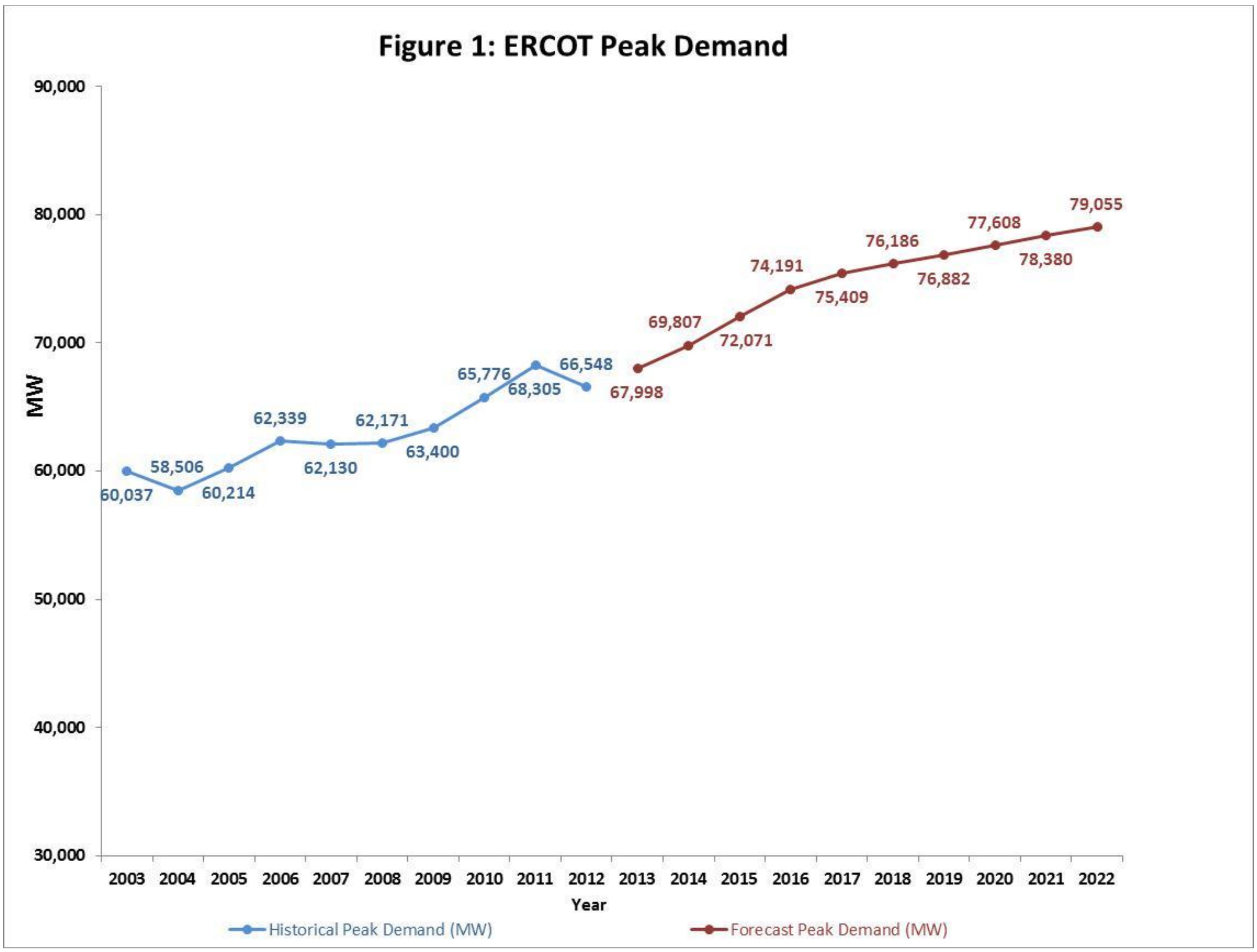
2013 ERCOT Planning

Long-Term Hourly Peak Demand and Energy Forecast

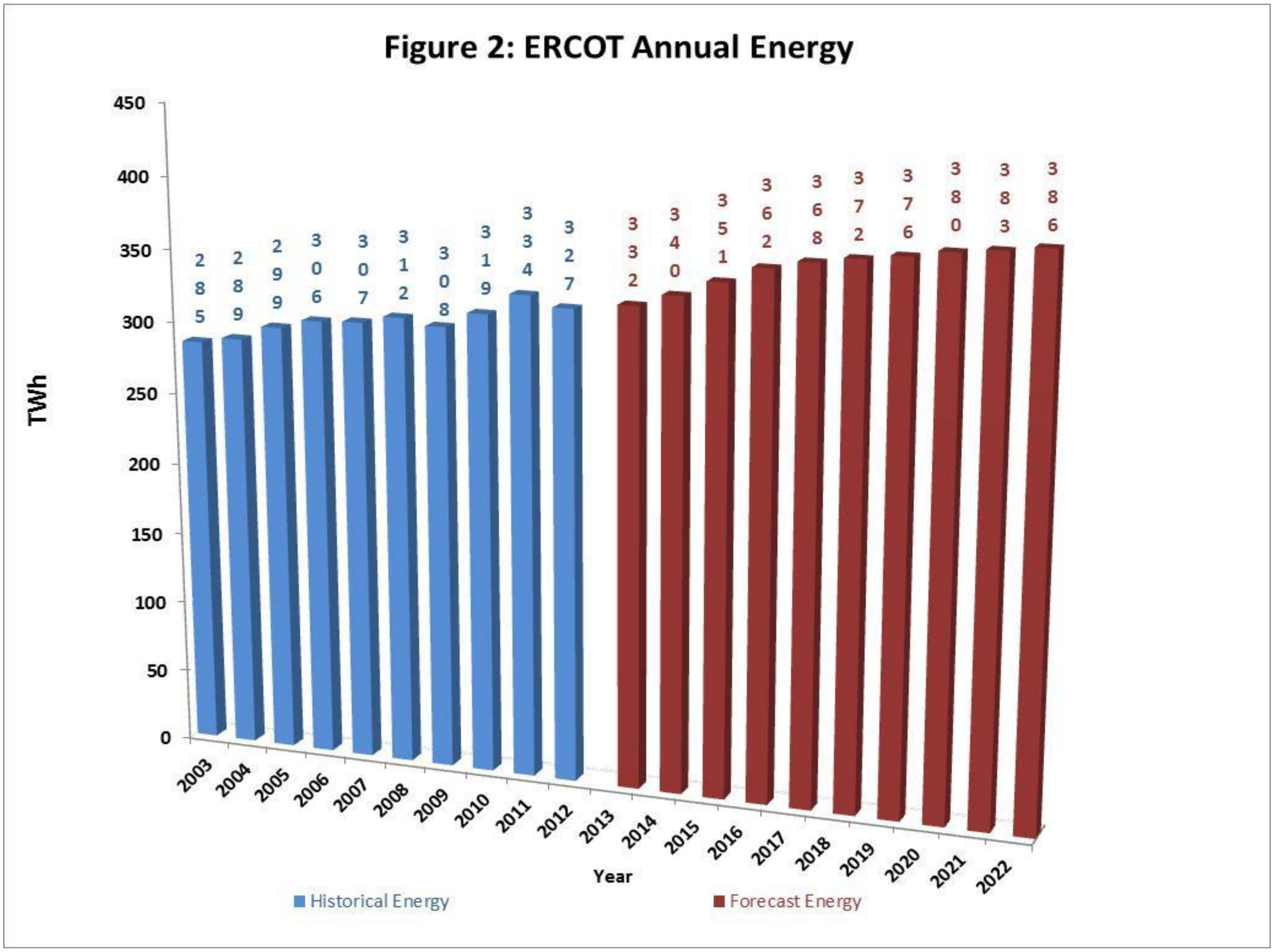
December 31, 2012

Executive Summary

The 2013 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 this 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) and weather variables (e.g., heating and cooling degree days). A county level forecast of economic and demographic data was obtained from Moody's. Fifteen 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, the 2013 LTDEF depicts system peak demand increasing around 2% to 3% for the 2013 to 2016 timeframe. After 2017, the growth in system peak demand is forecasted to slow to an average annual growth rate (AAGR) of approximately 1%. Seeing that the same "normal" weather profile is used for each year, the forecasted increase in peak demand is due strictly to Moody's economic forecast and the system peak tracks in lockstep with the economic forecast, as will be shown later in this report. ERCOT's peak demand occurs during the summer season.



Also suggested by Figures 1 and 2 are peak demand and energy AAGRs. Historically, annual energy for 2003 - 2012 grew at an AAGR of 1.5 percent. Peak demand grew at a slightly slower AAGR of 1.2 percent. The forecasted AAGRs for 2013-2022 are 1.9 percent for peak demand and energy. As will be elaborated on later in this document, economic growth is forecasted to accelerate for the next few years before slowing down. This underlies the energy and peak demand rate of growth.

<u>Introduction</u>

This report gives a high level overview of the 2013 LTDEF. The forecast methodology is described, highlighting its major conceptual and statistical underpinnings. The 2013 forecast results are presented in a manner comparing them to the 2012 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.

<u>Modeling Framework</u>

The 2013 LTDEF was produced with a set of econometric and neural network models that combine weather, economic, and calendar variables to capture and project the long-term trends extracted from the historical load data. Two sets of models were developed:

1. Daily Energy models and
2. Hourly Energy models.

<u>Daily Energy Models</u>

The long-term trend in daily energy is modeled by estimating a nonlinear relationship for each of the eight ERCOT weather zones between the dependent variable, Daily-MWh-Per-1000-Nonfarmjobs and the following:

1. Season,
    a. Summer (May, June, July, August, and September),
    b. Winter (December, January, and February),
    c. Spring (March and April), and
    d. Fall (October and November).

2. Day type,
    a. Weekdays excluding holidays,
    b. Saturday, and
    c. Sunday or holidays.

3. Weather variables, and
4. Daylight minutes.

The weather variables that are used may be different for each weather zone. Models for the summer season use two different cooling degree day thresholds (e.g., base 65, 68, 72, etc.) while models for the winter season use two different heating degree day thresholds (e.g., base 30, 33, 38, etc.). Models for both the fall and spring seasons use one heating degree day threshold and one cooling degree day threshold. Each cooling/heating degree day threshold is determined in a manner that maximizes the historical fit or performance of the model as measured by the R-square statistic. Using a model to determine cooling and heating degree thresholds is an improvement over the 2012 LTLF model.

Specifying degree days to multiple bases is a common method employed to enable using powerful linear regression techniques and still capture the inherent non-linear relationship between load and weather. A month like February of 2011, with a very moderate average monthly temperature can still exhibit a sizeable peak demand if it has a few days of extremely low temperatures. This is captured by including heating degree day variables to lower bases (e.g., base 40, base 30, etc.) in the model specification. Likewise, cooling degree days to higher bases (e.g., base 75, 80, etc.) will nicely capture the inherent non-linearity of extreme hot days.

It might be worthwhile to mention that this methodology is indeed powerful and the explanatory power as indicated by the coefficients-of-determination (r-square) for each zone are all greater than 0.9 and some approach 0.98, indicating that very little of the variation in the dependent variable is left unexplained. Such explanatory power is rare in cross-sectional models with a dependent variable expressed as a ratio (i.e., per 1000 jobs). Using a dependent variable ratio expression attenuates the forecasting risks posed by heteroscedasticity.

Seeing that load shapes are significantly different for weekdays, weekends, and holidays, a day type variable was included. In addition, daylight minutes were included in the model to account for the impacts of lighting.

The 2012 LTDEF was based on monthly energy models. Using daily energy models greatly increased the number of observations used to estimate the parameters in the forecast model (a daily model has 365 observations per year while a monthly model was limited to 12 observations per year).

Hourly Energy Model

The second stage in forecasting hourly load requires the allocation of the forecasted daily energy to each hour in the day. This is accomplished by using the forecasted daily energy as an input to a mathematical equation with the dependent variable being the Hour's-Fractional-Share-of-Daily-Energy. This highly non-linear equation is estimated with neural network models with the following input variables:

1. today's 7 a.m. dry bulb temperature,
2. today's noon dry bulb temperature,
3. today's 7 p.m. dry bulb temperature, and
4. the previous Hour's-Fractional-Share-of-Daily-Energy.

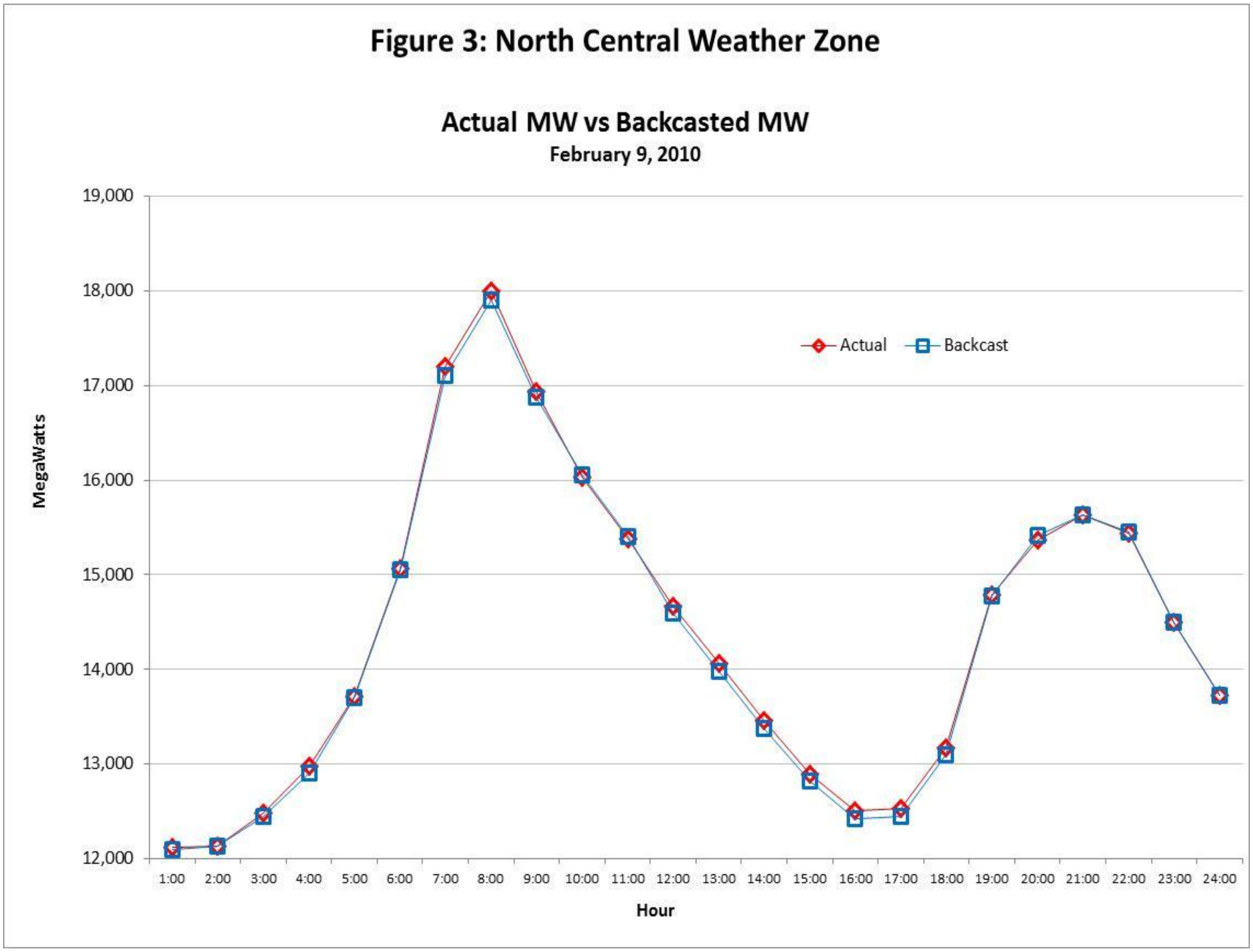
A separate neural network model was trained for:

(1) each Month (Jan-Dec),
(2) each Day type (Weekdays excluding holidays, Saturday, and Sunday or holidays), and
(3) each hour (1-24).

This resulted in a total of 864 trained neural network models for each weather zone used for forecasting.

Model validation was investigated by inputting actual monthly energy and employing the networks to backcast the hourly loads for each day in the historical load database. Figure 3 displays the typical results for one specific day.

Neural network models have a long and storied history in load forecasting technical literature. (For an earlier review of the literature, see Hippert, et al., "Neural Networks for Short-Term Load Forecasting: A Review and Evaluation," IEEE TRANSACTIONS ON POWER SYSTEMS, Vol. 16, No. 1, February 2001. For a nice conceptual treatment, see http://www.icfc.ilstu.edu/icfcpapers97/ynotpi.pdf).



<u>Determination of the Normal Weather Year</u>

A key input of both energy models is the forecasted weather. A normal (typical) weather hourly profile is used in both models. Using normal weather in the forecast models means that it is expected on a 50% probability basis, that the daily energy forecast (or peak demand forecast) has a 50% probability of being under or over the actual energy (or peak). This is also known as the 50/50 forecast.

There are many ways of deriving a normal weather year. Approaches such as the following can be used:

1. Based on average temperature,
2. Typical meteorological year,
3. Rank and Average methodology,
4. Based on weather conditions at time of peak,
5. Rotating historical weather through a calendar, and

6. Combinations of the above.

There is no universally accepted best approach. Each of the approaches has strengths and weaknesses. ERCOT's analysis included 15 years of weather data (1998–2012). The methodology that ERCOT used to create the "normal" weather year begins by calculating monthly temperature extremes (minimum temperature for the winter months and maximum temperature for the rest of the months of the year), for each weather zone, for each of the historical years from 1998 - 2012. Weather data for the months of June, July, August, and September is used to determine the annual maximum temperature. The 15 year average annual maximum temperature is assigned to the summer peak month (August). This better accounts for likely high temperatures at the time of the summer peak. Similarly, weather data for the months of December, January, and February is used to determine the annual minimum temperature. The 15 year annual minimum temperature is assigned to the winter peak month (January). This better accounts for likely low temperatures at the time of the winter peak. For the rest of the months, calculate each month's maximum temperature (for March, April, May, June, July, Sept, Oct, and Nov) or minimum temperature (Feb and Dec) and the 15 year average of these values. Using multiple months to determine the winter peak weather conditions was an improvement in this model as compared to the 2012 LTDEF.

At this point, each weather zone has the following:

1. 15 year average maximum monthly temperature (March through July and September through November),
2. 15 year average minimum monthly temperature (December and February),
3. 15 year average maximum annual temperature (assigned to August),
4. 15 year average minimum annual temperature (assigned to January), and
5. 15 year average monthly temperature (all months).

For each weather zone:

1. For each individual month of March through July and September through November, select the corresponding historical month that has the closest maximum temperature to the 15 year average maximum monthly temperature.
2. For the months of December and February, select the corresponding historical month that has the closest minimum temperature to the 15 year average minimum monthly temperature.
3. For the month of August, select the historical August that has the closest maximum temperature to the 15 year average maximum annual temperature.
4. For the month of January, select the January that has the closest minimum temperature to the 15 year average minimum annual temperature.

The hourly data from each selected historical month will be used to create the "normal" weather file for the corresponding month.

After the historical month is determined, a comparison is made between the selected historical month's average temperature and the 15 year average temperature of that month. The selected historical month's hourly temperatures are adjusted to reflect the 15 year average mean temperature for that month in a manner that does not change the maximum or minimum temperature. This process allows for a "normal" weather month to be created that reflects the 15 year average maximum (or minimum) and average temperatures.

The final step is to time align the date of the monthly maximum or minimum temperature. This is necessary in order to have representative weather conditions at the time of the monthly peaks.

ERCOT will continue to evaluate weather normalization approaches for use in their long-term forecasting process.

<u>Economic Forecast</u>

Another key input of both energy models is the forecast of non-farm employment. There is great uncertainty as to the current condition of the United States economy and to its future direction. Texas thus far has not been impacted to the same extent as the United States as a whole. This has led to Texas having somewhat stronger economic growth than most of the rest of the nation.

In the past, Moody's has provided ERCOT with three economic forecast scenarios:

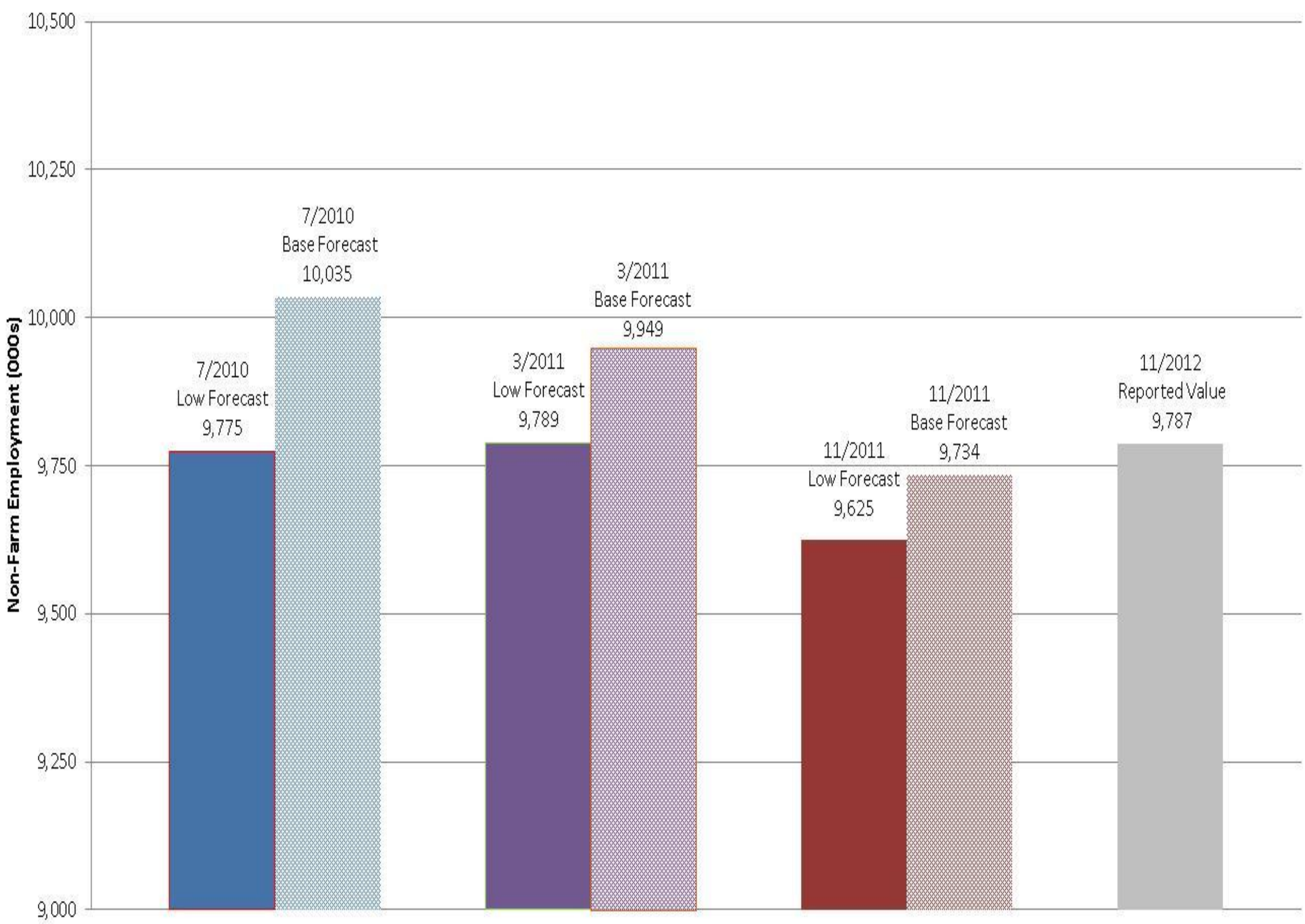
1. Low,
2. Base, and
3. High.

This year Moody's provided ERCOT with seven additional forecast scenarios:

1. Protracted Slump,
2. Deeper Second Recession,
3. Stronger Near-Term Rebound,
4. Fiscal Cliff,
5. Below Trend Long-Term Growth,
6. Mild Second Recession, and
7. Oil Price Increase / Dollar Crash Inflation.

A review of the last three forecasts from Moody's was conducted to determine their historical accuracy. Moody's created these forecasts in July of 2010, March of 2011, and November of 2011. Figure 4 shows 2012 year end non-farm employment values based on these three forecasts. The low and base scenarios are included. As indicated by Figure 4, the low scenario for July, 2010 and March, 2011 more accurately forecasted non-farm employment for 2012 than their respective base scenario. The November, 2011 base scenario more accurately forecasted non-farm employment than its associated low scenario.

Figure 4: Previous Moody's Non-Farm Employment Forecasts - 2012



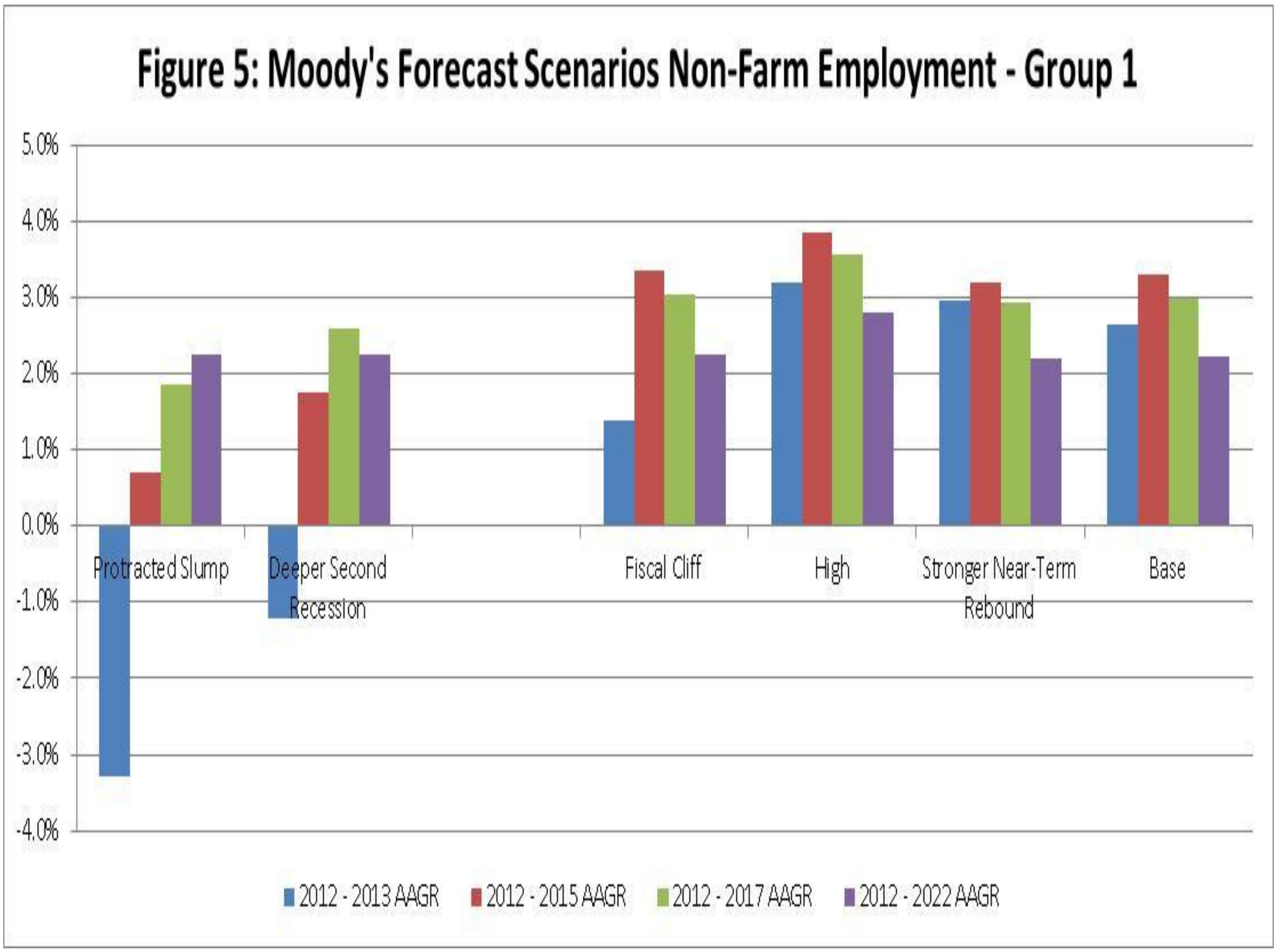
After completing the historical review of Moody's forecasts, an analysis was performed on the November, 2012 Moody's scenarios. This analysis focused on forecasted AAGRs for the next 3 years (2012 – 2015), 5 years (2012 – 2017), and 10 years (2012 – 2022). The forecasted AAGR's were compared to historical AAGR's for the most recent 3 years (2009 – 2012), 5 years (2007 – 2012), and 10 years (2002 – 2012).

The historical AAGR's were:

1. 2.1% for 2009 through 2012,
2. 0.8% for 2007 through 2012, and
3. 1.6% for 2002 through 2012.

The AAGR for 2007 through 2012 is very low compared to the other time periods due to the impact of the 2009 recession. This observation led to the 5 year AAGR comparison being removed from the analysis.

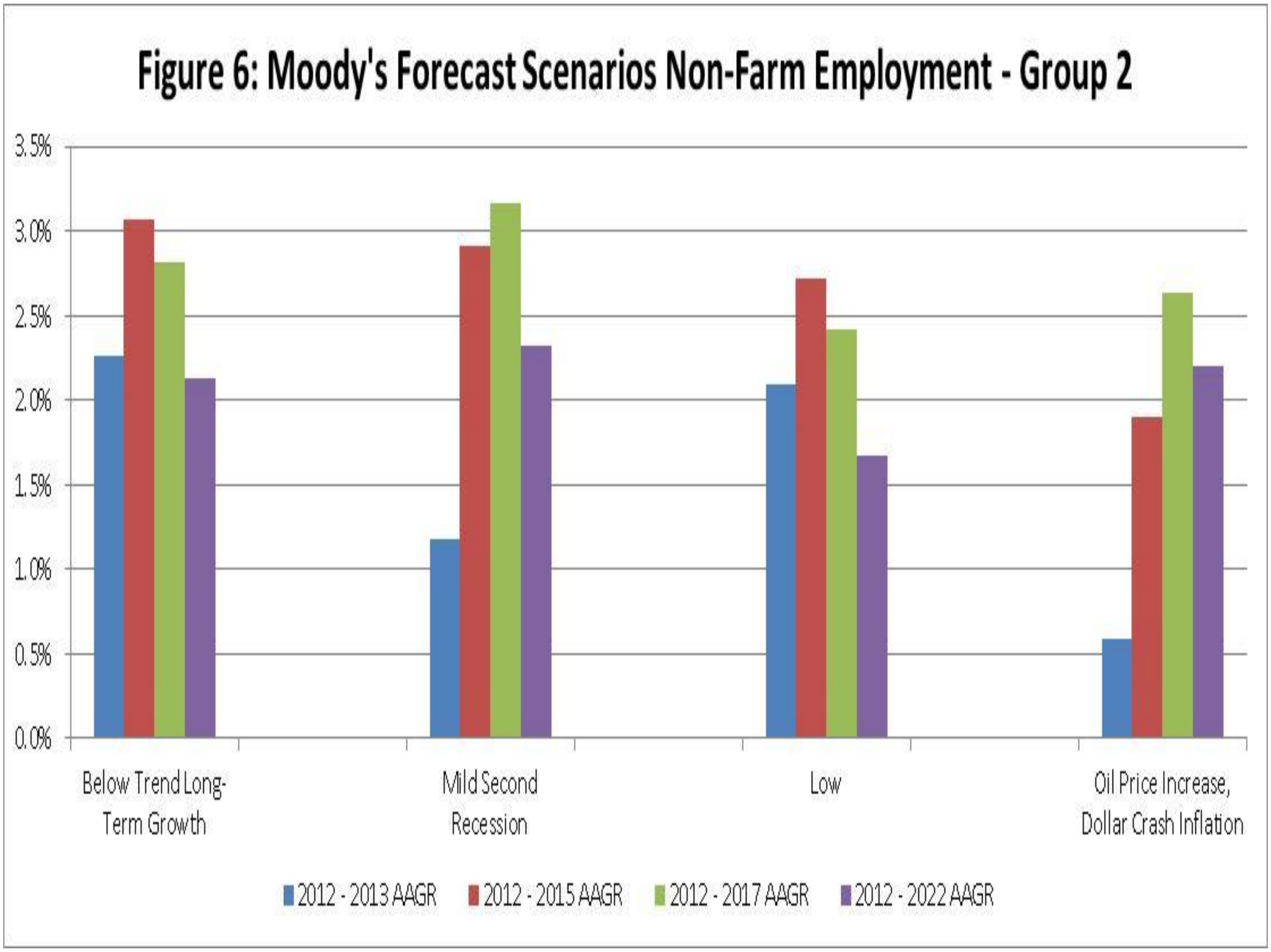
Figure 5 contains data for six of the ten scenarios that were provided by Moody's.



The Protracted Slump and the Deeper Second Recession scenarios were considered unlikely due to forecasted decreases in non-farm employment for 2013. The Fiscal Cliff, High, Stronger Near-Term

Rebound, and Base scenarios were also removed from consideration due to having forecasted 10 year and 3 year AAGRs well above the respective historical AAGRs.

Figure 6 contains data for the remaining four scenarios that were provided by Moody's.



The Below Trend Long-Term Growth, Mild Second Recession, and Oil Price Increase Dollar Crash Inflation scenarios were also removed from consideration due to forecasted 10 year AAGRs well above the historical 10 year AAGR (1.6%). Also the Below Trend Long-Term Growth and Mild Second Recession scenarios forecasted 3 year AAGRs well above the historical 3 year AAGR (2.1%).

As a result of the historical review and the analysis of current Moody's forecasts, ERCOT decided to use the Moody's low scenario of non-farm employment in the 2013 LTDEF. The 2012 LTDEF was based on the Moody's base scenario of non-farm employment.

In 2012, ERCOT added Woods and Poole as an additional economic data provider. Unfortunately their 2012 economic forecast will not be available in time to be included in this document. ERCOT will create a forecast based on Woods and Poole's forecast during the first quarter of 2013. The results will be available on ERCOT's website.

ERCOT will continue to evaluate economic data and trends for use in their long-term forecasting process. This will include evaluating the use of additional economic forecast providers.

Load Forecast Comparison

Figure 7 presents the ERCOT annual peak demand forecasts for 2013-2020 from the 2012 LTDEF and the 2013 LTDEF. The forecasted AAGR of demand is 1.9 percent for the 2013 LTDEF as compared to 2.8 percent from the 2012 LTDEF. ERCOT experiences its highest peak demand during the summer.

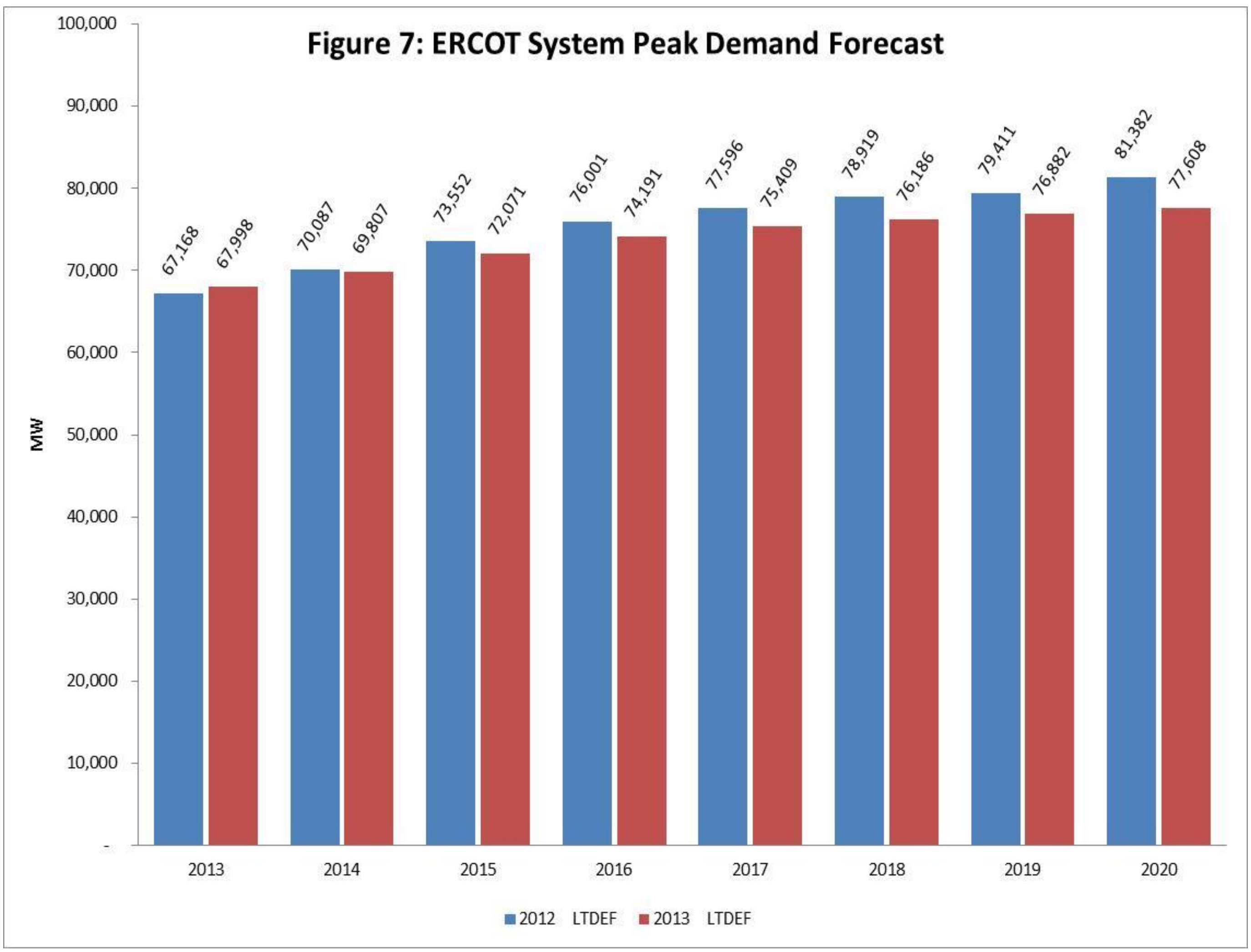
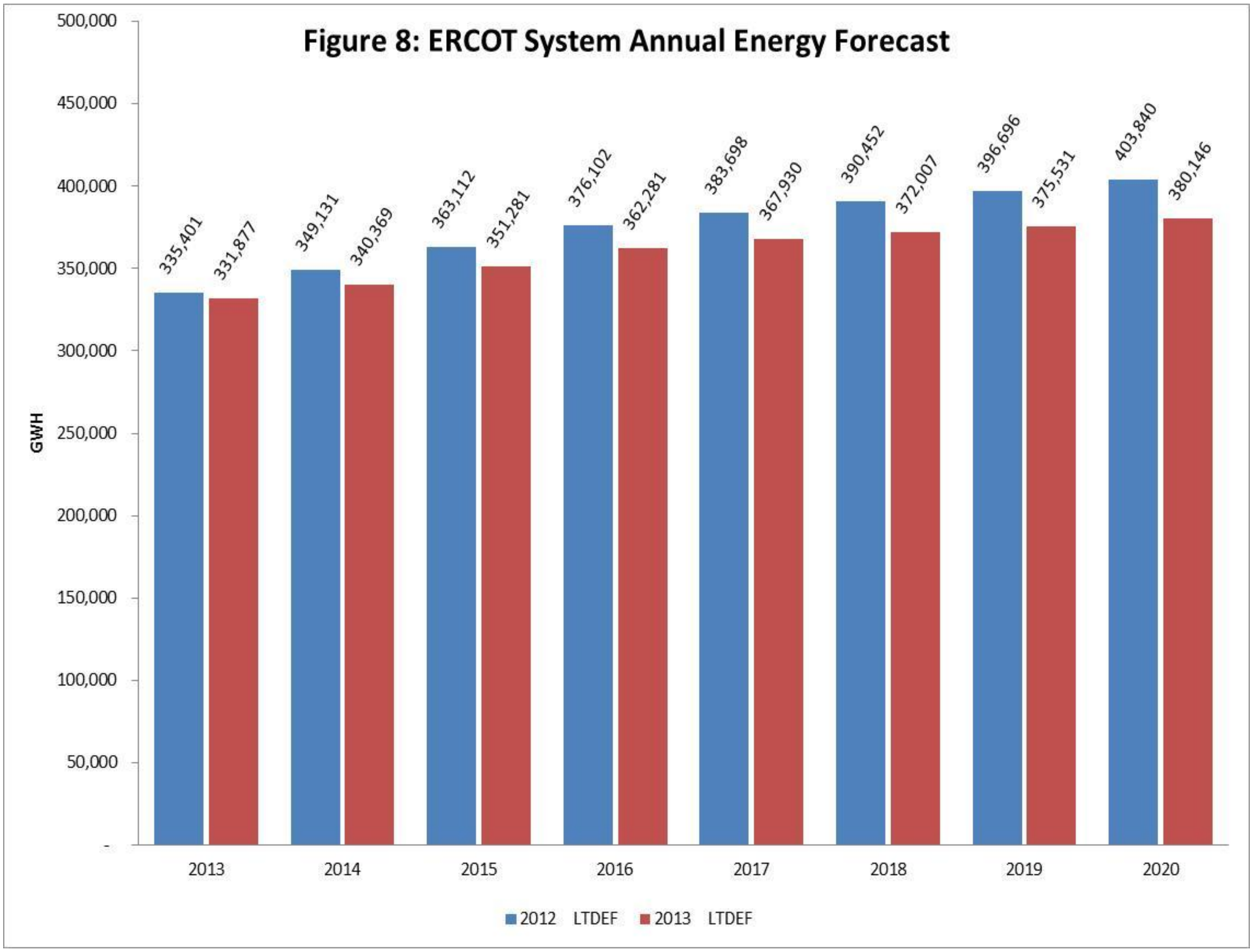
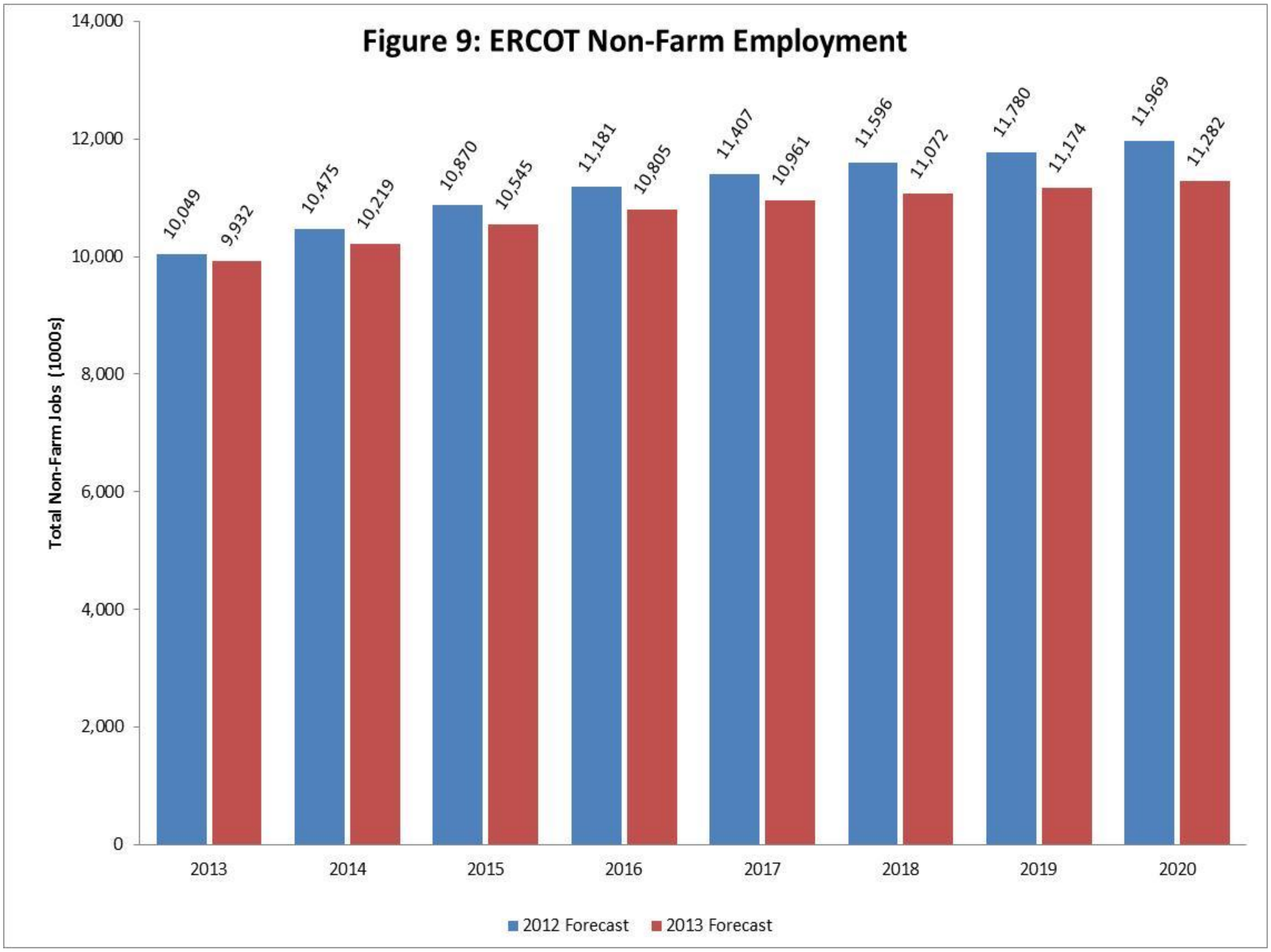


Figure 8 presents the ERCOT annual energy forecast for 2013-2020 from the 2012 LTDEF and the 2013 LTDEF. The forecasted AAGR of energy is 2.0 percent for the 2013 LTDEF as compared to 2.7 percent from the 2012 LTDEF.



Differences between the two forecasts are predominantly due to changes in the economic forecasts that were used. As stated previously, the 2013 LTDEF used the Moody's Low scenario while the 2012 LTDEF used the Moody's Base scenario.

Figure 9 shows the forecast of Non-farm Employment (the primary economic variable used by both forecasts). The 2013-2020 Non-farm Employment AAGR used in the 2013 LTDEF is 1.8 percent. For the 2012 LTDEF, it was 2.3 percent.



Load Forecast Uncertainty

There are six major sources of uncertainty:

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

Weather Uncertainty

Figure 10 suggests the significant role of weather in forecasting any specific year. This figure shows what the 2013 forecasted peak demand would be using the actual weather from any one of the past ten years as input in the model. As can be seen, there is considerable variability ranging from 63,000 MW using 2004 weather to upwards of 70,000 MW using 2011 weather.

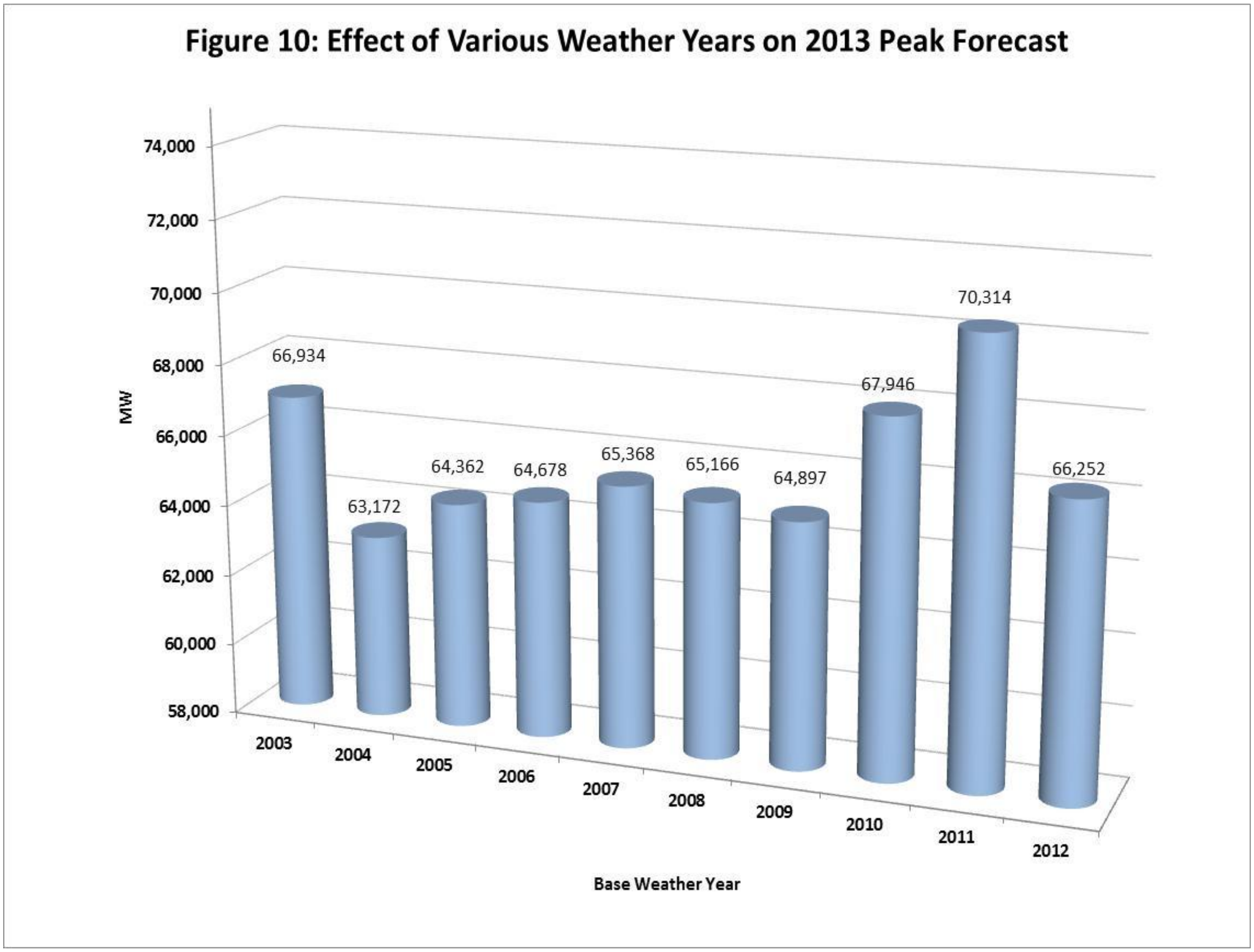
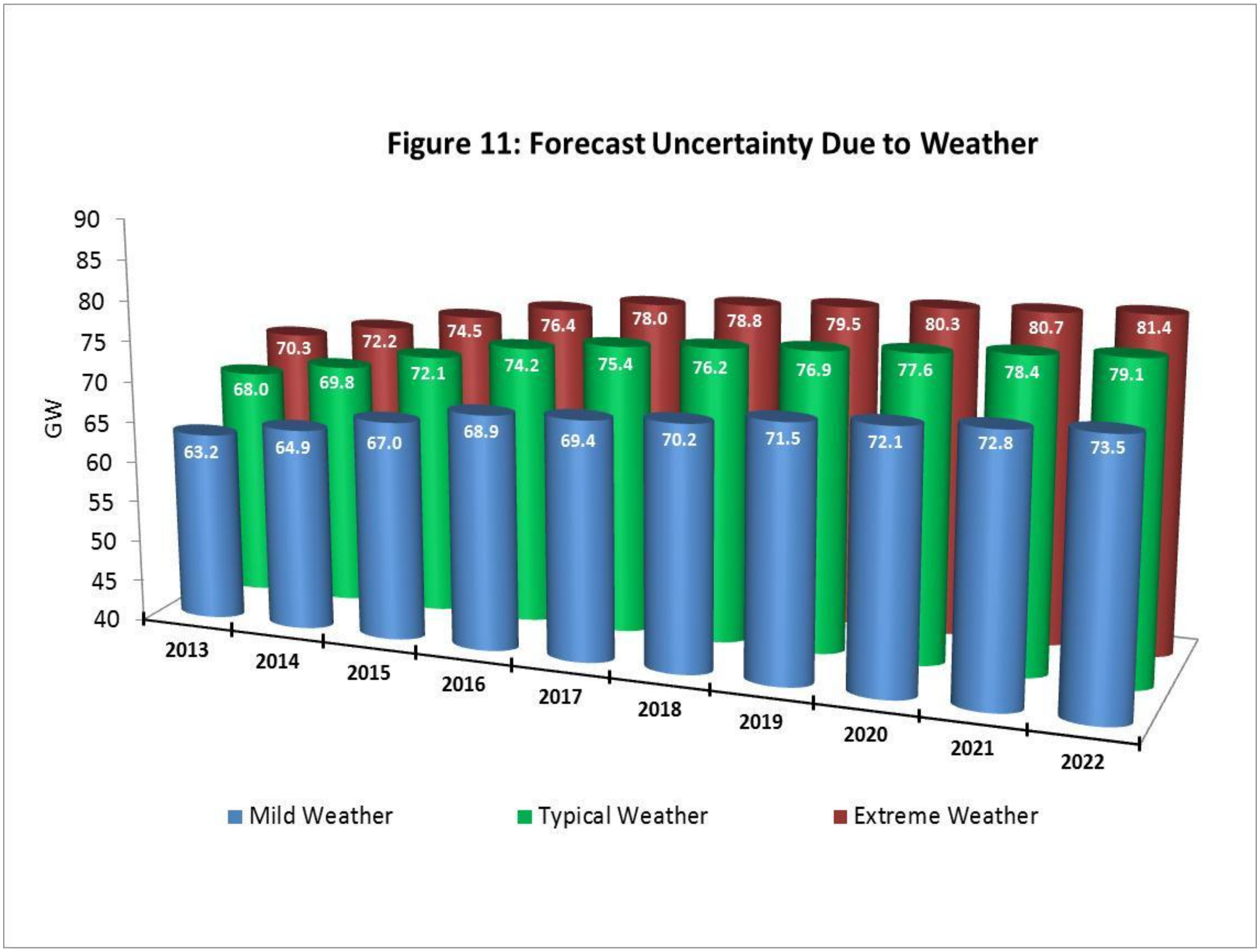


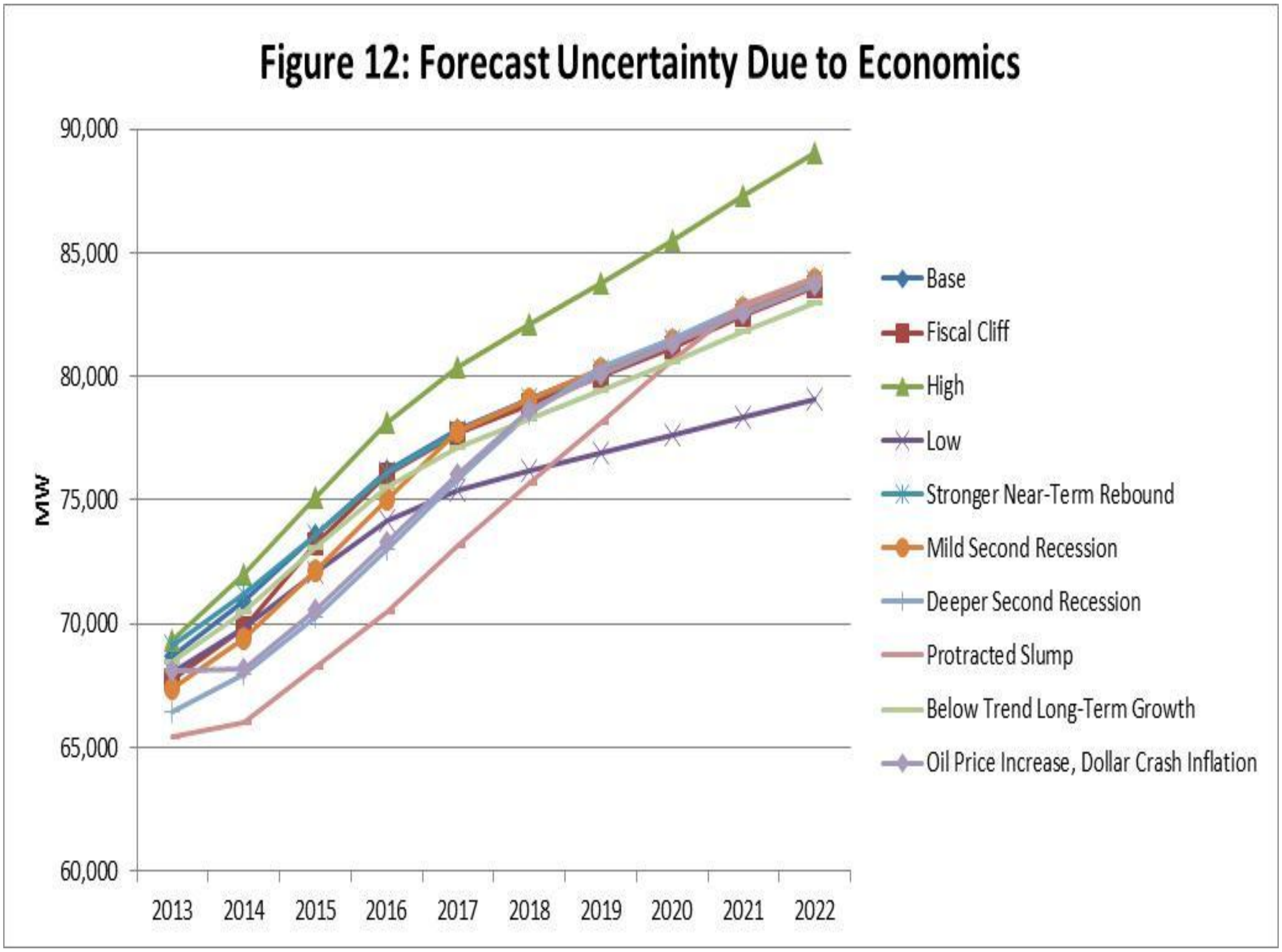
Figure 11 extends the uncertainty out to 2022. Assuming 2004 weather (identified as the mild weather scenario) in 2022, we would expect a peak of 73,500 MW. Assuming 2011 weather (identified as the extreme weather scenario) in 2022, results in a forecasted peak demand of 81,400 MW.



<u>Economic Uncertainty</u>

Figure 12 shows uncertainty deriving from economics. Based on Moody's Low economic scenario, we may expect, ceteris paribus[1], a 2022 peak of 79,055 MW. Using Moody's High economic scenario, we expect a 2022 peak of 89,056 MW. An interesting observation from Figure 12 is that by 2020, all of the additional Moody's scenarios converge to the base scenario leaving in effect only 3 different scenarios.

[1] Latin phrase, literally translated as "with other things the same," or "all other things being equal or held constant."



<u>Energy Efficiency Uncertainty</u>

A much more difficult source of uncertainty to quantify is that derived from energy efficiency. First off, it must be recognized that the 2013 LTDEF is a "frozen efficiency" forecast. That means the forecast model employs statistical techniques that unyieldingly fix the relationships between load, weather, and economics at their 2012 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 2012, then the model assumes the same proportion in all forecasted years.

ERCOT has developed additional energy efficiency forecast scenarios which are based on data from the Energy Information Administration (for a discussion of the EIA scenarios, see the "Buildings Sector Case" at <u>http://www.eia.gov/forecasts/aeo/appendixe.cfm</u>). In these scenarios, the coefficients are adjusted over time in order to reflect future improvements in energy consumption via improved energy efficiency. These scenarios will be published on ERCOT's website during the first quarter of 2013.

Demand Response Uncertainty

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 2013 LTDEF is a "frozen" forecast with respect to Demand Response. Demand Response is reflected in the forecast at the level that was present in 2012.

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 2013 LTDEF is 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 2012.

Electric Vehicles Uncertainty

Growth of Electric Vehicles (EVs) has been slow so far. This has not reduced future uncertainty as to the forecasted number of EVs for future years. The 2013 LTDEF is a "frozen" forecast with respect to EVs. EVs are reflected in the forecast at the level that was present in 2012.

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 2014 LTDEF.

Appendix A
Peak Demand and Energy Forecast Summary

Year	Summer Peak Demand (MW)	Energy (TWh)
2013	67,998	331.9
2014	69,807	340.4
2015	72,071	351.3
2016	74,191	362.3
2017	75,409	367.9
2018	76,186	372.0
2019	76,882	375.5
2020	77,608	380.1
2021	78,380	382.9
2022	79,055	386.3

Appendix B
Forecasted Temperatures at time of Summer Peak

Metropolitan Area	Summer Peak Temperature (^{o}F)
Austin/San Antonio	102.2
Dallas/Fort Worth	104.7
Houston	99.2