2011 ERCOT Planning

Long-Term Hourly Peak Demand and Energy Forecast

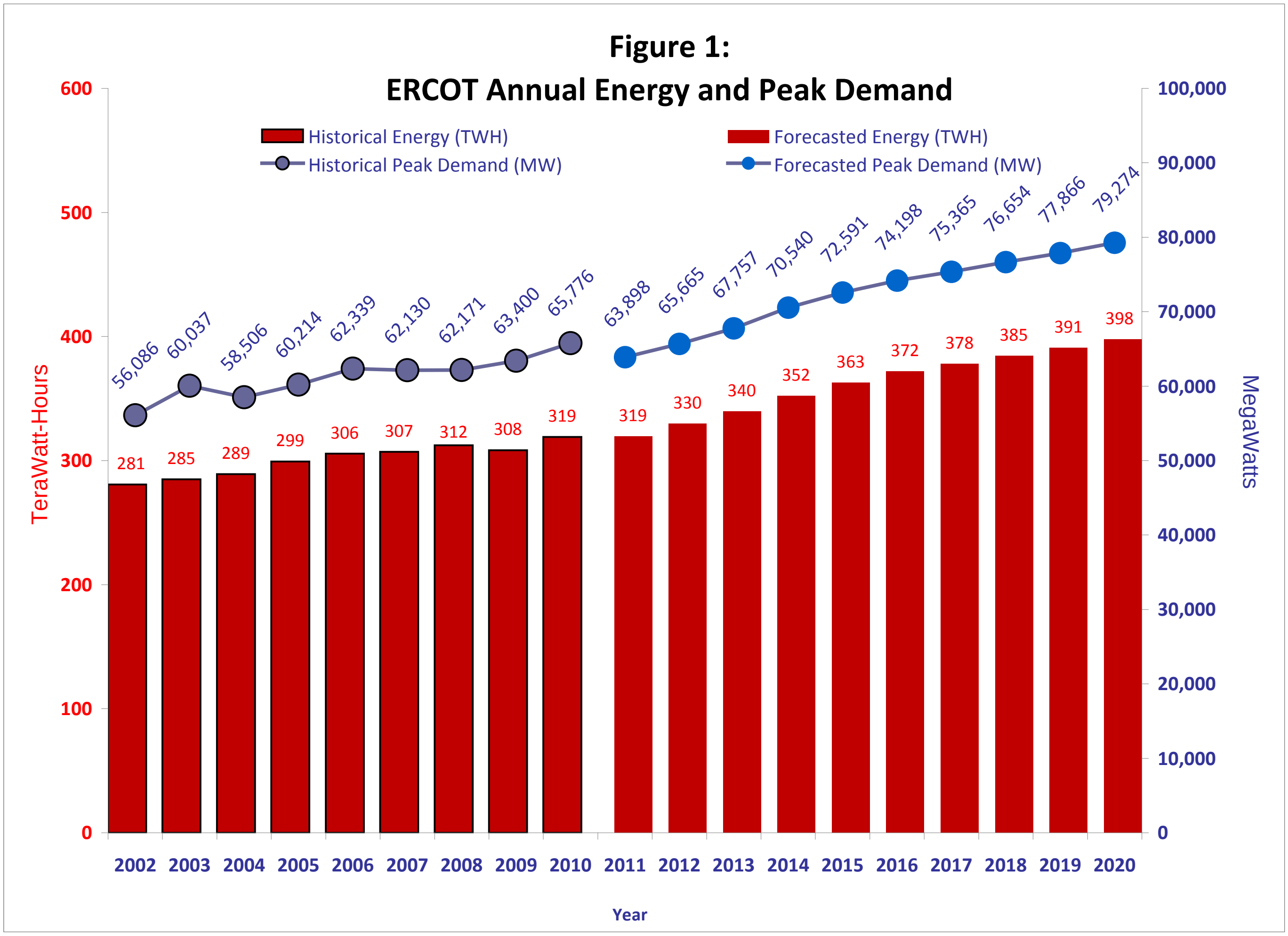
June 30, 2011

© 2011 Electric Reliability Council of Texas, Inc. All rights reserved.

Executive Summary

The 2011 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). 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.

As shown by Figure 1, the 2011 LTDEF depicts an initial two-year decrease in system peak demand from the 2010 value of 65,776 MW, followed by an eight-year (2013-2020) steady increase. The initial decrease is due to the assumption that "normal" (or typical) weather is milder during forecasted summer peak days than was experienced in 2010 and, furthermore, that this "normal" trend will (on average) persist throughout the 2011-2020 forecast period. The eight-year steady increase (2013-2020) 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.



Also suggested by Figure 1 are peak demand and energy annual growth rates. Historically, annual energy for 2002-2010 grew at a compound annual growth rate of 1.6 percent. Peak demand grew at a faster rate of 2.0 percent. The reason for the larger annual growth rate of peak demand as compared to energy is due to the extremely warm weather in 2010. The forecasted annual growth rates for 2011-2020 are 2.5 percent for energy and 2.4 percent for peak demand. 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 2011 Long-Term Demand and Energy Forecast (LTDEF). The forecast methodology is described, highlighting its major conceptual and statistical underpinnings. The 2011 forecast results are presented in a manner comparing them to the 2010 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.

Modeling Framework

The 2011 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

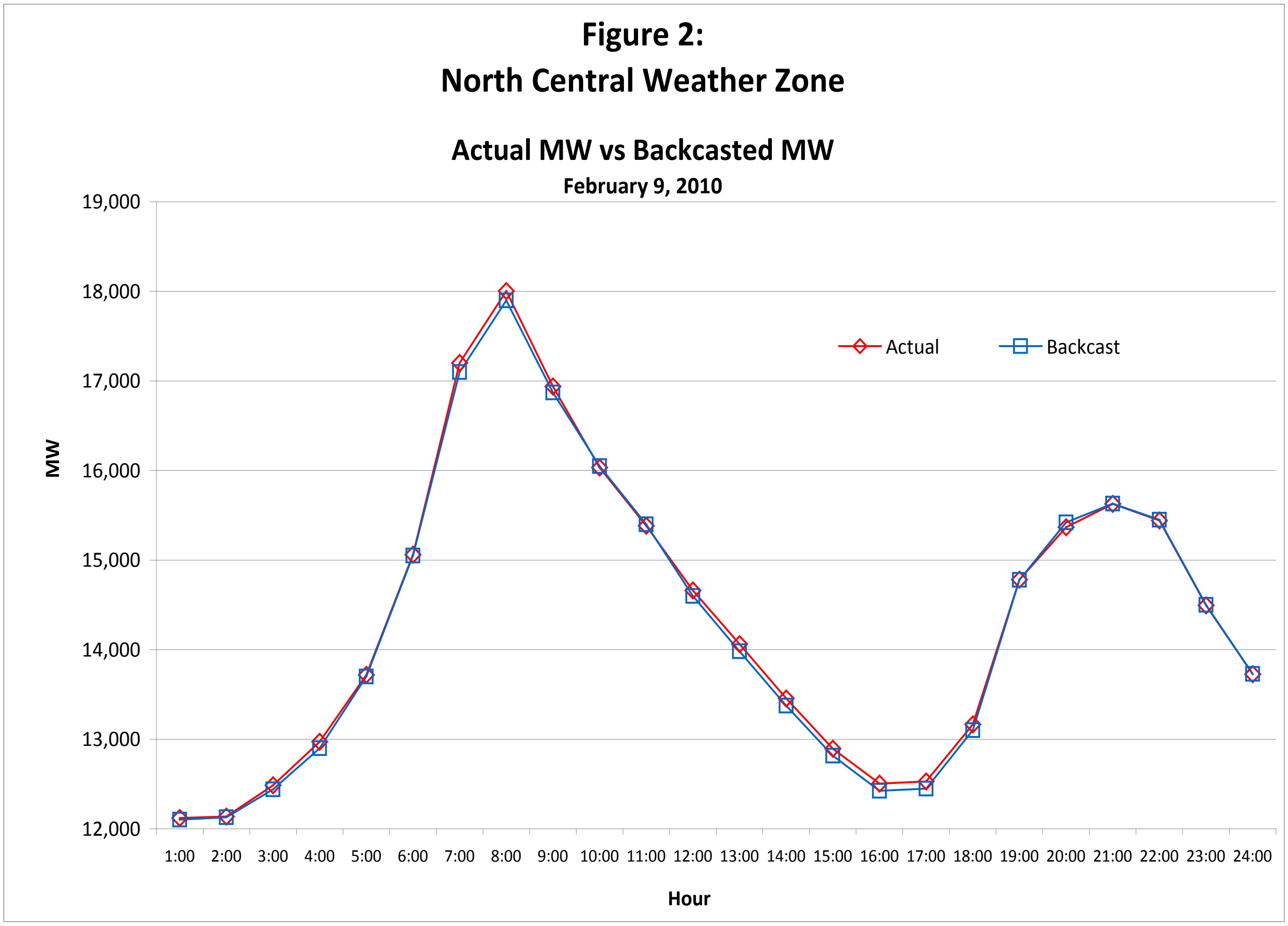
The long-term trend in monthly energy is modeled by estimating a non-linear relationship for each of the eight ERCOT weather zones between (a) the dependent variable, Monthly-MWh-Per-1000-Nonfarmjobs-Per-Day, and (b) a set of weather variables – cooling-degree-days-to-base-65 (cdd65), cooling-degree-days-to-base-75 (cdd75), cooling-degree-days-to-base-85 (cdd85), heating-degree-days-to-base-40 (hdd40), heating-degree-days-to-base-50 (hdd50), and 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 of 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 nicely 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 varies by zone. 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.

Hourly Energy Model

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: (1) yesterday's maximum daily dry bulb temperature (dbt); (2) yesterday's minimum dbt; (3) today's maximum dbt; (4) today's minimum dbt; (5) today's 7am dbt; (6) today's noon dbt; (7) today's 7pm dbt; (8) today's sunset time; (9) monthly average dbt; (10) year; and (11) the previous Hour's-Fractional-Share-of-Monthly-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) yielding a total of 864 trained 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 nine-year historical load database (2002–2010). Figure 2 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).



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 that it is expected on a 50% probability basis, that the monthly 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 (1996–2010). 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. The next step is to time-align the date of the weather zone non-coincident peak. 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 2010 LTDEF used the Rank and Average methodology. The Rank and Average methodology involves the following steps:

1. Rank the hourly temperatures for each year for each weather zone from highest to lowest,
2. Determine the median temperature for all years for each hour,
3. Calculate the sum of the absolute values of the difference of the median and the hourly temperatures for all hourly temperatures in each year,
4. Determine the year with the minimum summed value and select this year as the typical year profile, and
5. Use this year's profile to re-sort the median temperatures.

A result of using The Rank and Average methodology is that higher temperatures are forecasted during the summer peak than in using other normal year approaches (as mentioned above). This is why the forecasted peak demands are greater in the 2010 LTDEF as compared to the forecasted peak demands from the 2011 LTDEF for years 2011–2013 (see Figure 4). For 2014 on, the 2011 LTDEF peak forecast exceeds the 2010 LTDEF due to the 2011 forecast being based on a higher economic forecast.

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.

Since May of 2010, actual non-farm employment in Texas has been pretty much in agreement with the Moody's base economic forecast. Given this trend, ERCOT decided to use the Moody's base economic forecast of non-farm employment in the 2011 LTDEF.

As mentioned previously, the 2010 LTDEF was based on Moody's low case economic forecast of non-farm employment. Using a lower economic forecast resulted in lower projections of energy and peak demand when compared to the 2011 LTDEF.

ERCOT will continue to evaluate economic data and trends for use in their long-term forecasting process.

Load Forecast Comparison

Figure 3 presents the ERCOT annual energy forecast for 2011-2020 from the 2010 LTDEF and the 2011 LTDEF. The forecasted compound annual growth rate of energy is 2.5 percent for the 2011 LTDEF as compared to 1.7 percent from the 2010 LTDEF.

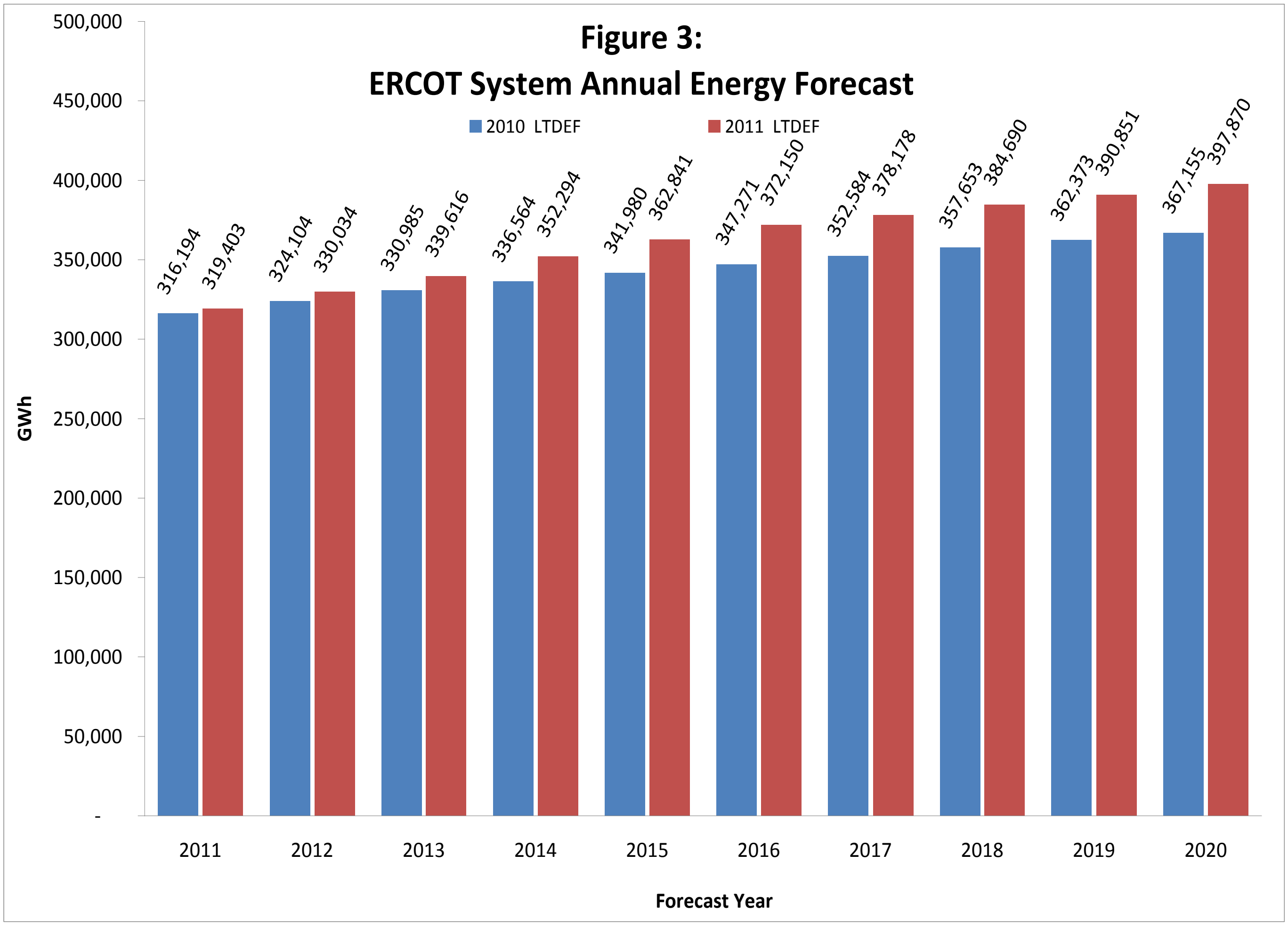
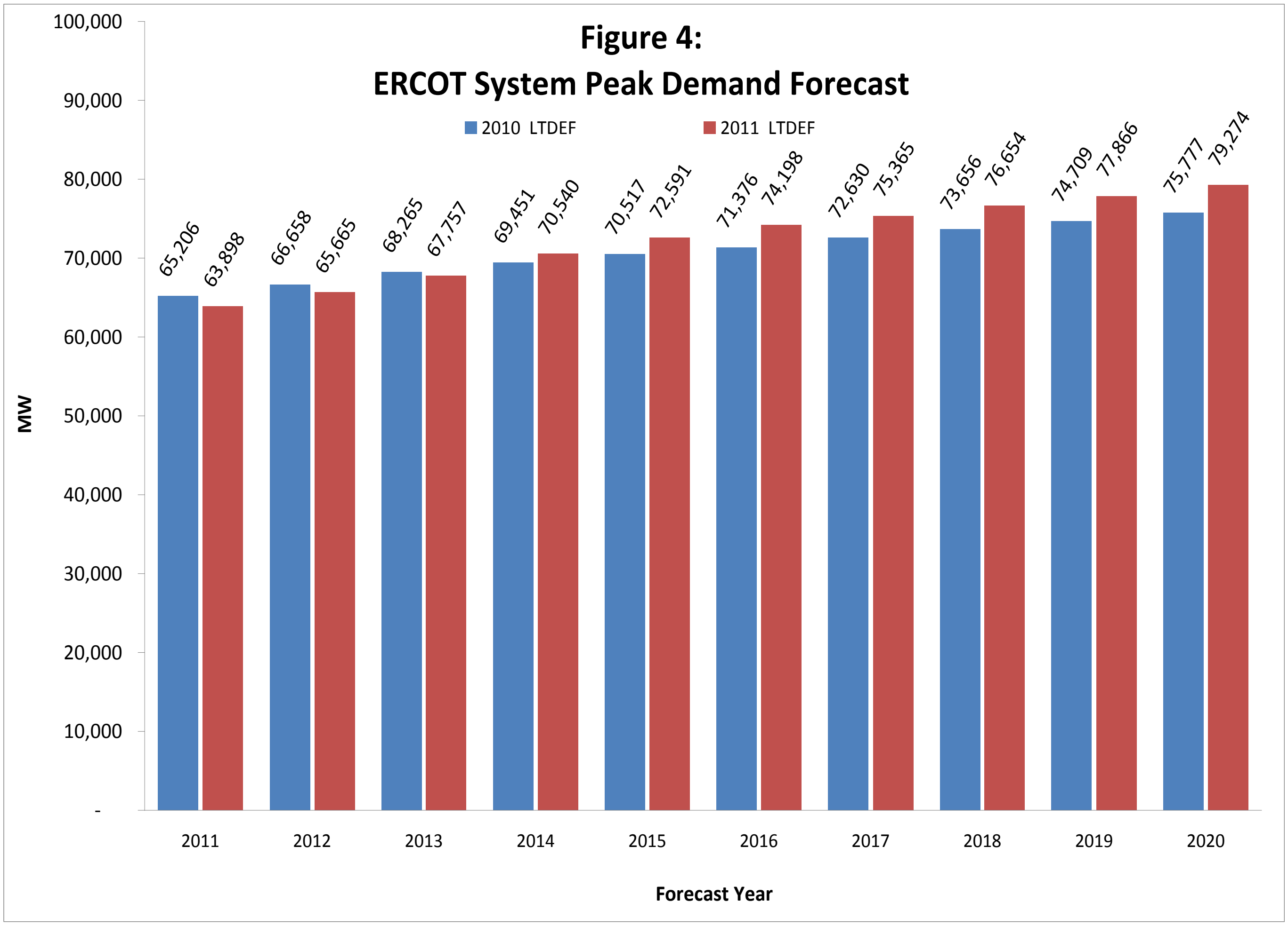
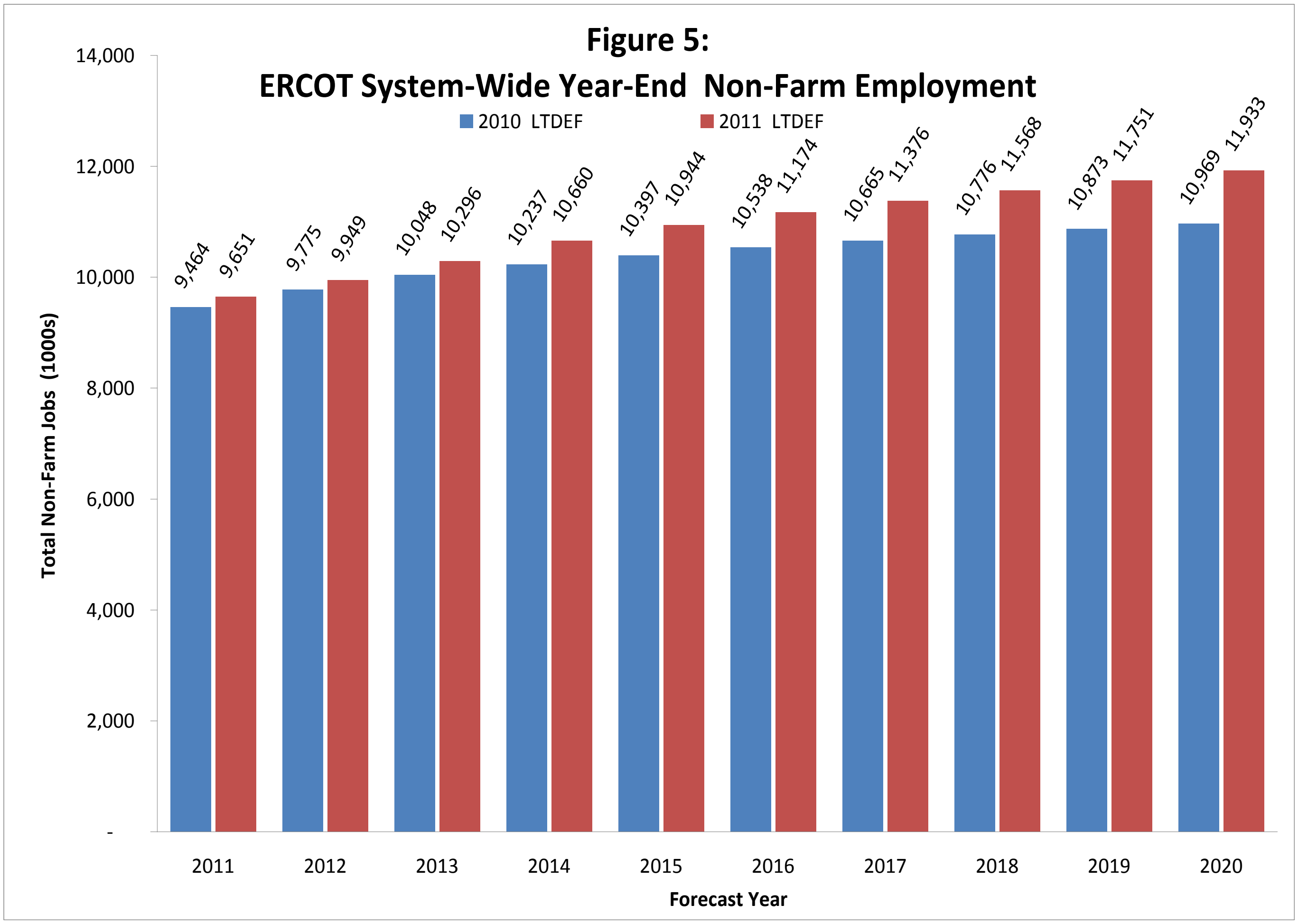


Figure 4 presents the ERCOT annual peak demand forecasts for 2011-2020 from the 2010 LTDEF and the 2011 LTDEF. The forecasted compound annual growth rate of demand is 2.4 percent for the 2011 LTDEF as compared to 1.7 percent from the 2010 LTDEF.



While there are some significant differences between the methodologies underlying the two forecasts, the differences between the two forecasted results are predominantly due to the different economic forecast scenarios that were used. The 2010 LTDEF was based on the Moody's 2010 Low economic forecast, while the 2011 LTDEF uses the Moody's 2011 Base economic forecast. Figure 5 shows the forecast of Nonfarm-Payroll-Employment (the primary economic variable used by both forecasts). The 2011-2020 Nonfarm-Employment growth rate for the 2010 LTDEF was 1.7 percent. For the 2011 LTDEF, it is 2.4 percent. Hence, the difference in the load forecasts derives directly from the difference between the economic forecasts.



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 6 suggests the significant role of weather in forecasting any specific year. This figure shows what the 2011 forecasted peak demand would be using the actual weather from any one of the past 12 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 66,000 MW using 2010 weather.

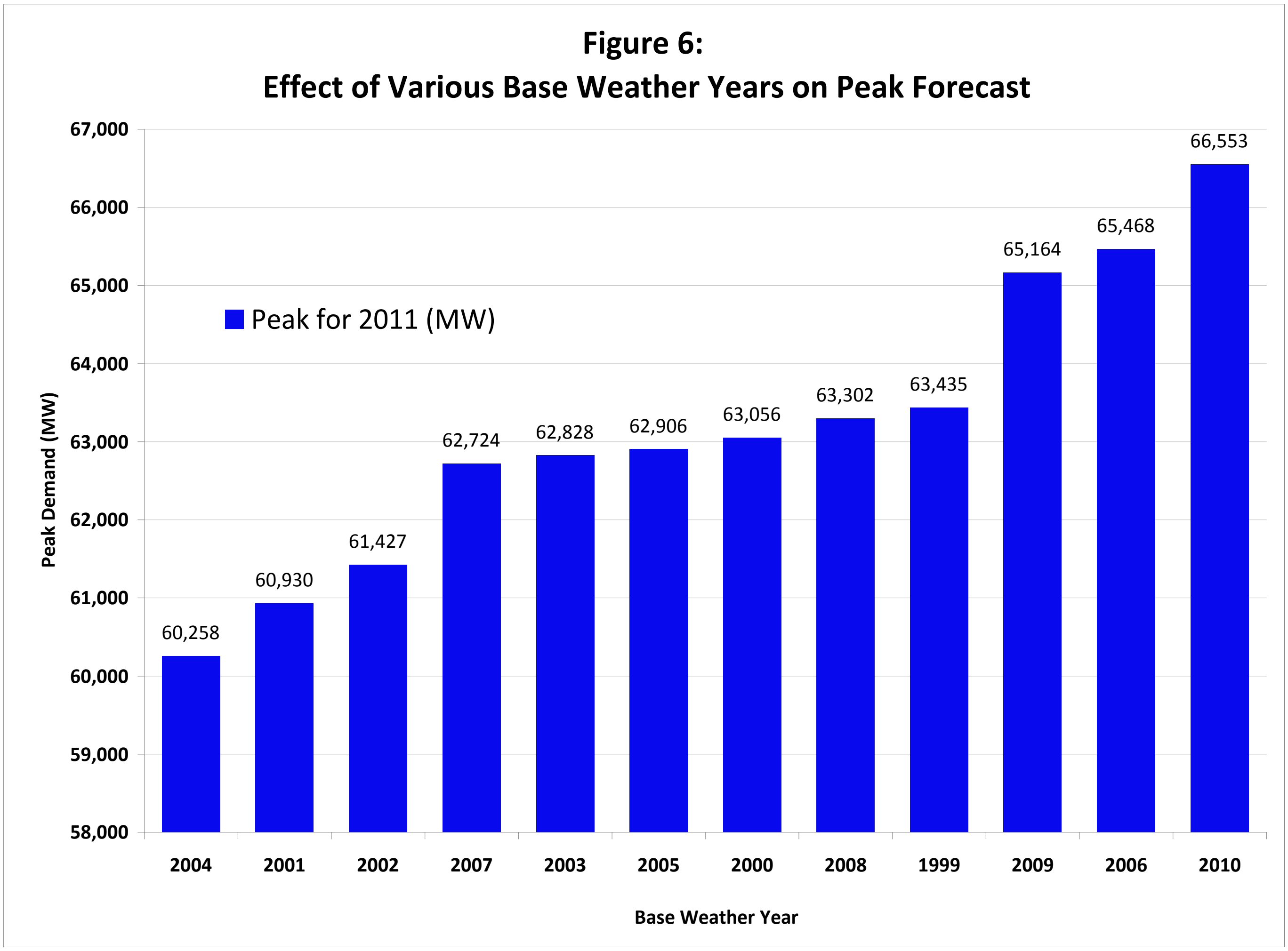
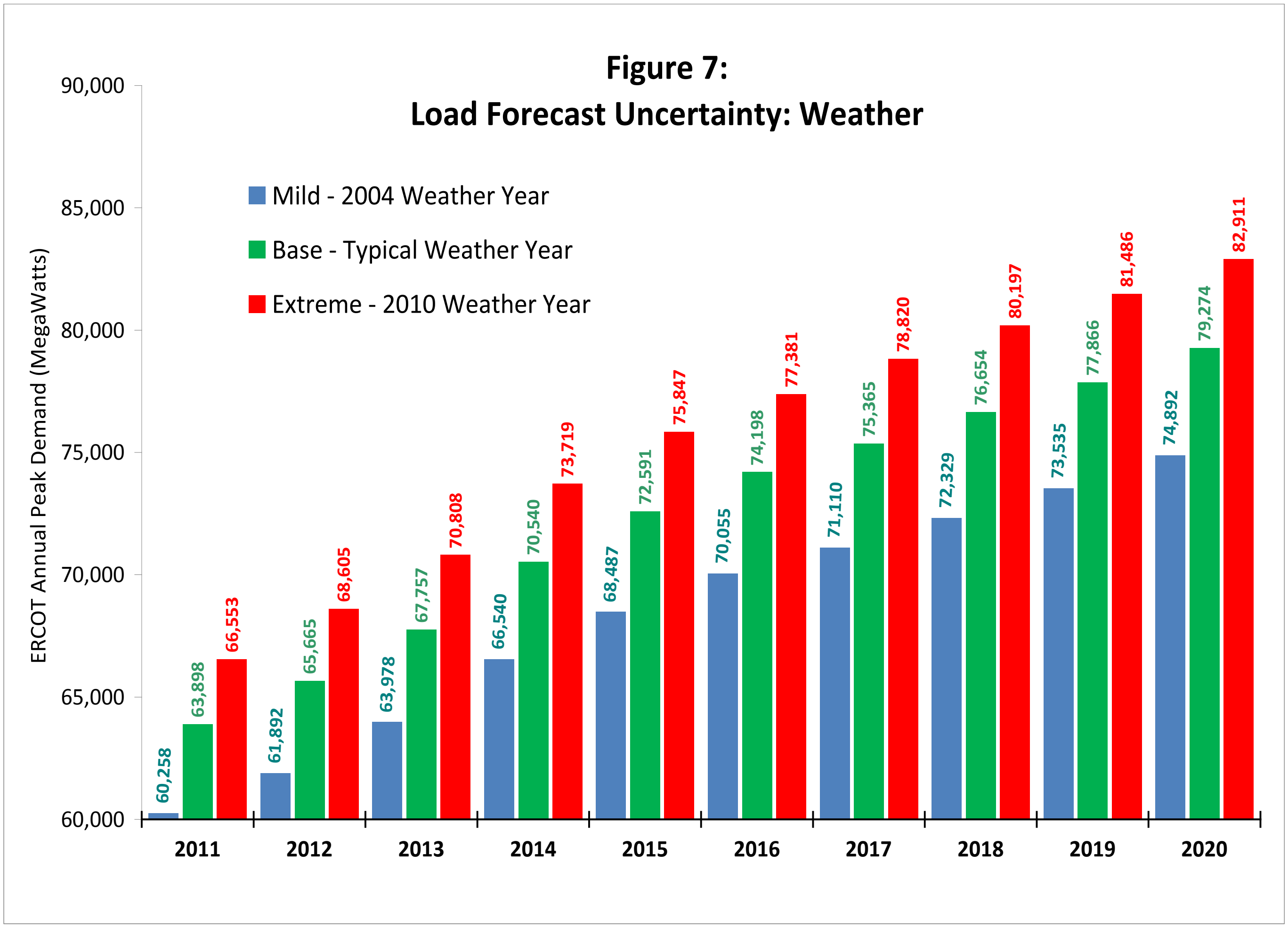
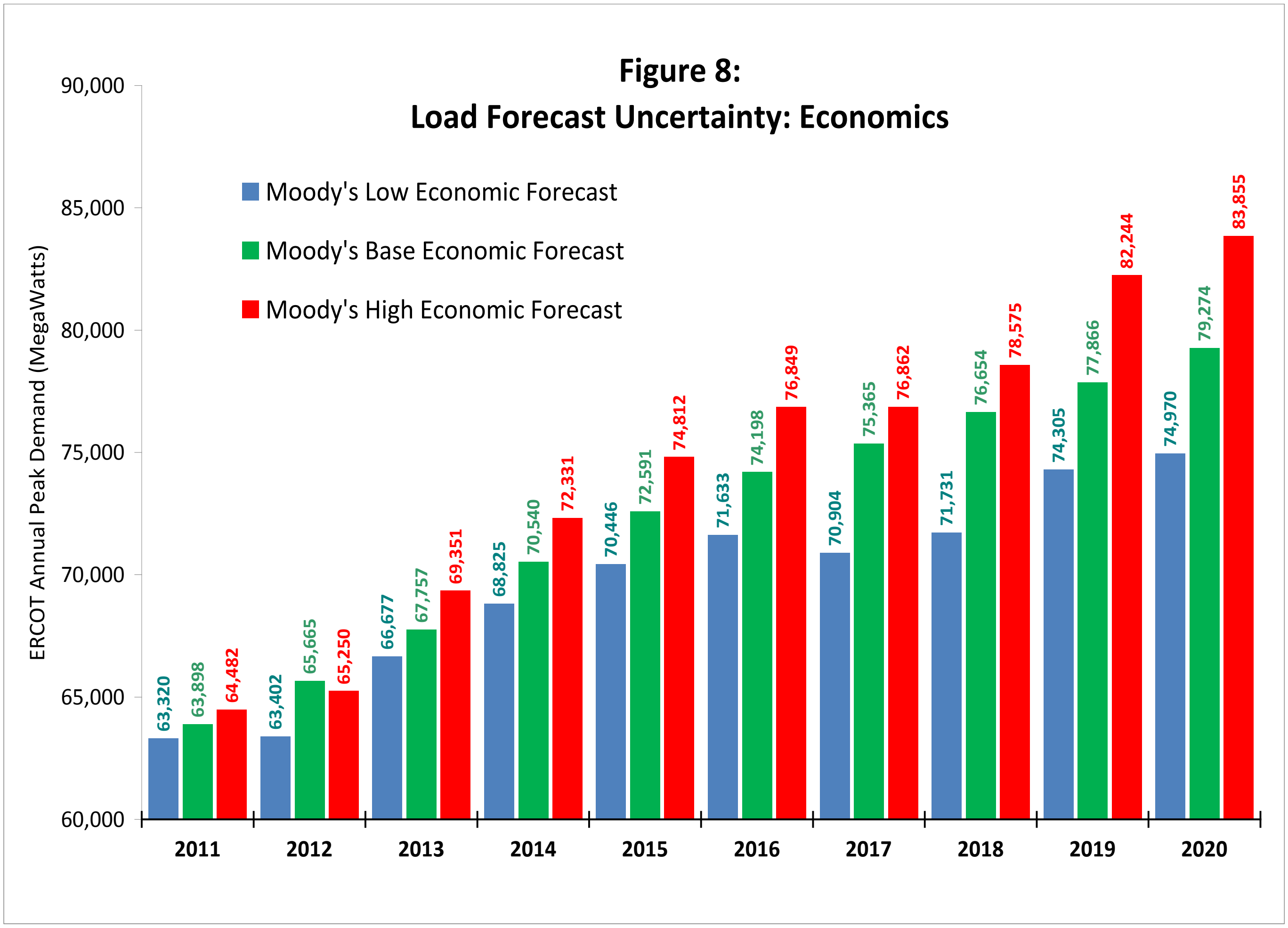


Figure 7 extends the uncertainty out to 2020. Assuming 2010 weather, we would expect a peak in 2020 of 82,911 MW. Assuming 2004 weather, in 2020 we would expect a peak of 74,892 MW.



Economic Uncertainty

Figure 8 shows uncertainty deriving from economics. Based on Moody's Low economic forecast, we may expect, ceteris paribus, a 2020 peak of 74,970 MW. Using Moody's High economic forecast, we expect a 2020 peak of 83,855 MW.

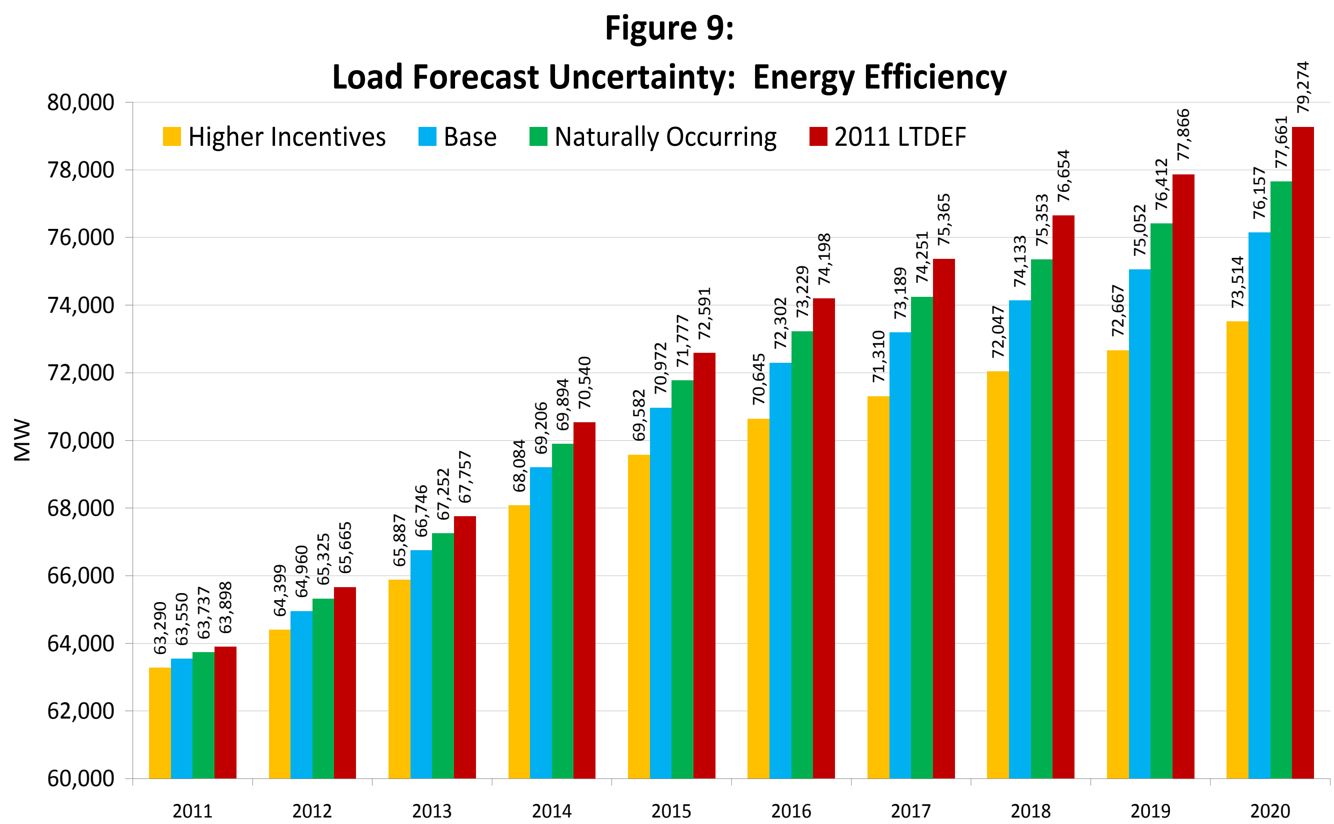


Energy Efficiency Uncertainty

A much more difficult source of uncertainty to deal with is that derived from energy efficiency. First off, it must be recognized that the 2011 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 2010 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 2010, then the model assumes the same proportion in 2020. Yet, we know that 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). Last month, a bill was signed into law with even greater ambition (see http://www.capitol.state.tx.us/tlodocs/82R/billtext/pdf/SB01125I.pdf#navpanes=0).

These developments cause concern in how much to depend on fixed coefficients for the extended long-term. While econometric forecasts are powerful and tend to yield especially accurate and reliable forecasts out a few years, it is important that other factors be examined when viewing the longer term.

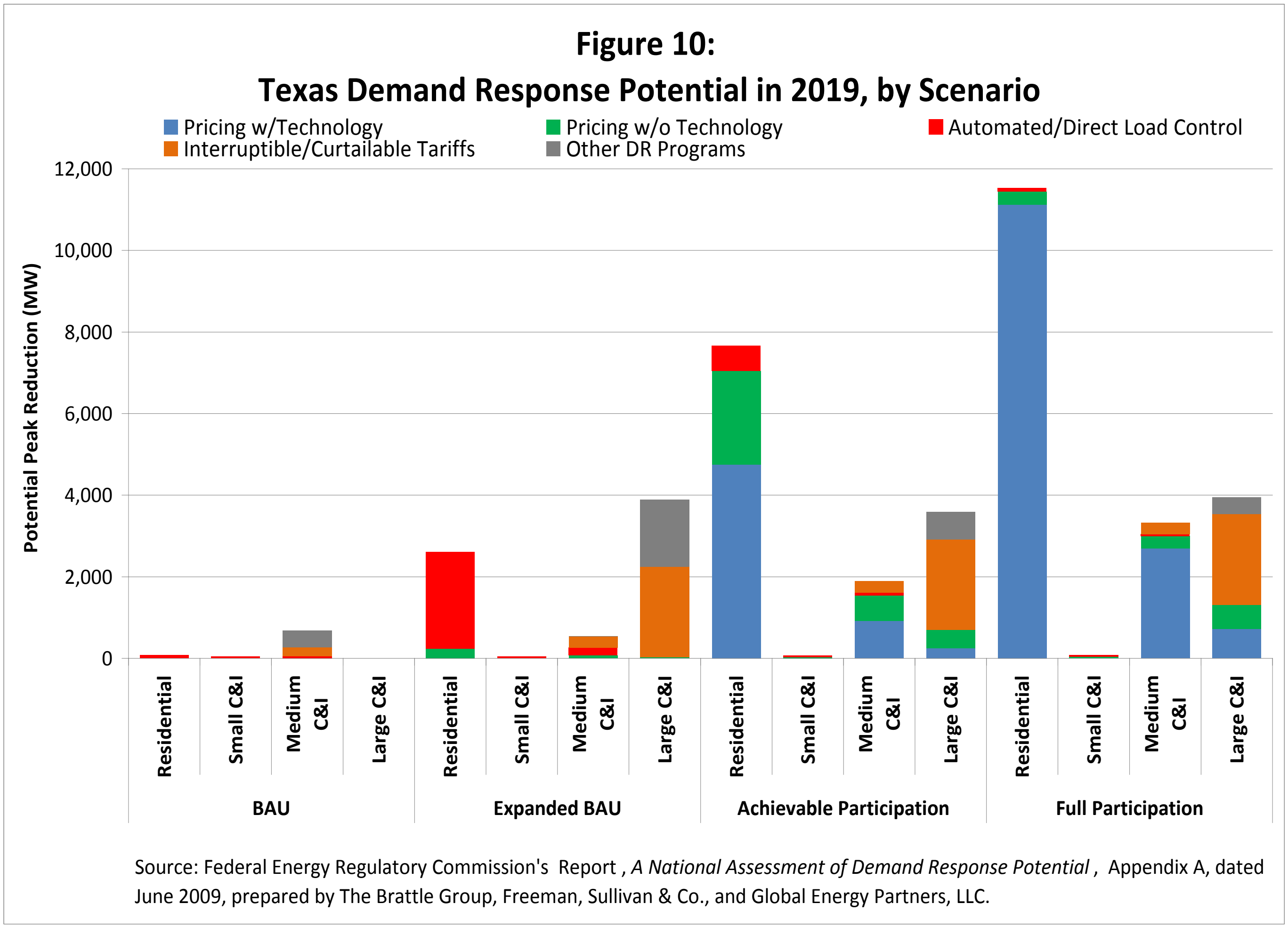
Figure 9 suggests the uncertainty indicated by a study sponsored by the Public Utility Commission of Texas. This figure was adapted from the report's Figure 7-4 by (a) adjusting their statewide estimate to reflect an ERCOT estimate, and (b) subtracting out the cumulative 2009-2010 savings from all the 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 9 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 9 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. So, in conclusion, it seems that weather, economics, and energy efficiency cast similar magnitudes of uncertainty on the load 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 Novemeber 12, 2008

Demand Response Uncertainty

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 10, the Achievable and Full Participation scenarios for Texas statewide suggests between 10,000 and 15,000 MW by 2019. It is probably worth noting that 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 10 is almost entirely due to the assumption that demand response is going to undergo an almost complete metamorphosis in nature from the more familiar products like ISO emergency programs, interruptible rates, and direct load control to the more “exotic” products based on dynamic pricing. The idea is that as AMI takes hold and is linked to enabling technologies like Home Area Networks and enabled appliances, new participants like aggregators and more incentivized Retail Electric Providers will provide an increasing number of products and services (reflected in the pale blue portion of the bars in Figure 10). There have been numerous dynamic pricing pilots showing promise but there is still probably considerable justification for viewing the Achievable and Full Participation scenarios as somewhat "conjectural."



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

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 2011 LTDEF does not even present any figures pertaining to EVs. 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 2011-2020) 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 will 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 2012 LTDEF.