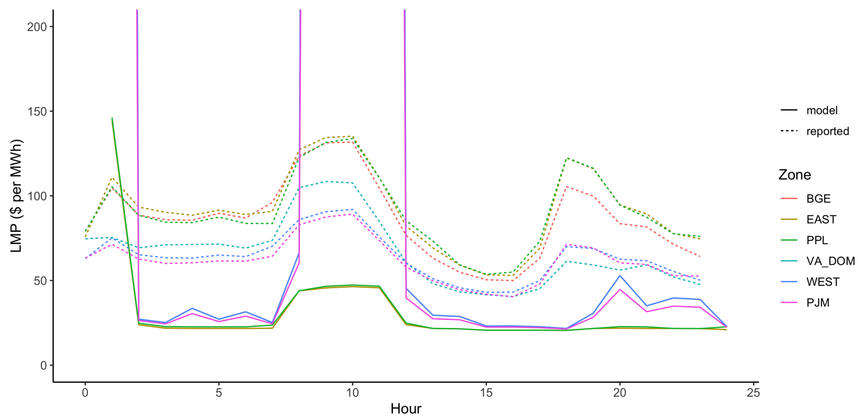

Figure 8: Zonal LMPs for Jan. 4, 2014. Values by hour from our optimization model are compared to actual values reported by PJM.

3.3 Reserve procurement using an ORDC

Figure 9 illustrates the amount of reserves procured in each hour on Jan. 4; the shading indicates how many of the ORDC segments were supplied. In addition, the red indicates the closing price of reserves. We can see that the model generally fulfills demand for all 10 ORDC segments in most hours. Although the the high price spikes correspond to the periods of high generation cost and unserved energy (as discussed more below), we can see that the model behaves as expected by foregoing some reserve procurement when energy prices are high, choosing instead to incur a penalty cost associated with the non-zero probability of lost load if there are high levels of unexpected generator forced outages.

4 Summary and next steps

We have completed a preliminary version of our model which optimizes the amount of energy served and reserves procured so as to minimize the disutility of unserved energy. Although our estimates of LMPs are overall lower than realized values and show several unstable price spikes, we are able to approximately replicate the hourly shape of the price curves. The model provides insight as to the quantity of reserves that should be purchased by the system operator after accounting for uncertainty in forced unit failures, load forecasting, and renewable resource availability. These recommended reserve quantities, which

[6]These spikes are likely an artifact of simplifications in our model; additional discussion on why these may be occurring and how we plan to address them is provided below.

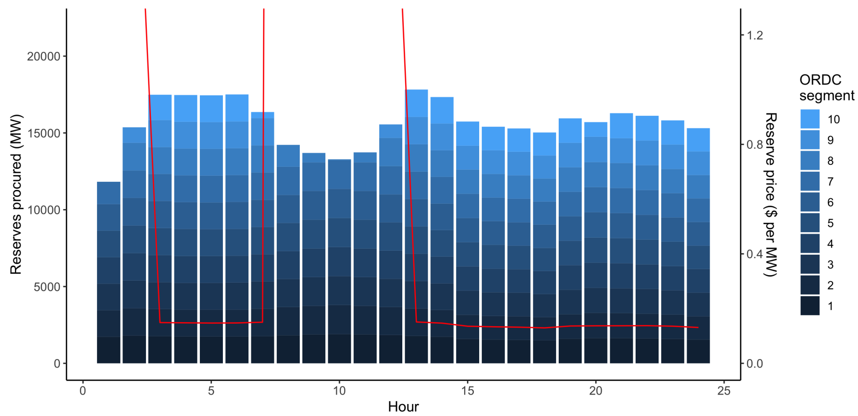

Figure 9: Amount of reserves procured by ORDC segment (left axis, in MW) by hour for Jan. 4, 2014, along with settling price for reserves (right axis, in $ per MWh

vary over time based on uncertainty in the above factors, would represent an improvement over PJM's current practices for procuring reserves.

Having largely finished setting up the optimization model formulation and acquiring data inputs for load and generator parameters, we will continue work on refining inputs to better match operational realities and pricing in PJM. For example, we will address the issue of unexpectedly high price spikes in several hours. Expected improvements include establishing more accurate initialization conditions for the model, refining the assignment of generators in PJM to their appropriate zone, better parameterization of constraints on generator ramping and minimum up/down time in PJM, and integration of data on scheduled generator outages so we have the appropriate generator fleet available for dispatch in our validation cases.

After finalizing the model, we will compare model runs for scenarios that include or omit correlation in force outages, which will serve as a proxy for PJM's proposed reserve pricing enhancements. By comparing these two scenarios, we hope to illustrate the implications of including (or omitting) these correlations when optimizing for energy and reserve procurement. We will also complete model runs for the rest of the Jan. 4-10, 2014 period to see how the recommendation for procured reserves changes over that time and better validate the model.

5 Appendix

5.1 Model Formulation

To be included in the final report.

References

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