L. OVERVIEW OF FORECASTING MODELS

This appendix explains and summarizes the long-term energy and demand forecasting models for Cheyenne Light and Black Hills Power.

Long-term energy forecasts use a combination of its billing data, weather data from the National Oceanic and Atmospheric Administration (NOAA), and economic and demographic data from Woods & Poole. Demand forecasts use a combination of hourly system demand data and the same weather, economic, and demographic data.

Forecasts are based on single sales or on separate use-per-customer sales for residential, commercial, industrial, and municipal models. Included are the formulas employed to develop these forecast models.

Overview of Long-Term Energy and Demand Forecasting Models for Black Hills Power, Inc. and Cheyenne Light Fuel and Power Company

for

Black Hills Corporation

by

Christensen Associates Energy Consulting, LLC
800 University Bay Drive, Suite 400
Madison, WI 53705-2299
Voice 608.231.2266 Fax 608.231.2108

April 18, 2021

Table of Contents

Overview of Long-Term Energy and Demand Forecasting Models for Black Hills Power, Inc. and Cheyenne Light Fuel and Power Company

for

Black Hills Corporation

by

CHRISTENSEN ASSOCIATES ENERGY CONSULTING, LLC

April 18, 2021

1. INTRODUCTION

Christensen Associates Energy Consulting, LLC (CA Energy Consulting) assisted Black Hills Corporation (Black Hills) in developing long-term energy and demand forecasts for Black Hills Power, Inc. and Cheyenne Light Fuel and Power Company. Black Hills is required to file an Integrated Resource Plan (IRP) in Wyoming and South Dakota before July 1, 2021.

Black Hills develops class-specific sales forecasts using a combination of its billing data, weather data from the National Oceanic and Atmospheric Administration (NOAA), and economic and demographic data from Woods & Poole. System demand is forecast using a combination of hourly system demand data with the weather and economic data listed above.

Section 2 provides a description of the principles we apply when developing forecasts. Section 3 describes the models developed for Black Hills Power, Inc. (BHP). Section 4 describes the models developed for Cheyenne Light Fuel and Power Company (CLFP).

2. OVERVIEW OF THE FORECAST DEVELOPMENT PROCESS

<u>Selecting the dependent variable</u>

Statistical forecast models begin by explaining historical variation in a dependent variable (e.g., class-level sales or use per customer (UPC)) with available explanatory variables.

Forecasts may be based on either a single sales model or separate UPC and customer count models. The latter method may be preferred for mass-market classes (e.g., residential), where intra-class customer differences are expected to be minor compared to, say, a large industrial class. Separately modeling UPC and customer counts for these classes can improve the estimates of the effect of the various explanatory variables. For example, the number of households may be a primary driver of the number of residential customers served, but not be strongly related to residential use per customer.

In each of the models presented here, we take the natural log of the dependent variable and the continuous explanatory variables.[1] This makes it easier interpret and compare the estimated coefficients, as they represent percentage effects. If the models were instead estimated without logging the variables, the estimated coefficients would represent *level* effects whose interpretation is affected by the scale of the variables.

Selecting the explanatory variables

The explanatory variables may include the following categories:

- Weather;
- Economic conditions;
- Demographics;
- Seasonal indicators; or
- Time trends or shift variables.

Weather variables are typically based on temperatures and commonly expressed as cooling degree days (CDDs) or heating degree days (HDDs). CDDs are intended to reflect cooling-related usage and are calculated for day *d* as follows:

$$CDD_d = \text{MAX}\{0, (MaxTemp_d + MinTemp_d) / 2 - Threshold)\}$$

The MAX function ensures that CDD values are always non-negative. $MaxTemp_d$ and $MinTemp_d$ represent the maximum and minimum temperatures for the day, respectively. *Threshold* is the average daily temperature at which cooling load tends to begin (typically around 60°F).

HDDs reflect heating-related loads and are calculated in a similar manner as CDDs, but reversing the order of the average daily temperature and the *Threshold*:

$$HDD_d = \text{MAX}\{0, Threshold - (MaxTemp_d + MinTemp_d) / 2)\}$$

Forecasting models often use monthly sales or UPC as the dependent variable, in which case the CDDs and HDDs are summed across the relevant days to form the variables used in the statistical model.

Economic factors reflect the effect of the economy on electricity use or the number of customers served. The relevant variables can vary with the customer class of interest and may include the following variables:

- Household income;
- Gross regional product (GRP); or
- Earnings, sales, or employment (total or by sector).

Demographic variables can reflect changes in the size or makeup of the utility's service territory, and may include the following variables:

- Number of households; or

[1] The exceptions for continuous variables are CDDs and HDDs, which are frequently zero and therefore drop out when logged.

- Persons per household.

Seasonal or monthly factors are “indicator” variables (sometimes called “dummy” variables)[2] that account for seasonal changes in usage that are not accounted for by other included explanatory variables (e.g., lighting-related usage that can vary with the hours of daylight).

Time trend and shift variables are sometimes needed to reflect changes in the dependent variable that are clearly visible in the data but are not explained by any available explanatory variables. For example, this may include changes in the definition of the customer class. Time trend variables reflect the rate of change in the dependent variable over time, while shift variables account for one-time changes in the dependent variable.

Note that any explanatory variable included in the statistical model must have both historical and forecast values to be of use in the development of the forecast. In the case of weather variables, the forecast values typically represent normal weather conditions (e.g., the average value over the previous 20 years). Economic and demographic variables are best employed when external forecasts of them are available. Black Hills uses data from Woods & Poole, which provides historical and forecast values for economic and demographic variables by county.

When evaluating explanatory variables for inclusion in statistical forecast models, we focus on the following factors:

1. Whether the included variables make intuitive sense.
2. Whether the estimated coefficients on the included variables make intuitive sense.
3. Whether the resulting forecast is a reasonable reflection of the past as well as expectations for the future.

Regarding the first point, we consider whether it’s plausible that the included economic and/or demographic variables have a causal effect on the dependent variable (e.g., use per customer, sales, or the number of customers). For example, farm employment is probably not going to drive outcomes for a customer class that does not consist of a high share of farm-related customers.

On the second point, the estimates should have the expected sign, a reasonable magnitude, and be statistically significantly different from zero.[3] For example, we expect electricity use, use per customer, and the number of customers to increase as economic conditions improve. That would be reflected by a positive sign on the estimated coefficient on the economic variable.[4]

[2] For example, a March indicator variable would equal 1 for March observations and 0 for all other observations.
[3] This is evaluated using the p-value associated with the estimate, which is based on a test that the estimated coefficient equals zero (the “null hypothesis”). If the estimated coefficient equals zero, it means that changes in the variable do not affect the dependent variable (e.g., sales). A point estimate that is not zero may be statistically equivalent to zero if the standard error associated with the estimate is sufficiently large. A low p-value (below 0.10 or 0.05) leads us to reject the null hypothesis that the variable has no effect.
[4] A negative sign would be expected for economic variables for which higher values represent worsening conditions, such as the unemployment rate.

Demographic changes such as the change in the number of households are also expected to have specific signs. For example, an increase in the number of households should lead to increases in sales and increases in the number of customers served (a positive coefficient). Increases in persons per household may lead to increases in residential use per customer (also a positive coefficient).

Evaluating the magnitude of the coefficient requires some judgment and people may reach different conclusions. Economic variables shouldn't have outsized effects. For example, in models with logged dependent and explanatory variables, estimated coefficients larger than 1.0 mean the percentage change in the dependent variable will be larger than the percentage change in the economic variable (e.g., a 2 percent increase in GRP leads to a greater than 2 percent increase in sales). That threshold is a good starting point for judging the reasonableness of the variable, though the reasonableness of the coefficient may also be apparent in the forecast growth rate (i.e., an economic effect that is too large may lead to a growth rate in electricity sales that appears too high relative to historical rates).

Note that sometimes there are no economic variables that provide an intuitively appealing explanation of the dependent variable. This can arise when sales or use per customer are declining, perhaps due to conservation and improved energy efficiency (whether sponsored by the utility or as part of general economic or regulatory trends). In these cases, a time trend variable can be useful to allow the model to explain changes over time. In some cases, the introduction of a time trend allows the model to be able to estimate a separate and reasonable economic effect, but this is not always the case.

Finally, the model should produce a forecast that is a reasonable reflection of expectations given prior trends and Company information. For example, if sales declined steeply from 8 to 10 years ago but have remained relatively flat in more recent years, one might expect the forecast to place a higher weight on the recent (flat) trend. Applying this criterion involves exercising judgment and isn't necessarily a right vs. wrong issue (in contrast to evaluating the sign of a coefficient).

Accounting for serial correlation

Serial correlation is present when the statistical model's error (the difference between the observed value and the value predicted by the model) in a time period is related to the error in a prior time period. The presence of serial correlation does not produce biased coefficient estimates but may lead to incorrect inferences regarding a coefficient's statistical significance.

The presence of first-order serial correlation (when the current and previous observation's errors are related) is detected using the Durbin-Watson test. If the test indicates that serial correlation is present, we estimate the model using a Prais-Winsten method rather than traditional Ordinary Least Squares (OLS).

Developing High and Low Forecast Scenarios

Black Hills requested that we develop an 80 percent confidence interval around the demand and sales forecasts. That is, the forecast represents the sales and demand levels we expect to occur on average. However, considerable uncertainty remains regarding the economic conditions that will occur during the forecast period. For example, a recession could arise, or a period of sustained growth could occur. The confidence interval provides an indication of the extent to which demand and sales can vary due to such uncertainties.

In order to capture a wide range of economic conditions, we base our variability calculations on data beginning in 1969 and ending with the most recent observed data point. The data are provided by Woods & Poole and focus on the variable used in the forecast models. The variability calculation takes a mid- to long-term perspective, based on the average annual percentage change over ten-year period.

Specifically, we calculate the year-to-year percentage changes in the economic variable (e.g., gross regional product, total employment, or personal income) and then calculate 10-year moving averages of those percentage changes. The peak demand model provides us with an estimate of the effect of changes in the economic variable on changes in peak demand, along with a standard error associated with the estimate. These two uncertainties (in economic conditions over time and in the estimated effect of economic conditions on peak demand) are combined to produce the confidence interval around the demand and sales forecasts.

Here is a description of the steps we used to develop the confidence interval:

1. Calculate the average annual 10-year percentage change in the economic variable for each 10-year window between 1969 and 2017, producing 39 separate percentage change values.
2. Calculate the mean and standard deviation of the percentage changes across these 39 observations.
3. From the peak demand model, obtain the estimated coefficient and standard error associated with the included economic variable.
4. The mean expected growth rate of demand is estimated as the product of the estimated coefficient and the mean of the 39 percentage change observations.
5. The standard deviation of the growth rate of demand is estimated by combining the standard error of the estimated coefficient with the standard deviation of the historical percentage changes in the economic variable.[5]
6. The coefficient of variation (CV) of the economic-based variability is calculated as the standard deviation calculated in step 5 divided by the mean expected growth rate calculated in step 4.
7. For any given forecast value, the high and low scenarios are simulated as the 90th and 10th percentile values (respectively) from a normal distribution, with a mean equal to

[5] This calculation is performed as the standard deviation of the product of two random variables, as follows: $Var(XY) = Var(X)Var(Y)+Var(X)(E(Y))^2+Var(Y)(E(X))^2$

the "base" forecast growth rate and the standard deviation equal to the absolute value of the base forecast growth rate[6] multiplied by the CV calculated in Step 6.

8. These high and low percentages are applied to the demand and sales forecasts in each of the forecast months.

3. THE BLACK HILLS POWER (SOUTH DAKOTA) FORECAST

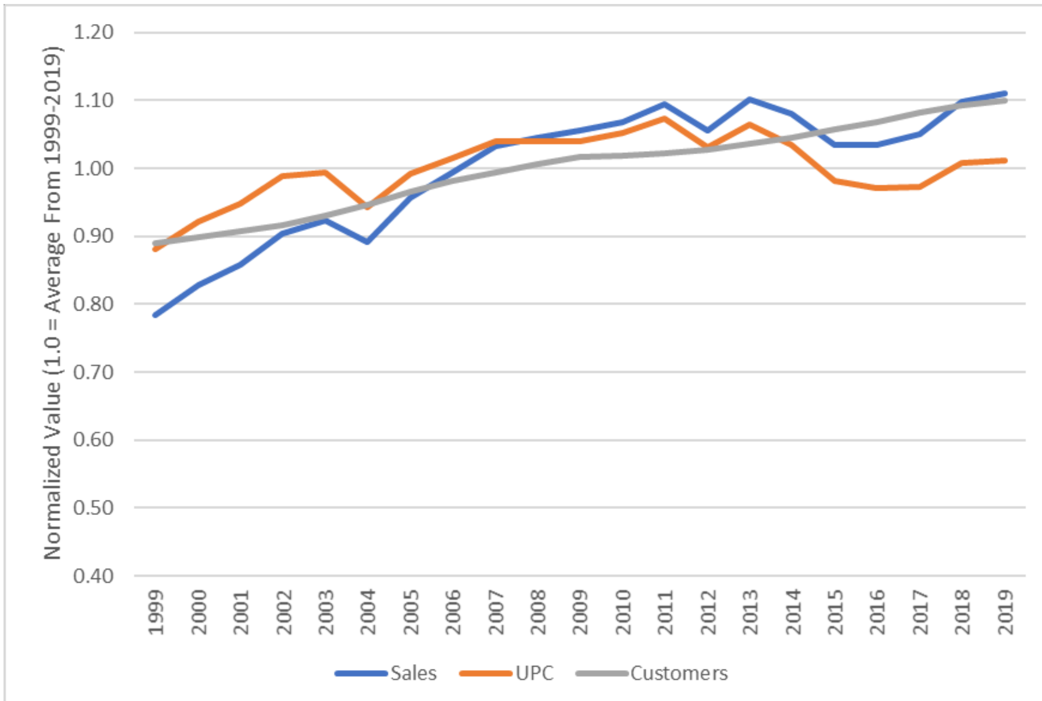
In this section, we describe the forecasting models for each customer class in the Black Hills Power (BHP) service territory. In each case, we show a graph reflecting historical annual sales, use per customer (UPC), and the number of customers over time. Each series is normalized to show a value that is indexed to the average across the time period shown (i.e., a value of 0.9 means that year's value is 90 percent of the average over the time period shown). This normalization facilitates a comparison of trends in the outcomes across years, which naturally occur on different scales. The figures show observed (non-weather normalized) values. The Appendix contains detailed results for each forecast model.

3.1 Residential

Figure 3.1 shows the normalized sales, UPC, and customer counts for BHP's Residential customer class. The upward trend in sales appears to be primarily driven by growth in customers served, while year-to-year variations in total sales are highly correlated with those of UPC. We estimate separate UPC and customer models to better account for these separate effects.

[6] Taking the absolute value of the forecast growth rate is necessary because standard deviations cannot be negative.

Figure 3.1: BHP Residential Normalized Sales, UPC, and Customer Counts



The Residential UPC model is:

$$\ln(upc_t) = a + b^{CDD} \times CDD_t + b^{HDD} \times HDD_t + b^{Trend} \times Trend_t + \Sigma_m(b^m \times Month_{m,t}) + e_t$$

In this equation, *a* and the *b*'s are estimated parameters; e_t is the error term; *t* indexes time periods; and *m* indexes months. The explanatory variables are:

- CDD_t = CDD using a 60°F threshold
- HDD_t = HDD using a 60°F threshold
- $Trend_t$ = Time trend
- $Month_{m,t}$ = month dummies[7]

The model is estimated using data from 2007 through 2019 using the Prais-Winsten serial correlation correction. No available economic or demographic variables produced a reasonable coefficient estimate. Data prior to 2007 is excluded due to the high growth in UPC during that period vs. more recent years. The time trend accounts for the slight downward trend in UPC following 2007 (approximately 0.5 percent per year).

[7] The model includes eleven month-specific dummies, with the January variable omitted to prevent perfect multicollinearity of the month variables. That is, the coefficients for the included months are interpreted as an effect relative to the omitted month.

The Residential customer model is:

$$\ln(custs_t) = a + b^{Emp} \times \ln(TotEmp_t) + \Sigma_m(b^m \times Month_{m,t}) + e_t$$

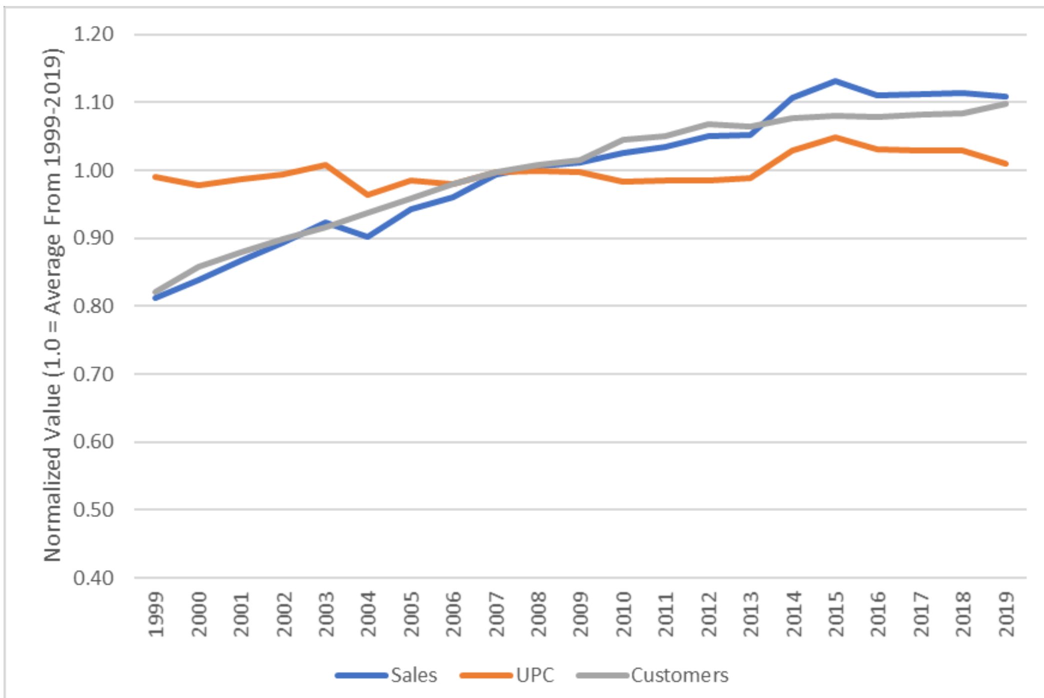
The explanatory variables are:
- $\ln(TotEmp_t)$ = the natural log of total employment (12-month moving average)
- $Month_{m,t}$ = month dummies

The model is estimated using data from 2007 through 2019 using the Prais-Winsten serial correlation correction. The estimated coefficient on the total employment variable reflects a positive relationship between economic conditions and the number of customers served.

3.2 Commercial

As Figure 3.2 shows, BHP's Commercial UPC (and as a result, total sales) increased to a higher level beginning around 2014. This upward shift appears to be due to customers changing classes, resulting in an influx of customers that led to a one-time shift in UPC. Class sales, which had been increasing prior to 2014, were largely flat following the class shift.

Figure 3.2: BHP Commercial Normalized Sales, UPC, and Customer Counts



The Commercial UPC model is:

$$\ln(upc_t) = a + b^{CDD} \times CDD_t + b^{HDD} \times HDD_t + b^{Shift} \times ClassShift_t + b^{Trend} \times Trend_t + b^{Emp} \times \ln(TotEmp_t) + \Sigma_m(b^m \times Month_{m,t}) + e_t$$

The explanatory variables are:

- CDD_t = CDD using a 60°F threshold
- HDD_t = HDD using a 60°F threshold
- $ClassShift_t$ = a "class shift" indicator variable equal to 1 beginning in June 2014 and 0 prior to that month
- $Trend_t$ = Time trend
- $\ln(TotEmp_t)$ = the natural log of total employment (12-month moving average)
- $Month_{m,t}$ = month dummies

The model is estimated using data from 1999 through 2019 using the Prais-Winsten serial correlation correction. The estimated coefficients for the employment and time trend variables reflect offsetting effects. Commercial UPC increases with employment, with a separate downward trend of approximately 0.6 percent per year. The estimated coefficient for the class shift variable indicates 6.1 percent higher UPC during the post-June 2014 period.

The Commercial customer model is:

$$\ln(custs_t) = a + b^{Emp} \times \ln(TotEmp_t) + b^{Emp\_Shift} \times (TotEmp_t \times ClassShift_t) + b^{Shift} \times ClassShift_t + \Sigma_m(b^m \times Month_{m,t}) + e_t$$

The explanatory variables are:

- $\ln(TotEmp_t)$ = The natural log of total employment (12-month moving average)
- $ClassShift_t$ = A "class shift" indicator variable equal to 1 beginning in June 2014 and 0 prior to that month
- An interaction between the ln(total employment) variable and the class shift variable
- $Month_{m,t}$ = month dummies

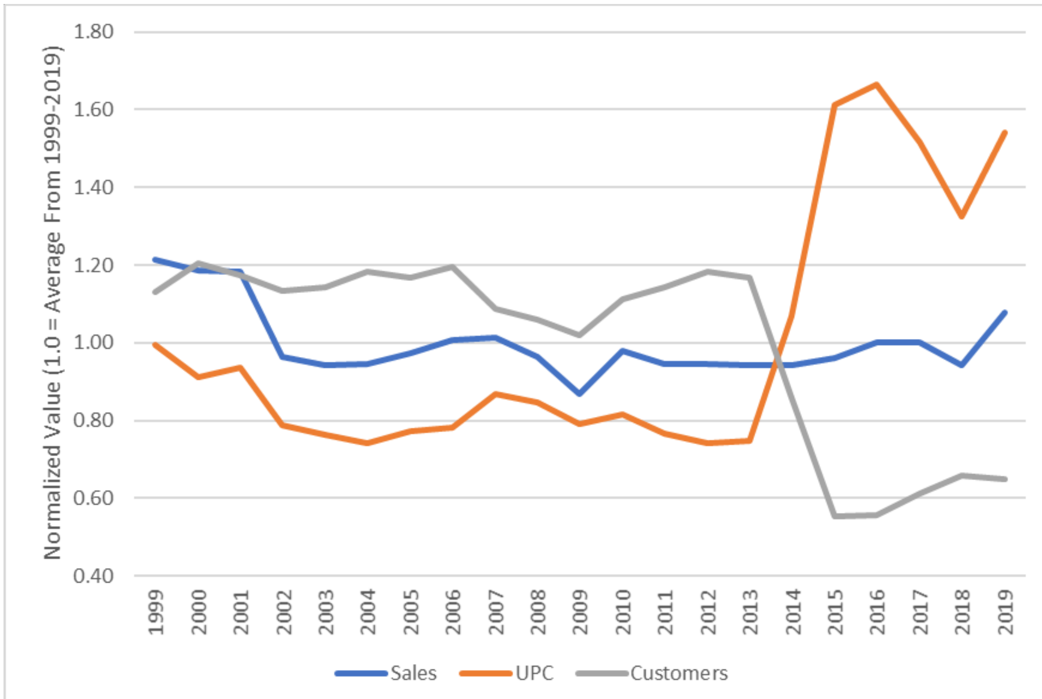
The model is estimated using data from 1999 through 2019 using the Prais-Winsten serial correlation correction. The interaction between the class shift variable and the total employment variable allows the effect of employment to differ before and after the class shift occurs. The estimates reflect a much higher employment effect in the pre-shift period.

The forecast produced by this model had a reasonable annual growth rate but some prediction error in the final year that resulted in a forecast that started from a level that appeared to be too high. To remedy this, we applied the forecast percentage growth rate to the last year's weather normalized sales. The weather normalization adjustment was developed as the difference between the model's predicted sales at normal and observed weather. That difference was added to observed sales to arrive at weather-normalized sales.

3.3 Industrial

This class is not forecast using a statistical model, with flat sales (i.e., no growth) assumed during the forecast period. Figure 3.3 shows the reasonableness of this assumption. The class shift described above for the Commercial class affected this class as well, resulting in a reduction in the number of customers and an increase in UPC. Note that the effect of the shift is more pronounced for this class, as it has fewer customers than the Commercial class (25 to 40 Industrial customers vs. more than 12,000 Commercial customers). Because the shifted customers represented a relatively low share of class sales, the class sales remained relatively flat through the 2014 class-shift period.

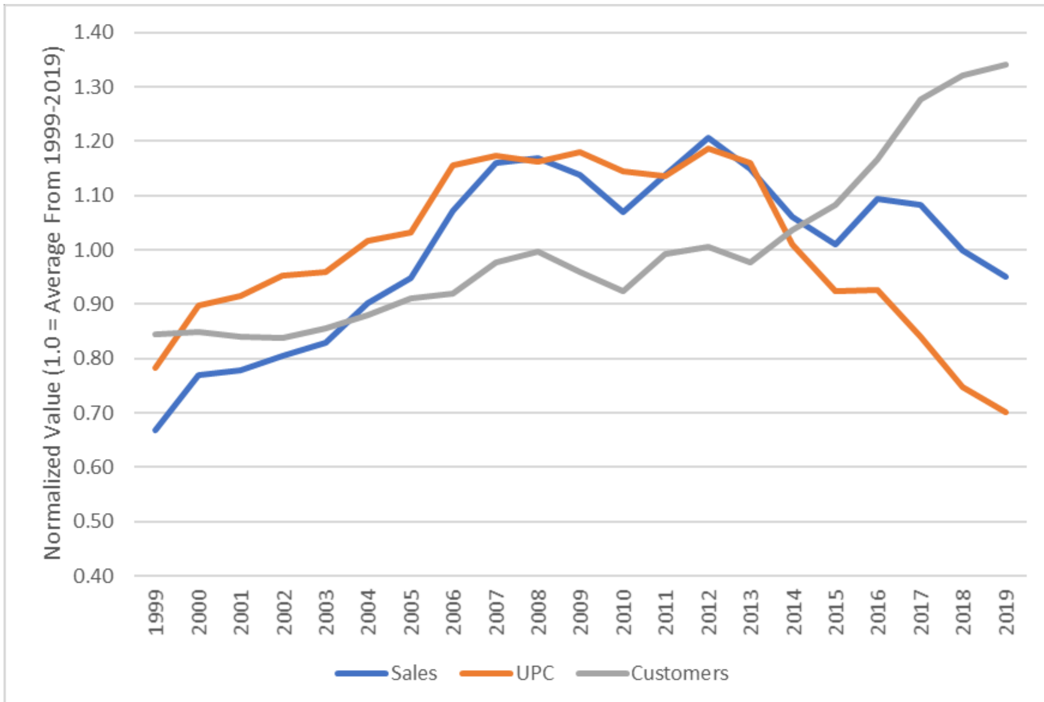
Figure 3.3: BHP Industrial Normalized Sales, UPC, and Customer Counts



3.4 Municipal

Sales to BHP's Municipal class have displayed varying dynamics from 1999 to 2019, with rapid increases through 2007 followed by a plateau and an eventual decline. No economic or demographic variables explain these changes over time. As a result, our forecasting model focuses on following the observed trends and basing the forecast on the post-2007 experience. Note that the Municipal class accounts for a small percentage of BHP's total sales (1.1% in 2019).

Figure 3.4: BHP Municipal Normalized Sales, UPC, and Customer Counts



The Municipal sales model is:

$$\ln(upc_t) = a + b^{CDD} \times CDD_t + b^{D2007} \times D2007_t + b^{Trend} \times Trend_t + b^{Trend07} \times (Trend_t \times D2007_t) + \Sigma_m(b^m \times Month_{m,t}) + e_t$$

The explanatory variables are:

- CDD_t = CDD using a 60°F threshold
- $D2007_t$ = a2007 indicator variable equal to 1 beginning in January 2007 and 0 prior to that month
- $Trend_t$ = Time trend
- An interaction between the 2007 indicator variable and the time trend
- $Month_{m,t}$ = month dummies

The model is estimated using data from 1999 through 2019 using the Prais-Winsten serial correlation correction. The estimated time trends show approximately 5.3 percent per year growth through 2006, with a -1.3 percent per year change in sales from 2007 on.

3.5 System Peak Demand

Forecasting system peak demand presents different challenges than forecasting monthly sales. The objective of the statistical model is to explain the factors that contribute to the most extreme observed loads. To increase the sample size of "peak-like" hours, we include all hours that are within 1 percent of each month's peak demand value.

The system demand model is:

$$\ln(MW_t) = a + b^{CDD} \times CDD_t + b^{HDD} \times HDD_t + b^{CDD\_d} \times CDD\_Day_t + b^{HDD\_d} \times HDD\_Day_t + b^{Wknd} \times Weekend_t + b^{PI} \times \ln(TotPI_t) + \Sigma_m(b^m \times Month_{m,t}) + e_t$$

The explanatory variables are:

- CDD_t = the date's CDD using a 60°F threshold
- HDD_t = the date's HDD using a 60°F threshold
- CDD_Day_t = average CDD per day during the month
- HDD_Day_t = average HDD per day during the month
- $\ln(TotPI_t)$ = the natural log of total personal income
- $Weekend_t$ = a weekend indicator variable (equal to 1 on weekends and zero on weekdays)
- $Month_{m,t}$ = month dummies

The date specific CDD and HDD variables account for the effect of the day's temperatures on the peak day's loads. The monthly average CDD and HDD variables reflect the overall weather conditions (e.g., heat or cold buildup) surrounding the peak day. The personal income variable reflects the effect of economic conditions on peak demand. The weekend indicator variable allows the model to explain the fact that weekend peaks are lower than weekday peaks, all else equal (by approximately 2.3 percent, according to our estimate). The month dummies reflect seasonal patterns in peak demand.

The model is estimated using data from 2010 through 2019. No correction is made for serial correlation.[8]

4. THE CHEYENNE LIGHT FUEL AND POWER (WYOMING) FORECAST

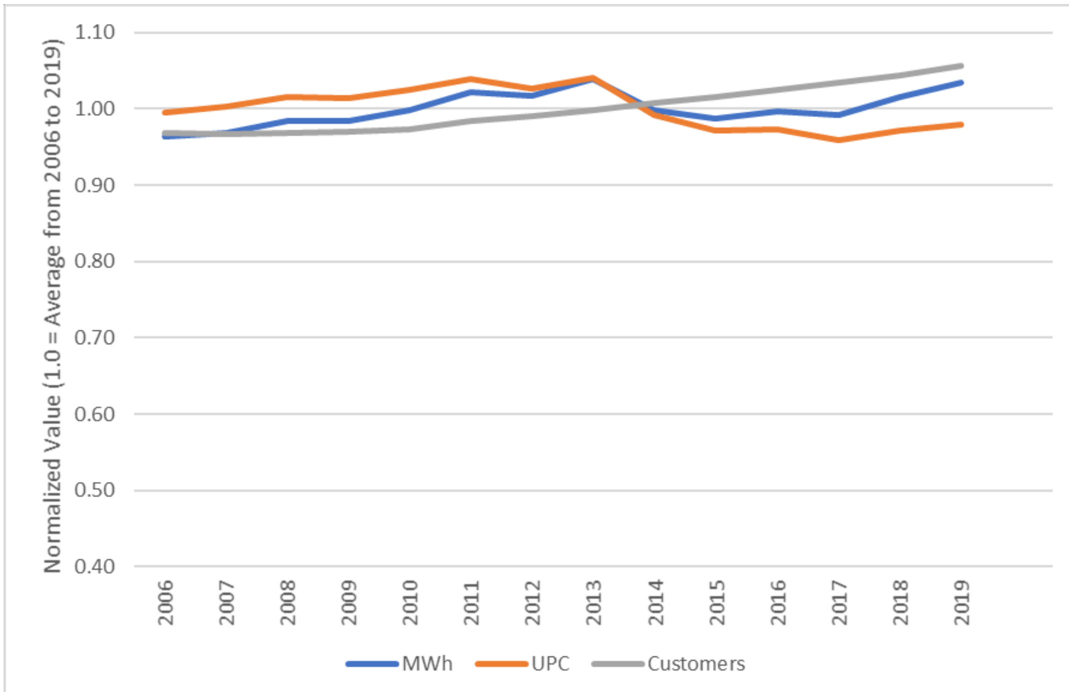
This section contains a description of each CLFP forecast model. The Appendix provides detailed results for each model.

4.1 Residential

Figure 4.1 shows the normalized sales, UPC, and customer counts for CLFP's Residential customer class. The overall upward trend in sales appears to be primarily driven by growth in customers served, while year-to-year variations in total sales are highly correlated with those of UPC. UPC (and therefore sales) drops in the years following 2013 but recovers somewhat in the most recent years. We estimate separate UPC and customer models to better account for these separate effects.

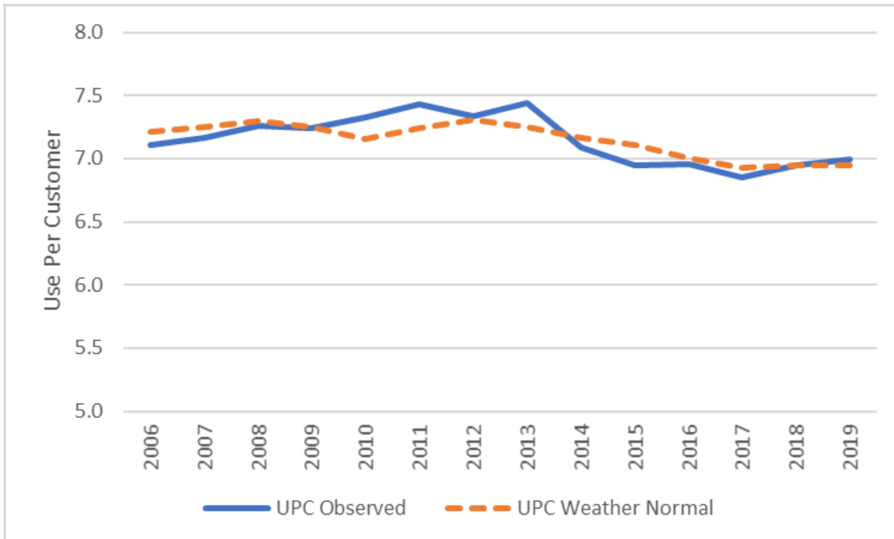
[8] Unlike the monthly class sales models, the interval between observations can vary in the peak demand model. This makes it difficult to identify and correct for serial correlation.

Figure 4.1: CLFP Residential Normalized Sales, UPC, and Customer Counts



We examined weather normalized UPC to test whether the dip in UPC that occurs from 2014 through 2017 was due to mild weather. In Figure 4.2 below, the blue line represents observed UPC while the dashed orange line reflects weather normalized UPC. We conclude from this that some of the reduction in UPC was due to weather, but the decline was still somewhat steady through those years.

Figure 4.2: BHP Residential Observed vs. Weather Normalized UPC



The Residential UPC model is:

$$\ln(upc_t) = a + b^{CDD} \times CDD_t + b^{HDD} \times HDD_t + b^{Inc} \times \ln(HhldInc_t) + b^{Trend} \times Trend_t + \Sigma_m(b^m \times Month_{m,t}) + e_t$$

The explanatory variables are:

- CDD_t = CDD using a 60°F threshold
- HDD_t = HDD using a 60°F threshold
- $\ln(HhldInc_t)$ = the natural log of real household total personal income (12-month moving average)
- $Trend_t$ = Time trend
- $Month_{m,t}$ = month dummies

The model is estimated using data from February 2005 through December 2019 using the Prais-Winsten serial correlation correction. The estimated time trend reflects a 0.7 percent per year decline in UPC, which is offset to some extent by the positive relationship between household income and UPC.

The Residential customer model is:

$$\ln(custs_t) = a + b^{Hhld\_pre} \times \{\ln(Hhlds_t) \times Pre2010_t\} + b^{Hhld\_CIS} \times \{\ln(Hhlds_t) \times CISplus_t\} + b^{CIS} \times CISplus_t + \Sigma_m(b^m \times Month_{m,t}) + e_t$$

The explanatory variables are:

- $\ln(Hhlds_t) \times Pre2010_t$ = the natural log of the number of households interacted with a pre-2010 indicator variable

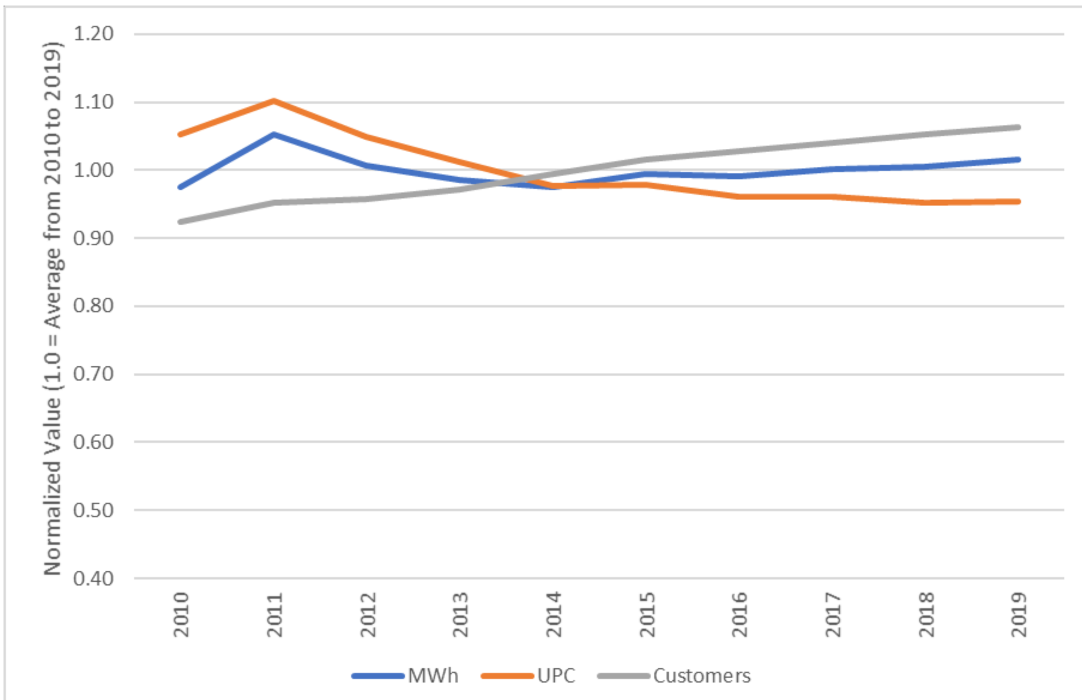
- ln($Hhlds_t$) x $CISplus_t$ = the natural log of the number of households interacted with a 2010+ indicator variable
- $CISplus_t$ = a 2010+ indicator variable, reflecting the approximate date that CLFP's new CIS system was implemented (and thus may have affected the recording of customer counts)

The model is estimated using data from February 2005 through December 2019 using the Prais-Winsten serial correlation correction. The number of households is positively related to the number of customers in the 2010+ period, with no statistically significant relationship estimated in the preceding years.

4.2 Commercial Non-Demand

Figure 4.3 shows large changes in sales and UPC for CLFP's Commercial Non-Demand customers during the 2010 to 2013 period, followed by a more stable period through 2019. In contrast, the number of customers increases steadily through the 2010 to 2019 period.

Figure 4.3: CLFP Commercial Non-Demand Normalized Sales, UPC, and Customer Counts



The Commercial Non-Demand UPC model is:

$$\ln(upc_t) = a + b^{CDD} \times CDD_t + b^{HDD} \times HDD_t + b^{Trend} \times Trend_t + \Sigma_m(b^m \times Month_{m,t}) + e_t$$

The explanatory variables are:

- CDD_t = CDD using a 60°F threshold
- HDD_t = HDD using a 60°F threshold
- $Trend_t$ = Time trend
- $Month_{m,t}$ = month dummies

The model is estimated using data from 2014 through 2019 using the Prais-Winsten serial correlation correction. No available economic or demographic variables produced a reasonable estimate. Data prior to 2014 is excluded due to the unexplained variability in UPC relative to more recent years. The time trend accounts for the slight downward trend in UPC from 2014 through 2019, at approximately 0.7 percent per year.

In the Commercial Non-Demand customer model, the sole explanatory variable is the natural log of total employment (12-month moving average).

$$\ln(custs_t) = a + b^{Emp} \times \ln(TotEmp_t) + e_t$$

We tested monthly indicator variables but found that they were not jointly statistically significant. The estimate on the employment variable indicates a positive relationship between economic conditions and the number of customers served.

4.3 Commercial General Service Secondary and Primary

Because of inter-class customer migrations during recent years, the forecast combines CLFP's General Service Secondary and Primary customers into a single forecast. Figures 4.4 and 4.5 show the changes in sales, UPC, and customer counts for each group. Notice how since 2013 sales have been persistently decreasing in the Secondary class and increasing in the Primary class. Customers re-classifying from Secondary to Primary are at least partially responsible for these trends. Figure 4.6 shows the corresponding values for the two classes combined, revealing a flatter sales trend since 2013.

Figure 4.4: CLFP GS Secondary Normalized Sales, UPC, and Customer Counts

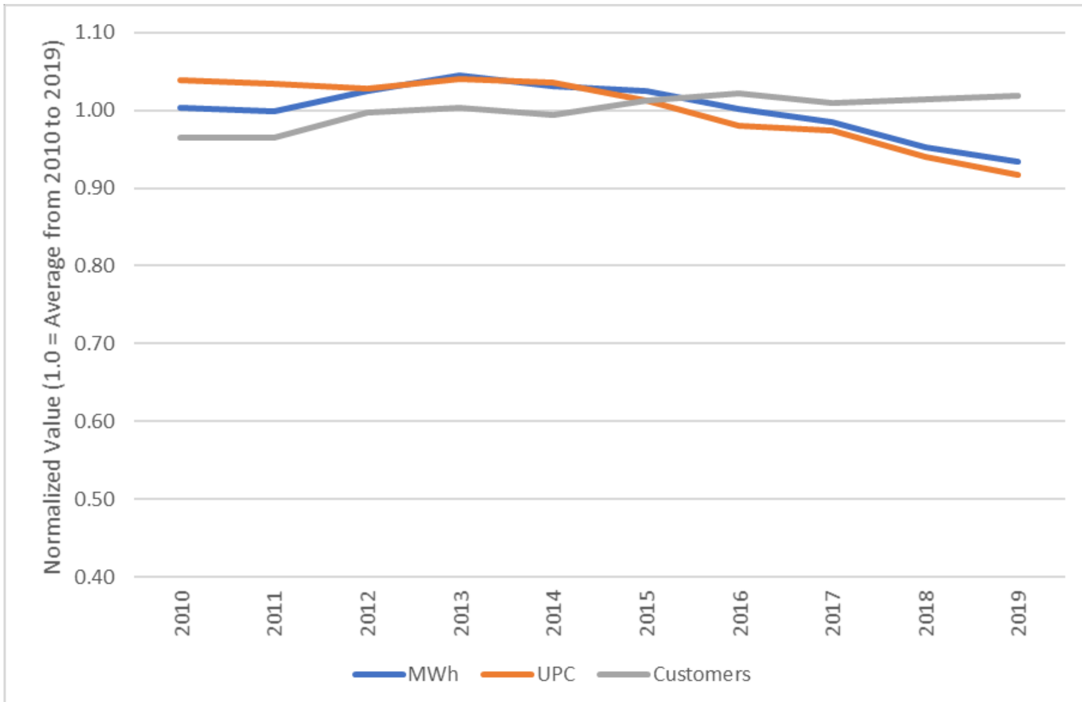


Figure 4.5: CLFP GS Primary Normalized Sales, UPC, and Customer Counts

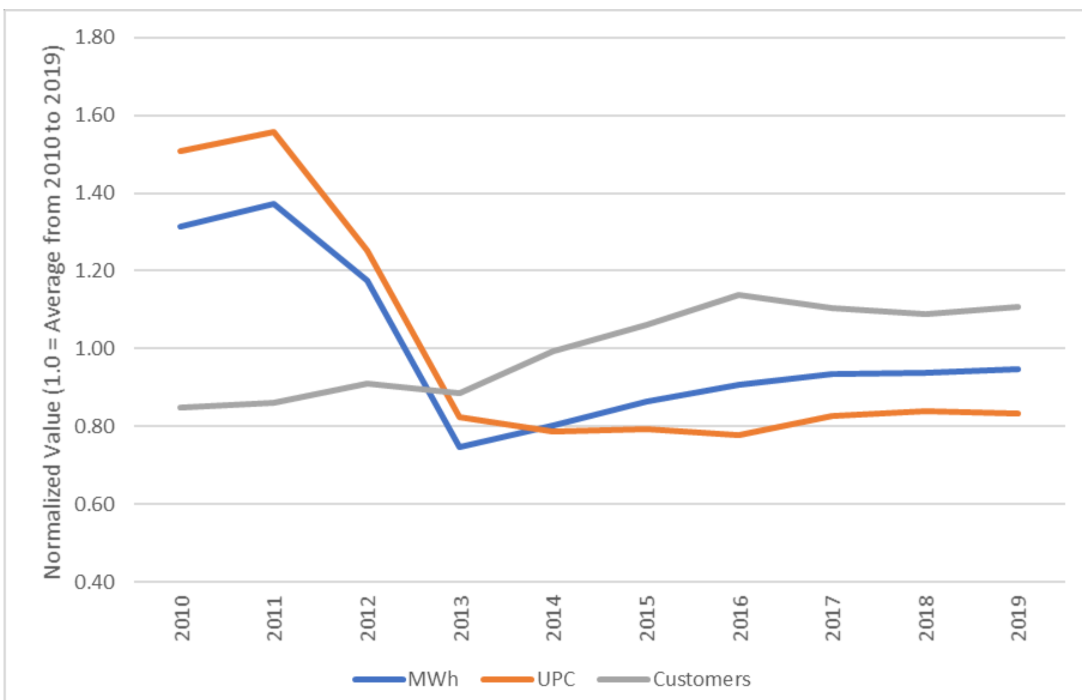
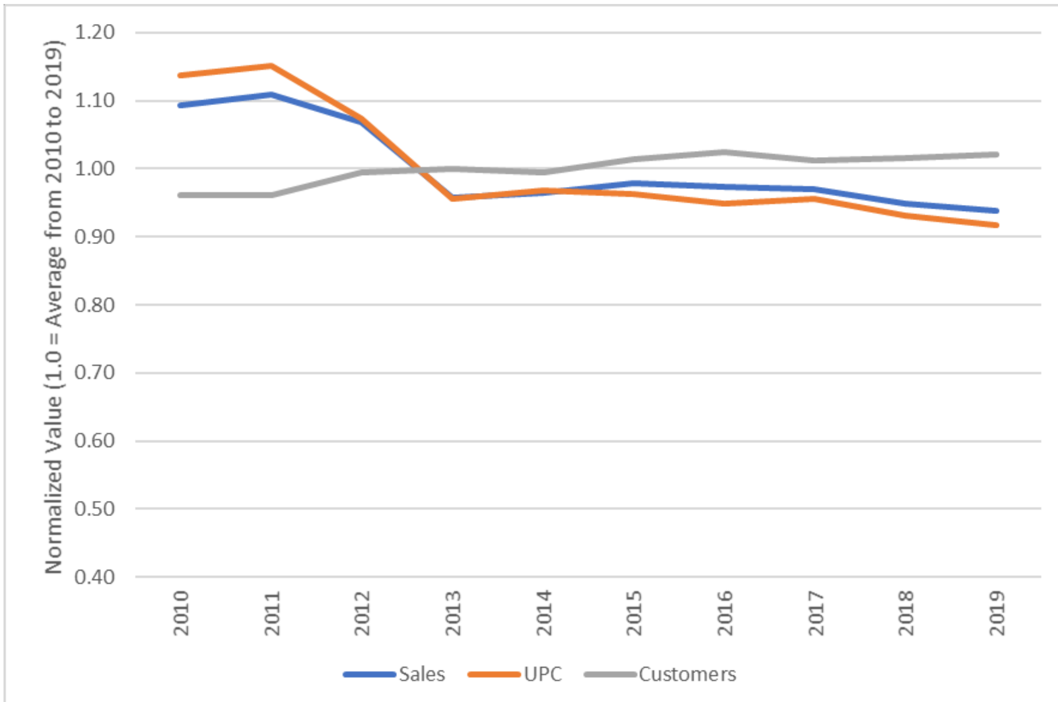


Figure 4.6: CLFP GS Secondary + Primary Normalized Sales, UPC, and Customer Counts

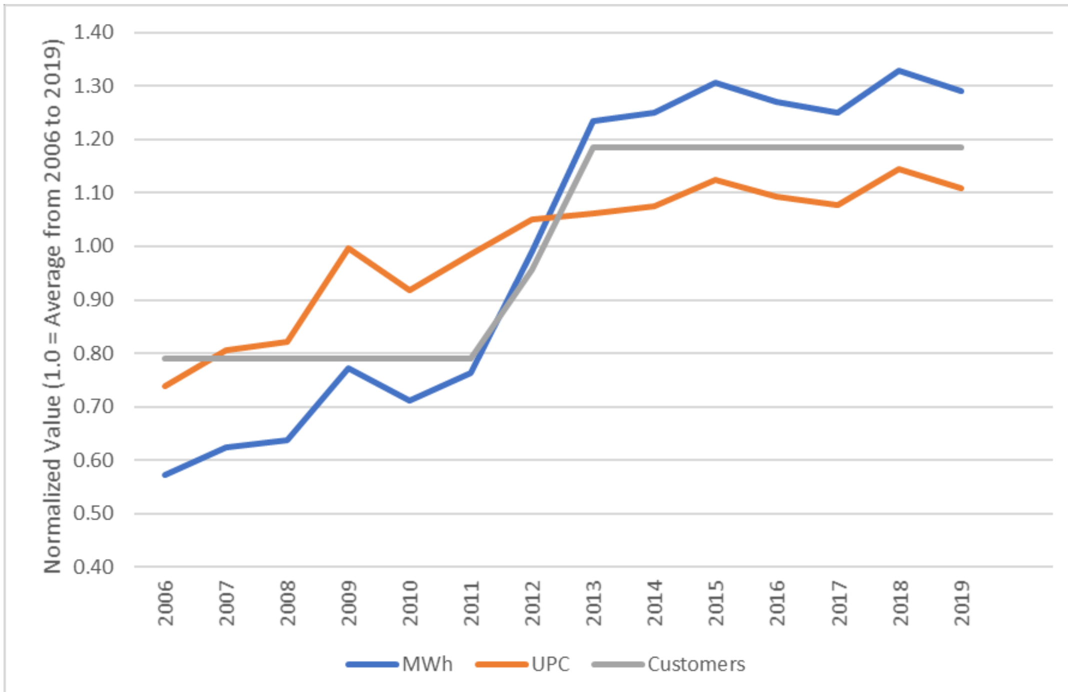


Statistical forecasting models developed for the combined General Service class produced declining sales, particularly in the 2030s and beyond. This contradicts Black Hills's expectations for this class, which is that sales will remain flat during the forecast period. Therefore, for this class Black Hills uses a forecast assumption of flat sales rather than a statistically based forecast.

4.4 Industrial

This class is not forecast using a statistical model, which is appropriate given that it only has two or three customers. With so few customers, variations in sales are likely more due to idiosyncratic effects on individual companies rather than reflections of widespread trends, making them difficult to explain using the data at hand. As Figure 4.7 shows, Industrial sales increase when a customer is added but have remained relatively constant in recent years.

Figure 4.7: CLFP Industrial Normalized Sales, UPC, and Customer Counts



4.5 System Peak Demand

As was the case for the BHP system peak demand model, the CLFP model includes all hours that are within 1 percent of each month's peak demand value.

The system demand model is:

$$\ln(MW_t) = a + b^{CDD} \times CDD_t + b^{HDD} \times HDD_t + b^{CDD\_d} \times CDD\_Day_t + b^{CDH} \times CDH_t + b^{HDH} \times HDH_t + b^{Emp} \times \ln(TotEmp_t) + \Sigma_m(b^m \times Month_{m,t}) + e_t$$

The explanatory variables are:

- CDD_t = the date's CDD using a 60°F threshold
- HDD_t = the date's HDD using a 60°F threshold
- CDD_Day_t = average CDD per day during the month
- CDH_t = Cooling degree hours (CDHs) during the peak hour[9]
- HDH_t = Heating degree hours (HDHs) during the peak hour[10]
- $\ln(TotEmp_t)$ = The natural log of total employment
- $Month_{m,t}$ = month dummies

[9] CDH_h = MAX{0, $Temp_h$ – 70}, where h is the hour in question.
[10] HDH_h = MAX{0, 50 – $Temp_h$}, where h is the hour in question.

The date specific CDD and HDD variables account for the effect of the day's temperatures on the peak day's loads. The CDH and HDH variables reflect temperatures in the peak hour itself. The monthly average CDD variable reflects the overall weather conditions (e.g., heat buildup) surrounding the peak day. The total employment variable reflects the effect of economic conditions on peak demand. The month dummies reflect seasonal patterns in peak demand.

The model is estimated using data from 2008 through 2019. As with the BHP peak demand model, no correction is made for serial correlation.

APPENDIX: ESTIMATED MODELS

BHP Residential UPC Model

```
Prais-Winsten AR(1) regression -- iterated estimates

      Source |       SS           df       MS      Number of obs   =       156
-------------+----------------------------------   F(14, 141)      =    279.48
       Model |  6.59638489        14   .47117035   Prob > F        =    0.0000
    Residual |   .23771102       141  .001685894   R-squared       =    0.9652
-------------+----------------------------------   Adj R-squared   =    0.9618
       Total |  6.83409591       155  .044090941   Root MSE        =    .04106

------------------------------------------------------------------------------
        lupc |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       cdd60 |   .0007491   .0000792     9.46   0.000     .0005925    .0009057
       hdd60 |   .0003371   .0000268    12.56   0.000      .000284    .0003901
       trend |  -.0053457   .0011228    -4.76   0.000    -.0075653    -.003126
          m2 |  -.0809981   .0146294    -5.54   0.000    -.1099194   -.0520769
          m3 |  -.0765306   .0176738    -4.33   0.000    -.1114705   -.0415906
          m4 |  -.1715452   .0214173    -8.01   0.000    -.2138857   -.1292046
          m5 |  -.2487149   .0261492    -9.51   0.000    -.3004101   -.1970197
          m6 |  -.2838251   .0317412    -8.94   0.000    -.3465753    -.221075
          m7 |   -.220695   .0402097    -5.49   0.000    -.3001869   -.1412031
          m8 |  -.1982313   .0444751    -4.46   0.000    -.2861556   -.1103071
          m9 |  -.2625503   .0377637    -6.95   0.000    -.3372066    -.187894
         m10 |  -.3046907   .0290236   -10.50   0.000    -.3620684   -.2473129
         m11 |  -.2245492   .0227044    -9.89   0.000    -.2694342   -.1796643
         m12 |  -.0621735   .0159359    -3.90   0.000    -.0936777   -.0306693
       _cons |   6.704262   .0353275   189.77   0.000     6.634422    6.774102
-------------+----------------------------------------------------------------
         rho |   .2203338
------------------------------------------------------------------------------
Durbin-Watson statistic (original)    1.688659
Durbin-Watson statistic (transformed) 2.075256
```

BHP Residential Customer Model

```
Prais-Winsten AR(1) regression -- iterated estimates

      Source |       SS           df       MS      Number of obs   =       156
-------------+----------------------------------   F(12, 143)      >  99999.00
       Model |  11.7509368        12  .979244731   Prob > F        =    0.0000
    Residual |  .000585916       143  4.0973e-06   R-squared       =    1.0000
-------------+----------------------------------   Adj R-squared   =    0.9999
       Total |  11.7515227       155  .075816275   Root MSE        =    .00202

------------------------------------------------------------------------------
       lcust |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
  lntotemp12 |   .8832825   .0454891    19.42   0.000     .7933645    .9732005
          m2 |  -.0001767   .0005589    -0.32   0.752    -.0012813     .000928
          m3 |   .0006558   .0007511     0.87   0.384    -.0008289    .0021405
          m4 |   .0001208   .0008707     0.14   0.890    -.0016003    .0018418
          m5 |   .0001964   .0009466     0.21   0.836    -.0016746    .0020675
          m6 |   .0004601   .0009896     0.46   0.643    -.0014959    .0024161
          m7 |  -.0002992   .0010043    -0.30   0.766    -.0022843    .0016859
          m8 |    .001199   .0009921     1.21   0.229    -.0007621      .00316
          m9 |   .0015761   .0009518     1.66   0.100    -.0003053    .0034574
         m10 |   .0011851    .000879     1.35   0.180    -.0005525    .0029226
         m11 |   .0006704   .0007636     0.88   0.381     -.000839    .0021799
         m12 |   .0014634    .000579     2.53   0.013     .0003189    .0026079
       _cons |   7.853703    .158067    49.69   0.000     7.541253    8.166152
-------------+----------------------------------------------------------------
         rho |   .9162612
------------------------------------------------------------------------------
Durbin-Watson statistic (original)    0.198497
Durbin-Watson statistic (transformed) 2.673149
```

BHP Commercial UPC Model

```
Prais-Winsten AR(1) regression -- iterated estimates

      Source |       SS           df       MS      Number of obs   =       252
-------------+----------------------------------   F(16, 235)      =    152.52
       Model |  3.2015146        16  .200094662   Prob > F        =    0.0000
    Residual |  .308297984       235  .001311906   R-squared       =    0.9122
-------------+----------------------------------   Adj R-squared   =    0.9062
       Total |  3.50981258       251  .013983317   Root MSE        =    .03622

------------------------------------------------------------------------------
        lupc |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       cdd60 |   .0004078   .0000516     7.90   0.000     .0003062    .0005095
       hdd60 |   .0000878   .0000188     4.68   0.000     .0000508    .0001248
          m2 |  -.0520282    .011984    -4.34   0.000     -.075638   -.0284183
          m3 |  -.0386922   .0118223    -3.27   0.001    -.0619834    -.015401
          m4 |  -.0847384   .0139929    -6.06   0.000    -.1123059   -.0571708
          m5 |  -.0978604   .0170247    -5.75   0.000    -.1314009   -.0643199
          m6 |  -.0237413   .0208928    -1.14   0.257    -.0649023    .0174197
          m7 |   .0054528   .0265259     0.21   0.837    -.0468061    .0577117
          m8 |   .0245937   .0296813     0.83   0.408    -.0338816    .0830691
          m9 |  -.0073286   .0249257    -0.29   0.769     -.056435    .0417778
         m10 |  -.0483032   .0188734    -2.56   0.011    -.0854859   -.0111205
         m11 |  -.0999738   .0147761    -6.77   0.000    -.1290844   -.0708633
         m12 |  -.0056054   .0123565    -0.45   0.651     -.029949    .0187383
 class_shift |   .0605904   .0081693     7.42   0.000      .044496    .0766848
       trend |  -.0061663   .0028089    -2.20   0.029       -.0117   -.0006325
  lntotemp12 |   .4757653    .236463     2.01   0.045     .0099071    .9416235
       _cons |   6.844035   .7777653     8.80   0.000     5.311752    8.376318
-------------+----------------------------------------------------------------
         rho |  -.1303725
------------------------------------------------------------------------------
Durbin-Watson statistic (original)    2.237867
Durbin-Watson statistic (transformed) 1.976362
```

BHP Commercial Customer Model

```
Prais-Winsten AR(1) regression -- iterated estimates

      Source |       SS           df       MS      Number of obs   =       252
-------------+----------------------------------   F(14, 237)      =  13152.44
       Model |  14.0120084        14  1.00085775   Prob > F        =    0.0000
    Residual |  .018034924       237  .000076097   R-squared       =    0.9987
-------------+----------------------------------   Adj R-squared   =    0.9986
       Total |  14.0300434       251  .055896587   Root MSE        =    .00872

--------------------------------------------------------------------------------
         lcust |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
---------------+----------------------------------------------------------------
            m2 |  -.0038088   .0020341    -1.87   0.062     -.007816    .0001983
            m3 |  -.0015248   .0026583    -0.57   0.567    -.0067617    .0037121
            m4 |   .0036183   .0030146     1.20   0.231    -.0023205    .0095571
            m5 |   .0125077    .003226     3.88   0.000     .0061525    .0188629
            m6 |   .0186227    .003345     5.57   0.000      .012033    .0252123
            m7 |   .0214386   .0033801     6.34   0.000     .0147797    .0280976
            m8 |   .0277128   .0033456     8.28   0.000     .0211218    .0343038
            m9 |   .0211541   .0032357     6.54   0.000     .0147796    .0275286
           m10 |   .0148503   .0030301     4.90   0.000      .008881    .0208197
           m11 |   .0087593   .0026822     3.27   0.001     .0034752    .0140433
           m12 |    .000228   .0020735     0.11   0.913     -.003857    .0043129
    lntotemp12 |   1.490022   .0418228    35.63   0.000     1.407631    1.572414
lntotemp_shift |  -1.292099   .2045018    -6.32   0.000    -1.694973   -.8892259
   class_shift |   4.491643   .7154039     6.28   0.000      3.08228    5.901006
         _cons |   4.291352   .1422813    30.16   0.000     4.011054     4.57165
---------------+----------------------------------------------------------------
           rho |   .7318557
--------------------------------------------------------------------------------
Durbin-Watson statistic (original)    0.548459
Durbin-Watson statistic (transformed) 2.435974
```

BHP Municipal Sales Model

```
Prais-Winsten AR(1) regression -- iterated estimates

      Source |       SS           df       MS      Number of obs   =       252
-------------+----------------------------------   F(15, 236)      =     82.04
       Model |  13.5463717        15  .903091449   Prob > F        =    0.0000
    Residual |   2.5978093       236  .011007667   R-squared       =    0.8391
-------------+----------------------------------   Adj R-squared   =    0.8289
       Total |   16.144181       251  .064319446   Root MSE        =    .10492

------------------------------------------------------------------------------
      lsales |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       cdd60 |   .0010164   .0001617     6.29   0.000     .0006978     .001335
       trend |   .0533716   .0061685     8.65   0.000     .0412193    .0655239
 trend_d2007 |  -.0661732   .0068731    -9.63   0.000    -.0797138   -.0526326
       d2007 |   .7528875   .0587961    12.81   0.000     .6370553    .8687198
          m2 |  -.1061182   .0289156    -3.67   0.000    -.1630839   -.0491526
          m3 |  -.0802588    .032359    -2.48   0.014    -.1440082   -.0165094
          m4 |  -.0846191   .0331771    -2.55   0.011    -.1499801    -.019258
          m5 |  -.0232965   .0334686    -0.70   0.487    -.0892319    .0426389
          m6 |   .1198732    .037011     3.24   0.001     .0469591    .1927873
          m7 |   .1241075   .0616468     2.01   0.045     .0026591    .2455559
          m8 |   .0635651   .0754108     0.84   0.400    -.0849993    .2121295
          m9 |    .088161   .0548742     1.61   0.109    -.0199449    .1962669
         m10 |   .0585193   .0343227     1.70   0.090    -.0090986    .1261372
         m11 |  -.1457969   .0324917    -4.49   0.000    -.2098077   -.0817861
         m12 |  -.0417205   .0292042    -1.43   0.154    -.0992546    .0158136
       _cons |   6.874499   .0398607   172.46   0.000     6.795971    6.953028
-------------+----------------------------------------------------------------
         rho |   .2525515
------------------------------------------------------------------------------
Durbin-Watson statistic (original)    1.509298
Durbin-Watson statistic (transformed) 2.016210
```

BHP System Peak Demand Model

```
      Source |       SS           df       MS      Number of obs   =       230
-------------+----------------------------------   F(17, 212)      =    137.46
       Model |  3.03781492        17  .178694996   Prob > F        =    0.0000
    Residual |  .275587388       212  .001299941   R-squared       =    0.9168
-------------+----------------------------------   Adj R-squared   =    0.9102
       Total |  3.31340231       229  .014469006   Root MSE        =    .03605

----------------------------------------------------------------------------------
          lmwnat |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-----------------+----------------------------------------------------------------
           cdd60 |   .0086782   .0009586     9.05   0.000     .0067885    .0105678
           hdd60 |   .0027718   .0004093     6.77   0.000      .001965    .0035785
mnthcdd60perday |     .01034   .0020343     5.08   0.000     .0063298    .0143501
mnthhdd60perday |   .0042651   .0008499     5.02   0.000     .0025897    .0059405
         lntotPI |   .3380472   .0384863     8.78   0.000     .2621824    .4139121
         weekend |  -.0233456   .0114565    -2.04   0.043    -.0459288   -.0007625
              m2 |  -.0523044   .0116995    -4.47   0.000    -.0753668   -.0292421
              m3 |  -.0416192   .0138153    -3.01   0.003    -.0688522   -.0143861
              m4 |   -.080603   .0160687    -5.02   0.000    -.1122778   -.0489281
              m5 |  -.0320146   .0203971    -1.57   0.118    -.0722217    .0081925
              m6 |   .0932003   .0273189     3.41   0.001     .0393488    .1470519
              m7 |   .0802717     .03224     2.49   0.014     .0167197    .1438237
              m8 |   .0892537   .0299565     2.98   0.003     .0302028    .1483045
              m9 |   .0623604    .025859     2.41   0.017     .0113867     .113334
             m10 |  -.0339564   .0189731    -1.79   0.075    -.0713565    .0034436
             m11 |  -.0216245   .0155354    -1.39   0.165    -.0522481     .008999
             m12 |   -.027556    .011648    -2.37   0.019    -.0505167   -.0045953
           _cons |   2.867306   .2934284     9.77   0.000     2.288895    3.445717
----------------------------------------------------------------------------------
```

CLFP Residential UPC Model

```
Prais-Winsten AR(1) regression -- iterated estimates

      Source |       SS           df       MS      Number of obs   =       179
-------------+----------------------------------   F(15, 163)      =    114.28
       Model |  2.06797158        15  .137864772   Prob > F        =    0.0000
    Residual |  .196636554       163  .001206359   R-squared       =    0.9132
-------------+----------------------------------   Adj R-squared   =    0.9052
       Total |  2.26460814       178  .012722518   Root MSE        =    .03473

------------------------------------------------------------------------------
        lupc |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       cdd60 |   .0006874   .0000816     8.42   0.000     .0005263    .0008485
       hdd60 |   .0002053   .0000278     7.39   0.000     .0001504    .0002602
  lnincome12 |   .4358274   .0999293     4.36   0.000     .2385045    .6331504
       trend |  -.0067252    .001048    -6.42   0.000    -.0087946   -.0046559
          m2 |  -.1014795   .0126135    -8.05   0.000    -.1263864   -.0765726
          m3 |  -.1002444    .014534    -6.90   0.000    -.1289436   -.0715453
          m4 |  -.1743273    .017176   -10.15   0.000    -.2082435   -.1404111
          m5 |  -.2145596   .0207049   -10.36   0.000     -.255444   -.1736752
          m6 |  -.2040182   .0272919    -7.48   0.000    -.2579095   -.1501269
          m7 |  -.1671883   .0341282    -4.90   0.000    -.2345787   -.0997979
          m8 |  -.1762289   .0372566    -4.73   0.000    -.2497967   -.1026611
          m9 |  -.2100186   .0318326    -6.60   0.000     -.272876   -.1471612
         m10 |  -.2242816   .0248828    -9.01   0.000    -.2734158   -.1751474
         m11 |   -.184847   .0182471   -10.13   0.000    -.2208783   -.1488158
         m12 |  -.0530595    .013202    -4.02   0.000    -.0791285   -.0269905
       _cons |  -5.518172   1.151543    -4.79   0.000    -7.792037   -3.244308
-------------+----------------------------------------------------------------
         rho |   .0804959
------------------------------------------------------------------------------
Durbin-Watson statistic (original)    1.873708
Durbin-Watson statistic (transformed) 2.014441
```

CLFP Residential Customer Model

```
Prais-Winsten AR(1) regression -- iterated estimates

      Source |       SS           df       MS      Number of obs   =       179
-------------+----------------------------------   F(3, 175)       >  99999.00
       Model |  17.7840565         3  5.92801885   Prob > F        =    0.0000
    Residual |  .000921729       175  5.2670e-06   R-squared       =    0.9999
-------------+----------------------------------   Adj R-squared   =    0.9999
       Total |  17.7849783       178  .099915608   Root MSE        =    .00229

-------------------------------------------------------------------------------
       lcusts |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
--------------+----------------------------------------------------------------
  lhhld_pre10 |  -.0812966   .0565073    -1.44   0.152      -.19282    .0302268
lhhld_CISplus |   .6734902   .0222876    30.22   0.000     .6295031    .7174773
      CISplus |  -2.733243    .239088   -11.43   0.000     -3.20511   -2.261376
        _cons |     10.761   .2030163    53.01   0.000     10.36033    11.16168
--------------+----------------------------------------------------------------
          rho |   .7863497
-------------------------------------------------------------------------------
Durbin-Watson statistic (original)    0.433740
Durbin-Watson statistic (transformed) 2.368500
```

CLFP Commercial Non-Demand UPC Model

```
Prais-Winsten AR(1) regression -- iterated estimates

      Source |       SS           df       MS      Number of obs   =        72
-------------+----------------------------------   F(14, 57)       =     26.09
       Model |  .382507485        14  .027321963   Prob > F        =    0.0000
    Residual |   .05968656        57  .001047133   R-squared       =    0.8650
-------------+----------------------------------   Adj R-squared   =    0.8319
       Total |  .442194045        71  .006228085   Root MSE        =    .03236

------------------------------------------------------------------------------
        lupc |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       cdd60 |   .0004083   .0001487     2.75   0.008     .0001105    .0007061
       hdd60 |   .0001288   .0000395     3.26   0.002     .0000496    .0002079
       trend |  -.0073876   .0027641    -2.67   0.010    -.0129226   -.0018527
          m2 |  -.0487067   .0179134    -2.72   0.009    -.0845777   -.0128357
          m3 |  -.0659655   .0209113    -3.15   0.003    -.1078397   -.0240913
          m4 |  -.1196877   .0258481    -4.63   0.000    -.1714476   -.0679279
          m5 |  -.1510517   .0305823    -4.94   0.000    -.2122917   -.0898118
          m6 |  -.1560555   .0386278    -4.04   0.000    -.2334063   -.0787047
          m7 |  -.1050686   .0509712    -2.06   0.044    -.2071366   -.0030006
          m8 |  -.0874926   .0572705    -1.53   0.132    -.2021747    .0271895
          m9 |     -.1392   .0479274    -2.90   0.005     -.235173   -.0432271
         m10 |  -.1530321   .0363063    -4.22   0.000    -.2257342   -.0803299
         m11 |  -.1492752   .0271702    -5.49   0.000    -.2036827   -.0948678
         m12 |  -.0318684   .0196828    -1.62   0.111    -.0712825    .0075456
       _cons |   .0584828   .0505365     1.16   0.252    -.0427147    .1596803
-------------+----------------------------------------------------------------
         rho |    .184152
------------------------------------------------------------------------------
Durbin-Watson statistic (original)    1.680528
Durbin-Watson statistic (transformed) 1.996436
```

CLFP Commercial Non-Demand Customer Model

```
rais-Winsten AR(1) regression -- iterated estimates

      Source |       SS           df       MS      Number of obs   =        72
-------------+----------------------------------   F(1, 70)        =    232.39
       Model |  .050031725         1  .050031725   Prob > F        =    0.0000
    Residual |   .01507069        70  .000215296   R-squared       =    0.7685
-------------+----------------------------------   Adj R-squared   =    0.7652
       Total |  .065102415        71  .000916935   Root MSE        =    .01467

------------------------------------------------------------------------------
       lcust |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
  lntotemp12 |   1.224647   .0962394    12.73   0.000     1.032703     1.41659
       _cons |   3.202115   .4055417     7.90   0.000     2.393288    4.010943
-------------+----------------------------------------------------------------
         rho |  -.0108025
------------------------------------------------------------------------------
Durbin-Watson statistic (original)    2.021164
Durbin-Watson statistic (transformed) 1.993565
```

CLFP System Peak Demand Model

Source	SS	df	MS			
				Number of obs	=	382
				F(17, 364)	=	259.88
Model	2.7075761	17	.159269182	Prob > F	=	0.0000
Residual	.223080505	364	.000612859	R-squared	=	0.9239
				Adj R-squared	=	0.9203
Total	2.9306566	381	.007692012	Root MSE	=	.02476

lMWwoMS	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
cdh	.0019791	.0007083	2.79	0.005	.0005862	.0033719
cdd60	.0048258	.0009546	5.06	0.000	.0029485	.0067031
hdh	.0007178	.0003331	2.16	0.032	.0000628	.0013728
hdd60	.0006511	.0003106	2.10	0.037	.0000402	.001262
mnthcdd60perday	.0078491	.0016518	4.75	0.000	.0046009	.0110973
lntotemp	.6704658	.0296946	22.58	0.000	.6120712	.7288603
m2	-.0104943	.0068803	-1.53	0.128	-.0240245	.0030359
m3	-.0561029	.0074336	-7.55	0.000	-.070721	-.0414847
m4	-.1031688	.00717	-14.39	0.000	-.1172686	-.0890689
m5	-.1075987	.0081318	-13.23	0.000	-.1235899	-.0916074
m6	-.0583115	.0121855	-4.79	0.000	-.0822743	-.0343486
m7	-.0386051	.0172689	-2.24	0.026	-.0725645	-.0046456
m8	-.0577883	.0147434	-3.92	0.000	-.0867812	-.0287954
m9	-.066601	.0111045	-6.00	0.000	-.0884381	-.0447638
m10	-.0840245	.0082962	-10.13	0.000	-.1003389	-.06771
m11	-.0293447	.006979	-4.20	0.000	-.0430688	-.0156205
m12	.0229512	.0067193	3.42	0.001	.0097376	.0361648
_cons	2.265582	.1232518	18.38	0.000	2.023208	2.507957