



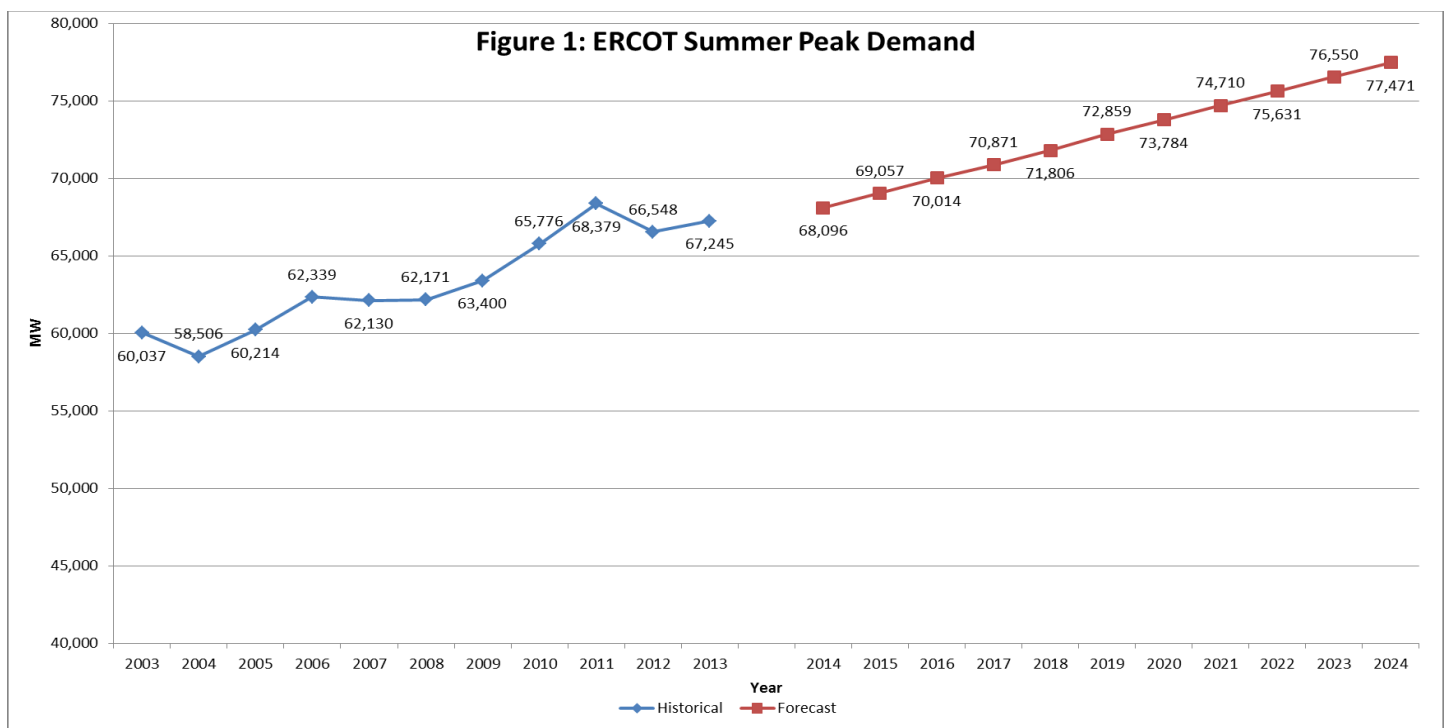
# **2014 ERCOT Planning**

## **Long-Term Hourly Peak Demand and Energy Forecast**

**March 31, 2014**

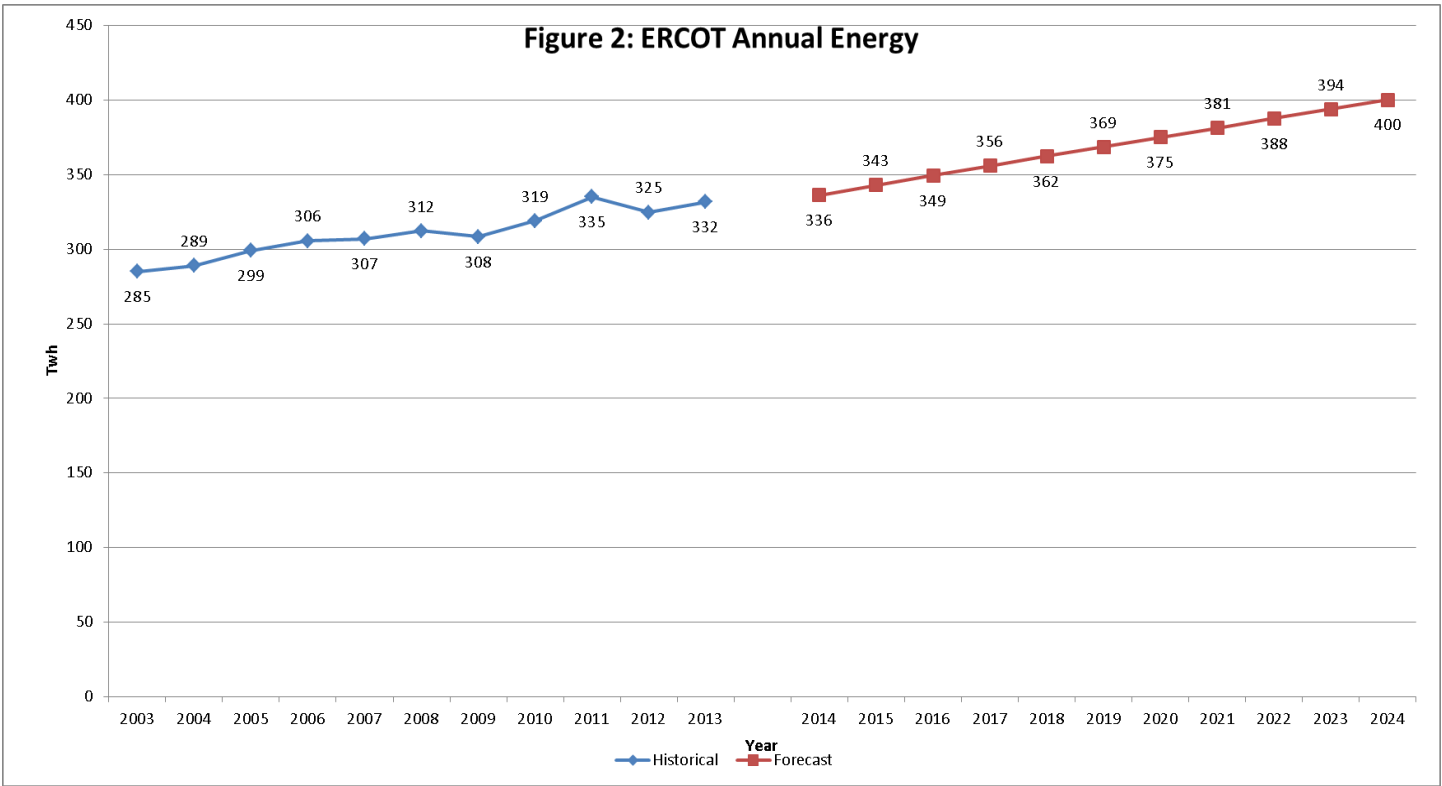
### Executive Summary

The 2014 Long-Term Demand and Energy Forecast (LTDEF) for the ERCOT region is presented in this report, including the methodology, assumptions, and data used in creating the forecast. This forecast is based on a set of econometric and neural network models describing the hourly load in the region as a function of certain economic (e.g., nonfarm payroll employment, housing stock, population) and weather variables (e.g., heating and cooling degree days). A county level forecast of economic and demographic data was obtained from Moody's. Twelve years of historical weather data (e.g., hourly dry bulb temperature, wind speed, and cloud cover) were provided by Telvent/DTN for 20 weather stations in ERCOT.



As shown by Figure 1 (above), the 2014 LTDEF depicts system peak demand increasing at an average annual growth rate (AAGR) of approximately 1.3% for the 2014 – 2024 timeframe. As a point of reference, historical summer peak demand grew at a 1.1% average annual growth rate (AAGR) for the 2003 – 2013 timeframe.

As shown in Figure 2 (below), historical annual energy for 2003 - 2013 grew at an AAGR of 1.5 percent. The forecasted AAGR for energy for 2014-2024 is 1.8 percent.



## Introduction

This report gives a high level overview of the 2014 LTDEF. The forecast methodology is described, highlighting its major conceptual and statistical underpinnings. The 2014 forecast results are presented in a manner comparing them to the 2013 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.

## Load Modeling

ERCOT consists of eight distinct weather zones (Figure 3 below). Weather zones<sup>1</sup> represent a geographic region in which climatological characteristics are similar for all areas within such region. In order to reflect the unique weather and load characteristics of each weather zone, separate load forecasting models were developed for each of the weather zones. All of the model descriptions included in this document should be understood as referring to weather zones. The ERCOT forecast is the sum of all of the weather zone forecasts.

## Modeling Framework

The 2014 LTDEF was produced with a set of neural network models that combine weather, premise data (including number of premises and average annual usage per premise), and calendar variables to capture and project the long-term trends extracted from the historical load data.

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<sup>2</sup>).

Two sets of models were developed:

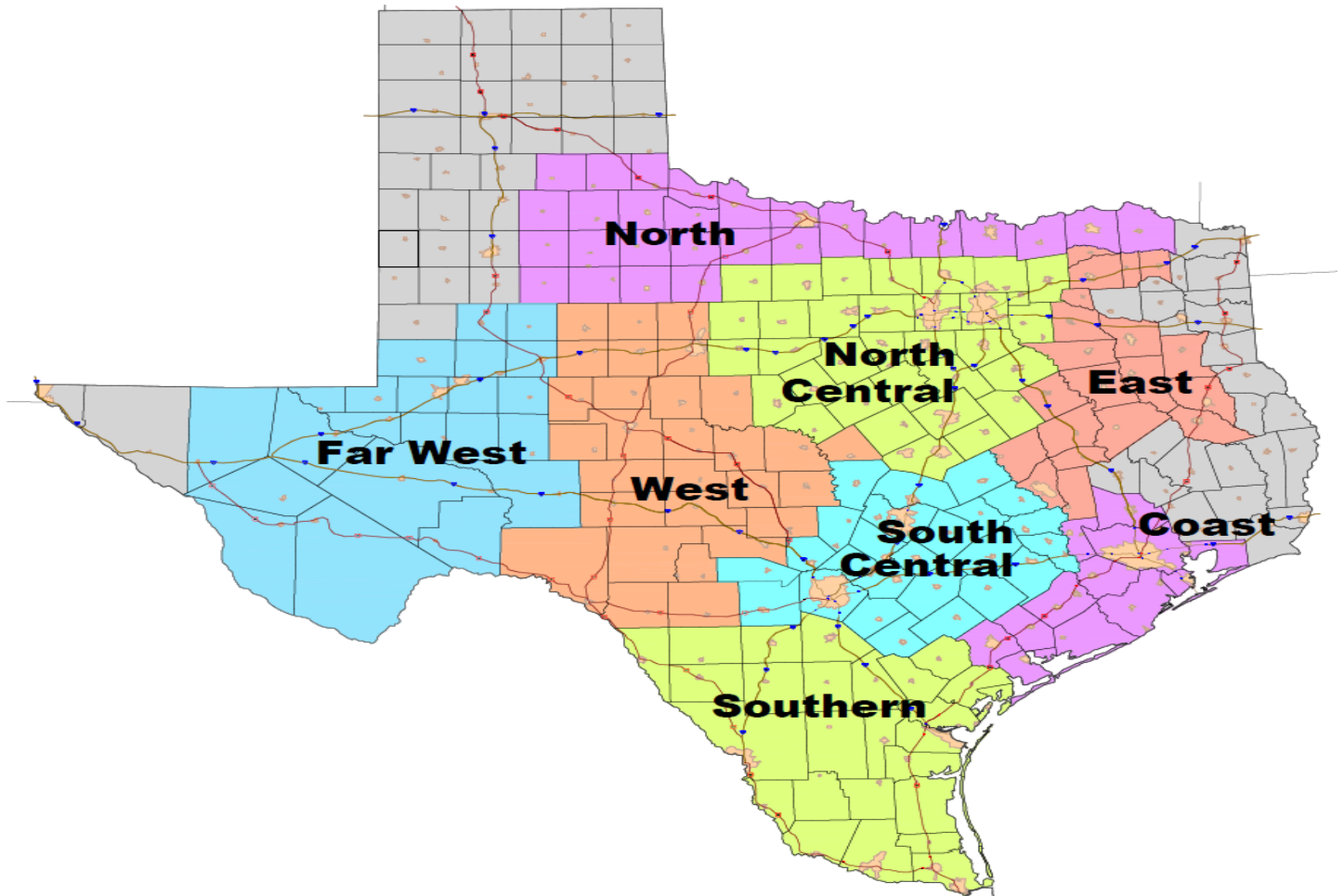
1. Daily energy models and
2. Premise count models.

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<sup>1</sup> See section ERCOT Nodal Protocols, section 2.

<sup>2</sup> See section ERCOT Nodal Protocols, section 18.6.1.

**FIGURE 3: ERCOT Weather Zones**



Daily Energy Models

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

1. Month and Season,
2. Day type,
  - a. Day of the week excluding holidays and
  - b. Holidays.
3. Weather variables,
  - a. Night Cooling Degree Days,
  - b. Morning Cooling Degree Days,
  - c. Afternoon Cooling Degree Days,
  - d. Evening Cooling Degree Days,

- e. Night Heating Degree Days,
- f. Morning Heating Degree Days,
- g. Afternoon Heating Degree Days,
- h. Evening Heating Degree Days,
- i. Cooling Degree Days from the previous day, and
- j. Heating Degree Days from the previous day.

Night was defined as hour beginning 0, 1, 2, 3, 4, and 5.

Morning was defined as hour beginning 6, 7, 8, 9, 10, and 11.

Afternoon was defined as hour beginning 12, 13, 14, 15, 16, and 17.

Evening was defined as hour beginning 18, 19, 20, 21, 22, and 23.

Cooling Degree Days and Heating Degree Days are calculated using 65 degrees Fahrenheit as the base.

4. Daylight minutes, and
5. Weighted premise index.

The weighted premise variable was calculated by multiplying the number of premises times their average annual usage for all 3 premise types (residential, business, and industrial) and then summing the 3 values.

Daily energy was forecasted based on a set of neural network models. The models were developed using historical data from 2009 to 2013. Thirty neural network models were developed for each weather zone. An average of the thirty models was used as the final daily energy forecast model.

### Model Building Process

The historical data (2009 to 2013) was divided into three different data sets:

1. Model building,
2. Model validation, and
3. Model testing.

The model testing data set was created first. Twenty percent of the historical data was randomly assigned as model testing data. 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 building had been completed.

The validation data set was created next. Twenty percent of the historical data was randomly assigned as model validation data. A validation data set was determined for each of the thirty models that were created for each weather zone. The validation data sets were different for each of the thirty models. This approach ensures a robust validation of the models that were being evaluated. The validation data was not included in model building. After model building was completed, the validation data set was used to determine the accuracy of the

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forecast model. Model performance was quantified for each of the validation data sets. The model may be updated based on the results from the validation evaluation.

The model building data set was comprised on the remaining sixty percent of the historical data. This data was used to determine various forecast models. These models were then evaluated using the validation data set. Based on the results of the forecast for the validation data set, the model may be updated. The model building process was an iterative process that was conducted multiple times.

At the conclusion of the model building process, thirty models were developed for each weather zone. An average of the thirty models was used as the daily energy forecast model.

### Daily energy forecast scenarios

Actual weather data from calendar years 2002 – 2013 was used as input for each of the weather zone’s final daily energy forecast models. The process began by using actual weather data from 2002 as weather input for all forecasted years (2014 – 2024). The actual weather data from all days in 2002 was copied into the same day for each of the forecasted years (2014 – 2024). For example, the actual weather data for January 1, 2002 was copied into January 1, 2014, January 1, 2015, ..., and January 1, 2024. Using 2002 weather as input into each of the weather zone’s final daily energy forecast models results in a forecast for 2014 – 2024 assuming 2002’s weather. This process was completed for each of the historical years (2002 – 2013). At the completion of this step, each weather zone had daily energy forecasts covering the time period of 2014 – 2024 each based on a historical weather year (2002 – 2013). Seeing that 12 historical years were used (2002 – 2013), there will be 12 different daily energy forecasts for each weather zone. These represent 12 different daily energy forecast scenarios each based on a corresponding historical weather year. We will use the following notation to denote weather zone daily energy forecast scenarios:

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

Where:

DEF = daily energy forecast,

y = historical weather year (2002 – 2013),

x = forecast date (mm/dd/yy covering 1/1/2014 – 12/31/2024), and

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

For example,  $DEF_{(West, 2008, 7/24/2019)}$ , would denote the daily energy forecast for 7/24/2019 which was based on weather from 2008 for the West weather zone.

### Hourly allocation factors

Historical hourly allocation factors were calculated for each weather zone for each day by using the actual hourly load divided by the total energy for that particular day. For example, the historical hourly allocation factor for the North Central weather zone on August 8, 2002 @ 5 pm was equal to the actual load for the North

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Central weather zone on August 8, 2002 @ 5 pm divided by the total load for the North Central weather zone for that day (August 8, 2002). The actual hourly allocation factors from all days in 2002 are copied into the same day for each of the forecasted years (2014 – 2024). For example, the actual hourly allocation factors for August 8, 2002 were copied into August 8, 2014, August 8, 2015, ..., and August 8, 2024. Coupling the 2002 actual hourly allocation factors with the daily energy forecast based on 2002's weather for each weather zone results in a forecast for 2014 – 2024 assuming 2002's weather. This coupling preserves actual customer behavior particularly at the time of ERCOT's summer peak. This process was completed for each of the historical years (2002 – 2013). At the completion of this step, each weather zone had allocation factors for each historical year (2002 – 2013) covering the time period of 2014 – 2024. Seeing that 12 historical years were used (2002 – 2013), there will be 12 different sets of hourly allocation factors for each weather zone. Each set of hourly allocation factors will cover a complete year. We will use the following notation to denote weather zone hourly allocation factors:

$$HAL_{(z,y,x,h)}$$

Where:

HAL = hourly allocation factor,

y = historical year (2002 – 2013),

x = forecast date (mm/dd/yy covering 1/1/2014 – 12/31/2024),

h = hour, and

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

For example,  $HAL_{(West, 2008, 7/24/2019, 7)}$ , would denote the hourly allocation factor for 7/24/2019 at 7 am which was based on the actual hourly load allocation value for the West weather zone from 7/24/2008 at 7 am.

### Hourly forecast scenarios

The daily energy forecast values and the hourly allocation factors are used to create the hourly forecast scenarios by the following formula:

$$HF_{(z,y,x,h)} = DEF_{(z,y,x)} \times HAL_{(z,y,x,h)}$$

Where:

HF = hourly forecast,

DEF = daily energy forecast,

HAL = hourly allocation factor,

y = historical year (2002 – 2013),

x = forecast date (mm/dd/yy covering 1/1/2014 – 12/31/2024), and

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



At the completion of this step, each weather zone will have unique hourly forecasts covering the time period of 2014 – 2024 each based on a different historical year (2002 – 2013). Seeing that 12 historical years were used (2002 – 2013), there will be 12 different hourly forecasts for each weather zone.

#### Normal weather (50/50) forecast

The process for creating the normal weather (50/50) forecast begins by taking each of the 12 hourly forecast scenarios for each weather zone. Each of these 12 hourly forecast scenarios which cover the time period of 2014 – 2024 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, take the average. 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 12 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 12 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.

#### Forecast calendar

The last step was 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 the peak value into the representative calendar's peak hour, assigning the second highest peak value into the representative calendar's second highest peak hour, and so on until all hours have been assigned.

#### Changes made since 2013 LTDEF

##### Daily Energy Model

In the 2013 LTDEF, the daily energy model was based on a regression model that forecasted daily energy per one thousand jobs.

##### Rationale for change:

While this approach was initially successful, recent changes in the historical values of non-farm employment impacting data for the previous two years compromised the forecasting accuracy. The new forecast framework is expected to produce more accurate forecasts based on its ability to better reflect the differing growth rates of demand and energy which has become evident over the last two years.

##### Hourly Energy Model

In the 2013 LTDEF, hourly models were developed that forecasted hourly allocation factors for each hour of each day. The hourly allocation factors were multiplied times the daily energy values to create an hourly forecast.

Rationale for change:

Creating a separate model of hourly allocation factors appeared to understate the impact of the 4 CP impact, other price responsive demand impacts, and energy efficiency at the time of ERCOT's summer peak. It is believed that using actual historical load allocation factors in lieu of an hourly allocation forecast model will better reflect these impacts. The impact of this change will be studied further during 2014.

#### Determination of the Normal Weather Year

In the 2013 LTDEF, hourly normal weather temperature profiles were created for each weather zone.

Rationale for change:

The previous approach tended to understate actual load diversity at the time of ERCOT's summer peak. The new approach does not involve creating hourly temperatures. Instead, actual historical weather data was used as model input. The forecasts based on historical weather are used to create a normal weather forecast based on the Rank and Average methodology. This approach more accurately reflects load diversity at the time of ERCOT's summer peak.

#### Premise Forecast

Premise forecast models were developed for each weather zone. Premises were separated into three different groups for modeling purposes:

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

#### Residential Premise Forecast

Historical residential premise values, housing stock values, and population values were indexed with the January, 2010 value assigned an indexed value of 1. A residential index model was created based on the following formula:

$$RIndex_{y,m} = \left( \frac{HStock_{y,m}}{HStock_{base}} \right)^{0.5} \times \left( \frac{Pop_{y,m}}{Pop_{base}} \right)^{0.5}$$

Where:

y = year.

m = month,

base = 2010.

The forecasted indexed value was converted to a forecasted premise value for use in the neural network models.

Note that the North and West weather zones were modeled using a 5 year average premise growth rate instead of the residential premise index model. This was due to difficulties in developing a statistical model for weather zones that have historically low growth rates (less than 1.0%).

### Business Premise Forecast

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. A business premise index model was created based on the following formula:

$$BusIndex_{y,m} = \left(\frac{HStock_{y,m}}{HStock_{base}}\right)^{0.33} x \left(\frac{Pop_{y,m}}{Pop_{base}}\right)^{0.33} x \left(\frac{EmpNF_{y,m}}{EmpNF_{base}}\right)^{0.33}$$

Where:

y = year.

m = month,

base = 2010.

The forecasted indexed value was converted to a forecasted premise value for use in the neural network models.

Note that the Far West weather zone was modeled using a 5 year average premise growth rate instead of the business premise index model. This was due to the growth in premises being linear over the historical timeframe (i.e., appears that premise growth was not as subject to economic variations as the other weather zones).

### Industrial Premise Forecast

Industrial premise forecast was based on a 5 year average premise growth rate instead of an industrial premise index model. Originally, premises were required to exceed 1,000 kW for 2 months during the previous 12 months to be classified as IDR customers. This threshold was lowered to 700 kW in 2006. The lowering of the threshold resulted in a significant increase in the number of industrial premises. This step 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.

In addition, ERCOT will meet with Transmission Service Providers (TSPs) to gather information on the expected growth of industrial premises in their service territories. ERCOT will use this information to adjust their forecasted industrial premises as necessary.

### Average Use Per Premise

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 – 2013

was analyzed to determine a representative time period with normal weather. The time period from 8/1/2012 – 7/31/2013 was selected to represent typical weather.

### Weighted Premise Index

A weighted premise index was calculated for each weather zone. The index was defined as:

$$\begin{aligned} \text{Premise Index}_{y,m,d} = & \\ & \text{Residential Premise Forecast}_{y,m,d} \times \text{Residential Average Use Per Premise}_{y,m,d} \\ & + \text{Business Premise Forecast}_{y,m,d} \times \text{Business Average Use Per Premise}_{y,m,d} \\ & + \text{Industrial Premise Forecast}_{y,m,d} \times \text{Industrial Average Use Per Premise}_{y,m,d} \end{aligned}$$

where:

y = year.

m = month,

d = day.

### Load Forecast Comparison

Figure 4 presents the ERCOT summer peak demand forecasts for 2014 - 2022 from the 2013 LTDEF and the 2014 LTDEF.

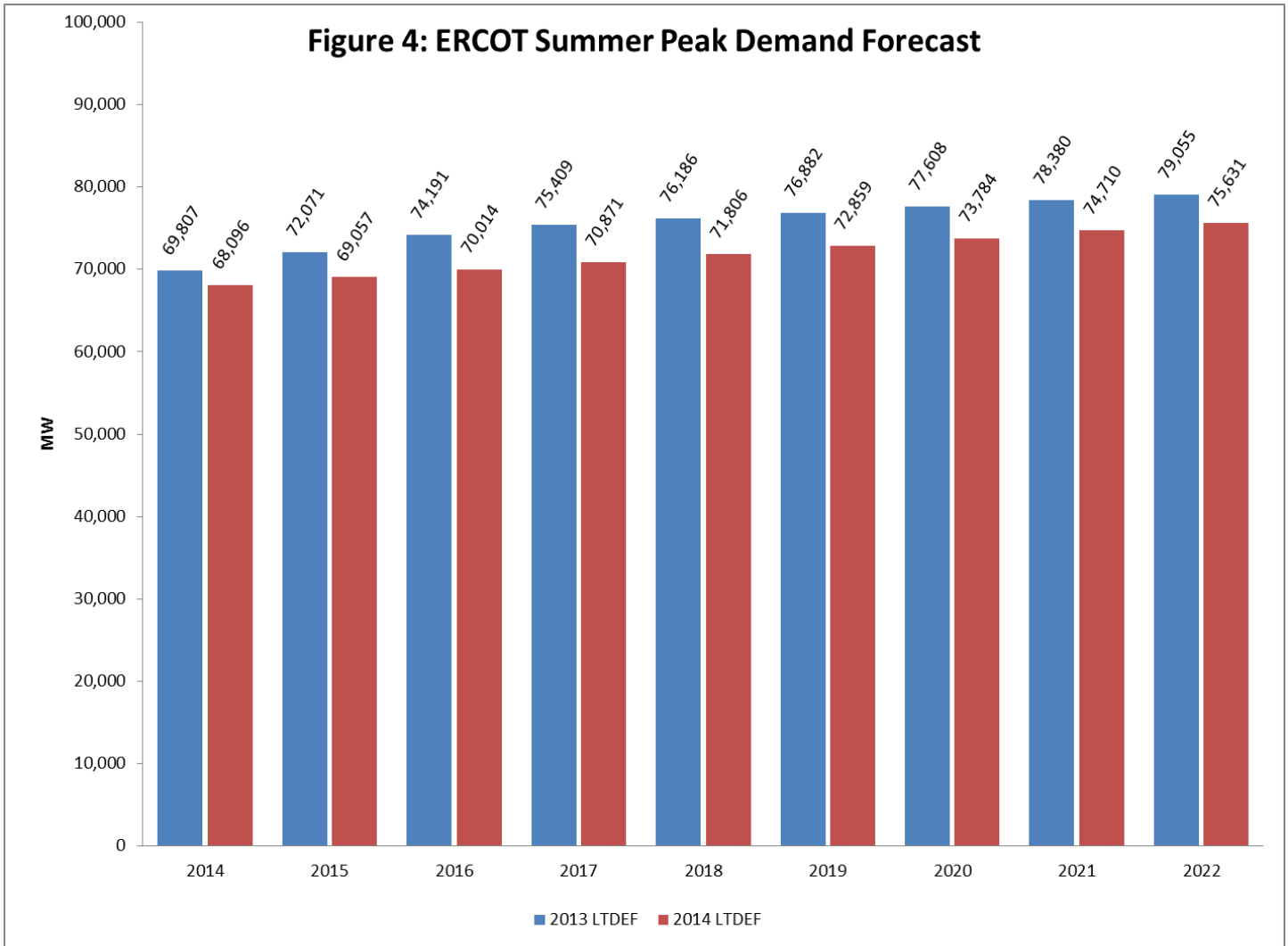
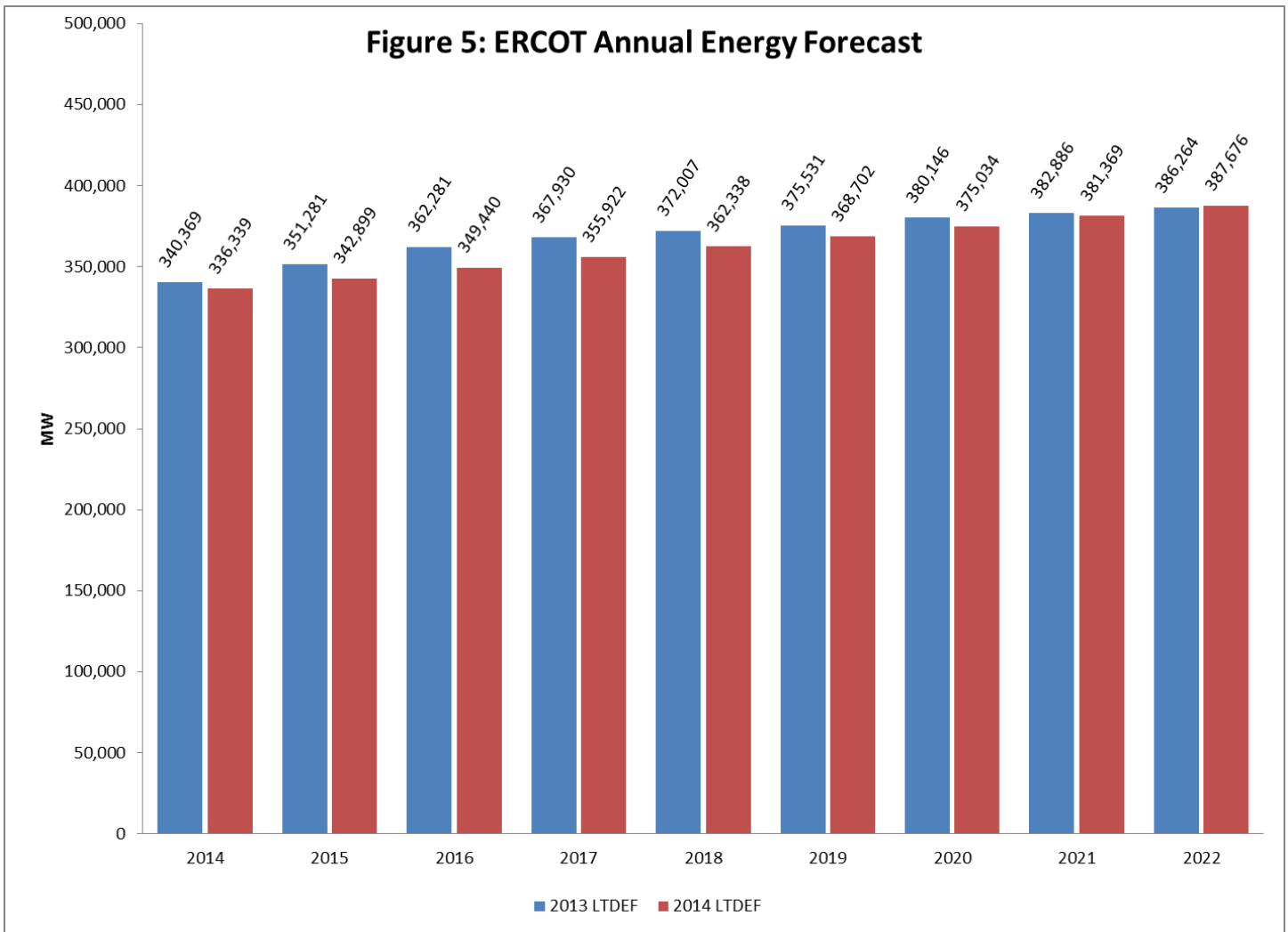


Figure 5 presents the ERCOT annual energy forecast for 2014 - 2022 from the 2013 LTDEF and the 2014 LTDEF.



Differences between the two forecasts are due to:

1. Previously, the daily energy models were linear regression models. The new models are neural network models.
2. Previously, non-farm employment was the key driver of load growth. The new models are based on a weighted premise index

### 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 six of these areas, namely:

1. Weather,
2. Economics,
3. Energy efficiency,
4. Demand response,
5. Onsite renewable energy technologies, and
6. Electric vehicles.

Weather Uncertainty

Figure 6 suggests the significant role of weather in forecasting any specific year. This figure shows what the 2014 forecasted peak demand would be using the actual weather from any one of the past twelve years as input in the model. As can be seen, there is considerable variability ranging from 64,090 MW using 2002's weather to 70,409 MW using 2011's weather. This equates to approximately a 10% difference in the forecast based on weather extremes.

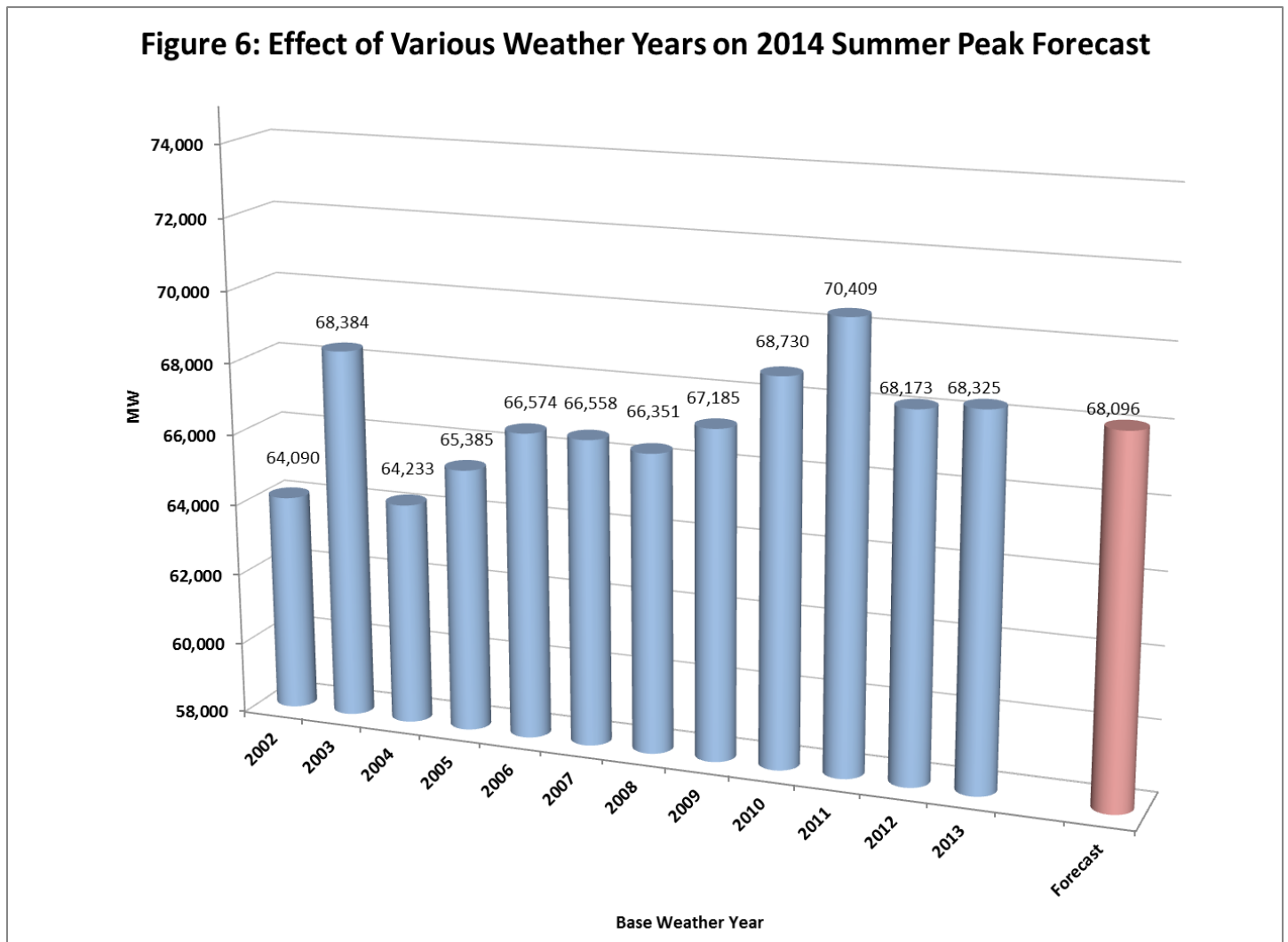
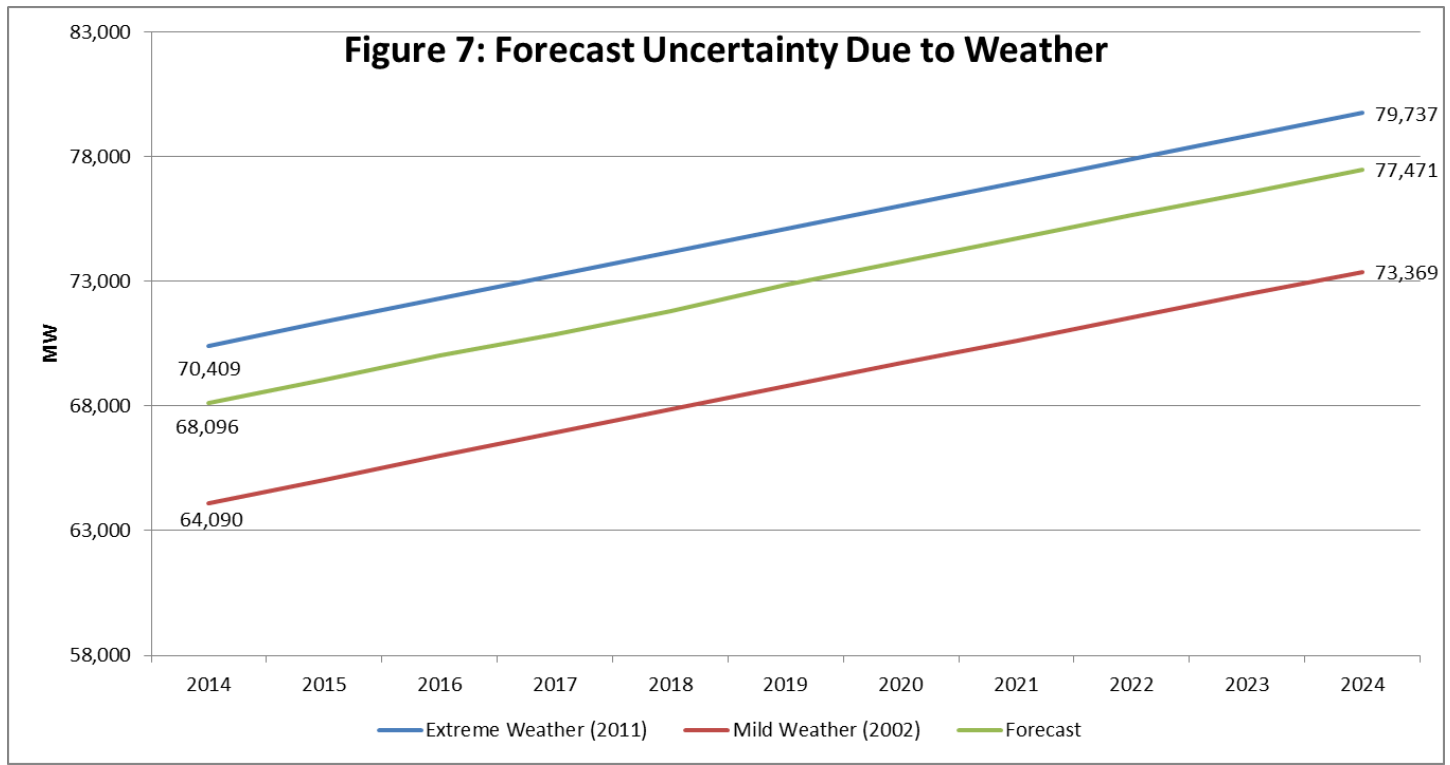


Figure 7 extends the uncertainty out to 2024. Assuming 2002 weather (identified as the mild weather scenario) in 2024, we would expect a peak of 73,369 MW. Assuming 2011 weather (identified as the extreme weather scenario) in 2024, results in a forecasted peak demand of 79,737 MW. This equates to approximately a 9% difference in the forecast based on weather extremes.



Economic Uncertainty

Economic uncertainty impacts the premise forecasts. Stated differently, significant changes in the economic forecasts will have impacts on the premise forecasts which in turn will be reflected in the forecast. Premise forecasts were based on Moody’s base economic scenario. ERCOT will create economic scenarios for the 2015 LTDEF.

Energy Efficiency

A much more difficult source of uncertainty to quantify was that derived from energy efficiency. First off, it must be recognized that the 2014 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 2013 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 12 in 2013, then the model assumes the same proportion in all forecasted years. The weather normalized average use per premise was held constant throughout the forecast time frame. In the future, ERCOT will create energy efficiency scenarios which adjust the average usage per premise based on data from the Energy Information Administration (EIA)<sup>3</sup>.

Demand Response Uncertainty

<sup>3</sup> For a discussion of the EIA scenarios, see the “Buildings Sector Case” at <http://www.eia.gov/forecasts/aeo/appendix.cfm>



Demand Response programs are in their infancy for much of ERCOT. There remains much uncertainty as to what future levels of demand response may be achieved. Similarly to Energy Efficiency, it must be recognized that the 2014 LTDEF was a “frozen” forecast with respect to Demand Response. Demand Response was reflected in the forecast at the level that was present in 2013. In the future, ERCOT will create Demand Response scenarios which will adjust the forecasted peak demands.

#### Onsite Renewable Energy Technologies Uncertainty

Another area of uncertainty is due to onsite renewable generation technologies. Examples include:

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 2014 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 2013. In the future, ERCOT will create scenarios for Onsite Renewable Energy Technologies.

#### Electric Vehicles Uncertainty

The growth of Electric Vehicles (EVs) has been accelerating. As an example, statistics indicate that the number of electric vehicles for the City of Austin has grown from 144 vehicles in 2010 to 988 this year (62% average annual growth rate). It appears that this trend will continue. Still the number of electric vehicles represents a very small percentage of the new car market in the United States. The 2014 LTDEF was a “frozen” forecast with respect to EVs. EVs are reflected in the forecast at the level that was present in 2013. ERCOT will continue to monitor the growth of electric vehicles in order to monitor their impact on the load forecast.

#### 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 2015 LTDEF.

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**Appendix A**  
**Peak Demand and Energy Forecast Summary**

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<b>Year</b>	<b>Summer Peak Demand (MW)</b>	<b>Energy (TWh)</b>
2014	68,096	336.3
2015	69,057	342.9
2016	70,014	349.4
2017	70,871	355.9
2018	71,806	362.3
2019	72,859	368.7
2020	73,784	375.0
2021	74,710	381.4
2022	75,631	387.7
2023	76,550	394.0
2024	77,471	400.2

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