Forecast Model Structures of the ISO New England Long-Run Energy and Seasonal Peak Load Forecasts

for the 2016 CELT Report

Contents

Peak Load and Energy Forecast Modeling Procedures 2016 1

1. Introduction 1
2. Gross and Net Forecasts 1
3. Energy Forecasts 1

3.1. The regression models 1

3.2. Economic Input Data – Real Gross Regional/State Product 2

4. Observations Regarding Historical and Projected Energy Consumption 3
5. Annual Energy to Annualized Monthly Moving Sum Energy 3
6. Peak Loads 4

6.1. Peak Load Forecast Distributions 4

6.1.1. Peak Load Distributions and Weather 4

6.2. Daily Peak Load Models 4

7. Observations Regarding the Projected Winter Peak 6
8. Observations Regarding the Projected Summer Peak 6

Appendix A: Forecasting Methodology, Evaluation and Testing 7

A.1. Peak Load Forecasting Methodology, Evaluation and Testing 7

A.1.1. Identification of the Autoregressive error structure. 7

A.1.2. Influential Observations 8

A.1.3. Goodness-of-Fit and Statistical Significance. 8

A.2. Energy Model Evaluation 8

Peak Load and Energy Forecast Modeling Procedures 2016

1. Introduction

ISO-New England prepares forecasts of annual energy and monthly and seasonal peak loads for the region as a whole and each of the six New England states. Forecast models are developed and estimated using econometric methods. Net energy for load (NEL) is modeled as a function of economic and other drivers. As such, it also is used to represent the underlying economic/demographic processes that influence peak load growth.

2. Gross and Net Forecasts

"Gross" load forecasts are developed by first adding the energy savings from behind-the-meter photovoltaics (PV) and passive demand resources (PDR) back into the historical NEL and daily peak load series before the models are estimated. The process of adding these savings back into the historical data is referred to as "reconstitution", and ensures the proper accounting of these resources, which are forecast separately[1], in the development of the long-term load forecasts. The reconstitution for PDR is done because these resources are reflected on the supply side in the capacity market and they would otherwise be double counted. PV reconstitution is necessary because the annual long-term PV forecast includes historical PV development that has reduced loads, and is therefore already embedded in the historical data. Consequently, the historical series needs to be "grossed up" to account for load reductions from PV to similarly avoid double-counting. While gross forecasts are derived directly from the models developed with data after reconstitution, "net" forecasts are obtained by subtracting exogenous forecasts of PV and PDR from the gross forecasts, and are therefore representative of the energy and loads expected to be observed in New England.

3. Energy Forecasts

As in years past, the 2016 energy forecast is produced using annual models of total energy consumption within the ISO-NE control area and the New England states. The goal is to specify a forecasting model that predicts electricity consumption as accurately as possible. To that end, regression models are designed to explain NEL in terms of variables believed to influence consumption. The forecast includes estimates of the impact of new Federal Electric Appliance Standards (2013 going forward).

3.1. The regression models

Seven annual energy forecasts are prepared for New England and the New England states. The models have the same fundamental structure, with some variation across states. The basic theoretical model is as follows:

$Energy_t = f(Energy_{t-1}, Economy_t, EnergyPrice_t, Weather_t, X_t)$, where:

[1] The ISO develops PDR forecasts using stakeholder input from the Energy-Efficiency Forecast Working Group (EEFWG) and the PV forecasts with stakeholder input from the Distributed Generation Forecast Working Group (DGFWG).

Energy (NEL_) = Annual NEL in year *t*, with PDR and PV added back in. For modeling purposes, NEL is reconstituted in order to capture historical performance of PDR and PV.

Economy (RGSP/RPI) = Economic activity is represented by Gross Regional/State Product adjusted for inflation (RGSP). It is from Moody's Economy.Com. Gross domestic product is adjusted for inflation by Moody's price deflator series. In some models (Maine and Rhode Island), real personal income (RPI) is used instead.

EnergyPrice (RP) = Annual Price of Energy adjusted for inflation (RPER), ¢/Kwh. The coefficient on the price of energy is insignificant in most of the models.

Weather = Weather is represented by two variables: Annual Heating Degree Days (HDD) and Annual Cooling Degree Days based on the temperature-humidity index (CDD). While both variables are included in most models, one or both may be considered "insignificant" in some cases[2].

X = Unobservable variables that affect Energy Demand. Binary variables for specific years are included in most models. The relevant variables are determined by examining the residuals: (observed NEL_t – modeled NEL_t). Large outliers are addressed by including a dummy variable for that year.

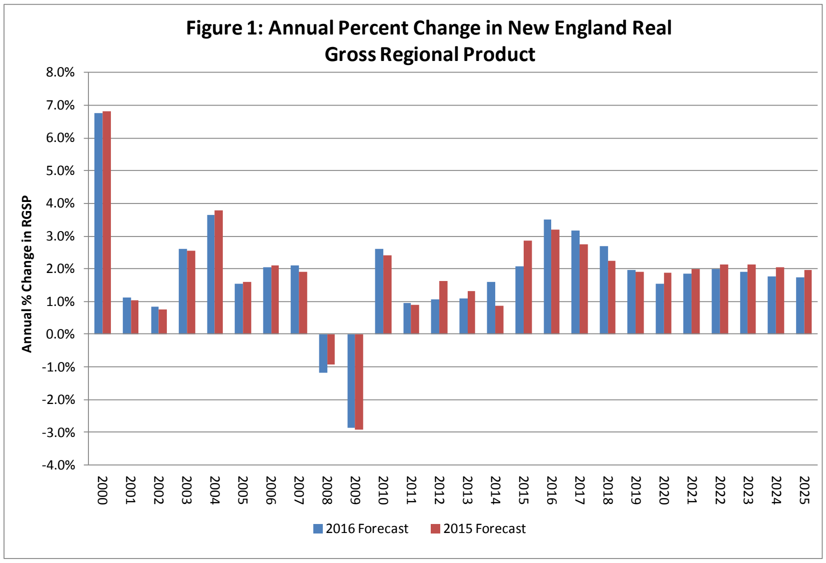
Sample Period: 1990-2015 for this forecast cycle.

3.2. Economic Input Data – Real Gross Regional/State Product

Real gross regional product represents overall economic activity in the energy models. Figure 1 presents historical and forecasted annual growth of the real gross regional product for New England used in the 2016 forecast, as compared to last year[3]. Economic activity started to slow in 2007, bottomed out in 2009, and has continued recovering more slowly than previously expected.

[2] Variables may be retained in an estimating equation because they are important theoretically.

[3] The Gross Regional Product series reflects revisions in the historical data by the Bureau of Economic Analysis.



4. Observations Regarding Historical and Projected Energy Consumption

Forecasting electricity demand continues to be challenging as the economic recovery moves more slowly than anticipated. As a result of lower economic forecasts, the 2016 NEL forecast projects that weather-normalized energy demand will be lower than expected in the 2015 forecast.

The long-run gross energy growth rate is forecasted to be 1.0%, while the net forecast predicts -0.2% growth. The 2016 energy forecast incorporates the annual energy savings expected from the introduction of the Federal Appliance Efficiency Standards in 2013, which reduces the forecast of electricity demand in 2016 by 181 GWh. The impact of the Federal Appliance Efficiency Standards is projected to increase gradually and amount to about 0.4 percent of energy demand by the end of the forecast horizon.

5. Annual Energy to Annualized Monthly Moving Sum Energy

Once the annual energy forecasts are prepared, they are processed further to generate annualized monthly moving sum values for use in the peak forecasting models.

(1) The NEL forecast is prepared for the forecast horizon.

(2) The monthly moving sum is calculated for the latest historical year (2015). For each month, the moving sum for NEL is the sum of NEL for the current month and the past 11 months.

(3) Using the forecasting model, weather-normalized annual NEL is estimated for the latest historical year (2015) (WNEL2015).

(4) Annual growth rates are calculated for the forecast period:

$$G_t = \frac{NEL_t}{WNEL_{2015}}, \text{ t=2016,…,2025}$$

(5) G_t is applied to the monthly moving sum NEL in time (t-1,m), $NEL\_SUM_{t-1,m}$

$$NEL\_SUM_{t,m} = NEL\_SUM_{t-1,m} * G_t$$

(6) $NEL\_SUM_{t,m}$ serves as the energy input for the monthly and seasonal peak models.

6. Peak Loads

6.1. Peak -Load Forecast Distributions

Weekly peak load forecast distributions are developed by combining output from the daily peak load models with energy forecasts and weekly distributions of weather variables over 40 years. Dry bulb temperatures correspond to the heating season (October-April), while the weighted temperature-humidity index (WTHI) is used for the cooling season (May-September).

6.1.1. Peak Load Distributions and Weather

The expected weather associated with the seasonal peak is considered to be the 50th percentile of the top 10% of the pertinent week's historical weather distribution. The monthly peak load is expected to occur at the weather associated with the 20th percentile of the top 10% of the pertinent week's weather distribution. The "pertinent week" is the week of the month or season with the most extreme weather distribution. For resource adequacy purposes, peak load distributions are developed for each week of the forecast horizon.

6.2. Daily Peak Load Models

Daily peak load models are estimated for the New England region as well as each of the New England states, for each season and nine or 10 months (depending on the state). There is one summer model for July/August, and one winter model for December/January. Altogether, 10 or 11 models are developed for New England and each state. While the models have a common theoretical basis, they are individually adjusted for the unique characteristics of the region/state and the sample period.

Fundamental Drivers. Annual electric energy (converted to NEL_SUM) and weather variables comprise the foundation of the peak load models. Weather is the predominant observable cause of day-to-day variation in peak load, and also differentiates seasons. Energy serves as the base load, and represents underlying economic and demographic drivers.

Dummy Variables. The sample period comprises *all* days of the week, including holidays and weekends, while the monthly/seasonal peak loads generally occur only on non-holiday weekdays. Including all days in the sample increases the sample size and reduces the number of "gaps" in the data. Significant gaps already exist due to the methodology of estimating separate models for each month and season. To accommodate the sample, dummy variables accounting for holidays and weekends are included in each model.

Sample Size. Because the forecast is based on "normal" weather, the estimation period must be long enough to capture significant variations in the weather; i.e. an abnormally warm or cool year cannot be allowed to unduly influence a long-run forecast. The sample period also must be short enough to assure reasonably consistent relationships between peak loads and the regressors[4].

[4] Analysis suggests 2000-2001 as a reasonable point for the beginning of the sample period for most models. The samples for a very few of the models stretch back into the late 1990s.

Peak Load Model. The basic peak load model is a nonlinear function of energy and weather, expressed as:

$$Peak\ Load_d = f(NEL\_SUM_{t,m}, W_d, TW_d, D_{w,d}, D_{h,d}, X_d)$$ where:

$Peak\ Load_d$ = Peak Load on day *d*

$NEL\_SUM_{t,m}$ = Annualized monthly moving sum Net Energy for Load for month m in year *t* (see page 1-2 for details).

W_d = Weather at the peak load hour on day *d*

= $(WTHI_d-55)^2$ for the months May-September

= $(65-db_d)^2$ for the months October-April

$WTHI_d$= 3-day weighted temperature-humidity index (THI) measured at the hour of the daily peak loads:

$$WTHI_d = \left\{\frac{[10*THI_d + 5*THI_{d-1} + 2*THI_{d-2}]}{17}\right\} - 55 \text{ , and}$$

$$THI_d = 0.5 * DryBulbTemp_d + 0.3 * DewPointTemp_d + 15$$

TW_d = Time Trend * $(WTHI_d-55)^2$ for the months May-September.

Time Trend is a year index; 1992=1, 1993=2, etc.

$D_{w,d}$ = Dummy variable: 1 if day *d* is a weekend, 0 otherwise.

$D_{h,d}$ = Dummy variable: 1 if day *d* is a holiday, 0 otherwise. Holidays take precedence; if day *d* is both a weekend day and a holiday, $D_{w,d} = 0$ and $D_{h,d} = 1$.

X_d = Vector of other (unobservable) variables explaining daily peak loads

While Energy and Weather variables explain a substantial amount of the trend and variation in Peak Load, there are many other largely unknowable factors (*X*) that can be included in the model only by proxy, if at all.

The basic non-linear estimating equation with autoregressive error structure is specified as:

$$Peak\ Load_d = b_0 + b_1*NEL\_SUM_{t,m} + b_2*W_d + b_3*TW_d + b_4*D_{w,d} + b_5*D_{h,d} + \hat{e}_d$$

$\hat{e}_d$ is the error term (residual), which follows an autoregressive process:

$\hat{e}_d = f(e_{d-1}, e_{d-2}, \ldots, e_{d-n})$

7. Observations Regarding the Projected Winter Peak

The slow economic recovery has had a less severe impact on the winter peak load than on the summer peak load, because the winter peak is determined mainly by residential load. As such, it occurs late in the afternoon (6 P.M.) and is strongly influenced by lighting load, with less exposure to deteriorating industrial and commercial demand.

The primary factors driving the current winter peak load forecast include:

(1) Economic activity, represented by the energy forecast, is the major driver of the winter peak load forecast. The non-weather-sensitive part of the load (for example, lighting) accounts for the largest share of the winter peak.

(2) The impacts of Federal Electric Appliance Standards on peak demand have been incorporated in the forecast.

8. Observations Regarding the Projected Summer Peak

The primary factors driving the current summer peak load forecast include:

(1) Economic activity, represented by the energy forecast, is a major driver of the summer peak load forecast.

(2) Weather sensitive load is the other major part of the summer peak load forecast, accounting for over half of the summer peak.

(3) The impact of Federal Electric Appliance Standards on peak demand has been incorporated into the forecasts.

Appendix A: Forecasting Methodology, Evaluation and Testing

A.1. Peak Load Forecasting Methodology, Evaluation and Testing

The process for developing econometric-based peak load forecasting models is discussed in this appendix. The final equation used to forecast seasonal and monthly peak loads is the result of many iterations of the following steps.

(1) Informed by past years' models, a nonlinear econometric model with an autoregressive error structure is specified and the parameters are estimated.

(2) The autoregressive error process is then further identified.

(3) The residuals are examined for extreme outliers.

(4) The residuals are examined to determine if they exhibit any trends or correlations.

(5) Influential observations are identified.

(6) Proxy variables that might help explain the trends and influences in the residuals are evaluated.

(7) Influential observations suspected of biasing the coefficient estimators are removed from the sample.

(8) Statistical tests for goodness-of-fit and significance of the regressors are evaluated.

The modeling process begins with analysis of last year's models because it is reasonable to expect that the forecasts will not change radically from one year to the next, in the absence of critical events. The changes from CELT 2015 to Celt 2016 derive primarily from adding a year of data to the sample period.

A.1.1. Identification of the Autoregressive error structure.

The following steps help to identify the autoregressive error process.

(1) Experience over the years has shown that the errors in the daily peak load models follow a process of *at least* AR(1). The first step, then, is to specify a first-order autoregressive model.

(2) Serial correlation in the errors may be evidence of problems with the model specification. Before testing for higher-order serial correlation, the residuals from the AR(1) model are examined for extreme outliers. To the extent possible, the reason for large outliers is determined. Very large residuals can often be explained by severe weather events or abnormalities on the electric system (e.g., distribution line outages causing loss of load during a storm), and these anomalous observations must be eliminated from the sample to prevent biased estimators[5]. In other cases, dummy variables may be introduced as proxies for unobservable variables.

[5] Ordinary Least Squares regression equations fit an "average" model. Extreme outliers carry too much weight, pulling the average in their direction. This biases the regression line in the direction of the outlier.

(3) The Durbin-Watson statistic tests for the presence of first-order autocorrelation. Since the errors are known to follow a process of AR(1) or greater, other evaluation techniques are used to assess the degree of serial correlation.

(4) Based on further analysis, the model is re-specified with the higher-order AR process.

(5) This process is repeated each time the equation is modified.

A.1.2. Influential Observations

(1) The residuals are examined for obvious patterns. In some instances, specific holidays or surrounding days need to be accounted for separately. Saturdays and Sundays may need to be specified individually, rather than combined into weekends. The effect of weekends can vary by year, in which case interactive year/weekend dummy variables are called for. The residuals may show patterns within a particular year, which suggests that a dummy variable for that year might improve the model's properties.

(2) Influential observations are identified. Specific observations can have a large influence on model estimation, causing biased estimators.

A.1.3. Goodness-of-Fit and Statistical Significance.

It is important for the model to fit the historical data as closely as possible. Forecasts from an econometric model assume that historical relationships will continue into the future. A model that does not fit the data well introduces additional uncertainty into the forecast.

The traditional measure of how well the model fits the data is the R^2 statistic. The better the model fits the data, the higher will be the R^2 score. The best fitting model is the one that maximizes R^2. For the summer peak models, this statistic ranges from 0.884 to 0.957, with a median of 0.949. For the winter peak models, R^2 ranges between 0.858 and 0.919, with a median value of 0.908.

The t-test evaluates the statistical significance of each regressor, under the null hypothesis that the coefficient on the regressor is zero. A "rule of thumb" commonly used to indicate the explanatory power of a regressor is $t \geq 2$. However, if a variable is considered to be important in the initial design, careful consideration is given to retaining it in the equation regardless of reported significance. For example, the coefficients on the "Saturday" and "Sunday" variables do not always have t-values greater than 2, but they are important for identifying non-peak days.

A.2. Energy Model Evaluation

The statistical model evaluation process is somewhat similar to the Peak Load model, but with several exceptions and limitations.

(1) Serial Correlation. The Durbin-Watson statistic tests for first-order autocorrelation in the error terms, and it cannot be used in the presence of lagged dependent variables. The Breusch-Godfrey Serial Correlation LM test checks for higher order serial correlation in the error terms and was evaluated at lag=2.

(2) Standard Statistical Tests. The R^2 goodness-of-fit measure ranges from 0.9703 to 0.9948. These high values are not unexpected, given the aggregate time-series nature of the data. The t-statistics on the coefficients of most regressors are over 2. Exceptions include some constant terms and an occasional variable considered *a priori* to be important for model fit.