This Integrated Resource Plan represents a snapshot of an ongoing resource planning process using current business assumptions. The planning process is constantly evolving and may be revised as conditions change and as new information becomes available. Before embarking on any final strategic decisions or physical actions, the Companies will continue to evaluate alternatives for providing reliable energy while complying with all regulations in a least-cost manner. Such decisions or actions will be supported by specific analyses and will be subject to the appropriate regulatory approval processes.

US Economy: The 30-Year Focus

First-quarter 2018

CONFIDENTIAL INFORMATION REDACTED

Electric Sales & Demand Forecast Process

PPL companies

Sales Analysis & Forecasting
September 2018

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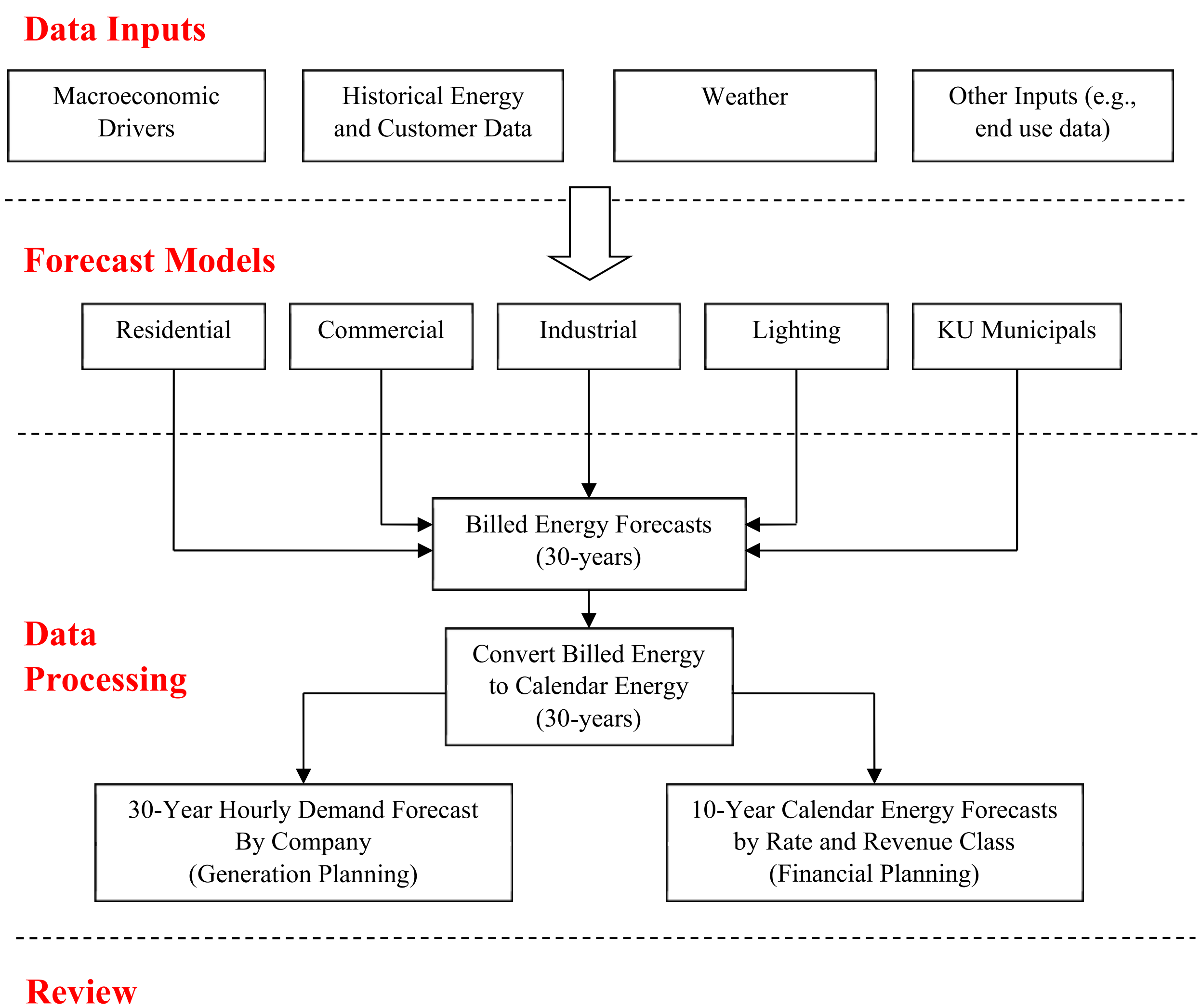
1. Introduction

The Sales Analysis & Forecasting group develops the sales and demand forecasts for Louisville Gas and Electric Company ("LG&E") and Kentucky Utilities Company ("KU") (collectively, "the Companies"). These forecasts serve as foundational inputs for the Generation Planning department's Generation Forecast and the Financial Planning department's Business Plan. This document summarizes the processes used to produce the sales and demand forecasts. The forecast process can be divided into four parts (see Figure 1).

Figure 1 – Load Forecasting Process Diagram



The first part of the forecast process involves gathering and processing input data. The following are key inputs to the forecast process:

- Macroeconomic data
- Historical energy and customer data
- Weather data (20-year normal degree-day series)

- Other data, including billing portion forecasts, class-level electricity price series, and residential appliance shares and efficiencies.

The input data is used to specify a number of forecast models for each company. Generally, each model is used to forecast energy sales for a group of customers with homogeneous energy-use patterns within the same, or similar, tariff rates.

Most of the forecast models produce monthly energy forecasts on a billed basis.[1] In the third part of the forecast process, the billed energy forecasts are allocated to calendar months and then to rate and revenue classes for the Financial Planning department.[2] In addition, a forecast of hourly energy requirements is developed for the Generation Planning department.[3]

The final part of the forecast process includes validating and documenting the forecast results. To ensure results are reasonable, the new forecast is compared to (i) the previous forecast and (ii) weather-normalized actual sales for the comparable period in prior years.

Each of these steps and the software tools used to produce the forecast are discussed in more detail in the following sections.

2. Software Tools

The following software packages are used in the forecast process:

- SAS, R
- Metrix ND (Itron)
- Microsoft Office: Excel, PowerPoint, Access
- @Risk

SAS, R, and Metrix ND are used to specify forecast models. The Microsoft Office tools are primarily used for analysis and presentations. Finally, @Risk is used to assess the reasonableness of the forecast.

[1] All customers are assigned to one of 20 billing portions. A billing portion determines what time of the month a customer's meter is read. Because the beginning and end of most billing portions do not coincide with the beginning and end of calendar months, most customers' monthly bills will include energy that was consumed in multiple calendar months. The energy on customers' bills is referred to as "billed" energy.

[2] Rate class defines the tariff assigned to each customer meter while Revenue class is a higher level grouping; a Revenue class consists of one or more rate classes.

[3] Energy requirements are equal to sales plus transmission and distribution losses.

3. Input Data

Table 1 provides a summary of data inputs. The sections that follow describe key processes used to prepare the data for use in the forecast process.

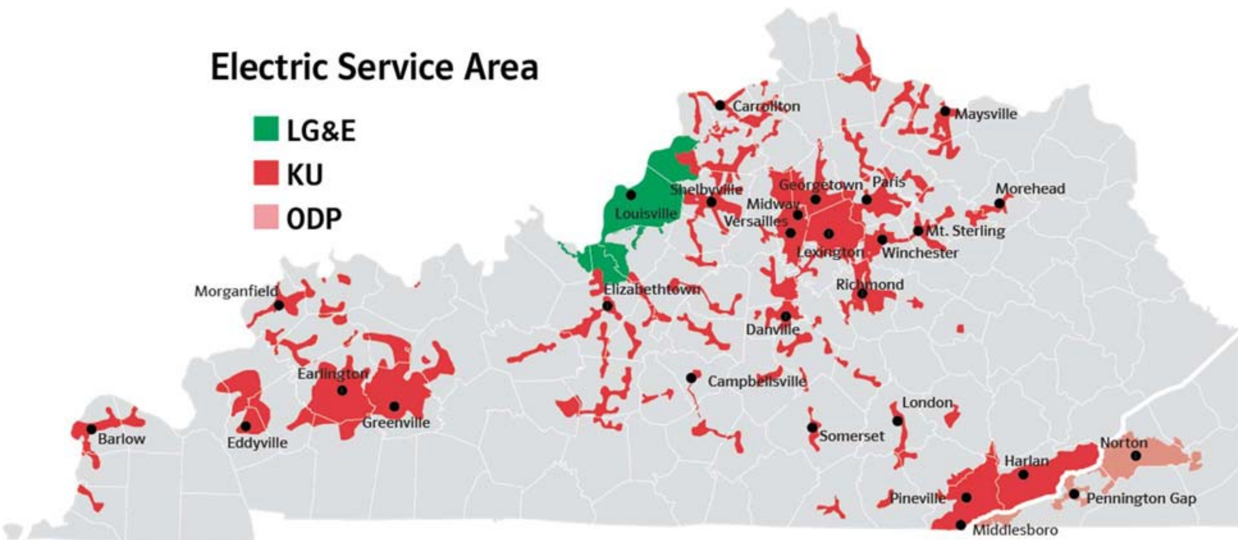
Table 1 – Summary of Forecast Data Inputs

Data	***Source***	***Format***
State Macroeconomic and Demographic Drivers (e.g., Employment, Wages, Households, Population)	IHS Markit, Kentucky Data Center	Annual or Quarterly by County – History and Forecast
National Macroeconomic Drivers	IHS Markit	Annual or Quarterly – History and Forecast
Personal Income	IHS Markit	Annual by County
Weather	National Oceanic and Atmospheric Administration ("NOAA")	Daily HDD/CDD Data and Hourly Solar Irradiance by Weather Station – History
Billing Portion Schedule	Revenue Accounting	Monthly Collection Dates – History and Forecast
Appliance Saturations/Efficiencies	Energy Information Administration ("EIA"), 2010 LG&E/KU Residential Customer Survey	Annual – History and Forecast
Structural Variables (e.g., dwelling size, age, and type)	EIA, 2010 LG&E/KU Residential Customer Survey	Annual – History and Forecast
Elasticities of Demand	EIA / Historical Trend	Annual – History
Billed Sales History	CCS Billing System	Monthly by Service Territory and Rate Group
Number of Customers History	CCS Billing System	Monthly by Service Territory and Rate Group
Energy Requirements History	Energy Management System ("EMS")	Hourly Energy Requirements by Company
Annual Loss Factors	2012 Loss Factor Study (by Management Applications Consulting, Inc.)	Annual Average Loss Factors by Company
Solar Installations	CCS Billing System, National Renewable Energy Laboratory ("NREL")	Net Metering/Qualifying Facility Customers, Solar Net Metering Customer Forecast
Electric Vehicles	IHS Markit, Bloomberg New Energy Finance ("BNEF"), NREL, Electric Power Research Institute ("EPRI")	Monthly Cars on Road (historical), Monthly Cars on Road (forecast), Hourly EV Charging Shapes

3.1 Service Territory-Specific Macroeconomic Forecasts

IHS Markit produces forecasts of macroeconomic drivers by county. With an understanding of the counties that make up each service territory, this data can be used to create service territory-specific forecasts of macroeconomic drivers. Figure 2 contains a map of the LG&E, KU, and ODP electric service territories.

Figure 2 – LG&E, KU, and ODP Service Territory Map



LG&E serves customers in Louisville and 16 surrounding counties. KU serves customers in 77 Kentucky counties and five counties in Virginia, where KU operates under the name Old Dominion Power Company ("ODP"). For the purposes of this document, the area served by KU in Kentucky is called the KU service territory; the area served by KU in Virginia is called the ODP service territory. Service territory-specific macroeconomic forecasts are created by aggregating the applicable county-specific forecasts for the counties in the LG&E, KU, and ODP service territories.

3.2 Processing of Weather Data

Weather is a key explanatory variable in the electric forecast models. The weather dataset from NOAA's National Climatic Data Center ("NCDC") contains temperature (maximum, minimum, and average), heating degree days ("HDD"), and cooling degree days ("CDD") for each day and weather station over the past 20+ years. This data is used to create (a) a historical weather series by billing month, (b) a forecast of "normal" weather by billing month, and (c) a forecast of "normal" daily weather.[4] Each of these processes is summarized below.

[4] "Normal" weather is defined as the average weather over a 20-year historical period. The Companies do not attempt to forecast any trends in weather.

3.2.1 Historical Weather by Billing Month

The process used to create the historical weather series by billing month consists of the following steps:

1. Using the historical daily weather data from the NCDC, sum the HDD and CDD values by billing portion.[5] Each historical billing month consists of 20 portions. The Companies' historical meter reading schedule contains the beginning and ending date for each billing portion.
2. Average the billing portion total HDDs and CDDs by billing month.

3.2.2 Normal Weather Forecast by Billing Month

The process used to produce the forecast of normal weather by billing month includes the production of a daily forecast of normal weather. The process used to develop the daily forecast (summarized below in Steps 2-5) is consistent with the process used by the NCDC to create its daily normal weather forecast.[6] The following steps are used to create the forecast of normal weather by billing month:

1. Compute the forecast of normal monthly weather by *calendar* month by averaging monthly degree-day values over the period of history upon which the normal forecast is based. The normal weather forecast is based on the most recent 20-year historical period. Therefore, the normal HDD value for January is the average of the 20 January HDD values in this period.
2. Compute "unsmoothed" daily normal weather values by averaging temperature, HDDs, and CDDs by calendar day. The unsmoothed normal temperature for January 1, for example, is computed as the average of the 20 January 1 temperatures in the historical period. This process excludes February 29.
3. Smooth the daily values using a 30-day moving average centered on the desired day. The "smoothed" normal temperature for January 1, for example, is computed as the average of the unsmoothed daily normal temperatures between December 16 and January 15.
4. Manually adjust the integer values in Step 3 so that the following criteria are met:
    a. The monthly average temperature – computed by averaging the daily temperatures by month and rounding to the nearest integer – should match the normal monthly temperatures in Step 1.
    b. The sum of the daily HDDs and CDDs by month should match the normal monthly HDDs and CDDs in Step 1.
    c. The daily temperatures and CDDs should be monotonically increasing from winter to summer and monotonically decreasing from summer to winter. The daily HDD series should follow a reverse trend.

    These criteria ensure the daily normal series is consistent with the monthly normal series.
5. The Companies' forecasted meter reading schedule contains the beginning and ending date for each billing portion through the end of the forecast period. In this step, sum the HDD

[5] Weather data in the electric forecast is taken from the weather stations at the Bowman Field Airport in Louisville, Bluegrass Field Airport in Lexington, and Tri-Cities Airport in Tennessee.

[6] The NCDC derives daily normal values by applying a cubic spline to a specially prepared series of the monthly normal values.

and CDD values by billing portion. Use the February 28 weather data as a proxy for February 29 when billing portions include leap days.

6. Average the billing portion totals by billing month.

4. Forecast Models

LG&E and KU's electricity sales forecasts are developed through econometric modeling of energy sales by rate class, but also incorporate specific intelligence on the prospective energy requirements of the utilities' largest customers. Econometric modeling captures the (observed) statistical relationship between energy consumption – the dependent variable – and one or more independent explanatory variables such as the number of households or the level of economic activity in the service territory. Forecasts of electricity sales are then derived from a projection of the independent variable(s).

This widely-accepted approach can readily accommodate the influences of national, regional and local (service territory) drivers of electricity sales. This approach may be applied to forecast the number of customers, energy sales, or use-per-customer. The statistical relationships will vary depending upon the jurisdiction being modeled and the class of service.

The LG&E sales forecast comprises one jurisdiction: Kentucky-retail. The KU sales forecast comprises three jurisdictions: Kentucky-retail, Virginia-retail, and FERC-wholesale.[7] Within the retail jurisdictions, the forecast typically distinguishes several classes of customers including residential, commercial, public authority, and industrial.

The econometric models used to produce the forecast pass two critical tests. First, the explanatory variables of the models must be theoretically appropriate and widely used in electricity sales forecasting. Second, the inclusion of these explanatory variables must produce statistically-significant results that lead to an intuitively reasonable forecast. In other words, the models must be theoretically and empirically robust to explain the historical behavior of the Companies' customers. These forecast models are discussed in detail in the following sections.

4.1 Residential Forecasts

The Companies develop a residential forecast for each service territory. For the KU and LG&E service territories, the residential forecast includes all customers on the Residential Service ("RS"), Residential Time of Day ("RTOD"), and Volunteer Fire Department ("VFD") rate schedules. The ODP Residential forecast includes all customers on the RS rate schedule.[8] Residential sales are forecasted for each service territory as the product of a customer forecast and a use-per-customer forecast.

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[7] For the purposes of this document, the KU service territory comprises KU's Kentucky-retail and FERC-wholesale jurisdictions. The ODP service territory comprises the Virginia-retail jurisdiction.

[8] KU's Virginia-retail jurisdiction does not have RTOD or VFD rate schedules.

4.1.1 Residential Customer Forecasts

The number of residential customers is forecasted by service territory as a function of the number of forecasted households or forecasted population in the service territory. Household and population data by county and Metropolitan Statistical Area ("MSA") is available from IHS Markit and the Kentucky Data Center.

4.1.2 Residential Use-per-Customer Forecasts

Average use-per-customer is forecast using a Statistically-Adjusted End-Use ("SAE") Model. The SAE model combines econometric modeling with traditional end-use modeling. The SAE approach defines energy use as a function of energy used by heating equipment, cooling equipment, and other equipment.

Use-per-Customer = a1*XHeat + a2*XCool + a3*XOther

Inputs for developing the heating, cooling, and other variables include weather (heating and cooling degree days), appliance saturations, efficiencies, and economic and demographic variables such as income, population, members per household and electricity prices. Once the historical profile of these explanatory variables has been established, a regression model is specified to identify the statistical relationship between changes in these variables and changes in the dependent variable, use-per-customer. A more detailed discussion of each of these components and the methodology used to develop them is contained in Appendix A.

4.2 Commercial and Industrial Forecasts

Table 2 lists the rate schedules included in the commercial and industrial forecasts. A relatively small number of the Companies' largest industrial customers account for a significant portion of total industrial sales, and any expansion or reduction in operations by these customers can significantly impact the Companies' load forecast. As a result, sales to these customers are forecast based on information obtained through direct discussions with these customers. These regular communications allow the Companies to directly adjust sales expectations given the first-hand knowledge of the utilization outlook for these companies. The following sections summarize the Companies' commercial and industrial forecasts.

Table 2: Commercial and Industrial Rate Schedules

Service Territory	Rate Schedules
LG&E	General Service (“GS”), Power Service (“PS”), Retail Transmission Service (“RTS”), Time-of-Day Primary Service (“TODP”), Time-of-Day Secondary Service (“TODS”)
KU	All-Electric School (“AES”), Fluctuating Load Service (“FLS”), GS, PS, RTS, TODP, TODS
ODP	GS, PS, RTS, TODP, TODS, Water Pumping Service (“M”)

4.2.1 General Service Forecasts

The general service forecasts include all customers on the GS rate schedule. For each service territory, the GS sales forecast employs an SAE model similar to the model used to forecast residential use-per-customer, and defines energy use as a function of energy used by heating equipment, cooling equipment, and other equipment as well as binary variables to account for anomalies in the historical data. A more detailed discussion of this model is included in Appendix B.

4.2.2 KU Secondary Forecast

The KU Secondary forecast includes all customers who receive secondary service on the PS rate schedule and all customers on the TODS rate schedule. Sales to these customers are modeled as a function of heating and cooling degree days, cooling efficiencies, and binary variables which account for anomalies in the historical data.

4.2.3 KU All-Electric School Forecast

The KU All-Electric School forecast includes all customers on the AES rate schedule. Sales to these customers are modeled as a function of the number of KU households, weather, and binary variables to account for anomalies in the historical data.

4.2.4 LG&E Secondary Forecast

The LG&E Secondary forecast includes all customers who receive secondary service on the PS rate schedule and all customers on the TODS rate schedule. Sales to these customers are modeled as a function of weather, specific economic drivers, the number of customers, and other binary variables to account for anomalies in the historical data.

4.2.5 LG&E Special Contract Forecast

LG&E has one customer that is served under a special contract. This customer’s consumption is forecasted separately based on information obtained through direct discussions with the customer.

4.2.6 ODP Secondary Forecast

The ODP Secondary forecast includes all customers who receive secondary service on the PS rate schedule and all customers on the TODS rate schedule. Sales to these customers are modeled as a function of weather, the number of customers, and other binary variables to account for anomalies in the historical data.

4.2.7 ODP Municipal Pumping Forecast

The ODP municipal pumping forecast consists of customers on the Water Pumping Service rate schedule. Sales to these customers are modeled using a trend based on recent sales.

4.2.8 KU Primary Forecast

The KU Primary forecast includes all customers who receive primary service on the PS rate schedule and all customers on the TODP rate schedule. Sales to these customers are modeled as a function of an industry-weighted Industrial Production Index and weather. If necessary, the forecast is adjusted to reflect significant expansions or reductions for large customers in these rate classes that are forecast individually based on information obtained through direct discussions with these customers.

4.2.9 KU Retail Transmission Service Forecast

The KU Retail Transmission Service forecast includes customers who receive service on the RTS rate schedule. Sales for a number of large KU RTS customers are forecast individually based on information obtained through direct discussions with these customers. The majority of the remaining RTS customers are mining customers. Sales to these customers are modeled as a function of a mining index.

4.2.10 KU Fluctuating Load Service Forecast

The KU Fluctuating Load Service forecast includes the one customer on the FLS rate schedule and is developed based on information obtained through direct discussions with this customer.

4.2.11 LG&E Primary Forecast

The LG&E Primary forecast includes all customers who receive primary service on the PS rate schedule and all customers on the TODP rate schedule. Sales to these customers are modeled as a function of an industry-weighted Industrial Production Index and weather. If necessary, the forecast is adjusted to reflect significant expansions or reductions for large customers on these rate schedules that are forecast individually based on information obtained through direct discussions with these customers.

4.2.12 LG&E Retail Transmission Service Forecast

The LG&E Retail Transmission Service forecast includes customers who receive service on the RTS rate schedule. Sales for a number of large LG&E RTS customers are forecast individually based on information obtained through direct discussions with these customers. Sales to the remaining customers are modeled using a trend based on recent sales.

4.2.13 ODP Industrial Forecast

The ODP industrial forecast includes all customers receiving primary service on the PS rate schedule as well as customers receiving service on the TODP or RTS rate schedules. ODP industrial sales are modeled as a function of mining production indices and weather.

4.3 KU Municipal Forecasts

KU's municipal customers develop their own sales forecasts. These forecasts are reviewed by KU for consistency and compared to historical sales trends. Any questions or concerns regarding the forecasts are directed to the municipal customers and any forecast revisions resulting from this process are made by the municipal customers.

4.4 Lighting Forecasts

The Lighting forecast includes customers receiving service on the following rate schedules:

- LG&E
  - Lighting Energy Service ("LES")
  - Outdoor Sports Lighting Service ("OSL")
  - Traffic Energy Service ("TES")
  - Unmetered Street Lighting ("UM")
- KU
  - LES
  - OSL
  - TES
  - UM
- ODP
  - UM

All Lighting-related energy is modeled using a trend based on recent sales.

4.5 Distributed Solar Generation Forecast

The distributed solar generation forecast comprises both a consumer choice model and a forecast for the Companies' service territories produced by NREL. The consumer choice model is driven by the levelized cost of energy ("LCOE") for solar installations and retail price of electricity from the grid. Over the forecast timeframe, the consumer choice model and NREL forecast are blended such that by 2050 the forecast is the NREL forecast. The modeling is at the combined Companies' level and capacities are allocated out to various rate schedules (primarily RS, GS, and PS).

4.6 Electric Vehicle Forecast

The electric vehicle forecast comprises both a consumer choice model and a forecast adapted to the Companies' service territories from BNEF. The consumer choice model is driven by the declines in the price of electric vehicles due to projected declines in battery pack costs as well as the cost of internal combustion engine vehicles. The consumer choice model forecast is the near-term forecast and is blended with the BNEF model over the forecast period such that by 2050 the

BNEF model is the forecast. Certain efficiency and miles driven assumptions are used to translate the vehicles-in-operation into an energy impact and that impact is allocated entirely to the Residential class.

4.7 Billed Demand Forecasts

Billed demand forecasts are developed for rate schedules with demand rates based on historical demand factors, where the demand factor is the ratio of the billed demand volume to the billed sales volume. The historical demand factors are multiplied by the forecast of monthly sales to compute forecasted billing demands.

4.8 Weather-Year Forecasts

The Companies develop their hourly energy requirements forecast with the assumption that weather will be average or "normal" in every year (see discussion below in Section 5.2). While this is a reasonable assumption for long-term resource planning, weather from one year to the next is never the same. For this reason, to support the Companies' Reserve Margin Analysis, the Companies produced 45 hourly energy requirement forecasts for 2021 based on weather in each of the last 45 years.

To create these "weather year" forecasts, the Companies develop a model to forecast daily energy requirements as a function of temperature and calendar variables such as day of week and holidays. This model is used to forecast daily energy requirements in each year of the forecast period based on weather from the prior 45 calendar years and calendar variables from the forecast period. Forecasted daily energy requirements are allocated to hours using daily load shapes derived from recent energy requirement profiles for days with similar weather. Finally, to ensure consistency with the Companies' energy forecast, the weather year forecasts are adjusted so that the mean of monthly energy requirements from the weather year forecasts equals monthly energy requirements in the base energy forecast.[9]

5. Data Processing

Most customers' monthly bills include energy that was consumed in portions of more than one calendar month. As a result, the majority of the Companies' forecast models are initially specified to forecast monthly "billed" sales. The following processes are completed to prepare the forecasts for use as inputs to the Companies' revenue and generation forecasts:

1. Billed-to-Calendar Energy Conversion
2. Hourly Energy Requirements Forecast

5.1 Billed-to-Calendar Energy Conversion

The following process is used to allocate sales volumes from billed forecasts to calendar months by rate and revenue class so that the allocated volumes can be used as inputs to the Companies' revenue forecast. Municipal customers and customers on the following rate schedules are billed

[9] The process for computing monthly energy requirements in the base forecast is discussed in Section 5.2.

on a calendar-month basis and are not included in this process: LG&E Special Contract and FLS.

1. Allocate billed forecast volumes for each service territory to calendar months to reflect energy consumption under normal weather conditions.
2. Allocate calendar-month forecast volumes for each service territory to rate schedule and revenue class. In a given month, each rate schedule's share of calendar-month sales is assumed to equal its share of total forecasted billed sales for the month. The allocation of volumes for each rate schedule to revenue class is based historical allocations. All forecast volumes are allocated to one of the following revenue classes: Residential, Commercial, Industrial, Public Authority, Wholesale, and Lighting.

5.2 Hourly Energy Requirements Forecast

The Generation Planning department uses the hourly energy requirements forecast to develop resource expansion plans and a forecast of generation production costs. An hourly energy requirements forecast is developed for each company by adding losses to calendar-month sales and allocating the sum to hours. The result reflects customers' hourly energy requirements under normal weather conditions. The following process is used to develop this forecast:

1. Sum calendar-month forecast volumes by company and add transmission and distribution losses to compute monthly energy requirements. The sum of calendar-month forecast volumes for KU includes forecast volumes for the KU and ODP service territories.
2. Develop normalized load duration curves for each company and month based on 10 years of historical hourly energy requirements. For KU, to model the impact of the municipal departure, this process is completed based on total-company energy requirements as well as energy requirements where the impact of the departing municipals has been removed.
    a. Compute the ratio of hourly energy requirements and monthly energy requirements for each hour and company. Rank the ratios in each month from highest to lowest.
    b. In all months except January and August, the normalized load duration curve is computed by averaging the ratios by month, rank, and company. Because the winter and summer peak can occur in multiple months and the average peak for a season is higher than the average peak for any individual month in the season, the normalized load duration curves for January and August are computed based on the Januaries and Augusts in the historical period with lower-than-average load factors.[10] This process produces seasonal peak demand forecasts for January and August.
3. Allocate monthly energy requirements to hours using the normalized load duration curves. For KU, the normalized load duration curves used to produce hourly energy requirements through April 2019 are based on total-company energy requirements over the past 10 years. Beyond April 2019, the normalized load durations curves reflect the municipal departure.

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[10] Specifically, of the ten Januaries and Augusts in the historical period, the analysis uses the months with the 2nd, 3rd, 4th, and 5th lowest load factors.

4. Assign hourly energy requirements to specific hours in each month based on the ordering of days and weekends in the month.
5. Adjust the hourly energy requirements forecast to reflect the forecasted impact of distributed solar generation and electric vehicle load.

6. Review

The final part of the forecast process includes validating and documenting the forecast results. To ensure results are reasonable, the new forecast is compared to (i) the previous forecast and (ii) weather-normalized actual sales for the comparable period in prior years. This process ensures that the forecast is consistent with recent trends in the way customers are using electricity.

Appendix A: Residential SAE Modeling Framework

The traditional approach to forecasting monthly sales for a customer class is to develop an econometric model that relates monthly sales to weather, seasonal variables, and economic conditions. Econometric models are well suited to identifying historical trends and to projecting these trends into the future. In contrast, end-use models are able to identify and isolate the end-use factors that are driving energy use. By incorporating end-use structure into an econometric model, the statistically adjusted end-use (SAE) modeling framework exploits the strengths of both approaches.

There are several advantages to this approach.

- The equipment efficiency and saturation trends, dwelling square footage, and thermal integrity changes embodied in the long-run end-use forecasts are introduced explicitly into the short-term monthly sales forecast. This provides a strong bridge between the two forecasts.
- By explicitly incorporating trends in equipment saturations, equipment efficiency, dwelling square footage, and thermal integrity levels, it is easier to explain changes in usage levels and changes in weather-sensitivity over time.
- Data for short-term models are often not sufficiently robust to support estimation of a full set of price, economic, and demographic effects. By bundling these factors with equipment-oriented drivers, a rich set of elasticities can be incorporated into the final model.

This section describes this approach, the associated supporting SAE spreadsheets, and the *MetrixND* project files that are used in the implementation. The main source of the SAE spreadsheets is the 2017 Annual Energy Outlook (AEO) database provided by the Energy Information Administration (EIA).

Statistically Adjusted End-Use Modeling Framework

The statistically adjusted end-use modeling framework begins by defining energy use ($USE_{y,m}$) in year (y) and month (m) as the sum of energy used by heating equipment ($Heat_{y,m}$), cooling equipment ($Cool_{y,m}$), and other equipment ($Other_{y,m}$). Formally,

$$\mathrm{USE}_{y,m} = \mathrm{Heat}_{y,m} + \mathrm{Cool}_{y,m} + \mathrm{Other}_{y,m} \quad (1)$$

Although monthly sales are measured for individual customers, the end-use components are not. Substituting estimates for the end-use elements gives the following econometric equation.

$$\mathrm{USE}_{m} = a + b_1 \times \mathrm{XHeat}_{m} + b_2 \times \mathrm{XCool}_{m} + b_3 \times \mathrm{XOther}_{m} + \varepsilon_{m} \quad (2)$$

$XHeat_m$, $XCool_m$, and $XOther_m$ are explanatory variables constructed from end-use information, dwelling data, weather data, and market data. As will be shown below, the equations used to construct these X-variables are simplified end-use models, and the X-variables are the estimated usage levels for each of the major end uses based on these models. The estimated model can then be thought of as a statistically adjusted end-use model, where the estimated slopes are the adjustment factors.

Constructing XHeat

As represented in the SAE spreadsheets, energy use by space heating systems depends on the following types of variables.

- Heating degree days
- Heating equipment saturation levels
- Heating equipment operating efficiencies
- Average number of days in the billing cycle for each month
- Thermal integrity and footage of homes
- Average household size, household income, and energy prices

The heating variable is represented as the product of an annual equipment index and a monthly usage multiplier:

$$XHeat_{y,m} = HeatIndex_{y,m} \times HeatUse_{y,m} \quad (3)$$

Where:

- $XHeat_{y,m}$ is estimated heating energy use in year (y) and month (m)
- $HeatIndex_{y,m}$ is the monthly index of heating equipment
- $HeatUse_{y,m}$ is the monthly usage multiplier

The heating equipment index is defined as a weighted average across equipment types of equipment saturation levels normalized by operating efficiency levels. Given a set of fixed weights, the index will change over time with changes in equipment saturations (*Sat*), operating efficiencies (*Eff*), building structural index (*StructuralIndex*), and energy prices. Formally, the equipment index is defined as:

$$HeatIndex_y = StructuralIndex_y \times \sum_{Type} Weight^{Type} \times \frac{\left(Sat_y^{Type} \Big/ Eff_y^{Type} \right)}{\left(Sat_{09}^{Type} \Big/ Eff_{09}^{Type} \right)} \quad (4)$$

The *StructuralIndex* is constructed by combining the EIA's building shell efficiency index trends with surface area estimates, and then it is indexed to the 2009 value:

$$StructuralIndex_y = \frac{BuildingShellEfficiencyIndex_y \times SurfaceArea_y}{BuildingShellEfficiencyIndex_{09} \times SurfaceArea_{09}} \quad (5)$$

The *StructuralIndex* is defined on the *StructuralVars* tab of the SAE spreadsheets. Surface area is derived to account for roof and wall area of a standard dwelling based on the regional average square footage data obtained from EIA. The relationship between the square footage and surface area is constructed assuming an aspect ratio of 0.75 and an average of 25% two-story and 75% single-story. Given these assumptions, the approximate linear relationship for surface area is:

$$SurfaceArea_y = 892 + 1.44 \times Footage_y \quad (6)$$

In Equation 4, 2009 is used as a base year for normalizing the index. As a result, the ratio on the right is equal to 1.0 in 2009. In other years, it will be greater than 1.0 if equipment saturation levels are above their 2009 level. This will be counteracted by higher efficiency levels, which will drive the index downward. The weights are defined as follows.

$$Weight^{Type} = \frac{Energy_{09}^{Type}}{HH_{09}} \times HeatShare_{09}^{Type} \tag{7}$$

In the SAE spreadsheets, these weights are referred to as *Intensities* and are defined on the *EIAData* tab. With these weights, the *HeatIndex* value in 2009 will be equal to estimated annual heating intensity per household in that year. Variations from this value in other years will be proportional to saturation and efficiency variations around their base values.

For electric heating equipment, the SAE spreadsheets contain two equipment types: electric resistance furnaces/room units and electric space heating heat pumps. Examples of weights for these two equipment types for the U.S. are given in Table 1.

Table 1: Electric Space Heating Equipment Weights

Equipment Type	Weight (kWh)
Electric Resistance Furnace/Room units	760
Electric Space Heating Heat Pump	126

Data for the equipment saturation and efficiency trends are presented on the *Shares* and *Efficiencies* tabs of the SAE spreadsheets. The efficiency for electric space heating heat pumps are given in terms of Heating Seasonal Performance Factor [BTU/Wh], and the efficiencies for electric furnaces and room units are estimated as 100%, which is equivalent to 3.41 BTU/Wh.

Price Impacts. In the 2007 version of the SAE models and thereafter, the Heat Index has been extended to account for the long-run impact of electric and natural gas prices. Since the Heat Index represents changes in the stock of space heating equipment, the price impacts are modeled to play themselves out over a 10-year horizon. To introduce price effects, the Heat Index as defined by

Equation 4 above is multiplied by a 10-year moving-average of electric and gas prices. The level of the price impact is guided by the long-term price elasticities:

$$HeatIndex_y = StructuralIndex_y \times \sum_{Type} Weight^{Type} \times \frac{\left(Sat_y^{Type} \middle/ Eff_y^{Type} \right)}{\left(Sat_{09}^{Type} \middle/ Eff_{09}^{Type} \right)} \times \left(TenYearMovingAverageElectricPrice_{y,m} \right)^{\phi} \times \left(TenYearMovingAverageGasPrice_{y,m} \right)^{\gamma} \tag{8}$$

Since the trends in the Structural index (the equipment saturations and efficiency levels) are provided exogenously by the EIA, the price impacts are introduced in a multiplicative form. As a result, the long-run change in the Heat Index represents a combination of adjustments to the structural integrity of new homes, saturations in equipment and efficiency levels relative to what was contained in the base EIA long-term forecast.

Heating system usage levels are impacted on a monthly basis by several factors, including weather, household size, income levels, prices, and billing days. The estimates for space heating equipment usage levels are computed as follows:

$$HeatUse_{y,m} = \left(\frac{WgtHDD_{y,m}}{HDD_{09}} \right) \times \left(\frac{HHSize_y}{HHSize_{09}} \right)^{0.25} \times \left(\frac{Income_y}{Income_{09}} \right)^{0.20} \times \left(\frac{ElecPrice_{y,m}}{ElecPrice_{09,7}} \right)^{\lambda} \times \left(\frac{GasPrice_{y,m}}{GasPrice_{09,7}} \right)^{\kappa} \tag{9}$$

Where:

- *WgtHDD* is the weighted number of heating degree days in year (*y*) and month (*m*). This is constructed as the weighted sum of the current month's HDD and the prior month's HDD. The weights are 75% on the current month and 25% on the prior month.
- *HDD* is the annual heating degree days for 2009
- *HHSize* is average household size in a year (*y*)
- *Income* is average real income per household in year (*y*)
- *ElecPrice* is the average real price of electricity in month (*m*) and year (*y*)
- *GasPrice* is the average real price of natural gas in month (*m*) and year (*y*)

By construction, the $HeatUse_{y,m}$ variable has an annual sum that is close to 1.0 in the base year (2009). The first two terms, which involve billing days and heating degree days, serve to allocate annual values to months of the year. The remaining terms average to 1.0 in the base year. In other years, the values will reflect changes in the economic drivers, as transformed through the end-use elasticity parameters. The price impacts captured by the Usage equation represent short-term price response.

Constructing XCool

The explanatory variable for cooling loads is constructed in a similar manner. The amount of energy used by cooling systems depends on the following types of variables.

- Cooling degree days
- Cooling equipment saturation levels
- Cooling equipment operating efficiencies
- Average number of days in the billing cycle for each month
- Thermal integrity and footage of homes
- Average household size, household income, and energy prices

The cooling variable is represented as the product of an equipment-based index and monthly usage multiplier. That is,

$$XCool_{y,m} = CoolIndex_{y} \times CoolUse_{y,m} \tag{10}$$

Where

- $XCool_{y,m}$ is estimated cooling energy use in year (y) and month (m)
- $CoolIndex_{y}$ is an index of cooling equipment
- $CoolUse_{y,m}$ is the monthly usage multiplier

As with heating, the cooling equipment index is defined as a weighted average across equipment types of equipment saturation levels normalized by operating efficiency levels. Formally, the cooling equipment index is defined as:

$$CoolIndex_y = StructuralIndex_y \times \sum_{Type} Weight^{Type} \times \frac{\left(Sat_y^{Type} \Big/ Eff_y^{Type} \right)}{\left(Sat_{09}^{Type} \Big/ Eff_{09}^{Type} \right)} \tag{11}$$

Data values in 2009 are used as a base year for normalizing the index, and the ratio on the right is equal to 1.0 in 2009. In other years, it will be greater than 1.0 if equipment saturation levels are above their 2009 level. This will be counteracted by higher efficiency levels, which will drive the index downward. The weights are defined as follows.

$$Weight^{Type} = \frac{Energy_{09}^{Type}}{HH_{09}} \times CoolShare_{09}^{Type} \tag{12}$$

In the SAE spreadsheets, these weights are referred to as *Intensities* and are defined on the *EIAData* tab. With these weights, the *CoolIndex* value in 2009 will be equal to estimated annual cooling intensity per household in that year. Variations from this value in other years will be proportional to saturation and efficiency variations around their base values.

For cooling equipment, the SAE spreadsheets contain three equipment types: central air conditioning, space cooling heat pump, and room air conditioning. Examples of weights for these three equipment types for the U.S. are given in Table 2.

Table 2: Space Cooling Equipment Weights

Equipment Type	Weight (kWh)
Central Air Conditioning	1,209
Space Cooling Heat Pump	238
Room Air Conditioning	175

The equipment saturation and efficiency trends data are presented on the *Shares* and *Efficiencies* tabs of the SAE spreadsheets. The efficiency for space cooling heat pumps and central air conditioning (A/C) units are given in terms of Seasonal Energy Efficiency Ratio [BTU/Wh], and room A/C unit efficiencies are given in terms of Energy Efficiency Ratio [BTU/Wh].

Price Impacts. In the 2007 SAE models and thereafter, the Cool Index has been extended to account for changes in electric and natural gas prices. Since the Cool Index represents changes in the stock of space heating equipment, it is anticipated that the impact of prices will be long-term in nature. The Cool Index as defined Equation 11 above is then multiplied by a 10-year moving average of electric and gas prices. The level of the price impact is guided by the long-term price elasticities.

$$CoolIndex_y = StructuralIndex_y \times \sum_{Type} Weight^{Type} \times \frac{\left(Sat_y^{Type} / Eff_y^{Type} \right)}{\left(Sat_{09}^{Type} / Eff_{09}^{Type} \right)} \times \left(TenYearMovingAverageElectric\,Price_{y,m}\right)^{\phi} \times \left(TenYearMovingAverageGas\,Price_{y,m}\right)^{\gamma} \qquad (13)$$

Since the trends in the Structural index, equipment saturations and efficiency levels are provided exogenously by the EIA, price impacts are introduced in a multiplicative form. The long-run change in the Cool Index represents a combination of adjustments to the structural integrity of new homes, saturations in equipment and efficiency levels. Without a detailed end-use model, it is not possible to isolate the price impact on any one of these concepts.

Cooling system usage levels are impacted on a monthly basis by several factors, including weather, household size, income levels, and prices. The estimates of cooling equipment usage levels are computed as follows:

$$CoolUse_{y,m} = \left(\frac{WgtCDD_{y,m}}{CDD_{09}}\right) \times \left(\frac{HHSize_y}{HHSize_{09}}\right)^{0.25} \times \left(\frac{Income_y}{Income_{09}}\right)^{0.20} \times \left(\frac{Elec\,Price_{y,m}}{Elec\,Price_{09}}\right)^{\lambda} \times \left(\frac{Gas\,Price_{y,m}}{Gas\,Price_{09}}\right)^{\kappa} \qquad (14)$$

Where:

- *WgtCDD* is the weighted number of cooling degree days in year (*y*) and month (*m*). This is constructed as the weighted sum of the current month's CDD and the prior month's CDD. The weights are 75% on the current month and 25% on the prior month.
- *CDD* is the annual cooling degree days for 2009.

By construction, the *CoolUse* variable has an annual sum that is close to 1.0 in the base year (2009). The first two terms, which involve billing days and cooling degree days, serve to allocate annual values to months of the year. The remaining terms average to 1.0 in the base year. In other years, the values will change to reflect changes in the economic driver changes.

Constructing XOther

Monthly estimates of non-weather sensitive sales can be derived in a similar fashion to space heating and cooling. Based on end-use concepts, other sales are driven by:

- Appliance and equipment saturation levels
- Appliance efficiency levels
- Average number of days in the billing cycle for each month
- Average household size, real income, and real prices

The explanatory variable for other uses is defined as follows:

$$XOther_{y,m} = OtherEqpIndex_{y,m} \times OtherUse_{y,m} \qquad (15)$$

The first term on the right-hand side of this expression ($OtherEqpIndex_y$) embodies information about appliance saturation and efficiency levels and monthly usage multipliers. The second term (*OtherUse*) captures the impact of changes in prices, income, household size, and number of billing-days on appliance utilization.

End-use indices are constructed in the SAE models. A separate end-use index is constructed for each end-use equipment type using the following function form.

$$ApplianceIndex_{y,m} = Weight^{Type} \times \frac{\left(Sat_y^{Type} \Big/ \frac{1}{UEC_y^{Type}} \right)}{\left(Sat_{09}^{Type} \Big/ \frac{1}{UEC_{09}^{Type}} \right)} \times MoMult_m^{Type} \times \qquad (16)$$

$$(TenYearMovingAverageElectric\,Price)^{\lambda} \times (TenYearMovingAverageGas\,Price)^{\kappa}$$

Where:

- *Weight* is the weight for each appliance type
- *Sat* represents the fraction of households, who own an appliance type
- $MoMult_m$ is a monthly multiplier for the appliance type in month (m)
- *Eff* is the average operating efficiency the appliance
- *UEC* is the unit energy consumption for appliances

This index combines information about trends in saturation levels and efficiency levels for the main appliance categories with monthly multipliers for lighting, water heating, and refrigeration.

The appliance saturation and efficiency trends data are presented on the *Shares* and *Efficiencies* tabs of the SAE spreadsheets.

Further monthly variation is introduced by multiplying by usage factors that cut across all end uses, constructed as follows:

$$ApplianceUse_{y,m} = \left(\frac{BDays_{y,m}}{30.44}\right) \times \left(\frac{HHSize_y}{HHSize_{09}}\right)^{0.46} \times \left(\frac{Income_y}{Income_{09}}\right)^{0.10} \times \left(\frac{ElecPrice_{y,m}}{ElecPrice_{09}}\right)^{\phi} \times \left(\frac{GasPrice_{y,m}}{GasPrice_{09}}\right)^{\lambda} \quad (17)$$

The index for other uses is derived then by summing across the appliances:

$$OtherEqpIndex_{y,m} = \sum_k ApplianceIndex_{y,m} \times ApplianceUse_{y,m} \quad (18)$$

Supporting Spreadsheets and MetrixND Project Files

The SAE approach described above has been implemented for each of the nine Census Divisions. A mapping of states to Census Divisions is presented in Figure 15. This section describes the contents of each file and a procedure for customizing the files for specific utility data. A total of 18 files are provided. These files are listed in Table 3.

Figure 15: Mapping of States to Census Divisions

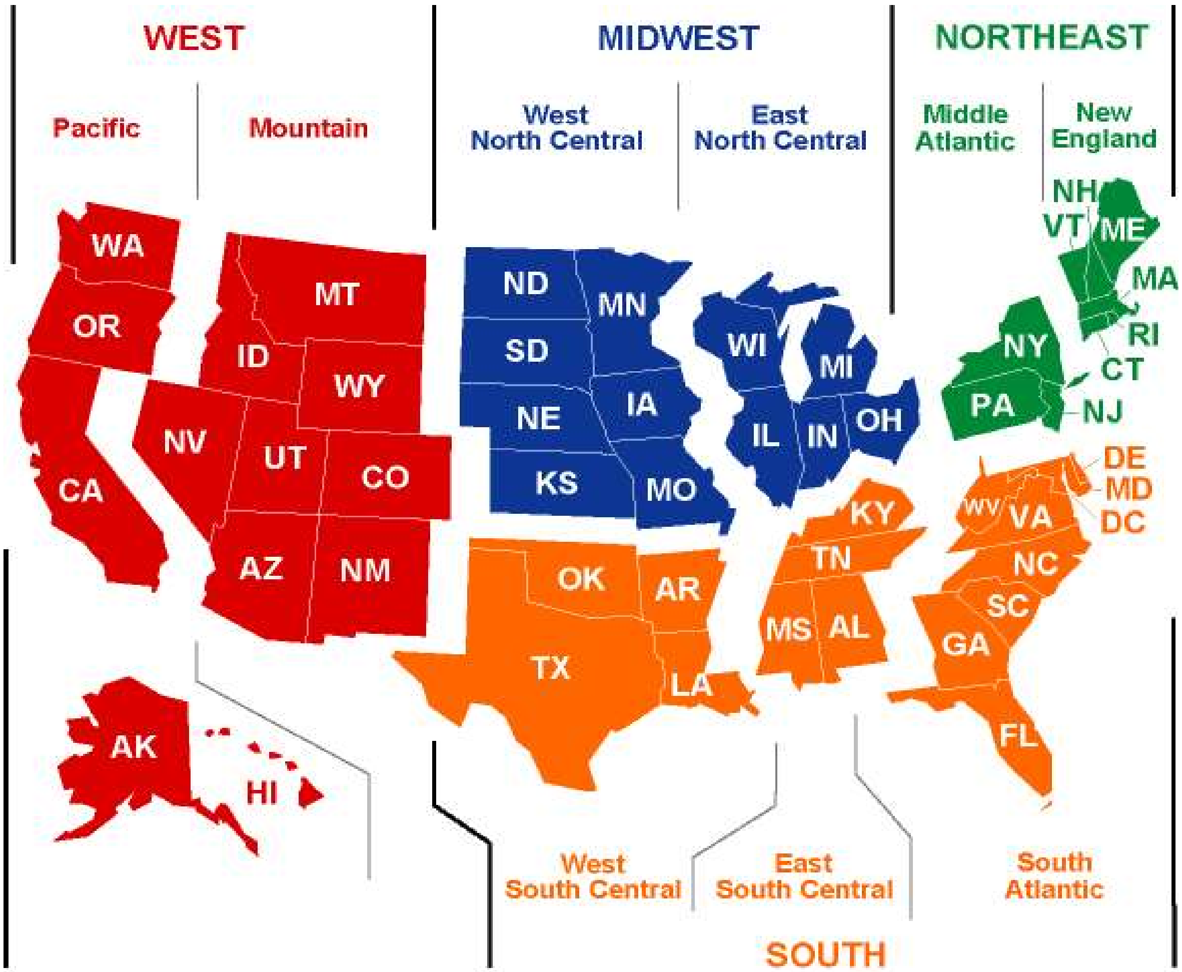

Table 3: List of SAE Files

Spreadsheet	*MetrixND* Project File
NewEngland.xls	SAE_NewEngland.ndm
MiddleAtlantic.xls	SAE_MiddleAtlantic.ndm
EastNorthCentral.xls	SAE_EastNorthCentral.ndm
WestNorthCentral.xls	SAE_WestNorthCentral.ndm
SouthAtlantic.xls	SAE_SouthAltantic.ndm
EastSouthCentral.xls	SAE_EastSouthCentral.ndm
WestSouthCentral.xls	SAE_WestSouthCentral.ndm
Mountain.xls	SAE_Mountain.ndm
Pacific.xls	SAE_Pacific.ndm

As defaults, the SAE spreadsheets include regional data, but utility data can be entered to generate the *Heat*, *Cool*, and *Other* equipment indices used in the SAE approach. The *MetrixND* project files link to the data in these spreadsheets. These project files calcualte the end-use *Usage* variables are constructed and the estimated SAE models.

Each of the nine SAE spreadsheets contains the following tabs:

- **Definitions -** Contains equipment, end use, worksheet, and Census Division definitions.
- **Intensities -** Calculates the annual equipment indices.
- **Shares -** Contains historical and forecasted equipment shares. The default forecasted values are provided by the EIA. The raw EIA projections are provided on the *EIAData* tab.
- **Efficiencies -** Contains historical and forecasted equipment efficiency trends. The forecasted values are based on projections provided by the EIA. The raw EIA projections are provided on the *EIAData* tab.
- **StructuralVars -** Contains historical and forecasted square footage, number of households, building shell efficiency index, and calculation of structural variable. The forecasted values are based on projections provided by the EIA.
- **Calibration -** This tab contains calculations of the base year *Intensity* values used to weight the equipment indices.
- **EIAData -** Contains the raw forecasted data provided by the EIA.
- **MonthlyMults -** Contains monthly multipliers that are used to spread the annual equipment indices across the months.
- **EV -** Worksheet for incorporating electric vehicle (EV) impacts.
- **PV -** Worksheet for incorporating photovoltaic battery (PV) impacts.

The *MetrixND* Project files are linked to the *AnnualIndices*, *ShareUEC*, and *MonthlyMults* tabs in the spreadsheets. Sales, economic, price and weather information for the Census Division is provided in the linkless data table *UtilityData*. In this way, utility specific data and the equipment indices are brought into the project file. The *MetrixND* project files contain the objects described below.

Parameter Tables

- **Elas.** This parameter table includes the values of the elasticities used to calculate the *Usage* variables for each end-use. There are five types of elasticities included on this table.

  - Economic variable elasticities
  - Short-term own price elasticities
  - Short-term cross price elasticities
  - Long-term own price elasticities

- Long-term cross price elasticities

The short-term price elasticities drive the end-use usage equations. The long-term price elasticities drive the Heat, Cool and other appliance indices. The combined price impact is an aggregation of the short and long-term price elasticities. As such, the long-term price elasticities are input as incremental price impact. That is, the long-term price elasticity is the difference between the overall price impact and the short-term price elasticity.

Data Tables

- **AnnualEquipmentIndices** links to the *AnnualIndices* tab for heating and cooling indices, and *ShareUEC* tab for water heating, lighting, and appliances in the SAE spreadsheet.
- **UtilityData** is a linkless data table that contains sales, price, economic and weather data specific to a given Census Division.
- **MonthlyMults** links to the corresponding tab in the SAE spreadsheet.

Transformation Tables

- **EconTrans** computes the average usage, and household size, household income, and price indices used in the usage equations.
- **WeatherTrans** computes the HDD and CDD indices used in the usage equations.
- **ResidentialVars** computes the *Heat*, *Cool* and *Other Usage* variables, as well as the *XHeat*, *XCool* and *XOther* variables that are used in the regression model.
- **BinaryVars** computes the calendar binary variables that could be required in the regression model.
- **AnnualFcst** computes the annual historical and forecast sales and annual change in sales.
- **EndUseFcst** computes the monthly sales forecasts by end uses.

Models

- **ResModel** is the Statistically Adjusted End-Use Model.

Steps to Customize the Files for Your Service Territory

The files that are distributed along with this document contain regional data. If you have more accurate data for your service territory, you are encouraged to tailor the spreadsheets with that information. This section describes the steps needed to customize the files.

Minimum Customization

- Save the *MetrixND* project file and the spreadsheet into the same folder
- Select the spreadsheet and *MetrixND* project file from the appropriate Census Division

- Open the spreadsheet and navigate to the *Calibration* tab
- In cell "B9", replace base year Census Division use-per-customer with observed use-per-customer for your service territory
- Save the spreadsheet and open the *MetrixND* project file
- Click on the *Update All Links* button on the *Menu* bar
- Review the model results

Further Customization of Starting Usage Levels

In addition to the minimum steps listed above, you can also utilize model-based calibration process described above on pages 15-16 to further fine-tune starting year usage estimates to your service territory.

Customizing the End-use Share Paths

You can also install your own share history and forecasts. To do this, navigate to the *Share* tab in the spreadsheet and paste in the values for your region. Make sure that base year shares on the *Calibration* tab reflect changes on the *Shares* tab.

Customizing the End-use Efficiency Paths

Finally, you can override the end-use efficiency paths that are contained on the *Efficiencies* tab of the spreadsheet.

Appendix B:
Commercial Statistically Adjusted End-Use Model

The traditional approach to forecasting monthly sales for a customer class is to develop an econometric model that relates monthly sales to weather, seasonal variables, and economic conditions. From a forecasting perspective, econometric models are well suited to identifying historical trends and to projecting these trends into the future. In contrast, end-use models are able to incorporate the end-use factors driving energy use. By including end-use structure in an econometric model, the statistically adjusted end-use (SAE) modeling framework exploits the strengths of both approaches.

There are several advantages to the SAE approach.

- The equipment efficiency trends and saturation changes embodied in the long-run end-use forecasts are introduced explicitly into the short-term monthly sales forecast, thereby providing a strong bridge between the two forecasts.
- By explicitly introducing trends in equipment saturations and efficiency levels, SAE models can explain changes in usage levels and weather-sensitivity over time.
- Data for short-term models are often not sufficiently robust to support estimation of a full set of price, economic, and demographic effects. By bundling these factors with equipment-oriented drivers, a rich set of elasticities can be built into the final model.

This document describes this approach, the associated supporting Commercial SAE spreadsheets, and *MetrixND* project files that are used in the implementation. The source for the commercial SAE spreadsheets is the 2017 Annual Energy Outlook (AEO) database provided by the Energy Information Administration (EIA).

1.1 Commercial Statistically Adjusted End-Use Model Framework

The commercial statistically adjusted end-use model framework begins by defining energy use ($USE_{y,m}$) in year (y) and month (m) as the sum of energy used by heating equipment ($Heat_{y,m}$), cooling equipment ($Cool_{y,m}$) and other equipment ($Other_{y,m}$). Formally,

$$USE_{y,m} = Heat_{y,m} + Cool_{y,m} + \text{Other}_{y,m} \tag{1}$$

Although monthly sales are measured for individual customers, the end-use components are not. Substituting estimates for the end-use elements gives the following econometric equation.

$$USE_m = a + b_1 \times XHeat_m + b_2 \times XCool_m + b_3 \times XOther_m + \varepsilon_m \qquad (2)$$

Here, $XHeat_m$, $XCool_m$, and $XOther_m$ are explanatory variables constructed from end-use information, weather data, and market data. As will be shown below, the equations used to construct these X-variables are simplified end-use models, and the X-variables are the estimated usage levels for each of the major end-uses based on these models. The estimated model can then be thought of as a statistically adjusted end-use model, where the estimated slopes are the adjustment factors.

Constructing XHeat

As represented in the Commercial SAE spreadsheets, energy use by space heating systems depends on the following types of variables.

- Heating degree days,
- Heating intensity,
- Commercial output and energy price.

The heating variable is represented as the product of an annual equipment index and a monthly usage multiplier. That is,

$$XHeat_{y,m} = HeatIndex_y \times HeatUse_{y,m} \qquad (3)$$

Where

- $XHeat_{y,m}$ is estimated heating energy use in year y and month m,
- $HeatIndex_y$ is the annual index of heating equipment, and
- $HeatUse_{y,m}$ is the monthly usage multiplier.

The heating equipment index is composed of electric space heating intensity. The index will change over time with changes in heating intensity. Formally, the equipment index is defined as:

$$HeatIndex_y = HeatSales_{13} \times \frac{(HeatIntensity_y)}{(HeatIntensity_{13})} \qquad (4)$$

In this expression, 2013 is used as a base year for normalizing the index. The ratio on the right is equal to 1.0 in 2013. In other years, it will be greater than 1.0 if intensity levels are above their 2004 level.

$$HeatSales_{04} = \left(\frac{kWh}{Sqft}\right)_{Heating} \times \left(\frac{CommercialSales_{13}}{\sum_{e} {kWh}/{Sqft_e}}\right) \tag{5}$$

Here, base-year sales for space heating is the product of the average space heating intensity value and the ratio of total commercial sales in the base year over the sum of the end-use intensity values. In the Commercial SAE Spreadsheets, the space heating sales value is defined on the *BaseYrInput* tab. The resulting $HeatIndex_y$ value in 2013 will be equal to the estimated annual heating sales in that year. Variations from this value in other years will be proportional to saturation and efficiency variations around their base values.

Heating system usage levels are impacted on a monthly basis by several factors, including weather, commercial level economic activity, and prices. Using the COMMEND default elasticity parameters, the estimates for space heating equipment usage levels are computed as follows:

$$HeatUse_{y,m} = \left(\frac{WgtHDD_{y,m}}{HDD_{13}}\right) \times \left(\frac{Output_y}{Output_{13}}\right) \times \left(\frac{\Pr ice_{y,m}}{\Pr ice_{13}}\right)^{-0.18} \tag{6}$$

Where

- *WgtHDD* is the weighted number of heating degree days in year *y* and month *m*. This is constructed as the weighted sum of the current month's HDD and the prior month's HDD. The weights are 75% on the current month and 25% on the prior month
- *HDD* is the annual heating degree days for 2013,
- *Output* is a real commercial output driver in year *y*,
- *Price* is the average real price of electricity in month *m* and year *y*,

By construction, the $HeatUse_{y,m}$ variable has an annual sum that is close to 1.0 in the base year (2013). The first terms, which involve heating degree days, serves to allocate annual values to months of the year. The remaining terms average to 1.0 in the base year. In other years, the values will reflect changes in commercial output and prices, as transformed through the end-use elasticity parameters. For example, if the real price of electricity goes up 10% relative to the base year value, the price term will contribute a multiplier of about .98 (computed as 1.10 to the -0.18 power).

Constructing XCool

The explanatory variable for cooling loads is constructed in a similar manner. The amount of energy used by cooling systems depends on the following types of variables.

- Cooling degree days,
- Cooling intensity,
- Commercial output and energy price.

The cooling variable is represented as the product of an equipment-based index and monthly usage multiplier. That is,

$$XCool_{y,m} = CoolIndex_y \times CoolUse_{y,m} \tag{7}$$

Where

- $XCool_{y,m}$ is estimated cooling energy use in year y and month m,
- $CoolIndex_y$ is an index of cooling equipment, and
- $CoolUse_{y,m}$ is the monthly usage multiplier.

As with heating, the cooling equipment index depends on equipment saturation levels (*CoolShare*) normalized by operating efficiency levels (*Eff*). Formally, the cooling equipment index is defined as:

$$CoolIndex_y = CoolSales_{13} \times \frac{\left(CoolShare_y / Eff_y \right)}{\left(CoolShare_{13} / Eff_{13} \right)} \tag{8}$$

Data values in 2013 are used as a base year for normalizing the index, and the ratio on the right is equal to 1.0 in 2013. In other years, it will be greater than 1.0 if equipment saturation levels are above their 2013 level. This will be counteracted by higher efficiency levels, which will drive the index downward. Estimates of base year cooling sales are defined as follows.

$$CoolSales_{13} = \left(\frac{kWh}{Sqft} \right)_{Cooling} \times \left(\frac{CommercialSales_{13}}{\sum_e kWh / Sqft_e} \right) \tag{9}$$

Here, base-year sales for space cooling is the product of the average space cooling intensity value and the ratio of total commercial sales in the base year over the sum of the end-use intensity values. In the Commercial SAE Spreadsheets, the space cooling sales value is defined on the *BaseYrInput* tab. The resulting *CoolIndex* value in 2013 will be equal to the estimated annual cooling sales in that year. Variations from this value in other years will be proportional to saturation and efficiency variations around their base values.

Cooling system usage levels are impacted on a monthly basis by several factors, including weather, economic activity levels and prices. Using the COMMEND default parameters, the estimates of cooling equipment usage levels are computed as follows:

$$CoolUse_{y,m} = \left(\frac{WgtCDD_{y,m}}{CDD_{13}}\right) \times \left(\frac{Output_y}{Output_{13}}\right) \times \left(\frac{Price_{y,m}}{Price_{13}}\right)^{-0.18} \tag{10}$$

Where

- *WgtCDD* is the weighted number of cooling degree days in year *y* and month *m*. This is constructed as the weighted sum of the current month's CDD and the prior month's CDD. The weights are 75% on the current month and 25% on the prior month.
- *CDD* is the annual cooling degree days for 2013.

By construction, the *CoolUse* variable has an annual sum that is close to 1.0 in the base year (2013). The first two terms, which involve billing days and cooling degree days, serve to allocate annual values to months of the year. The remaining terms average to 1.0 in the base year. In other years, the values will change to reflect changes in commercial output and prices.

Constructing XOther

Monthly estimates of non-weather sensitive sales can be derived in a similar fashion to space heating and cooling. Based on end-use concepts, other sales are driven by:

- Equipment intensities,
- Average number of days in the billing cycle for each month, and
- Real commercial output and real prices.

The explanatory variable for other uses is defined as follows:

$$XOther_{y,m} = OtherIndex_{y,m} \times OtherUse_{y,m} \tag{11}$$

The second term on the right hand side of this expression embodies information about equipment saturation levels and efficiency levels. The equipment index for other uses is defined as follows:

$$OtherIndex_{y,m} = \sum_{Type} Weight_{13}^{Type} \times \left(\frac{Share_{y}^{Type} \Big/ Eff_{y}^{Type}}{Share_{13}^{Type} \Big/ Eff_{13}^{Type}} \right) \tag{12}$$

Where

- *Weight* is the weight for each equipment type,
- *Share* represents the fraction of floor stock with an equipment type, and
- *Eff* is the average operating efficiency.

This index combines information about trends in saturation levels and efficiency levels for the main equipment categories. The weights are defined as follows.

$$Weight_{13}^{Type} = \left(\frac{kWh}{Sqft} \right)_{Type} \times \left(\frac{CommercialSales_{13}}{\sum_{e} kWh \big/ Sqft_{e}} \right) \tag{13}$$

Further monthly variation is introduced by multiplying by usage factors that cut across all end-uses, constructed as follows:

$$OtherUse_{y,m} = \left(\frac{BDays_{y,m}}{30.44}\right) \times \left(\frac{Output_y}{Output_{13}}\right) \times \left(\frac{\Pr ice_{y.m}}{\Pr ice_{13}}\right)^{-0.18} \quad (14)$$

In this expression, the elasticities on output and real price are computed from the COMMEND default values.

1.2 Supporting Spreadsheets and *MetrixND* Project Files

The SAE approach described above has been implemented for each of the nine census divisions. This section describes the contents of each file and a procedure for customizing the files for specific utility data. A total of 18 files are provided. These files are listed in Table 1.

Table 1: List of SAE Files

Spreadsheets	***MetrixND* Project Files**
NewEnglandCom17.xls	NewEnglandCom17.ndm
MiddleAtlanticCom17.xls	MiddleAtlanticCom17.ndm
EastNorthCentralCom17.xls	EastNorthCentralCom17.ndm
WestNorthCentralCom17.xls	WestNorthCentralCom17.ndm
SouthAtlanticCom17.xls	SouthAltanticCom17.ndm
EastSouthCentralCom17.xls	EastSouthCentralCom17.ndm
WestSouthCentralCom17.xls	WestSouthCentralCom17.ndm
MountainCom17.xls	MountainCom17.ndm
PacificCom17.xls	PacificCom17.ndm

As defaults, the SAE spreadsheets include regional data, but utility data can be entered to generate the *Heat*, *Cool*, and *Other* equipment indices used in the SAE approach. The data from these spreadsheets are linked to the *MetrixND* project files. In these project files, the end-use *Usage* variables (Equations 6, 10, and 14 above) are constructed and the SAE model is estimated.

The nine spreadsheets contain the following tabs.

- **EIAData** contains the raw forecasted data provided by the EIA
- **BaseYrInput** contains base year Census Division intensities by end-use and building type as well as default building type weights. It also contains functionality for changing the weights to reflect utility service territory.
- **Efficiency** contains historical and forecasted end-use equipment efficiency trends. The forecasted values are based on projections provided by the EIA.
- **Shares.** This tab contains historical and forecasted end-use saturations.
- **Intensity** contains the annual intensity (kWh/sqft) projections by end-use.
- **AnnualIndices** contains the annual *Heat*, *Cool* and *Other* equipment indices.
- **FloorSpace** contains the annual floor space (sqft) projections by end-use.
- **PV** incorporates the impact of photovoltaic batteries into the forecast.
- **Graphs** contains graphs of Efficiency and Intensities, which can be updating by selecting from the list in cell B2.

The *MetrixND* project files contain the following objects.

Parameter Tables

- **Parameters.** This parameter table includes the values of the annual HDD and CDD in 2013 used to calculate the *Usage* variables for each end-use.
- **Elas.** This parameter table includes the values of the elasticities used to calculate the *Usage* variables for each end-use.

Data Tables

- **AnnualIndices.** This data table is linked to the *AnnualIndices* tab in the Commercial SAE spreadsheet and contains sales-adjusted commercial SAE indices.
- **Intensity.** This data table is linked to the *Intensity* tab in the Commercial SAE spreadsheet.
- **FloorSpace.** This data table links to *FloorSpace* tab in the Commercial SAE spreadsheet.
- **UtilityData.** This linkless data table contains Census Division level data. It can be populated with utility-specific data.

Transformation Tables

- **EconTrans.** This transformation table is used to compute the output and price indices used in the usage equations.
- **WeatherTrans.** This transformation table is used to compute the HDD and CDD indices used in the usage equations.
- **CommercialVars.** This transformation table is used to compute the *Heat*, *Cool* and *Other Usage* variables, as well as the *XHeat*, *XCool* and *XOther* variables that are used in the regression model. Structural variables based on the intensity/floor space combination are also calculated here.
- **BinaryVars.** This transformation table is used to compute the calendar binary variables that could be required in the regression model.
- **AnnualFcst.** This transformation table is used to compute the annual historical and forecast sales and annual change in sales.
- **EndUseFcst.** This transformation table breaks the forecast down into its heating, cooling and other components.

Models

- **ComSAE:** The commercial SAE model (energy forecast driven by end-use indices, price, and output projections).
- **ComStruct:** Simple stock model (energy forecast driven by end-use energy intensities, and square footage).