ERCOT Planning

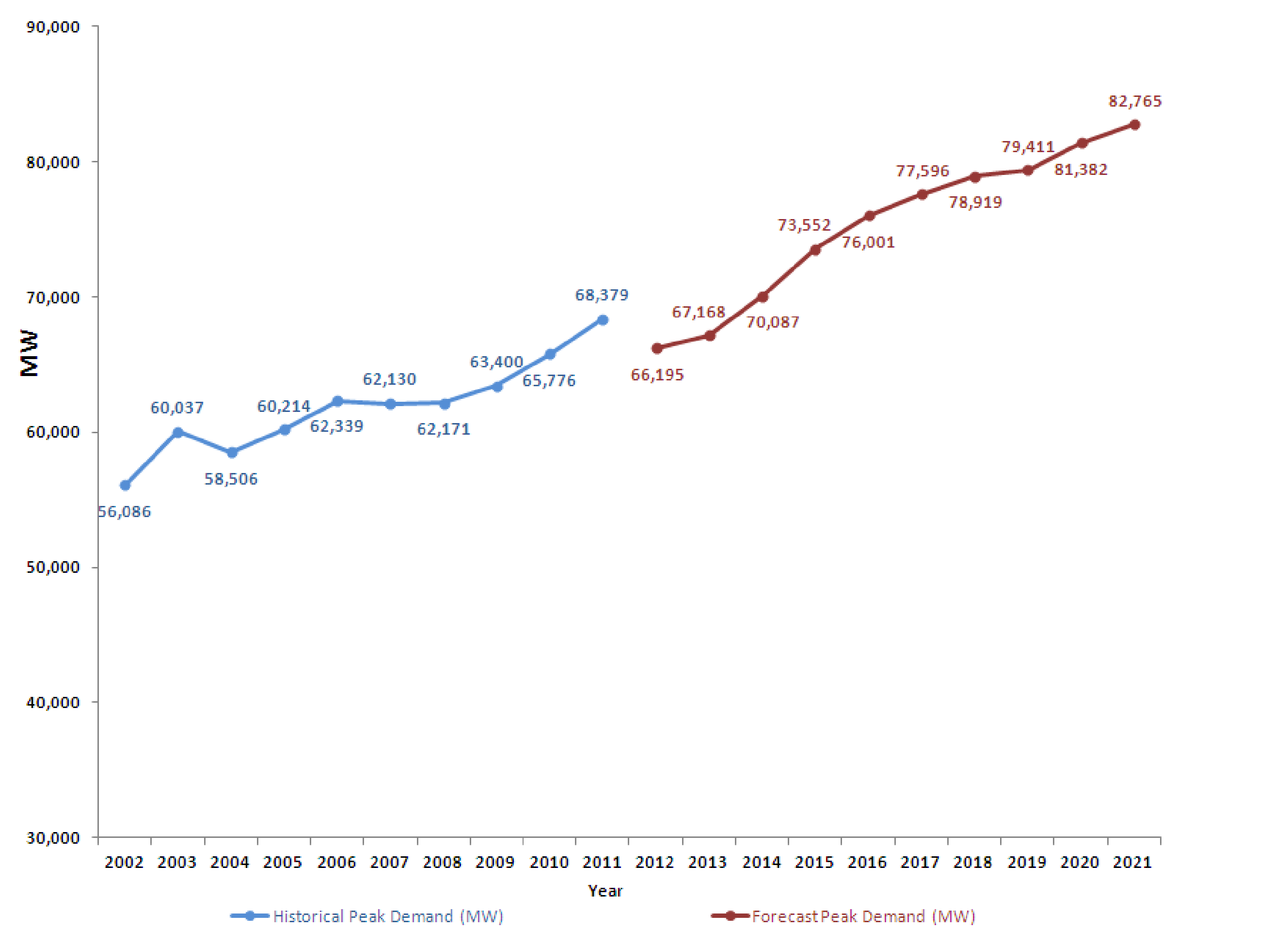
2012 Long-Term Demand and Energy Forecast

December 31, 2011

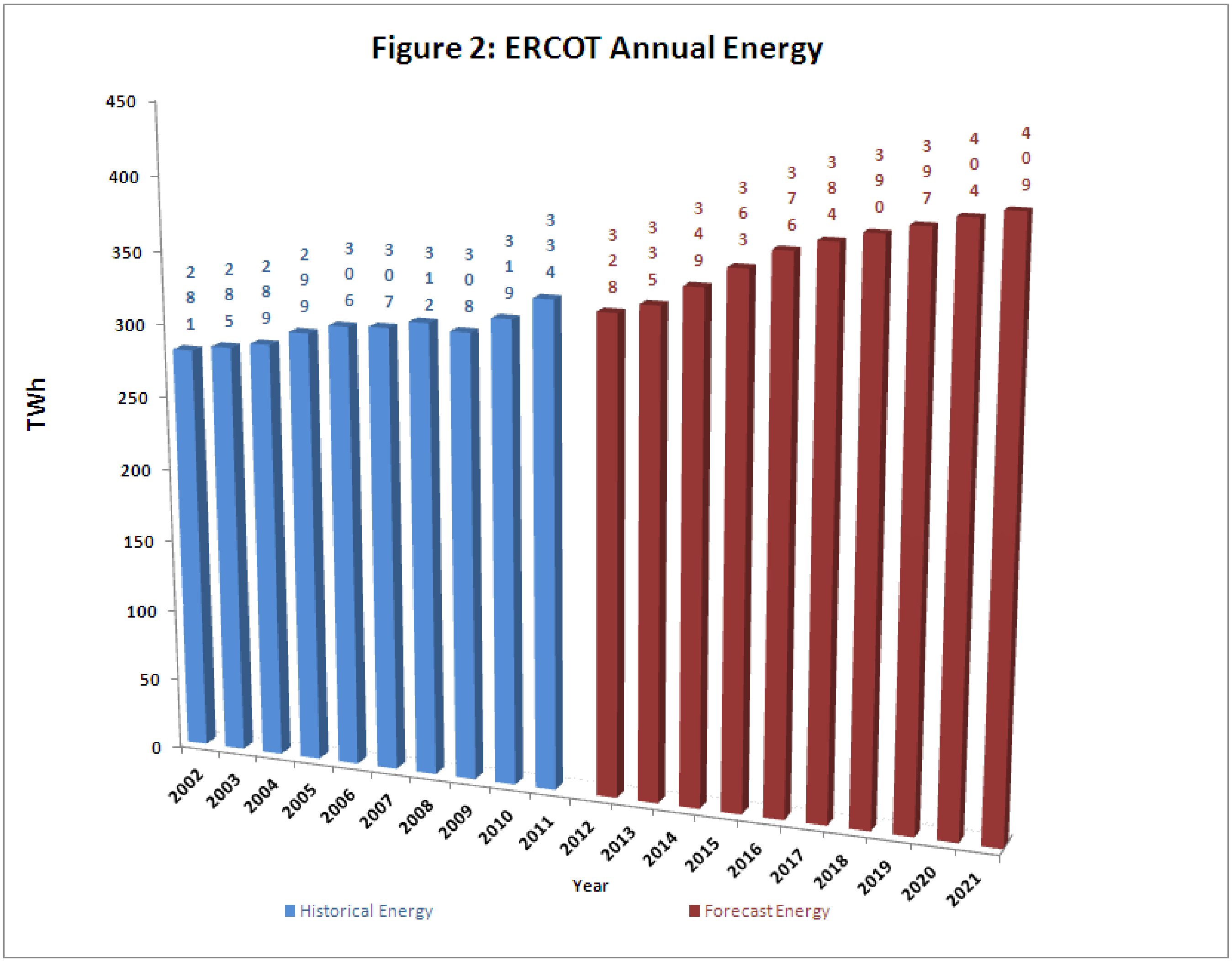
Executive Summary

The 2012 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., non-farm payroll employment) and weather variables (e.g., heating and cooling degree days). Economic and demographic data, including a county-level forecast, are obtained on a monthly basis from Moody's Economy.com. Historical monthly economic and demographic data for each county are provided back to 1990. 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.

Figure 1: ERCOT Peak Demand



As shown by Figure 1, the 2012 LTDEF depicts an initial two-year decrease in system peak demand from the 2011 value of 68,379 MW, followed by an eight-year (2014-2021) steady increase. The initial decrease is due to the forecasted weather being "normal" (or typical) based on the most recent 15 years' weather data coupled with the fact that the summer of 2011 was one of the hottest summers ever in the state of Texas. Seeing that the same "normal" weather profile is used for each year, the forecasted increase in peak demand and for energy can be attributed to the Moody's economic forecast.



Also shown in Figures 1 and 2, annual energy for 2002-2011 grew at a compound annual growth rate of 2.0 percent. Peak demand grew at a slightly faster rate of 2.2 percent. The forecasted annual growth rates for 2012-2021 are 2.5 percent for peak demand and energy. Again, as will be elaborated on later in this document, economic growth is forecasted to accelerate and underlies the energy and peak demand growth rates.

Introduction

This report gives a high level overview of the 2012 Long-Term Demand and Energy Forecast (LTDEF). The forecast methodology is described, highlighting its major conceptual and statistical underpinnings. The 2012 forecast results are presented in a manner comparing them to the 2011 LTDEF. This allows for a direct comparison of results and also facilitates an explanation for the changes. Finally, an examination of the six major sources of forecast uncertainty is presented: weather, economics, energy efficiency, demand response, onsite renewable energy technologies, and electric vehicles.

Modeling Framework

The 2012 Long-Term Demand and Energy Forecast 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 of the past eight years. Two sets of models were developed:

1. Monthly energy models and
2. Hourly energy models.

Monthly Energy Models

The long-term trend in monthly energy is modeled by estimating a non-linear relationship for each of the eight ERCOT weather zones between the dependent variable, monthly-mwh-per-1000-non-farmjobs-per-day, and a set of weather variables including:

i. Cooling-degree-days-to-base-65 (cdd65),
ii. Cooling-degree-days-to-base-75 (cdd75),
iii. Cooling-degree-days-to-base-85 (cdd85),
iv. Heating-degree-days-to-base-40 (hdd40),
v. Heating-degree-days-to-base-50 (hdd50), and
vi. Heating-degree-days-to-base-65 (hdd65).

Different models were created by season with the summer season including April, May, June, July, August, and September and the winter season including October, November, December, January, February, and March. Specifying degree days to the various 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 2011, with a very moderate *"average"* monthly temperature can still exhibit a sizeable monthly load if it has a week of extremely low temperatures. This is captured by including the hdd40 variable in the model specification. Likewise, the cdd85 variable will capture summer non-linearity. The specific set of weather variables for each weather zone (i.e., Coast, East, Far West, North, North Central, South, South Central, and West) is determined on the basis of statistical significance. The set of degree day variables differs by zone. All of these models have coefficient-of-determination (R-Square) values greater than 0.9. Using a dependent variable ratio expression attenuates the forecasting risks posed by heteroscedasticity.

<u>Hourly Energy Model</u>

The second stage in forecasting hourly load requires the allocation of the forecasted monthly energy to each hour in the month. This is accomplished by using the forecasted monthly energy as an input to a mathematical equation with the dependent variable being the hour's-fractional-share-of-monthly-energy.

This highly non-linear equation is estimated with neural network models with the following input variables:

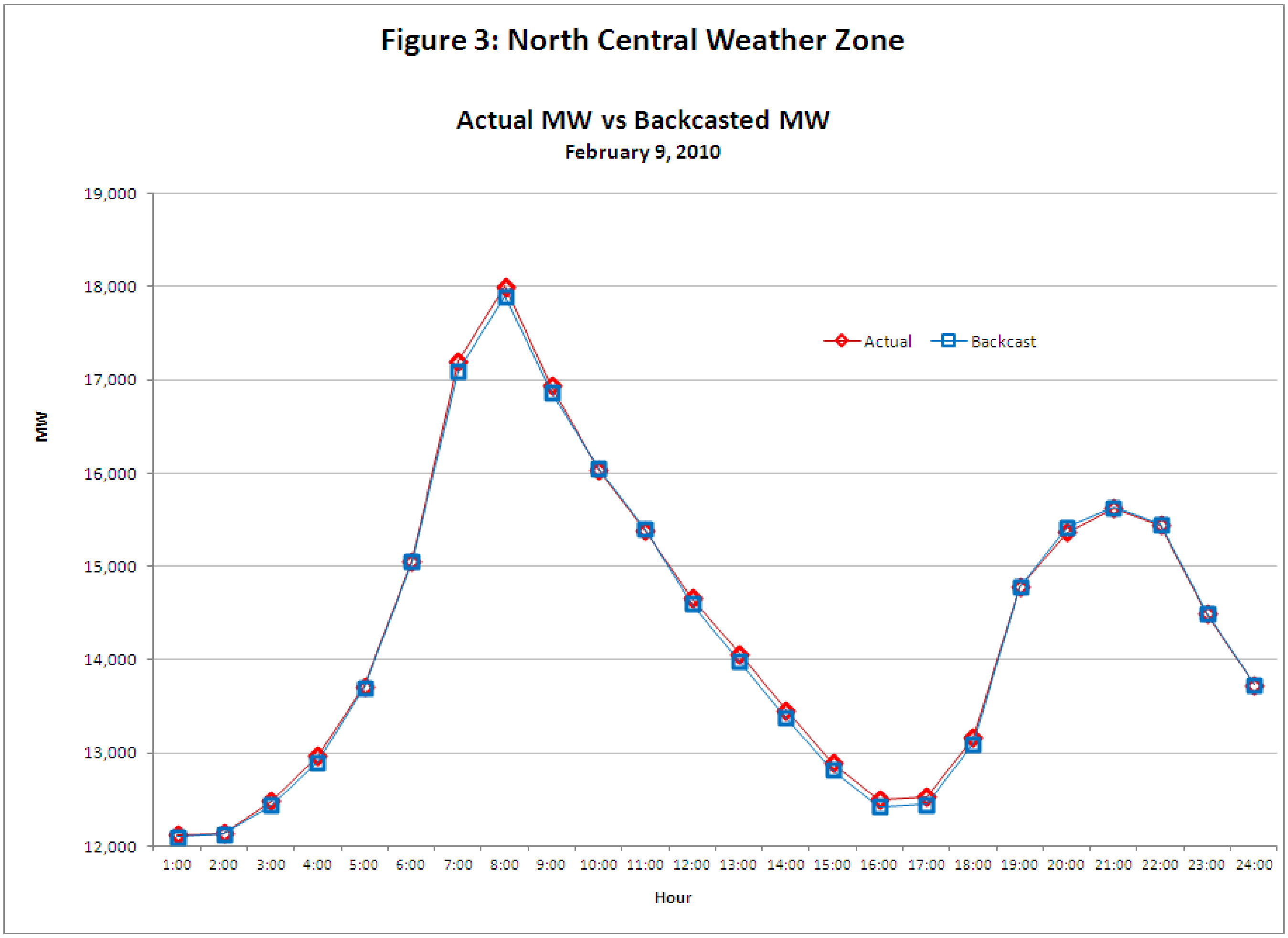
i. the previous day's maximum daily dry bulb temperature (dbt),
ii. the previous day's minimum dbt,
iii. the forecasted day's maximum dbt,
iv. the forecasted day's minimum dbt,
v. the forecasted day's 7a.m. dbt,
vi. the forecasted day's noon dbt,
vii. the forecasted day's 7p.m. dbt,
viii. the forecasted day's sunset time,
ix. monthly average dbt,
x. year, and
xi. the previous hour's-fractional-share-of-monthly-energy.

A separate neural network model was trained for:

i. each month (Jan-Dec),
ii. each day-type (weekdays excluding holidays, Saturdays, and Sundays or holidays), and
iii. each hour (1-24).

A total of 864 trained network models were developed. Model validation was investigated by inputting actual monthly energy and employing the networks to backcast the hourly loads for each day in the nine-year historical load database (2002–2010). 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 conceptual treatment, see http://www.icfc.ilstu.edu/icfcpapers97/ynotpi.pdf).



Determination of the Normal Weather Year

A key input of both energy models is the forecasted weather. A normal (typical) weather hourly profile is used in both models. Normal weather means what is expected on a 50% probability basis; i.e., that the forecast for the monthly energy or peak demand 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 these approaches has strengths and weaknesses. ERCOT's analysis included 15 years of weather data (1997–2011). The methodology that ERCOT selected to create the "normal" weather year ranks monthly weather data based on temperature extremes (hot temperatures in the summer and cold temperatures in the winter) and on the average temperature for each weather zone. The "normal" weather month is determined by selecting the historical month which is closest to the median, based on extreme and average temperatures. One change this year was to use the highest temperature that occurred during the summer months (June, July, August, and September) and assign this temperature as the temperature at the time of the summer peak (August) instead of using the highest temperature that occurred only during the month of August. The next step is to time-align the date of the monthly maximum or minimum temperature. This is necessary since different historical years of weather data (for each weather zone) can be used for a particular month, which results in understating ERCOT's coincident peak demand.

The 2011 LTDEF used a very similar approach as was used in the 2012 LTDEF. The two main differences were:

1) Average monthly temperatures were determined by using historical monthly temperatures for all months, and
2) The individual weather zone peak days were time aligned.

A result of using the highest summer temperature and assigning it as the temperature at the time of the summer peak instead of using the high temperature from August is that higher temperatures were used in the model at the time of the summer peak. A summary of forecasted temperatures at the time of peak is included in Appendix B.

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

Economic Forecast

Another key input of both energy models is the forecast of non-farm employment. The current condition of the United States economy and its future direction is an element of great uncertainty. 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.

Since May of 2010, there has been reasonably close agreement between actual non-farm employment in Texas and Moody's base economic forecast. Given this trend, ERCOT used the Moody's base economic forecast of non-farm employment in the 2012 LTDEF. The 2011 LTDEF was also based on Moody's base case economic forecast of non-farm employment. ERCOT will continue to evaluate economic data and trends for use in their long-term forecasting process.

Load Forecast Comparison

Figure 4 presents the ERCOT annual peak demand forecasts for 2012-2020 from the 2011 LTDEF and the 2012 LTDEF. The forecasted compound annual growth rate of demand is 2.5 percent for the 2012 LTDEF as compared to 2.4 percent from the 2011 LTDEF. ERCOT experiences its highest peak demand during the summer.

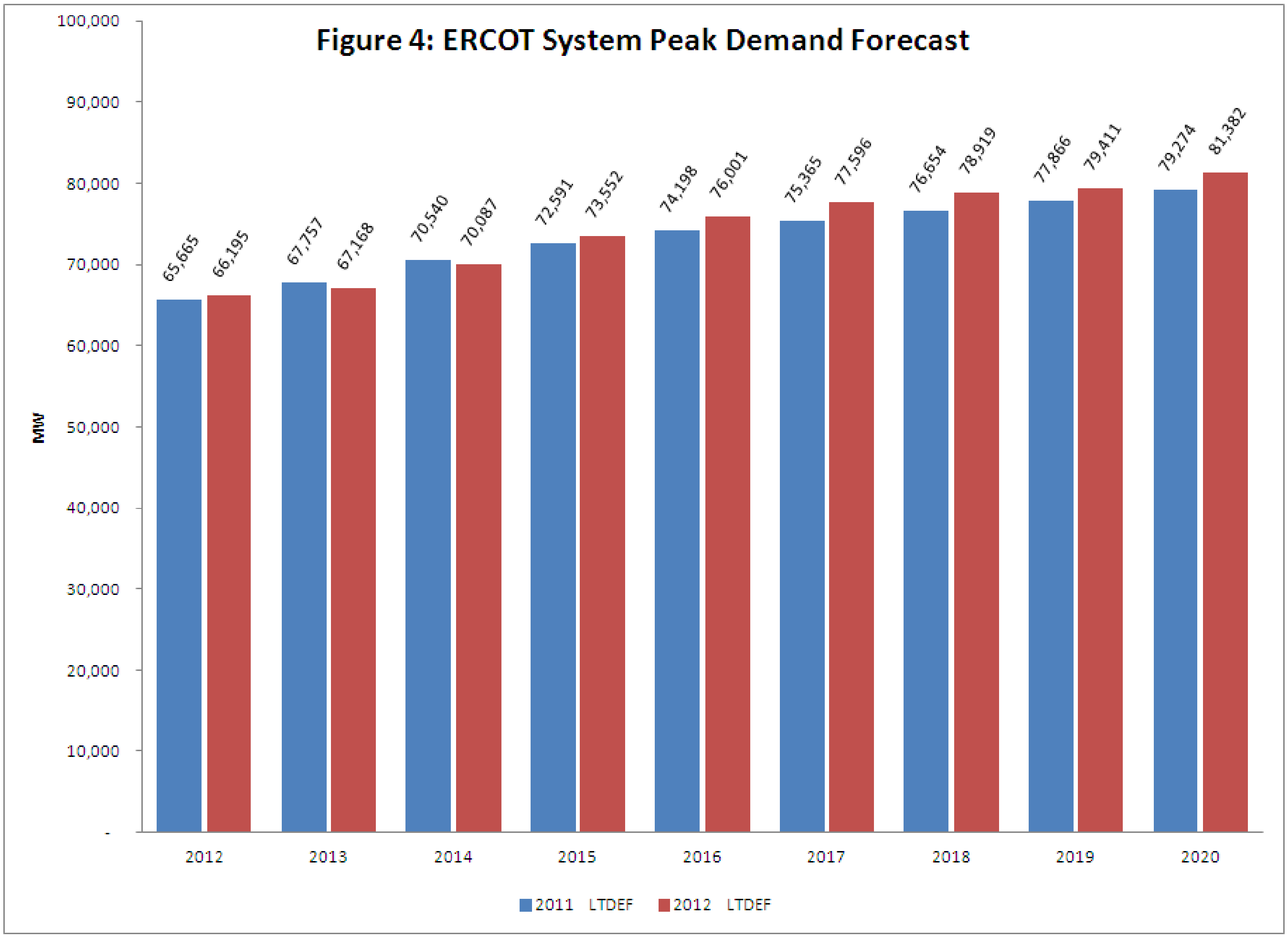
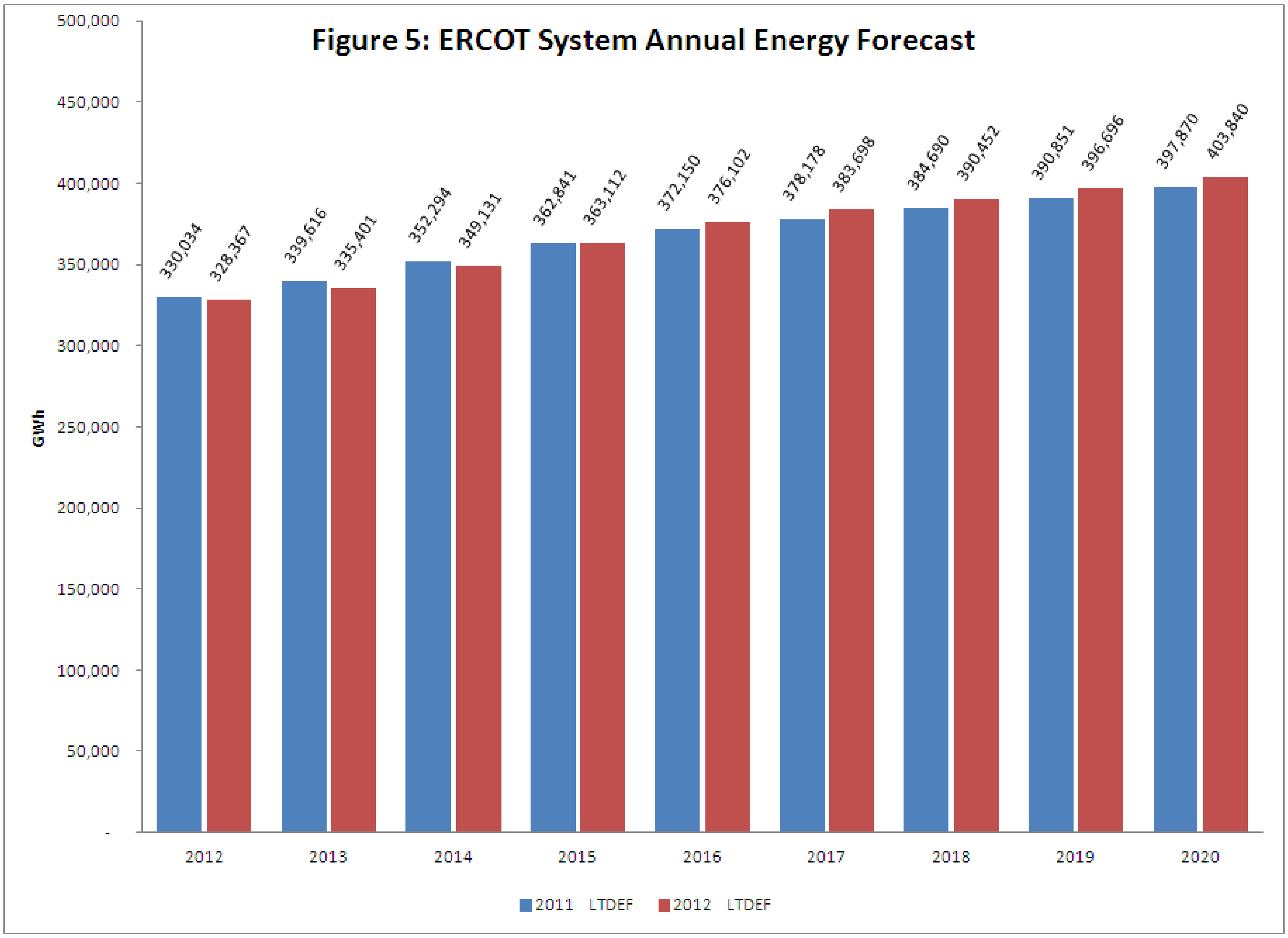
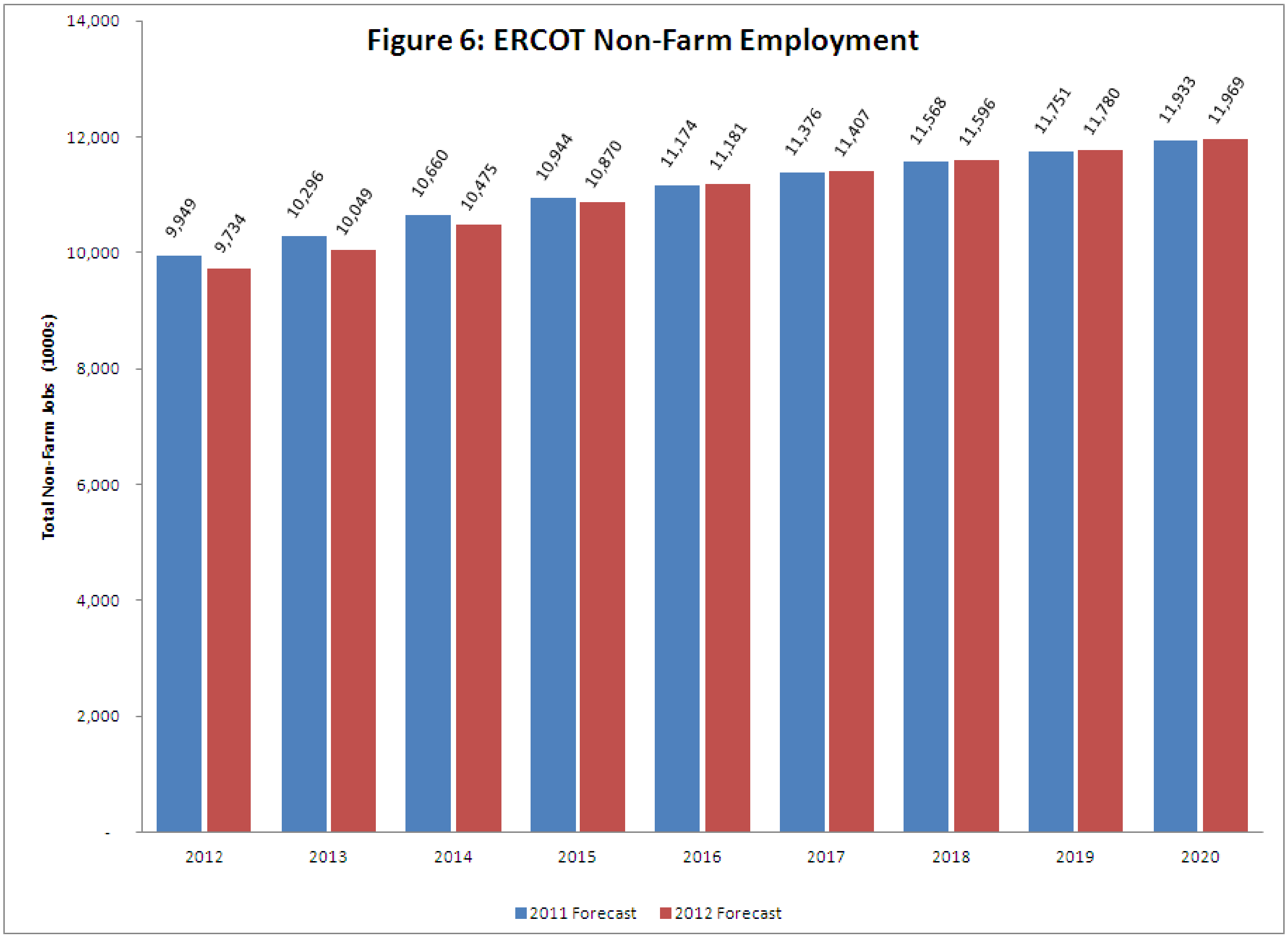


Figure 5 presents the ERCOT annual energy forecast for 2012-2020 from the 2011 LTDEF and the 2012 LTDEF. The forecasted compound annual growth rate of energy is 2.5 percent for the 2012 LTDEF which is unchanged from the growth rate in the 2011 LTDEF.



Differences between the two forecasts are predominantly due to changes in the economic forecasts that were used. The 2012 LTDEF and the 2011 LTDEF were both based on Moody's base economic forecast.

Figure 6 shows the forecast of non-farm-employment (the primary economic variable used by both forecasts). The 2012-2020 non-farm-employment compound annual growth rate for the 2012 LTDEF is 2.6 percent. For the 2011 LTDEF, it was 2.3 percent.



<u>Load Forecast Uncertainty</u>

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 7 suggests the significant role of weather in forecasting any specific year. This figure shows what the 2012 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 below 61,000 MW using 2004 weather to upwards of 71,000 MW using 2011 weather.

Figure 7: Effect of Various Weather Years on 2012 Peak Forecast

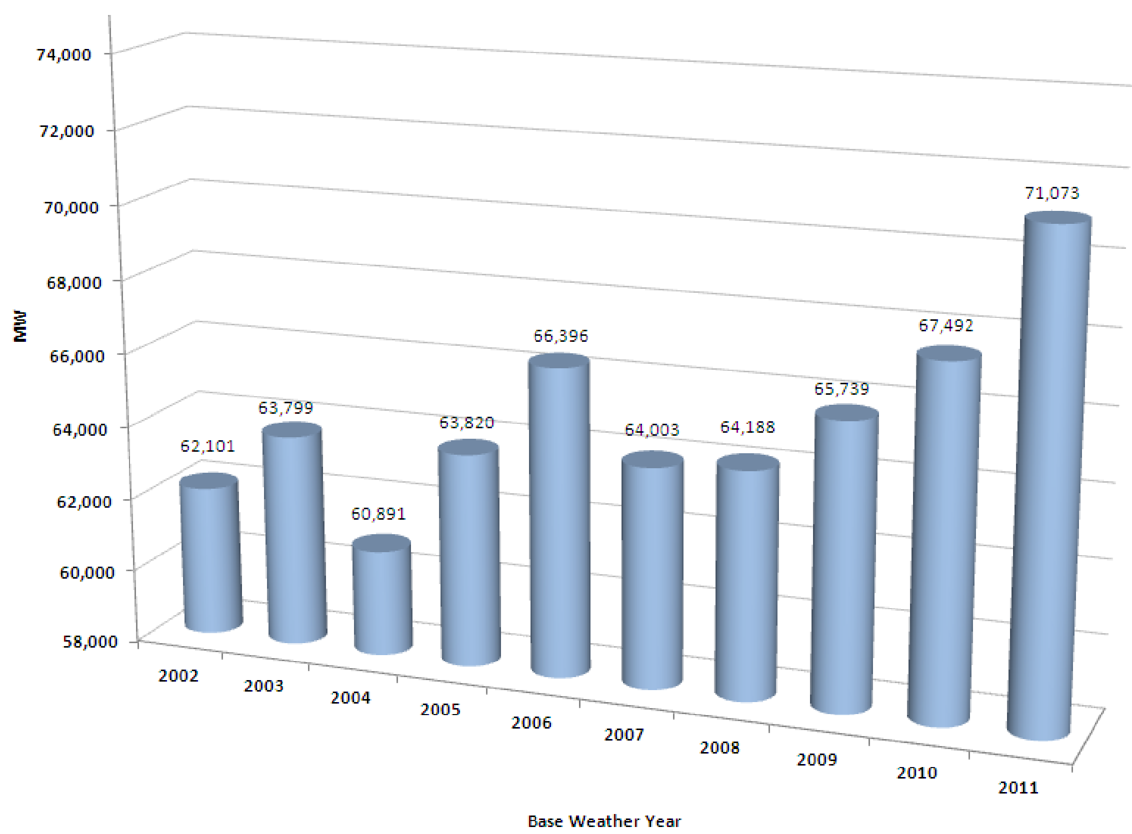
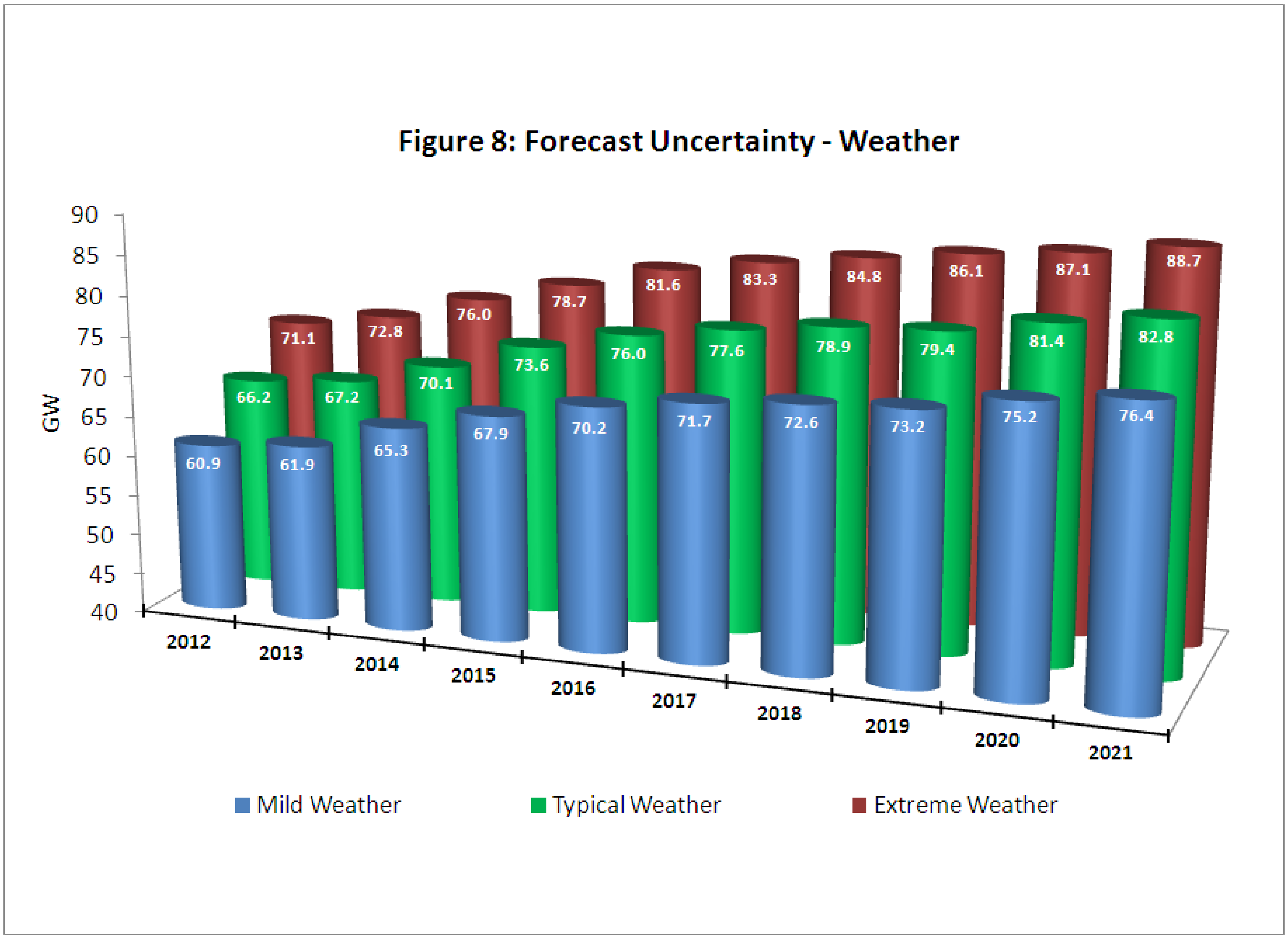
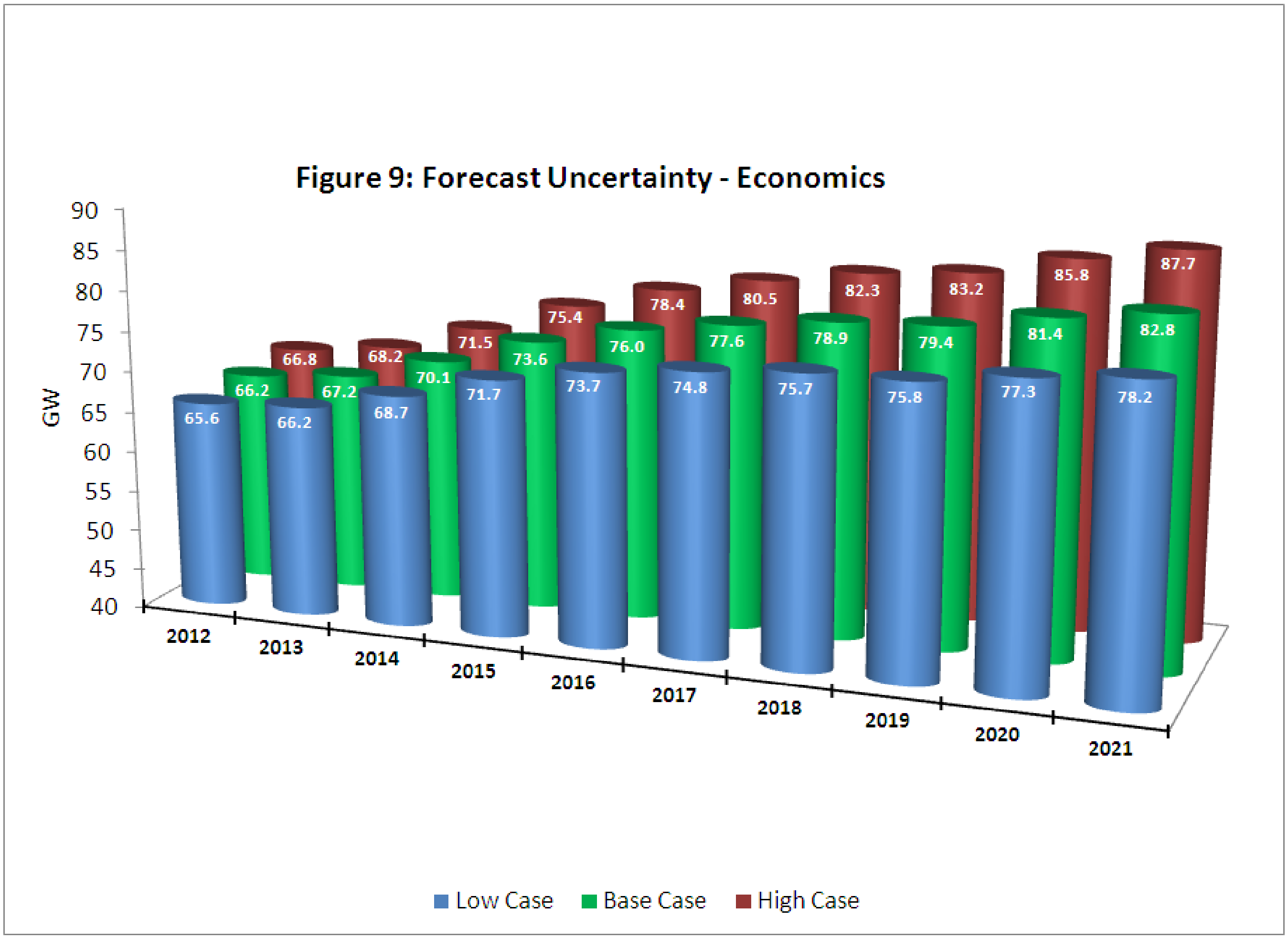


Figure 8 extends the uncertainty out to 2021. Assuming 2011 weather (identified as the extreme weather scenario) in 2021, results in a forecasted peak demand of 88,657 MW. Assuming 2004 weather (identified as the mild weather scenario) in 2021, we would expect a peak of 76,420 MW.



Economic Uncertainty

Figure 9 shows uncertainty deriving from economics. Based on Moody's low economic forecast, we may expect, ceteris paribus, a 2021 peak of 78,167 MW. Using Moody's high economic forecast, we expect a 2021 peak of 87,706 MW.



Energy Efficiency Uncertainty

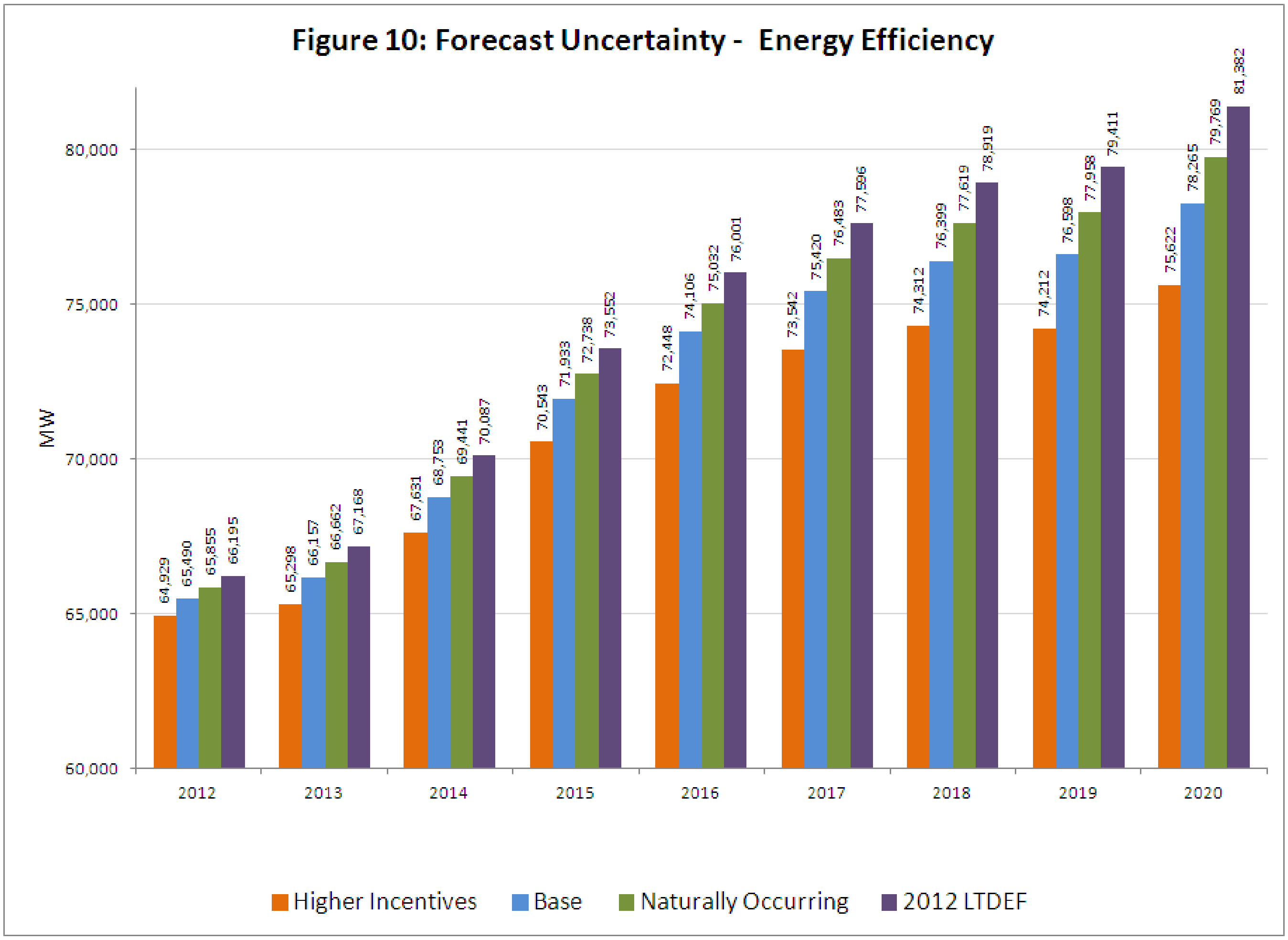
A much more challenging source of uncertainty to quantify is the effect from energy efficiency. The 2012 LTDEF is a "frozen efficiency" forecast meaning the forecast model employs statistical techniques that fix the relationships between load, weather, and economics at their 2011 state. Such an assumption 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 30% 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 2011, then the model assumes the same proportion in 2020.

Recent developments cause more uncertainty in how much to depend on fixed coefficients for the long-term. In 1999 Texas was the first state to institute an Energy Efficiency Performance Standard – and 27 states have followed suit since (see "Extreme Efficiency," PUBLIC UTILITIES FORTNIGHTLY, September 2010, pp. 48-53). Senate bill 1125, signed into law even more ambitious energy efficiency targets beginning in January 2013 (see http://www.capitol.state.tx.us/tlodocs/82R/billtext/pdf/SB01125I.pdf#navpanes=0).

Figure 10 suggests the uncertainty indicated by a study sponsored by the Public Utility Commission of Texas. This figure was adapted from the report's Figure 7-4 by (a) adjusting their statewide estimate to reflect an ERCOT estimate, and (b) subtracting out the cumulative 2009-2010 savings from all the subsequent years because the model was estimated with data through 2010 and, hence, reflects the in-place 2010 appliance stock. The data presented in Figure 10 is from Itron's High Avoided Cost scenario (meaning a greater set of Energy Efficiency [EE] measures will be cost-effective – avoided costs are a principal component of the cost-effectiveness evaluation used to establish incentives for individual EE measures). The Naturally Occurring category indicates the efficiency expected to occur solely in response to price with no extra incentives. The Higher Incentives category reflects more aggressive incentives than are currently being offered. As Figure 10 shows, an aggressive incentives scenario yields a 2020 peak of a magnitude similar to the Mild (2004) weather scenario, or the Low economic growth scenario.

In conclusion, it seems that weather, economics, and energy efficiency cast similar magnitudes of uncertainty on the load forecast. Further work is needed in order to create a separate forecast for energy efficiency impacts to the long-term forecast.



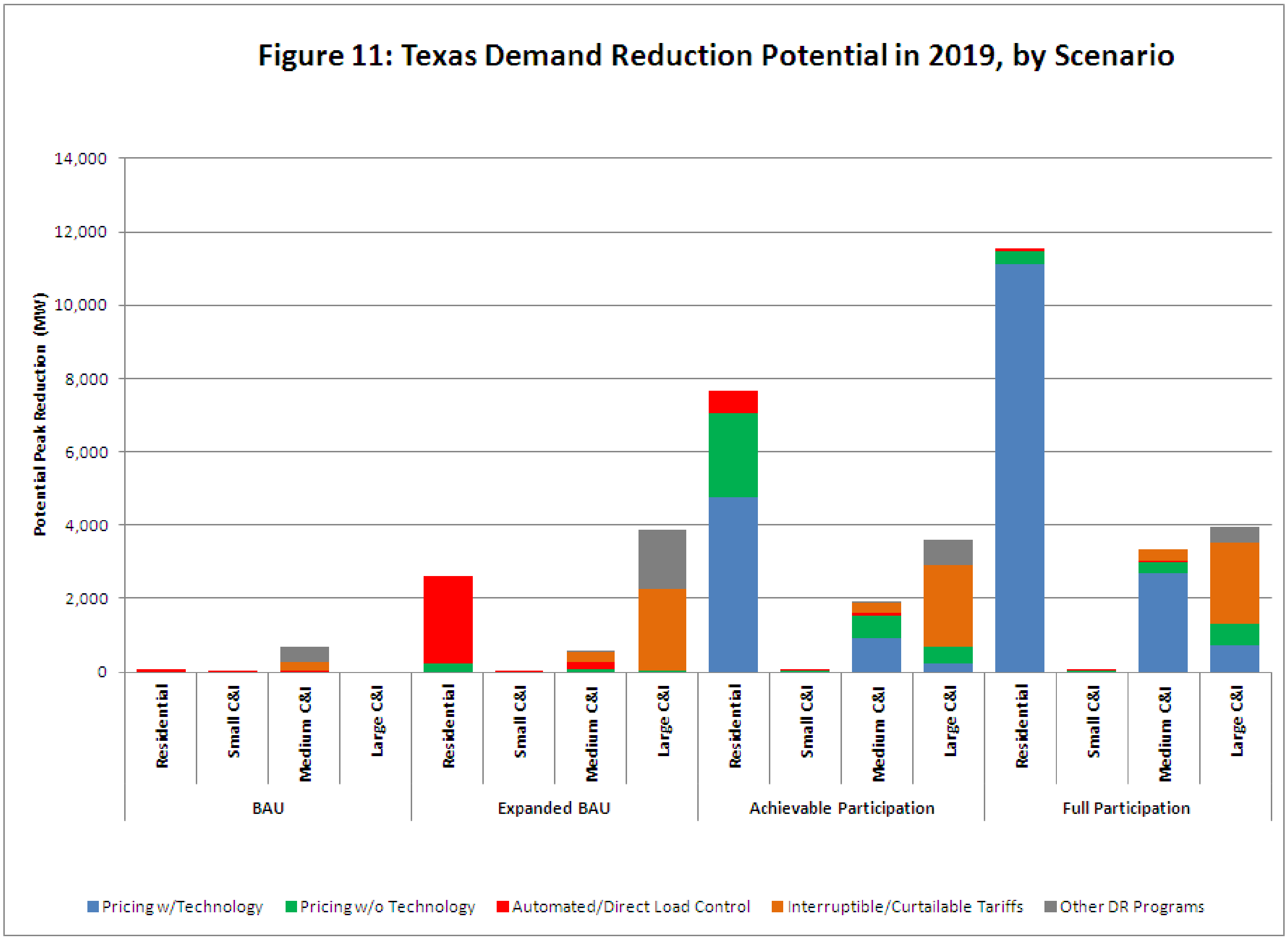
Source: Adaptation of Figure 7-4 from Itron Report to the Public Utility Commission of Texas, *Assessment of the Feasible and Achievable Levels of Electricity Savings from Investor Owned Utilities in Texas: 2009-2018*, dated November 12, 2008.

<u>Demand Response Uncertainty</u>

Of much greater uncertainty is the potential impact of demand response. According to the national study reporting state-by-state results conducted by the Federal Energy Regulatory Commission, Texas is close to the top in demand response potential. As indicated by Figure 11, the Achievable and Full Participation scenarios for Texas statewide suggest between 10,000 and 15,000 MW by 2019.

There may be a level of "speculativeness" that characterizes the uncertainty due to energy efficiency, demand response, and electric vehicles that is unlike the uncertainty due to weather and economics. The surge in demand response potential for the Achievable and Full Participation scenarios shown in Figure 11 is almost entirely due to the assumption that demand response will undergo a complete metamorphosis from the more familiar products like ISO emergency programs, interruptible rates, and direct load control to the more "exotic" products based on dynamic pricing. With more than four million advanced meters installed with enabling technologies like Home Area Networks and *smart* appliances, new participants like aggregators and more incentivized Retail Electric Providers can provide an increasing number of products and services. The demand reduction potential of these services for Texas in 2019 is reflected in the pale blue portion of the bars in Figure 11.

Numerous dynamic pricing pilots have shown promise but there is still considerable justification for viewing the Achievable and Full Participation scenarios as somewhat "conjectural."



Source: Federal Energy Regulatory Commission's Report, *A National Assessment of Demand Response Potential*, Appendix A, dated June 2009, prepared by The Brattle Group, Freeman, Sullivan & Co., and Global Energy Partners, LLC.

Onsite Renewable Energy Technologies Uncertainty

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

1. Distributed onsite wind,
2. Photovoltaics (PV), and
3. Solar water heating.

The demand savings from these technologies is estimated to be approximately 3% of peak demand by 2023 (see Elliot, et al., "Potential for Energy Efficiency, Demand Response, and Onsite Renewable Energy to Meet Texas's Growing Electricity Needs," Report Number E073, March 2007 (http://www.aceee.org/sites/default/files/publications/researchreports/e073.pdf).

Electric Vehicles Uncertainty

Perhaps an even more conjectural matter is the uncertainty due to electric vehicles. The 2012 LTDEF does not even present any figures pertaining to electric vehicles (EVs) and plug-in hybrid electric vehicles (PHEVs). That, of course, does not mean that there are no potentially large load forecast implications presented by EVs and PHEVs. The conventional wisdom seems to be that EV penetration will be gradual and halting. If that is the case then the load forecast implications for 2012-2021 will not be great. However, some parties envision a different future. Planners at the utility serving ERCOT's fourth largest load center (Austin) have suggested that a high growth scenario for them would have 200,000 EVs/PHEVs on the road by 2020 (see, "Austin Plugs In," PUBLIC UTILITIES FORTNIGHTLY, June 2011, p. 37). If there are that many in the fourth largest load center, then there would likely be considerably more in other metropolitan areas. There are reports that preparations are already underway for the projected increase (see http://media.fordvehicles.com/article_display.cfm?article_id=33253).

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 2013 LTDEF.

Appendix A
Peak Demand and Energy Forecast Summary

Year	Summer Peak Demand (MW)	Annual Energy (TWh)
2012	66,195	328.4
2013	67,168	335.4
2014	70,087	349.1
2015	73,552	363.1
2016	76,001	376.1
2017	77,596	383.7
2018	78,919	390.5
2019	79,411	396.7
2020	81,382	403.8
2021	82,765	409.4

Appendix B
Forecasted Temperatures at time of Summer Peak

Metropolitan Area	Summer Peak Temperature (^oF)
Austin/San Antonio	101.5
Dallas/Fort Worth	105.0
Houston	99.1