Newington Station
Continuing Unit Operations Study: Modeling System Overview

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The modeling of future uncertain energy net revenues and capacity revenues together with incremental fixed expenses is described in this document. Virtually all of the information discussed here was provided in the same or similar form in response to various Staff interrogatories. The primary objectives of this model system description are twofold: first, to provide a comprehensive overview of the numerous data inputs and model calculations; and, second, to delineate the essential data inputs and model calculation steps in order for the New Hampshire Public Utilities Commission to be acquainted with the building blocks of the modeling system used by LAI to quantify Newington Station's energy net revenues and capacity revenues under uncertainty.

The modeling system consists entirely of LAI proprietary models and procedures. No fundamental regional system production cost simulation models were used in this set of tools. The modeling components and data are shown in the process flow diagram in Figure 1. In the diagram, the yellow rectangles identify the types and sources of data used. Where LAI is listed after PSNH for providing Newington Station operational and financial inputs, LAI's additional inputs were restricted to minor variables or assumptions. The numbered trapezoids are the models or calculation procedures, colored to identify the modeling platform (Excel, Excel+RiskSolver, MATLAB, and Stata). The green rectangles identify the intermediate outputs passed from one model to another, and the final outputs. One MATLAB main procedure runs models 5, 6, and 8 in sequence with a single command, producing stochastic fuel and energy prices as MATLAB files. The other intermediate and final outputs are in Excel format. An overview of each of the ten model components is provided in the following sections.

Throughout this document the term "scenario" is used in the sense of a discrete chronological time path of values regardless of how the values are generated. The 250 energy net revenue scenarios are based on 250 sets of fuel prices and energy prices created through Monte Carlo random draws, and 250 unit commitment-dispatch simulations with Monte Carlo random draws of unit outages. The three capacity price scenarios were created first by a base model of ISO-NE Forward Capacity Model (FCM) prices, and adjusted to create low and high price scenarios around a base or mid price scenario.

For a long-term simulation with an hourly time step, 250 scenarios provides a reasonably close approximation to the theoretical distribution of simulated prices and outages, and can be completed in [redacted] The modeling system can also readily accommodate running either fewer (e.g., 100) or more (e.g., 500) scenarios. Both 100 and 500 scenarios were tested during development.

Figure 1. High Level Process Flow Diagram

[redacted]

1. *Fuels Monthly Forwards Pricing Models*

Natural Gas at Dracut

LAI's forecast of natural gas prices at Dracut is based on two parts, the Henry Hub spot price and an adder to account for the basis differential between the Henry Hub and Dracut.

The Henry Hub prices are the NYMEX forward curve that settled on August 27, 2010.

The basis adder used to calculate the Dracut price is based on the historical relationship between Henry Hub and Dracut prices. To determine this relationship, LAI compiled daily spot prices for the period March 2003 to February 2010. For each day, the basis between Henry Hub and Dracut was calculated and expressed as a percentage of the Henry Hub price for that day. Stated another way, basis is expressed as a percentage adder over the Henry Hub price. These basis adders were then averaged on a monthly basis. For example, all of the January adders were averaged to calculate a single adder used for each January in the forecast. Historic data were provided by Bloomberg LP.

RFO and 2FO at New York Harbor

LAI's forecasts of RFO and 2FO are based on the historic relationship between those fuels and WTI. That relationship is then applied to the WTI forward curve that settled August 27, 2010.

In order to determine the relationships between RFO and 2FO with WTI, LAI compiled average monthly data since 1985 for all three fuels. LAI then ran linear regressions on the monthly series [redacted] These coefficients were then applied to the WTI forward curve for the period beyond the forward curve horizons for RFO and 2FO in order to forecast spot prices.

2. *Energy Monthly Forwards Pricing Model*

The Newington node price forecast used two distinct methods for extending on-peak and off-peak forward prices at the MassHub, the NYMEX method and the System Heat Rate (SHR) method. The energy forward pricing model also adjusts the projected MassHub prices for seasonal basis differentials between MassHub and the Newington node. Newington node prices are generally lower than MassHub prices.

NYMEX Method

NYMEX monthly forwards for MassHub are the starting point. NYMEX forwards after 2012 converge to annual products that require shaping using historical MassHub LMPs. Shaping factors are calculated for on-peak and off-peak prices separately and applied to the forward curves. This provides the forecast of prices at MassHub.

That MassHub forecast is adjusted based on the historical basis differential between MassHub and the Newington node. Basis adders are calculated separately for on-peak and off-peak products by month and are a percentage of the MassHub price. Adders are negative to reflect typically lower prices at Newington, both on-peak and off-peak. The NYMEX method produces a forecast of on-peak and off-peak Newington prices through 2015.

SHR Method

SHRs are based on the historical relationship between RT prices at Newington and Dracut gas prices. Average SHRs are calculated separately for on-peak and off-peak for each month (i.e. there are 24 SHRs). These shaped SHRs are then applied to the forecast of Dracut gas prices, described above, to generate the price forecast. The SHR method produces a forecast of on-peak and off-peak Newington prices for the entire forecast.

Final Forecast Splicing

The NYMEX method was used to calculate prices for 2010-2014. The SHR method was used to calculate prices for 2016-2020. For 2015, the forecast price was the average of the two methods. The resulting series is a forecast of average on-peak and off-peak clearing prices at Newington by month for the period September 2010 through December 2020.

3. Fuels Price Short-term and Long-term Stochastic Parameters Statistical Procedure

The stochastic parameters for the three fuel price variables are:

- Short-run daily mean-reversion rate for each commodity by monthly season
- Short-run daily volatility rate for each commodity by monthly season
- Short-run random deviation correlation rates for each pair of commodities by monthly season
- Long-run daily volatility rate for each commodity
- Long-run random deviation correlation rates for each pair of commodities.

The same [redacted] equation form was used to estimate the SR and LR mean reversion and volatility parameters. The regression estimates were converted to their continuous-time representations and reported as one day rates.[1] Contemporaneous residuals of regressions for each commodity pair were used to calculate linear correlation coefficients. The long-run mean reversion rates were very small, so to simplify the simulation model, the estimated long-run mean reversion rates were not used. Mean reversion and volatility rates are normalized to a daily basis, the

[1] See [redacted]

time step used for ST and LT random draws in the fuel price simulation model. To account for distributions of prices that differ substantially from the assumed lognormal distribution, the estimated volatilities may be reduced.

Short-term Stochastic Parameters Estimation

Short-term stochastic parameters were statistically-estimated based on daily spot prices from Bloomberg for NG at Dracut, RFO at NYH, and 2FO at NYH, using data from 1/3/2005 to 8/20/2010.

The ST stochastic parameter estimation steps are:

1. Transform the prices into monthly [redacted]

2. Transform the [redacted]

3. Estimate the autoregressive parameter of a mean reversion equation for each fuel and monthly season. The [redacted] regression function was used ([redacted] regression tool could be used).

4. Calculate the continuous-time mean reversion parameter (alpha) from the autoregressive parameter and the continuous-time volatility parameter (sigma) from the standard error of the regression and then [redacted]

5. Calculate the linear correlation parameter (rho) between the regression residuals for each pair of commodities for each month. The [redacted] correlation function ([redacted]) was used.

Long-term Stochastic Parameters Estimation

Long-term stochastic parameters were statistically-estimated based on annual average prices from the Energy Information Administration (EIA) for NG purchased by the electric power sector, RFO, and 2FO, from 1978 to 2009.

The LT stochastic parameter estimation steps are:

1. Transform the prices [redacted]

2. Transform the [redacted]

3. Estimate the autoregressive parameter of a mean reversion equation for each fuel. The [redacted] regression function was used.

4. Calculate the continuous-time mean reversion parameter (alpha) from the autoregressive parameter and the continuous-time volatility parameter (sigma) from the standard error of the regression. The [redacted] is used in the calculation of the continuous parameters.

5. Calculate the linear correlation parameter (rho) between the regression residuals for each pair of fuels. The [redacted] correlation function was used for this purpose.

4. System Heat Rate Seasonal Elasticity Parameters Statistical Procedure

Energy price to natural gas price elasticity parameters were estimated from regression equations for each calendar month for weekday peak, weekend peak, and nighttime periods.

The energy price to gas price elasticities by month and TOU block were calculated by running ordinary least squares (OLS) regressions on the [redacted] as independent variables. Data were for the period 3/1/2003 to 7/14/2010. Separate regressions were run for each month of the year in Stata, a commercial statistical analysis software package.

5. Fuels Daily Prices Simulation Model

The first step was to include Dracut to Newington Station seasonal basis adders and an oil handling adder. The second step was to form a single RFO product price series by using prices for RFO 1% S through the end of 2017 and then switching to the higher prices for RFO 0.5% S.

Then the main step was to use Monte Carlo simulation of fuel price uncertainties, accounting for the generally positive correlations among the three fuel products' prices. Fuel prices were modeled with a two-factor lognormal model in which the short-term (ST) equation is a mean-reversion process of daily deviations around a long-term (LT) random walk equation of daily deviations. For each day, Monte Carlo random draws from a normal distribution are taken to simulate uncertain ST and LT disturbances to the price process for each fuel.

The expected fuel price forecasts play the role of initial equilibrium values. The seasonal cycles and annual trend embedded in the expected fuel prices are used to calculate deterministic "drift" changes between days. While distinct LT equilibrium paths are created for each scenario, they all share the same deterministic annual cycle and trend patterns.

The daily draws of LT price deviations result in a distinct LT equilibrium path for each scenario.

The daily draws of ST price deviations from that scenario's LT equilibrium prices result in spot prices that deviate from each scenario's LT equilibrium value. The mean reversion effect in the ST deviation equation pulls the spot price of the previous day back towards the scenario's LT equilibrium price, while new daily random deviations cause the final spot price to move either closer to or farther from the LT equilibrium price.[2]

Both the ST and LT random deviates are correlated within the ST and LT vectors of daily random draws, but short-term deviations were independent of long-term deviations. The [redacted] method was used to correlate the ST and LT vectors of daily random draws for the three fuels. ST and LT random draws for each fuel and between fuels were assumed to be independent (zero correlation).

As a technical note, [redacted]

6. *Energy Hourly Prices Simulation Model*

TOU by month energy prices in each scenario are dependent on the stochastic natural gas prices, forward energy and natural gas prices, and a SHR elasticity parameter, which plays the role of adjusting the base SHR down (up), depending on whether the statistical estimate of the elasticity is less (greater) than one. The energy price to gas price elasticity parameters are used [redacted] in an equation to calculate scenario TOU block energy prices driven by the scenario natural gas prices relative to the (expected) forward natural gas prices and forward energy prices.

Randomness is then added at the hourly level with "historical" simulation of hourly energy price shapes. Distinct hourly DA and RT prices for each scenario are calculated from the scenario TOU block energy prices using historical simulation of hourly price factors with weekly random draws from the historical hourly price factors. This approach allows for simulating the actual diurnal and weekly price patterns that are more irregular than using deterministic average DA and RT price shapes. For the approximately seven years of historical data, there are about 28 weeks to sample from within each month. By

[2] A standard reference for this two-factor ST/LT lognormal model is Eduardo Schwartz and James E. Smith, "Short-Term Variations and Long-Term Dynamics in Commodity Prices," *Management Science* (July 2000, pp. 893-911).

simulating many (250) price paths, the average of the randomly sampled historical price shapes is very close to the historical average shapes.

The historical weekly-sampled hourly price factors are multiplied by the TOU block energy prices to calculate the hourly prices for each scenario.

7. Emissions Allowance Forwards Pricing Model

The emissions allowance forwards pricing "model" uses assumed escalation rates to extend the available traded emissions allowance futures prices. SO_2 emission allowance prices were based on Sulfur Financial Instrument (SFI) futures contracts through vintage year 2020, on trade date 8/27/2010 on the Chicago Climate Futures Exchange (CCFE). NO_x emission allowance prices were based on Nitrogen Financial Instrument (NFI) futures contracts through vintage year 2014, on trade date 8/27/2010 on the CCFE. NFI prices were held constant beyond the year (2014) of the last traded vintage. CO_2 allowance prices were based on RGGI Futures Contracts through vintage year 2012, on trade date 8/27/2010 on the CCFE. Beyond 2012, RGGI Futures were assumed to increase 2.5% per year through 2020.

8. Dispatch Simulation Model

The objective of the dispatch simulation model is to maximize the net operating revenue of Newington Station. In the dispatch model, the operational behavior of the unit dynamically reacts to randomly changing prices and outage events as they unfold in the forward chronological simulation of each time path (scenario). Commitment and dispatch are simulated for the period Jan. 1, 2011 through Dec. 31, 2020 for each of the 250 scenarios.

Key stochastic operating input variables include:

- Daily spot natural gas, RFO, and 2FO prices at the unit
- Hourly DAM and RTM energy prices at the unit's injection node
- Daily random outage events.

Key deterministic operating input variables include:

- Maximum and minimum operating capacities
- Planned maintenance schedule period
- Expected forced outage rate
- Variable O&M costs on RFO and natural gas
- Winter and summer natural gas basis above the Dracut price
- Cold and hot start fuel use
- Cold and hot start times
- Cold start threshold time
- Minimum run time and minimum down time
- Ramp rate

- Heat rate curve
- Natural gas combustion limits at three load states
- SO_2 and NO_x emission rates on gas and RFO and both fuels at two load states
- CO_2 emission rates on RFO and gas
- SO_2, NO_x, and CO_2 emissions of 2FO for start fuel.

Key output variables include:

- Available capacity
- Number of starts
- Natural gas, RFO, and 2FO use
- Energy sales in the DAM and the RTM
- SO_2, NO_x, and CO_2 emissions.

LAI used a proprietary model for Newington Station dispatch simulation. An hourly chronological unit commitment and dispatch model is used to first commit and schedule the unit against DA fuel and energy prices, and then further commit and dispatch against RT energy prices and the same daily spot fuel prices if profitable. The DAM commitment and dispatch decisions are made without knowledge of the next day's RT energy prices. The RT commitment and dispatch decisions are made hour-by-hour. The commitment and dispatch loadings respected all of the cost, capacity, heat rate, emission rate, and natural gas limitations by loading state, and chronological constraint variables listed above.

Monte Carlo random draws are used to simulate forced outage events. Based on historical outage data, each simulated outage was assumed to take 16 hours to repair. [redacted]

9. *Capacity Price Scenarios Model*

LAI used a proprietary model to forecast outcomes in the FCM. The primary input is LAI's forecast of reserve margins over the forecast period. The reserve margin forecast is based on expected future load compared to the future capacity expected to exist in the market. The yearly reserve margins are based on an analysis LAI conducted as part of a previous engagement and is based on an ISO-NE load forecast and a schedule of plant retirements and additions.

For each case, the excess capacity is adjusted to account for a reduction of the imports of capacity from New York. LAI expects clearing prices in that market to increase over the forecast horizon, thus eroding incentives to export capacity into New England.

Excess is also adjusted in the High Case to account for an additional 500 MW of capacity retirements. In the Low Case, a lower retirement assumption is utilized; additionally, an 200 MW of infra-marginal capacity intended to represent the increased penetration of demand response (DR) is added, thereby increasing the market excess.

The capacity model also utilizes the cost of new entry assumption (Net CONE) used by the New York Independent System Operator (NYISO) in its capacity auctions conducted for NYISO Rest of State Region. The escalated value of Net CONE places an effective cap on capacity clearing prices in New England. LAI assumes that prices above this level would cause new capacity to enter the market, thus clearing the market at Net CONE.

All assumptions regarding retirements, import reductions, and the addition of infra-marginal capacity are based on LAI's professional judgment.

The Mid Case was assigned a 50% chance of occurrence in the financial simulation model. The High Case and Low Case were assigned chances of occurrence of 30% and 20%, respectively.

10. Financial Simulation Model

The financial simulation model is a *pro forma* model for calculating going-forward revenue requirement costs to ratepayers. A negative net revenue requirement value is a positive customer net benefit. The model uses assumptions to forecast going-forward fixed O&M expenses, depreciation of incremental (future) capital investments in Newington Station, and return on incremental capital investments. Sunk cost is ignored. The model also assumes that future ancillary service revenues are a small deterministic revenue stream. In addition to these deterministic expense and revenue elements, uncertain future energy market net revenues and capacity market revenues were simulated.

Both energy net revenue scenarios and capacity price scenarios are randomly sampled in the financial simulation model. The FrontLine RiskSolver add-in tool for Excel was used for Monte Carlo sampling of the energy net revenue scenarios and the capacity price scenarios. The RiskSolver Monte Carlo function was used to draw 10,000 samples of energy net revenues and capacity prices from the 250 sets of annual energy revenues and expenses, and the three capacity price scenarios. In memory, RiskSolver recalculates the Excel financial model *pro forma* values for each of the 10,000 mega-scenarios. Each of the 10,000 scenarios has equal weight, but the sampling accounts for the unequal weights given to the three capacity price scenarios.

The financial simulation model calculates *pro forma* annual net revenue requirements for the continued operation of Newington for the study period 2011 through 2020 under each of the 10,000 mega-scenarios of the Monte Carlo simulation. The model also calculates the present value of the net revenue requirement stream and of each major component stream in each iteration. These results are stored by RiskSolver and available for the calculation of distribution statistics such as expected value (mean), standard deviation, and percentile values. The model uses RiskSolver functions to extract relevant statistics and creates the charts of cumulative probability and the histograms shown in the Study Report.