SEATTLE CITY LIGHT LOAD FORECASTING REVIEW

FINAL REPORT

Prepared for:
Seattle City Light

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EXECUTIVE SUMMARY

Seattle City Light's (City Light) long-term retail load forecasting function has recently moved from the Resource Planning, Forecasting & Analysis Unit in the Power Management Division to the Financial Planning Unit in the Finance Division, with support from a forecasting team which includes members from all affected organizational units.

In addition, with the departure of their lead forecaster, City Light recently lost some institutional knowledge of historical forecasting practices. City Light took advantage of the opportunity presented by these changes to solicit a third-party review of their existing load forecasting methods and practices. The purpose of this review was to determine whether the existing methodological framework and physical processes are meeting needs across the company and whether they are in line with industry best practices. In addition, City Light also wanted to identify potential improvements in both methods and processes that would allow it to meet a variety of objectives in the coming years.

City Light contracted with AEG (Applied Energy Group) and Integral Analytics (the AEG Team) to conduct a review of its current forecasting process, provide information on how that process compares to best practices, and make recommendations on how to better align current processes with industry best practice, and meet the objectives listed above. The project was conducted in four key steps.

- First, the AEG Team collected data relevant to the load forecasting process. The team reviewed this data in detail to garner a preliminary understanding of the existing approach and methodology.
- Next, the AEG Team met with City Light staff on-site to confirm our initial understanding of the current approach and dive deeper into the existing methods and future requirements.
- The AEG Team developed a preliminary set of recommendations and reviewed them with City Light in an in-person meeting.
- Finally, the Team synthesized the information gathered during the previous steps to provide City Light with the refined recommendations in this report.

CITY LIGHT'S PREVIOUS FORECASTING PROCESS AND CURRENT NEEDS

City Light has been producing energy and peak-demand forecasts. The energy forecast methodology consisted of a regional economic model that provides inputs to a set of energy sales econometric models for the major customer classes: residential, commercial/government, and industrial. The regional economic model consists of a complex and integrated set of econometric models that were created by Dr. Conway at the University of Washington and brought in-house for annual updating and maintenance. The key economic factors include local employment, income, unemployment rate, households, population, housing permits and inflation.

In addition to the sales forecasting models, a peak forecast has been prepared using system-level load factors intended to represent a 50% and 95% probability level. The load factors are applied to the monthly sales projections originating from the energy forecast models.

One of the first steps of the project was to review the previous forecasting process and to understand the needs of various departments with respect to the forecast. The AEG Team found that the existing sales and energy forecasting methodology at City Light is cumbersome, outdated and misaligned with industry best practices. Specifically, the industry has moved away from using regional economic models to forecast local economic data to drive the sales forecasts. Instead, utilities purchase local economic data from national vendors (such as Moody's or Global Insight). The specification of the econometric sales models could also be improved by replacing some variables, such as the employment rate, with drivers that are more correlated with energy sales for example: real per capita personal income, regional GDP, producer price index, and employment.

Table ES-1 summarizes the needs within various City Light departments for forecasting results. This was an important input into the recommendation-development process.

Table ES-1 Summary of City Light's Current Needs

Business Units	Annual	Monthly	Daily	Hourly	Peak
Finance		Best possible load forecast for revenue forecasting			For cost allocation and rate design
Customer Energy Solutions	For CPA[1], before incremental DSR[2]				
Resource Planning and Analysis	For IRP[3], before incremental DSR	For HERA[4] and STOMP[5], HLH[6] and LLH[7]	For STOMP, HLH and LLH	For IRP, before incremental DSR	For HERA and STOMP, HLH and LLH
Risk Management	Load forecast				Load forecast
Engineering	Load forecast	Load Forecast		Load forecast	Load forecast

[1] CPA – Conservation potential assessment
[2] DSR – Demand side resources
[3] IRP – Integrated resource plan
[4] HERA – Hedge evaluation risk analysis
[5] STOMP – Short term operations planning
[6] HLH – High-low-high
[7] LLH – Low-low-high

Key Goals

We also identified several key goals oriented toward improvement of current processes that will help City Light to meet their overall forecasting objectives. These goals fall into four general categories:

1. Goals related to the energy forecast. Develop an econometric energy forecasting model that is in line with current industry best practices. In addition, integrate DSRs and codes and standards (C&S) into the energy forecast.
2. Goals related to the peak forecast. Develop an hourly/daily peak forecast.
3. Cross-cutting goals. Revisit current approaches to weather normalization, normal weather year development, and calendarization of billing data.
4. General goals. Break down departmental silos and move away from simple "point forecasting."

Recommendations

The AEG Team developed recommendations based on three factors: City Light's forecast needs (summarized in Table ES-1), existing models and approaches available at City Light, and industry best practices. Central to the development of our recommendations was a desire to improve City Light's ability to address myriad forecast drivers including demand-side resources (DSRs) and codes and standards (C&S). In addition, we want to provide City Light with tools to explain changing trends in energy consumption over recent years, particularly in the residential class, that result in slow, flat, or even negative growth at the per customer level. To address these needs, more sophisticated models than traditional econometric models are now being used routinely throughout the industry. There is no one single best approach; instead there are several "best-practice" approaches, each with its own strengths and costs in terms of forecasting power, staff time, and possibly software and/or vendor costs.

Forecast Process

We developed three-key process-related recommendations. For each one, we recommend establishing procedures which, to the best of our knowledge, do not currently exist at City Light. Adopting these processes will provide City Light with a formal structure that can facilitate the development of an official forecast that meets needs across the company.

- Use more than one approach to develop the load forecast. In the past, City Light has relied on its econometric forecast as the primary forecast. During this project, we discovered that City Light's CPA process involves development of an end-use forecast. In addition, City Light is using small-area forecasting to support distribution planning. One of the main advantages of including these alternate approaches is that their more "bottom-up" approach facilitates the development of a story about how and why the forecast is changing. These approaches are particularly applicable to City Light because both the end-use forecast and small-area forecasts are already in place.
- Establish a Forecast Review Committee to vet the forecast. This small, multidisciplinary group would review key forecast assumptions, as well as the preliminary forecast results. It will also critique the preliminary forecast and provide guidance for refinements. This group should include representatives from key users of the forecast as well as key contributors to the forecast. In addition to acting as a sounding board and QA/QC check, the group can also ensure that the final forecast meets companywide needs.
- Perform sensitivity analyses. In addition to developing the official forecast, City Light should undergo a formal process to understand the sensitivity of the forecast to changes in key assumptions. City Light should also consider describing alternative scenarios and assessing the resulting forecasts. These efforts will provide more confidence in the ultimate forecast results.

The Energy Forecast

For the energy forecast, we recommend using a three-pronged approach to develop the official forecast. The first, and most important step, is to develop the new econometric model. Detailed recommendations surrounding model development and the timing of relative activities can be found in Section 4. The other two pieces of the approach include leveraging the end-use and small-area load forecasting models. Figure ES-2 summarizes our recommendations as they pertain to each piece of the approach.

Figure ES-2 Energy Forecast Recommendations

Develop new econometric model

- Develop a new econometric model, which includes several underlying rate class level models
- Implement statistically adjusted end-use (SAE) approach and adjust for DSR for major rate classes
- Prepare separate forecasts for large and special customers/groups
- Continue to develop quarterly forecasts for 2017, but transition to monthly in 2018 or sooner
- Develop a new customer forecast
- Acquire economic forecasts from vendor

Leverage end-use model

- Use model from CPA to develop annual end-use model by rate class
- When possible, use same exogenous variables as econometric models
- Isolate impacts from C&S and DSR and provide to econometric to support SAE appraoch
- Use econometric model results to allocate annual forecast to quarters and months

Leverage small-area forecasting model

- Roll up the feeder-level forecast used by Distribution Planning to the system level
- Recommend interaction and collaboration among Engineering, CES and Load Forecasting

Developing a new econometric model will allow City Light to both update and streamline its modeling approach by retiring the cumbersome Conway Regional model. This updated model, and underlying rate class level models, should include robust economic drivers, leverage a new (externally obtained) economic forecast, and be tied to actual meter counts. It should also leverage monthly, rather than quarterly, data to eliminate the current shaping processes, prepare for the onset of AMI and establish better relationships between weather and consumption. As progress is made, regional end-use information[1] can be incorporated into the econometric model to better capture both embedded (naturally occurring) and programmatic (originating from utility programs) efficiency.

In addition to the econometric model, we recommend leveraging the end-use model and the small area model. Each model will allow City Light to better explain the forecast by telling a story about what is changing in the future. In addition, each model will provide information that can be used to adjust or develop the final load forecast.

- The end-use model develops forecasts by customer segments and end uses / technologies within sectors. This will allow City Light staff to tell a detailed story about anticipated changes in technologies, appliance standards, segment-specific energy use patterns and other factors and how they impact the forecast. Also, discontinuities caused by drivers that have not been observed historically.
- Similarly, the small area forecast allows City Light to tell a story about where growth is expected to occur and the impacts of feeder-level changes.

THE PEAK FORECAST

Our recommendations related to the peak forecast mirror the three-pronged approach recommended for the energy forecast. This is intentional, as most peak models are tied directly to the energy model by using the predicted energy as an input to the peak demand model. In this way, the new econometric model will do much of the heavy lifting for the peak forecast. The end-use and small-area forecast models provide granularity by end use and geographic location. Our recommendations are summarized in Figure ES-3.

Figure ES-3 Peak Forecast Recommendations

Develop new econometric model

- Forecasted energy captures overall changes in consumption through time, as a result the remaining job of the peak model is to capture changes related to weather and season
- Develop seasonal peak model in 2017
- Develop hourly or daily model in 2018

Use end-use model to obtain end-use breakout

- Using end-use "peak factors" included in the end-use model, City Light can develop implied end-use breakdown of the peak

Leverage small-area forecasting model

- Roll up feeder-level forecast used by Distribution Planning to system level
- Recommend interaction and collaboration among Engineering, CES and Load Forecasting
- Future growth pockets are identified specifically in the small-area model

[1] Forecasted regional energy consumption data by building and end-use can be found as part of the Energy Information Administration's (EIA) Annual Energy Outlook (AEO). Historical data can also be found through the EIA as part of the Residential Energy Consumption Survey (RECS) and Commercial Buildings Energy Consumption Survey (CBECS).

Cross-cutting Activities

As mentioned above, we identified several analyses that cut across forecasting activities. A summary of our recommendations with respect to these activities is as follows:

- **Normal weather**. Move from a simple average for defining normal weather to a rank-and-median (see the appropriate subsection below for definition) approach. Use a backcasting method to determine the appropriate timeframe for years of weather data to include in the approach.
- **Weather normalization**. Use weather-related coefficients from the forecasting models to normalize historical sales.
- **Calendarization**. Move from quarterly load forecasts to monthly load forecasts as soon as practical.
- **Develop class level load shapes** using one of the following approaches:
  - Leverage existing (albeit old) load research data
  - Use feeder and substation level forecasts from small-area model
  - Borrow load research data from nearby utilities
  - Use MV-90 data for large customers
- **Sensitivity analyses**. Using the near-final forecast models, we recommend conducting sensitivity analyses around key variables, including:
  - Extreme weather
  - Economic variables
  - DSRs and electric vehicles
  - Codes and standards
  - Levels of energy-efficiency and demand response activity (e.g., participation, spending)

Time Horizon

It is important to recognize that it will take a few years to implement these recommended changes and to achieve best practices. Forecasting is an ongoing learning process, where continuous improvement is achieved through experience. This journey will require the application of judgment at every step so it will be important to review, discuss and make course corrections. The Forecast Review Committee will play a vital role.

Similar Experience Across the Country

Utilities across the country are dealing with these same issues. Most have already found it necessary to use some form of SAE or end-use approach to improve forecast accuracy and allow for the incorporation of DSR impacts into the forecast. Duke Energy, Idaho Power, and Vectren are all good examples of utilities that have adopted an in-house SAE approach. Both PG&E and Nashville Municipal Utility leverage small-area or spatial forecasts to help triangulate their demand forecasts. And, Southern Company and Public Service Company of New Mexico, both use end-use forecasting models to varying degrees as part of their energy forecasting approach.

Next Steps

City Light can continue to enhance its forecasting process and approaches immediately. We recommend the following steps:

- **Examine internal resources and develop a system of accountability**. In the context of the above recommendations, examine internal resources and make preliminary assignments. This includes identifying the key forecasting staff, as well as other supporting staff. Also, determine the composition of the Forecast Review Committee and begin to hold meetings to implement steps below.

- **Determine which recommendations to tackle.** We have provided numerous recommendations and it is likely that there are too many to tackle at once. However, we believe that City Light has the internal resources to move forward with enhancements to the econometric model (described below) with only light support, possibly, from a consultant who could provide guidance. While determining which recommendations to pursue, we recommend that City Light also remain cognizant that the costs of implementing recommendations need to be weighed against the benefits.
- **Develop a formal plan to move forward.** The formal plan should include detailed steps which identify a clear path forward for each of the identified recommendations. This will involve the following steps:
    - Prioritize recommendations
    - Assign responsibilities
    - Lay out a timeline that spans the various business units
    - Develop an approach to track progress and maintain accountability

While not absolutely necessary, we recommend City Light consider engaging with a consultant to lead the development of the plan with City Light input. While the in-house capability to develop a plan exists, working with a consultant would allow for the plan to be developed and implemented more quickly and enhance City Lights ability to move through the phased recommendations. In addition, it would allow City Light staff to focus on other responsibilities, and possibly get started on the econometric forecast piece, which stands alone, while the plan to tackle other activities is fully fleshed out.

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Introduction

Project Overview

Seattle City Light's long-term retail load forecasting function has recently moved from the Resource Planning, Forecasting & Analysis Unit in the Power Management Division to the Financial Planning Unit in the Finance Division, with support from a forecasting team which includes members from all affected organizational units. In addition, with the departure of their lead forecaster, City Light recently lost some institutional knowledge of historical forecasting practices. City Light took advantage of the opportunity presented by these changes to solicit a third-party review of their existing load forecasting methods and practices. The purpose of this review was to determine whether the existing methodological framework and physical processes are meeting needs across the company and whether they are in line with industry best practices. In addition, City Light also wanted to identify potential improvements in both methods and processes that would allow it to meet several objectives in the coming years. These include, but are not limited to:

- Improving long and short-run energy and peak demand forecasts
- Understanding and quantifying the causes of load uncertainty
- Understanding the base load and identifying factors causing changes in loads
- Predicting drivers that cause shifts in load between major rate classes
- Predicting reasons for geographic load shifts within the service area
- Providing insights on tactics that could be taken to alter load for specific geographic areas or rate classes
- Supporting scenario assessments associated with changes in penetration rates of customer investments in distributed resources (DR), which additionally impact monthly load patterns due to various photovoltaic (PV), electric vehicle (EV), and storage that will fundamentally change the system load shape over time
- Measuring the effect of existing or prospective energy efficiency programs on the load forecast, including alternate program penetration rates
- Coordinating and aligning load forecasting processes to support the need for small area forecasts used for transmission and distribution capacity planning
- Creating system-level forecasts that reconcile and/or are consistent with the circuit and substation forecasts used by planning and operations departments, while recognizing that the summation of substation non-coincident peak loads differs from the system coincident peak load forecast.

City Light contracted with AEG and Integral Analytics (the AEG Team) to conduct a review of its current forecasting process, provide information on how that process compares to best practices, and make recommendations on how to better align current processes with industry best practice, and meet the objectives listed above. The project was conducted in four key steps.

- First, the AEG Team collected data relevant to the load forecasting process. The team reviewed this data in detail to garner a preliminary understanding of the existing approach and methodology.
- Next, the AEG Team met with City Light staff on-site to confirm our initial understanding of the current approach and dive deeper into the existing methods and future requirements.

- The AEG Team developed a preliminary set of recommendations and reviewed them with City Light in an in-person meeting.
- Finally, the Team synthesized the information gathered during the previous steps to provide City Light with the refined recommendations in this report.

City Light's Key Goals

As the AEG team moved through the steps of the project, we identified several key goals oriented toward improvement of current processes that will help City Light to meet their overall forecasting objectives. These goals fall into four general categories:

1. Goals related to the energy forecast. Develop an econometric energy forecasting model that is in line with current industry best practices. In addition, integrate DSRs and codes and standards (C&S) into the energy forecast.
2. Goals related to the peak forecast. Develop an hourly/daily peak forecast.
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2

OVERVIEW OF CITY LIGHT'S PREVIOUS LOAD FORECASTING PROCESS

The City Light Load Forecast (LF) is an integral component to the company's planning process and has been prepared once each year. The LF represents a key component for many activities at City Light:

- Resource Planning's integrated resource plan (IRP)
- Finance's revenue and rate model
- Customer Energy Solutions' demand-side resource plan
- Distribution Planning's (Engineering's) reliability assessment and distribution capital budget

While the LF is used by multiple groups across City Light, the execution of and planning for the forecast has been conducted independently within a single group. The key pieces of information that flow across the planning areas from the LF group to the other four planning functions are the long-term customer class forecasts of energy and average hourly MW, at the system level.

In the subsections that follow, we summarize City Light's previous approach to the load forecast.

Load Forecast Model Structure

City Light has been producing both an energy and demand forecast. First, we discuss the structure, or approach, used for the energy forecast.

The LF methodology includes a service area, or regional, economic model as well as a set of energy sales econometric models for the major customer classes: residential, commercial/government, and industrial. The regional economic model consists of a complex and integrated set of econometric models that were created by Dr. Conway at the University of Washington and brought in-house for annual updating and maintenance. The economic model provides a projection of quarterly values for key economic factors that are available for use within the LF's econometric models to project class-level electricity sales. The key economic factors include local employment, income, unemployment rate, households, population, housing permits and inflation.

The electric sales forecast has been developed primarily using three econometric models, one for each major customer class: residential, commercial/government, and industrial. The key independent factors included in these models are: heating degree days, real average electric price and the unemployment rate. The dependent variables are: residential use per household for the residential class, commercial and governmental use per employee for the commercial class, and industrial use per manufacturing employee for the industrial class. With projections of households and employment, obtained as outputs from the economic model, the energy models produce forecasts of weather-normal, quarterly sales for each customer class. These are subsequently allocated to the respective rate classes for revenue budgeting purposes. Quarterly sales are aggregated into annual sales and then the annual sales projections go through a shaping process to create monthly and daily loads for the duration of the forecast horizon.

In addition to the sales forecasting models, a peak forecast has been prepared using system-level load factors intended to represent a 50% and 95% probability level. The load factors are applied to the monthly sales projections originating from the energy forecast models.

Data Supporting the Load Forecast

The regional economic forecasting models include national forecast data and historic regional economic data for King County as well as the City Light service area.

The econometric forecasting equations rely on internal sales information (primarily from bi-monthly meter readings for the residential class and monthly meter readings for other classes), tariff information, heating degree days, and the economic history and forecast data from the regional economic model.

Load Forecast Process

For each forecast cycle, the process employed by City Light's load forecasting staff involved updating the historical data for all the models, estimating the econometric forecasting equations for the regional economic model and for the electric sales models, and generating the forecast. The projection of class-level sales has been aggregated together and then summed with a projection of other sales (minor amount) and losses to create a forecast of total energy. The forecast has not been adjusted for past or projected future impacts from City Light's demand-side resource programs or other emerging distributed energy resources (e.g., PV, EV, Storage). Instead, the future demand-side resource impacts are incorporated as part of the IRP process. The forecast of industrial sales has also been disaggregated into several key industry groups based on an allocation process using recent industry shares of the total industrial usage.

Variance analysis has been conducted on a regular basis to compare the forecast of total system energy with an estimate of the weather-normal level of actual total energy. The process of weather normalization was conducted by Resource Planning using a statistical model (vintage 1998) relating load and weather data.

Load Forecast Resources

In previous years, City Light had one full-time economist assigned to the load forecast. As part of the transition the staffing has changed somewhat. Currently, City Light staff assigned part-time to the LF includes two professionals with training in economics and forecasting. In addition, City Light has eight additional analysts who are available to support the forecasting process in the future.

The EViews software is used to estimate the econometric models for the regional economic model and the energy sales models and to forecast the levels of the economic factors as well as electricity sales.

Other Forecasting Activities at City Light

While the official load forecast has been developed as described above, the AEG Team learned during the interviews with City Light departments that two additional "forecasting-related" activities have been taking place. These activities provide City Light with additional options for how to move forward in refining its forecasting process. They are described briefly as follows:

- End-use forecasting. As part of the conservation potential assessment (CPA) studies, an end-use model is developed as the starting point for the estimation of future conservation potential. City Light is in possession of two end-use models developed by Cadmus and AEG.
- Small-area forecasting. The Engineering Group uses the LoadSEER model to prepare circuit and substation level forecasts of peak load in planning the distribution system. This model uses much of the same types of information as used for the system forecast (e.g., weather and economic data), but with a more granular focus.

3

MOVING TOWARD BEST PRACTICES

OVERVIEW OF BEST PRACTICES

Load forecasting models generally fall into three categories: econometric models, end-use models and statistically adjusted end-use (SAE) models:

- Econometric models are regression models that use economic, weather, and various other variables to predict future energy usage.
- End-use models employ a bottom-up approach that draws on information regarding appliance stock, saturations, and efficiencies to build future load requirements based on how customers use appliances and, therefore, energy.
- SAE models use an econometric framework, but incorporate end-use information into the model as explanatory variables.

Since the energy crisis of the 1970s until the mid-1990s, many companies used both an econometric and end-use approach, as each had its strengths. Although forecasters generally preferred an econometric approach, regulators often required an end-use forecast. It was common for forecasters to use the results of their econometric model for the first 3 to 5 years of the forecast period and to transition to the end-use forecast for the remainder of the forecast horizon, which was typically 20 years.

With industry restructuring in the mid-1990s, the requirements for end-use forecasts largely went away. Most utilities abandoned end-use forecasting in light of shifting focus in the industry. As a result, load forecasting groups shrank, including only one or maybe two forecasters using an econometric approach. At the same time, retail markets lessened the emphasis on demand-side resources (DSR) in the utility industry.

However, in recent years political and industry focus on green energy and concepts like "DSR as a resource" has spurred a radical increase in the amount of DSR utilities are pursuing. This uptick in DSR, increased emphasis on conservation in general, and new codes and standards, have resulted in a renewed interest in incorporating aspects of end-use forecasting into the forecasting process because end-use forecasts are better equipped to handle changes in efficiency.

Many utilities have turned to an SAE approach to incorporate some of these end-use aspects. The advantages of the approach include minimal changes from the econometric framework and a minimal increase in workload. However, it is important to note that while SAE models do a better job at capturing end-use trends, forecasters are finding that econometric methods still struggle to produce realistic longer term forecasts and that a single forecasting approach simply cannot meet forecasting needs across the company. Considering this, many utilities are considering multiple approaches to triangulate their forecasts, rather than using the output of a single model.

Best practices, therefore, have evolved over time and continue to evolve to meet the changing requirements of the future. In the following subsections, we discuss, in detail, each of City Light's goals in the context of industry best practices. We describe City Light's previous practice with respect to each goal, the industry best practice, and, our recommendations on how to get from current practices to best practices. To summarize the analysis, in each area we present a table which identifies the following:

- Goal: City Light's goal in the specific area
- Previous practice: what City Light has been doing

- Key best practices: Best practices in the industry as they relate to City Light's goals
- Moving toward best Practices: Identifies what City Light would need to develop, acquire, or achieve to meet their goal and move toward industry best practices
- Gap assessment: An assessment of the gap between current practices and the identified needs. Zero percent (0%) means existing practices are in line with needs and 100% means that either the existing practices do not meet the identified needs at all or that there is not an existing practice in place.

The text surrounding the tables provides additional context for the goal and detail surrounding best practices and our gap assessment.

Econometric Energy Forecast

The AEG Team found that the existing sales and energy forecasting methodology is cumbersome, outdated and misaligned with industry best practices. Specifically, the industry has moved away from regional economic models to drive the sales forecasts. Instead, utilities purchase local economic data from national vendors (such as Moody's or Global Insight). The specification of the econometric sales models could also be improved by replacing some variables, such as the employment rate, with drivers that are more correlated with energy sales.

These findings come as no surprise to City Light staff. Across each of the groups there was a desire to start fresh, simplify where possible, and improve the robustness of the methodology where needed. In addition, City Light staff identified a need to incorporate the impacts of demand side resources (DSRs) more uniformly into the energy forecast.

In Table 3-1 directly below, and Table 3-2 in the next subsection, we summarize some of the key aspects of our review of the energy forecast.

Table 3-1 Best Practices and Needs Related to the Energy Forecast Model

Goal: Develop an econometric energy forecasting model that is in line with industry best practices		
Previous Practice	Use regional economic model to develop inputs to the forecast	Use econometric model to develop the load forecast
Key Best Practices	Obtain forecast inputs from government and/or paid subscription services. Forecast customers based on meter counts, economic variables, and trend variables.	Models should incorporate economic variables with meaningful interpretations, robust model validation, potentially incorporate end-use information
Moving toward Best Practices	Develop or purchase new forecast inputs. Develop new customer forecasts and develop a better understanding of how customers shift across rate classes.	Develop new econometric model
Gap Assessment	100%	100%

Assessment of the Energy Forecast

The design of the current econometric models was developed more than 20 years ago, in the absence of good regional forecast data. The econometric structure is good for checking for co-integration between dependent and independent variables. However, the structure makes it difficult to understand forecast variance, to weather normalize the actual loads, and to evaluate the reasonableness of the elasticities and other coefficients. It is also quite complex and difficult to execute.

Best-practice models generally use external data sources to develop their regional forecasts. These might include purchasing data from a vendor, such as Moody's or Global Insight, or obtaining regional economic forecast variables from a local university. City Light's implementation of LoadSEER uses customer-specific housing characteristics and demographics. These data might be extended for use in load forecasting.

Several types of variables are generally included as explanatory variables in econometric models:

- Key economic variables:
  - Some measure of overall economic health such as state-level gross domestic product (GDP)
  - For residential customers, real income or median real disposable income
  - For commercial and industrial customers, the producers' production index (PPI), employment or real retail sales
- Other important variables:
  - Weather in the form of monthly cooling degree days (CDD) and heating degree days (HDD)
  - Electricity prices (marginal price or typical electric bill)
  - Other industry specific regional variables

Time-series variables can also be included to control for autocorrelation, and potentially capture other time related trends not picked up by the economic variables. However, these variables should be included carefully and sparingly to correct for known issues rather than be used for their explanatory power. The best models rely on tangible variables and their relationships to energy consumption to explain variation and forecast changes in load. Models that are mostly time-series variables have little explanatory power and are more difficult to justify and explain.

The forecasting models might take on a variety of functional forms. Forecasters often use transformations such as the natural logarithm to correct for variables that may not be normally distributed. Transformations can also be used to correct for other problems such as heteroscedasticity and nonlinearity. The log transformation is often used because the coefficients in the model can then be interpreted as percent changes or elasticities.

In addition, best practices frequently include the incorporation of appliance saturations and end use efficiencies as variables in the models. This can be performed as a hybrid end-use econometric or the SAE methodology (which is a specific type of hybrid end-use econometric approach). Either approach should include estimates of the energy stock of equipment along with the efficiency. These can be obtained either directly from survey data, or indirectly by adjusting the regional EIA projections that are part of the Annual Energy Outlook (AEO). They could also come from the model used to develop the CPA. The way these types of variables are included in the models could take several forms. The two most common include:

- Explicitly including saturations of key end-uses such as gas heat, electric resistance heat, heat pumps, and air conditioners (central and window).
- Creating indexes that blend together saturations of several related end-uses such as all heating equipment, all cooling equipment, lighting, refrigeration, water heating, and a miscellaneous or other category.

A typical SAE model might look like the example below:

$$AvgUse_t = b_0 + (b_1 \times XHeat_t) + (b_2 \times XCool_t) + (b_3 \times XOther_t) + \varepsilon_t \tag{1}$$

where:

$$XCool_{y,m} = CoolIndex_y * CoolUse_{y,m} \tag{2}$$

$$CoolIndex_y = Structural\ Index_y \times \sum_{Type} UEC_{01}^{Type} \times \frac{\left(Sat_y^{Type} \big/ Eff_y^{Type} \right)}{\left(Sat_{01}^{Type} \big/ Eff_{01}^{Type} \right)} \quad (3)$$

$$CoolUse_{y,m} = \left(\frac{Price_{y,m}}{Price_{01}} \right)^{-0.15} \times \left(\frac{Income_{y,m}}{Income_{01}} \right)^{0.20} \times \left(\frac{HHSize_{y,m}}{HHSize_{01}} \right)^{0.20} \times \left(\frac{CDD_{y,m}}{CDD_{01}} \right) \quad (4)$$

Calculations for XHeat and XOther are similar.

Customer Forecasts

For most utilities, best practices include a forecast of energy where the dependent variable is use per customer, use per employee or use per square foot. This also necessitates generating customer forecasts for both the total number of residential customers, commercial customers, and industrial customers, often by rate class. These customer forecasts should use as their key inputs:

- Historical meter counts or building counts for each customer class or rate
- Explanatory variables that include: energy forecast, population counts, square footage, and potentially time-series variables.

Large Customer Forecasts

Best practice for large customers is to forecast those customers individually or in selected key industry groups. The forecast may be based not on an econometric model but rather on past usage. Typically, information from customer representatives regarding likely future activities is included in the forecast development.

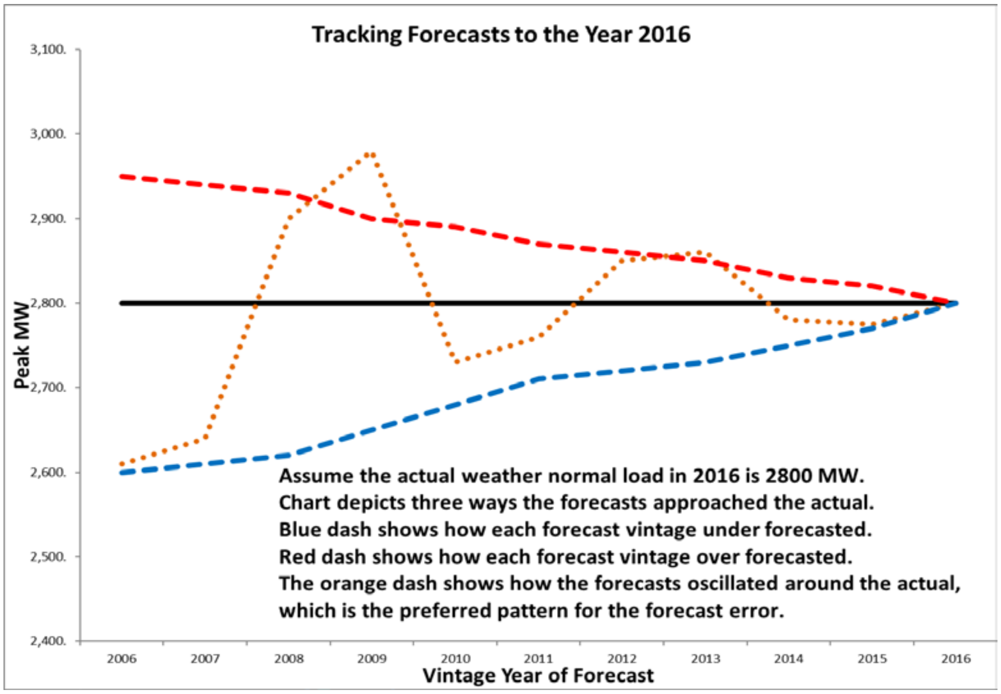
Model Validation

Best practice in model validation involves execution on several fronts. The activities described below work together to allow the forecaster to improve accuracy, minimize bias, and enhance robustness.

- Review model errors (residuals) to identify significant outliers. If outliers are identified, check to see if there is an explanation for such outliers such as a labor strike, an unusual weather event, or a billing error. Accessing and tracking, on a monthly basis, the billings of the top 100 or so customers can help identify such issues. Keeping a historical log of such occurrences can help justify the use of qualitative variables.
- Review the model elasticities (e.g., price, key economic factors, weather) for reasonableness against values found in the electric energy forecasting literature.
- Examine the errors in the last year of the historical period to identify if there is a trend to over or under explain the most recent history. This can be further facilitated through a backcasting process, which refers to the practice of estimating the model while holding out the most recent data. Then, forecast the most recent data to check the ability to forecast that recent historical experience. Also, check to see if key elasticities changed as a result of holding out the recent data.
- Check for model issues associated with autocorrelation (time-dependent errors) and heteroscedasticity (error volatility). Corrections for these may require adjusting the historical window on which the model is based.
- Conduct a forecast variance analysis on an actual- and weather-normal basis. The forecasting equations used to prepare the forecast should also be used to develop the estimates of weather-normal sales for comparison to the projected levels of sales. Tracking the divergence over time provides insights on forecast error and bias. For example, one can monitor how a forecast approaches a future value for each year in the future for the next ten years (see Figure 3-1 below). Is the forecast prepared in 2006 for the year 2016 above or below the actual on a weather normal basis? Then, check the forecast for 2016 prepared in 2007, 2008 and so on. Hopefully the forecast

will oscillate around the actual value for 2016. Tracking these error trends helps to identify inherent model bias.

Figure 3-1 Model Validation by Tracking Model Variance



INTEGRATING DSR AND C&S

As savings from utility programs have increased over the past few decades, utilities have found it to be increasingly important to account for these savings in their load forecasting models. Econometric models can capture and project trends from historic programmatic efficiency; however, those projections will assume that the trend in efficiency gains continues indefinitely into the future at an average rate. To capture changes in efficiency related to utility programs, forecasted impacts are generally explicitly included in one of three ways.

- Subtraction method. In this method, incremental programmatic DSR savings are subtracted from the output of the econometric model.
- Addition and subtraction method. In this case, the historical impacts are first added back to the historical consumption data to estimate consumption in absence of utility programs. Then the models are estimated using the adjusted historical values. Finally, the entire DSR forecast is subtracted from the historical and forecast data.
- Modeling approach. The third approach more directly integrates the impacts into the model by including them in some fashion as explanatory variables.

In addition to programmatic savings utilities must also consider the effects of future C&S. Adjustments related to C&S are generally made outside of the econometric models and can rely on either publicly available EIA data from the AEO, or from the C&S assumptions surrounding a current conservation potential assessment (CPA). C&S can also be accounted for within the econometric model when using an SAE approach. This can be achieved by adjusting the assumed efficiencies of the appliance mix of the end-use related variables consistent with the implementation of known C&S.

Table 3-2 summarizes our assessment of integrating DSE and C&S into the load forecast.

Table 3-2 Best Practices and Needs Related to Integrating DSR and C&S

Goal: Integrate DSR and C&S into the energy forecast			
Previous Practice	Track DSR impacts and participation	Assess C&S as part of CPA	Adjust corporate forecast based on incremental savings in IRP
Key Best Practices	Carefully track programmatic impacts from DSR measures. Also, carefully track participation in DSR programs over time.	Use either an end-use model or use EIA projections to develop an estimate of the impact of codes and standards on energy consumption	Use an appropriate method to incorporate and account for DSR and C&S in the official energy forecast, including scenarios for new DSRs such as PV, Storage, EV.
Moving toward Best Practices	Customer Energy Solutions possesses this data as well as historical appliance saturation information.	Develop data base for end-use forecasting.	Assess current approach (used in IRP) and then select either that approach or another approach to integrate DSR and C&S into the corporate forecast, consistent with existing LoadSEER functionality.
Gap Assessment	0%	100%	15%

Peak Forecast

During our review, the AEG Team concluded that the City Light's previous method of developing a peak load forecast is not meeting needs across the company. More specifically, the forecast that has been developed is not truly a peak forecast, but an adjusted energy forecast which probably does not accurately reflect true monthly peaks or weather variations. In Table 3-3 below we summarize some of the key aspects of our review of the peak forecast.

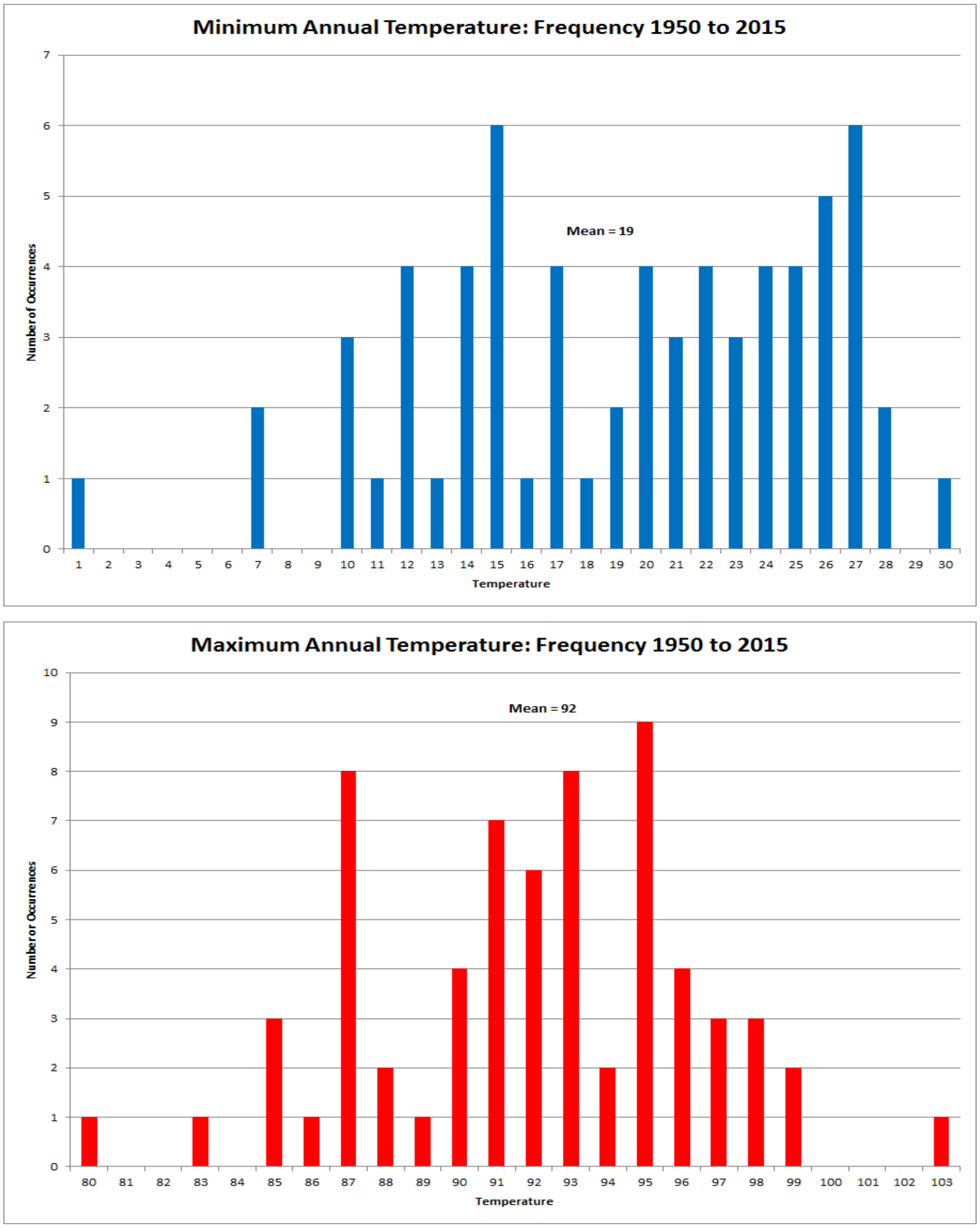
Table 3-3 Best Practices and Needs Related to the Peak Forecast

Goal: Develop a daily peak forecasting model			
Previous Practice	Adjust monthly energy forecast using a load-factor approach		
Key Best Practices	Base the peak forecast on hourly system load, hourly weather (historical, normal and extreme), customer counts, and/or forecasted energy	Use econometric models to forecast daily peak load under various weather conditions and potential growth scenarios.	If the peak is at the system level, use load research data to allocate peaks to the individual classes.
Moving toward Best Practices	Obtain hourly system load data and hourly weather data for the Seattle area	Develop an econometric model that reflects industry best practice	Use load research data to estimate both class contribution to peak, and class level load shapes.
Gap Assessment	80%	100%	100%

Assessment of the Peak Forecast

Best practices include the development of a peak model using hourly or daily maximum system load data. The peak models generally use hourly system load, hourly weather variables, calendar variables, and weather normalized system energy as inputs. These models tend to be highly dependent on weather and so developing reasonable normal weather (discussed in the next section) is also of critical importance. It is also important to properly account for extreme weather when building the peak forecast, Figure 3-2 below illustrates extreme conditions in City Light's territory over the past 65 years.

Figure 3-2 Identifying Extreme Weather



There are many valid approaches to developing a peak load forecast. However, it is important to recognize that the nature of the problem, i.e., forecasting a peak load for one hour out of the year, possesses considerable uncertainty. Often, using multiple methods can help triangulate on the best estimate. But, one common thread underlies the peak forecast process and that is the energy forecast. Developing a peak forecast independent of the energy forecast can break a fundamental relationship reflected in the load factor. Ultimately, computing and checking the load factor forecast is a good test to the validity of the peak forecast.

Peak Load Model Structure

Peak models are typically built on a monthly or seasonal basis. These models are structured in several different ways. Using January and monthly modeling as an example, the model could use historical data for the past ten or so years for the coldest weekdays, defined according to some relevant criterion (such as all days where the average temperature was below some threshold, say 20 degrees F). Then, the model structure would have the peak (dependent variable) as a function of weather-normalized energy for the month and key weather variables, such as temperature and wind speed. Weather normalized energy captures the overall level of economic activity. One might also need to identify whether the loads on those days occurred in the morning or the evening. Given the non-linear nature of the relationship between hourly load and the weather, this process builds a model using load data associated with more extreme weather. This model can then be simulated through 30 years of historical weather to identify typical peak January weather conditions.

An alternate approach is to use the historical daily peak loads and weather conditions and build a model of daily peak loads using a similar structure. However, care must be taken to ensure that the model is capturing any inherent non-linearity as one cuts across from mild to colder weather conditions.

These approaches should also be tried on a seasonal basis (winter and summer) to forecast the seasonal peaks. Given that the most extreme weather in a season does not always fall in the same month, using a broader dataset is required to forecast the seasonal peak. For example, the winter season model could be built using data from December through February or March. But, the peak forecast would be placed in the month where the peak usually occurs.

One final point to mention on the peak forecast is that it is important to look at the error or residual for the last peak data point in the history. It often is appropriate to use that error to adjust the peak forecast from the econometric model.

With respect to the 8,760-hourly forecast, econometric models of historical hourly loads can be developed to convert the monthly energy and peak load forecast into an 8,760-hour shape.

Peak Model Validation

All econometric models should be validated using the process described above for the energy forecasting model. However, one additional consideration is the ability of the model to hit the highest historical peak loads. One may develop a model with apparently great statistical results, but is under or over on all the actual peak days. This is a critical check on peak model validity.

CLASS LEVEL LOAD RESEARCH

Best practices in load research involve four key steps: sample design and selection, meter installations, data collection and validation, and data analysis. We have provided a very brief description of each step below. However, a more comprehensive treatment should be sought if City Light intends to revive their load research program.[2]

- Sample Design and Selection. Most load research is conducted using a stratified random sample design at the rate-class level. A stratified design is used because stratification can result in smaller sample sizes. Even utilities with AMI may choose to use stratification or segmentation to ensure that estimates can be made for specific population subgroups.
- Meter Installations. After the samples have been selected either interval meters need to be installed, or simply identified in the case where a utility has AMI.

[2] The most complete load research reference that we are aware of is the Association of Edison Illuminating Companies (AEIC) Load Research Manual. The Manual is usually updated every few years, and includes detailed information, including statistical sampling formulas and guidelines, on each step of the load research process. The Manual is available for purchase via the AEIC website, or is provided as part of the Introduction to Load Research course offered by the same group. http://aeic.org/committees/load-research/publications/

- Data Collection and Validation. In general, one year of interval data is needed for typical load research activities. Regardless of whether AMI meters or traditional MV90 meters are being used, data should be carefully screened for erroneous values and outliers.
- Data Analysis. The most common analysis is the creation of class level 8,760 load shapes for applications in rate design, cost of service, and load forecasting. The load shapes should be created using the appropriate expansion technique and associated formulas to calculate means, variances, and confidence intervals.[3]

Cross-Cutting Activities

During our review, the AEG Team also reviewed several activities that affect multiple aspects of the forecast. These activities include: weather normalization of historical sales, development of normal weather, and calendarization of billing data. In each of these activities there is significant room for improvement in methods and approaches. In Table 3-4 below we summarize some of the key aspects of our review of these activities.

Table 3-4 Best Practices and Needs Related to the Cross-Cutting Activities

Goal: Revisit current weather normalization, normal weather development, and calendarization approaches			
Previous Practice	Used an antiquated weather normalization model to WN historical sales	Used 30-year normal weather year	Used in-house spreadsheet based methods to turn bi-monthly to quarterly data
Key Best Practices	Weather normalize historical sales and/or peak using the energy and peak forecasting models	Use at the least a typical meteorological year (TMY), or a normal year developed using a rank and mean approach. Check for reasonableness of a 30-year normal	Calendarize monthly billing data to reflect calendar months vs. billing months
Moving toward Best Practices	An updated approach to weather normalizing historical sales that minimizes the differences from use of alternate models	Hourly and monthly normal weather that reflects natural variation in weather patterns	Monthly historical input data for creating estimates of monthly sales. Load research data would improve the billed to calendar process as well as the process to develop monthly sales from the bi-monthly meter reads
Gap Assessment	80%	80%	80%

Best Practices

Weather Normalization of Historical Sales

Best practices include using the forecast equations to weather normalize historical sales. Using this approach results in the fairest comparison of actual to projected sales by eliminating the differences in sales that result simply from using different weather normalization techniques. In addition, the models should be simulated over 30 plus years of weather data to better understand the weather probability distribution and weather risk associated with the sales forecast.

[3] The Load Research Manual contains the correct formulas for expansion to the population using mean per-unit, ratio, proportional, or simple random sample estimates.

Creating Normal Weather

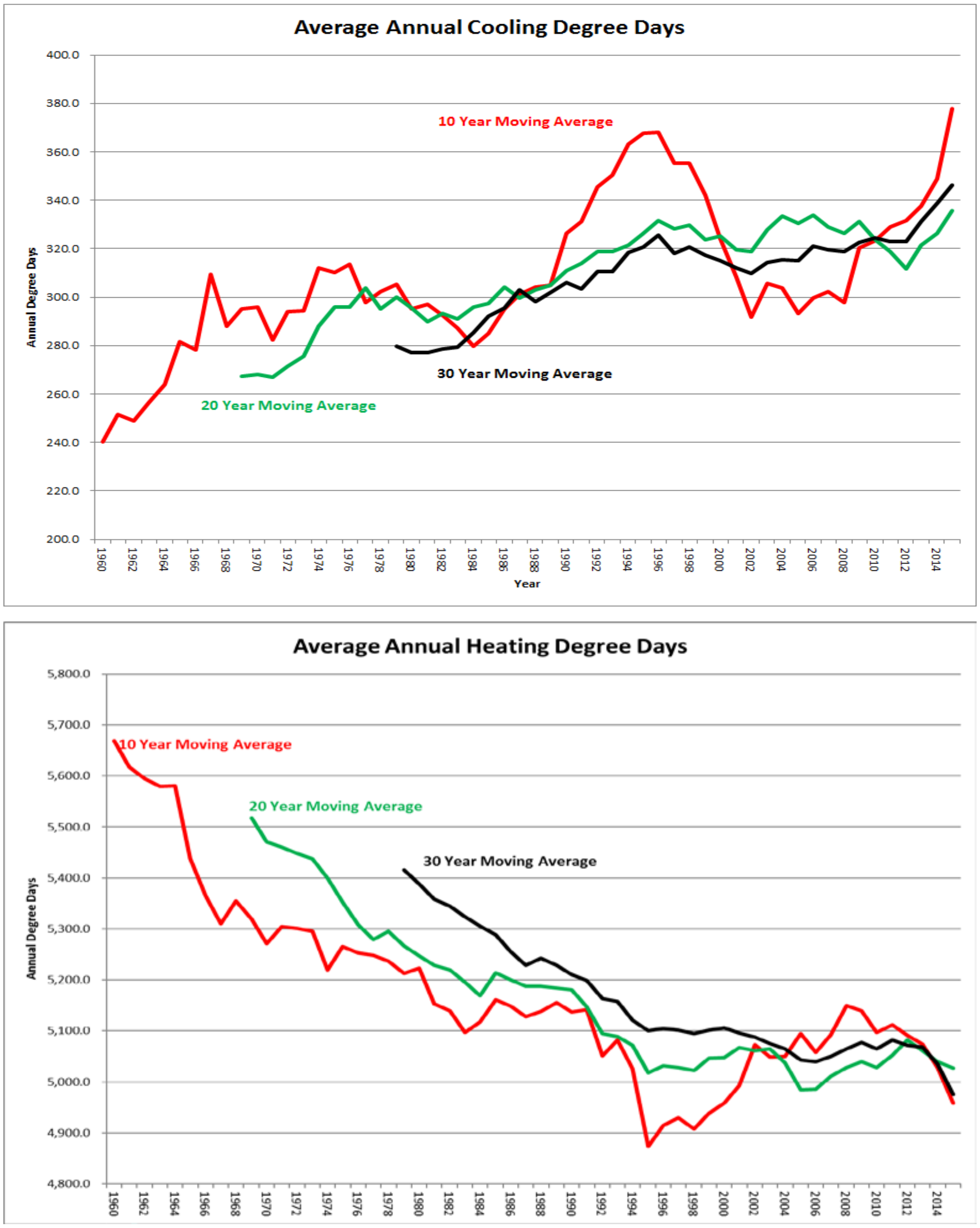
There are several approaches that can be used to create normal or typical weather. A simple way to obtain typical values is to average the weather data from all available years. This method is suitable for obtaining monthly values, such as calendar or billing month degree days, but not for applications in which daily or hourly weather patterns are a factor because it reduces the normal variation between days. Using a simple average eliminates weather variability that could otherwise influence forecasted energy or peak.

Best practices include using, at a minimum, a typical meteorological year (TMY) or, even better, either a rank-and-mean or rank-and-median approach especially for daily or hourly applications. Rank and mean/median can also be used to easily create extreme or mild weather scenarios. These approaches are described as follows:

- The National Renewable Energy Laboratory developed the typical meteorological year (TMY2, where the 2 indicates a refinement over an older but similar method). TMY2 data sets consist of individual representative months from historical weather data from 1961–1990 that have been combined to create a typical year for each weather station. The statistical method used to pick which month is "most representative" takes into account temperature, wind, and solar radiation variables, with the greatest weight given to the solar variables. These data provide complete hourly variables and realistic weather patterns.
- The rank and mean method selects days that accurately reflect the range of hot and cold days in a month. For each month of historical data, this method selects the mean hottest day, then the mean second hottest day, and so on. These mean days are then carefully arranged in a pattern that matches the variation of days throughout the year. This method (and others based on rank) provides typical weather data that are consistent across weather stations near each other. However, while temperatures can be averaged, some other weather variables cannot, so this approach does not readily provide all hourly weather variables.
- The rank and median method is like rank and mean, but it selects the days that are the medians for their rank position. Because these are actual days, all the other hourly weather variables from these days can be used in the weather data set as well. Smoothing techniques can help reduce any discontinuities between days.

In addition to the method used to create the normal or typical weather, it is important to consider the length of the historical time period and whether longer time horizons are truly representative of current conditions. We see many utilities turning to shorter time horizons, such as 10 years, vs. the 30 years that were commonly used in forecasting in the past.

Figure 3-3 Comparison of 10, 20, and 30-Year Moving Average CDD and HDD



Calendarization Methods

Best practice involves estimating models using monthly data. City Light currently calendarizes their bi-monthly billing data into quarterly observations. However, moving to monthly observations would be the preferred approach.

General Goals

One of the key things that the AEG Team identified during its review of the City Light forecasting process was a desire to move away from using the output of the econometric models as given, often referred to as "point forecasting," and toward a more collaborative and probabilistic approach. This new approach would leverage the wealth of data that exists across the company to inform the forecast from more than one perspective. In Table 3-5 below we summarize the key aspects of our review in this area.

Table 3-5 Best Practices and Needs Related to the Overall Forecasting Process

Goal: Move away from "point forecasting" toward collaborative process			
Previous Practice	Use the direct output of the econometric models as the official load forecast.		
Key Best Practices	Triangulate or align a forecast based on best available data. Include scenarios	Compare energy forecasts using different approaches or different sources (i.e., in house end-use and small-area forecasting models, national models such as EIA's Annual Energy Outlook) and validate growth trends	Compare peak forecasts using both a top-down (econometric) and bottom-up (distribution planning) approach to adjust or validate growth trends
Moving toward Best Practices	Develop a collaborative approach to the load forecast that leverages all relevant information across City Light and enhances understanding of forecast uncertainty	Perform a secondary check against the energy forecast that either can or does incorporate trends external to the econometric forecast	Perform a secondary check against the peak forecast based on a bottom up approach
Gap Assessment	70%	80%	70%

BEST PRACTICES

Because in forecasting we know that the forecast will always be wrong, it is important to use as many valid sources of information and approaches to inform the forecast as possible and practical. As we discussed earlier, econometric forecasts cannot account for external forces which might influence energy use for which there is no history in the data such as: new codes and standards, new EE or DR programs, geographic/spatial trends of growth and decline, and new energy use trends such as increasing penetrations of distributed generation, or electric vehicles. These distributed resources not only lack a data history, they also fundamentally change the system load shape itself beyond just monthly peaks and energy. Estimating these changes requires a "bottom-up" approach in addition to traditional econometric modeling. While most utilities still use econometric models as the basis of their forecasts, they also either adjust for or incorporate information to account for changes in consumption that cannot be explained by the econometric model. They do this by looking both internally, to other groups within the organization, and externally to national or regional projections by the EIA, or other sources.

Specifically, we noted that minimal linkage exists between the load forecast and distribution planning. Best practices include much closer integration of these two groups and processes, particularly with respect to peak forecasting. Similarly, collaboration with Customer Energy Solutions and leveraging the end-use models used to develop the CPA studies provides another valuable source of information.

Another aspect of this goal is the need to perform sensitivity analyses and develop scenarios with respect to the load forecast. Not only are utilities looking at multiple sources of information to inform the forecast, but best practices also include analyzing forecast outcomes as assumptions change. Sensitivity analyses are often performed around the following attributes:

- Extreme weather and/or mild weather
- Increased and/or decreased codes and standards
- High electric vehicle (EV) adoption rates
- Scenarios surrounding programmatic EE or DR savings
- Scenarios for rooftop installation of solar panels, grid scale solar, solar/storage combinations and zero net energy scenarios
- Changes in electricity rates

- Economic scenarios
- Other utility-specific attributes, such as increased building in certain areas, or specific large customers entering or leaving the service territory.

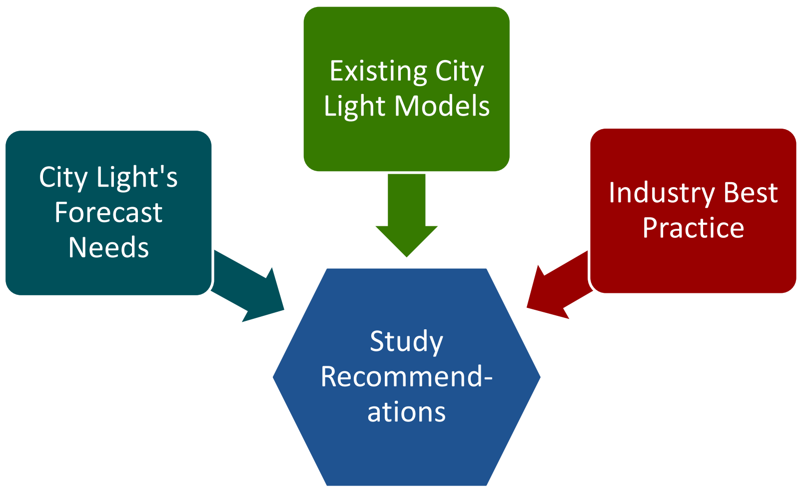
In addition, many utilities also develop scenarios, which include a combination of the above attributes, to construct an alternative view of the future.

4

RECOMMENDATIONS AND NEXT STEPS

In this section, we present our recommendations related to City Light's forecasting processes and specific modeling approaches. The AEG Team developed these recommendations based not only on industry best practices but also on City Light's specific needs related to the forecasts and resources already available at City Light. If implemented, our recommendations will put City Light at the forefront of best practices.

Figure 4-1 Approach to Developing Recommendations



Central to the development of our recommendations was a desire to improve City Light's ability to address a myriad of forecast drivers, including DSRs and C&S. In addition, we want to provide City Light with tools to explain changing trends in energy consumption over recent years, particularly in the residential class, that result in slow, flat, or even negative growth at the per customer level. In order to address these needs, more sophisticated models than traditional econometric models are now being used routinely throughout the industry. There is no one single best approach; instead there are several "best-practice" approaches, each with its own strengths and costs in terms of forecasting power, staff time and possibly software and/or vendor costs:

- Hybrid approaches start with a traditional econometric model and include end-use factors or factors not typically included in econometric models.
- Statistically-adjusted end-use models are econometric models with some end-use content. They can be home grown or purchased. These models do a much better job of incorporating trends in end uses but still struggle with incorporating energy efficiency and emerging DSRs.
- Multiple approaches that may include econometric models, time-series models, SAE models and / or end-use models. Forecast results are compared and final forecast is developed using judgment. For example:
    - The econometric model might be used for the first two years and then the forecast transitions to the end-use model.
    - The results of the most plausible forecasts are averaged.

Because City Light has developed econometric forecasts previously and also has access to end-use and small-area forecasting models, we recommend the third option above. Our recommendations revolve around improving and streamlining the econometric forecast, and incorporating both the end-use and small-area forecasts into the process.

High-level Recommendations

Before presenting our more detailed recommendations, in this subsection we present some high-level recommendations regarding the forecasting process, modeling approaches, and the cross cutting activities identified in previous chapters. We also provide some guidance regarding the time horizon for implementation and present some immediate next steps.

Forecast Process

Below, we describe three key process-related recommendations. In each case, we recommend establishing procedures which, to the best of our knowledge, do not currently exist at City Light. Adopting these processes will provide City Light with a formal structure that can facilitate the development of an official forecast that meets needs across the company. The recommendations are also summarized in Figure 4-2.

- *Use more than one approach to developing the load forecast.* In the past, City Light has relied on its econometric forecast as the primary forecast. During this project, we discovered that City Light is also developing end-use forecasts as part of its CPA process and is using small-area forecasting to support distribution planning. One of the main advantages of including these alternate approaches is that their more "bottom-up" approach facilitates the development of a story about how and why the forecast is changing. These approaches are particularly applicable to City Light because both the end-use forecast and small-area forecasts are already in place.
- *Establish a forecast review committee to vet the forecast*. This small, multidisciplinary group would review key forecast assumptions, as well as the preliminary forecast results. It will also critique the preliminary forecast and provide guidance for refinements. This group should include representatives from key users of the forecast as well as key contributors to the forecast. In addition to acting as a sounding board and QA/QC check, the group can also ensure that the final forecast meets companywide needs.
- *Perform sensitivity analyses.* In addition to developing the official forecast, City Light should undergo a formal process to understand the sensitivity of the forecast to changes in key assumptions. City Light should also consider describing alternative scenarios and assessing the resulting forecasts. These efforts will provide more confidence in the ultimate forecast results.

Figure 4-2 Summary of Forecast Process Recommendations

Use multiple approaches	Establish Forecast Review Committee	Perform probabilistic forecasting and scenario analyses
• Use a variety of methods for energy and peak load forecasts • Compare and contrast forecasts and use judgment to develop "final" forecasts	• Create a small team that reviews the key forecast assumptions and results to: • Guide development of the "final" forecast • Vet the forecast prior to presentation to executives	• Triangulate or align forecasts based on best available data • Identify sensitivity to key forecast drivers • Develop and analyze scenarios

The Energy Forecast

For the energy forecast, we recommend using a three-pronged approach to develop the official forecast. The first, and most important, step is to develop the new econometric model. Detailed recommendations surrounding model development and the timing of relative activities can be found in subsequent sections. The other two pieces of the approach include leveraging the end-use and small-area load forecasting models. Figure 4-3 summarizes our recommendations as they pertain to each piece of the approach.

Figure 4-3 Energy Forecast Recommendations

Develop new econometric model

- Develop a new econometric model, which consists of several rate class level models
- Implement SAE approach and adjust for DSR for major rate classes
- Prepare separate forecasts for large and special customers/groups
- Continue to develop quarterly forecasts for 2017, but transition to monthly in 2018
- Develop a new customer forecast
- Acquire economic forecasts from vendor

Leverage end-use model

- Use model from CPA to develop annual end-use model by rate class
- When possible, use same exogenous variables as econometric models
- Isolate impacts from C&S and DSR and provide to econometric to support SAE appraoch
- Use econometric model results to allocate annual forecast to quarters and months

Leverage small-area forecasting model

- Roll up feeder-level forecast used by Distribution Planning to system level
- Recommend interaction and collaboration among Engineering, CES and Load Forecasting

Developing a new econometric model will allow City Light to both update and streamline their modeling approach by retiring the cumbersome Conway Regional model. This updated model should include robust economic drivers, leverage a new (externally obtained) economic forecast, and be tied to actual meter counts. It should also leverage monthly, rather than quarterly, data to eliminate the current shaping processes, prepare for the onset of AMI and establish better relationships between weather and consumption. As progress is made, regional end-use information can be incorporated into the econometric model to better capture both embedded and programmatic efficiency.

In addition to the econometric model, we recommend leveraging the end-use model and the small area model. Each model will allow City Light to better explain the forecast by telling a story about what is changing in the future. In addition, each model will provide information that can be used to adjust or develop the final load forecast.

- The end-use model develops forecasts by customer segments and end uses / technologies within sectors. This will allow City Light staff to tell a detailed story about anticipated changes in technologies, appliance standards, segment-specific energy use patterns and other factors and how they impact the forecast.
- Similarly, the small area forecast allows City Light to tell a story about where growth is expected to occur and the impacts on feeder-level loads.

The Peak Forecast

Our recommendations related to the peak forecast mirror the three-pronged approach recommended for the energy forecast. This is intentional, as most peak models are tied directly to the energy model by using the predicted energy as an input to the peak demand model. In this way, the new econometric model will do much of the heavy lifting for the peak forecast. The end-use and small-area forecast models provide granularity by end use and geographic location. Our recommendations are summarized in Figure 4-4.

Figure 4-4 Peak Forecast Recommendations

Develop new econometric model

- Forecasted energy captures overall changes in consumption through time, as a result the remaining job of the peak model is to capture changes related to weather and season
- Develop seasonal peak model in 2017
- Develop hourly or daily model in 2018

Use end-use model to obtain end-use breakout

- Using end-use "peak factors" included in the end-use model, City Light can develop implied end-use breakdown of the peak

Leverage small-area forecasting model

- Roll up feeder-level forecast used by Distribution Planning to system level
- Recommend interaction and collaboration among Engineering, CES and Load Forecasting
- Future growth pockets are identified specifically in the small-area model

Cross-cutting Activities

As mentioned in previous chapters, we identified several analyses that cut across forecasting activities. Our recommendations with respect to these activities is as follows:

- **Normal weather.** Move from a simple average for defining normal weather to a rank-and-median approach. Also, use a backcasting (aka out-of-sample testing) method to determine the appropriate number of years of weather data to include in the approach. The objective is to identify the number of years of historical data to use to compute normal degree days. One should test different levels to identify the one that provides the best estimate for the next year. Accuracy can be evaluated based upon mean percent error (MPE) and mean absolute percent error (MAPE).
- **Weather normalization.** Use weather-related coefficients from the forecasting models to normalize historical sales. Switching to this approach will eliminate the additional sources of variation being introduced by weather normalizing using two different methods, one for historical sales, and one for future sales.
- **Calendarization.** Move from quarterly load forecasts to monthly load forecasts as soon as practical. One approach that could help with this shift is to develop regression models relating average daily energy use and degree days for each rate class and billing cycle. These can be used to allocate bi-monthly meter readings to monthly sales estimates as well as estimate calendar level sales.
- **Develop class level load shapes.** There are several options for doing this:
    - Leverage existing (albeit old) load research data. While the sample itself is quite old, data being collected on that sample exists through 2012. Post stratification could be used to make the old sample more representative of the current population, and class level load shapes using the 2012 load research data could be developed of the post-stratified sample.

- Use feeder-level forecasts from small-area model. By looking at feeder load shapes that are known to be primarily residential, commercial, or industrial, City Light could develop a pretty good proxy for class level load research data. Weighting based on existing customers could further improve the representativeness of the shapes.
- Borrow load research data from nearby utilities. This may be a viable option either as a replacement for internal analysis, or to use as a cross check to internal analysis.
- Use MV-90 data for large customers. City Light has access to interval data for its largest customers. This data can be collected and analyzed to provide insights into how the largest customers use energy, and contribute to overall system energy and peak.

- **Sensitivity analyses.** Using the near-final forecast models, we recommend conducting sensitivity analyses around key variables, including:
  - Extreme weather
  - Economic variables
  - DSRs and electric vehicles
  - Codes and standards
  - Levels of energy-efficiency and demand response activity (e.g., participation, spending)

TIME HORIZON

It is important to recognize that it will take a few years to implement these recommended changes and to achieve best practices. Forecasting is an ongoing learning process, where continuous improvement is achieved through experience. This journey will require the application of judgment at every step so it will be important to review, discuss and make course corrections. The Forecast Review Committee will play a vital role.

NEXT STEPS

City Light can continue to enhance its forecasting process and approaches immediately. We recommend the following steps:

- **Examine internal resources and develop a system of accountability**. In the context of the above recommendations, examine internal resources and make preliminary assignments. This includes identifying the key forecasting staff, as well as other supporting staff. Also, determine the composition of the Forecast Review Committee and begin to hold meetings to implement steps below.
- **Determine which recommendations to tackle.** We have provided numerous recommendations and it is likely that there are too many to tackle at once. However, we believe that City Light has the internal resources to move forward with enhancements to the econometric model (described below) with only light support, possibly, from a consultant who could provide guidance.
- **Develop a formal plan to move forward.** The plan should include a detailed path forward for each of the recommendations City Light plans to tackle. This will involve the following steps:
  - Prioritize recommendations
  - Assign responsibilities
  - Lay out a timeline that spans the various business units
  - Develop an approach to track progress and maintain accountability

While not absolutely necessary, we recommend City Light staff engage with a consultant to lead the development of the plan with City Light input. This would allow City Light staff to focus on other responsibilities and possibly get started on the econometric forecast piece, which stands alone, while the plan to tackle other activities is fully fleshed out.

SPECIFIC RECOMMENDATIONS FOR THE ECONOMETRIC ENERGY MODEL

Below we present our specific recommendations for aligning City Light's econometric approach with best practices. The recommendations are presented in phases, acknowledging that it would not be reasonable for all improvements to be made concurrently. We prioritized the most important recommendations over what we believe to be less important improvements.

THE ECONOMETRIC MODEL – PHASE I

During this first phase, City Light will move away from the Conway model and develop a new econometric energy forecasting model. This involves several steps, described below.

Step 1. Select a Source for Regional Economic Data Inputs and Retire Conway's Regional Economic Model

We recommend that City Light select one of the following input data options to use moving forward.

- Purchase regional economic forecast data from a vendor, such as Global Insights or Moody's. The data should be county level and include high and low economic growth scenarios.

Under each scenario, we would also recommend cross checking the new regional variables with the most recent Conway output, keeping in mind that changes in input forecasts will lead to changes in output that should be explained preemptively. EIA economic projections can also be obtained and compared to the new input data as an additional check.

Step 2a. Update the Econometric Models

Updating the econometric models in phase one is simply about building a new traditional econometric model for each customer class. We recommend waiting to incorporate end-use information until a traditional econometric model has been built and tested.

- The first step in updating the models is to determine the specification of the dependent variables. We recommend starting where the Conway model left off, specifying dependent variables in the same way, i.e. use-per-customer vs. total retail sales for residential customers. However, in some cases it may be appropriate to change the way a dependent variable is specified, so we recommend that City Light remain flexible.
- Next, for each customer class select a potential pool of explanatory, or independent, variables. We recommend exploring potential variables in four broad categories including: economic, weather, price, and time series. Not all classes will have the same economic drivers or weather drivers.
  - Economic variables might include:
    - Residential – median household or real per capita income, real regional GDP, CPI
    - Commercial and Industrial – employment, manufacturing output, industrial output, real regional GDP, PPI
  - Weather variables should be developed to capture the relationships between each class and actual weather. Often, visual representations of weather response, such as a scatter plot of per customer usage vs. average daily temperature, can help determine the appropriate bases for CDDs and HDDs, and determine if multiple CDD and HDD variables should be included.
  - Price variables should be developed to eliminate the identification problem that arises under inverted block rates. Because price drives consumption, and under an inverted block rate schedule consumption also drives price, alternative price specifications should be explored. The simplest solution is to include the price of a single tier to capture the overall changes in price across time.[4]

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[4] The paper "Elasticity of Demand in Econometric Models" embedded in Appendix A, describes the issues in more detail and includes a detailed bibliography of the topic as it exists in the econometric literature.

- Time series variables can be included if indicated, i.e. to control for autocorrelation that is not explained by other variables; however, we caution against the inclusion of too many time series variables, and encourage City Light to rely on economic, price, and weather variables to explain most of the variation in the models.

- After developing a pool of dependent and independent variables, hypothesize various functional forms to test. Most econometric models still use a log-log functional form to make the interpretation of variables easy, but log-linear, first differencing, distributed lags, and other forms could be considered.
- Finally develop a robust model testing and validation approach to select the best econometric model. This approach should include: judgement, goodness of fit, out of sample testing, and MAPEs comparisons. Each of these are discussed in the best practices section above.

Step 2b. Develop New Customer Forecasts

Concurrent with the development of the new econometric models City Light will need to develop customer forecasts to replace the customer forecasts coming from the Conway model. In general, the steps to creating new customer forecasts are similar to those for developing the new econometric models. A couple of specific recommendations include:

- The biggest drivers of customer forecasts tend to be variables such as population and perhaps new housing permits for residential; and square footage and/or employment for commercial. Again, time series variables should be included with caution. Using a first difference model can be a good alternative for controlling autocorrelation issues.
- Customer forecasts should be based on meter counts, not total population.
- The manufacturing sector may be broken down to NAICS groups or aggregations that capture the larger energy users (whether industrial or commercial).

Step 3. Incorporate DSR

Once City Light has developed some energy and customer count forecasts that they are comfortable with, the next step is to account for the impacts of DSR in order to produce both a before and after EE projection. Initially that adjustment for EE can be done using simple approaches which are described briefly below. More detail on incorporating the impact of DSR into forecasts can be found in Appendix A.[5]

- First, compile the estimates of historical and forecasted EE impacts from CES into a time series that aligns with the class-level energy forecasts. Then proceed with one of the two options below:
  - **Option 1.** Include historical estimates of EE as a separate variable in each class sales forecasting model.
    - The coefficient should be negative and indicates the portion of utility EE impacts not captured by the econometric model.
    - This coefficient is used to finalize the EE impacts to be subtracted from the forecast.
  - **Option 2**. Prepare a frozen efficiency forecast. This can be performed in two ways.
    - Sub-option 1. Add the historical EE impacts to the kWh sales. Estimate the econometric models and prepare a forecast in the normal manner. Subtract the full utility projected EE impacts (last year actual is added to the projected new impacts) from the frozen efficiency forecast.
    - Sub-option 2. If the price of electricity is projected to increase in real terms, freeze the real price and prepare a forecast with no increase in the price. The difference between the frozen price forecast and the before EE forecast represents EE impacts already captured

[5] The paper "Integrating DSM into Energy Forecast: Issues and Potential Solutions" explores the two methods mentioned in much greater detail.

in the load forecast due to price elasticity. The projected future EE impacts are reduced by this price elasticity impact.

- Regardless of the approach, City Light should leverage information from the end-use model or most recent CPA to cross-validate adjustments and potentially adjust further for codes and standards

Years of Historical Data

- In developing forecasting models, there is often concern about the amount of historical data that should be employed.
- Generally, one should use as much data as is available, but the resulting model should be checked for coefficient stability. This check can be performed using a Chow Test or visually checking the stability of the model coefficients using different historical periods.

The Econometric Model Phase II

In the second phase of econometric model enhancements, we recommend beginning to incorporate end-use information into the new econometric models, transforming them from a traditional econometric model to a hybrid model.

Step 1. Expand the use of CPA Data

The first step is to expand the scope of the data sources from the CPA to include historical appliance saturations and efficiencies, and expected trends in codes and standards. If it has not already been included, begin including the historical utility sponsored load impacts as variables in the econometric model to identify what portion of the impacts are captured by the econometric model.

Step 2. Determine how to Move Forward with the Hybrid Model

Once the data has been collected and organized City Light will need to determine how to move forward in developing a hybrid, or SAE model.

- One option is to select a firm to develop the model for City Light such as Itron.
- The second option is to develop the model internally.

We recommend developing the model internally, at least at first. The main reason for this recommendation is that City Light staff will be able to learn a lot about how customer energy use and appliance saturations and efficiencies are driving consumption through the development of the model.

Step 3. Develop Hybrid Model Variables and Specifications.

- Fist, develop variables that can be included in the econometric model. These variables are often developed as indexes that relate to cooling and heating efficiencies. The sample specifications below provide a few examples of how difference variables can be incorporated into a traditional econometric model.
- A typical residential model specification might be as follows:
    - *Res kWh per customer = b(0) + b(1)x(Appliance Stock)x(Real Income) + b(2)x(Appliance Stock)x(Real Electric Price) + b(3)x(Heating Deg Days)x(Heating Equip Efficiency)x(Shell Integrity) + b(4)x(Cooling Deg Days)x(Cooling Equip Efficiency)x(Shell Integrity) + e*
- A typical commercial model specification might be:
    - *Total Commercial kWh = c(0) + c(1)x(Commercial Employment)*(Efficiency Trend) + c(2)x(Real Electricity Price)+ c(3)x(Heating Deg Days)x(Heating Equip Efficiency)x(Shell Integrity) + c(4)x(Cooling Deg Days)x(Cooling Equip Efficiency)x(Shell Integrity) + e*
- Finally, it will be important to compare econometric models to available bottom-up models.
    - Comparison with the CPA model at each step can help ensure that, as the projections of the econometric model are adjusted (by incorporating end-use information), those changes are reasonable when compared with the same effects in the end-use model. For example, the effect

of C&S is explicitly estimated as part of the CPA model. If these same effects are simulated in the econometric model the resulting changes should be compared to the end-use model estimate for reasonableness.

- o Forecasting results which are reconciled to the system forecasts are fundamentally important for improving the accuracy of power flow modeling results performed within Engineering. Load forecasts per small area from LoadSEER are imported into Cyme or Synergi power flow models to obtain much more accurate power flow analysis leading to improved interconnection modeling of DSRs, voltage, protection and other power planning needs beyond current system forecasting requirements.

Rate Class Shifts

An additional activity that could be undertaken as part of the Phase II model enhancements would be to try to get a better understanding of shifts across rate classes amongst the largest energy users. There are a couple possible analyses that could be used to attempt to tease out this information.

- Methods can be employed that rely on combinations of two types of models: (1) econometric models based on shares of customers using logistic functions and (2) econometric energy sales forecast models.
- Alternatively, one could develop forecast models for each customer. Then, changes in the size of customers can be projected to understand when there would be a move to a different rate class.

However, regardless of approach, the need to project these movements across rate classes can create more complexity than it may be worth. If the need to understand this links to the revenue budgeting process, typical practice involves allocating customer class sales forecasts to the rate classes. The economic data aligns better with the customer class structure than the rate class. The value of this economic linkage outweighs the benefit and complexity associated with forecasting movement across rate classes.

NEXT STEPS

As discussed above, the next steps will involve first determining which of the recommendations to tackle, and then developing a plan to move forward. We have laid out a phased approach here, but City Light should develop their plan based on actual available resources and interval priorities. It is also important to keep in mind that creating forecasts is a constant learning process where one gains insight from the review of past forecast accuracy. In addition, it requires application of judgment at every step in the process.

SPECIFIC RECOMMENDATIONS FOR THE ECONOMETRIC PEAK MODEL

As mentioned above, many of the recommendations for the energy model also hold true for the peak model and similar steps should be taken during model development. The econometric model should relate system peak loads to the total energy as well as key weather concepts, which will require an analysis of typical peak weather conditions for each month and season. This analysis can also be used to develop alternate peak forecasts under different weather probabilities. The forecast of energy also needs to be used to create an 8,760-hour forecast that matches the energy and the projected monthly peaks.

We also recommend a two-phased approach to developing the peak model with the individual steps in each phase being very similar, varying the time interval on which the model is built.

- In the first phase, it is likely to be easier to focus only on seasonal peaks, developing two models to predict the summer and winter peak MW.
- In the second phase, focus should shift to building monthly, daily, or even hourly peak models. In these models the dependent and independent variables are similar to those in the seasonal peak models, but the granularity of the variables increases.

Peak Model Steps

- Again, the first step is to develop the dependent variable. This may be monthly or daily system peak, or it could even be hourly system load. Daily and hourly system load is being collected by the engineering team.
- Explanatory variables should include the weather normalized output of the energy forecast. Because the system level energy forecast already includes overall energy growth, the effect of economic drivers, and DSR, using it as an explanatory variable in the peak model is a handy way to incorporate all those drivers with a single variable.
- After including the energy forecast output, weather is the key remaining significant source of variation in system load. When developing weather variables it is important to:
  - Examine the relationship between loads and weather; graphical approaches are generally sufficient. Look for changes in the slope at different temperature levels and look for relationships with variables other than temperature. Example models might include:
    - *Winter Peak MW = f(Weather normal energy for the day, month, or season; minimum morning or evening temperature; lagged minimum temperature day before; wind speed; time of day; day of week)*
    - *Summer Peak MW = f(Weather normal energy for the day, month or season; maximum afternoon temperature; lagged maximum temperature day before; humidity; day of week)*
- All model development should involve a similar model validation process to the one described for the energy forecasting models above. Judgement, goodness of fit, out-of-sample testing (or backcasting) and MAPE comparisons are all excellent tools.

Next Steps

As discussed above, next steps will involve first determining which of the recommendations to tackle, and then developing a plan to move forward.

Leveraging The End-use Model

City Light's Customer Energy Solutions group performs a CPA study every two years. The consultants who have performed these studies for City Light, Cadmus and AEG, have each performed the analyses using a modeling framework grounded in end-use forecasting. This means that City Light has not one, but two, end-use forecasting models populated with data and ready to use to develop an alternative forecast.

A Standalone End-use Forecast

End-use models use a bottom-up, deterministic approach to develop a forecast of energy use by sector, customer segment, end-use and technology. An end-use model can capture shifts (not just trends) in economic variables. It explicitly captures the effects of building codes and appliance standards. The current generation of end-use models also explicitly models effects of DSRs, which is their primary purpose for the CPA study. Finally, and very importantly, end-use models provide the ability and information to tell a story about what is happening in the forecast.

Although City Light already has end-use models, they were developed expressly for the CPA studies by consultants. So, they have a lot of detail that might be too extensive for internal staff to manage. As a result, we recommend a transition or at least a translation before simply using the models to develop a load forecast. Some of the things that should be reviewed closely and discussed are:

- Does the definition of sectors within the end-use model align with the sector definitions used for the econometric model? Typically, econometric models develop forecasts by rate or customer class. The end-use models, in contrast, may focus on building types. So, care must be taken in comparing the sectors. To the extent that the sector definitions are different and there is a desire to align them, assess ways to make this happen with the least amount of effort.
- Is the level of disaggregation within the end-use models appropriate for load forecasting purposes or would it be helpful to streamline the segmentation to make it more manageable? The good news

is that all the detailed data have been developed so it's much easier than starting from scratch. However, a fewer number of segments has its advantages as well.

- Does the model need to be updated to be ready for the forecasting process? For example, given the rich history of end-use data in the region, it might be desirable to calibrate the first year of the model to a base year five to ten years in the past and then to run the model to predict actual sales. This is what Southern Company does with their end-use models and it bolsters their confidence in the results.
- The CPA models provide estimates of "potential." It may, or may not, be advisable to revisit the CPA estimates of achievable potential to confirm that these are truly the best forecast. This is not to suggest that anything is awry with the estimates, just that the perspective is now different. Rather than estimating the savings from DSRs, which is the delta between a baseline forecast and a potentials forecast, the focus is now on the absolute value of expected sales in the future.
- The modeling of appliance standards and building codes should also be revisited from the perspective of the forecaster.
- Naturally-occurring conservation. The end-use models are also able to model naturally occurring conservation, which we are seeing now with LED lamps and could experience in the future with other disruptive technologies.

In addition to providing alternative load forecasts that can be compared and contrasted with the econometric and small area forecasts, the end-use framework lends itself to more strategic analysis. Because they are simulation models, City Light can explore a variety of emerging technologies: solar, electric vehicles, battery storage, solar with batteries, etc. This capability will be helpful for scenario analysis.

Supporting an SAE Model with End-Use Data

End-use models can provide historical information about appliance saturations, impacts from codes and standards and even historical estimates of DSRs. If and when City Light decides to develop an SAE model, it would be appropriate to evaluate what data the end-use models could provide to support this. Other sources of end-use data for the SAE approach would be the regional surveys (RBSA and CBSA, which have a long history) and regional data from EIA's Annual Energy Outlook.

Next Steps

As a first step, City Light should choose which end-use model they want to use going forward. Although City Light is working with Cadmus on the current CPA, it could choose another model for forecast development. In the longer term, the end-use model could provide data and a baseline forecast to the CPA rather than the other way around. Once a model is selected, it would be reviewed to determine what, if any, changes might be appropriate to make. Certainly, it would be possible to use the model as is at the outset and to refine it over time. This would be part of the planning process we have recommended for the forecasting process overall.

Incorporating the Small-Area Load forecast

The Load Forecast and Engineering Group should meet to examine and compare coincident and non-coincident peak projections. The Engineering Group's small area projections can be aggregated to the system level for comparison to the Load Forecast's projection for the system peak. This can provide additional insight on the reasonableness of the system level forecast. Care must be taken to make sure the comparisons are on a similar basis regarding assumptions about economic growth, impacts of C&S, and projected penetration of energy efficiency. In addition, examining the differences between the coincident and non-coincident peak loads can provide a further check on forecast reasonableness.

A

APPENDIX A

Integrating DSM
into Forecasts (GEP-

Elasticity of
Demand _LAMS 006_

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