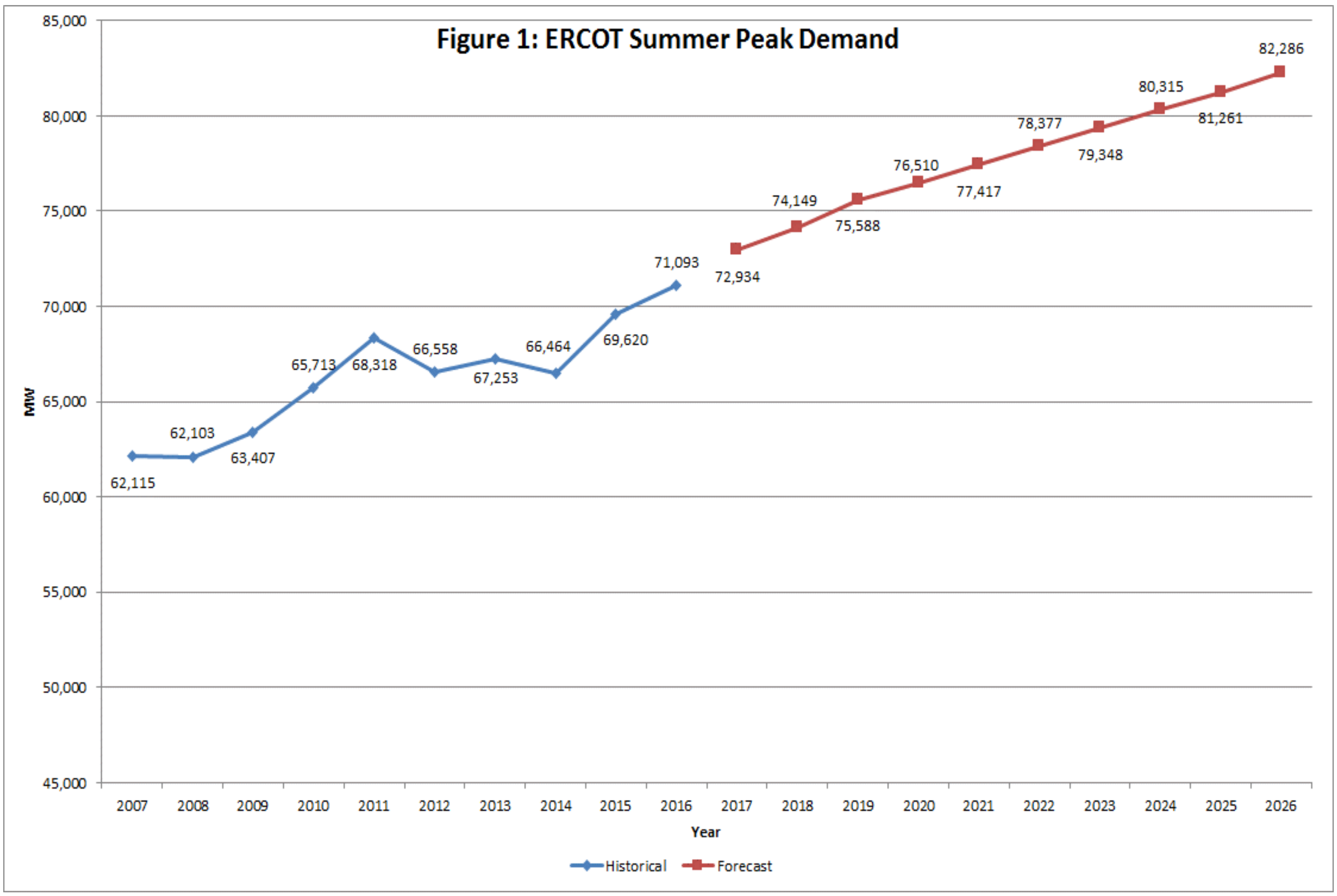
2017 ERCOT System Planning

Long-Term Hourly Peak Demand and Energy Forecast

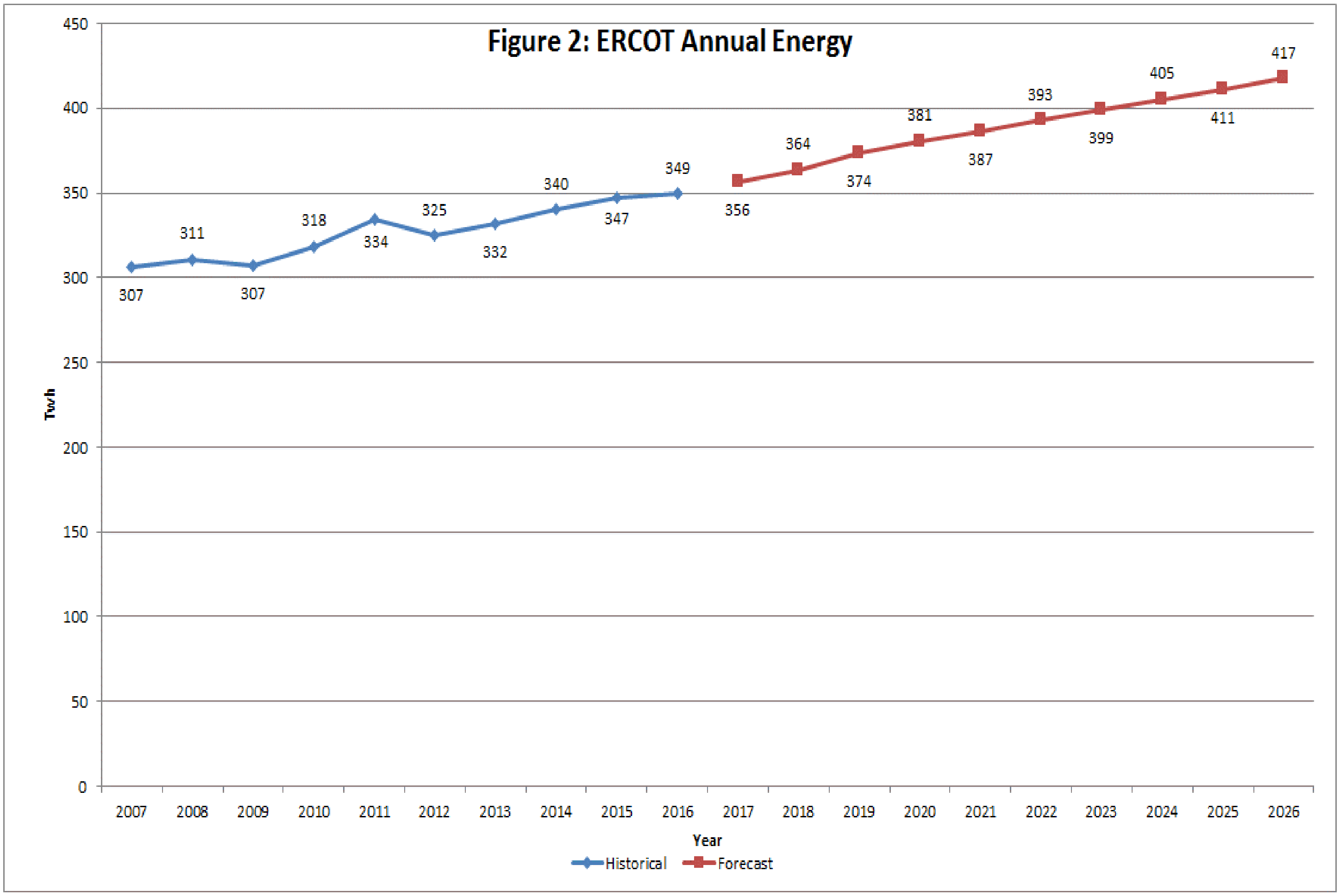
December 14, 2016

Executive Summary

The 2017 Long-Term Demand and Energy Forecast (LTDEF) for the ERCOT region is presented in this report, which includes the methodology, assumptions, and data used to 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, dew point) 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. Fourteen years of historical weather were provided by Schneider Electric/DTN for 20 weather stations.



As shown in Figure 1, the 2017 LTDEF depicts system peak demand increasing at an average annual growth rate (AAGR) of approximately 1.3% from 2017-2026. Historically, summer peak demand has grown at AAGR of 1.5% from the 2007-2016.



As shown in Figure 2, historical annual energy for calendar years 2007-2016 grew at an AAGR of 1.5%. The forecasted AAGR for energy for 2017-2026 is 1.8%.

Introduction

This report gives a high level overview of the 2017 LTDEF. The forecast methodology is described, highlighting its major conceptual and statistical underpinnings. The 2017 forecast results are presented in a manner comparing them to the 2016 LTDEF. This allows for a direct comparison of results and also facilitates an explanation for the changes. Finally, an examination is presented describing the major sources of forecast uncertainty.

2017 Modeling Framework

ERCOT consists of eight distinct weather zones (Figure 3). Weather zones[1] 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 2017 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 were mapped into a unique weather zone (Figure 3). Premise forecasts were created for each weather zone.

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 meter[2]).

All premise models were developed using historical data from January-2010 through August-2016. An econometric linear regression autoregressive model (AR1) was used for all premise models.

Residential Premise Forecast

Residential premise counts were modeled by estimating a relationship between the dependent variable (residential premises) and the following:

1. Housing Stock and
2. Population.

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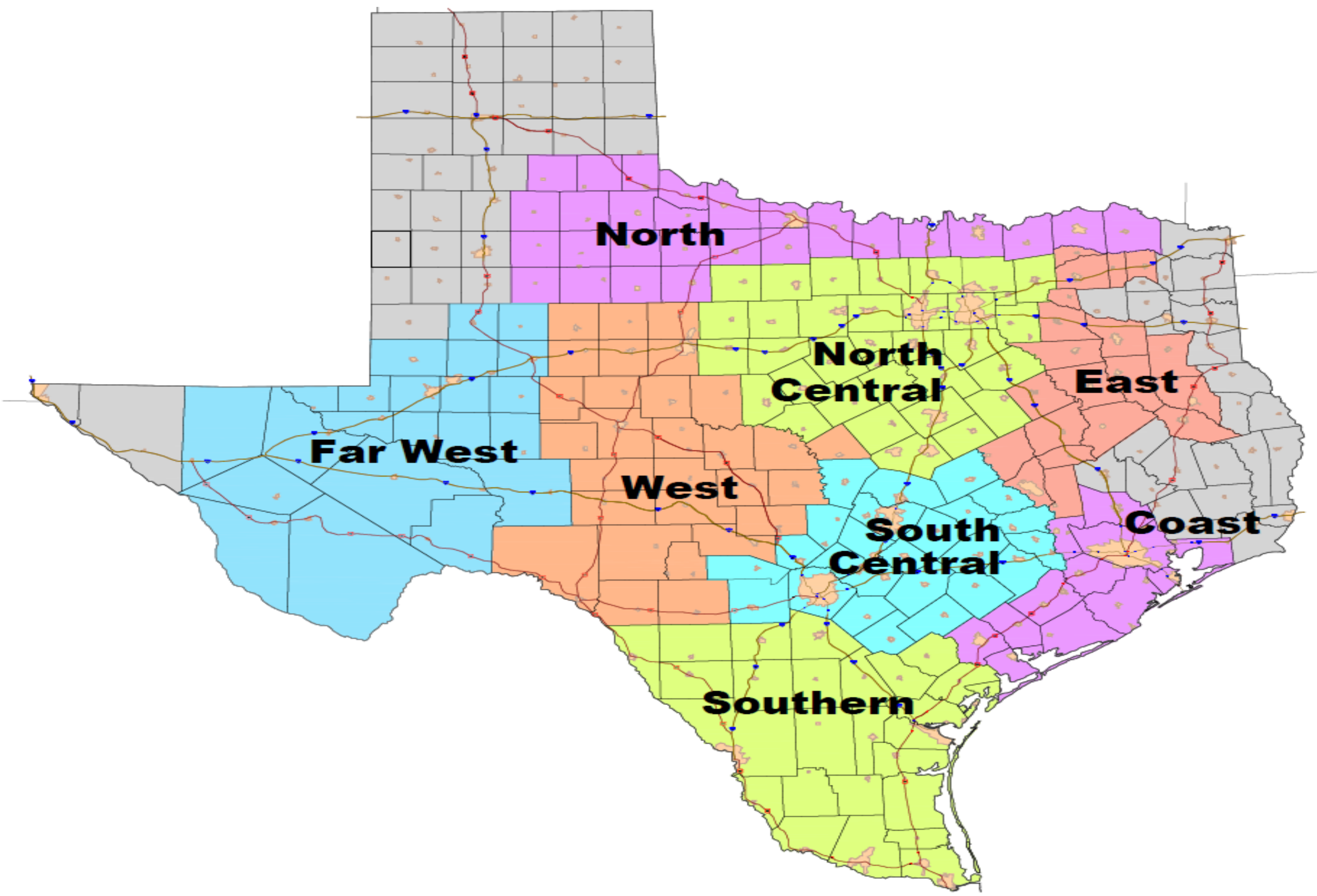
[1] *See ERCOT Nodal Protocols, Section 2.*
[2] *See ERCOT Nodal Protocols, Section 18.6.1.*

Figure 3: ERCOT Weather Zones



Business Premise Forecast

Business premise counts were modeled by estimating a relationship 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 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, 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, while the underlying economic variables were increasing. This would imply that premise counts decrease as employment or population increase.

As a result of these two problems, premise forecast models were not used 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. Season,
3. Day Type (day of week, holiday),
4. Weather Variables,
    a. Temperature,
    b. Temperature Squared,
    c. Temperature Cubed,
    d. Dew Point,
    e. Cloud Cover,
    f. Wind Speed,
    g. Cooling Degree Days[3] (base 65),
    h. Heating Degree Days[3] (base 65),
    i. Lag Cooling Degree Days[3] (1,2, or 3 previous days),
    j. Lag Heating Degree Days[3] (1,2, or 3 previous days), and
    k. Lag Temperature (1, 2, 3, 24, 48, or 72 previous hours).
5. Interactions
    a. Hour and Day of Week,
    b. Hour and Temperature,
    c. Hour and Dew Point,
    d. Temperature and Dew Point, and
    e. Hour and Temperature and Dew Point.

[3] *All Degree Day variables are calculated versus 65 deg F.*

6. Number of Premises[4], and
7. Non-Farm Employment/Housing Stock/Population.

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 (1/1/2010 – 8/22/2016) 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 1/1/2010 through 12/31/2014. 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 2015. 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.

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 1/1/2016 through 8/22/2016. 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 1/1/2011 through 8/22/2016 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, seasonal models were developed for each weather zone.

Weather Load Forecast Scenarios

Actual weather data from calendar years 2002 through 2015 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

[4] *Used in Far West, North, and West weather zones.*

years (2017-2026). The actual weather data from all days in 2002 was copied into the same day and hour for each of the forecasted years (2017 – 2026). For example, the actual weather data for 1/1/2002 was copied into 1/1/2017, 1/1/2018, etc. …, and 1/1/2026. 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 (2017-2026). This process was completed for each of the historical weather years (2002-2015) and resulted in fourteen weather load forecast scenarios for 2017-2026.

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.

Load Forecast Summary

The following load forecasts are created:

1) Weather Zone Normal Weather (P50) Summer Peak Demand Forecast,
2) Weather Zone 90th Percentile (P90) Summer Peak Demand Forecast,
3) ERCOT Normal Weather (P50) Summer Peak Demand Forecast,
4) ERCOT Normal Weather (P50) Winter Peak Demand Forecast,
5) ERCOT Normal Weather (P50) Monthly Peak Demand Forecast (excluding the summer and winter peak months), and
6) ERCOT Normal Weather (P50) Monthly Energy Forecast.

Descriptions of each can be found in the sections below.

Weather Zone Normal Weather (P50) Summer Peak Demand Forecast

The fourteen weather load forecast scenarios are used as the basis for creating the normal weather (50th percentile denoted as the P50) summer peak forecast. Each of the fourteen hourly weather load forecast scenarios for each weather zone, covering calendar years 2017-2026 are separated into individual calendar year forecasts. Each individual calendar year forecast was ordered from the highest value to the lowest value. The highest value from each weather load forecast scenario was selected from each forecasted year. The average was calculated of these values. For example, to determine the normal weather (P50) forecasted peak value for calendar year 2017, take the highest forecasted value from each of the fourteen weather load forecast scenarios for calendar year 2017 and average them. The forecasted summer peak values were assigned to the month of August.

Example:
Table 1 shows the top five forecasted hourly peaks for the Coast weather zone for 2017 based on historical weather years of 2002-2015.

Table 1: Coast Weather Zone
2017 Summer Peak Forecast Scenarios

	Historical Weather Year															
Rank	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	P50	P90
1	19,178	20,572	19,838	19,940	19,806	20,437	19,594	20,295	20,165	20,903	21,063	20,028	19,761	20,775	20,168	20,983
2	19,125	20,472	19,735	19,885	19,674	20,200	19,411	20,239	20,112	20,829	21,042	19,947	19,718	20,589	20,070	20,935
3	19,101	20,318	19,722	19,735	19,647	20,170	19,373	20,165	19,923	20,815	20,904	19,871	19,596	20,360	19,979	20,859
4	19,092	20,252	19,662	19,684	19,347	20,056	19,327	20,133	19,874	20,714	20,814	19,831	19,591	20,312	19,906	20,764
5	18,999	20,207	19,605	19,673	19,174	20,004	19,323	20,120	19,829	20,711	20,370	19,817	19,576	20,268	19,834	20,540

The P50 column is the average of the fourteen forecasts for each row. The P90 column is the 90th percentile of the fourteen forecasts.

Weather Zone (P90) Summer Peak Demand Forecast
Another forecast of interest is the 90th (P90) percentile weather zone summer peak demand forecast. The process for determining the 90th percentile weather zone summer peak demand forecast is identical to the process used for calculating the P50 forecast except that instead of calculating the average highest value of the fourteen weather load forecast scenarios, the 90th percentile is calculated.

ERCOT Normal Weather (P50) Summer Peak Demand Forecast
The Weather Zone Normal Weather (P50) Summer Peak Demand Forecasts are used to determine ERCOT's Normal Weather (P50) Summer Peak Demand Forecast. Each weather zone's summer peak demand forecast is multiplied by a coincident factor. This resultant value is referred to as the weather zone summer peak coincident forecast. The coincident factor is based on historical data that represents the ratio of each weather zone's demand at the time of ERCOT's summer peak divided by the weather zone's summer peak demand. The weather zone summer peak coincident forecast values are summed to arrive at the ERCOT summer peak forecast. ERCOT continues to use coincident factors based on the summer of 2003. The forecasted summer peak demand is assigned to the month of August.

Weather Load Forecast Scenarios (ERCOT system)
The fourteen weather load forecast scenarios are used as the basis for creating the weather load forecast scenarios for the ERCOT system. Each of the hourly values from each weather zone are summed for each year, month, day, and hour. This process was completed for each of the forecast scenarios and resulted in fourteen ERCOT hourly load forecasts for 2017-2026.

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

$$\sum_{z=1}^{8} EHF_{(z,x,y)}$$

Where:
EHF = ERCOT 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, $HF_{(7/24/2008\ 1700,\ 7/24/2019\ 1700)}$, 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 ERCOT system.

ERCOT Normal Weather (P50) Winter Peak Demand Forecast
Each of the fourteen hourly weather load forecast scenarios for the ERCOT system, covering calendar years 2017-2026 are separated into individual calendar year forecasts. For each calendar year, the forecasted winter peak demand is calculated. The winter season includes the months of December, January, February, and March. The forecasted winter peak values are averaged. The forecasted winter peak is assigned to the month of January.

ERCOT Normal Weather (P50) Monthly Peak Demand Forecast (excluding August and January)
Each of the fourteen hourly weather load forecast scenarios for the ERCOT system, covering calendar years 2017-2026 are separated into individual calendar year forecasts. For each calendar year, the forecasted monthly peak demands are calculated. For all months except for August and January, the forecasted monthly peak values are averaged.

Forecast Adjustments
A large liquefied natural gas (LNG) facility started construction in Freeport in November 2014[7]. 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 dates[5]. 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).

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[5] *http://www.freeportlng.com/Project_Status.asp*

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 2016 LTDEF

1. Models were developed based on seasons
   In the 2016 LTDEF, models were developed for each month.

2. Dew Point was included as a weather variable
   In the 2016 LTDEF, Dew Point was not included in the models.

3. Cooling Degree Hour and Heat Degree Hour variables were removed
   In the 2016 LTDEF, Cooling Degree Hour and Heating Degree Hour variables were included.

   Rationale for changes:
   During model development, these changes improved the model's performance based on historical data when compared to the previous approach.

Load Forecast Comparison
Figure 4 presents the ERCOT summer peak demand forecasts for 2017-2025 from the 2016 LTDEF and the 2017 LTDEF.

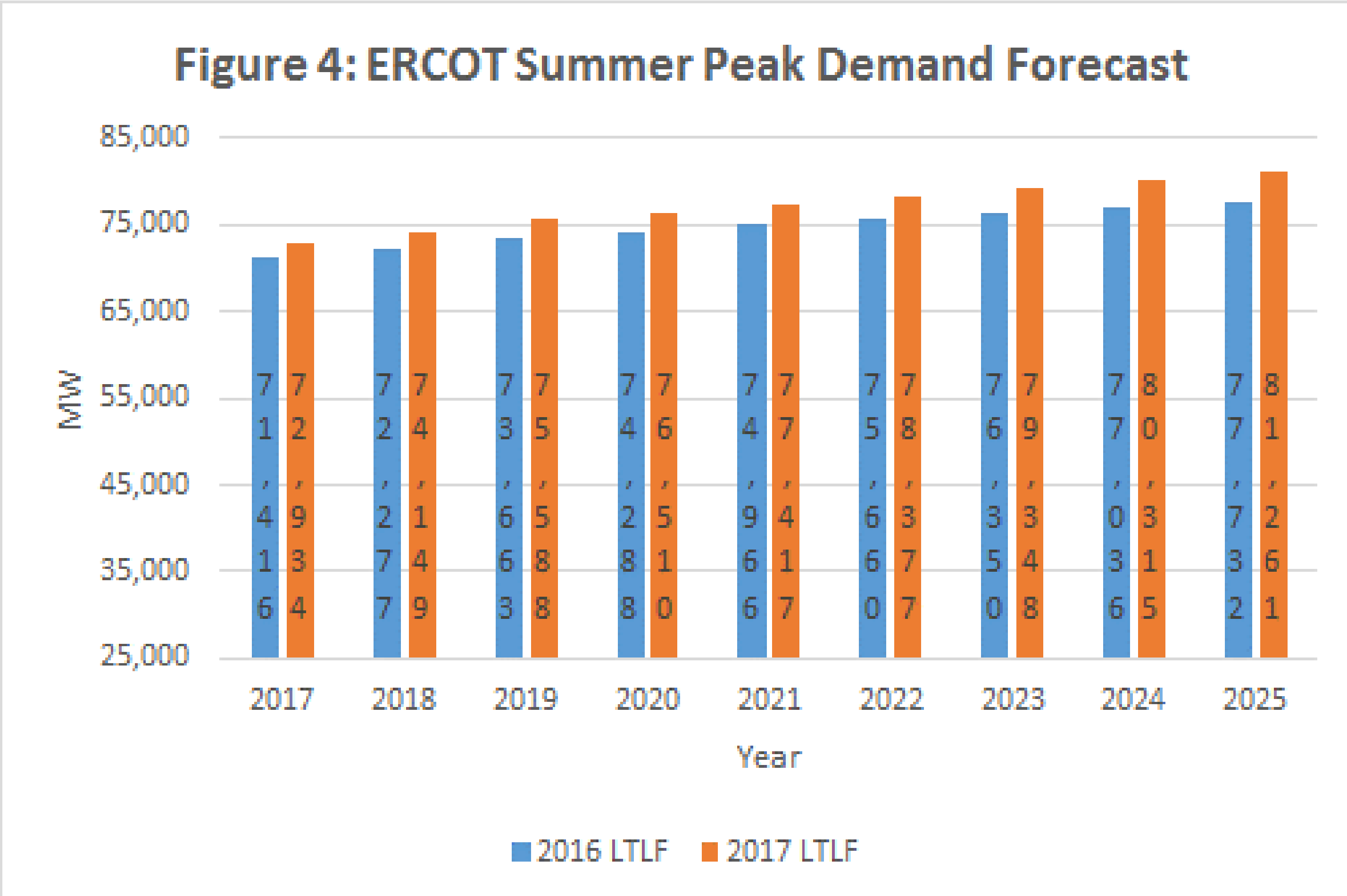
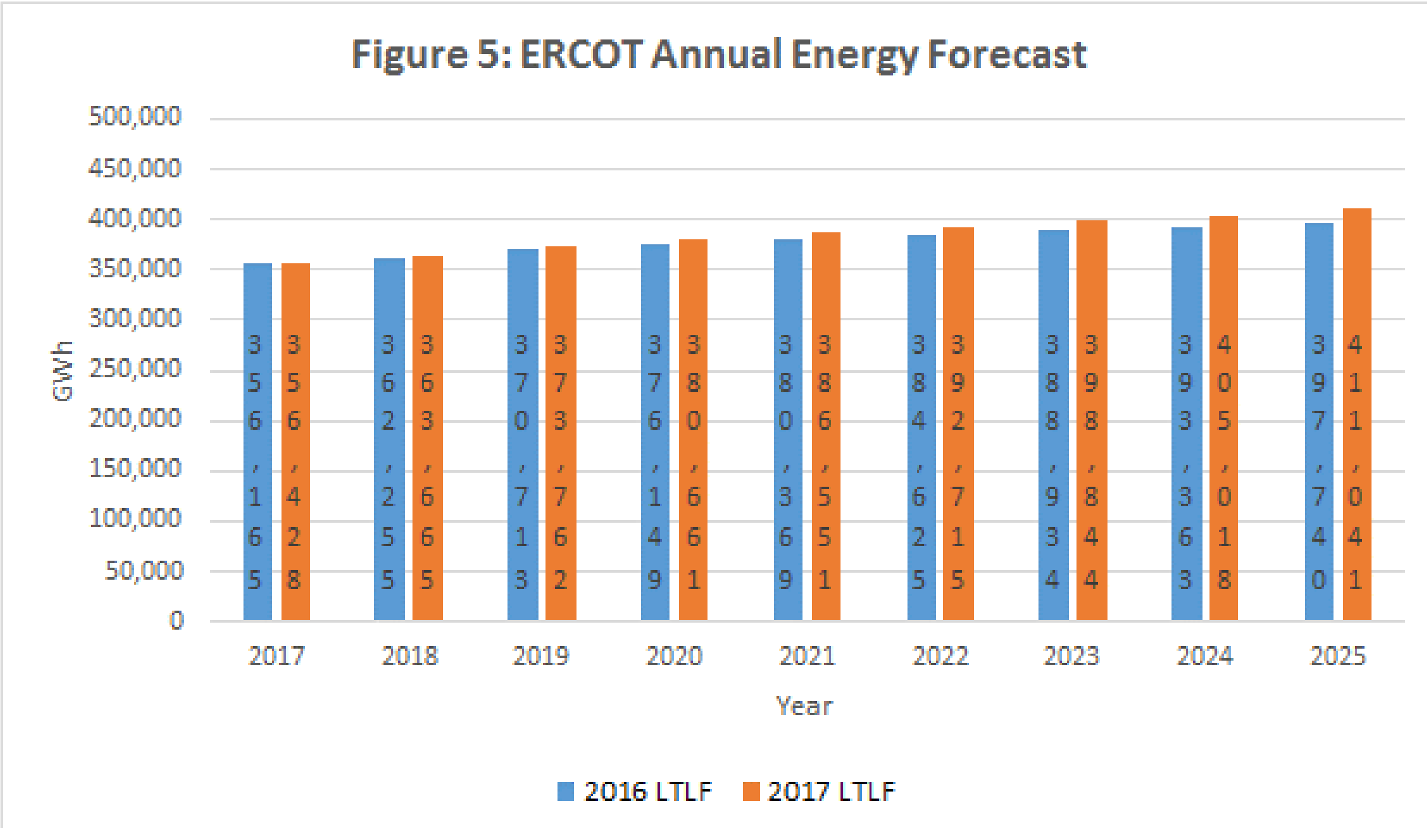


Figure 5 presents the ERCOT annual energy forecast for 2017-2025 from the 2016 LTDEF and the 2017 LTDEF.



<u>Load Forecast Uncertainty</u>

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 nine areas:

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

<u>Weather Uncertainty</u>

Figure 6 suggests the significant impact of weather in forecasting any specific year. This figure shows what the 2017 forecasted peak demand would be using the actual weather from each of the past fourteen years as input in the model. As shown, there is considerable variability ranging from 68,481 MW using 2004's weather to 76,522 MW using 2011's weather. This equates to approximately a 10% difference in the forecast based on historical weather volatility.

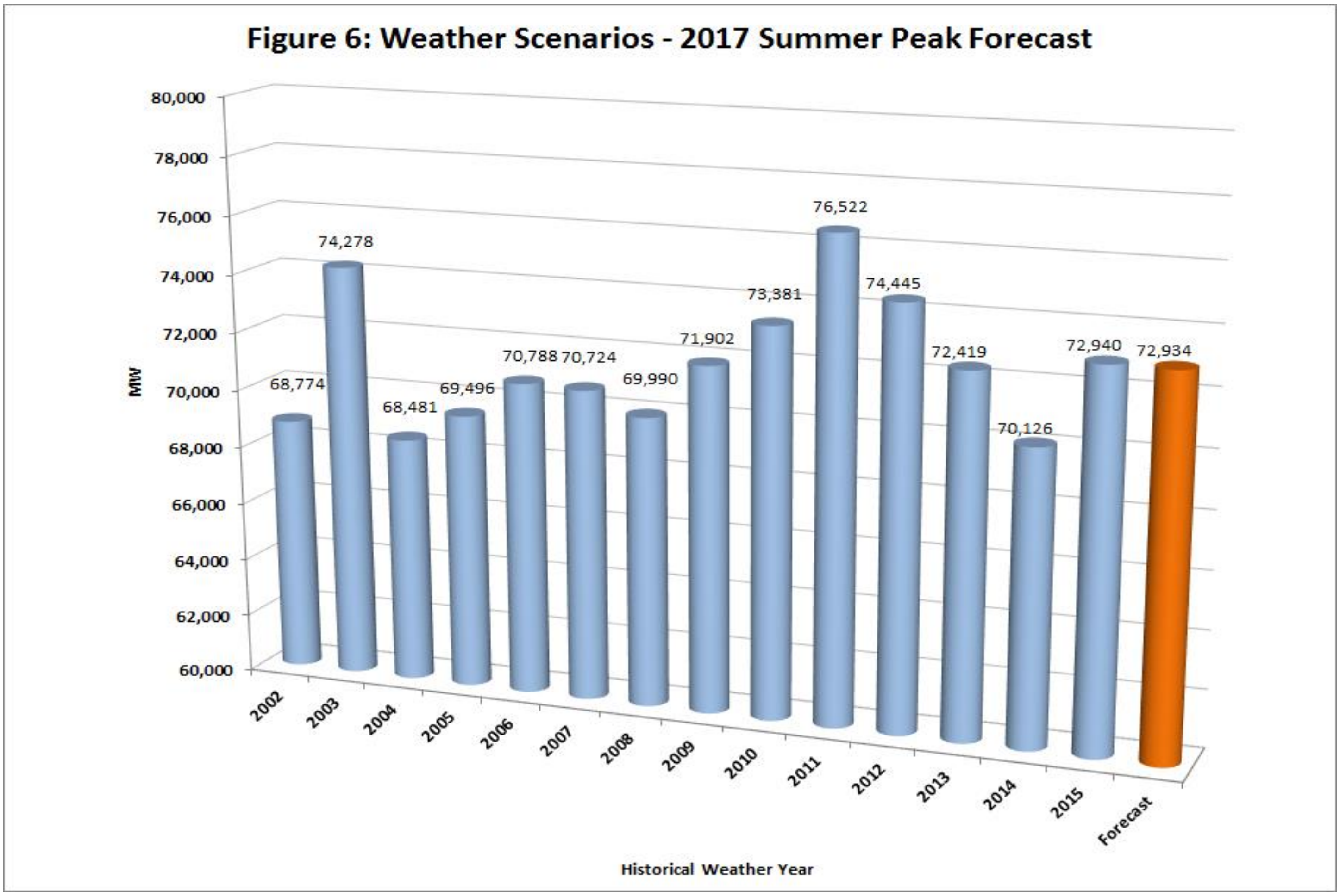
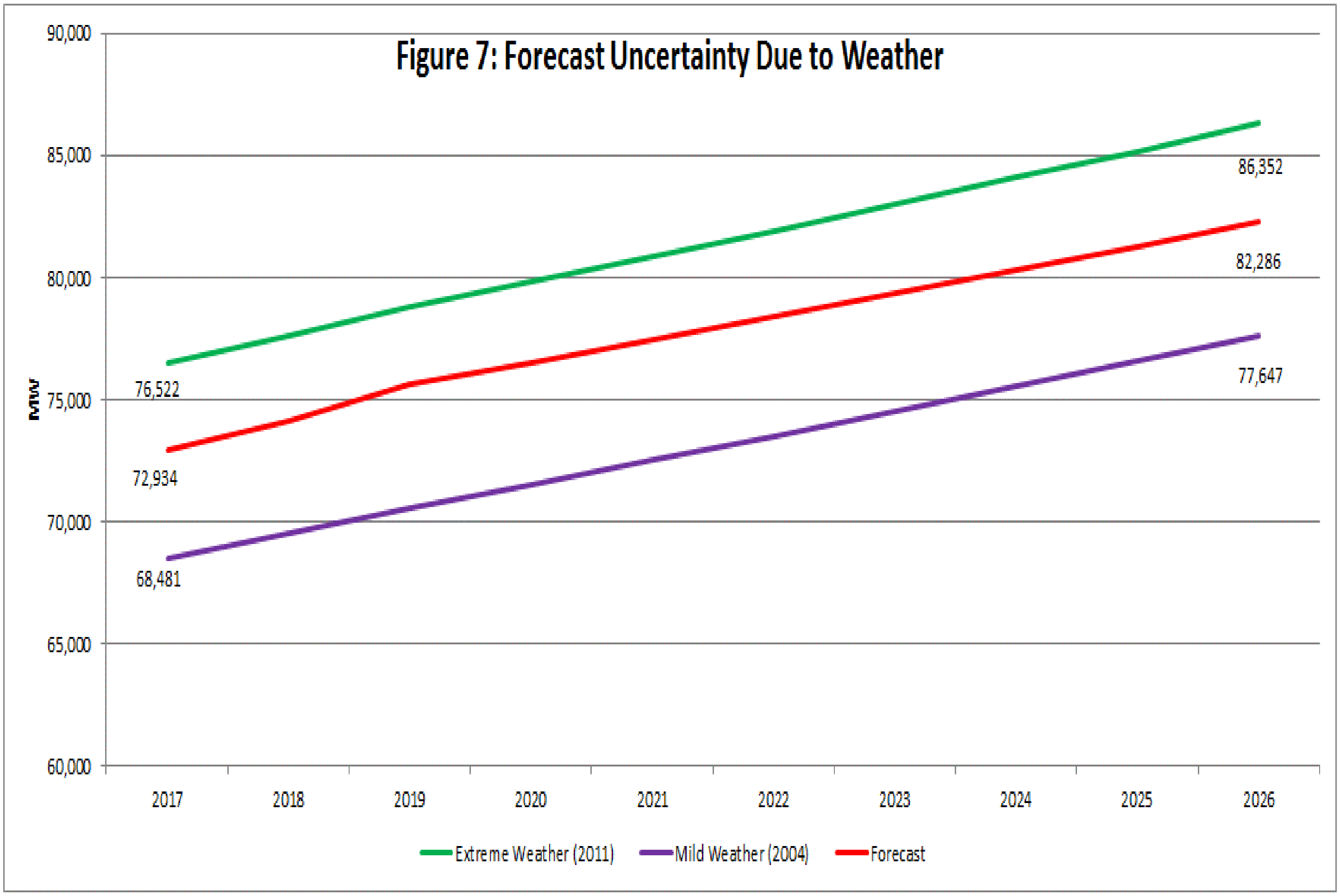


Figure 7 depicts weather volatility out to 2026. Assuming 2004 weather (identified as the mild weather scenario) in 2026, we would expect a peak of 77,647 MW. Assuming 2011 weather (identified as the extreme weather scenario) in 2026, results in a forecasted peak demand of 86,352 MW. This equates to approximately a 10% difference in the forecast based on weather extremes.



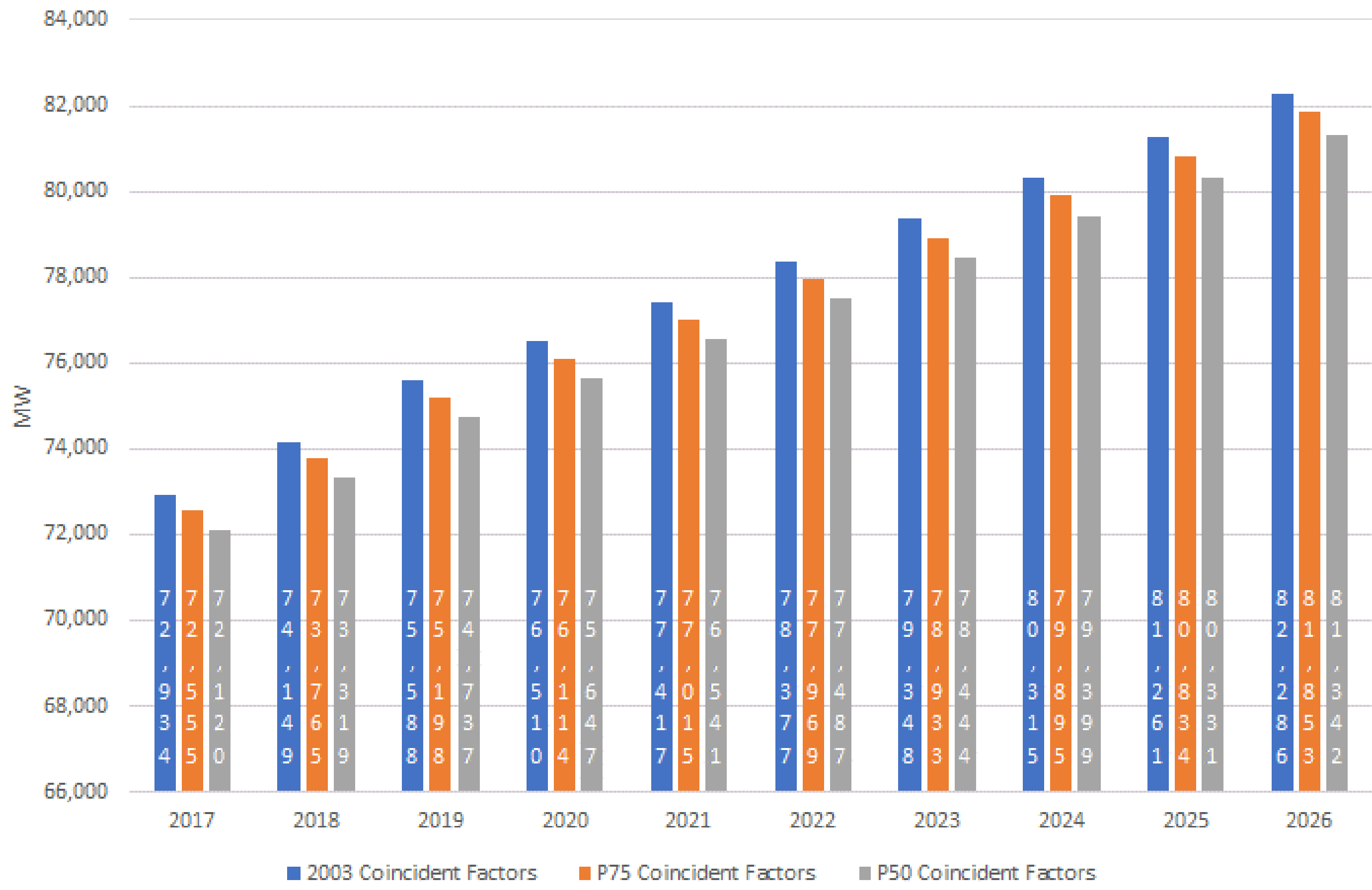
<u>Economic Uncertainty</u>

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.

<u>Coincident Factors</u>

Figure 8 depicts the impact of historical coincident factors on ERCOT's summer peak forecast. ERCOT continues to create their forecast using the coincident factors from 2003. The choice of coincident factors can impact the forecasted peak demand by approximately 10%.

Figure 8: Uncertainty Due to Coincident Factors



Energy Efficiency

Energy efficiency is a much more difficult uncertainty to quantify. First, it must be recognized that the 2017 LTDEF was a "frozen efficiency" forecast. This means the forecast model employs statistical techniques that unyieldingly fix the relationships between load, weather, and economics at their 2016 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 2016, 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)[6].

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

[8] *For a discussion of the EIA scenarios, see the "Buildings Sector Case" at* http://www.eia.gov/forecasts/aeo/appendixe.cfm

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 2017 LTDEF was a "frozen" forecast with respect to price responsive loads. Price responsive loads are reflected in the forecast at the level that was present in 2016. In the future, ERCOT may create price responsive load scenarios, which will adjust the forecasted peak demands.

<u>Onsite Renewable Energy Technologies Uncertainty</u>

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

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

Onsite renewable generation technologies are also characterized by much uncertainty as to what future levels may be achieved. The 2017 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 2016. In the future, ERCOT may create scenarios for Onsite Renewable Energy Technologies.

<u>Electric Vehicles Uncertainty</u>

The growth of Electric Vehicles (EVs) continues to accelerate. The 2017 LTDEF was a "frozen" forecast with respect to EVs. EVs are reflected in the forecast at the level that was present in 2016. ERCOT will continue to monitor the growth of electric vehicles in order to monitor their impact on the load forecast.

<u>Large Industrial Loads</u>

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 its 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 the forecast. As an example, the 2017 Long-Term Load Forecast (LTLF) was adjusted for the Freeport LNG facility.

<u>Change in ERCOT's Service Territory</u>

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 2017 LTLF does not include any changes to ERCOT's service territory.

<u>Looking Ahead</u>

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 2018 LTDEF.

Appendix A
Peak Demand and Energy Forecast Summary

Year	Summer Peak Demand (MW)	Energy (TWh)
2017	72,934	356
2018	74,149	362
2019	75,588	371
2020	76,510	376
2021	77,417	380
2022	78,377	385
2023	79,348	389
2024	80,315	393
2025	81,261	398
2026	82,286	417