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

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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. The forecasts will be used in integrated resource plans and for internal budget forecasts.

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).

2. OVERVIEW OF THE FORECAST DEVELOPMENT PROCESS

Selecting the dependent variable

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

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

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
- 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] 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

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[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.

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).

Method for creating forecast values

The 2022 weather normalized UPC (or sales) values are used as the "starting point" for the forecasts. This is done to remove the effect of forecast error from the level of the forecast.[5] That is, the effect of growth-related variables (e.g., economic, demographic, and time-trend variables) is applied to the 2022 weather normalized UPC (or sales). For example, if we estimated a 1.1 percent annual trend in UPC, the 2023 forecast UPC values would be 1.1 percent higher than the weather normalized UPC for the corresponding month in 2022.

The weather normalization adjustment is applied as follows:

Weather Normalized Value = Observed Value + Estimated Weather Effect x (Normal Weather – Observed Weather)

This equation has the effect of *reducing* Sales or UPC when observed weather is *more* extreme than normal (i.e., hotter summer or colder winter than normal) and *increasing* sales or UPC when observed weather is *less* extreme than normal.

For the customer models, we anchor the forecasts to the observed values in 2022, with the effect of growth variables applied to that starting point. The number of customers served is not affected by weather, so we did not need to weather adjust the 2022 starting values.

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

[5] Statistical models cannot perfectly predict usage, so in any given month there is likely to be a difference between observed sales or UPC and the sales or UPC that the model predicts given the variables included in the model. This is called forecast error.

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 2021, producing 43 separate percentage change values.
2. Calculate the mean and standard deviation of the percentage changes across these 43 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 43 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.[6]
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 the "base" forecast growth rate and the standard deviation equal to the absolute value of the base forecast growth rate[7] 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

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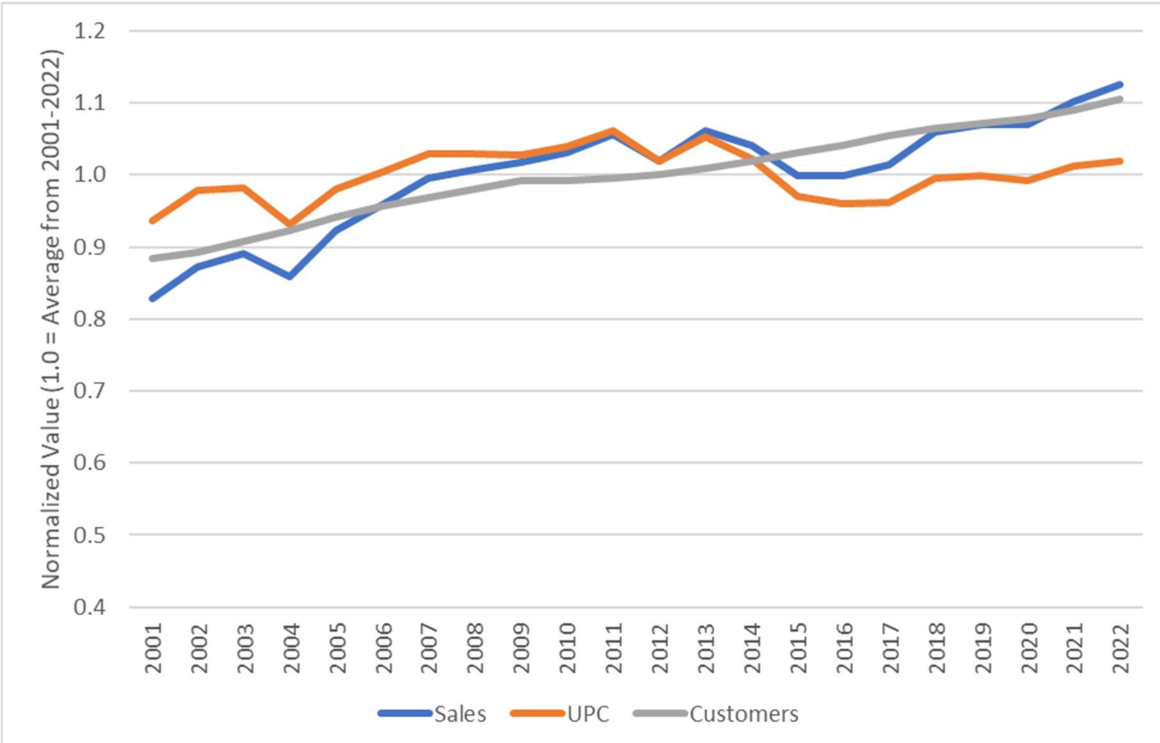
[6] This calculation is performed as the standard deviation of the product of two random variables, as follows: $Var(XY) = Var(X)Var(Y)+Var(X)(E(Y))^2+Var(Y)(E(X))^2$

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

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.

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



The Residential UPC model is:

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

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
- $\ln(HhldInc_t)$ = the natural log of real household total personal income (12-month moving average)
- $Month_{m,t}$ = month dummies[8]

[8] 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 model is estimated using data from 2000 through 2022 using the Prais-Winsten serial correlation correction. Economic effects are represented a household income variable.

The Residential customer model is:

$$\ln(custs_t) = a + b^{Hhld} \times \ln(Hhlds_t) + e_t$$

The explanatory variables are:

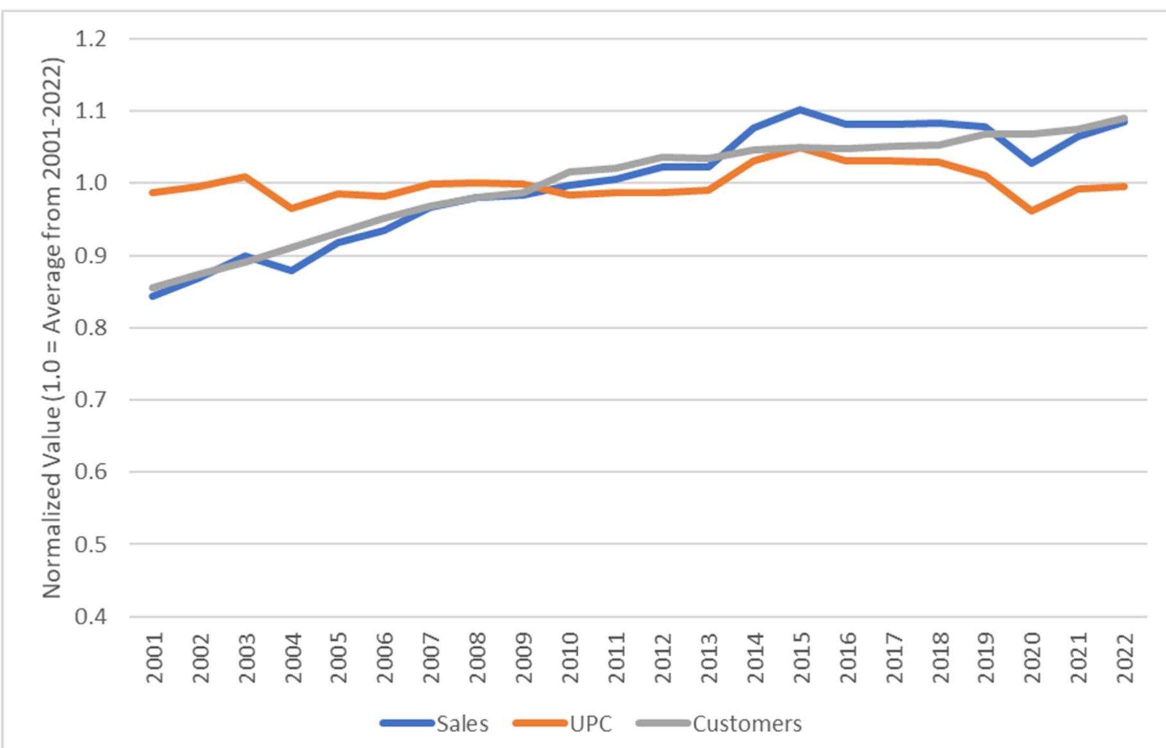
- $\ln(Hhlds_t)$ = the natural log of the number of households

The model is estimated using data from 2000 through 2021 using the Prais-Winsten serial correlation correction. The estimated coefficient on the households variable reflects a positive relationship between demographic 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. An exception is 2020, during which sales and UPC decreased temporarily, which we believe is due to the COVID-19 pandemic.

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



The Commercial UPC model is:

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

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)
- $COVID_t$ = an indicator variable equal to 1 from March through August 2020 and 0 otherwise
- $Month_{m,t}$ = month dummies

The model is estimated using data from 2000 through 2022 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 1.4 percent per year. The estimated coefficient for the class shift variable indicates 6.6 percent higher UPC during the post-June 2014 period. The COVID variable indicates a 6.6 percent reduction in UPC during the assumed COVID period. Note that this effect is modeled as a temporary reduction that ended in August 2020.[9]

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

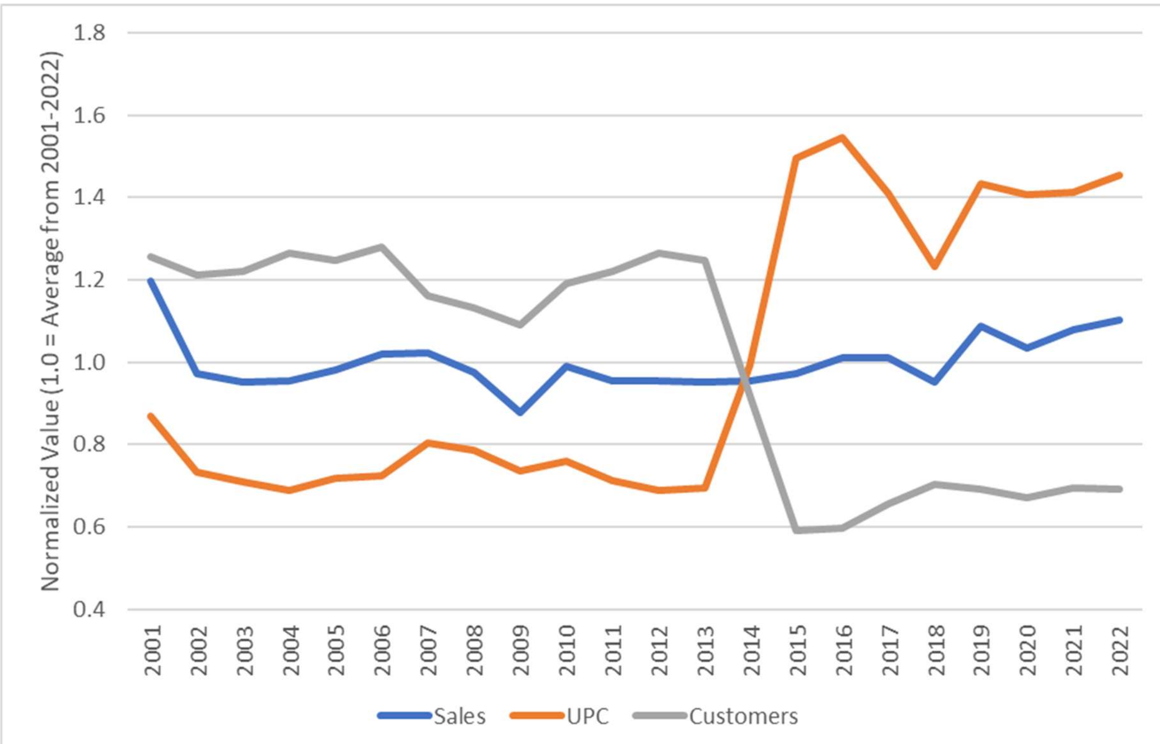
The model is estimated using data from 2000 through 2022 using the Prais-Winsten serial correlation correction. The interaction between the class shift variable and the total employment variable allows the effect of employment to differ before and after the class shift occurs. The estimates reflect a much higher employment effect in the pre-shift period.

[9] We tested a range of COVID date ranges and found that March through August 2020 provided the best fit to the data. We tested for COVID effects for other customer classes as well. No other BHP customer classes had a statistically significant COVID effect.

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.

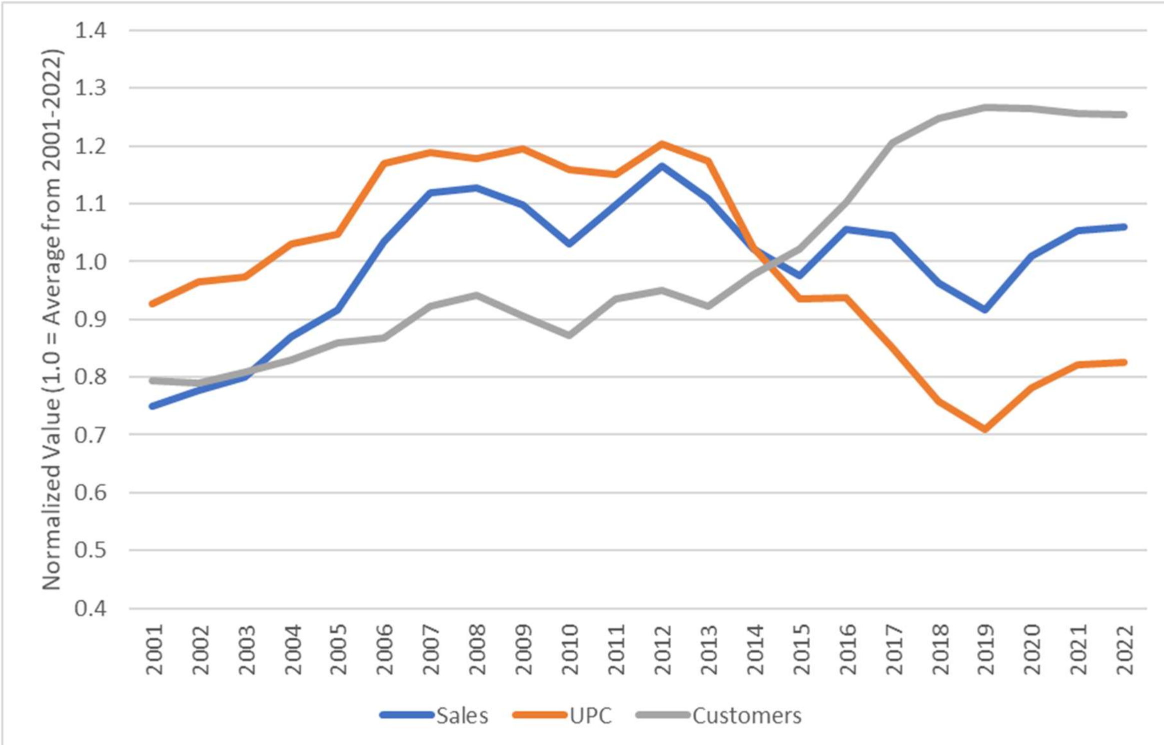
Figure 3.3: BHP Industrial Normalized Sales, UPC, and Customer Counts



3.4 Municipal

Sales to BHP's Municipal class have displayed varying dynamics from 2001 to 2022, 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 (1.2% in 2022).

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 2000 through 2022 using the Prais-Winsten serial correlation correction. The estimated time trends show approximately 5.3 percent per year growth through 2006, with a -0.9 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, after restricting the data to include only the peak demand hour of each day.

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 1.9 percent, according to our estimate). The month dummies reflect seasonal patterns in peak demand.

The model is estimated using data from 2010 through 2022. No correction is made for serial correlation.[10]

[10] 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.

APPENDIX: ESTIMATED MODELS

BHP Residential UPC Model

Prais-Winsten AR(1) regression with iterated estimates

Source	SS	df	MS			
				Number of obs	=	275
				F(14, 260)	=	380.24
Model	10.7530409	14	.768074352	Prob > F	=	0.0000
Residual	.525198927	260	.002019996	R-squared	=	0.9534
				Adj R-squared	=	0.9509
Total	11.2782399	274	.041161459	Root MSE	=	.04494

lupc	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
cdd60	.000695	.0000639	10.87	0.000	.0005691	.0008209
hdd60	.0002697	.0000215	12.55	0.000	.0002274	.000312
lnincome12	.1761467	.0482464	3.65	0.000	.0811432	.2711501
m2	-.0962187	.0111947	-8.60	0.000	-.1182626	-.0741749
m3	-.0818633	.0145424	-5.63	0.000	-.1104992	-.0532274
m4	-.1955924	.0178874	-10.93	0.000	-.230815	-.1603699
m5	-.2757443	.0218129	-12.64	0.000	-.3186968	-.2327919
m6	-.2974246	.0266989	-11.14	0.000	-.3499983	-.244851
m7	-.2291228	.033878	-6.76	0.000	-.2958329	-.1624126
m8	-.2136385	.0380493	-5.61	0.000	-.2885625	-.1387145
m9	-.2816226	.0315752	-8.92	0.000	-.3437983	-.2194469
m10	-.3251122	.0240407	-13.52	0.000	-.3724514	-.277773
m11	-.2422197	.017812	-13.60	0.000	-.2772938	-.2071455
m12	-.0665269	.0120407	-5.53	0.000	-.0902365	-.0428172
_cons	4.632217	.5528106	8.38	0.000	3.543661	5.720773
rho	.4487829					

Durbin-Watson statistic (original) = 1.198043
Durbin-Watson statistic (transformed) = 2.122623

BHP Residential Customer Model

Prais-Winsten AR(1) regression with iterated estimates

Source	SS	df	MS			
				Number of obs	=	276
				F(1, 274)	>	99999.00
Model	1.46632388	1	1.46632388	Prob > F	=	0.0000
Residual	.001212153	274	4.4239e-06	R-squared	=	0.9992
				Adj R-squared	=	0.9992
Total	1.46753603	275	.005336495	Root MSE	=	.0021

lcust	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
lhhld12	.6910307	.07046	9.81	0.000	.552319	.8297425
_cons	8.901736	.2036208	43.72	0.000	8.500876	9.302596
rho	.9927694					

Durbin-Watson statistic (original) = 0.042830
Durbin-Watson statistic (transformed) = 2.755288

BHP Commercial UPC Model
Prais-Winsten AR(1) regression with iterated estimates

Source	SS	df	MS			
Model	3.99357963	17	.234916449	Number of obs	=	275
Residual	.323314065	257	.001258031	F(17, 257)	=	186.73
Total	4.3168937	274	.015755086	Prob > F	=	0.0000
				R-squared	=	0.9251
				Adj R-squared	=	0.9202
				Root MSE	=	.03547

lupc	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
cdd60	.0003942	.000045	8.76	0.000	.0003056	.0004828
hdd60	.0000875	.0000179	4.90	0.000	.0000523	.0001227
m2	-.0439751	.0114179	-3.85	0.000	-.0664596	-.0214906
m3	-.0265592	.0115914	-2.29	0.023	-.0493855	-.0037329
m4	-.0723252	.0139651	-5.18	0.000	-.0998258	-.0448246
m5	-.0893989	.0171697	-5.21	0.000	-.1232101	-.0555876
m6	-.0147155	.0211748	-0.69	0.488	-.0564138	.0269828
m7	.0174451	.0260115	0.67	0.503	-.0337777	.068668
m8	.0383619	.0287205	1.34	0.183	-.0181955	.0949194
m9	.0062652	.0245082	0.26	0.798	-.0419972	.0545275
m10	-.0364795	.0192452	-1.90	0.059	-.0743778	.0014188
m11	-.0925491	.0143715	-6.44	0.000	-.1208501	-.0642482
m12	-.0039131	.0119847	-0.33	0.744	-.0275139	.0196877
class_shift	.0662378	.0075454	8.78	0.000	.0513791	.0810964
trend	-.0139721	.0018519	-7.54	0.000	-.0176189	-.0103253
lntotemp12	1.218746	.1715136	7.11	0.000	.8809947	1.556497
covid	-.065547	.0137752	-4.76	0.000	-.0926736	-.0384205
_cons	4.372712	.5667215	7.72	0.000	3.256703	5.488721
rho	-.1432451					

Durbin-Watson statistic (original) = 2.264265
Durbin-Watson statistic (transformed) = 1.993840

BHP Commercial Customer Model
Prais-Winsten AR(1) regression with iterated estimates

Source	SS	df	MS			
Model	14.0368076	14	1.00262912	Number of obs	=	288
Residual	.02462275	273	.000090193	F(14, 273)	=	11116.46
Total	14.0614304	287	.048994531	Prob > F	=	0.0000
				R-squared	=	0.9982
				Adj R-squared	=	0.9982
				Root MSE	=	.0095

lcust	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
m2	-.0045838	.0020995	-2.18	0.030	-.008717	-.0004507
m3	-.0009737	.0027178	-0.36	0.720	-.0063243	.0043768
m4	.0036047	.0030593	1.18	0.240	-.0024181	.0096276
m5	.0114781	.0032564	3.52	0.000	.0050673	.0178889
m6	.0182555	.0033635	5.43	0.000	.0116337	.0248772
m7	.0213837	.0033957	6.30	0.000	.0146987	.0280687
m8	.027204	.0033646	8.09	0.000	.0205801	.0338278
m9	.0207265	.0032641	6.35	0.000	.0143005	.0271524
m10	.0123837	.0030721	4.03	0.000	.0063357	.0184317
m11	.007713	.0027381	2.82	0.005	.0023225	.0131035
m12	.0000293	.0021335	0.01	0.989	-.004171	.0042295
lntotemp12	1.4924	.0400903	37.23	0.000	1.413475	1.571326
lntotemp_shift	-1.008568	.1541334	-6.54	0.000	-1.312009	-.7051266
class_shift	3.50103	.5396877	6.49	0.000	2.438551	4.563508
_cons	4.283933	.1363829	31.41	0.000	4.015437	4.552429
rho	.6917914					

Durbin-Watson statistic (original) = 0.623496
Durbin-Watson statistic (transformed) = 2.427154

BHP Municipal Sales Model
Prais-Winsten AR(1) regression with iterated estimates

Source	SS	df	MS			
Model	15.8985054	15	1.05990036	Number of obs	=	275
Residual	3.53888497	259	.013663649	F(15, 259)	=	77.57
Total	19.4373904	274	.070939381	Prob > F	=	0.0000
				R-squared	=	0.8179
				Adj R-squared	=	0.8074
				Root MSE	=	.11689

lsales	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
cdd60	.0010979	.0001589	6.91	0.000	.000785	.0014107
trend	.0528453	.0069556	7.60	0.000	.0391486	.066542
trend_d2007	-.0616105	.0072277	-8.52	0.000	-.075843	-.0473779
d2007	.7058767	.0540334	13.06	0.000	.5994761	.8122774
m2	-.113015	.033641	-3.36	0.001	-.1792598	-.0467702
m3	-.0762045	.0348665	-2.19	0.030	-.1448624	-.0075466
m4	-.0987406	.0349585	-2.82	0.005	-.1675797	-.0299016
m5	-.0230447	.035027	-0.66	0.511	-.0920186	.0459293
m6	.1044047	.0385868	2.71	0.007	.0284209	.1803885
m7	.0837303	.062339	1.34	0.180	-.0390255	.2064862
m8	.0137216	.0764035	0.18	0.858	-.1367296	.1641728
m9	.0761635	.0551807	1.38	0.169	-.0324965	.1848235
m10	.0260511	.0360795	0.72	0.471	-.0449955	.0970977
m11	-.1226917	.0348904	-3.52	0.001	-.1913967	-.0539868
m12	-.0566493	.033668	-1.68	0.094	-.1229472	.0096486
_cons	6.874868	.047665	144.23	0.000	6.781008	6.968729
rho	.0762653					

Durbin-Watson statistic (original) = 1.848904
Durbin-Watson statistic (transformed) = 2.016372

BHP System Peak Demand Model

Source	SS	df	MS			
Model	3.20557715	17	.188563361	Number of obs	=	222
Residual	.309250498	204	.001515934	F(17, 204)	=	124.39
Total	3.51482764	221	.015904197	Prob > F	=	0.0000
				R-squared	=	0.9120
				Adj R-squared	=	0.9047
				Root MSE	=	.03893

lmwnat	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
cdd60	.0077083	.001073	7.18	0.000	.0055928	.0098238
hdd60	.0021424	.0004071	5.26	0.000	.0013398	.002945
mnthcdd60perday	.0123391	.0024008	5.14	0.000	.0076054	.0170727
mnthhdd60perday	.0049599	.0008964	5.53	0.000	.0031925	.0067272
lntotPI	.2771603	.0272441	10.17	0.000	.2234441	.3308764
weekend	-.0186558	.012546	-1.49	0.139	-.0433922	.0060806
m2	-.0283045	.0129156	-2.19	0.030	-.0537697	-.0028393
m3	-.0135394	.0147548	-0.92	0.360	-.0426309	.015552
m4	-.0652277	.0174146	-3.75	0.000	-.0995633	-.0308921
m5	-.0161189	.0222675	-0.72	0.470	-.0600229	.0277851
m6	.1101476	.0305745	3.60	0.000	.0498649	.1704302
m7	.0940399	.0358945	2.62	0.009	.0232682	.1648117
m8	.1247258	.032677	3.82	0.000	.0602978	.1891539
m9	.0915224	.0275305	3.32	0.001	.0372416	.1458033
m10	-.0164165	.0201448	-0.81	0.416	-.0561352	.0233023
m11	-.0184189	.0146854	-1.25	0.211	-.0473736	.0105358
m12	-.0226329	.0129257	-1.75	0.081	-.0481179	.0028521
_cons	3.307392	.2092829	15.80	0.000	2.894757	3.720027