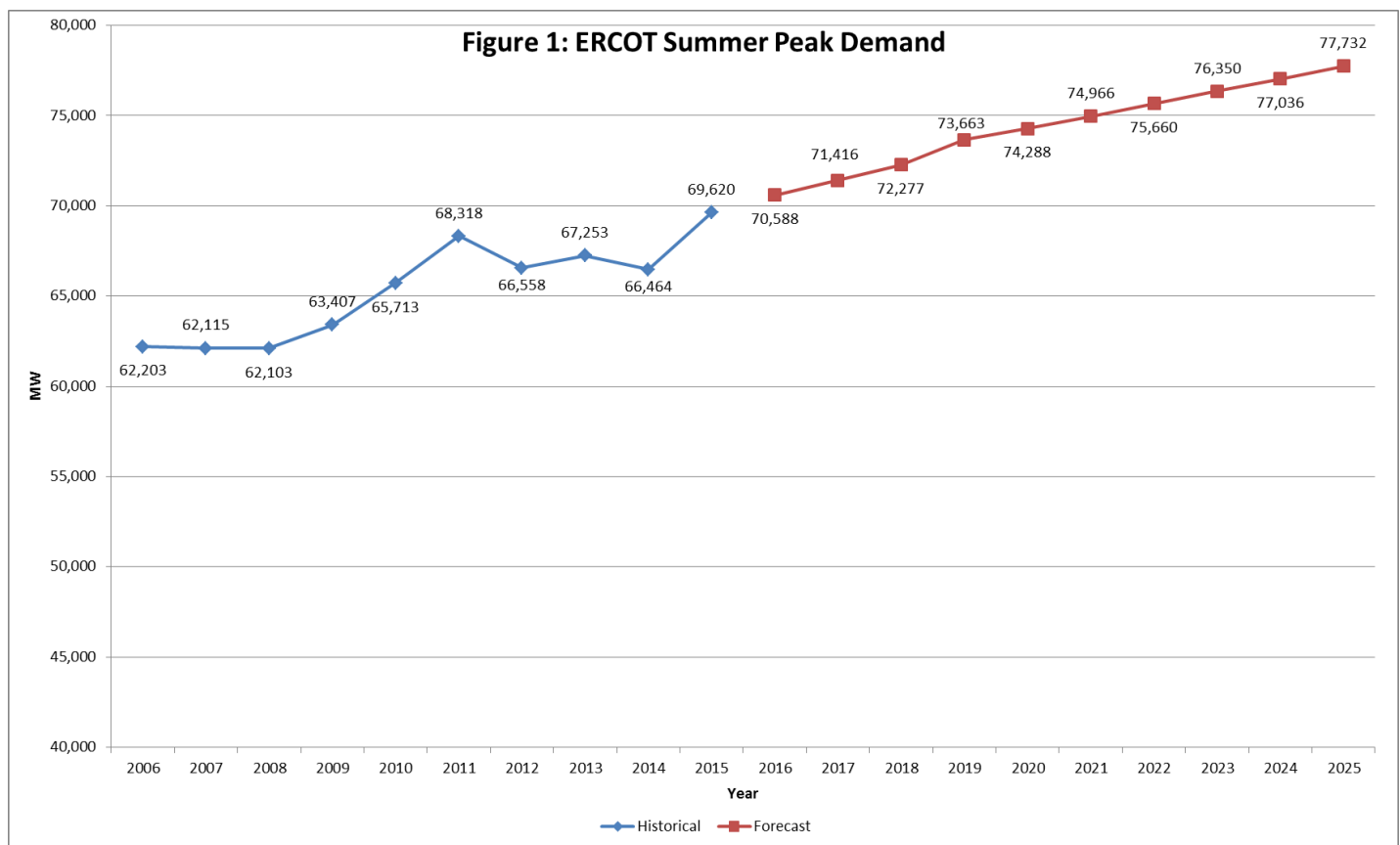




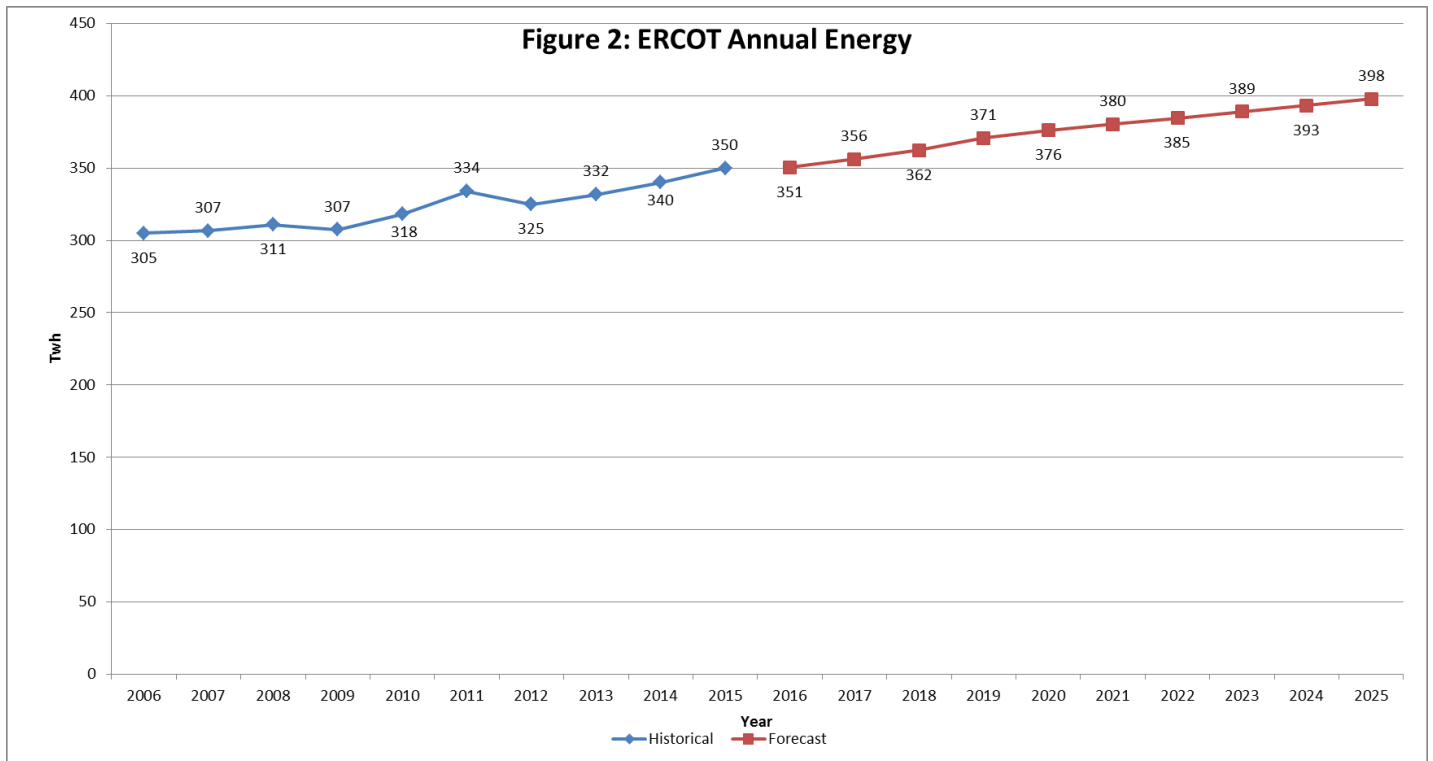
2016 ERCOT System Planning
Long-Term Hourly Peak Demand and Energy Forecast
December 31, 2015

Executive Summary

The 2016 Long-Term Demand and Energy Forecast (LTDEF) for the ERCOT region is presented in this report, and includes the methodology, assumptions, and data used to in create the forecast. This forecast is based on a set of econometric models describing the hourly load in the region as a function of the number of premises in various customer classes (residential, business, and industrial), weather variables (e.g., heating and cooling degree days, temperature, cloud cover, wind speed) and calendar variables (day of week, holiday). Premise forecasts are based on a set of econometric autoregressive models (AR1) and are based on certain economic (e.g., nonfarm payroll employment, housing stock, population) data. A county level forecast of economic and demographic data was obtained from Moody's. Thirteen years of historical weather were provided by Schneider Electric/DTN for 20 weather stations.



As shown in Figure 1, the 2016 LTDEF depicts system peak demand increasing at an average annual growth rate (AAGR) of approximately 1.1% from 2016-2025. Historically, summer peak demand has grown at AAGR of 1.3% from the 2006-2015.



As shown in Figure 2, historical annual energy for the calendar years 2006-2015 grew at an AAGR of 1.5%. The forecasted AAGR for energy for 2016-2025 is 1.4%.

Introduction

This report gives a high level overview of the 2016 LTDEF. The forecast methodology is described, highlighting its major conceptual and statistical underpinnings. The 2016 forecast results are presented in a manner comparing them to the 2014 LTDEF. This allows for a direct comparison of results and also facilitates an explanation for the changes. Finally, an examination is presented describing the six major sources of forecast uncertainty: weather, economics, energy efficiency, demand response, onsite renewable energy technologies, and electric vehicles.

2016 Modeling Framework

ERCOT consists of eight distinct weather zones (Figure 3). Weather zones¹ represent a geographic region in which climatological characteristics are similar for all areas in the region. Each weather zone has either two or three weather stations that provide data for the assigned weather zone. In order to reflect the unique weather and load characteristics of each zone, separate load forecasting models were developed for each of the weather zones.

The 2016 LTDEF was produced with a set of linear regression models that combine weather, premise data, and calendar variables to capture and project the long-term trends extracted from the historical load data. Premise forecasts were also developed.

All of the model descriptions included in this document should be understood as referring to weather zones. The ERCOT forecast is calculated as a sum of all of the weather zone forecasts.

Premise Forecast Models

The key driver in the forecasted growth of demand and energy is the number of premises. County-level economic data was used to capture and project the long-term trends extracted from the historical premise data. Counties are mapped into a unique weather zone (Figure 3).

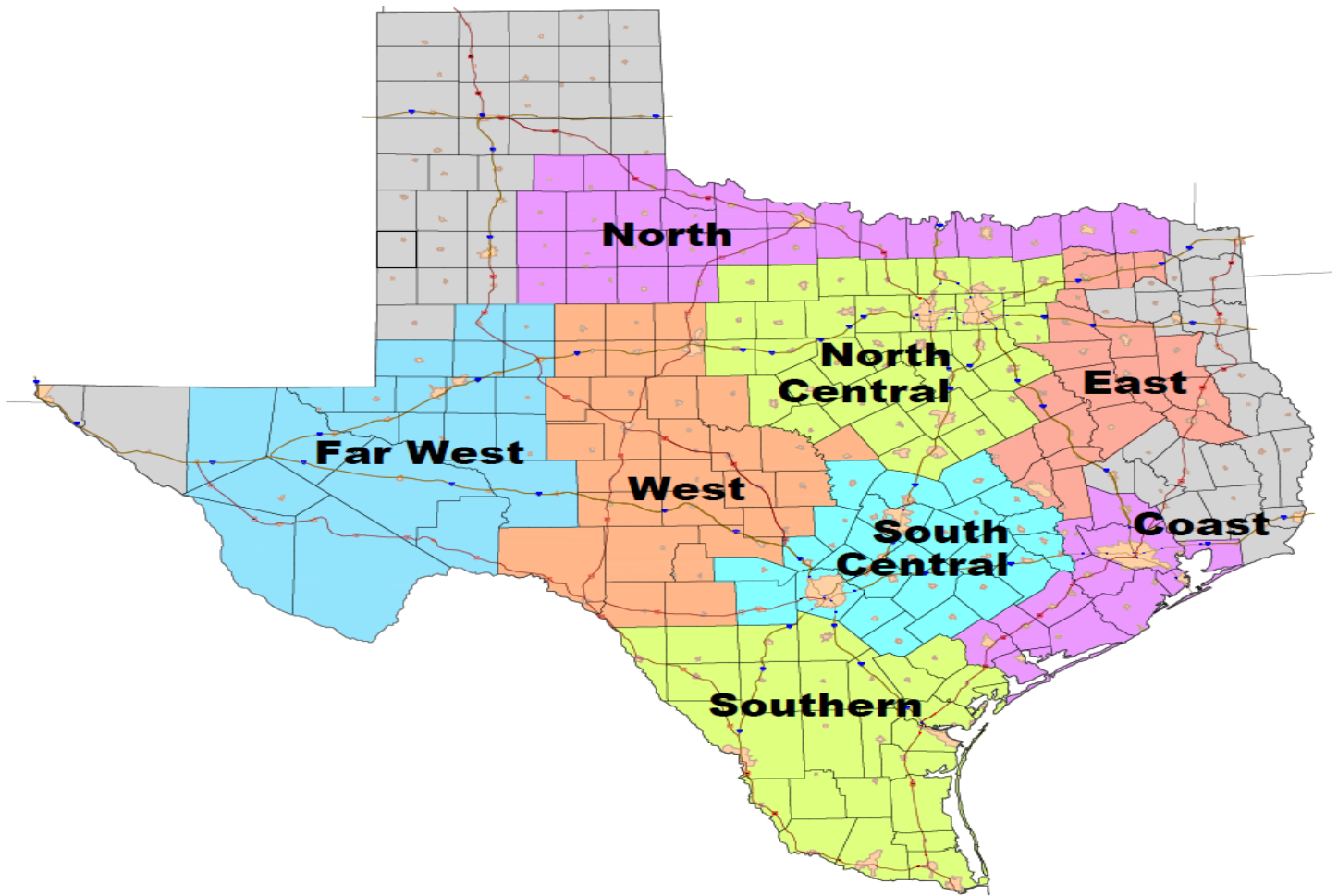
Premises were separated into three different customer classes for modeling purposes:

1. Residential (including lighting),
2. Business (small commercial), and
3. Industrial (premises which are required to have an IDR meter²).

¹ See *ERCOT Nodal Protocols*, Section 2.

² See *ERCOT Nodal Protocols*, Section 18.6.1.

Figure 3: ERCOT Weather Zones



All premise models were developed using historical data from January-2009 through August-2015. An autoregressive model (AR1) was used for all premise models.

Residential Premise Forecast

Residential premise counts were modeled by estimating a relationship for each of the eight ERCOT weather zones between the dependent variable (residential premises) and the following:

1. Housing Stock and
2. Population.

Business Premise Forecast

Business premise counts were modeled by estimating a relationship for each of the eight ERCOT weather zones between the dependent variable (business premises) and the following:

1. Housing Stock,
2. Population, and
3. Non-Farm employment.

Industrial Premise Forecast

Industrial premise counts were modeled by estimating a relationship for each of the eight ERCOT weather zones between the dependent variable (industrial premises), and the following:

1. Housing Stock,
2. Population, and
3. Non-Farm employment.

Premise Model Issues

During the review process for the previously mentioned premise models, two problems were identified.

The first problem, which was noted in the Far West and West weather zones, was that during the historical timeframe used to create the models, there was a significant increase in the number of premises in the middle of 2014. This increase was due to an entity opting in to ERCOT's competitive market and due to an expansion of ERCOT's service territory.

The second problem, which was noticed in the North weather zone, was that premise counts were relatively flat, which made it difficult to be modeled using economic data.

As a result of these two problems, premise forecast models were not able to be created for the Far West, West, and North weather zones.

The second problem was for the North weather zone, premise counts were relatively flat which made it difficult to be modeled using economic data.

As a result of these two problems, premise forecast models were not able to be created for the Far West, West, and North weather zones. These three weather zones used economic variables as the key driver in the forecasted growth of demand and energy.

Hourly Energy Models

The long-term trend in hourly energy was modeled by estimating a relationship for each of the eight ERCOT weather zones between the dependent variable, hourly energy and the following:

1. Month,
2. Day Type (day of week, holiday)
3. Weather Variables,
 - a. Cooling Degree Hours³(base 65),
 - b. Heating Degree Hours³ (base 65),
 - c. Lag Cooling Degree Hours³ (1,2, 3, 24, 48, or 72 previous hours),
 - d. Lag Heating Degree Hours³ (1,2, 3, 24, 48, or 72 previous hours),
 - e. Lag Cooling Degree Days⁴ (1,2, or 3 previous days),

³ All Degree Hour variables are calculated versus 65 deg F.

- f. Lag Heating Degree Days⁴ (1,2, or 3 previous days),
 - g. Lag Cooling Degree Days⁴ from the previous day, and
 - h. Temperature,
 - i. Lag Temperature (1,2, 3, 24, 48, or 72 previous hours),
 - j. Temperature Squared,
 - k. Lag Temperature Squared,
 - l. Cloud Cover, and
 - m. Wind Speed.
4. Interactions
- a. Hour and Day of Week,
 - b. Hour and Temperature,
 - c. Hour and Cooling Degree Hours³,
 - d. Hour and Heating Degree Hours³,
 - e. Premise and Temperature,
 - f. Premise and Cooling Degree Hours³, and
 - g. Premise and Heating Degree Hours³.
5. Number of premises⁵
6. Non-Farm Employment/Housing Stock/Population⁶

All of the variables listed above are used to identify the best candidates for inclusion in the forecast model and to provide details on the types of variables that were evaluated in the creation of the model. Not every variable listed above was included in each model. Unique models were created for each weather zone to account for the different load characteristics for each area.

Model Building Process

Historical data (1/1/2009 – 8/19/2015) was divided into three different data sets:

- 1. Model Building,
- 2. Model Validation, and
- 3. Model Testing.

The model building data set was comprised of data from 1/1/2009 through 12/31/2013. This data was used to create various forecast models. The model building process was an iterative process that was conducted multiple times.

After model building was complete, the validation data set was used to determine the accuracy of the various forecast models. The validation data set consisted of data for calendar year 2014. Each model's performance was calculated based on the forecasting performance for data contained in the validation data set. Based on the results of the forecast for the validation data set, the model may be updated.

⁴ All Degree Day variables are calculated versus 65 deg F.

⁵ Used in Coast, East, North Central, South, and South Central weather zones.

⁶ Used in Far West, North, and West weather zones.

After model validation was complete, the model testing data set was used to determine the accuracy of the various forecast models. The model testing data set contained data from 1/1/2015 through 8/19/2015. The model testing data was not included in model building or model validation. Model testing data was used to determine the accuracy of the model after model validation had been completed. The most accurate models were selected based on their performance on the model testing data set.

The last step in the model building process was to update the selected model for each weather zone by using data from 1/1/2010 through 8/19/2015 in order to update the variable coefficients. Typically only five years of historical data are used to develop models. Using only five years of historical data enables the model to be created based on data that better reflects the current appliance stock, energy efficiency measures, price responsive load impacts, etc.

At the conclusion of the model building process, twelve models (one for each month) were developed for each weather zone.

Forecast Scenarios

Actual weather data from calendar years 2002 through 2014 was used as input for each weather zone's final forecast models. The process began by using actual weather data from 2002 as weather input for all forecasted years (2016-2025). The actual weather data from all days in 2002 was copied into the same day and hour for each of the forecasted years (2016 – 2025). For example, the actual weather data for 1/1/2002 was copied into 1/1/2016, 1/1/2017, etc. ..., and 1/1/2025. Using 2002's weather as input into each weather zone's forecast model results in what is referred to as the 2002 weather load forecast scenario. The 2002 weather load forecast scenario is a forecast that assumes 2002's weather would occur for each forecasted calendar year (2016-2025). This process was completed for each of the historical weather years (2002-2014) and resulted in thirteen weather load forecast scenarios for 2016-2025.

The following notation can be used to denote weather load forecast scenarios:

$$HF_{(z,x,y)}$$

Where:

HF = hourly energy forecast,

x = historical weather date and time,

y = forecast date and time, and

z = weather zone (Coast, East, Far West, North, North Central, South, South Central, and West).

For example, $HF_{(West, 7/24/2008\ 1700, 7/24/2019\ 1700)}$, would denote the forecast for 7/24/2019 at 5:00 pm, which was based on weather from 7/24/2008 at 5:00 pm, for the West weather zone.

Normal Weather (50/50) Forecast

The process for creating the normal weather (50/50) forecast begins by taking each of the 13 hourly forecast scenarios for each weather zone. Each of these 13 hourly forecast scenarios, covering calendar years 2016-2025

are separated into individual calendar year forecasts. Each individual calendar year forecast was ordered from the highest value to the lowest value. Then, for each ordered value, the average was calculated. For example, to determine the normal weather (50/50) forecasted peak value for calendar year 2017, take the highest forecasted value for each of the 13 historical weather years for calendar year 2017 and average them. To determine the second highest peak value for calendar year 2017, take the second highest forecasted value for each of the 13 historical weather years for calendar year 2017 and average them. Repeat this process for all hours in calendar year 2017. This process is commonly referred to as the Rank and Average methodology. At the completion of this step, the normal weather (50/50) forecast was completed for each ordered value.

Example:

Table 1 shows the top five forecasted hourly peaks for the Coast weather zone for 2016 based on historical weather years of 2002-2014.

Table 1: ERCOT Weather Zones

Rank	Historical Weather Year													50/50 Forecast
	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	
8760	18,627	19,902	19,409	19,864	19,237	19,857	19,493	19,954	19,442	20,973	20,432	19,547	19,134	19,682
8759	18,583	19,711	19,164	19,703	19,021	19,770	19,437	19,943	19,440	20,947	20,409	19,378	19,059	19,582
8758	18,443	19,681	19,133	19,637	18,930	19,745	19,188	19,689	19,439	20,704	20,298	19,312	18,990	19,476
8757	18,439	19,506	18,981	19,547	18,874	19,691	19,177	19,615	19,413	20,634	20,235	19,203	18,960	19,406
8756	18,419	19,411	18,880	19,413	18,693	19,603	19,070	19,572	19,316	20,436	20,161	19,141	18,910	19,310

The 50/50 Forecast column is the average of the thirteen forecasts for each row. At the completion of this step, the 50/50 forecast has been created and is sorted from the largest value to the smallest value. Notice though, that there is no assigned month, day, or hour for the 50/50 weather zone forecast yet.

Forecast Calendar

The last step is to take the ordered values from the normal weather (50/50) forecast for each weather zone for each calendar year and associate them into a representative calendar. This process involves assigning each ranked value of the 50/50 forecast to the month, day, and hour where the historical ranked value occurred. 2003 was selected as the representative calendar to use. This calendar was chosen seeing that it has a conservative amount of load diversity between the weather zones at the time of ERCOT's summer peak. 2003 has been used as the representative calendar for the last few ERCOT forecasts.

Example:

From Table 1, the 50/50 peak forecast for Coast for 2016 is 19,682 MW. Using the 2003 historical calendar, we know that the peak demand value for Coast occurred on 8/7/2003 at 5:00 pm. The forecasted peak value (19,682 MW) is assigned to 8/7/2016 at 5:00 pm. The second highest forecasted peak value is 19,582 MW. Using the 2003 historical calendar, we know that the second highest peak demand value for Coast occurred on 8/7/2003 at 4:00 pm. The second highest forecasted peak value (19,582 MW) is assigned to 8/7/2016 at 4:00 pm. All of the remaining forecasted values are assigned in a similar manner.

Forecast Adjustments

A large liquefied natural gas (LNG) facility started construction in Freeport in November 2014⁷. This facility expects to begin operations of the first liquefaction train in September 2018. The second liquefaction train has an in-service date of February 2019 followed by the third liquefaction train with an in-service date of August 2019. The Freeport LNG facility is located in the Coast weather zone. This facility will have an estimated load of 655 MW once all three trains are in-service. This load will be served by ERCOT (i.e., this load will not be self-served).



To account for this large load addition, the Coast forecast was increased by the estimated load for each train (approx. 218 MW) based on the published in-service dates⁷. The assumptions regarding this load are as follows.

- 1) The load will be served by ERCOT (i.e., this load will not be self-served).
- 2) The load will not be price responsive (i.e., this load will not actively be reduced to avoid transmission charges as part of ERCOT's four Coincident Peak calculations, high price intervals, etc.).

Changes Made Since 2014 LTDEF

1. Daily Energy Model was not used

In the 2014 LTDEF, a daily energy model was used to forecast energy for each day. Historical hourly allocation factors were applied to the daily energy model to create the hourly energy forecasts.

Rationale for change:

During model development, a single hourly model had lower forecast errors when compared to the previous approach.

⁷ http://www.freeportlng.com/Project_Status.asp

2. Residential Premise Models are no longer based on indexed values

In the 2014 LTDEF, historical residential premise values, housing stock values, and population values were indexed with the January 2010 value assigned an indexed value of 1.

Rationale for change:

Indexing did not result in an improvement in forecasting accuracy for the hourly model.

3. Business Premise Models are no longer based on indexed values

In the 2014 LTDEF, historical business premise values, housing stock values, population values, and non-farm employment values were indexed with the January 2010 value assigned an indexed value of 1.

Rationale for change:

Indexing did not result in an improvement in forecasting accuracy for the hourly model.

4. Industrial Premise Models are no longer based on a five year average premise growth rate

In the 2014 LTDEF, the industrial premise forecast was based on a five year average premise growth rate instead of an industrial premise index model. Originally, premises were required to exceed 1,000 kW for two months during the previous twelve months to be classified as IDR customers. This threshold was lowered to 700 kW in 2006. The lower threshold resulted in a significant increase in the number of industrial premises. This change in the underlying historical premise counts caused difficulty in creating a statistical model. As additional data is gathered over the next few years, ERCOT will revisit creating an industrial premise index model.

Rationale for change:

Using historical data from 2009 onward alleviated the problem of creating an industrial premise forecast.

5. Average Use Per Premise was not included

In the 2014 LTDEF, an average use per premise forecast was created for each weather zone. The average use per premise was based on normal or typical weather for a contiguous 12-month time frame. Historical data from 2009 through 2013 was analyzed to determine a representative time period with normal weather. The time period from 8/1/2012 through 7/31/2013 was selected to represent typical weather.

Rationale for change:

Average Use Per Premise was not a statistically significant variable in the hourly energy model.

6. Weighted Premise Index was not included

In the 2014 LTDEF, a weighted premise index was calculated for each weather zone.

Rationale for change:

Better model performance was achieved by using a single individual premise forecast instead of using weighted premises in the hourly model.

Load Forecast Comparison

Figure 4 presents the ERCOT summer peak demand forecasts for 2016-2024 from the 2014 LTDEF and the 2016 LTDEF.

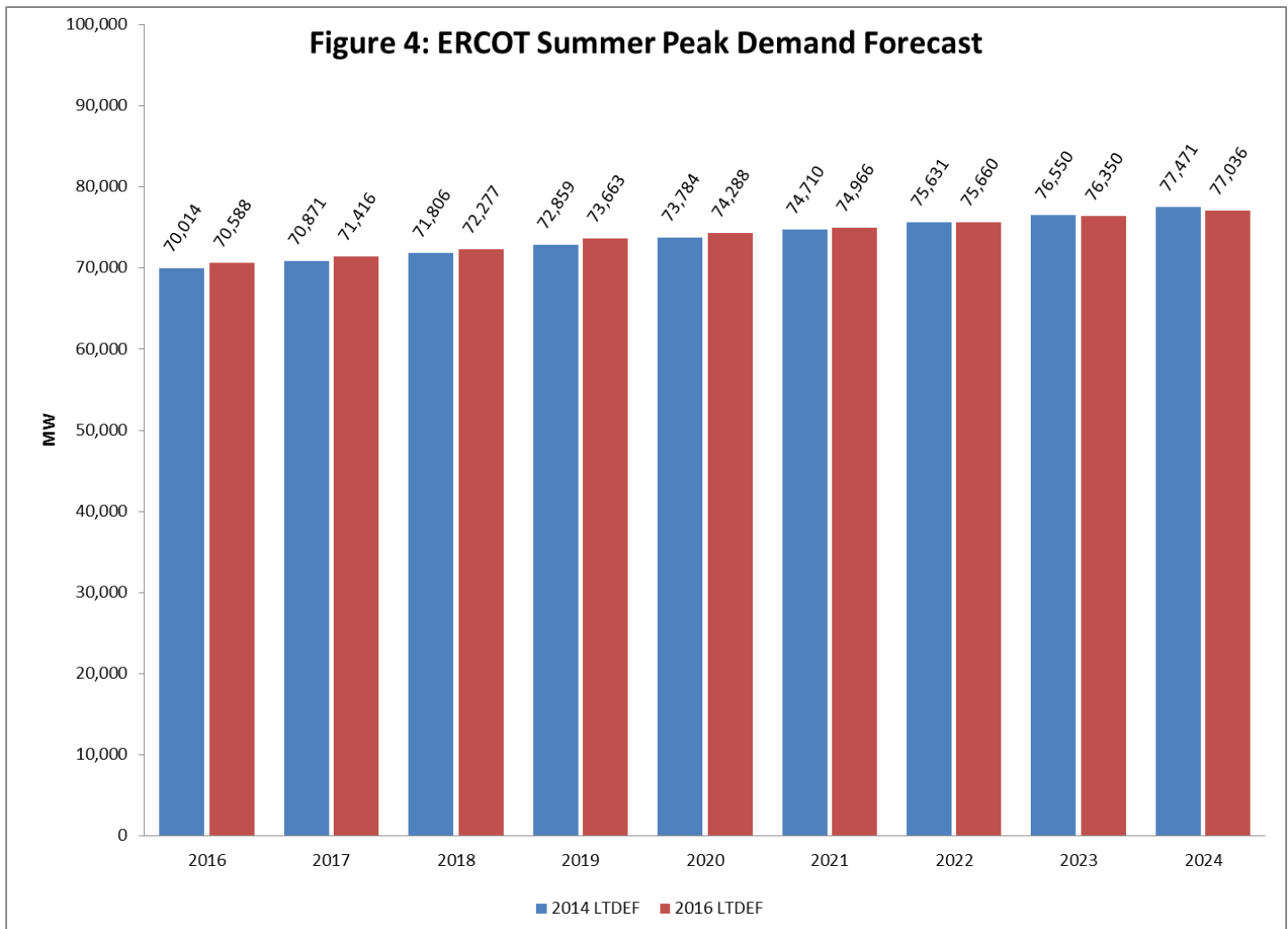
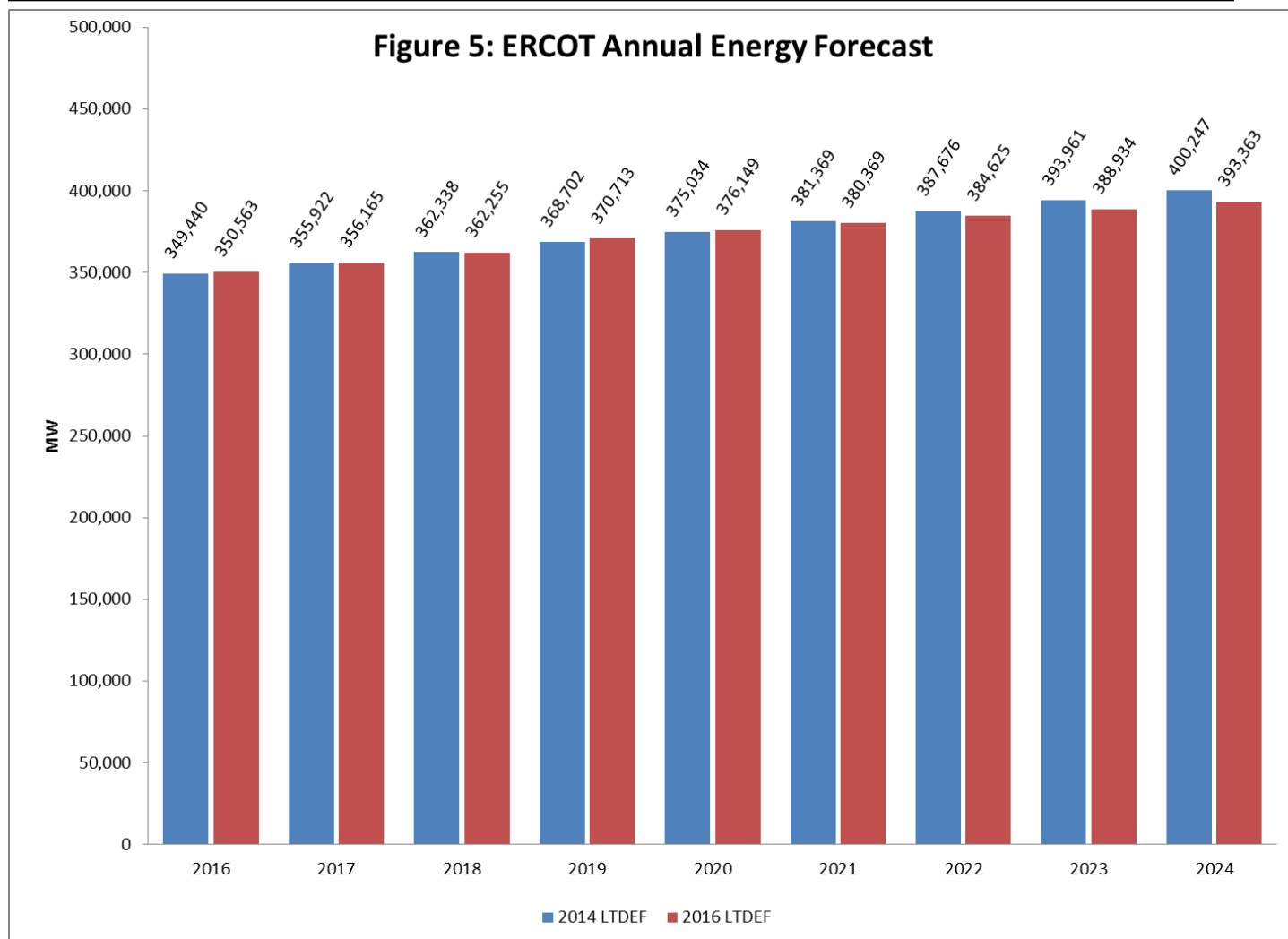


Figure 5 presents the ERCOT annual energy forecast for 2016-2024 from the 2014 LTDEF and the 2016 LTDEF.



Load Forecast Uncertainty

A long-term load forecast can be influenced by a number of factors. The volatility of these factors can have a major impact on the accuracy of the forecast. This document will cover the following eight areas.

1. Weather,
2. Economics,
3. Energy Efficiency,
4. Price Responsive Loads,
5. Onsite Renewable Energy Technologies,
6. Electric Vehicles.
7. Large Industrial Loads, and
8. Change in ERCOT's Service Territory.

Weather Uncertainty

Figure 6 suggests the significant impact of weather in forecasting any specific year. This figure shows what the 2016 forecasted peak demand would be using the actual weather from each of the past thirteen years as input in the model. As shown, there is considerable variability ranging from 66,636 MW using 2004's weather to 73,342

MW using 2011's weather. This equates to approximately a 10% difference in the forecast based on historical weather volatility.

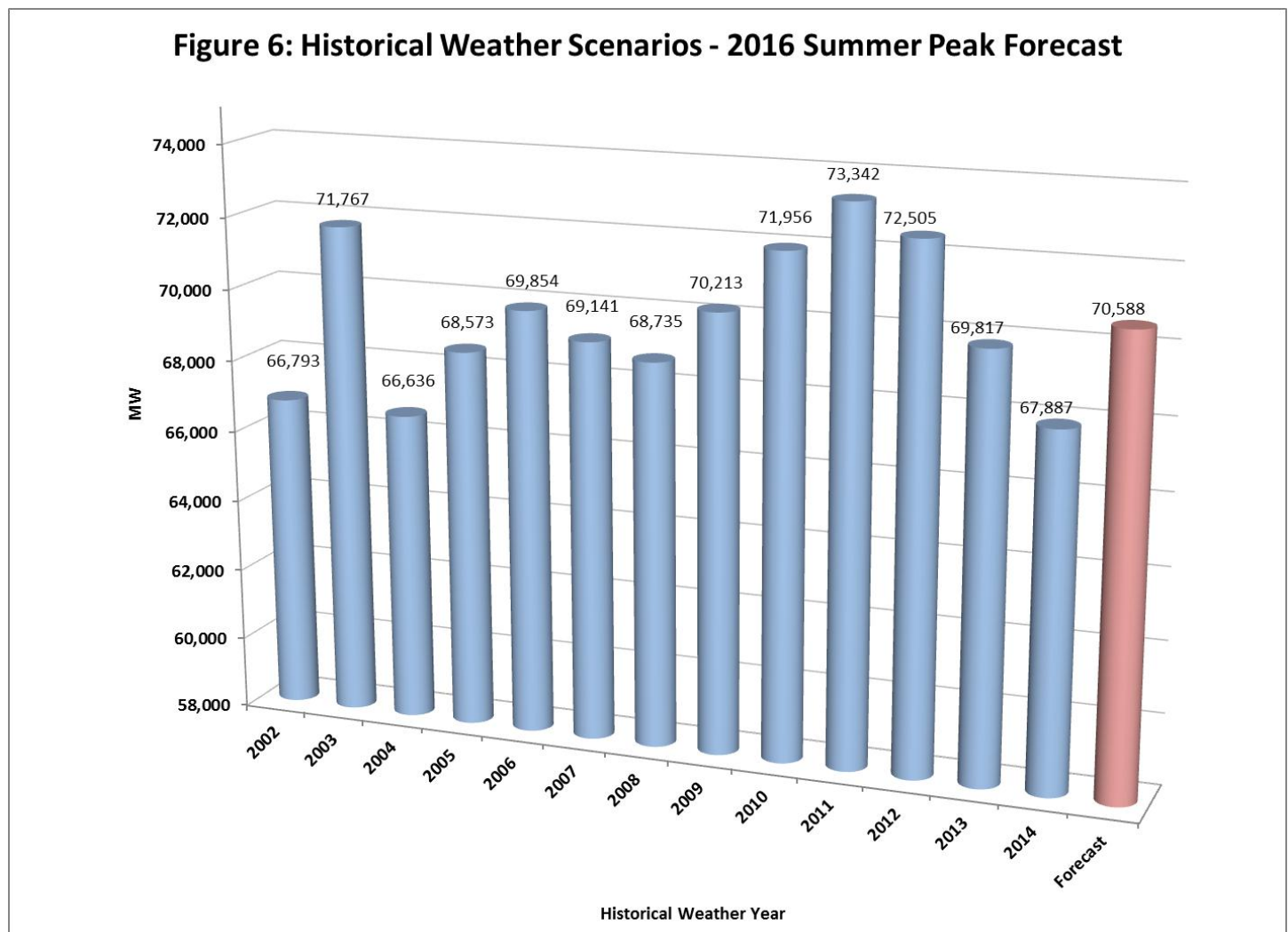
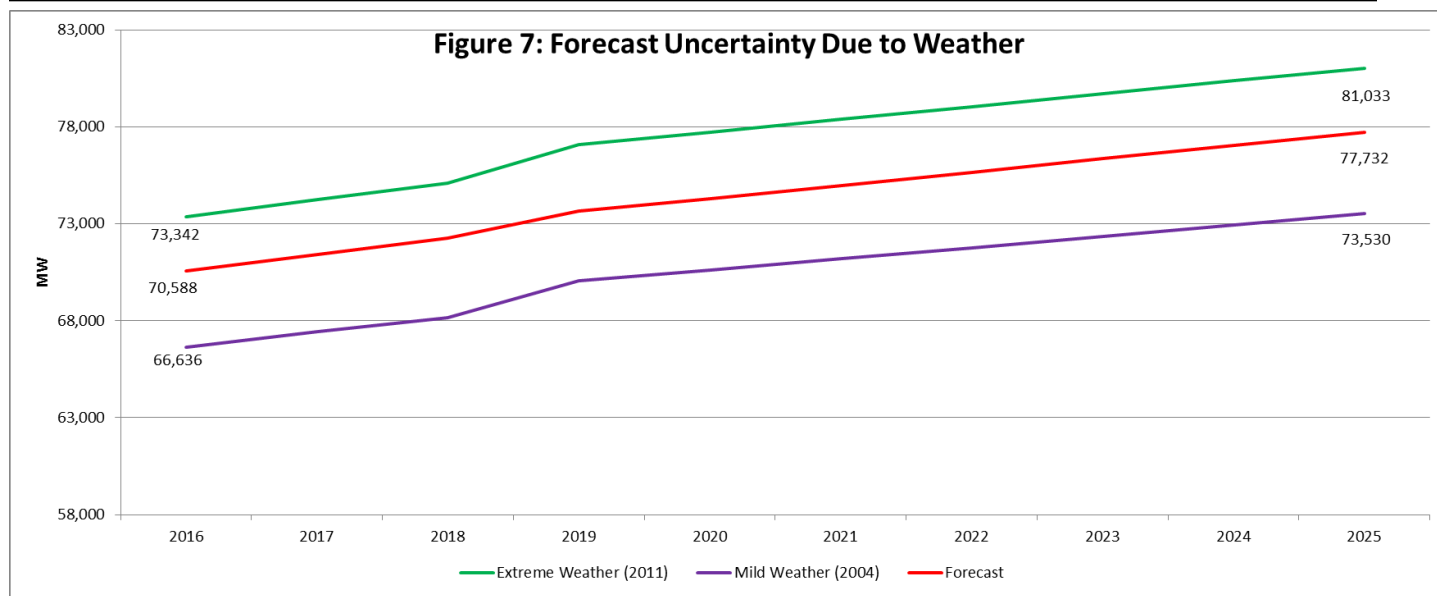


Figure 7 depicts weather volatility out to 2025. Assuming 2004 weather (identified as the mild weather scenario) in 2025, we would expect a peak of 73,530 MW. Assuming 2011 weather (identified as the extreme weather scenario) in 2025, results in a forecasted peak demand of 81,033 MW. This equates to approximately a 10% difference in the forecast based on weather extremes.



Economic Uncertainty

Economic uncertainty impacts the premise forecasts. Stated differently, significant changes in economic forecasts will have impacts on the premise forecasts, which in turn, will be reflected in the peak demand and energy forecasts. Premise forecasts were based on Moody's Analytics base economic scenario.

Energy Efficiency

Energy efficiency is a much more difficult uncertainty to quantify. First, it must be recognized that the 2016 LTDEF was a "frozen efficiency" forecast. That means the forecast model employs statistical techniques that unyieldingly fix the relationships between load, weather, and economics at their 2015 state. Such an assumption has significant implications. Among other things, it means that the thermal characteristics of the housing stock and the characteristics of the mix of appliances will remain fixed. If thirty percent of the residential central air conditioners in the South Central weather zone have Seasonal Energy Efficiency Ratios (SEER—a measure of heat extraction efficiency) of twelve in 2015, then the model assumes the same proportion in all forecasted years. In the future, ERCOT will create energy efficiency scenarios which adjust the load forecast based on data from the Energy Information Administration (EIA)⁸.

Price Responsive Loads

Price responsive load programs are in their infancy for much of ERCOT. Determining the impact of these programs is challenging especially when you consider that over the last few years, ERCOT's price caps have increased from \$1,000/MWh to \$9,000/MWh. Discussions are underway to explore ways to enable loads to participate in ERCOT's real-time energy market by submitting demand response offers to be deployed by the Security Constrained Economic Dispatch. There remains much uncertainty as to what future levels these programs may achieve. Similarly to Energy Efficiency, it must be recognized that the 2016 LTDEF was a "frozen" forecast with respect to price responsive loads. Price responsive loads are reflected in the forecast at

⁸ For a discussion of the EIA scenarios, see the "Buildings Sector Case" at <http://www.eia.gov/forecasts/aeo/appendix.cfm>

the level that was present in 2015. In the future, ERCOT may create price responsive load scenarios, which will adjust the forecasted peak demands.

Onsite Renewable Energy Technologies Uncertainty

Another area of uncertainty is due to onsite renewable generation technologies such as the following.

1. Distributed Onsite Wind,
2. Photovoltaic (PV), and
3. Solar Water Heating.

Onsite renewable generation technologies are also characterized by much uncertainty as to what future levels may be achieved. The 2016 LTDEF was a “frozen” forecast with respect to onsite renewable generation technologies. Onsite renewable generation technologies are reflected in the forecast at the level that was present in 2015. In the future, ERCOT may create scenarios for Onsite Renewable Energy Technologies.

Electric Vehicles Uncertainty

The growth of Electric Vehicles (EVs) has been accelerating. As an example, industry forecasts indicate that the number of electric vehicles in Texas will grow from 5,000 to approximately 100,000 by 2023. Still, the number of electric vehicles represents a very small percentage of the new car market in the United States. The 2016 LTDEF was a “frozen” forecast with respect to EVs. EVs are reflected in the forecast at the level that was present in 2015. ERCOT will continue to monitor the growth of electric vehicles in order to monitor their impact on the load forecast.

Large Industrial Loads

A key challenge in creating a load forecast is to determine if the model is adequately capturing the impact of future large industrial loads. Examples include liquefied natural gas facilities, oil and gas exploration, chemical processing plants, Tesla battery plants, etc. In addition, ERCOT had discussions with Transmission Service Providers (TSPs) and gathered information on the expected growth of industrial load within their service territories. ERCOT carefully reviews the historical performance of their long-term load forecasts to determine how well large industrial growth has been captured. Based on the results of this evaluation and on data gathered from the TSPs, ERCOT may use this information to adjust their forecast. As an example, the 2016 Long-Term Load Forecast (LTLF) was adjusted for the Freeport LNG facility.

Change in ERCOT’s Service Territory

Another challenge in creating a load forecast is the potential for ERCOT’s service territory to change. As an example, discussions are underway to determine if the City of Lubbock should join ERCOT. Lubbock’s peak load is approximately 600 MW. The 2016 LTLF does not include any changes to ERCOT’s service territory.

Looking Ahead

As more information becomes available and additional data analysis is performed for each of these highlighted areas of forecast uncertainty, ERCOT will begin developing models which quantify their impacts on future long-term demand and energy forecasts. These themes will likely be revisited in the 2017 LTDEF.

Appendix A
Peak Demand and Energy Forecast Summary

Year	Summer Peak Demand (MW)	Energy (TWh)
2016	70,588	350.6
2017	71,416	356.2
2018	72,277	362.3
2019	73,663	370.7
2020	74,288	376.1
2021	74,966	380.4
2022	75,660	384.6
2023	76,350	388.9
2024	77,036	393.4
2025	77,732	397.7