ORIGINAL

TEP
Tucson Electric Power
88 East Broadway Blvd., P.O. Box 711
Tucson, Arizona 85702

October 30, 2015

Docket Control
Arizona Corporation Commission
1200 West Washington Street
Phoenix, AZ 85007

Re: Notice of Filing – Tucson Electric Power Company Load Forecasting Re-examination
Decision No. 75068, Docket No. E-00000V-13-0070

Pursuant to Decision No. 75068 (May 08, 2015) ("Decision"), page 14, lines 26 through 28 and page 15, lines 1 through 2, Tucson Electric Power Company ("TEP") is required to file a report on the results of the re-examination of their load forecasting techniques on or before October 31, 2015. Enclosed please find TEP's Load Forecasting Re-examination Report, in compliance with the Decision.

If you have any questions, please do not hesitate to contact me at (520) 884-3680.

Sincerely,

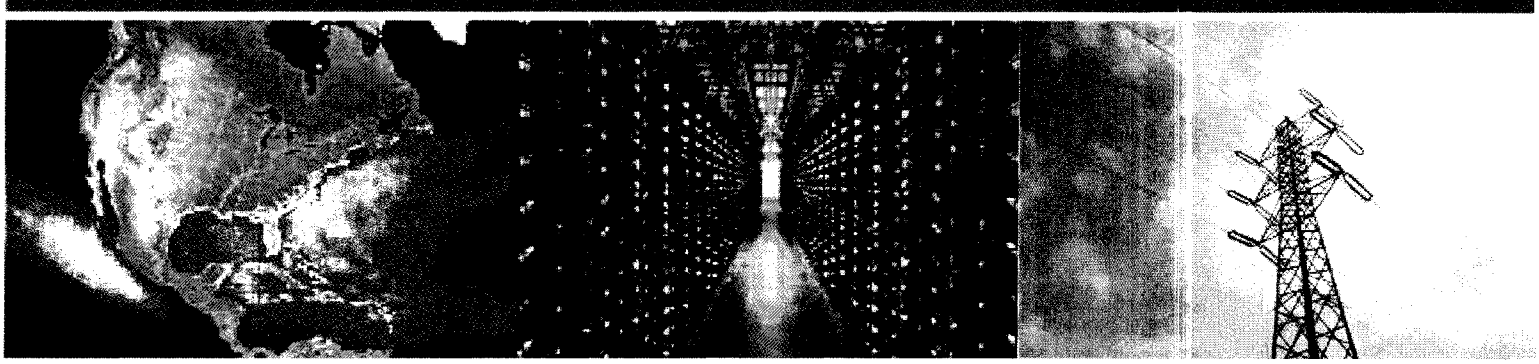
Melissa Morales
Regulatory Services

cc: Compliance Section, ACC

Tucson Electric Power
2016 TEP Load Forecast Update

October 30, 2015

2016 IRP Supplemental Report



Acknowledgements

Tucson Electric Power Load Forecast Team

Gregory Strang, Senior Forecasting Analyst
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Introduction

As ordered in Decision # 75068 within Docket No. E-00000V-13-0070, Tucson Electric Power (TEP) respectfully submits the following report. This particular Order called for TEP to submit a re-examination of its load forecasting techniques in preparation of the 2016 Integrated Resource Plan (IRP). The Utilities Division Staff (Staff) and its consultants Global Energy & Water Consulting, JLC and Evans Power Consulting, Inc. felt that the TEP load forecast appeared to be optimistically high and that it assumed a rapid return to historical load growth. Staff recommended that TEP re-examine its load forecasting techniques prior to the filing of the 2016 IRP. This report details the methodology that goes into developing a load forecast.

TEP Forecast Methodology

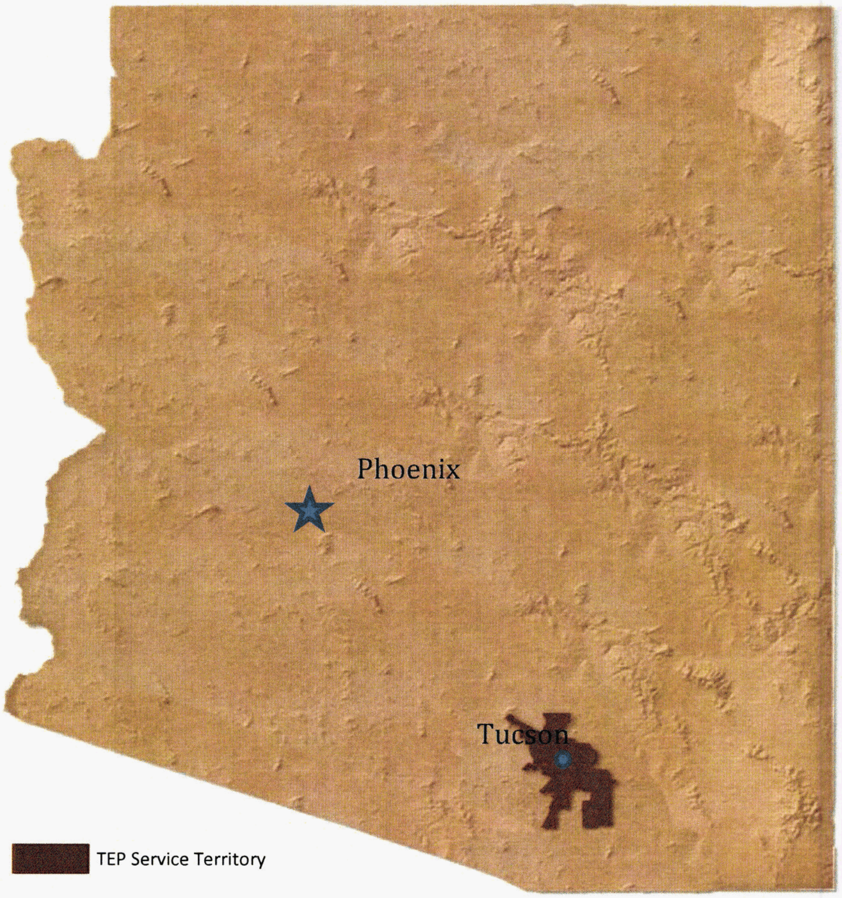
The energy forecast used by TEP is produced using a "bottom up" approach. A separate monthly energy forecast is prepared for each of the major rate classes (residential, commercial, industrial, and mining). As the factors impacting usage in each of the rate classes vary significantly, the methodology used to produce the individual rate class forecasts also varies. The large industrial and mining customers are tracked and the sales are forecasted on an individual basis. The residential, commercial, and small industrial class sales are forecasted on a class basis by combining a customer forecast for each class with a monthly Use Per Customer (UPC) forecast for each class. The retail peak forecast is based on the historical relationship between hourly demand load, weather, calendar effects, and sales growth.

Below the Company discusses each of the forecasts necessary to put together a total retail sales forecast as well as a retail peak forecast. First, the residential and commercial customer forecast methodology will be discussed, followed by the residential and commercial use per customer (UPC) forecast. The overall approach used for the residential and commercial classes. The residential and commercial UPC forecasts are the most involved and require the most explanation. Next, the large industrial and mining sales forecast will be discussed. We will then look at the small industrial sales forecast. The small industrial sales forecasts is composed of a customer forecast and an UPC forecast, similar to the residential and commercial rate classes, but the small industrial customer and UPC forecasts are arrived at using a different, less complex process. Finally, we will consider the retail peak forecast. The Company will provide graphs throughout to illustrate the results of the different components of the total retail sales forecast and the retail peak forecast.

Residential and Commercial Customer Forecasts

The first step in obtaining residential and commercial energy sales forecasts, is to forecast residential and commercial customer growth. TEP serves more than 400,000 customers in the Tucson metro area (Pima County).

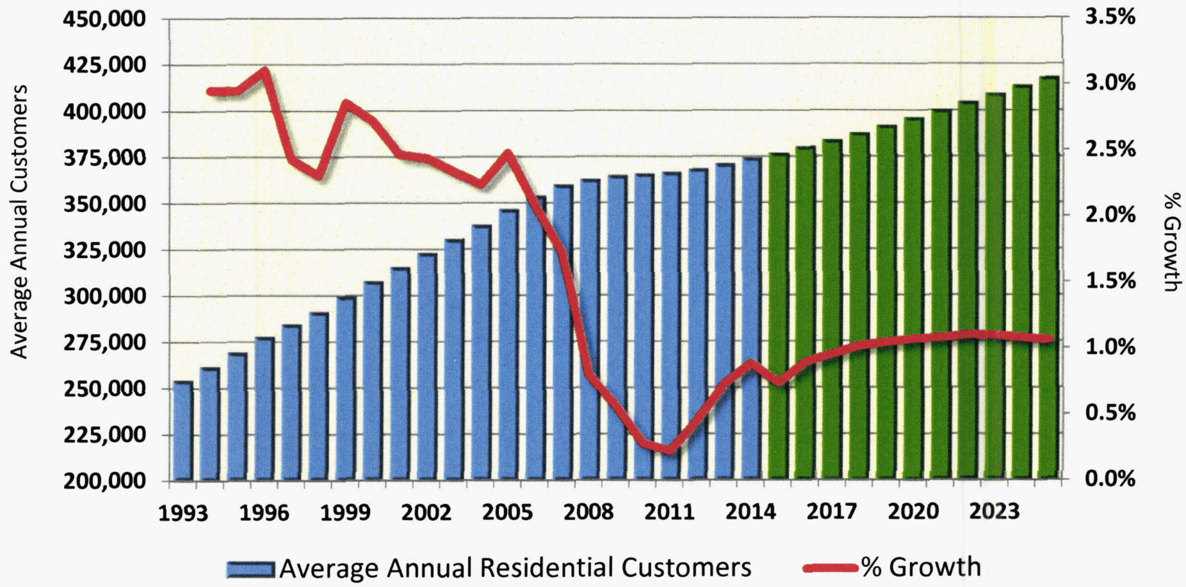
Map 1 - Service Area of Tucson Electric Power



To obtain the residential and commercial customer forecasts, TEP begins by obtaining the most recent Pima County population forecast from IHS Global Insight. In recent years, population growth in Pima County and customer growth at TEP have slowed dramatically due to the severe recession and slow recovery. Customer growth, which is forecast based on population growth, is currently recovering from its recessionary lows but is not expected to return to its pre-recession pace based on the projections from IHS Global Insight and the Forecasting Project at the University of Arizona.

TEP then uses an ARIMAX (Auto-Regressive Integrated Moving Average with eXogenous inputs) model to forecast the residential customer growth. Further explanation of this type of model is provided in the UPC forecast section. The model uses the historical TEP residential customer growth and Pima County population growth relationship, while accounting for season trends, e.g. moving in and out of University of Arizona students or snow birds, to produce a residential customer growth forecast based on IHS Global Insight's population growth forecast. Before considering the residential growth forecast final, model statistics are checked. If the model statistics are not acceptable, the model is revisited and will be adjusted as is reasonable. Chart 1 shows residential customer growth. The blue bars represent historical residential customer numbers and the green bars represent forecasted residential customer numbers.

Chart 1 - TEP Residential Customer Growth



Once the residential customer forecast is completed, it is time to do the commercial forecast. The commercial customer forecast uses an ARIMAX model as well. The major difference between the residential customer forecast and the commercial customer forecast is that the residential customer forecast looks at the relationship between Pima County population growth and residential customer growth, and the commercial forecast looks at the relationship between the residential population growth and the commercial establishment growth. To do this, the residential customer forecast is used in the forecast period of the commercial customer forecast.

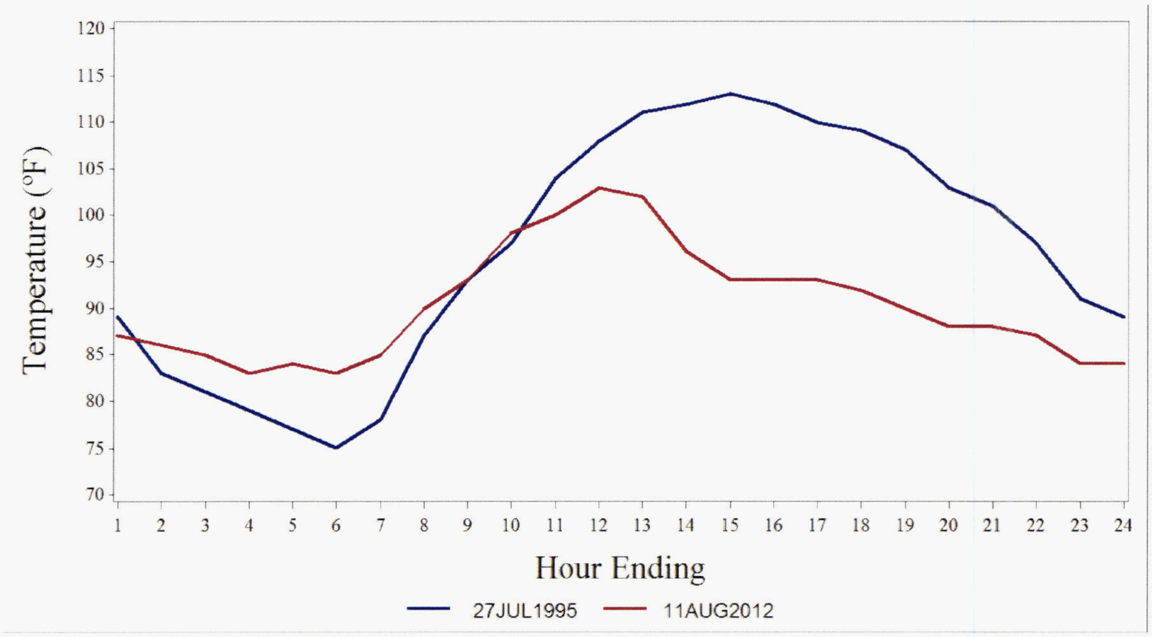
The Company's current forecast does not show customer growth returning to the previous levels in the next decade for two reasons. First, the historical growth rate represents a period that has been described as a bubble. Secondly, IHS Global Insight projects slower population growth in the Tucson-area than during the decade ending 2000—when it grew at an annual average of 2.3% per year—or even during the decade ending in 2010 when the population grew by 1.5% per year. During the current ten-year horizon through 2020, the area population is expected to see 1.0% growth per annum. Now that the residential and commercial customer growth forecasts have been completed, it is time to move onto the residential and commercial UPC forecasts. This process is involved and will be fleshed out over multiple sections.

Weather History and Weather Variable Selection

Perhaps the single most significant driver of electric load is weather which is why the Company carefully scrutinizes the weather data and weather variable selection. This section will discuss how TEP obtains weather information as well as what weather variables the Company uses. The Company acquires weather data from the National Oceanic and Atmospheric Administration (NOAA), which can provide historical data going back many years. The Company analyzes this data using SAS, a widely-used statistical software package. Any gaps in the weather data are filled using accepted industry practice as outlined by Chen and Claridge [Chen].

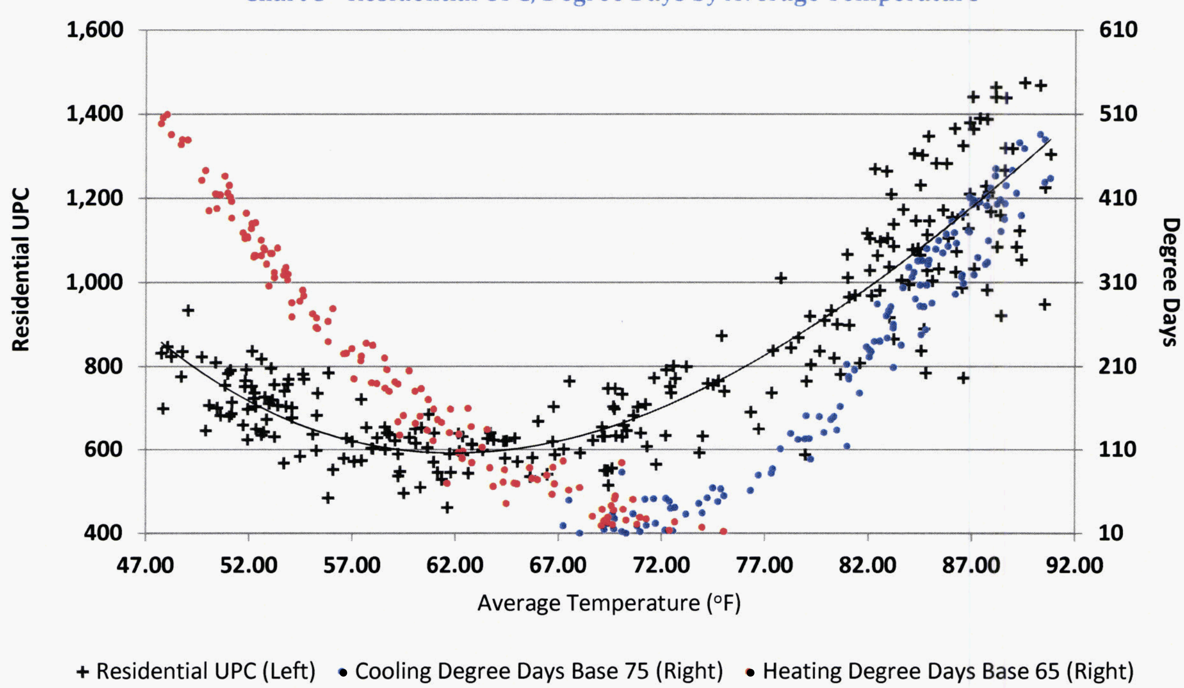
TEP previously represented daily weather through use of heating and cooling degree days as an approximation of daily weather. The main advantages of degree days are that they require two easily recordable data points (min and max temperature) and a simple formula to compute. However, the disadvantages of degree days are numerous. The standard base temperature of 65 degrees has historically been used to differentiate the point where customers begin heating or cooling. The reality is that 65 degrees is an arbitrary number based on Sir Richard Strachey's judgment related to crop growth from over 100 years ago when degree days were established [Lempfert]. While heating and cooling degree days merely represent variance from an arbitrarily defined base temperature, average hourly temperature is a raw number that allows the model to determine what the most appropriate minimum load temperature should be. Additionally, average hourly temperatures more accurately represents daily weather because they include 24 daily data points instead of two. The use of 24 equally spaced data points per day creates a more accurate representation of weather that varies from the typical daily temperature pattern. For example, the temperature fluctuations brought on by a monsoon storm cannot be accurately represented by degree days. Two days can have very dissimilar weather patterns and very different average temperature despite having the same degree day value. Chart 2 below is an example of this. Both days have the same cooling degree value, 19, but have dramatically different average temperatures. The weather on July 27, 1996 (represented by the blue line) exhibits a typical diurnal pattern, with an average temperature of 96.8 °F. On August 11, 2012 (the red line), an afternoon monsoon storm caused untypical mid-day cooling which resulted in an average temperature of 90.3°F. It is possible to generate graphs for days that have similar average temperatures and disimilar weather patterns, but those days occur far less frequently.

Chart 2 – Comparison of Typical Summer Days



Finally, because the model can easily estimate how the change in average temperature affects load, models can be built that are simpler than those based on degree days. Chart 3 will help illustrate these differences.

Chart 3 - Residential UPC, Degree Days by Average Temperature



The easiest thing to notice is the misalignment of the 65 degree base temperature for heating degree days and the 75-degree base for cooling degree days. On an average temperature basis the minimum load temperature is approximately 62 degrees, which is different from the baseline for degree days. Next, notice how the relationship between temperature and use per customer is approximated well by a simple polynomial model. Also notice that although related, degree days do not match the changes in monthly use per customer well. A similar graph of commercial customer usage would make the problems with degree days even more apparent. The base temperature for commercial customers is closer to 50 degrees and the relationship between degree days and use per customer is even worse. Due to the significant misalignment of base temperatures, the heating degree day coefficients for commercial customers are typically negative suggesting that as heating load increases, kWh consumption decreases. Even if commercial customers relied predominantly on gas for heating, one would still expect kWh consumption to rise with additional heating requirements due to ventilation load. This gives further credence to using average temperature over degree days.

In addition to average hourly temperature, the NOAA data sets contain many valuable weather variables, including measures of humidity. Anecdotally, the start of monsoon season causes many customers to switch from evaporative cooling to vapor-compression cycle cooling. This is because as the dew point rises, evaporative coolers cannot sufficiently decrease the temperature of outside air to provide a comfortable indoor climate. Vapor-compression cycle coolers can sufficiently decrease air temperatures and humidity, increasing customer comfort and justifying their higher price. Because of this switching, the Company investigated using dew point and relative humidity as additional regression variables. The NOAA data sets contains only dew point data, so standard approximations were made to calculate relative humidity [Stull][Buck]. There have been various studies on how humidity affects human comfort. One variable, the heat index, attempts to represent how a certain temperature feels based on humidity [Steadman]. Rather than use heat index directly, the Company simply uses dew point or relative humidity as an additional model variable, depending on which is more significant, and allows the model to identify the relationships between UPC, average temperature and measures of humidity. This method better captures the impact of humidity in TEP's service territory.

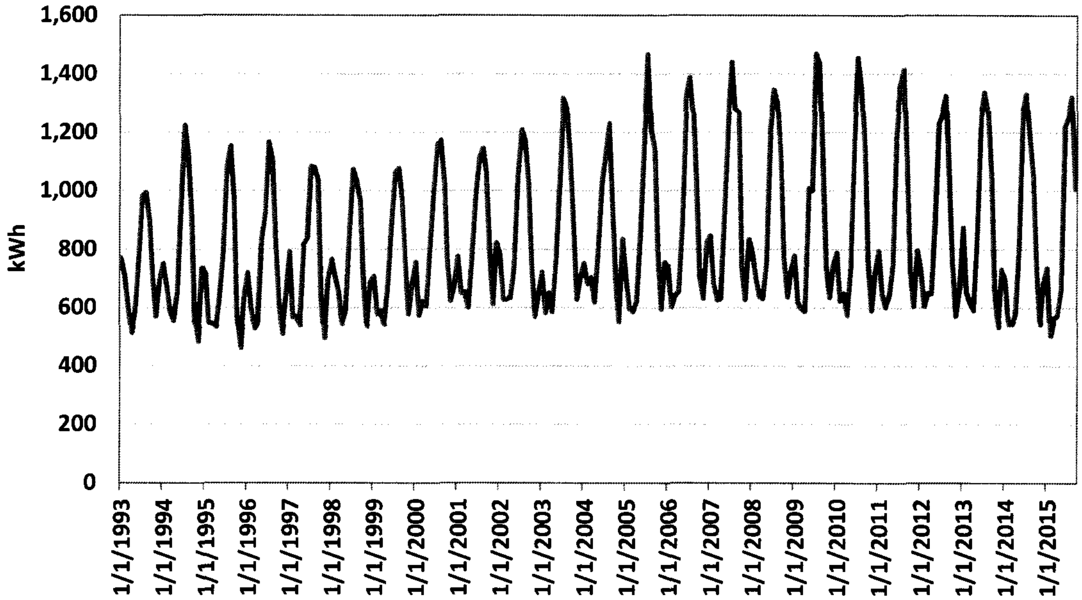
In summary, the Company uses hourly data provided by NOAA as its historical weather data source. Due to the limitations of degree days the Company does not use degree days as a weather regression variable. Instead it uses the far superior average hourly temperature as a regression variable for use per customer. Finally, because of its effect on use per customer, the Company also uses dew point as an explanatory variable. Now that the Company has reviewed the type of weather data it uses, the model selection process for the residential and commercial UPC forecasts, which greatly relies on this weather data, will be discussed.

Residential and Commercial UPC Forecasts

Exploratory Analysis

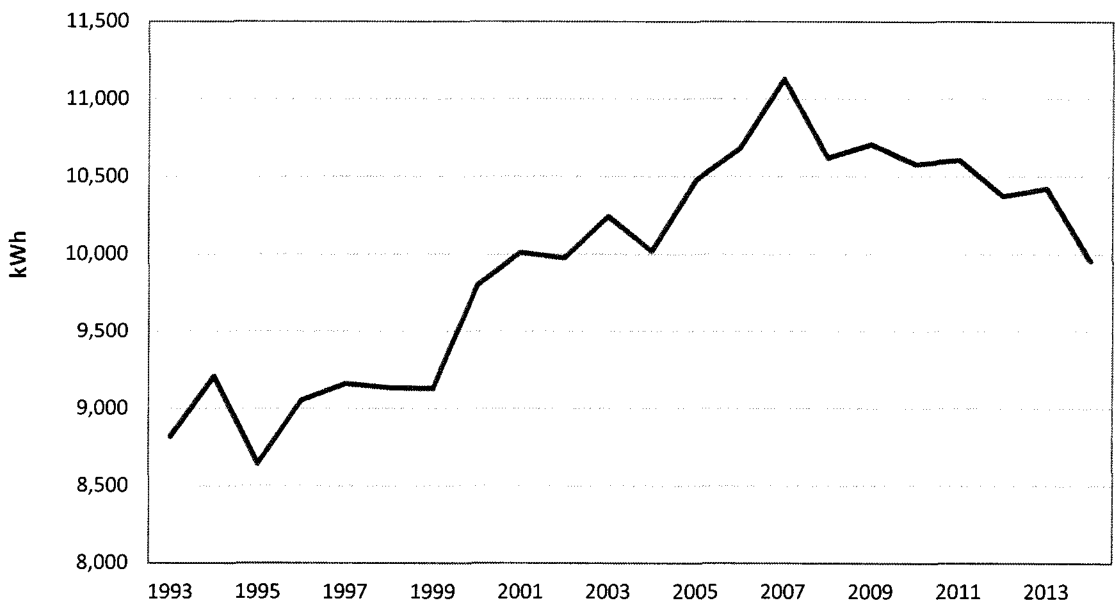
The first step to forecasting residential and commercial UPC is the acquisition of historical UPC data. The data for this purpose is gathered from monthly accounting reports with UPC defined as the total class sales divided by the total class customers. The Company has this data going back as far as 1993 and uses that entire data history when building its models. Once the data are collected, it is important to do exploratory analysis of the data. The simplest place to start is to graph the data with respect to time, as show in Chart 4 below.

Chart 4 - Residential Use Per Customer



At this level of granularity it is immediately clear that there is a strong seasonal pattern to the data. One would expect this seasonality due to significant electricity consumption from space heating and cooling. Thus, it is expected that the model used would incorporate weather to help account for weather related changes in use per customer. It also appears that there is a trend component in the data but at this level of granularity it is difficult to interpret. For this reason, the data in Chart 5 is grouped by year.

Chart 5 - Annual Residential Use Per Customer



In Chart 5 it is immediately clear that there is a strong trend in the data. Before the 2007-2009 recession, UPC was increasing strongly; since then it has declined. This corresponds both with an economic downturn and with the increasing popularity of energy efficient (EE) products and distributed generation (DG) in the form of rooftop solar. To address the EE and DG factors, the Company uses what is known as the add-back method. Explicitly, the Company adds back the estimated lost sales related to EE and DG to the historical sales numbers before generating the historical UPC. Some companies have questioned this method, suggesting that EE and DG should stand as their own variables in the model. If the EE and DG numbers are accurate, then the expectation is the coefficient related to those numbers should be very close to 1. This is indeed the case for the Company's EE and DG related numbers, giving us confidence in their accuracy and allowing us to retain the historical relationship between UPC and economic trends. After the forecasts are generated, the same values for EE and DG are removed from the forecast. Chart 6 below illustrates the before and after add-back of EE and DG to residential UPC.

Chart 6 - Annual Residential Use Per Customer

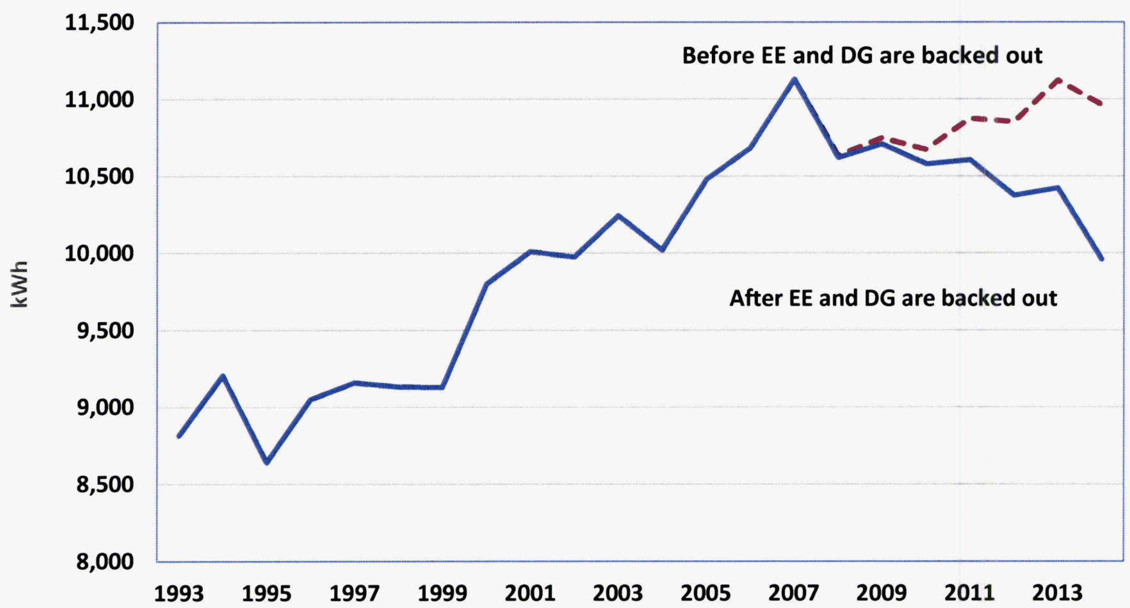


Chart 6 makes clear that there should be some trend component consideration included in the model. It is also clear that a simple economic trend is unlikely to capture all of the year over year variance in UPC. This lends further credence to using a variable like weather to help explain the annual difference in UPC. After the exploratory analysis, the model selection process begins. While working through the model selecting process, the Company will use the information learned during its exploratory analysis: the UPC data shows both seasonality, consistent with the idea that weather effects electric usage, as well as a trend. Lost UPC to EE and DG has also been added back into the historical UPC, so any trend related to EE and DG have temporarily been removed.

Model Selection Process

The Company's method of model selection is to start with the most basic model available, then look to the next level of complexity and show that it performs better than the previous model. If both models perform similarly, then the simpler model is chosen. This is known as the principle of parsimony and is good practice in model fitting to prevent an over-fit model being selected. Over-fit models tend to very accurately approximate the predicted variable in the fitting period while performing poorly in an actual forecast period. The Company also pays attention to the various statistical necessities for a model to be valid. An example of a statistical necessity that would exclude a model from use is the presence of serial autocorrelation in residuals as identified by a Ljung – Box test. To fit models and generate forecasts and coefficients the Company makes extensive use of the various procedures in SAS.

The Company uses a handful of best practices to determine which model is the "best." First, TEP employs statistics of fit like root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE). Models are fit using a fit period and then tested using a validation period to see how well they would have performed had they been the actual forecast. Using the fit and validation periods helps ensure that a model can explain the historical series well without falling victim to issues like over-fitting while forecasting. Table 1 shows the models discussed above and their various performance levels.

The Company will now walk through the model selection process. The Company starts with a naïve benchmark model that models UPC following the prior year's magnitude and pattern. These models can actually perform quite well for time series that do not exhibit strong trends but have a seasonal pattern that can mostly be explained by simple calendar timing. The usage of TEP's large industrial customers can be effectively modeled with this method. However, in the case of residential and commercial UPC forecasting, neither of these are true so this model can easily be beaten. This model is the Naïve – Last Year model in Table 1.

The next model the Company considers is an Auto-Regressive Integrated Moving Average (ARIMA) model. ARIMA modeling is a highly developed method for estimating time series data. The accuracy of this model can be explained by analyzing its component parts. The ***Auto-Regressive*** portion estimates how the value of a time series at a previous point in time effects the value at a future time. Pure AR models are great at estimating highly regular events. The ***Integrated*** portion refers to differencing, which explores how the change in a time series at a previous time affects the change in a series at a future time. The integrated portion of a model effectively estimates the trend component of a time series. Finally, the *Moving Average* component estimates how the error of a previous period affects the error of a future period. For example, if a model is consistently underestimating, the Moving Average component will help to correct the underestimation. The main strength and weakness of an ARIMA model is that it is fully dependent on the time series itself. When it is relatively unclear what is causing a variable to change with respect to time, it is helpful that the model does not require explanatory variables. For example, airline passenger volumes are highly seasonal because people tend to travel around holidays and when children are out of school. This type of model can do a very good job at forecasting passenger volumes under such circumstances because it predicts a consistent trend and it also handles seasonal changes very well. TEP's UPC growth from 1993-2007 was very consistently trending upward at a regular pace. Also, although weather varies year over year, it's safe to assume that July will be hot and January will be cold. This type of Naïve model can be hard to beat with a pure regression model. This model is the Naïve – ARIMA model in Table 1. Looking at the comparison statistics (RMSE, MAE, MAPE) in the Validation Period, the Naïve – ARIMA model has smaller statistic values than the Naïve – Last Year model. In terms of RMSE, MAE, and MAPE, the smaller number indicates that the model is likely to perform better. This table indicates that Naïve – ARIMA model is likely to perform better than the Naïve – Last Year model.

The next step up in model complexity for the model selection step is a regression based model. This type of model requires historical and future values for all of the regression variables. As stated in the weather section, TEP relies heavily on weather data in our regression models. For forecast values of weather, TEP uses either an average of the last decade or an average of forecast outputs for an ensemble of historical years. The Company also uses economic variables to predict the trend growth in UPC. For residential UPC the Company uses real personal income. UPC and real personal income are highly correlated, presumably because people with higher incomes tend to buy larger appliances and houses that consume more energy. For commercial UPC, the Company uses an amalgam of employment indicators which are again highly correlated because businesses that hire more employees will presumably increase their energy usage. The Company first looked at a regression model with cooling degree days and heating degree days as explanatory variables and found the fit is not as good as the ARIMA model. For the reasons noted in the weather section, degree days don't fit changes in UPC well. To compensate for this poor fit, the degree days are partitioned into months in what is known as a seasonal dummy variable. That is to say, a value of cooling degree days in July will generate a different level of UPC than the same number of cooling degree days in August. This model ends up over-fitting the data by having so many monthly coefficients and still does not perform as well as the ARIMA model. The next regression model that is fit uses average temperature. It performs better than the degree day model but not as well as the seasonal dummy model. However, the average temperature model is far more parsimonious (has fewer variables) compared to the seasonal dummy model. None of these regression models can beat the plain ARIMA model, though, which is completely naïve of how weather and economics relate to energy consumption. In Table 1 there are 3 tested regression models. Looking at the test statistics in the Validation Period, it can be seen that that Naïve – ARIMA model outperforms each of the regression models tested.

This brings us to the final model that the Company fits during the model selection process: an ARIMAX model combines and ARIMA model with a regression model. The *X* in the acronym stands for e*X*ogenous inputs, otherwise known as regression variables. By combining the power of both of these models, the effects of weather and economic trends can be isolated from non-weather related seasonal patterns. This produces a truly robust set of weather coefficients that greatly increases the reliability of the weather normalization compared to pure regression coefficients. TEP's service territory is subject to seasonal trends that happen independently of weather but would otherwise be rolled into monthly weather coefficients. For example, the student population at the University of Arizona swells significantly each August when students move in and diminishes each May when students move out. This occurs every year at the same time of year but is wholly unrelated to weather. An ARIMAX model accounts for these types of changes better than a plain ARIMA model and, in this case, the additional complexity is worth the decrease in parsimony. In Table 1, the ARIMAX model is labeled as "Mixed", meaning a mix of the ARIMA and regression methods. Looking at the test statistics in the Validation Period, both tested ARIMAX models (or "Mixed" models) performed better than the Naïve ARIMA model.

Table 1 - Model Comparison Results

		Fit Period 1993-2010			Validation Period 2011-2014		
Model Type	Description	RMSE	MAE	MAPE	RMSE	MAE	MAPE
Naïve	Last Year	88.55	65.03	7.85%	74.44	56.86	6.25%
Naïve	ARIMA	74.94	54.57	6.74%	57.24	45.85	4.95%
Regression	DD +DD^2 + Econ Trend	76.37	59.28	7.43%	67.21	52.59	6.09%
Regression	Monthly DD + Econ Trend	64.96	51.39	6.38%	69.79	56.77	6.37%
Regression	AVET + AVETS + AVEDP + Econ Trend	70.18	54.91	7.15%	69.43	55.28	6.42%
Mixed	AVET + AVETS + AVEDP + AVEDPS + Econ Trend + ARIMA	52.69	39.39	5.00%	53.10	42.29	4.74%
Mixed	AVET + AVETS + AVEDP + AVEDPS + Econ Trend + ARMA	54.45	40.92	5.26%	52.30	39.95	4.48%

Table 1 Acronyms

DD = Heating and cooling degree days

Monthly DD = Seasonal dummy heating and cooling degree days where statistically significant

AVET = Average Hourly Temperature

AVETS = Average Hourly Temperature Squared

AVEDP = Average Hourly Dew Point

AVEDPS = Average Hourly Dew Point Squared

RMSE = Root Mean Square Error

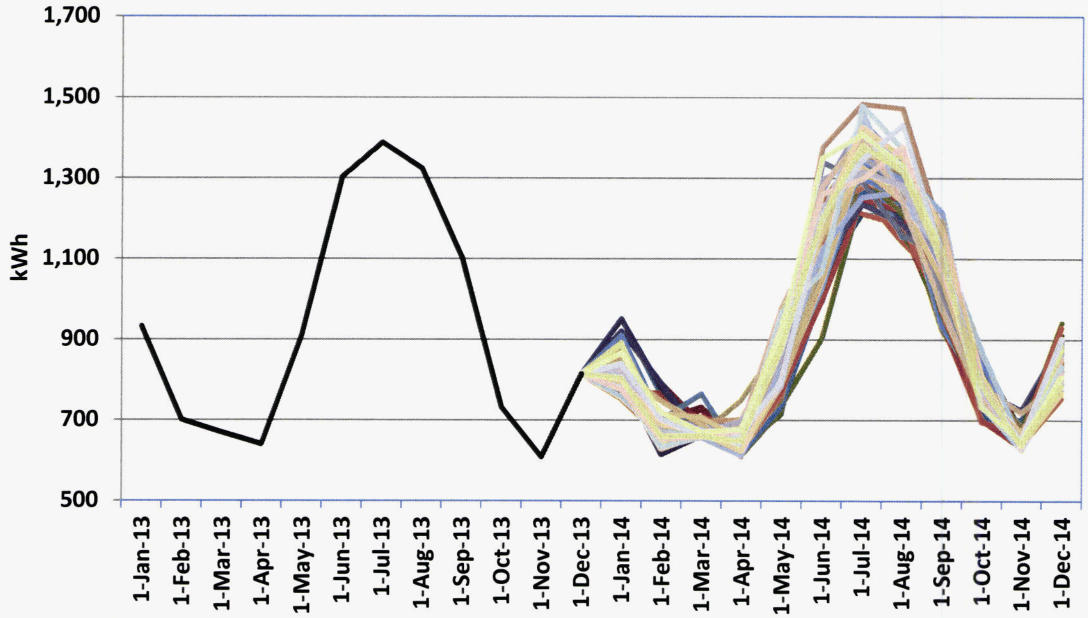
MAE = Mean Absolute Error

MAPE = Mean Absolute Percentage Error

Note: when using RMSE, MAE, and MAPE, smaller values indicate that the model will likely perform better than a model with larger values.

In addition to scrutinzing the forecast model used, TEP evaluates the variables used for the forecast portion. It is standard practice to use a 30-year average of weather for the predicted weather in the same manner that NOAA defines its averages. There has been a push to use shorter periods for weather to account for emerging trends such as climate change and heat islanding. For both of these methods, a problem results because of the non-linear response of UPC to temperature. To account for this, the Company uses an ensemble of historical weather scenarios. In essence, the forecast predicts future consumption based on what would happen if the weather is the same as it was in a previous year. For example, it might seek to determine what this year's UPC would be if the weather was the same as it was in 1994. Once these multiple scenarios are created they are averaged together to create the final forecast. To better illustrate this concept, Chart 7 shows the various forecast outputs for the forecast year of 2014 with weather scenarios from 1984-2013 ***before the EE and DG were backed out of the forecast.***

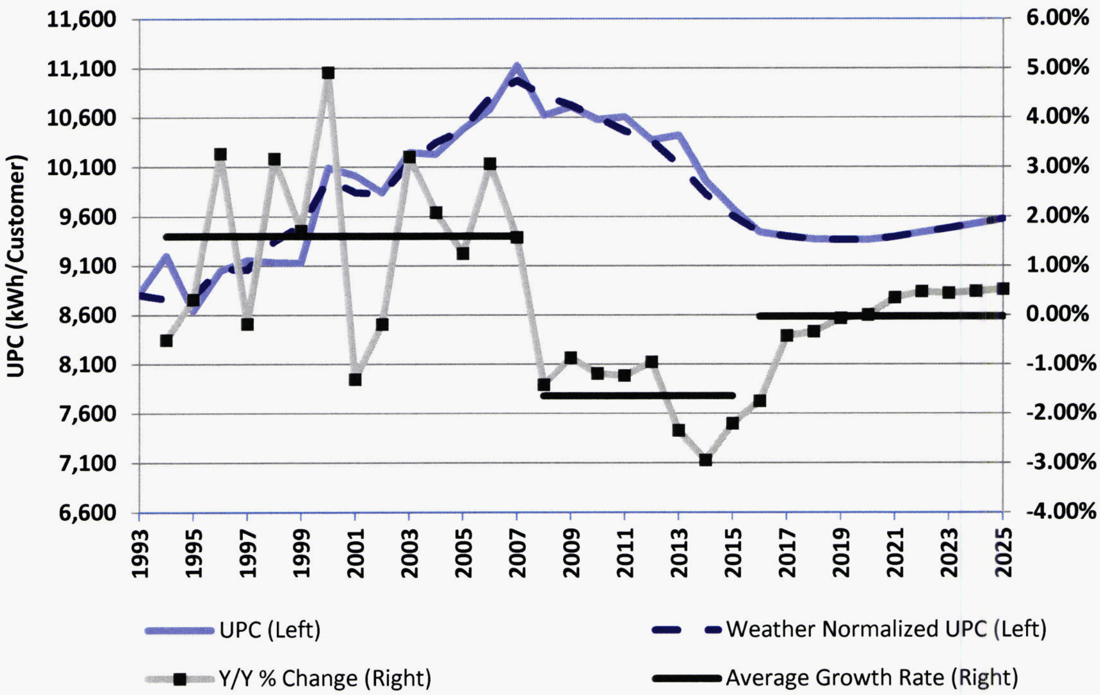
Chart 7 - Residential UPC



Other models might theoretically produce incremental gains in forecast accuracy. However, all of these models are far more complex than an ARIMAX model. The next most obvious choice would be the use of an Artificial Neural Network (ANN) model. ANN models are incredibly powerful tools of prediction but they come at a very high cost. They require extensive training datasets and often do not provide meaningful insight in how forecast drivers change results. Even 20 plus years of monthly history would provide a very small data set to fit an ANN model. An extensive training dataset is needed to support ANN's use multiple input variables which filter through sets of "neurons" to generate outputs and to properly solve the coefficients at each step. With monthly data, this would almost certainly result in over-fitting; therefore, in practice it would perform poorly as a forecast tool. This type of model is best fit to datasets that include hundreds of thousands of examples to learn, such as 20 years of hourly data. Additionally, because many of these neurons are hidden, it is difficult to truly understand how temperature is affecting energy consumption making weather normalization an impossible task.

Currently, the Company is expecting UPC to remain relatively flat for the foreseeable future. This is in stark contrast to the past, when UPC grew steadily for many years. The Company finds this forecast credible as emerging economic growth is expected to be accompanied by increasing use of EE and DG, which reduce UPC. Chart 8 below illustrates historical and forecasted UPC. The light blue line shows nominal UPC, while the dark blue dashed line shows weather-normalized UPC. Notice that the dark blue dashed line changes consistently year over year, suggesting that the volatile weather component has actually been removed. This does not occur when using degree days, as the weather normalized line remains highly volatile. The grey, dotted line shows the Y/Y% change in UPC and the black lines show the average growth for various periods.

Chart 8 - Residential Annual UPC



The same process that is explained above for the residential UPC forecast is then repeated for the commercial UPC forecast. Once these UPC forecasts have been obtained, we are now able to obtain the residential and commercial sales forecasts. The residential sales forecast is produced by multiplying the monthly residential customer forecast by the monthly residential UPC forecast. Likewise, the commercial sales forecast is obtained by multiplying the monthly commercial customer forecast by the monthly commercial UPC forecast. Up to this point it has been discussed how TEP forecasts residential and commercial energy use. It is now time to look at how TEP forecasts large industrial and mining energy use.

Large Industrial and Mining Customer Sales Forecasts

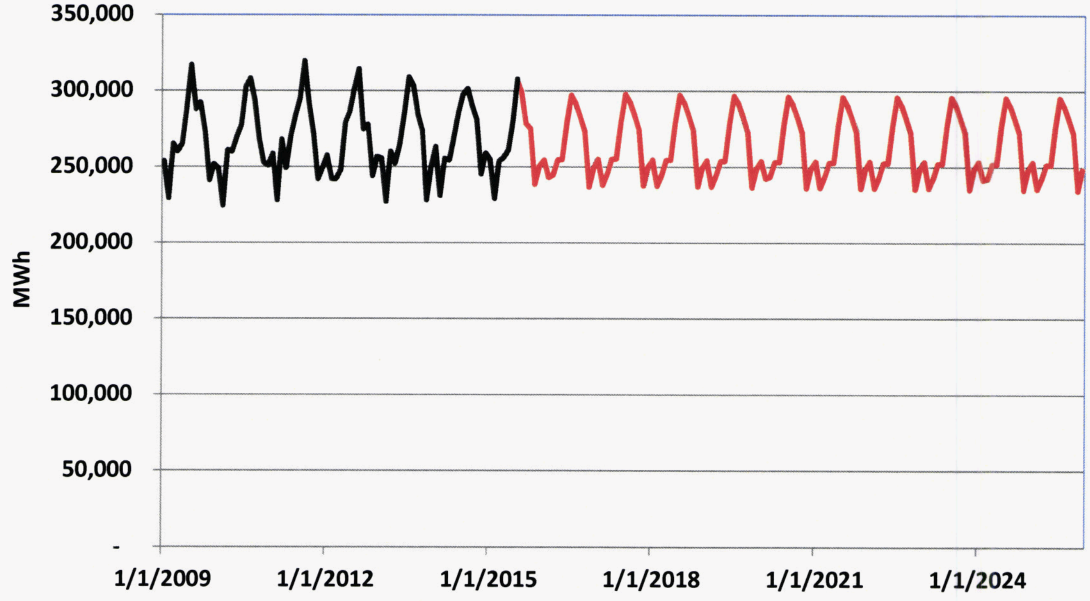
For purposes of forecasting and internal reporting, the industrial class is broken into small and large subsets. The large industrial class is a subset of customers who have maximum peak demands over 3,000 kW. The mining class is a part of this subset because they all have maximum peak demands over 3,000 kW. Mining is separated only for reporting reasons, but they are modeled the same way as the other large industrial customers and also share the same rates. There are currently 18 customers in these two categories but this small customer base accounts for approximately 25% of TEP's annual retail sales. The small industrial class of customers are those customers that have maximum demand over 200 kW but typically less than 3,000 kW. There are almost 600 customers in this class and they comprise approximately 13% of annual sales.

The customer forecast is fairly stable for the large industrial and mining customers. There is very rarely any change in the number of customers. When there is an expected addition/loss of a customer, this information is passed on to the forecasting group by the Account Managers who work with the large electric customers. When such information is received, the customer forecast is updated to include a new customer starting in the appropriate month, or to remove a current customer starting in the appropriate month.

For the large industrial and mining classes, energy and peak demand forecasts are produced for each individual customer on a case by case basis. The sales and peak demand forecast are based on historical information. For a customer who is operating under a business as usual manner, the forecast will take the average of their previous kW and kWh and roll this forward into subsequent years on a monthly basis. This method inherently predicts the customer's typical seasonal changes to operations if they exist. When necessary, these forecasts are adjusted to reflect changes in customer behavior, e.g. a planned outage or the switch to a more energy efficient process, as that information is communicated from the customer to the Account Managers, and then from the Account Mangers to the forecasting group. When a new customer is added, the forecasting group, using information from the Account Managers, attempt to model the customer as accurately as possible. As historical information becomes available for the customer, the forecast is able to transition into the standard forecast method for this class.

Chart 9 shows large industrial and mining sales. The black portion of the line is historical and the red portion of the line is forecast. Note that the forecast shows no expected customer energy sales growth or decline. Given current weakness in industrial metal prices, Freeport McMoRan is expected to curtail their operations in TEP's service territory. *This reduction is <u>not</u> reflected in the Chart 9* due to current uncertainty regarding the customer's operating plans.

Chart 9 - TEP Large Industrial and Mining Sales



Small Industrial Customer Sales Forecasts

For the small industrial classes, there are too many customers to track on an individual basis. The small industrial customer count forecast is produced by taking the previous month's customers and applying the forecasted annual residential and commercial growth rate. The UPC forecast looks at the previous, rolling actual year and projects that year going forward. The monthly sales forecast is arrived at by multiplying the customer count and the UPC number for the month together. Effectively, applying the class average customer usage to the expected new customers. The small industrial class is one of the most challenging classes to forecast accurately. It is too large to track on an individual basis but too small to be forecast well statistically. The ability of a single customer to sway the class results make this segment highly volatile. Due to this challenge, the forecast is constantly scrutinized and simple methods like those discussed are used to forecast this class in an attempt to limit forecast error.

Overview of TEP 2016 Retail Sales Forecasts

All miscellaneous consumption that falls outside the major rate categories (such as municipal street lighting) are forecasted at last year's value for the month. This is because regression analysis performs poorly for this purpose and the time requirements of ARIMA forecasting make it cost prohibitive for this small class. After all the monthly energy forecasts are produced, they are aggregated to produce a monthly energy forecast for the Company.

The historical annual average growth rate between 1993 and 2008 was 2.5%. The growth rate for the period between 2014 and 2030 is expected to be 0.7%. Chart 10 contains the growth rate from 1993 to 2030. The black portion represents the historical growth rate and the red represents the forecasted growth rate.

Chart 10 - Weather Normalized Y/Y Change in Total TEP Retail Sales

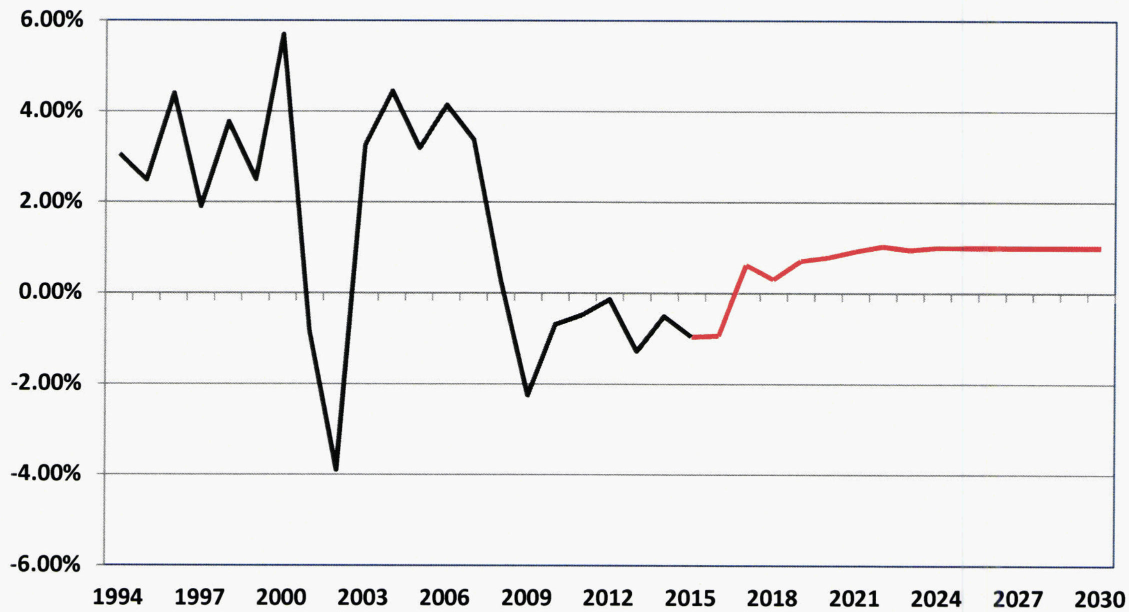


Chart 11 represents total TEP retails sales. The black portion of the line represents historical retail sales and the red portion represents forecasted retail sales.

Chart 11 - Weather Normalized Total TEP Retail Sales

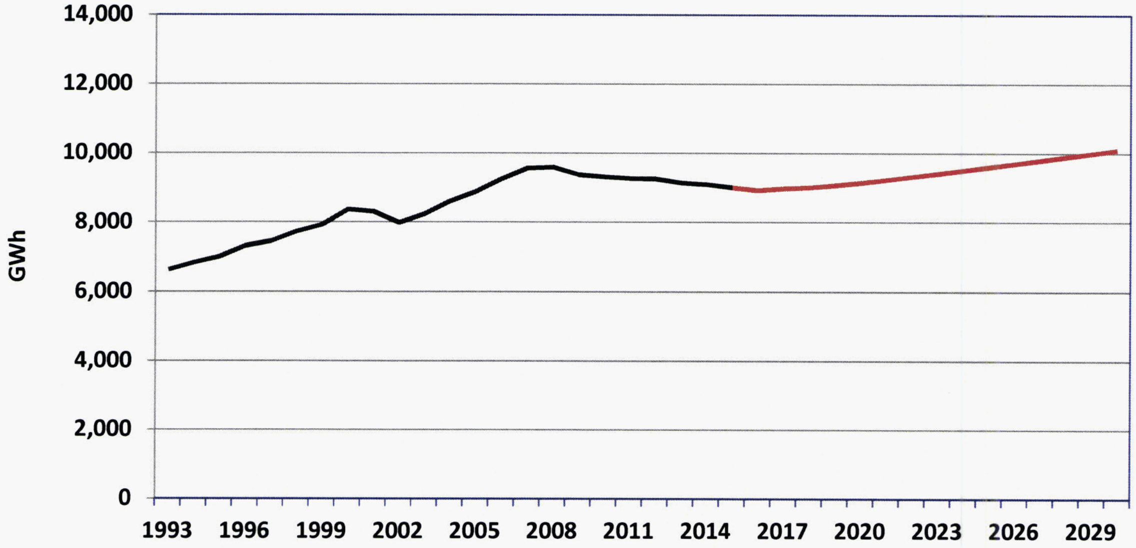


Chart 12 shows TEP's estimated 2016 retail sales by rate class. The residential and commercial rate classes are expected to account for approximately 64 percent of 2016 retail sales, while the industrial and mining rate classes are expected to account for approximately 35 percent of 2016 retail sales. Customer classes such as municipal street lighting, etc., account for the remaining sales.

Chart 12 - Estimated 2016 Retail Sales % by Class

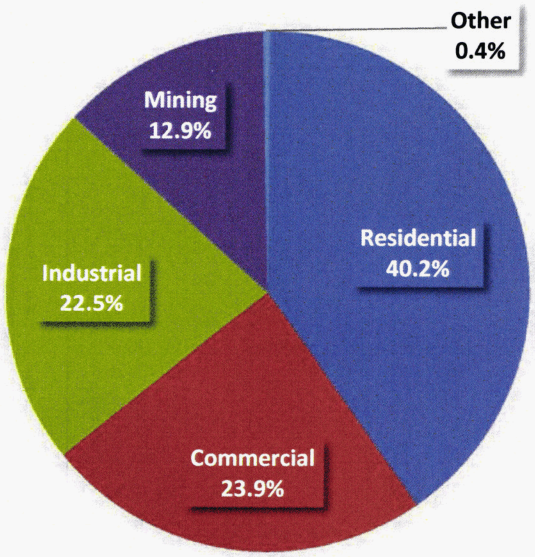
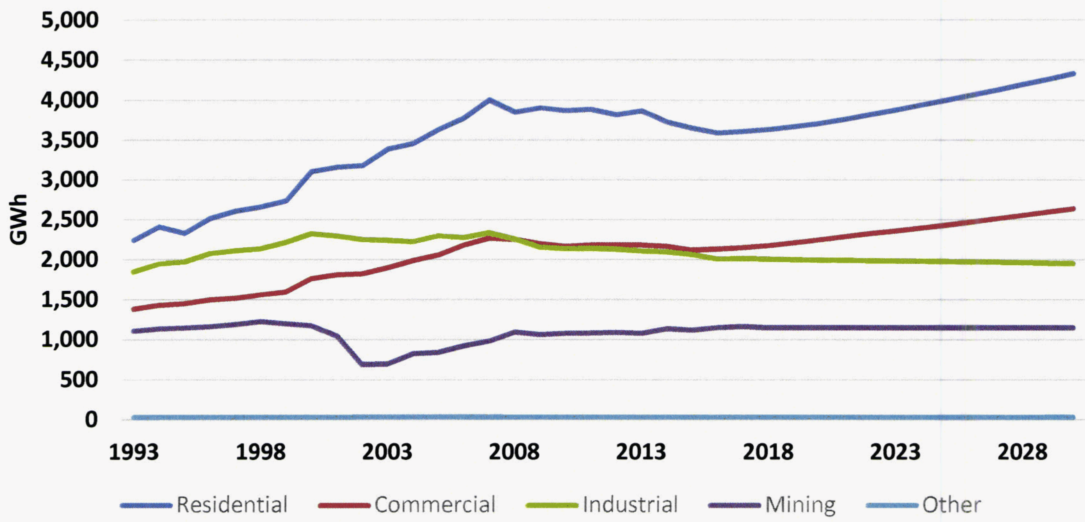


Chart 13 illustrates the historical and forecasted energy sales trends for each major rate class. Chart 13 does not reflect any changes to Freeport McMoRan's operation which could significantly affect the mining sales.

Chart 13 - Retail Energy Sales by Rate Class

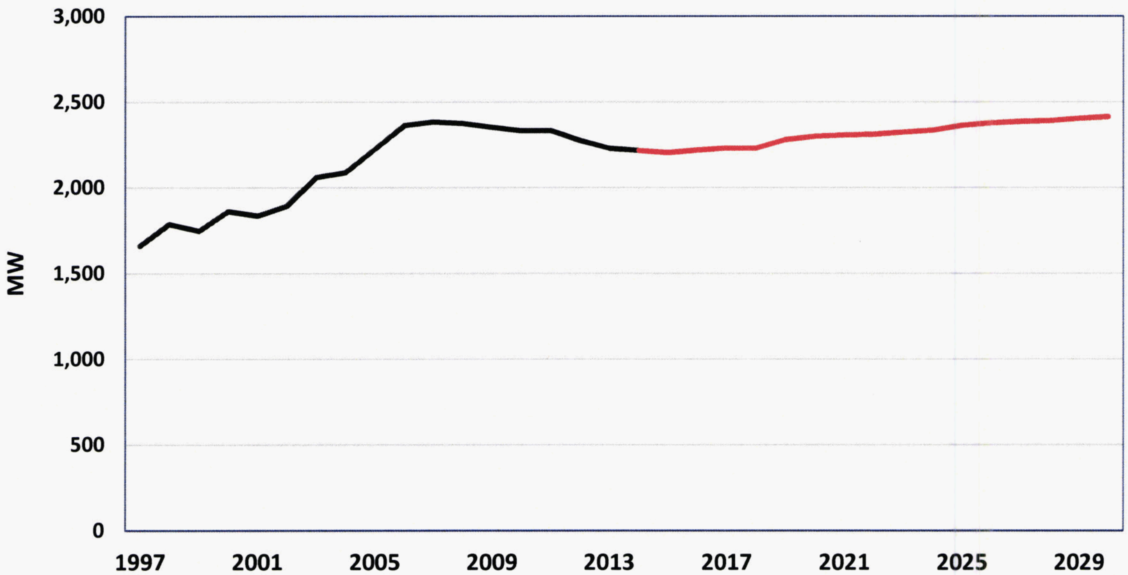


As this chart indicates, the Company is not forecasting a return to historical growth rates due to diminished customer growth and the increasing use of EE and DG.

TEP's Peak Forecast

TEP's peak forecast methodology is essentially the one outlined by Tao Hong in his book, "Electric Load Forecasting: Fundamentals and Best Practices." The process begins by collecting historical hourly load. The Company uses data dating back to Jan 1, 2002, as this is the longest period for which this data was available. Hourly weather data is collected as outlined in the weather section. A series of calendar variables are used to partition the weather data into various buckets using a General Linear Model. The calendar variables include, hour ending, day of the week, type of holiday, and month. Finally the historical and forecast monthly sales are fed into the model by rate class as the trending variable for the model. Instead of using one single weather forecast, an ensemble of historical years is used to generate an ensemble of forecast outputs as suggested by Tao. The mean of the forecast outputs are then used as the most likely value for the forecast peak in the coming years. Using this ensemble method helps estimate the likelihood of extreme weather events and the resulting impact on TEP's peak load. The graph below shows the mean of the ensemble forecasts actualized through 2014.

Chart 14 - Peak Retail One Hour Max Consumption



The retail peak load is not expected to grow significantly during the forecast period compared to historical growth rates. This is consistent with the sales forecast and is largely caused by energy efficiency and to a lesser extent, due to its low peak coincidence factor, distributed generation.

After re-examining the Company's load forecasting techniques, the Company feels it is currently utilizing the best techniques available given current resources and data. The retail sales and retail peak forecasts reflect weaker than pre-recession growth that is in agreement with the current economic conditions of Pima County, as well as the increased adoption of EE and DG.

Conclusions

Decision # 75269 within Docket NO. E-00000V-15-0094 in effect, deferred the major requirements and ultimately the final Integrated Resource Plan (IRP) until April 3, 2017. This was a prudent decision given that at that time, the Environmental Protection Agency's Clean Power Plan was pending. The contents of this report addresses the techniques and methodology used to derive TEP's load forecast, it does not represent the actual load forecast that will be submitted in the preliminary IRP that is due on March 1, 2016. TEP's Load Forecasting group will provide subsequent load forecasts updates and scenario analysis based on the Companies most up to date assumptions for both the March 2016 and April 2017 IRP filings.

Appendix

Data Sources Used in the Forecast Process

As outlined above, the Reference Case plan forecast requires a broad range of inputs (demographic, economic, weather, etc.) For internal forecasting processes, TEP utilizes a number of sources for these data:

- IHS Global Insight
- The University of Arizona Forecasting Project
- National Oceanic and Atmospheric Administration (NOAA)
- Weather Underground Forecasting Service

Risks to Reference Case Plan Forecast and Risk Modeling

As always, there is uncertainty with regard to projected load growth. While an exhaustive list would be impossible to produce, some of the key risks to the current forecast include:

- Strength and timing of the economic recovery
- Possible structural changes to customer behavior, including potential changes in post-recession consumption patterns
- Volatility in industrial metal prices and associated shifts in electric use by mining customers
- Efficacy of energy efficiency programs (i.e. what percentage of load growth can be offset by demand side management?)
- Technological innovations (e.g. plug in hybrid vehicle penetration)
- Volatility in demographic assumptions (e.g. much higher or lower population growth than currently assumed)
- Disconnection of sales from historically significant measures of the economy

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