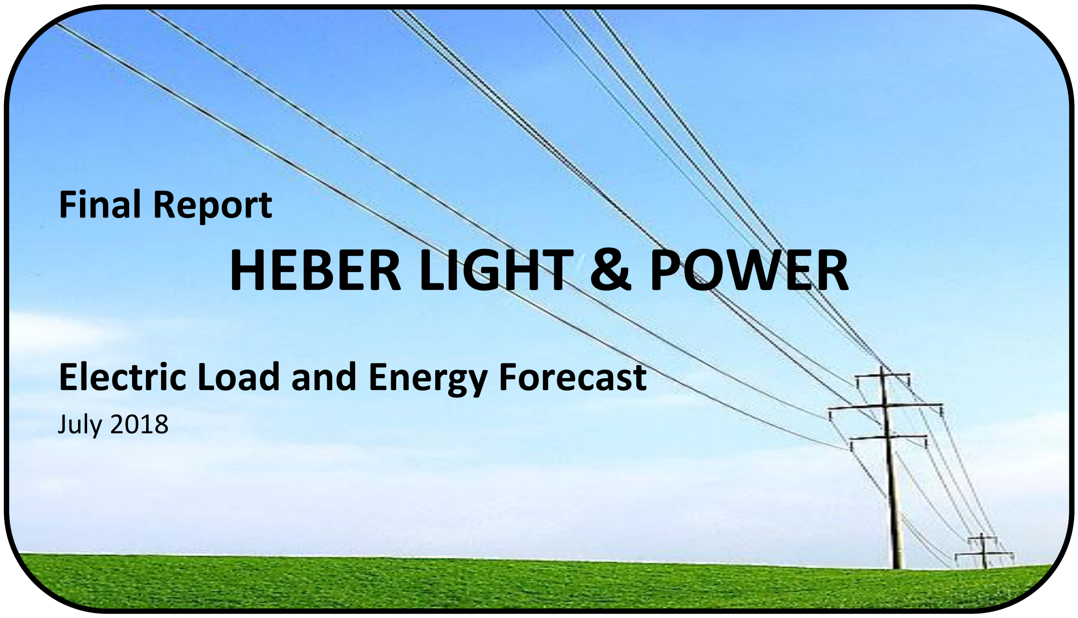

Final Report

HEBER LIGHT & POWER

Electric Load and Energy Forecast

July 2018

UFS

Utility Financial Solutions, LLC

Specializing in Cost of Service, Rate Design, and Financial Analysis

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Utility Financial Solutions, LLC

July 2018

Jason Norlen
Heber Light & Power
31 South 100 West
Heber, UT 84032

Dear Mr. Norlen;

We are pleased to present an econometric modeling and long-term forecasting study for Heber Light & Power (HL&P). This report was prepared to provide the HL&P with a comprehensive examination and projection of future load growth and energy consumption between 2018 – 2040.

The specific purpose of this study is to identify and project the overall trend of HL&P capacity and energy in future years to assist in planning future generation capacity needs.

This report includes a discussion on the statistical models developed to fit historical usage patterns using several data sets including: demographics, weather, installation of renewables, and energy efficiency programs. The statistical models utilized independent variables that had significant impact on energy sales and HL&P's peak demands.

The models developed produced forecasted projections. Variations will occur between forecasts and actuals and some variations may be significant. Certain assumptions used in development of the models are based on current best estimates and may not materialize. In addition, unforeseen events can and will occur and have the potential to significantly alter the trends currently shown in the forecasts.

This report is intended for information and use by utility and management for the purposes stated above and is not intended to be used by anyone except the specified parties.

UFS intends to be a resource to you in the future. Please do not hesitate to contact us with questions. Thank you for the opportunity to work with Heber Light & Power.

Sincerely,

Utility Financial Solutions, LLC
Mark Beauchamp
CPA, MBA, CMA
185 Sun Meadow Ct
Holland, MI 49424

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Project Overview

Utility Financial Solutions completed two long-term econometric projections over the forecast period of 2018 through 2040 for Heber Light & Power. UFS forecasts included:

1) projection of peak monthly demands (kW), and
2) projection of monthly energy consumption (kWh)

An econometric model identifies relationships between demographic and/or weather variables (such as population, employment, temperature and degree days) and demand and energy consumption of customers served by Heber Light and Power. The average growth results of the forecast are listed in the table below and summarize the increases in peak demand and energy consumption.

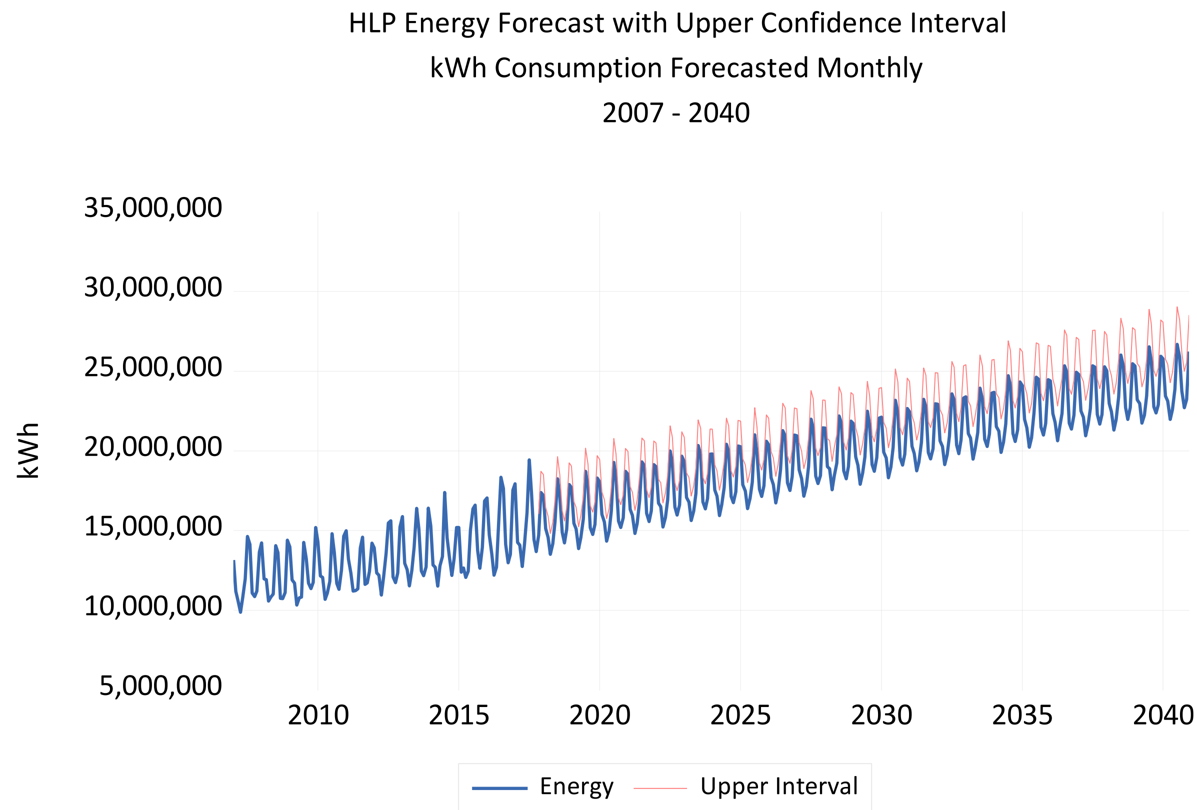
Growth	***Energy***	***Peak***
5 Year	2.3%	2.2%
10 Year	2.0%	1.8%
Forecast Period	1.9%	2.1%

Energy Projection (kWh's)

HL&P energy sales are projected to grow at a rate of 2.3% for the period between 2018 – 2023; 2.0% between 2018 and 2028, and 1.9% between 2018 and 2040. The table below shows annual energy sales projections.

Historical		**Projected**		**Projected**	
Year	**Energy Sales**	**Year**	**Energy Sales**	**Year**	**Energy Sales**
2007	143,066,024	2018	187,608,548	2029	235,944,145
2008	145,186,521	2019	192,456,491	2030	237,727,372
2009	146,974,529	2020	197,990,881	2031	241,774,042
2010	150,620,753	2021	202,380,723	2032	247,197,983
2011	152,661,690	2022	208,194,718	2033	251,945,813
2012	157,350,395	2023	212,418,254	2034	258,185,221
2013	164,297,115	2024	216,718,733	2035	262,603,752
2014	163,683,387	2025	216,390,455	2036	267,783,141
2015	168,834,254	2026	222,103,662	2037	271,271,500
2016	178,512,044	2027	227,156,443	2038	276,129,112
2017	184,198,041	2028	231,944,495	2039	279,958,365
				2040	284,202,479

The historical and projected data was based on monthly observations. The graph below depicts monthly energy consumption with 2007 – 2017 historical data and 2018 – 2040 forecasted values. The table below shows projected energy and the upper boundary. One standard deviation (96% confidence level) from the mean was used to identify the upper boundary.

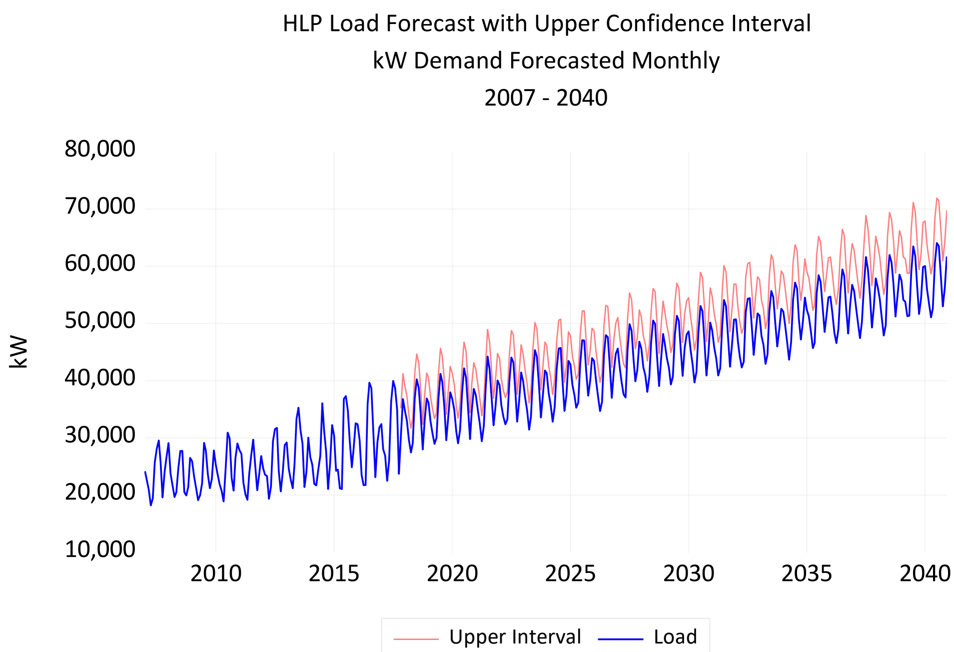


Peak Demand Projection (kW's)

HL&P demands are projected to grow at a rate of 2.2% for the period between 2018 – 2023; 1.8% between 2018 and 2028, and 2.1% average growth rate between 2018 and 2040. The table below is the projected annual peak demands.

Historical		Projected		Projected	
Year	Peak Demand	Year	Peak Demand	Year	Peak Demand
2007	29,558	2018	40,244	2029	49,737
2008	29,102	2019	41,188	2030	51,511
2009	29,111	2020	42,169	2031	52,634
2010	30,909	2021	42,642	2032	53,141
2011	29,683	2022	43,864	2033	54,369
2012	31,725	2023	45,132	2034	55,944
2013	35,205	2024	45,565	2035	57,354
2014	35,863	2025	45,420	2036	58,437
2015	37,025	2026	46,191	2037	60,646
2016	39,302	2027	47,208	2038	61,074
2017	39,408	2028	48,829	2039	62,609
				2040	63,198

The historical and projected data was based on monthly observations. The graph below depicts monthly peak demand with 2007 – 2017 historical data and 2018 – 2040 forecasted values. The upper boundary is one standard deviation from the mean representing a 96% confidence level.



The following sections include the statistical tests and results of the forecasts.

Statistical Tests

To ensure statistical validity of the models, several tests were performed. The following tests substantiate that changes occurring in dependent variables (Energy Sales and Peak Demand) are properly explained with changes in the independent variables (population, cooling degree days, etc). Gauss-Markov assumptions are parameters used to confirm the coefficients in the model are the best linear unbiased estimates[1]. The first four assumptions ensure unbiasedness, while the last provides the lowest variance.

Gauss-Markov Assumptions

1. **Linearity in the parameters** – A linear relationship between the independent and dependent variables must exist to ensure integrity in the resulting models. The linear relationships are tested using observations and the **Ramsay Test.**
2. **Error Term Expected Value is 0** – To ensure an unbiased relationship exists between variables the error terms expected value must be zero. To help ensure an unbiased relationship exists a constant is used to absorb any differentials between the independent variables.
3. **Homoskedasticity** - Variance in error terms between actual and projected observations implies uncertainty in the model. If substantial variations occur, it may imply an omitted variable exists. An **ARCH** test was used to test homoscedasticity.
4. **Error Term is Independently Distributed** – If an independent variable is highly correlated with previous values of itself it signals serial or auto correlation exists. A **Serial Correlation LM test** was used to identify if serial correlation exists.
5. **Each variable is uncorrelated with the error term** – If independent variables are correlated with the error term, it implies omission of an important variable, or an incorrect functional form. A **Ramsay Test** was used to test for this error.

Multicollinearity

Multicollinearity is an inefficiency that occurs when two independent variables are highly correlated with each other, which can lead to unreliable and unstable regression coefficients. To test for this inefficiency, we used the Variance Inflation Indicators (VIFs). These indicators measure how much of the variance of a coefficient is inflated due to linear dependence on other predictors. These measurements may be safely ignored for monthly dummy variables. Lower VIFs are desired.

[1] Best linear unbiased estimates mean the estimated coefficients on the independent variables have the lowest variance (best) and the expected value of the sample mean is equal to the true value of the population mean (unbiased).

Four additional statistics are important to note:

1. Adjusted R-Squared: This statistic measures how well the independent variables measure the dependent variable. Adjusted R-Squared adjusts for the number of independent variables used.
2. Akaike Info Criterion (AIC): A predictor of forecasting capability of the model. We want to minimize this value.
3. Schwarz Criterion (SIC): Another predictor of forecasting capability, but SIC penalizes models that include independent variables of little explanatory power. We also want to minimize this value.
4. Durbin-Watson Stat: In addition to the LM test for Serial Correlation, Durbin-Watson is another measure of the relationship between the dependent variable and previous lags of itself within the residuals. We look for a DW statistic of 2, implying no serial correlation exists.

The additional statistics are found on the bottom portion of the output data for each model.

Model Specification

To build each model, historical data from 2007 through 2017 was used. Independent variables were tested against historical data and included based on t-statistic and significance level. Specific listings of independent variables used in each model can be found on pages 7 and 8.

To provide a statistically valid forecast, various model-types were tested for relevance. One aspect of ordinary least squares regressions and time series models is stationarity, meaning, the mean and variance do not vary based on time. When data is not stationary, regression results may be invalid. Testing for stationarity was done using the augmented Dickey-Fuller test and the data was found to be non-stationary. Differencing the data (observation 2 – observation 1), provided a stationary dataset. Therefore, modeling was performed in differences and transformed after forecasting.

Due to the nature of energy and demand data, auto-regressive and moving-average terms were required to alleviate serial correlation (correlation to previous lags of the dependent variable). This issue can cause statistically invalid results. The subsequent models are referred to as ARIMA(p,I,q) models and are described in more detail on page 9.

Additionally, manual adjustments were made for both the historical data sets and the forecasted values to properly account for the effects of energy efficiency programs and distributed generation. After providing HL&P with an initial set of models for both energy and demand, modifications were made to better reflect market knowledge of HL&P. These adjustments are explained in detail on page 10.

Energy Projection Output

Dependent Variable: D(ENERGY)
Method: ARMA Generalized Least Squares (Gauss-Newton)
Date: 03/19/18 Time: 16:01
Sample: 2007M02 2016M12
Included observations: 119
Failure to improve objective (non-zero gradients) after 16 iterations
Coefficient covariance computed using outer product of gradients
d.f. adjustment for standard errors & covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	2615162.	226291.9	11.55659	0.0000
D(CDD)	89959.33	27841.83	3.231085	0.0017
D(UNIPOP)	335.1930	138.8350	2.414326	0.0176
D(TLOW)	-13167.52	7395.389	-1.780504	0.0780
@MONTH=1	-2818516.	339090.6	-8.311987	0.0000
@MONTH=2	-4748734.	314513.4	-15.09867	0.0000
@MONTH=3	-2885877.	369315.4	-7.814126	0.0000
@MONTH=4	-3700245.	318030.5	-11.63487	0.0000
@MONTH=5	-1956779.	324832.3	-6.023965	0.0000
@MONTH=6	-1599460.	300340.2	-5.325496	0.0000
@MONTH=7	-361681.7	350545.3	-1.031769	0.3047
@MONTH=8	-3153735.	305912.6	-10.30927	0.0000
@MONTH=9	-4876065.	368044.0	-13.24859	0.0000
@MONTH=10	-3185531.	267016.3	-11.93010	0.0000
@MONTH=11	-2115004.	317294.9	-6.665736	0.0000
AR(1)	0.435609	0.102788	4.237930	0.0001
AR(2)	0.135758	0.109107	1.244268	0.2163
AR(3)	-0.346021	0.099026	-3.494229	0.0007
MA(1)	-1.000000	261.5563	-0.003823	0.9970

R-squared	0.930931	Mean dependent var	36931.40
Adjusted R-squared	0.918499	S.D. dependent var	1749901.
S.E. of regression	499569.5	Akaike info criterion	29.26711
Sum squared resid	2.50E+13	Schwarz criterion	29.71084
Log likelihood	-1722.393	Hannan-Quinn criter.	29.44729
F-statistic	74.87934	Durbin-Watson stat	1.970120
Prob(F-statistic)	0.000000		

The Energy Model Independent variables are as follows:

- D(CDD): Differenced Cooling Degree Days
- D(UNIPOP): Differenced Population forecast from the University
- D(TLOW): Differenced Low Temperature
- Monthly Dummy Variables January through November (December is omitted with the inclusion of constant, C to avoid perfect collinearity)
- Auto-Regressive Terms (AR): AR(1), AR(2), AR(3)
- Moving-Average Terms (MA): MA(1)

Demand Projection Output

Dependent Variable: D(LOAD)
Method: ARMA Generalized Least Squares (Gauss-Newton)
Date: 03/18/18 Time: 16:53
Sample: 2007M02 2017M10
Included observations: 129
Failure to improve objective (non-zero gradients) after 26 iterations
Coefficient covariance computed using outer product of gradients
d.f. adjustment for standard errors & covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	5042.038	1035.185	4.870662	0.0000
D(TLOW)	-58.14182	26.00985	-2.235377	0.0274
D(THIGH)	92.17468	35.45799	2.599546	0.0106
D(ROLLING)*(MAY+JUN)	147.0292	49.17176	2.990116	0.0034
@MONTH=1	-5738.083	1294.025	-4.434289	0.0000
@MONTH=2	-8144.681	1522.676	-5.348926	0.0000
@MONTH=3	-8034.103	1613.772	-4.978462	0.0000
@MONTH=4	-7575.825	1496.893	-5.061034	0.0000
@MONTH=5	-5801.371	1446.960	-4.009352	0.0001
@MONTH=6	370.1844	1489.260	0.248569	0.8042
@MONTH=7	-852.3507	1438.413	-0.592563	0.5547
@MONTH=8	-6092.369	1230.351	-4.951731	0.0000
@MONTH=9	-9976.629	1038.404	-9.607658	0.0000
@MONTH=10	-9798.718	1023.068	-9.577776	0.0000
@MONTH=11	-799.1807	1134.258	-0.704585	0.4826
AR(1)	0.345951	0.100629	3.437885	0.0008
AR(2)	0.022169	0.107778	0.205692	0.8374
AR(3)	0.003914	0.105419	0.037128	0.9705
AR(4)	-0.198800	0.102224	-1.944754	0.0544
MA(1)	-1.000000	378.5755	-0.002641	0.9979

R-squared	0.868163	Mean dependent var	-3.441860
Adjusted R-squared	0.845182	S.D. dependent var	4462.070
S.E. of regression	1755.686	Akaike info criterion	17.95786
Sum squared resid	3.36E+08	Schwarz criterion	18.40125
Log likelihood	-1138.282	Hannan-Quinn criter.	18.13802
F-statistic	37.77783	Durbin-Watson stat	1.945943
Prob(F-statistic)	0.000000		

The Demand Model independent variables are as follows:

- D(THIGH): Differenced High Temperature
- D(TLOW): Differenced Low Temperature
- D(ROLLING)*(MAY+JUN): Differenced rolling average of high temperatures, multiplied by May and June dummy variables – this variable models the spike due to irrigation pumping in the summer months.
- Monthly Dummy Variables January through November (December is omitted with the inclusion of constant, C to avoid perfect collinearity)
- Auto-Regressive Terms (AR): AR(1), AR(2), AR(3), AR(4)
- Moving-Average Terms (MA): MA(1)

When evaluating the regression equation, the farthest column on the right gives the p-value for the significance of our parameters. A highly significant parameter typically shows a p-value of less than .05, however, the effect of an insignificant variable on forecasting capability (AIC/SIC criterion) are also considered. For example, despite the insignificance of differenced low temperature in the energy model, low temperature lowered the AIC and SIC when included – indicating a valid relationship when forecasting. Additionally, concern over insignificance of a few monthly dummy variables is also safely ignored. It would not make economic sense to remove them, therefore despite their insignificance, they will remain in the model as to not jeopardize theoretical validity.

Independent Variables

Independent variable data sets were generated through the following sources:

Woods & Poole Economics Inc.: An independent firm that specializes in long-run economic and demographic data projections by county in the U.S..

University of Utah, Policy Institute: In 2017 the University issued long-term demographic and economic projects for the counties in Utah.

HLP Staff: Historical weather data, such as temperatures and cooling degree days, were provided by HLP staff. Additional variables such as savings due to energy efficiency and distributed generation were also supplied by HLP.

Mathematical Explanation of ARIMA Terms:

ARIMA(p,i,q) Model

$$d_i(Y_t) = C + \sum_{n=1}^{p} \varphi_P Y_{t-p} + a_t - \sum_{n=1}^{p} \theta_p a_{t-p}$$

p: Number of AR terms used (i.e. AR(1) … AR(5))
q: Number of MA terms used (i.e. MA(1))
Yt: Current Energy Value
C: Constant term
φ: Coefficient on AR term
a_t: Current Residual value

The Auto Regressive portion of this model corresponds to the first mathematical sum and the Moving Average component refers to the second sum. Auto Regressive (AR) components make slight adjustments to the forecasted values by modeling a relationship between the dependent variable and previous lags of itself. The Moving Average (MA) component makes a slight adjustment for dependent variable correlation to error terms. Please note that the error terms were estimated with the Gauss-Newton method. The "I" term within the ARIMA model stands for "Integration." We would consider this model i=1 because the energy data was first differenced. First differencing the data creates a stationary time-series process, which is essential for the use of ARMA terms in forecasting.

To not model ARMA relationships can cause severe model misspecification, serial correlation, and data inefficiencies.

Manual Adjustments

The models were generated using data from 2007 through 2017. To adjust for the exclusion of energy efficiency and distributed generation data within the original dataset, actual kWh and kW savings were added back to the energy and demand for modeling and forecasting. Following the forecast, kWh and kW savings were subtracted from the data sets from 2007 through 2040. Savings from energy efficiency and distributed generation programs were estimated with growth assumptions provided by HL&P.

Temperature Forecast

The temperature forecast is performed following the Double Season Block Bootstrap Resampling method, outlined in Rob J Hyndman and Shu Fan's research in forecasting for long-term peak electricity demand. Using hourly historic temperature observations, seasonal blocks of length 240 (20 days) were allotted for the years of historical data, thus breaking each year into approximately 36 blocks.

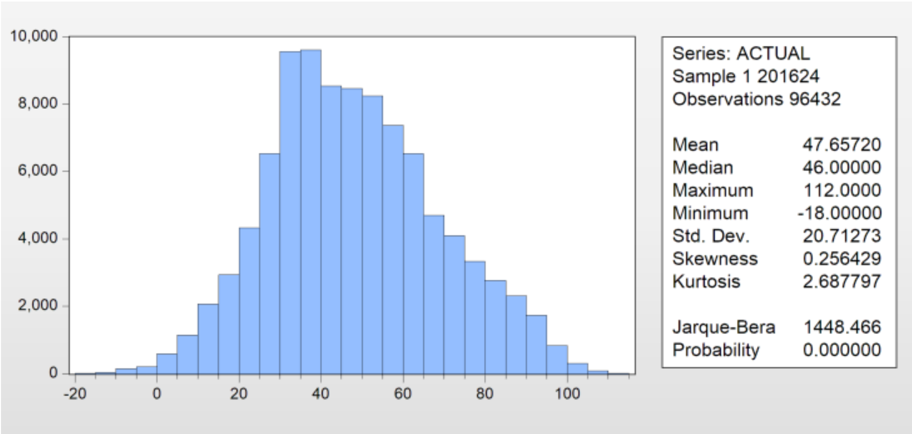
Year 2007	B1: 2007	B2:2007	B3:2007	…	B36: 2007
Year 2008	B1: 2008	B2:2008	B3:2008	…	B36: 2008
Year 2009	B1: 2009	B2:2009	B3:2009	…	B36: 2009
.					
.					
.					
Year 2017	B1: 2017	B2:2017	B3:2017	…	B36: 2017

To forecast, the sample blocks are contained within block number, but come from a randomly selected year. For example, in year 2019, block 1 temperatures may come from 2007, block 2 temperatures 2015, block 3 from 2009, and so on. Since the years are randomly selected, we have a large range of possible series combinations. A series may comprise the following:

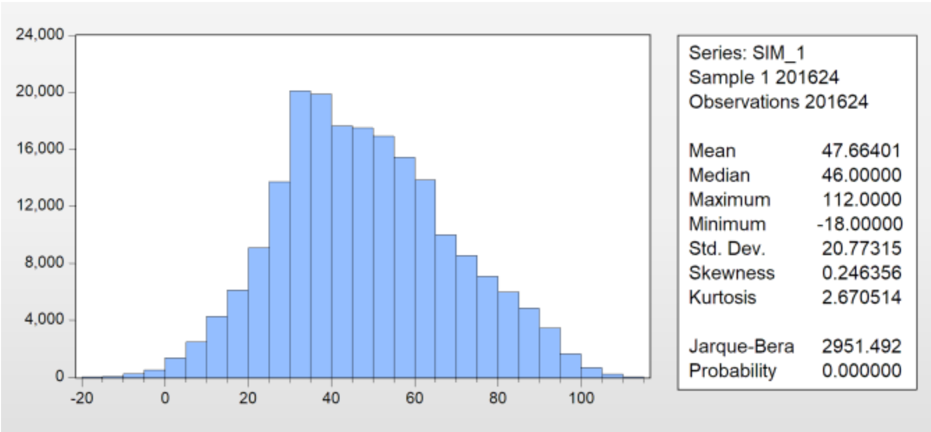
Forecast Y1	B1: 2007	B2:2015	B3:2009	…	B36: 2013
Forecast Y2	B1: 2015	B2:2009	B3:2015	…	B36: 2010
Forecast Y3	B1: 2014	B2:2014	B3:2013	…	B36: 2009
.					
.					
.					
Forecast Y20	B1: 2008	B2:2017	B3:2016	…	B36: 2015

Related cooling and heating degree days were calculated from the resulting sample. This method ensures integrity of seasonality and allows for a probability distribution that more closely mirrors actual temperature data opposed to other methods of weather forecasting, such as moving average. This is shown with HL&P data in the charts on the following page.

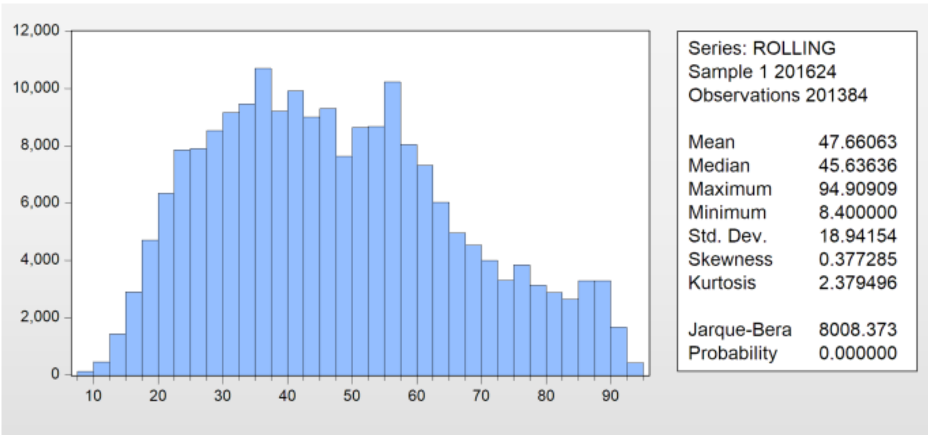
HL&P historic temperature distribution is shown below:



HL&P double season block bootstrap temperature forecast closely mirrors the distribution above:



HL&P Moving average forecast does not closely mirror the actual historical distribution:



Discussion with Board of Directors

Utility Financial Solutions discussed the results of the econometric modeling study with HL&P Board of Directors. Attached are questions asked with formal answers provided by UFS.

1. **Explain what an econometric model is and what statistical tests are performed.**

An econometric model summarizes patterns in data, specifically HLP Energy usage and Load. The models provide a picture of how various factors (such as weather) affect an outcome (such as load growth). Examples of factors used are population growth, temperature, degree days, and seasonality.

Statistical tests are performed to ensure the model is fitted correctly for the historical data. There are specific tests important for all forecasters to perform.

a. Coefficients are linear – or if not linear, the non-linearity is modeled.
   TEST: Ramsey Reset Test
b. Expected value of error is 0
   TEST: Constant included in model
c. Homoskedasticity – no variance in the error term
   TEST: ARCH test
d. Error Term is Independently Distributed – Error term should not be correlated to previous values of itself, i.e. "it's just noise"
   TEST: Serial Correlation LM Test
e. Variables are not correlated with the Error term – again, the error is just random noise
   TEST: Ramsey Reset Test

Additional Statistics Used

Adjusted R-Squared – estimates goodness of fit of the model
Akaike Information Criterion (AIC) – Estimates forecasting capability of model
Schwarz Information Criterion (SIC) – Estimates forecasting capability of model with adjustments for insignificant variables
Durbin – Watson Statistic – measures relationship between current observation of the dependent variable and past observations (serial correlation). This statistic should be close to 2.
Mean Absolute Percentage Error (MAPE) – Forecasting error when testing the model values against the actual values

2. **Why is an econometric model and good fit for a load forecast?**
   Examples of simplistic models would include increasing load by expected growth or by a statistical measure such as Consumer Price Index. While these models might approximate the change in load, they do little to help us understand what affects load in different ways. An econometric model takes multiple variables such as weather and population and allows us to summarize patterns and form links.

3. **Explain why the ARMA model was used?**
   In forecasting it is important to be as simple as possible. The statistical tests noted above drive choices on included variables and type of model.

   The nature of load and energy consumption is seasonal and weather dependent. It is also dependent on community activity and customer patterns. These items are continuous in nature, such that yesterday's weather or activity often affects our usage today.

   The dependency of usage and load on previous values is what causes the need for an ARMA model. After attempting to model load without the inclusion of the ARMA terms, the model failed the Serial Correlation LM test. This indicates that the relationship between yesterday's load and today's load Is not being reflected in the model. ARMA terms capture this relationship.

   AR and MA are two separate types of variables. I will briefly describe each.

   AR (Auto Regressive) can be thought of as a relationship to a previous value, for example, January usage is similar to December usage because of cold weather patterns. The number of AR terms needed in the models indicated strong seasonal relationships in the data.

   MA (Moving Average) occurs when the error term is correlated to previous error terms. This can happen when data is continuous, but we are forecasting specific points. Including the MA term helps model the continuity missing from our data.

4. **What are the independent variables used in the model?**
   Demand Model:

- Independent Variables
  - Differenced high temp
  - Differenced low temp
  - Rolling average temp * (may + June)
  - Monthly Dummy Variables
  - Constant
  - ARMA Terms
    - AR(1) – 1st lag of load
    - AR(2) – 2nd lag of load
    - AR(3) – 3rd lag of load
    - AR(4) – 4th lag of load
    - MA(1) – 1st lag of residuals (errors)

Energy Model

- Independent Variables
  - Differenced Population
  - Differenced Cooling Degree Days
  - Differenced Low Temp
  - Monthly Dummy Variables
  - Constant
  - ARMA Terms
    - AR(1) – 1st lag of energy
    - AR(2) – 2nd lag of energy
    - AR(3) – 3rd lag of energy
    - MA(1) – 1^{st} lag of residuals (errors)

5. **Provide a brief description of the data sources (*e.g.*, Woods and Pool data, weather, demographic data, energy efficiency).**
   Demographic data was provided by Woods & Poole and University of Utah. Woods & Poole is a small independent economics firm in Washington D.C.. Woods & Poole's database contains more than 900 variables of economic data and demographic data for the U.S. and all states, regions, counties, and Core Based Statistical Areas for every year from 1970 to 2050. Woods & Poole has been making county forecasts since 1983. This comprehensive database is updated annually.
   Weather data was provided by HLP (2009 – current) and weather underground (2007 – 2009). Weather data was forecasted using historical weather data.
   Energy efficiency data was provided by HLP. Data was forecasted with a modest growth and maximum capacity assumption reviewed with HLP staff.

6. **What are the strongest factors contributing to load growth for HL&P system load and demand?**
   HLP Usage increases are largely driven by the growth in population expected. System Load growth is driven by the patterns picked up through the ARMA terms such as historical swings and previous load growth. The historical ten-year average load growth is 3.0%, five-year average is 4.5% and historical three-year average is 3.2%. These strong growth factors are driving the future trend.

7. **What is the confidence level of the forecast? (One of our customers has specifically requested an explanation of the confidence interval, and asked, "What is the probability that growth could be outside of the confidence band?")**
   The confidence interval provides a range of values (higher and lower) with a probability of 96% that the forecasted value lies within the range. The probability that growth could be outside the bands is 4%. When compared to historic values, the forecast produces a margin of error that is used to calculate upper and lower confidence intervals.