2013 Plan Electric Energy & Demand Forecast Process Document

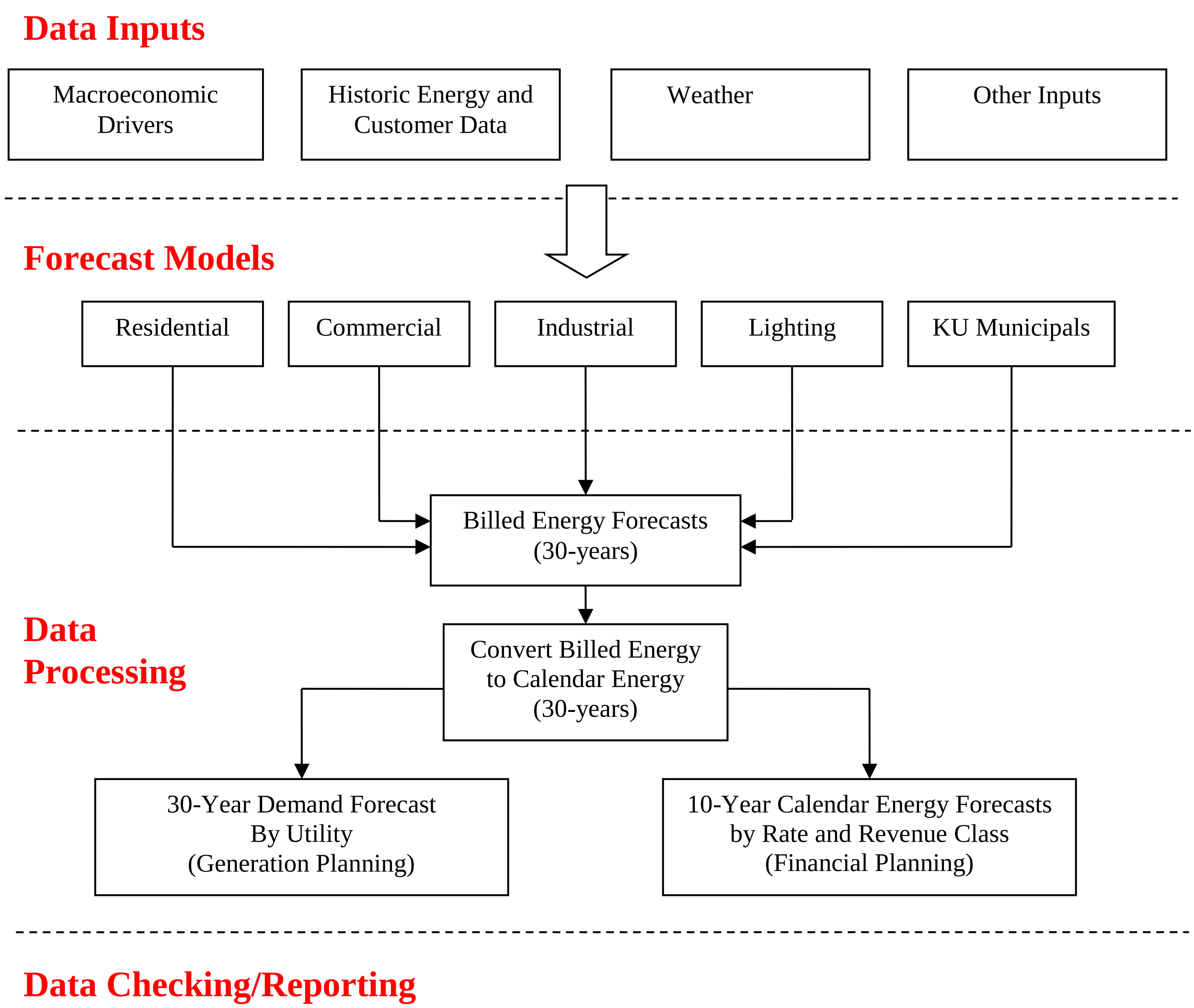
Sales Analysis & Forecasting
July 2012

Table of Contents

0. Introduction

Each year, the Sales Analysis & Forecasting group develops the utilities' sales and demand forecasts. These forecasts serve as foundational inputs to the Generation Planning department's Integrated Resource Plan and the Financial Planning department's Medium- and Long-Term Plans. The purpose of this document is to summarize the processes used to produce the 2011-vintage forecast ("2013forecast"), which is an input into the 2013 Business Plan ("2013 Plan"). The "2013" forecast is synonymous with the "2013 Plan" forecast. 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 cycle forecasts, class-level electricity price series, and residential appliance shares and efficiencies.

Once the input data is prepared, this data is used to specify and run various forecast models. The company's energy forecast is comprised of approximately thirty forecast models. Generally, each model is used to forecast energy usage for a group of customers with homogenous usage patterns and therefore the same, or similar, tariff rates.

Most of the forecast models produce energy forecasts on a billed basis[1]. In the third part of the forecast process, energy from the forecast models is processed to meet the needs of the forecast end users. The billed energy forecasts must first be converted to calendar (or "as-used") forecasts. The billed and calendar sales forecasts are allocated by rate and revenue class for the Financial Planning department. In addition, a forecast of hourly demands is developed for the Generation Planning department. This forecast is developed as the sum of several class-specific hourly forecasts.

The final part of the forecast process includes the process of checking and documenting the forecast results. To make sure the results are reasonable, the new forecast – among other checks/comparisons – is compared to (i) the previous forecast and (ii) weather-normalized actual usage for the comparable period in prior years. Each of these parts will be discussed in more detail in the following sections of the report.

[1] All customers are assigned to one of 20 billing cycles. A billing cycle determines what time of the month, generally, a customer's meter is read. Because most billing cycles do not coincide directly with the boundaries 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.

1. Input Data

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

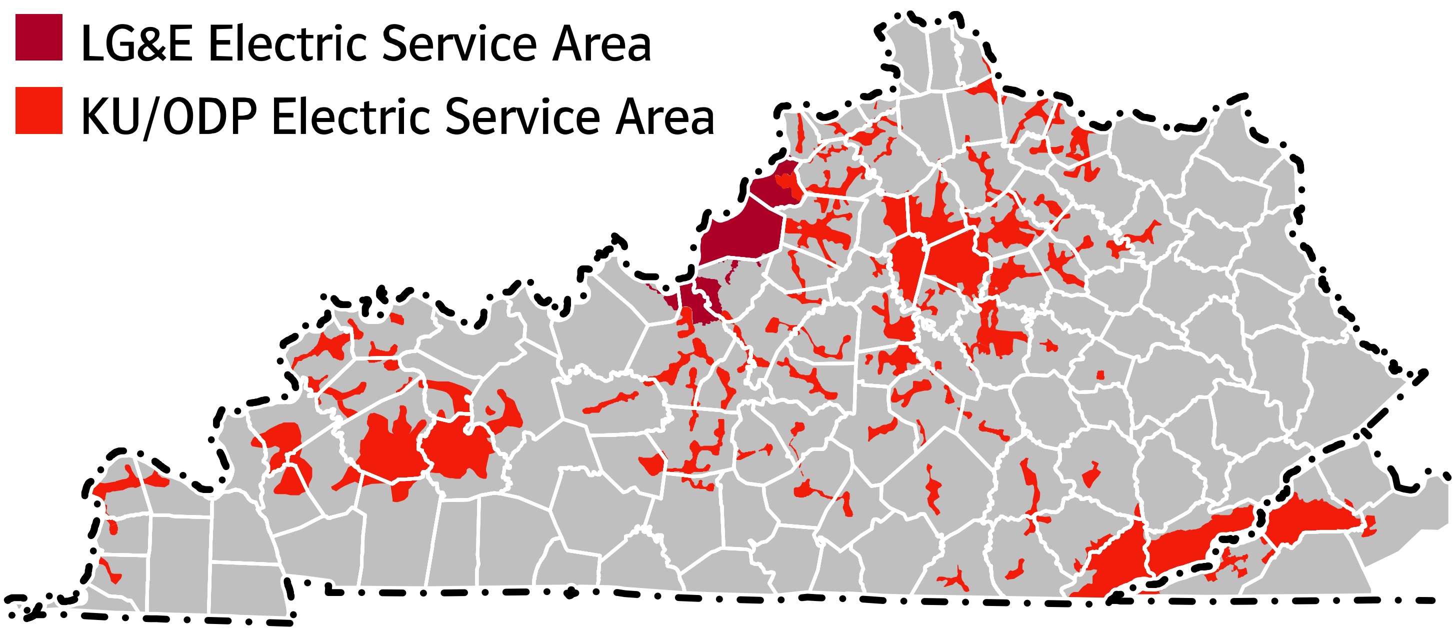
Table 1 – Summary of Forecast Data Inputs

Data	***Source***	***Format***
State Macroeconomic and Demographic Drivers (e.g., Employment, Wages, Households, Population)	IHS Global Insight	Annual by County – History and Forecast
National Macroeconomic Drivers	IHS Global Insight	Annual – History and Forecast
Personal Income	IHS Global Insight	Annual by County
Weather	NOAA	Daily HDD/CDD Data by Weather Station – History
Bill Cycle Schedule	Revenue Accounting	Monthly Collection Dates – History and Forecast
Appliance Saturations/Efficiencies	EIA 2010 Residential Customer Survey	Annual – History and Forecast
Structural Variables (e.g., dwelling size, age, and type)	2010 Residential Customer Survey	Annual – History
Elasticities of Demand	EIA	Annual – History
Billed Usage History	Variance Report_0233	LG&E, KU and ODP – Monthly by Rate Group
Customer Count History	LG&E – SBR Report KU/ODP – SBR Report	LG&E, KU and ODP – Monthly by Rate Group

1.1 Service Territory-Specific Macroeconomic Forecasts

IHS Global Insight 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 and KU/ODP electric service territories.

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



Two counties make up the majority of the LG&E service territory, whereas KU serves customers in pockets of over 70 counties[2]; ODP's service territory includes pockets of five counties in western Virginia. Service territory-specific macroeconomic forecasts are created by aggregating the county-specific forecasts for the counties in LG&E, KU, and ODP service territories.

1.2 Processing of Weather Data

Weather is a key explanatory variable in the electric forecast models. The weather dataset from the National Oceanic & Atmospheric Administration's (NOAA) National Climatic Data Center (NCDC) contains temperatures (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[3]. Each of these processes is summarized below.

1.2.1 Historical Weather by Billing Month

The methodology used to create the historical weather series by billing month is fairly straightforward:

[2] Appendix A contains a list of the counties in each service territory.
[3] "Normal" weather can be defined as the average weather over a historical period and is used in the forecast because of its stability.

1. Using the historical daily weather data from the NCDC, sum the HDD and CDD values by billing cycle[4]. Each historical billing month consists of 20 or 21 billing cycles[5]. The company's historical meter reading schedule contains the beginning and ending date for each billing cycle.
2. Average the billing cycle totals by billing month.

1.2.2 Normal Weather Forecast by Billing Month

The methodology used to produce the forecast of normal weather by billing month includes the production of a daily forecast of normal weather. The methodology used to develop the daily forecast (summarized in Steps 2-5) is consistent with the methodology 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 weather by *calendar* month by averaging the monthly degree-day values and the average monthly temperatures by calendar month over the period of history upon which the normal forecast is based. The 2013 Plan normal weather forecast was based on the 20-year period between 1992 and 2011. Therefore, the normal HDD value for January is the average of the 20 January HDD values in this period. Round the results to the nearest integer.
2. Compute "unsmoothed" daily normal weather values by averaging the 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 about 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. Round the daily weather data in Step 3 to the nearest integer.
5. Manually adjust the integer values in Step 4 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.
    d. These criteria ensure that the daily normal series is consistent with the monthly normal series.
6. The company's forecasted meter reading schedule contains the beginning and ending date for each billing cycle through the end of the forecast period. In this step, sum the HDD

[4] Weather data in the electric forecast is taken from the weather station at the Bowman Field Airport (LOU) in Louisville.
[5] To be consistent with KU, LG&E moved from 21 to 20 billing cycles beginning in January 2005.
[6] The NCDC derives daily normal values by applying a cubic spline to a specially prepared series of the monthly normal values. See http://lwf.ncdc.noaa.gov/oa/climate/normals/usnormals.html#Products for more information about the processes used by the NCDC.

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

7. Average the billing cycle totals by billing month.

1.2.3 Daily Normal Weather Forecast

A daily normal weather forecast is used to produce the forecast of hourly demands (see Section 3.3). The daily normal weather forecast is based on twenty years of historical weather data (1992-2011). The following process is used to compute the daily normal weather forecast:

1. For each company, month and year, sort the days from coldest to warmest. For a given January, the coldest day has a "rank" of one; the warmest day has a rank of 31.
2. Average the daily temperatures by company, month and rank. In the daily normal weather forecast, the average temperature for the coldest January day is computed as the average of the coldest January day in each of the past twenty years. The average temperature for the second coldest January day is computed as the average of the second coldest January day in each of the past twenty years, and so on.
3. These temperatures are then allocated to days throughout the month, using a process to ensure that the top ranked temperature (and therefore, peak day) falls on a weekday.

1.3 Industry-weighted Industrial Production Indices

IHS Global Insight provides industrial production indices on a 3-digit NAICS code basis. These IPIs are used to create production indices for each industrial tariff by the process summarized below. These are then used as drivers in the rate forecasts:

1. Assign each of the customers managed by the Major Accounts department (approximately 1160 customers in total) to an industry sector.
2. Summarize usage for these customers by tariff and assign any remaining smaller customers (not included in the largest 1160) to a general industrial index.. Based on this information, industry sector weights for each forecast class are calculated.
3. Use the industry sector weights and industry-specific forecasts of industrial production from IHS Global Insight to compute industry-weighted forecasts of industrial production for each tariff.

2. Forecast Models

The company's energy forecast is comprised of approximately thirty forecast models. All models forecast energy on a monthly basis. These forecasts are discussed in detail in the following sections.

2.1 Residential Forecast

The Residential forecast is comprised of three classes: KU Residential, LG&E Residential, and ODP Residential. Residential sales are forecasted for each company as the product of a customer forecast and a use-per-customer forecast.

2.1.1 KU Residential Forecast

The KU residential forecast includes all customers on the Residential Service (RS) and Volunteer Fire Department (VFD) rate schedules. Residential sales are forecasted as the product of a use-per-customer forecast and a forecast of the number of customers.

2.1.1.1 KU Residential Customer Forecast

The number of KU residential customers was forecasted as a function of the number of households in the KU service territory. Household data by county – history and forecast – was provided by Global Insight.

2.1.1.2 KU Residential Use-per-Customer Forecast

Average use per customer is forecasted using a Statistically-Adjusted End-Use (SAE) Model. Such a model combines an econometric model – that relates monthly sales to various explanatory variables such as weather and economic conditions – 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

The heating, cooling and other components (the X variables) are based on various input variables including weather (heating and cooling degree days), appliance saturations, efficiencies[7], 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 discussion of each of these components and the methodology used to develop them is contained in Appendix B.

[7] Because changes in efficiencies are directly included, the impact of Company-sponsored DSM programs must be applied with caution so as to not double count its impact. See Appendix D for details.

2.1.2 LG&E Residential Forecast

The LG&E residential forecast includes all customers on the Residential Service (RS) and Volunteer Fire Department (VFD) rate schedules. Residential sales are forecasted as the product of a use-per-customer forecast and a forecast of the number of customers.

2.1.2.1 LG&E Residential Customer Forecast

The number of LG&E residential customers was forecasted as a function of the number of households in the LG&E service territory. Household data by county – history and forecast – was provided by Global Insight.

2.1.2.2 LG&E Residential Use-Per-Customer Forecast

Average use per customer is forecasted using a Statistically-Adjusted End-Use (SAE) Model. Such a model combines an econometric model – that relates monthly sales to various explanatory variables such as weather and economic conditions – 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.

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

The heating, cooling and other components (the X variables) are based on various input variables including weather (heating and cooling degree days), appliance saturations, efficiencies[8], 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 discussion of each of these components and the methodology used to develop them is contained in Appendix B.

2.1.3 ODP Residential Forecast

The ODP residential forecast includes all customers on the Residential Service (RS) rate schedule. Residential sales were forecasted as the product of a use-per-customer forecast and a forecast of the number of customers.

2.1.3.1 ODP Residential Customer Forecast

The number of ODP residential customers was forecasted as a function of the number of households in the ODP service territory. Household data by county – history and forecast – was provided by Global Insight.

[8] Because changes in efficiencies are directly included, the impact of Company-sponsored DSM programs must be applied with caution so as to not double count its impact. See Appendix D for details.

2.1.3.2 ODP Residential Use-Per-Customer Forecast

Average use per customer is forecasted using a Statistically-Adjusted End-Use (SAE) Model. Such a model combines an econometric model – that relates monthly sales to various explanatory variables such as weather and economic conditions – 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

The heating, cooling and other components (the X variables) are based on various input variables including weather (heating and cooling degree days), appliance saturations, efficiencies[9], 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 discussion of each of these components and the methodology used to develop them is contained in Appendix B.

2.2 Commercial Forecast

The Commercial forecast is comprised of eight classes: KU General Service, KU Large Commercial, KU All-Electric Schools, LG&E Small Commercial, LG&E Large Commercial, ODP General Service, ODP Schools and ODP Municipal Pumping. Each of these classes was forecasted separately on a monthly basis over the thirty-year forecast period. The period of historical data used in the models varied depending on the patterns in each class's history.

2.2.1 KU General Service

Model Description: see Appendix C for details

The KU general service forecast includes all customers on the General Service rate and is comprised of two separate forecasts: a use-per-customer and a customer forecast. The former employed a Statistically-Adjusted End-Use model (SAE), which defines energy use as a function of energy used by heating equipment, cooling equipment, and other equipment (see description under KU Residential, 2.1.1.2 and Appendix C). (same comments apply re: DSM; see Appendix D for details)

The customer forecast was tied to the Residential customer forecast since, historically, the two have moved together. Based on historical growth relative to the growth rate of Residential customers, the GS customer forecast was allowed to grow at the same rate as the Residential customer forecast.

[9] Because changes in efficiencies are directly included, the impact of Company-sponsored DSM programs must be applied with caution so as to not double count its impact. See Appendix D for details.

2.2.2 KU Large Commercial

The KU Large Commercial forecast includes all customers on the PS Secondary and TOD Secondary rates. Sales to PS Secondary customers were modeled as a function of heating and cooling degree days, Retail and Wholesale Employment Indices, and binary variables, which account for oddities in the data.

2.2.3 KU All-Electric Schools (AES)

The KU All-Electric Schools forecast includes all customers on the All-Electric School rate schedule. KU AES sales were modeled as a function of the number of KU households, weather, and monthly binaries.

2.2.4 LG&E Small Commercial

The LG&E Small Commercial forecast includes all customers on the General Service ("GS") rate schedule and is comprised of two separate forecasts: a use-per-customer and a customer forecast. The former employed a Statistically-Adjusted End-Use model (SAE), which defines energy use as a function of energy used by heating equipment, cooling equipment, and other equipment (see description under LG&E Residential, 2.1.2.2 and Appendix C). (same comments apply re: DSM; see Appendix D for details)

The customer forecast was tied to the Residential customer forecast since, historically, the two have moved together. Based on historical growth relative to the growth rate of Residential customers, the GS customer forecast was allowed to grow at a the same rate as the Residential customer forecast.

2.2.5 LG&E Large Commercial (LC)

The LG&E Large Commercial forecast includes all customers on the CPS Primary, CPS Secondary, CTOD-Primary, and CTOD-Secondary rate schedules. LG&E Large Commercial sales were forecasted in total as a function of weather, the Industrial Production index, the number of households, and other monthly binary variables to account for oddities in the data.

2.2.6 ODP General Service (GS)

The ODP general service forecast includes customers on the general service rate schedule. ODP general service sales were forecasted as the product of a use-per-customer forecast and a forecast of the number of customers.

2.2.6.1 ODP General Service Customer Forecast

The number of ODP GS customers was forecasted as a function of the most recent year of historical actual (from SBR reports).

2.2.6.2 ODP General Service Use-Per-Customer Forecast

ODP GS use-per-customer was forecasted using a Statistically-Adjusted End-Use model (SAE), which defines energy use as a function of energy used by heating equipment, cooling equipment, and other equipment (see description under ODP Residential, 2.1.3.2 and Appendix C). (same comments apply re: DSM; see Appendix D for details)

2.2.7 ODP Schools

The ODP Schools forecast includes all customers on the School Service (SS) rate schedule. Sales to the ODP schools were modeled as a function of the number of households, weather, and monthly binaries.

2.2.8 ODP Municipal Pumping

The ODP municipal pumping forecast consists of customers on the Water Pumping Service rate schedule. ODP municipal pumping sales were forecasted to remain flat at May 2011-April 2012 levels.

2.3 Lighting Forecast

The Lighting forecast is comprised of five classes: LG&E Lighting, KU Street Lighting, KU Customer Outdoor Lighting (COL), ODP Street Lighting, and ODP Customer Outdoor Lighting (COL). LG&E/KU Lighting energy was forecasted in total using flat trend. Usage has been constant for the last 24 months and our company has no intelligence indicating that there will be a change in usage in the future. The LGE Company lighting forecast was adjusted upward from the 2011 MTP due to a change in the way the historical usage is compiled. This change raised the historical numbers, leading to an increase in the forecast. However, the 2013 Plan bears the same trend as the 2012 MTP.

2.4 Industrial Forecast

The industrial class is unique in the fact that the relatively small number of customers in the class make up a significant portion of the company's load. Plans to expand or shut-down operations by the larger industrial customers can have a significant impact on the company's load forecast. For this reason, the company works directly with its largest industrial customers (Major Accounts) wherever possible to develop a five-year forecast for these customers.

In the 2013 Plan forecast, Industrial sales are forecasted in groups and then allocated by historical percentages to each tariff. This was done to account for customer switching and usage fluctuation on individual rates that caused poor data correlation. Then, the Major Account forecasts are used to adjust the total usage forecast if a significant change is expected (e.g., an expansion is expected for one of the Major Account customers). In theory, since the historical usage data includes the impact of business expansions and shut-downs, most "normal" fluctuations in the Major Account forecasts will be incorporated in the total usage forecast. Therefore, only "exceptional" fluctuations will result in adjustments to the total forecast. The 2013 Plan industrial usage forecast is comprised of thirteen industrial forecast models.

2.4.1 KU Industrial Forecast

The KU industrial forecast is comprised of five forecast models. Table 2 summarizes the rate codes used in each model and the forecast methodology. The forecast models were created by grouping rate codes by voltage level.

Table 2 - KU Industrial Forecast Models

Model	***Rate Code***	***Forecast Methodology***
PS Primary (formerly LP Primary, STODP)	561 – Power Service, Primary	Econometric
RTS	550 – Retail Transmission Service	Econometric
FLS-T	730 – Fluctuating Load Service - Transmission	Trend – based on inputs from Account Managers
LTOD (formerly LCI-TOD Primary)	563 – Large TOD, Primary	Econometric
TOD-Primary	571– TOD Service, Primary	Econometric

2.4.1.1 PS Primary

The PS Primary forecast includes all customers on the PS rate schedule that take service at the primary distribution voltage except the GS customers of PS Primary. Sales to PS Primary customers were modeled as a function of cooling degree days, the Industrial Production Index, real price, and binary variables, which account for oddities in the data.

2.4.1.2 Retail Transmission Service

The RTS forecast includes all retail customers previously on a Transmission-level rate. One of the largest components was the usage by Mine Power customers so a Mine-Power related Industrial Production Index was included as a forecast driver as well as a customer count driver.

2.4.1.3 Fluctuating Load Service - Transmission

The FLS-T forecast includes one customer on the Large Industrial Time-of-Day ("LITOD") rate schedule. The LITOD forecast is developed based on discussions with that customer.

2.4.1.4 LTOD Primary

The Large Time-of-Day (LTOD) Primary forecast includes all customers on the LTOD rate schedule that take service at the primary distribution voltage. Sales to LTOD primary customers are modeled as a function of an industry-weighted Industrial Production Index and customer count.

2.4.1.5 TOD Service Primary

The Large Time-of-Day (LTOD) Primary forecast includes all customers on the TODS rate schedule that take service at the primary distribution voltage. Sales to LTODS primary customers are modeled as a function of an industry-weighted Industrial Production Index and customer count.

2.4.2 LG&E Industrial Forecast

The LG&E industrial forecast consists of six forecast models: Industrial Power Service Primary and Secondary, Industrial Time of Day Primary, Secondary and Primary (interruptible) and Retail Transmission Service. Each of these tariffs is forecast separately with its own economic drivers and weather sensitivity coefficients.
Due to customer switching that began in 2010 and has continued up to the beginning of the forecast period, some rate categories are forecasted on a combined basis and then allocated based on historical percentages in order to account for fluctuation between rates. Due to the nature of the econometric forecast model used, rate drivers were not feasible. Historically rates as well as usage have both grown, creating a positive correlation for the regression.

2.4.2.1 IPS-Primary and ITOD Primary

The IPS Primary and ITOD Primary forecast includes all customers on Industiral primary rates and were forecasted together due to customer switching from the PS Rate to the TOD rate. Monthly sales were modeled as a function of an industry-weighted Industrial Production Index and major account usage for both the Primary IPS rate and ITOD Primary rate.

2.4.2.2 IPS-Secondary and ITOD-Secondary

The IPS Secondary and ITOD Secondary forecast includes all customers on Industiral primary rates and were forecasted together due to customer switching from the PS Rate to the TOD rate. Monthly sales were modeled as a function of an industry-weighted Industrial Production Index and major account usage for both the Secondary IPS rate and ITOD Secondary rate.

2.4.2.3 Retail Transmission Service

The RTS forecast includes all retail customers previously on a Transmission-level rate. An Industrial Production Index was included as a forecast driver. RTS now includes Carbide Graphite, formerly on the ITOD-Primary Interruptible rate.

2.4.3 ODP Industrial Forecast

The ODP industrial forecast consists of one forecast model: ODP Large Power. The ODP Large Power forecast includes customers on the PS-Primary, PS-Secondary, TOD-Primary and TOD-Secondary rate schedules. Large power sales were forecasted as a function of weather and monthly binary variables. Table 3 lists the rate codes included in the ODP Industrial Forecast. The ODP territory experienced very little change over the 2011 calendar year for Industrial customers, so the 2013 BP ODP Industrial forecast was kept equal to the 2012 BP ODP Industrial forecast given that there was no impetus to create a new forecast.

Table 3 – ODP Industrial Forecast

Model Name	Rate Code
LP	551 – PS Primary 556 – PS Primary PF 552 – PS Secondary 558 – PS Secondary PF 571 – TOD Primary 572 – TOD Secondary 643 – RTS

2.5 KU Municipal Forecast

In the past, the KU municipal forecast consisted of three forecast models: KU Transmission Municipals, KU Primary Municipals, and the City of Paris. The City of Paris, which takes service at transmission voltages, was forecasted separately because it provides some of its own generation. For the 2013 BP, the forecasts provided by the munis themselves were evaluated and found to be superior to those produced in the traditional way. They were then grouped into transmission or primary. Each of these models is discussed in more detail in the following sections.

2.5.1 Transmission

With the exception of the City of Paris, the transmission municipal forecast includes all municipal customers on rate schedule WPS-87(M) who take service at transmission voltages. Sales to transmission municipal customers were modeled as a function of weather, the number of households, incomes and prices in the counties where the transmission municipal customers are located, and monthly binaries. The Transmission Municipal customers are Barbourville, Berea, Corbin, Frankfort, and Nicholasville.

2.5.2 Primary

The primary municipal forecast includes all municipal customers on the rate schedule WPS-87(M) who take service at the primary distribution voltage. Sales to transmission municipal customers were modeled as a function of weather, the number of households in the counties where the primary municipal customers are located and monthly binaries. The Primary Municipal customers are Bardstown, Bardwell, Benham, Falmouth, Madisonville, and Providence.

2.5.3 City of Paris

Sales to the City of Paris were modeled as a function of weather, the number of households in Bourbon County, and monthly binaries.

3. Data Processing

KU and LG&E customers are assigned to one of 20 billing cycles. Because most billing cycles do not coincide directly with the boundaries 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. Most historical usage data is recorded on a billed basis. As a result, most energy forecasts are produced initially on a billed basis. To meet the needs of the forecast end users, the billed energy must be processed further. The following processes are discussed in more detail in the following sections:

1. Billed-to-Calendar Energy Conversion
2. Rate Code and Revenue Class Allocation
3. Hourly Demand Forecast
4. Uncurtailed Hourly Demand Forecast

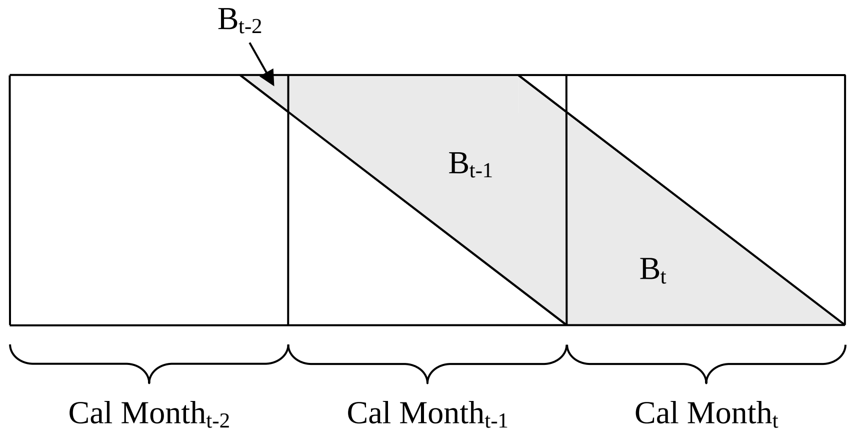
3.1 Billed-to-Calendar Energy Conversion

The billed volumes for most forecast classes do not coincide directly with the boundaries of calendar months. For this reason, most class forecast volumes must be converted from a billed to calendar basis to meet the needs of the Financial Planning department. The forecasts for the following rate classes do not have to be converted from a billed to calendar basis: KU FLS-T, Retail Transmission Service, and KU municipals. The customers in these forecast classes are billed on a calendar-month basis.

The shaded area in Figure 3 represents a typical billing month (B). Area B_t represents the volumes in the billing month that were consumed in the current calendar month (time = t). Area B_{t-1} represents the volumes in the billing month that were consumed in the previous calendar month (time = t-1). Area B_{t-2} represent the volumes in the billing month that were consumed in the calendar month two months prior to the current month (time = t-2)[10]. In this process, ratios of historical monthly calendar sales by revenue class to annual monthly calendar sales by revenue class are developed to allocate forecasted billed sales to calendar sales.

[10] Not all billing months include volumes that were consumed in the calendar month two months prior to the current month.

Figure 3 – Billed and Calendar Energy



A new approach was taken this year. Using 20 years of historical sales data from EMS by company (KUODP, LG&E) to obtain monthly allocation ratios, the annual billed sales forecasts (by company) were allocated into months using the monthly allocation ratios. This yields monthly calendar sales forecasts by company.
Then these monthly calendar sales by company were then allocated into rate categories (i.e., tariffs) using the ratio of billed sales by rate to total sales, again by company.

3.2 Rate Group and Revenue Class Allocation

To meet the needs of the Financial Planning department, the billed and calendar energy forecasts must be allocated by rate group and revenue class. In addition, forecasts of customers and billing demand – by rate group and revenue class – must also be developed. This information is used by the Financial Planning department to develop a forecast of revenues for the three year medium-term planning period. The development of the rate group and revenue class forecasts is summarized in the following:

- Billed and calendar forecasts are allocated by rate group and revenue class using a set of monthly allocation ratios. These ratios are derived based on historical sales data from CCS for energy, demand, and customers.

3.3 Hourly Demand Forecast

The Generation Planning department uses the hourly demand forecast to develop capacity expansion plans and a forecast of generation production costs. The hourly demand forecast is created in four steps. First, the monthly calendar sales forecasts for each class are allocated to hours using class-specific load shapes. These load shapes were created using load research data. Second, Energy Independence and Security Act (EISA) reductions are "layered" in using MetrixLT. Third, DSM reductions are "layered" in using MetrixLT. Fourth, losses are calculated and added to the forecast in Excel. After these steps are completed, the hourly load data is imported into Access to convert it into the proper format for Generation Planning.

3.3.1 Hourly Demand Forecast – Part 1

In the first part of the hourly demand forecast process, the monthly calendar sales forecasts are allocated to hours in MetrixLT using class-specific load shapes. There are 13 forecast classes for KU (including ODP, which is modeled as one class) and 7 forecast classes for LG&E.

The General Service and Residential class load shapes are developed in MetrixND. The process used to develop the remaining load shapes is summarized below:

1. Compute average hourly class profiles by month and day type using hourly class profile data.
2. For each month and class, specify daily average load models as a function of weather and day type.
3. Using the average class profiles from step 1, the weather and day type parameters from step 2, and a daily normal weather forecast (see Section 1.2.3), develop class load shapes for each forecast class.

Several large commercial and industrial customers are served on time-of-day rates. The time-of-day rates give customers an incentive to shift usage (and peak demand) from peak to off-peak periods. The impact of these rates is implicitly included in the hourly load shapes since the historical load profile data (upon which these shapes are based) reflects the impact of these rates.

3.3.2 Hourly Demand Forecast – Part 2

In the second part of the process, EISA-related reductions are layered into the hourly forecast (from part one) using MetrixLT. Each of the class-specific reductions that were made in this part of the process is discussed below.

EISA-Related Lighting Reductions

The EISA was signed into law by President Bush in December 2007. The provisions in EISA are primarily designed to increase energy efficiency and the availability of renewable energy. LG&E and KU electricity sales will be impacted primarily by provisions in the act that tighten lighting and appliance efficiency standards as well as foster the development of new building and commercial equipment standards. The impact of the new lighting efficiency standards is factored into the forecast in this part of the hourly demand forecasting process, as well as in the Residential and General Service SAE models. This means that existing incandescent bulbs will eventually be phased out as a result of these reductions, which are scheduled to take place between 2012 and 2014.

Residential, commercial, industrial, and municipal sales classes are expected to be impacted by the new lighting standards. For the large commercial, industrial, and municipal classes, energy reductions reflecting EISA from EIA are incorporated through MetrixLT. The impact of the new efficiency, building, and commercial equipment standards is captured by the residential and general service end-use models.

3.3.3 Hourly Demand Forecast – Part 3

In the third part of the hourly demand forecast process, the company’s DSM programs are ‘layered’ into the hourly demand forecast (from part two) using MetrixLT. For the 2013 Plan forecast, estimates of annual energy reductions were provided by the Energy Efficiency group.

For forecasting purposes, each program is assigned to one of six categories: Residential, Residential Lighting, General Service, Commercial Lighting, Refrigerator, and Appliances (which includes multiple different appliance end-use shapes). Table 4 contains a list of the DSM programs and their associated categories.

Table 4 – DSM Programs and DSM Categories

DSM Program	**Forecast Category**
Residential Conservation (HEPP)	Residential
Residential Low Income Weatherization	Residential
Residential Lighting	Residential Lighting
Residential HVAC Tune Up	Residential
Residential New Construction	Residential
Residential Demand Conservation	Dispatchable
Residential Smart Energy Profile	Residential
Residential Refrigerator Removal	Refrigerator
Residential Incentives	Appliances
Commercial Conservation/Rebates	Commercial Lighting
Commercial HVAC Tune Up	General Service
Commercial Demand Conservation	Dispatchable

The forecast category determines how each DSM program is layered into the hourly demand forecast. The annual energy reduction for 'Lighting' programs, for example, is allocated to hours based on a residential or commercial lighting usage profile. Since the variability in total residential and commercial sales is driven largely by heating and cooling usage, the annual energy reductions for programs associated with heating and cooling are allocated to hours based on a residential or general service usage profile.

The 'Dispatchable' programs are unique in the fact that the Generation Dispatch group can call upon these programs to reduce demand during peak periods. The 'Dispatchable' programs are layered into the hourly demand forecast in a way that is consistent with the way the Generation Dispatch group utilizes these programs in practice.

3.3.4 Hourly Demand Forecast – Part 4

In the fourth part of the hourly demand forecast process, losses are added to the hourly demand forecast (from part 3) to determine energy requirements. Losses are calculated as a percentage of load depending on the month, with higher losses in peak months, as well as higher losses at peak times.

4. Data Checking and Reporting

The forecast production process involves an enormous amount of data and calculations. For this reason, every aspect of the forecast must be checked for errors. The following is a list of key "checks".

1. Check input data for accuracy. Plot all inputs to check for abnormal trends. When monthly input data are created from annual data, check process for accuracy.
2. Review forecast model specification before forecasts are produced. Each analyst presents his/her forecast model(s) to remainder of group.
3. Check forecast results against prior year's forecast. Explain/understand differences in trends.
4. Check near-term forecast results against weather-normalized actual sales. Focus on the following:
    a. Monthly distribution of energy in forecast should be consistent with history. If November usage, for example, is consistently lower than October usage for a given class, the forecast should reflect this fact.
    b. Location of peak month in forecast should be consistent with history. If peak consistently occurs in winter months for a given class, the forecast should reflect this fact.
    c. Year-over-year growth should be consistent with history or explained if different from history.
    d. Sales levels in the first year of the forecast should be consistent with weather-normalized actual sales and recent variance reporting experience.
5. Check billed-to-calendar conversion process/results.
6. Check demand forecast process/results.
7. Check rate/revenue class allocation process/results.
8. Check uncurtailed demand process/results.

Appendix A – Service Territories and Their Component Counties

Kentucky Utilities		LG&E Electric	LG&E Gas	Old Dominion Power
Adair	Hopkins	Bullitt	Barren	Dickenson,VA
Anderson	Jessamine	Hardin	Bullitt	Lee, VA
Ballard	Knox	Jefferson	Green	Russell, VA
Barren	Larue	Meade	Hardin	Scott, VA
Bath	Laurel	Oldham	Henry	Wise, VA
Bell	Lee	Trimble	Hart	
Bourbon	Lincoln		Jefferson	
Boyle	Livingston		Larue	
Bracken	Lyon		Marion	
Bullitt	McCracken		Meade	
Caldwell	McCreary		Metcalfe	
Campbell	McLean		Nelson	
Carlisle	Madison		Oldham	
Carroll	Marion		Shelby	
Casey	Mason		Spencer	
Christian	Mercer		Trimble	
Clark	Montgomery		Washington	
Clay	Muhlenberg			
Crittenden	Nelson			
Daviess	Nicholas			
Edmonson	Oldham			
Estill	Owen			
Fayette	Pendleton			
Fleming	Pulaski			
Franklin	Robertson			
Fulton	Rockcastle			
Gallatin	Rowan			
Garrard	Russell			
Grant	Scott			
Grayson	Shelby			
Green	Spencer			
Harlan	Taylor			
Hardin	Trimble			
Harrison	Union			
Hart	Washington			
Henderson	Webster			
Henry	Whitley			
Hickman	Woodford			

Appendix B – Residential Use-per-Customer Forecast

The following sections summarize the design of the companies' residential use-per-customer model and key input data sources. Average monthly use per customer is forecast for LG&E, KU and ODP under the assumption of normal weather.

Model Design

Average use per customer is forecasted using a Statistically-Adjusted End-Use (SAE) Model. Such a model combines an econometric model – that relates monthly sales to various explanatory variables such as weather and economic conditions – 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.

$$\text{Use-per-Customer} = a_1 * \text{XHeat} + a_2 * \text{XCool} + a_3 * \text{XOther}$$

The heating, cooling and other components (the X variables) are based on various input variables like appliance saturations, efficiencies, and economic and demographic variables such as income, population, member per household and electricity prices. Once these components have been computed, a regression model is specified to forecast use-per-customer as a function of these components. Each of these components is discussed in more detail in the following paragraphs.

X Variables: XHeat

Heating use is dependent upon heating degree days, heating equipment saturation levels, heating equipment operation efficiencies, thermal integrity of homes, average household size, average household income, and electric price. The heating variable is represented as the product of an annual equipment index and a usage multiplier as illustrated below:

$$\text{XHeat}_{y,m} = \text{HeatIndex}_y * \text{HeatUse}_{y,}$$

Where:

$\text{XHeat}_{y,}$ = Estimated heating energy use for the year
HeatIndex_y = Annual index of heating equipment
HeatUse_y = Annual usage multiplier

The Heating Index variable above is defined as a weighted average of equipment saturation levels in conjunction with operating efficiency levels by type of heating equipment. Heating equipment modeled include heat pumps, electric space heating, and electric furnaces. Formally, this heating equipment index is:

$$HeatIndex_y = \sum_{Type} Wgt^{Type} * \frac{\left(HeatShare^{Type}_y \Big/ Eff^{Type}_y \right)}{\left(HeatShare^{Type}_{by} \Big/ Eff^{Type}_{by} \right)}$$

Where:

$HeatShare^{Type}_y$ = Share of heating appliance for each year
$HeatShare^{Type}_{by}$ = Share of heating appliance in base year
Eff^{Type}_y = Efficiency of heating appliance for each year
Eff^{Type}_{by} = Efficiency of heating appliance in base year
Wgt^{Type} = Base year heating appliance energy divided by total households in base year

The HeatUse variable defined above is impacted by the following exogenous variables: heating degree-days, household size, household income, and electric price. The heating degree-days are derived using daily high/low temperature observations (from the Lexington and Louisville weather stations for KU and LG&E, respectively) and a 65-degree base. The HeatUse variable is defined as:

$$HeatUse_{y,m} = \left(\frac{HDD_y}{NormHDD}\right)\left(\frac{HHSize_y}{HHSize_{by}}\right)^{0.35}\left(\frac{Income_y}{Income_{by}}\right)^{0.20}\left(\frac{Price_y}{Price_{y-1,2,3}}\right)^{-e}$$

Where:

HDD_y = Heating Degree days in a given year
NormHDD = Normal value of annual heating degree days
$HHSize_y$ = Average household size in a year
$HHSize_{by}$ = Average household size in a base year
$Income_y$ = Average real income per household in a year
$Income_{by}$ = Average real income per household in base year
$Price_y$ = Average real price of electricity in base year
$Price_{y-1,2,3}$ = Average real price of electricity in previous years
e = Price elasticity

X Variables: XCool

The construction of the cooling use component is similar to that of the heating use component in that it is dependent upon cooling degree-days, cooling equipment saturations, cooling equipment operation efficiencies, and average household size, average household income, and electric energy prices. The cooling variable is represented as the product of an annual equipment index and a usage multiplier as illustrated below:

$$XCool_{y,m} = CoolIndex_y * CoolUse_y$$

Where:

$XCool_y$	= Estimated cooling energy use for the year
$CoolIndex_y$	= Annual index of cooling equipment
$CoolUse_y$	= Annual usage multiplier

The Cooling Index variable above is defined as a weighted average of equipment saturation levels in conjunction with operating efficiency levels by type of cooling equipment. Cooling equipment modeled includes heat pumps, room air conditioners, and central air conditioners. Formally, this Cooling equipment index is:

$$CoolIndex_y = \sum_{Type} Wgt^{Type} * \frac{\left(CoolShare^{Type}_y \big/ Eff^{Type}_y \right)}{\left(CoolShare^{Type}_{by} \big/ Eff^{Type}_{by} \right)}$$

Where:

$CoolShare^{Type}_y$	= Share of cooling appliance for each year
$CoolShare^{Type}_{by}$	= Share of cooling appliance in base year
Eff^{Type}_y	= Efficiency of cooling appliance for each year
Eff^{Type}_{by}	= Efficiency of cooling appliance in base year
Wgt^{Type}	= Base year cooling appliance energy divided by total households in base year

The CoolUse variable defined above is impacted by the following exogenous variables: cooling degree-days, household size, household income, and electric price. As for the HDDs, the cooling degree-days are derived using daily high/low temperature observations against a 65-degree base. The CoolUse variable is defined as:

$$CoolUse_y = \left(\frac{CDD_y}{NormCDD}\right)\left(\frac{HHSize_y}{HHSize_{by}}\right)^{0.35}\left(\frac{Income_y}{Income_{by}}\right)^{0.20}\left(\frac{Price_y}{Price_{y-1,2,3}}\right)^{-e}$$

Where:

CDD_y	= Cooling Degree days in year and month
$NormCDD$	= Normal value of annual cooling degree days
$HHSize_y$	= Average household size in a year
$HHSize_b$	= Average household size in base year

$Income_y$	= Average real income per household in a year
$Income_{by}$	= Average real price of electricity in base year
$Price_{y-1,2,3}$	= Average real price of electricity in previous years
e	= Price elasticity

X Variables: XOther

The "Other" use component is a monthly estimate of non-weather sales and is derived from appliance and equipment saturation levels, appliance efficiency levels, average number of billing days per month, average household size, average household income, and electric prices. The explanatory variable for Other use is defined as follows:

$$XOther_y = OtherIndex_y * OtherUse_y$$

Where:

$XOther_y$	= Estimated heating energy use for the year
$OtherIndex_y$	= Annual index of non heating or cooling equipment
$OtherUse_y$	= Annual usage multiplier

The OtherIndex variable embodies information about appliance saturation levels and efficiency levels. The appliances modeled include electric water heaters, refrigerators, freezers, electric cooking stoves, electric dryers, dishwashers, washing machines, and miscellaneous appliances. The equation is defined as follows:

$$OtherIndex_{y,m} = \sum_{Type} Wgt^{Type} * \frac{\left(Sat^{Type}_{y} \middle/ Eff^{Type}_{y} \right)}{\left(Sat^{Type}_{by} \middle/ Eff^{Type}_{by} \right)}$$

Where:

Sat^{Type}_{y}	= Share of appliance type per year
Sat^{Type}_{b}	= Share of appliance type in base year
Eff^{Type}_{y}	= Efficiency of appliance per year
Eff^{Type}_{by}	= Efficiency of appliance in base year

The OtherUse variable is impacted by the following exogenous variables: billing days, household size, household income and electric price. Billing days are defined as the number of billing days for the year. The OtherUse variable is defined as:

$$OtherUse_{y,m} = \left(\frac{BillingDays_y}{365} \right) \left(\frac{HHSize_y}{HHSize_{by}} \right)^{0.46} \left(\frac{Income_y}{Income_{by}} \right)^{0.10} \left(\frac{Price_y}{Price_{y-1,2,3}} \right)^{-e}$$

Where:

$BillingDays_y$ = Billing days for the year

$HHSize_y$	= Average household size in a year
$HHSize_{by}$	= Average household size in base year
$Income_y$	= Average real income per household in a year
$Income_{by}$	= Average real income per household in base year
$Price_y$	= Average real price of electricity for the year
$Price_{y-1,2,3}$	= Average real price of electricity in previous years
e	= Price elasticity

Input Data Sources

Developing the 'X' variables for the SAE model is data intensive, employing inputs from a number of sources. The residential forecast models rely on inputs from the Energy Information Administration (EIA) forecasts of saturations and efficiencies, which are inputs into the Index variables mentioned above. The results of a KU/LG&E appliance saturation survey conducted in 2009 provided base-year saturations, as well as demographic variables such as the number of people per household, and structural variables such as dwelling size, age and type (single-family, multi-family, mobile home). Unit Energy Consumption (UEC) values were obtained from the EIA (also an input into the aforementioned Index variables).

Use variables are predominantly functions of weather, demographics, and economics. Data sources include the National Oceanic & Atmospheric Association (NOAA) and Global Insight. The elasticities of demand (i.e., the exponents of each of the components in the Use equations) were derived by Itron except for the price elasticity where EIA values were used. The real electricity price series, which is extended through the forecast period, is developed by the Finance department. The real price series was extended based on the average growth in real prices for the last three years from the Finance department's forecast.

Model Implementation

This section details the methodologies employed in the construction of the following variables:

- Saturations of Heating and Cooling equipment, other appliances;
- Efficiencies of Heating and Cooling equipment, other appliances;
- Unit Energy Consumption values;
- Thermal or structural index

Appliance Saturations

Each year, the EIA produces an Annual Energy Outlook that contains a 25-year forecast of energy sales, fuel prices, equipment stock, households, and even fuel-switching by region and by housing type[11].

In 2010, a residential end-use appliance saturation survey was conducted for KU, LG&E, and ODP to gain a better understanding of appliance saturation and energy use. These results superseded estimates that were provided by the EIA which has appliance saturation estimates by region.

[11] Kentucky is in the East South Central region.

Appliance Efficiencies

The 2013 Plan forecast model efficiencies came from the EIA and incorporated the most current regulations promulgated by the Department of Energy[12].

In order to obtain a sense of the effect of the change in efficiency standards on the residential use-per-customer forecasts, the EIA efficiencies were adjusted in two ways. First, the EIA efficiencies only incorporate known and measurable changes in policy; as a result, no gains in efficiency are expected beyond 2030 in the EIA forecasts. This assumption was changed to allow the efficiencies of the appliances in the XOther category (non-weather sensitive) to continue to improve at their current levels. Second, the level of improvement attained in 2030 was carried forward through the forecast period for the central air conditioner and the Heat Pump (cooling).

Unit Energy Consumption (UEC) Values

The 2013 Plan forecast employed UEC values that were similar to those employed in the 2011 MTP forecast. Itron files that contain UEC values per appliance, in conjunction with EIA estimates, were used for KU/LG&E's specific region (East South Central region).

Structural Indices

The 2013 Plan forecast models include structural variables like the size of a dwelling, its surface area (SA), and an index that measures the efficiency of the thermal shell of its structure. These variables were incorporated into a structural index (S.I.) that was used to modify the Heating and Cooling Use variables in the following manner:

$$\mathbf{X}\ \text{Index}_y = \sum_{\text{Type}} \text{SI}_y * \text{Wgt}^{\text{Type}} * \frac{\left(\text{Sat}^{\text{Type}}{}_y \big/ \text{Eff}^{\text{Type}}{}_y \right)}{\left(\text{Sat}^{\text{Type}}{}_{by} \big/ \text{Eff}^{\text{Type}}{}_{by} \right)}$$

Where

$$\text{SI}_y = \text{SA}_y * \text{Shell Efficiency}_y \,/\, \text{SA}_{by} * \text{Shell Efficiency}_{by}$$

$$\text{SA}_y = 892 + 1.44 * \text{Dwelling size (square feet)}$$

[12] Namely, the Energy Independence and Security Act of 2007

Appendix C – Commercial Use-per-Customer Forecast

The following sections summarize the design of the companies' commercial use-per-customer model and key input data sources. Average monthly use per customer is forecast for LG&E, KU and ODP under the assumption of normal weather.

2009 Commercial Electric
Statistically Adjusted End-Use (SAE) Spreadsheets

The 2009 Commercial SAE spreadsheets and models have been updated to reflect the Energy Information Agency's (EIA) most recent Annual Energy Outlook (AEO). This forecast reflects both the expected impacts of the 2007 Energy Independence and Security Act (EISA) and 2009 American Recovery and Reinvestment Act (ARRA). Elements that have been updated include:

- End-use energy intensity projections
- End-use efficiency projections
- End-use saturation projections
- Census division commercial SAE project files (MetrixND)

1.1 Energy Intensity Forecast Update

The primary factor driving the commercial indices are the long-term end-use energy intensity projections. Commercial energy intensity is measured in terms of energy use per square foot. The end-use energy intensities incorporate end-use efficiency trends, increase in end-use saturation, and change in long-term term usage driven by price, and economic conditions. Commercial energy intensities are calculated for each of the primary end-uses:

- Heating
- Cooling
- Ventilation
- Water Heating
- Cooking
- Refrigeration
- Outdoor Lighting
- Indoor Lighting
- Office Equipment (PCs)
- Miscellaneous

Appendix A:
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, the strength of econometric models is that they are well suited to identifying historical trends and to projecting these trends into the future. In contrast, the strength of the end-use modeling approach is the ability to identify 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 trends and saturation 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 introducing trends in equipment saturations and equipment efficiency 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 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 2009 Annual Energy Outlook (AEO) database provided by the Energy Information Administration (EIA).

1.5 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,

$$\text{Use}_{y,m} = \text{Heat}_{y,m} + \text{Cool}_{y,m} + \text{Other}_{y,m} \qquad (1)$$

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.

$$\text{Use}_m = a + b_1 \times \text{XHeat}_m + b_2 \times \text{XCool}_m + b_3 \times \text{XOther}_m + \varepsilon_m \qquad (2)$$

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 equipment saturation levels,
- Heating equipment operating efficiencies,
- Average number of days in the billing cycle for each month, and
- 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,

$$\text{XHeat}_{y,m} = \text{HeatIndex}_y \times \text{HeatUse}_{y,m} \qquad (3)$$

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 equipment saturation levels normalized by operating efficiency levels. The index will change over time with changes in heating equipment saturations (*HeatShare*) and operating efficiencies (*Eff*). Formally, the equipment index is defined as:

$$HeatIndex_y = HeatSales_{04} \times \frac{\left(HeatShare_y \big/ Eff_y \right)}{\left(HeatShare_{04} \big/ Eff_{04} \right)} \qquad (4)$$

In this expression, 2004 is used as a base year for normalizing the index. The ratio on the right is equal to 1.0 in 2004. In other years, it will be greater than one if equipment saturation levels are above their 2004 level. This will be counteracted by higher efficiency levels, which will drive the index downward. Base year space heating sales are defined as follows.

$$HeatSales_{04} = \left(\frac{kWh}{Sqft} \right)_{Heating} \times \left(\frac{CommercialSales_{04}}{\sum_e kWh \big/ Sqft_e} \right) \qquad (5)$$

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 2004 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, prices and billing days. Using the COMMEND default elasticity parameters, the estimates for space heating equipment usage levels are computed as follows:

$$HeatUse_{y,m} = \left(\frac{BDays_{y,m}}{30.5} \right) \times \left(\frac{WgtHDD_{y,m}}{HDD_{04}} \right) \times \left(\frac{Output_y}{Output_{04}} \right)^{0.20} \times \left(\frac{Price_{y,m}}{Price_{04}} \right)^{-0.18} \qquad (6)$$

where, *BDays* is the number of billing days in year (y) and month (m), these values are normalized by 30.5 which is the average number of billing days

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 2004, *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 one in the base year (2004). 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 one 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 equipment saturation levels,
- Cooling equipment operating efficiencies,
- Average number of days in the billing cycle for each month, and
- Commercial output and energy price.

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

$$\mathrm{XCool}_{y,m} = \mathrm{CoolIndex}_{y} \times \mathrm{CoolUse}_{y,m} \tag{7}$$

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:

$$CoolIndex_y = CoolSales_{04} \times \frac{\left(CoolShare_y / Eff_y \right)}{\left(CoolShare_{04} / Eff_{04} \right)} \tag{8}$$

Data values in 2004 are used as a base year for normalizing the index, and the ratio on the right is equal to 1.0 in 2004. In other years, it will be greater than one if equipment saturation levels are above their 2004 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.

$$CoolSales_{04} = \left(\frac{kWh}{Sqft}\right)_{Cooling} \times \left(\frac{CommercialSales_{04}}{\sum_e kWh/Sqft_e}\right) \qquad (9)$$

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 2004 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:

$$CoolUse_{y,m} = \left(\frac{BDays_{y,m}}{30.5}\right) \times \left(\frac{WgtCDD_{y,m}}{CDD_{04}}\right) \times \left(\frac{Output_y}{Output_{04}}\right)^{0.20} \times \left(\frac{Price_{y,m}}{Price_{04}}\right)^{-0.18} \qquad (10)$$

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 2004.

By construction, the *CoolUse* variable has an annual sum that is close to one in the base year (2004). 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 one 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 saturation levels,
- Equipment efficiency levels,
- 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:

$$\mathrm{XOther}_{y,m} = \mathrm{OtherIndex}_{y,m} \times \mathrm{OtherUse}_{y,m} \tag{11}$$

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:

$$OtherIndex_{y,m} = \sum_{Type} Weight_{04}^{Type} \times \left(\frac{Share_y^{Type} / Eff_y^{Type}}{Share_{04}^{Type} / Eff_{04}^{Type}} \right) \tag{12}$$

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.

$$Weight_{04}^{Type} = \left(\frac{kWh}{Sqft} \right)_{Type} \times \left(\frac{CommercialSales_{04}}{\sum_e kWh / Sqft_e} \right) \tag{13}$$

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

$$OtherUse_{y,m} = \left(\frac{BDays_{y,m}}{30.5} \right) \times \left(\frac{Output_y}{Output_{04}} \right)^{0.20} \times \left(\frac{Price_{y,m}}{Price_{04}} \right)^{-0.18} \tag{14}$$

Appendix D: Demand-Side Management (DSM) in the 2013 BP

To reconcile efficiencies between the SAE models and the Companies' DSM programs, the following steps are taken:

For each SAE-generated forecast the level of efficiency was held flat at the 2012 amount (measured in Unit Energy Consumption, or UEC). These results were then compared to a forecast in which the efficiencies were not held flat, i.e., a base-case forecast. The difference between these two is the expected amount of energy savings that result from using the SAE model.

Then, the expected savings from Company DSM programs was compared to the expected energy savings from the SAE models, the latter of which produced higher estimates of energy savings for most of the forecast period. For KU Residential, the SAE model projections were higher than our own Company projects beginning in 2013 and for LGE Residential they were higher beginning in 2015; as such, for LG&E Residential the difference between the two was then subtracted from the SAE-generated forecast to equal the Company DSM program estimates for 2013 and 2014.

In the case of the General Service forecasts, Company DSM projections were slightly higher through 2016, and the difference between Company and the SAE-generated forecasts energy savings was subtracted from the SAE-generated forecasts so that the 2013 BP forecasts have at least as much energy efficiency as projected by the Company.