2.0 Load Forecast and Forecasting Methodology

2.1 Summary of KPCo Load Forecast

The KPCo load forecast was developed by the American Electric Power Service Corporation (AEPSC) Economic Forecasting organization and completed in June 2016.[4] The final load forecast is the culmination of a series of underlying forecasts that build upon each other. In other words, the economic forecast provided by Moody's Analytics is used to develop the customer forecast, which is then used to develop the sales forecast, which is ultimately used to develop the peak load and internal energy requirements forecast.

Over the next 15-year period (2017-2031)[5], KPCo's service territory is expected to see population and non-farm employment decline of 0.1% per year. KPCo is projected to see customer count decline at a similar rate of 0.2% per year. Over the same forecast period, KPCo's retail sales are projected to decline at 0.2% per year with growth expected from the industrial class (+0.1% per year) while the residential class experiences a decline (0.5% per year) over the forecast horizon. Finally, KPCo's internal energy and peak demand are expected to decline at an average rate of 0.2% and 0.3% per year, respectively, through 2031.

2.2 Forecast Assumptions

2.2.1 Economic Assumptions

The load forecasts for KPCo and the other operating companies in the AEP System incorporate a forecast of U.S. and regional economic growth provided by Moody's Analytics. The load forecasts utilized Moody's Analytics economic forecast issued in December 2015.

[4] The load forecasts (as well as the historical loads) presented in this Report reflect the traditional concept of internal load, i.e., the load that is directly connected to the utility's transmission and distribution system and that is provided with bundled generation and transmission service by the utility. Such load serves as the starting point for the load forecasts used for generation planning. Internal load is a subset of *connected load*, which also includes directly connected load for which the utility serves only as a transmission provider. Connected load serves as the starting point for the load forecasts used for transmission planning.

[5] Fifteen year forecast period begins with the first full forecast year of 2017.

Moody's Analytics projects moderate growth in the U.S. economy during the 2017-2031 forecast period, characterized by a 2.0% annual rise in real Gross Domestic Product (GDP), and moderate inflation, with the implicit GDP price deflator expected to rise by 2.0% per year. Industrial output, as measured by the Federal Reserve Board's (FRB) index of industrial production, is expected to grow at 1.5% per year during the same period. Moody's projects employment growth of -0.1% per year during the forecast period and real regional income per-capita annual growth of 2.1% for the KPCo service area.

2.2.2 Price Assumptions

The Company utilizes an internally developed service area electricity price forecast. This forecast incorporates information from the Company's financial plan for the near term and the U.S. Department of Energy (DOE) Energy Information Administration (EIA) outlook for the East North Central Census Region for the longer term. These price forecasts are incorporated into the Company's energy sales models, where appropriate.

2.2.3 Specific Large Customer Assumptions

KPCo's customer service engineers are in frequent touch with industrial and commercial customers about their needs and activities. From these discussions, expected load additions or deletions are relayed to the Company.

2.2.4 Weather Assumptions

Where appropriate, the Company includes weather as an explanatory variable in its energy sales models. These models reflect historical weather for the model estimation period and normal weather for the forecast period.

2.2.5 Demand Side Management (DSM) Assumptions

The Company's long term load forecast models account for trends in EE both in the historical data as well as the forecasted trends in appliance saturations as the result of various legislated appliance efficiency standards (Energy Policy Act of 2005 [EPAct], Energy

Independence and Security Act [EISA] of 2007, etc.) modeled by the EIA. In addition to general trends in appliance efficiencies, the Company also administers multiple Demand-Side Management (DSM) programs that the Commission approved as part of its DSM portfolio. The load forecast utilizes the most current Commission-approved programs at the time the load forecast is created to adjust the forecast for the impact of these programs.

2.3 Overview of Forecast Methodology

KPCo's load forecasts are based mostly on econometric, statistically adjusted end-use and analyses of time-series data. This is helpful when analyzing future scenarios and developing confidence bands in addition to objective model verification by using standard statistical criteria.

KPCo utilizes two sets of econometric models: 1) a set of monthly short-term models which extends for approximately 24 months and 2) a set of monthly long-term models which extends for approximately 30 years. The forecast methodology leverages the relative analytical strengths of both the short- and long-term methods to produce a reasonable and reliable forecast that is used for various planning purposes.

For the first full year of the forecast, the forecast values are generally governed by the short-term models. The short-term models are regression models with time series errors which analyze the latest sales and weather data to better capture the monthly variation in energy sales for short-term applications like capital budgeting and resource allocation. While these models produce extremely accurate forecasts in the short run, without logical ties to economic factors, they are less capable of capturing structural trends in electricity consumption that are more important for longer-term resource planning applications.

The long-term models are econometric, and statistically adjusted end-use models which are specifically equipped to account for structural changes in the economy as well as changes in customer consumption due to increased energy efficiency. The long-term forecast models incorporate regional economic forecast data for income, employment, households, output, and population.

The short-term and long-term forecasts are then blended to ensure a smooth transition from the short-term to the long-term forecast horizon for each major revenue class. There are some instances when the short-term and long-term forecasts diverge, especially when the long-term models are incorporating a structural shift in the underlying economy that is expected to occur within the first 24 months of the forecast horizon. In these instances, professional judgment is used to ensure that the final forecast that will be used in the peak models is reasonable. The class level sales are then summed and adjusted for losses to produce monthly net internal energy sales for the system. The demand forecast model utilizes a series of algorithms to allocate the monthly net internal energy to hourly demand. The inputs into forecasting hourly demand are internal energy, weather, 24-hour load profiles and calendar information.

A flow chart depicting the sequence of models used in projecting KPCo's electric load requirements as well as the major inputs and assumptions that are used in the development of the load forecast is shown in Figure 3, below.

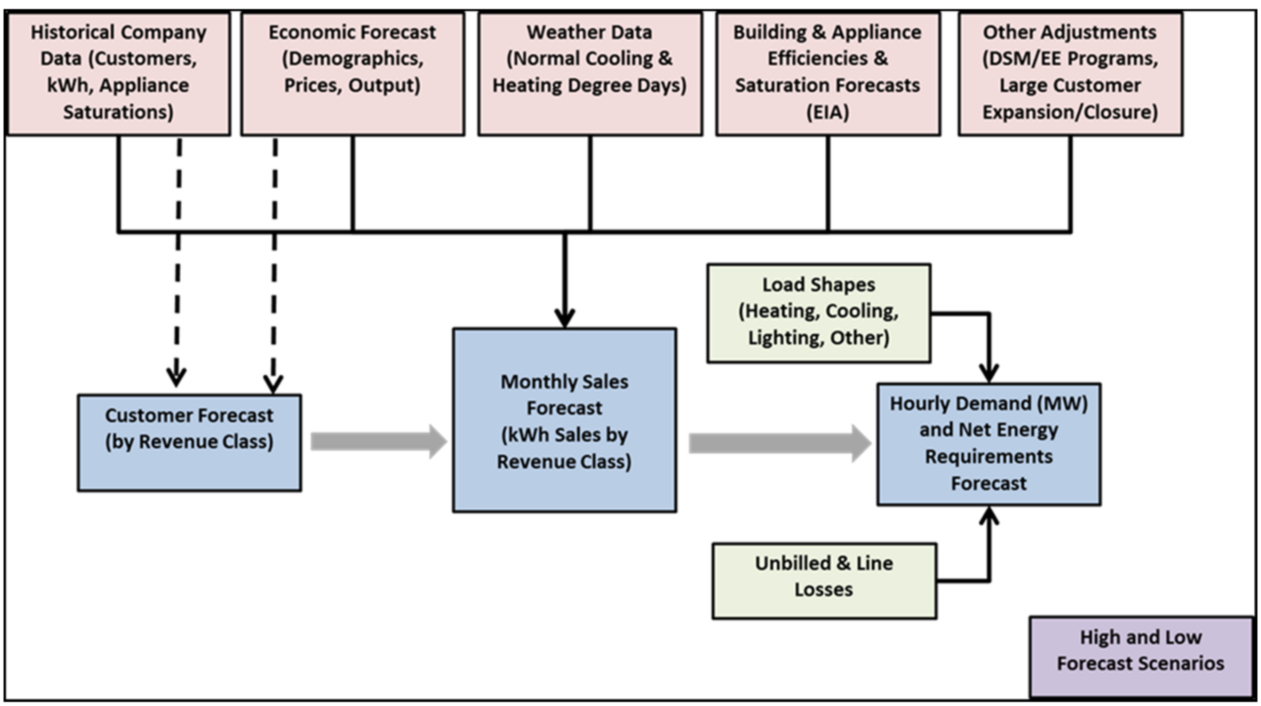

Figure 3. KPCo Internal Energy Requirements and Peak Demand Forecasting Method

2.4 Detailed Explanation of Load Forecast

2.4.1 General

This section provides a more detailed description of the short-term and long-term models employed in producing the forecasts of KPCo's energy consumption, by customer class. Conceptually, the difference between short- and long-term energy consumption relates to changes in the stock of electricity-using equipment and economic influences, rather than the passage of time. In the short term, electric energy consumption is considered to be a function of an essentially fixed stock of equipment. For residential and commercial customers, the most significant factor influencing the short term is weather. For industrial customers, economic forces that determine inventory levels and factory orders also influence short-term utilization rates. The short-term models recognize these relationships and use weather and recent load growth trends as the primary variables in forecasting monthly energy sales.

Over time, demographic and economic factors such as population, employment, income, and technology influence the nature of the stock of electricity-using equipment, both in size and composition. Long-term forecasting models recognize the importance of these variables and include all or most of them in the formulation of long-term energy forecasts.

Relative energy prices also have an impact on electricity consumption. One important difference between the short-term and long-term forecasting models is their treatment of energy prices, which are only included in long-term forecasts. This approach makes sense because although consumers may suffer sticker shock from energy price fluctuations, there is little they can do to impact them in the short-term. They already own a refrigerator, furnace or industrial equipment that may not be the most energy-efficient model available. In the long term, however, these constraints are lessened as durable equipment is replaced and as price expectations come to fully reflect price changes.

2.4.2 Customer Forecast Models

The Company also utilizes both short-term and long-term models to develop the final customer count forecast. The short-term customer forecast models are time series models with intervention (when needed) using Autoregressive Integrated Moving Average (ARIMA) methods of estimation. These models typically extend for 24 months into the forecast horizon.

The long-term residential customer forecasting models are also monthly but extend for 30 years. The explanatory jurisdictional economic and demographic variables include gross regional product, employment, mortgage rate, population, real personal income and households are used in various combinations. In addition to the economic explanatory variables, the long-term customer models employ a lagged dependent variable to capture the adjustment of customer growth to changes in the economy. There are also binary variables to capture monthly variations in customers, unusual data points and special occurrences.

The short-term and long-term customer forecasts are blended as was described earlier to arrive at the final customer forecast that will be used as a primary input into both short-term and long-term usage forecast models.

2.4.3 Short-term Forecasting Models

The goal of KPCo's short-term forecasting models is to produce an accurate load forecast for the first full year into the future. To that end, the short-term forecasting models generally employ a combination of monthly and seasonal binaries, time trends, and monthly heating cooling degree-days in their formulation. The heating and cooling degree-days are measured at weather stations in the Company's service area. The forecasts relied on ARIMA models.

The estimation period for the short-term models was January 2006 through January 2016. There are models for residential, commercial, industrial, other retail, and wholesale sectors. The industrial models are comprised of 10 large industrial models and models for the remainder of the industrial sector. The wholesale forecast is developed using models for the cities of Vanceburg and Olive Hill.

Off-system sales and/or sales of opportunity are not relevant to the net energy requirements forecast as they are not requirements load or relevant to determining capacity and energy requirements in the IRP process.

2.4.4 Long-term Forecasting Models

The goal of the long-term forecasting models is to produce a reasonable load outlook for up to 30 years in the future. Given that goal, the long-term forecasting models employ a full range of structural economic and demographic variables, electricity and natural gas prices, weather as measured by annual heating and cooling degree-days, and binary variables to produce load forecasts conditioned on the outlook for the U.S. economy, for the KPCo service-area economy, and for relative energy prices.

Most of the explanatory variables enter the long-term forecasting models in a straightforward, untransformed manner. In the case of energy prices, however, it is assumed, consistent with economic theory, that the consumption of electricity responds to changes in the price of electricity or substitute fuels with a lag, rather than instantaneously. This lag occurs for reasons having to do with the technical feasibility of quickly changing the level of electricity use even after its relative price has changed, or with the widely accepted belief that consumers make their consumption decisions on the basis of expected prices, which may be perceived as functions of both past and current prices.

There are several techniques, including the use of lagged price or a moving average of price that can be used to introduce the concept of lagged response to price change into an econometric model. Each of these techniques incorporates price information from previous periods to estimate demand in the current period.

The general estimation period for the long-term load forecasting models was 1995-2015 The long-term energy sales forecast is developed by blending of the short-term forecast with the long-term forecast. The energy sales forecast is developed by making a billed/unbilled adjustment to derive billed and accrued values, which are consistent with monthly generation.

2.4.4.1 Supporting Models

In order to produce forecasts of certain independent variables used in the internal energy requirements forecasting models, several supporting models are used, including natural gas price and coal production models for KPCo’s service areas. These models are discussed below.

2.4.4.1.1 Consumed Natural Gas Pricing Model

The forecast price of natural gas used in the Company's energy models comes from a model of natural gas prices for the state’s three primary consuming sectors: residential, commercial, and industrial. In the state natural gas price models sectoral prices are related to East North Central Census region’s sectoral prices, with the forecast being obtained from EIA’s “2015 Annual Energy Outlook.” The natural gas price model is based upon 1980-2015 historical data.

2.4.4.1.2 Regional Coal Production Model

A regional coal production forecast is used as an input in the mine power energy sales model. In the coal model, regional production depends on mainly Appalachian coal production, as well as on binary variables that reflect the impacts of special occurrences, such as strikes. In the development of the regional coal production forecast, projections of Central Appalachian and U.S. coal production were obtained from EIA’s “2015 Annual Energy Outlook.” The estimation period for the model was 1998-2015.

Coal mining activity plays a significant role in the local economy of the Kentucky Power service territory. Figure 4 below provides coal production in Eastern Kentucky between 2000 and 2015. During this period coal production dropped from nearly 105 million tons to approximately 29 million tons or a decline of approximately 72%.

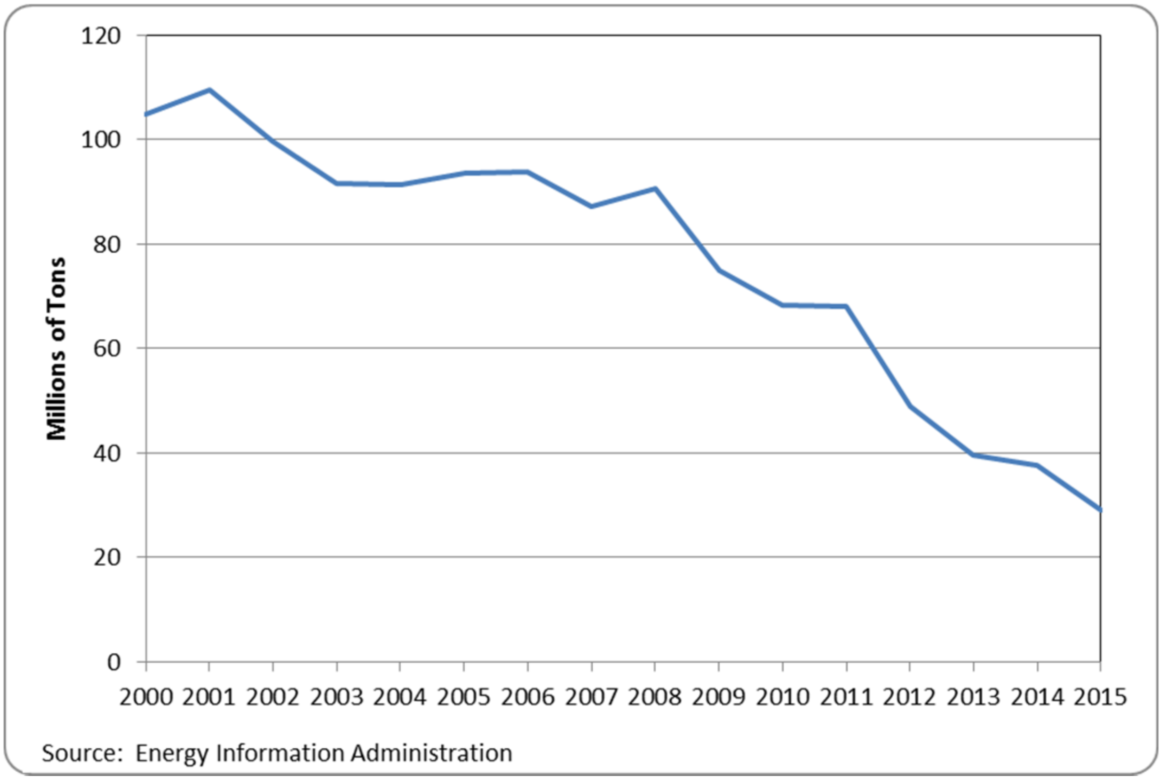

Figure 4. Eastern Kentucky Coal Production (Millions of Tons) 2000-2015

2.4.4.2 Residential Energy Sales

Residential energy sales for KPCo are forecasted using two models, the first of which projects the number of residential customers, and the second of which projects kWh usage per customer. The residential energy sales forecast is calculated as the product of the corresponding customer and usage forecasts.

The residential usage model is estimated using a Statistically Adjusted End-Use model (SAE), which was developed by Itron, a consulting firm with expertise in energy modeling. This model assumes that use will fall into one of three categories: heat, cool, and other. The SAE model constructs variables to be used in an econometric equation where residential usage is a function of Xheat, Xcool, and Xother variables.

The Xheat variable is derived by multiplying a heating index variable by a heating use variable. The heating index incorporates information about heating equipment saturation; heating equipment efficiency standards and trends; and thermal integrity and size of homes. The heating use variable is derived from information related to billing days, heating degree-days, household size, personal income, gas prices, and electricity prices.

The Xcool variable is derived by multiplying a cooling index variable by a cooling use variable. The cooling index incorporates information about cooling equipment saturation; cooling equipment efficiency standards and trends; and thermal integrity and size of homes. The cooling use variable is derived from information related to billing days, heating degree-days, household size, personal income, gas prices and electricity prices.

The Xother variable estimates the non-weather sensitive sales and is similar to the Xheat and Xcool variables. This variable incorporates information on appliance and equipment saturation levels; average number of days in the billing cycle each month; average household size; real personal income; gas prices and electricity prices.

The appliance saturations are based on historical trends from KPCo's residential customer survey. The saturation forecasts are based on EIA forecasts and analysis by Itron. The efficiency trends are based on DOE forecasts and Itron analysis. The thermal integrity and size of homes are for the East North Central Census Region and are based on DOE and Itron data.

The number of billing days is from internal data. Economic and demographic forecasts are from Moody's Analytics and the electricity price forecast is developed internally.

The SAE residential models are estimated using linear regression models. These monthly models are typically for the period January 1995 through January 2016. It is important to note, as will be discussed later, that this modeling *has* incorporated the reductive effects of the EPAct, EISA, American Recovery and Reinvestment Act of 2009 (ARRA) and Energy Improvement and Extension Act of 2008 (EIEA2008) on the residential (and commercial) energy usage based on analysis by the EIA regarding appliance efficiency trends.

The long-term residential energy sales forecast is derived by multiplying the "blended" customer forecast by the usage forecast from the SAE model.

2.4.4.3 Commercial Energy Sales

Long-term commercial energy sales are forecast using SAE models. These models are similar to the residential SAE models. These models utilize efficiencies, square footage and equipment saturations for the East North Central Region, along with electric prices, economic drivers from Moody's Analytics, heating and cooling degree-days, and billing cycle days. As with the residential models, there are Xheat, Xcool and Xother variables derived within the model framework. The commercial SAE models are estimated similarly to the residential SAE models.

2.4.4.4 Industrial Energy Sales

Based on the size and importance of the Mine Power sector to the overall KPCo Industrial base as well as the unique outlook for the mining sector in the long run, the Company models the Mine Power sales separately from the rest of the Industrial manufacturing sales in the long-term forecast models.

2.4.4.4.1 Manufacturing Energy Sales

The Company uses some combination of the following economic and pricing explanatory variables: service area gross regional product manufacturing, and service area industrial electricity prices. In addition binary variables for months are special occurrences and are incorporated into the models. Based on information from customer service engineers there may be load added or subtracted from the model results to reflect plant openings, closures or load adjustments. The last actual data point for the manufacturing energy sales models is January 2016.

2.4.4.4.2 Mine Power Energy Sales

For its mine power energy sales models, the Company uses some combination of the following economic and pricing explanatory variables: regional coal production, and service area mine power electricity prices. In addition binary variables for months are special occurrences and are incorporated into the models. Based on information from customer service engineers there may be load added or subtracted from the model results to reflect mine openings, closures or load adjustments. The last actual data point for the mine power energy sales models is January 2016.

2.4.4.5 All Other Energy Sales

The forecast of public-street and highway lighting relates energy sales to service area commercial employment and binary variables.

Wholesale energy sales are modeled relating energy sales to economic variables such as service area employment, energy prices, heating and cooling degree-days and binary variables.

2.4.5 Internal Energy Forecast

2.4.5.1 Blending Short and Long-Term Sales

Forecast values for 2016 and 2017 are taken from the short-term process. Forecast values for 2018 are obtained by blending the results from the short-term and long-term models. The blending process combines the results of the short-term and long-term models by assigning weights to each result and systematically changing the weights so that by July 2018 the entire forecast is from the long-term models. The goal of the blending process is to leverage the relative strengths of the short-term and long-term models to produce the most reliable forecast possible. However, at times the short-term models may not capture structural changes in the economy as well as the long-term models, which may result in the long-term forecast being used for the entire forecast horizon.

2.4.5.2 Losses and Unaccounted-For Energy

Energy is lost in the transmission and distribution of the product. This loss of energy from the source of production to consumption at the premise is measured as the average ratio of all Federal Energy Regulatory Commission (FERC) revenue class energy sales measured at the premise meter to the net internal energy requirements metered at the source. In modeling, Company loss study results are applied to the final blended sales forecast by revenue class and summed to arrive at the final internal energy requirements forecast.

2.4.6 Forecast Methodology for Seasonal Peak Internal Demand

The demand forecast model is a series of algorithms for allocating the monthly internal energy sales forecast to hourly demands. The inputs into forecasting hourly demand are blended revenue class sales, energy loss multipliers, weather, 24-hour load profiles and calendar information.

The weather profiles are developed from representative weather stations in the service area. Twelve monthly profiles of average daily temperature that best represent the cooling and heating degree-days of the specific geography are taken from the last 30 years of historical values. The consistency of these profiles ensures the appropriate diversity of the company loads.

The 24-hour load profiles are developed from historical hourly Company or jurisdictional load and end-use or revenue class hourly load profiles. The load profiles were developed from segregating, indexing and averaging hourly profiles by season, day types (weekend, midweek and Monday/Friday) and average daily temperature ranges.

In the end, the profiles are benchmarked to the aggregate energy and seasonal peaks through the adjustments to the hourly load duration curves of the annual 8,760 hourly values. These 8,760 hourly values per year are the forecast load of KPCo and the individual companies of American Electric Power (AEP) that can be aggregated by hour to represent load across the spectrum from end-use or revenue classes to total AEP-East, AEP-West, or total AEP System. Net internal energy requirements are the sum of these hourly values to a total company energy need basis. Company peak demand is the maximum of the hourly values from a stated period (month, season or year).

2.5 Load Forecast Results and Issues

All tables referenced in this section can be found in Exhibit C of the appendix to this report.