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.

CONFIDENTIAL

Executive Summary: US Economic Outlook

May 2021

Electric Sales & Demand Forecast Process

PPL companies

Sales Analysis & Forecasting
July 2021

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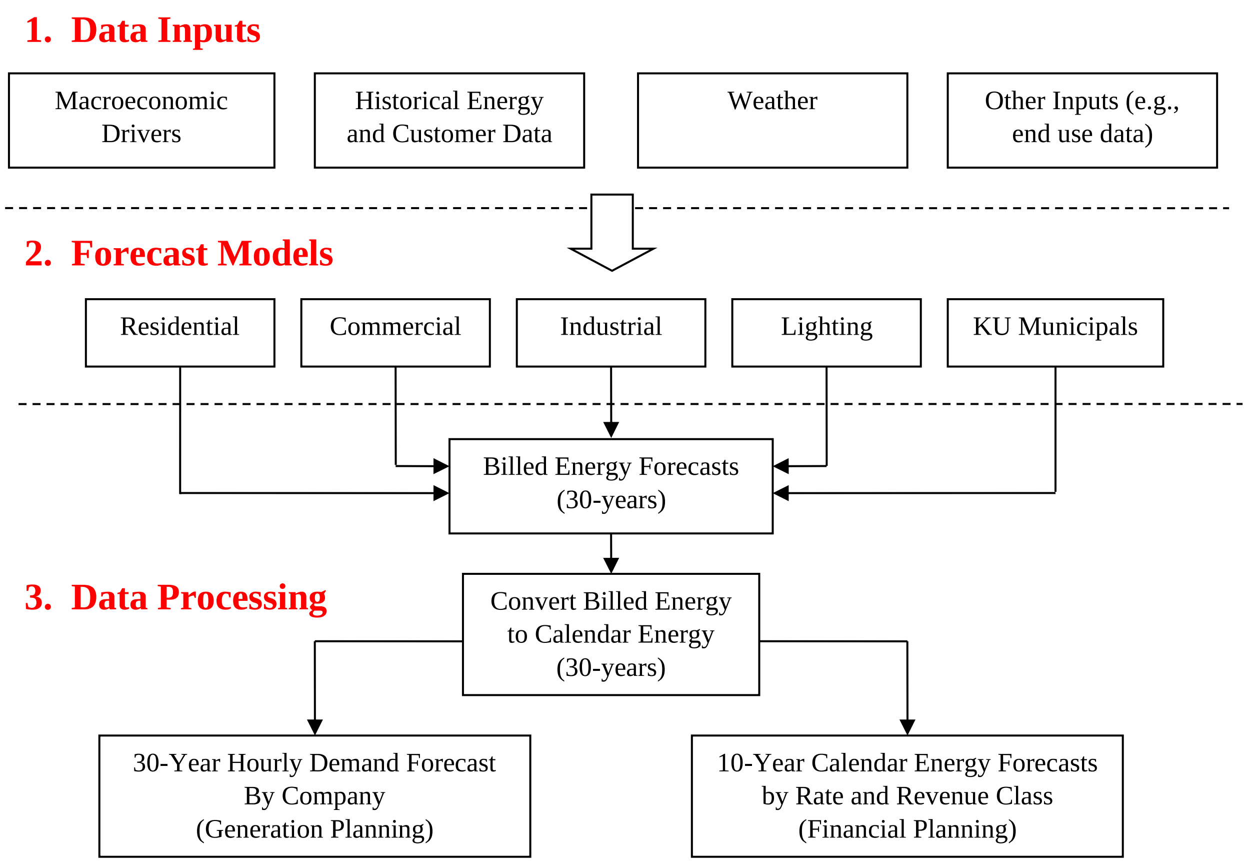
1. Introduction

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 three parts (see Figure 1). The first part of the forecast process involves gathering and processing input data. Key inputs to the forecast process include macroeconomic data, historical energy and customer data, weather data, and other data such as residential appliance shares and efficiencies.

Figure 1 – Load Forecasting Process Diagram



In the second part of the forecast process, 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]

Throughout the forecast process, the forecast results are reviewed to ensure they are reasonable. For example, 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 parts 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 day of the month, generally, 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”), ITRON	Annual – History and Forecast
Structural Variables (e.g., dwelling size, age, and type)	EIA, ITRON	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”)	Monthly Net Metering/Qualifying Facility Customers, Private Solar Costs
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 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 period, (b) a forecast of "normal" weather by billing period, and (c) a forecast of "normal" daily weather.[4] Each of these processes is summarized below.

3.1.1 Historical Weather by Billing Period

The process used to create the historical weather series by billing period 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 period 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 period.

3.1.2 Normal Weather Forecast by Billing Period

The process used to produce the forecast of normal weather by billing period 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 period:

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:

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[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.

[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.

   a. The sum of the daily HDDs and CDDs by month should match the normal monthly HDDs and CDDs in Step 1.
   b. 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 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 period.

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"),

[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.

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 forecast for each service territory as the product of a customer forecast and a use-per-customer forecast.

4.1.1 Residential Customer Forecasts

The number of residential customers is forecast 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.

$$\text{Use-per-Customer} = a1*XHeat + a2*XCool + a3*XOther$$

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 affect the Companies' load forecast. As a result, sales to these customers are forecast based on information obtained through direct discussions with these customers. During these discussions, the customers are given the opportunity to review and comment on the usage and billed demand forecasts that the Companies create for them. 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.

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

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, School Service (“SS”), 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, with the main difference being it forecasts total sales (rather than use-per-customer) 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 weather, economic variables, end-use intensity projections, cooling efficiencies, and binary variables that 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 AES customers (which is modeled using EIA projections for education floor space in the East South Central region as an input), weather and monthly binaries, and binary variables to account for anomalies in the historical data.

4.2.4 ODP School Service Forecast

The ODP School Service forecast includes all customers on the SS rate schedule. Sales to these customers are modeled as a function of the number of ODP SS customers (which is modeled using IHS projections of real gross county product for Wise and Lee counties in VA as an input), weather and monthly binaries, and binary variables to account for anomalies in the historical data.

4.2.5 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, economic variables, end-use intensity projections, and other binary variables to account for anomalies in the historical data.

4.2.6 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.

4.2.7 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, economic variables, end-use intensity projections, and other binary variables to account for anomalies in the historical data.

4.2.8 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.

4.2.9 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 economic variable. 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.

4.2.10 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 and an economic variable.

4.2.11 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.

4.2.12 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 economic variable. 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.

4.2.13 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 as a function of historical monthly usage.

4.2.14 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 forecasts, recent sales, 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 and EV Charging Forecasts

The Lighting and EV Charging forecasts include customers receiving service on the following rate schedules:

- LG&E
  - Electric Vehicle Charging (“EVC”)
  - Electric Vehicle Fast Charging (“EV Fast”)
  - Lighting Energy Service (“LES”)
  - Outdoor Sports Lighting Service (“OSL”)
  - Traffic Energy Service (“TES”)
  - Unmetered Street Lighting (“UM”)
- KU
  - EVC
  - EV Fast
  - LES
  - OSL
  - TES
  - UM
- ODP
  - UM

All Lighting and EV Charging energy is modeled using a trend based on recent sales.

4.5 Distributed Solar Generation Forecast

The distributed solar generation forecast is based upon a consumer choice model. The consumer choice model is driven by the levelized cost of energy (“LCOE”) for solar installations and retail price of electricity from the grid. There is an assumption that the Investment Tax Credit (ITC) will be extended for another 10 years, and this is included in the LCOE in the model. Because the ITC will no longer end in 2022, the model was trained though 2019 for KU and LG&E (2018 for ODP) to flatten out a recent steep increase in adoptions, which is thought to be related to the (supposed) end of the ITC and not indicative of a continued trend. The sizes of new solar installations follow the historical linear trend for the corresponding rate categories. The modeling is at the individual Company level, and the forecast is allocated as a reduction the RS, GS, and PS forecasts.

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 EIA. 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 output is used in the initial period of the forecast and is blended gradually towards the EIA adapted forecast output, which acts as an anchor point in 2050. 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. The EV sales forecast is allocated as an increase to the RS forecasts.

4.7 Billed Demand Forecasts

For most rates, regression models are developed to forecast billed demands primarily as a function of energy. For some rates, billed demand forecasts are developed by applying historical ratios of billed demand and energy to the energy forecast. For a given customer and month, tariff provisions can impact the relationship between billed demands and energy. For example, the base demand for a TODP customer is computed as the greater of several factors including the customer's contract capacity and highest measured demand for the preceding 11 billing periods. The Companies' forecasting process considers the potential impact of these factors on the overall forecasts. Base, peak, and intermediate demands for the Companies' largest customers are developed with input from the customer.

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 and other studies focused on generation reliability, the Companies produced 48 hourly energy requirement forecasts for each year of the forecast based on actual weather in each of the last 48 years (1973 through 2020).

To create these "weather year" forecasts, the Companies develop a model to forecast hourly energy requirements as a function of temperature and calendar variables such as day of week and holidays. This model is used to forecast hourly energy requirements in each year of the forecast period based on hourly temperatures from the prior 48 calendar years and calendar variables from the forecast period. 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

All customers are assigned to one of 20 billing portions. A billing portion determines what day of the month, generally, a customer's meter is read. Most customers' monthly bills include energy that was consumed in portions of more than one calendar month. This energy is referred to as "billed" energy and the majority of the Companies' forecast models are initially specified to forecast "billed" sales. The following processes are completed to prepare the forecasts for use as inputs to the Companies' revenue and generation forecasts:

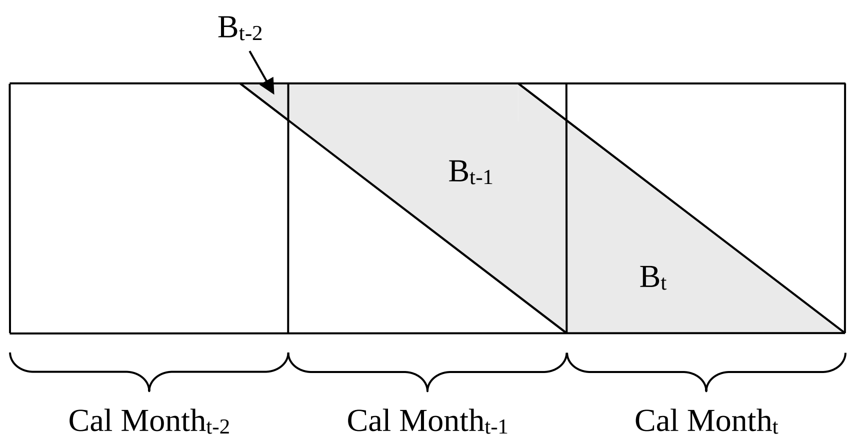
1. Billed-to-Calendar Energy Conversion
2. Hourly Energy Requirements Forecast

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

5.1 Billed-to-Calendar Energy Conversion

Most forecast volumes must be converted from a billed to calendar basis to meet the needs of the Financial Planning department. The shaded area in Figure 2 represents a typical billing period (B). Area B_t represents the portion of billed energy consumed in the current calendar month (Cal Month$_t$). Area B_{t-1} represents the portion of billed energy consumed in the previous calendar month (Cal Month$_{t-1}$). Area B_{t-2} represents the portion of billed energy consumed in the calendar month two months prior to the current month (Cal Month$_{t-2}$). Not all billing periods include volumes that were consumed in the calendar month two months prior to the current month.

Figure 2 – Billed and Calendar Energy

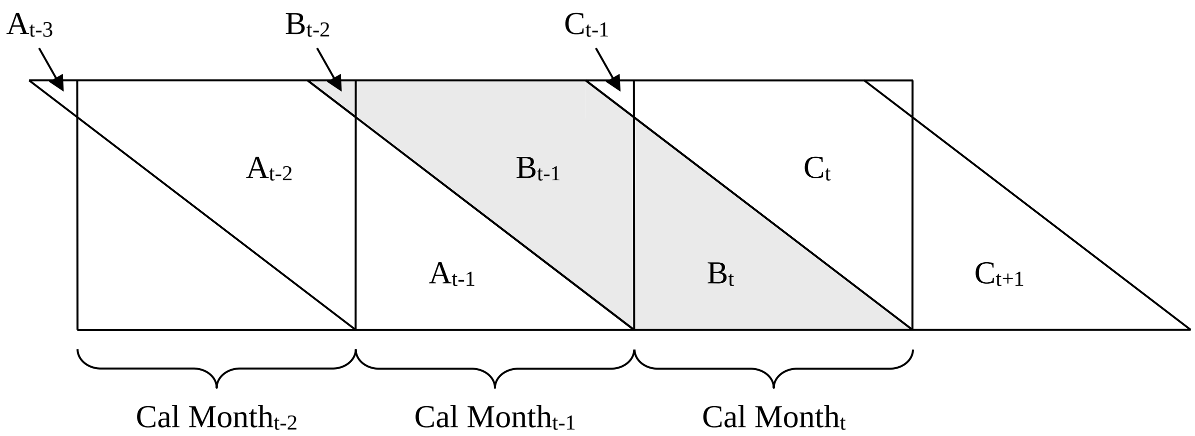


In this process, billed energy is allocated to calendar months based on when the energy is consumed. Furthermore, the weather-sensitive portion of the billed energy forecast is allocated to calendar months based on degree days (HDDs and CDDs) and the non-weather-sensitive portion is allocated based on billing days.[10] For example, the June billing period includes portions of June, May, and possibly April. Under normal weather conditions, June will have more CDDs than May. Therefore, a greater portion of the weather-sensitive energy in the June billing period will be allocated to the calendar month of June.

Figure 3 contains two additional billing periods (A & C). Calendar sales for Cal Month$_{t-1}$ is equal to the sum of energy in in billing period segments A_{t-1}, B_{t-1}, and C_{t-1}.

[10] For a given billing period, the number of degree days and billing days in each calendar month is computed as an average over the 20 billing portions.

Figure 3 – Billed and Calendar Energy



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 losses and company uses 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 historical energy requirements from which 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 peaks 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 a subset of the Januaries and Augusts in the last 10 years.[11]
3. Allocate monthly energy requirements to hours using the normalized load duration curves.
4. Assign hourly energy requirements to specific hours in each month based on the ordering of days and weekends in the month.

[11] Specifically, for January, the high and low are ignored and the average of the other 8 years is used. For August, the analysis uses the months in the historical period with the 2nd, 3rd, 4th, and 5th lowest load factors.

5. Adjust the hourly forecast as needed to ensure forecasted peaks are reasonable (i.e., consistent with weather-normalized historical peaks and any changes in forecasted energy requirements).
6. 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.