2010 ERCOT Planning

Long-Term Hourly Peak Demand and Energy Forecast

June 25, 2010

Executive Summary

The 2010 Long-Term Demand and Energy Forecast (LTDEF) for the ERCOT region is presented in this report, including the methodology, assumptions and data upon which this forecast is based. The forecast is based on a set of econometric models describing the hourly load in the region as a function of certain economic and weather variables (primarily temperatures, 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. Fifteen years of weather data are provided by DTN Meteorologix for 20 weather stations in ERCOT. The data provided by these vendors under contract with ERCOT are used as input to the energy and demand forecast models. The forecast does not account for load reductions under ancillary service programs since those programs are accounted-for in the ERCOT Capacity, Demand and Reserves report as reductions to demand for the purpose of reserve calculations.

The 2010 LTDEF reflects an initial modest economic increase in 2010, due to the sluggish recovery from the economic recession, which was projected to start in the 2010-2012 time frame. For each year of the ten-year forecast period, the projected system peak demands are lower than those projected in last year's forecast (Figure 9). Figure 1 shows the historical peak demands from 2002 to 2009 and forecasts from 2010 until 2019. The 2010 summer peak demand forecast of 64,052 MW represents an increase of 1.0% from the 2009 actual peak demand of 63,400 MW, which was set with higher than normal temperatures (August). The historical compound growth rate for the last eight years (2002-2009) has been approximately 1.77%.

However, due to the sluggish recovery reflected in the economic forecast, the nine-year growth rate for 2010-2019 is 1.72%, compared to last year's (2009 LTDEF) of 2.00% forecast growth rate for 2009 to 2019.

The key factor driving the lower peak demands and energy consumption (MWh), in comparison to the 2009 LTDEF, is the overall outlook of the economy, as measured by economic indicators such as the real per capita personal income, population, gross domestic product, and various employment measures including non-farm employment and total employment. The model was also recalibrated to include the effects of having an additional year of historical load data.

Also shown in Figure 1 are the forecast scenarios using statistical analysis and weather uncertainty profiles. The red dashed line on the top is a plot of the system peak demand forecasts using temperatures that exceed 90% of the historical temperatures (90th percentile) experienced during the last fourteen years. This temperature uncertainty scenario forecast is referred to in the figure as the High hourly forecast 90-10. The low hourly forecast 10-90 refers to the forecasts obtained by using temperatures exceeding 10% of all temperatures during the last fourteen years. The forecast for 2010 is 64,052 MW and the 90% band is 67,280 MW or approximately 5.03% higher than the forecast using normal weather.

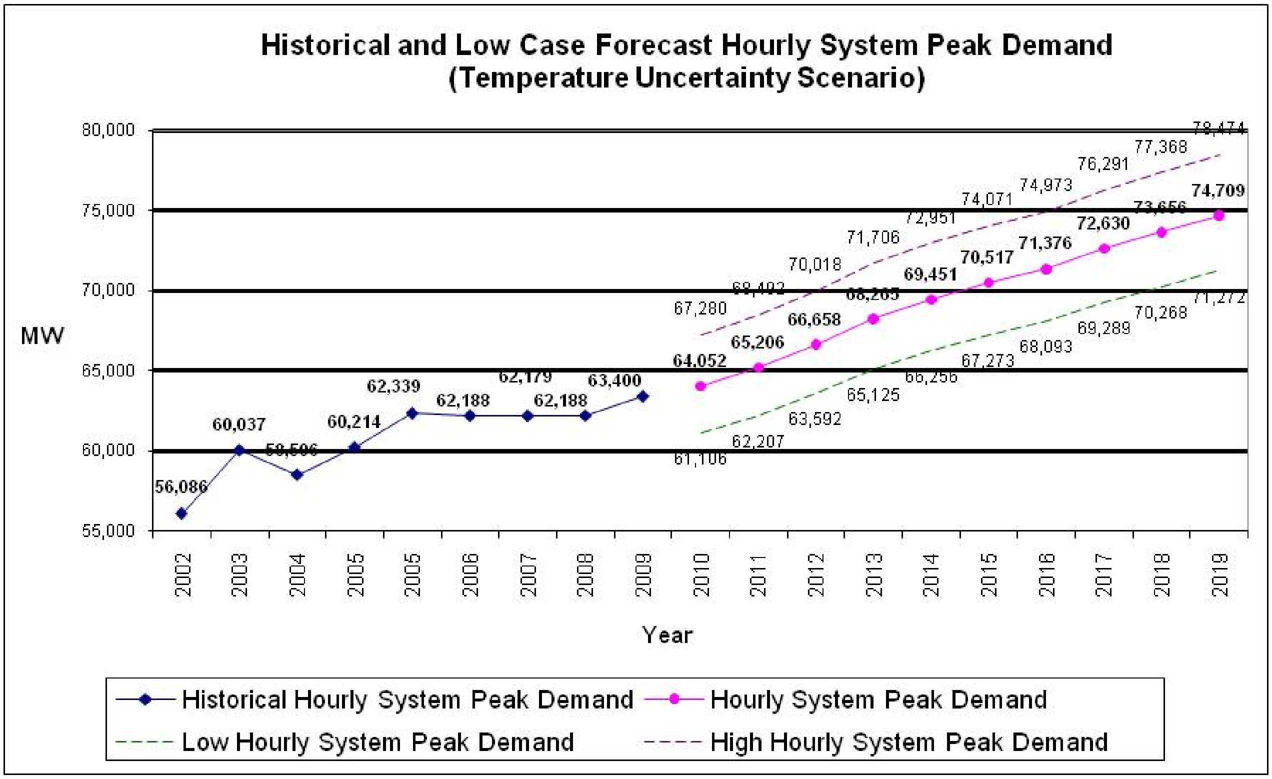


Figure 1 – Historical and Low Forecast Hourly Peak Demand

The energy consumption forecast is shown in Figure 2. The energy forecast for 2010 to 2019 is lower than the levels projected in last year's forecast. The key factor in the decline in energy consumption is the slower than expected recovery in the economic outlook for Texas, which is captured by economic indicators such as the real per capita personal income, gross domestic product, and various employment measures including non-farm employment and total employment.

The energy consumption forecast for 2010 of 310,444 GWh represents an increase of 0.07% from the 2009 actual energy consumption of 308,278 GWh. The ERCOT Long-Term Demand and Energy Forecast (2010 LTDEF) energy growth rate for 2010 to 2019 is 1.3% per year, compared to last year's (2009 LTDEF) 2.04% forecast growth rate for 2009 to 2019.

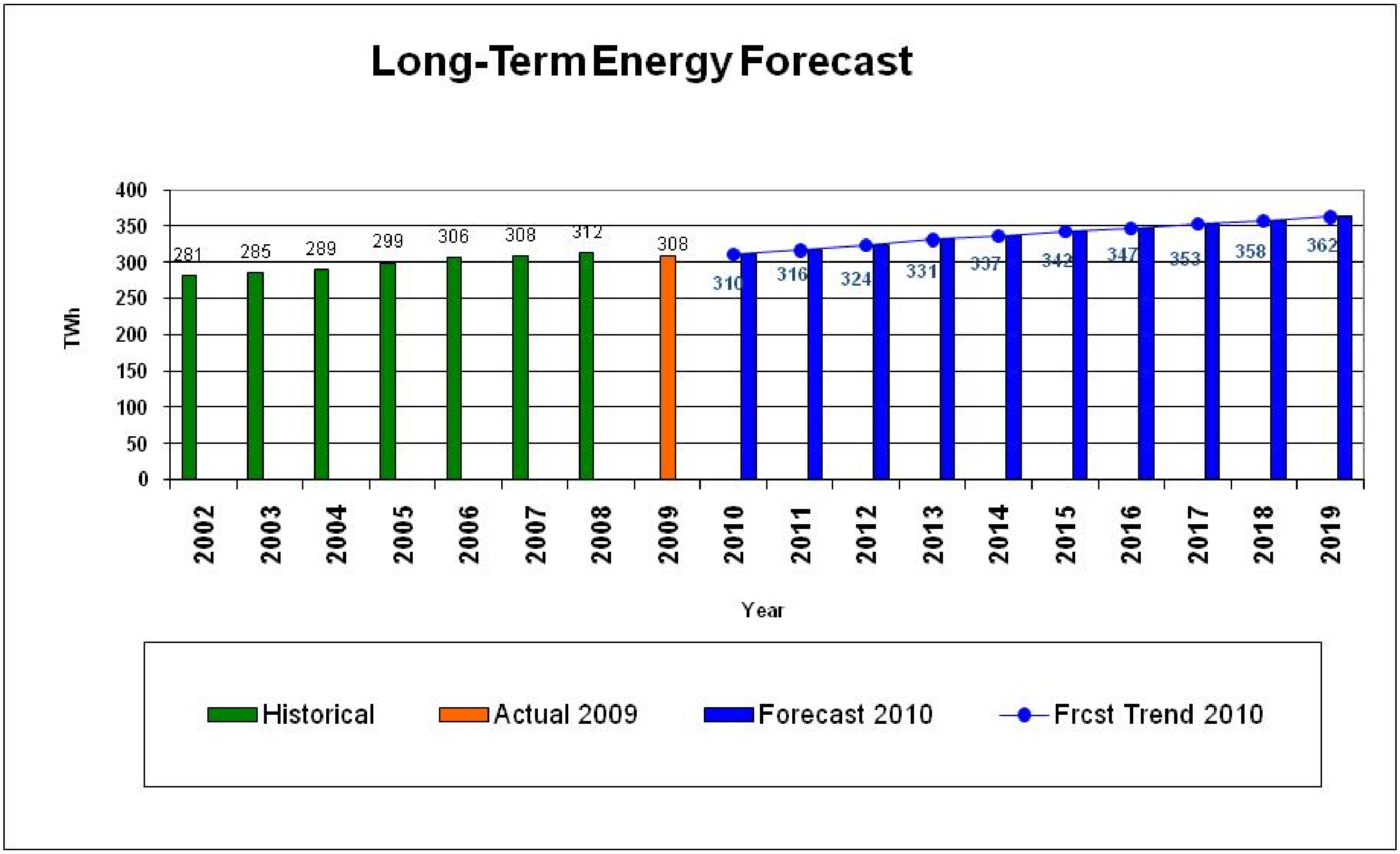


Figure 2 – Historical and Forecast Energy (TWh) Consumption

Introduction

This report gives a high level overview of the forecasts obtained from the 2010 Long-Term Forecast Model. The methodology is briefly described, highlighting the major aspects involved in producing the forecast, including the data inputs used in the process. Second, a historical perspective of the load growth in the ERCOT's territory is provided and final results of the forecast peak demands and energy from 2010 to 2019 are presented in a graphical form and summarized in a table summary format. Third, a discussion of the major drivers of peak demands and energy consumption is included, along with the uncertainties associated with the forecast, and the differences with last year's forecast. The final hourly load shape forecast is presented in a graphical form giving a perspective or comparison of the actual and forecast trends out into the period 2010 to 2019. Finally, a more detailed description of the econometric forecasting methodology used by ERCOT is provided in Appendix 3.

General Background: Forecast Development Description

The 2010 Long-Term Demand and Energy forecast was produced with a set of econometric models that use weather, economic and demographic data and calendar variables to capture and project the long-term trends in the historical load data for the past six years.

First, a representative hourly load shape by weather zone is forecasted using an average weather profile of temperatures and Cooling Degree Hours (CDH) and Heating Degree Hours (HDH) obtained from historical data to project the load shape into the future. Other factors such as seasonal daily, weekly, monthly and yearly load variations and holidays, in addition to exogenous variable interactions, such as of weather and weekends and weekdays are also considered. This hourly ERCOT Load Shape only describes the hourly load fluctuations within the year and in itself does not reflect the long-term trend.

The long-term trend is provided by the energy forecast. The monthly energy forecast models for each weather zone use Cooling Degree Days (CDD) and Heating Degree Days (HDD), economic and demographic data, and indicator variables for special events to project the monthly energy for next eighteen years (2010 - 2019).

Data Sources

Economic and demographic data, including a 20-year forecast at the county level, are obtained on a monthly basis from Moody's Economy.com. These data are used as input to the monthly energy models. With the uncertainty as to the timing of when the economy would begin recovering from the recession and the uncertainty as to the magnitude of the recovery, it was decided that the Moody's low case economic forecast was more indicative of future economic growth.

Fifteen years of weather data are available from DTN Meteorologix for 20 weather stations in ERCOT. Data from these weather stations are used to develop weighted hourly weather profiles for each of the eight weather zones. These data are used in ERCOT's Load Shape models. Monthly CDD and HDD are used in the monthly energy models.

The economic and demographic, and weather data are provided by the vendors above, and as such, are proprietary data and under contracts which require that these data not be released to the public.

Historical load data are available on an hourly basis from ERCOT's data aggregation systems since July 31, 2001 when ERCOT began operations under a single control area. Prior to 2001, ERCOT obtained hourly load data from Transmission and Distribution Service Providers (TDSPs) going back to 1995. Historical weather zone load data have only been collected from July 31, 2001.

ERCOT's Historical and Forecasted Peak Demands and Average Load Growth

Figure 3 (below) compares ERCOT's average hourly load with the annual system peak demand. The growth of the average hourly load is considered almost as a fixed amount that can be estimated with a reasonable degree of accuracy. The peak demand growth, however, is a much more volatile variable and more difficult to predict. The many factors affecting peak demand and the high degree of uncertainty in the long run make it a challenging variable, in term of assessing its behavior in the future.

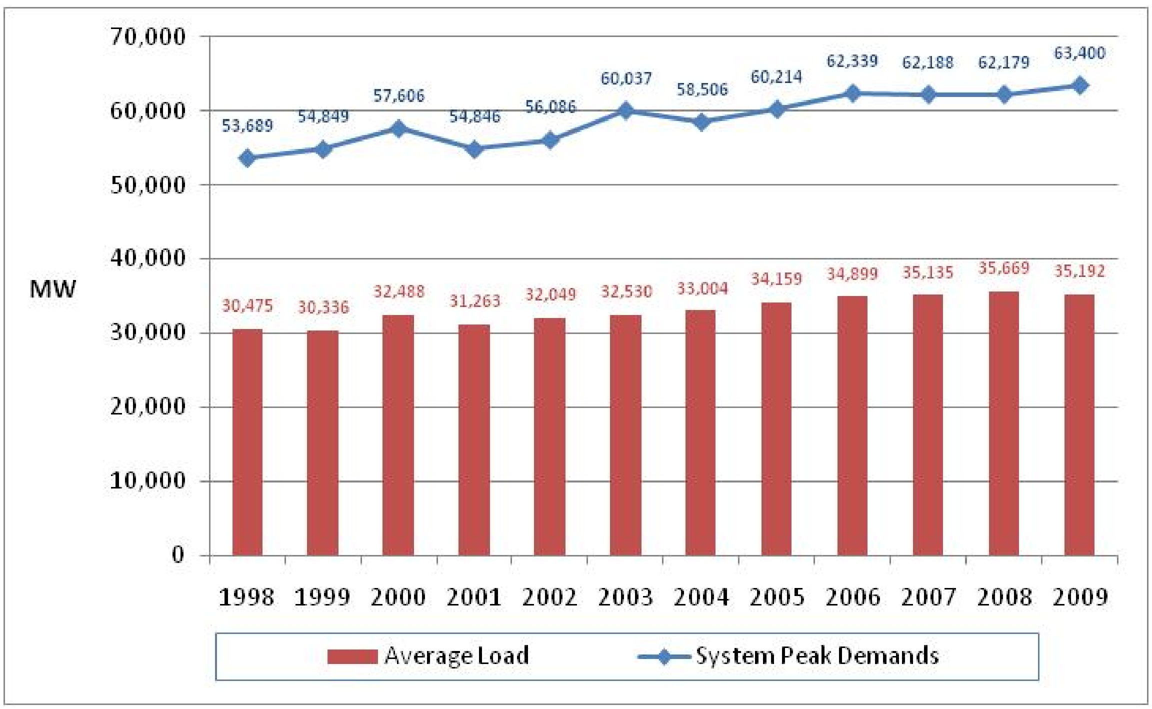


Figure 3 – ERCOT Historical Average Load versus System Peak

Over the period from 1998 to 2009, ERCOT's average hourly load grew 15.48%. By comparison, ERCOT's system peak grew 18.12%. The average annual growth rate of the system peak was 1.51% over this period.

From 2002 to 2009, a similar pattern can be detected. The average load growth rate was 9.81% versus 13.07% for the system peak. The actual system peak demand from 1998 to 2006 experienced a high growth rate which can be attributed to the specific weather for that period. The same cannot be said for the growth in system peak demand for 2006/2007 and 2007/2008. It is not likely that these specific weather patterns will be reproduced in the future, or that the relationship between average load and peak demand growth will be kept the same as in either of these periods. Although the system peak demand is affected by economic and demographic factors, it is predominantly determined by weather. On the other hand, the average load growth intrinsically reflects growth associated with economic and demographic factors.

The 2010 Long-Term peak demand and average load forecast is graphed below in Figure 4. Over the ten year period (2010-2019) the average load is projected to grow 16.73% or at a 1.67% average annual growth rate. The total system peak demand growth over the same period is 16.64%, equivalent to a 1.66% average annual growth rate. The equivalent compounded growth rate equates to 1.72%.

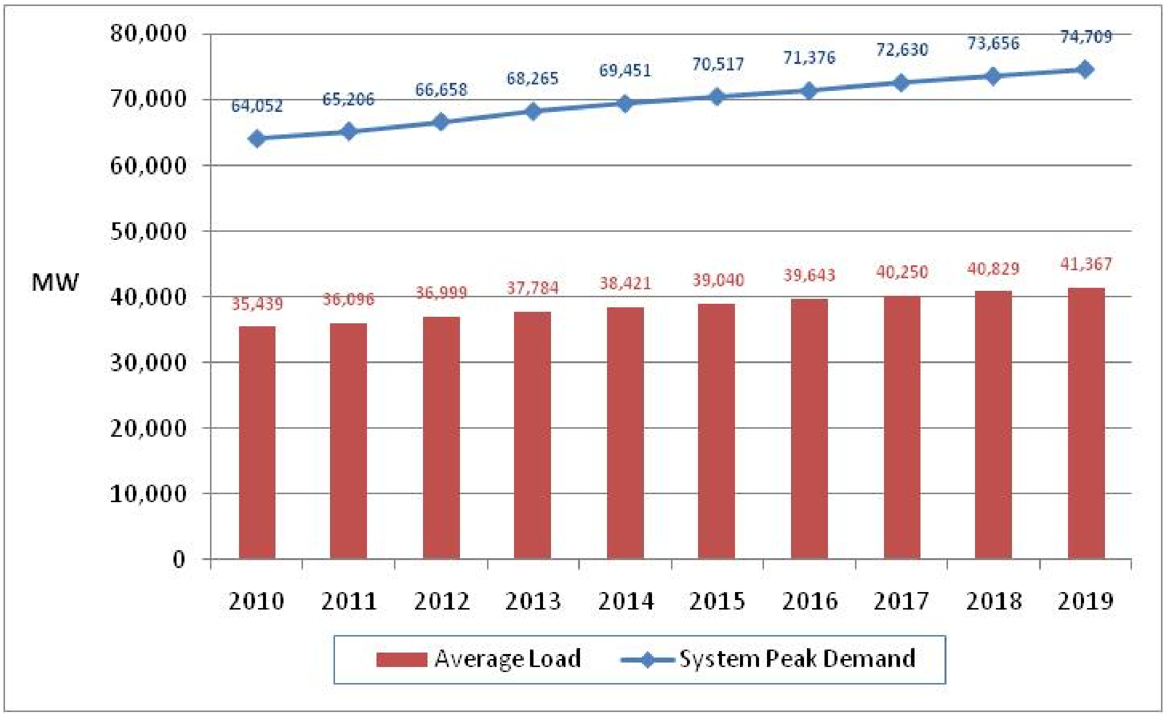


Figure 4 – ERCOT Forecast Average Load versus System Peak Forecast

ERCOT's Peak Demand and Energy Forecasts

The annual historical and forecast peak demands, and energy consumption, are displayed in figures 5 and 6, below. The historical peak demand compound growth rate from 2002 to 2009 was 1.77% and the energy growth rate over the same period was 1.31%. The 2010 LTDEF peak demand and energy forecast produced compounded growth rates of 1.72% for the peaks from 2010 to 2019 and 1.74% for the energy over the same period.

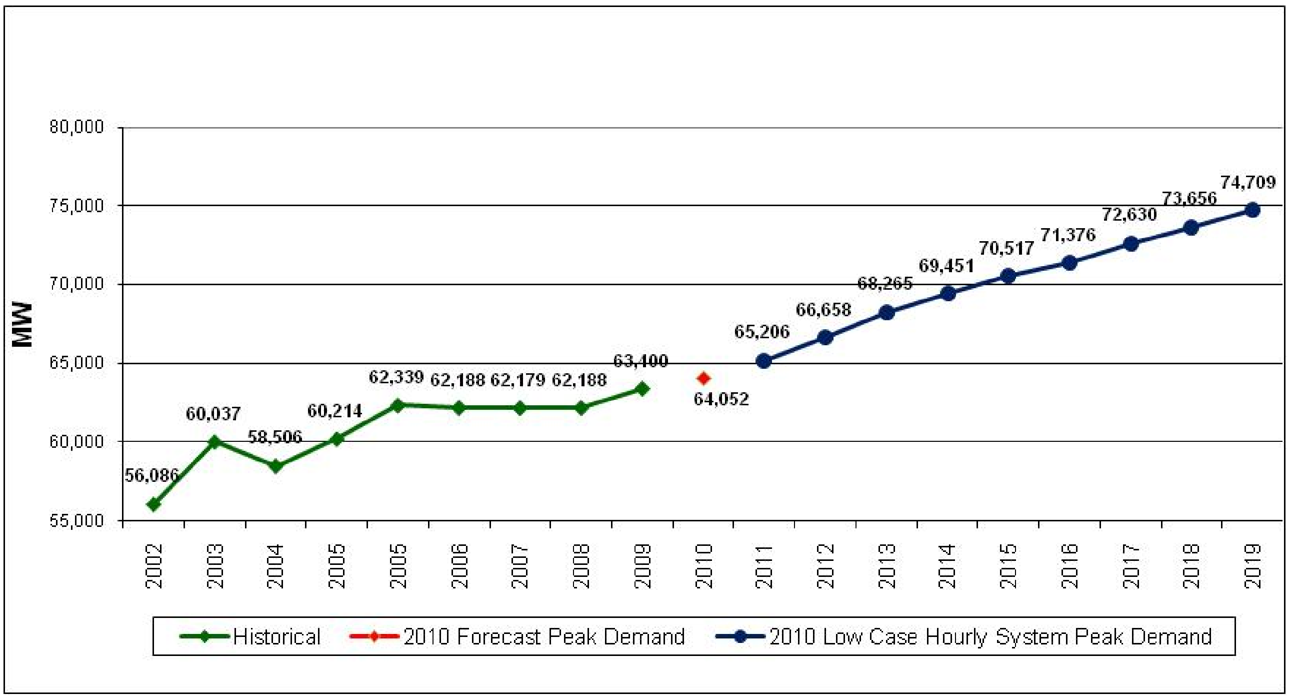


Figure 5 – Historical and Forecast Hourly Peak Demands

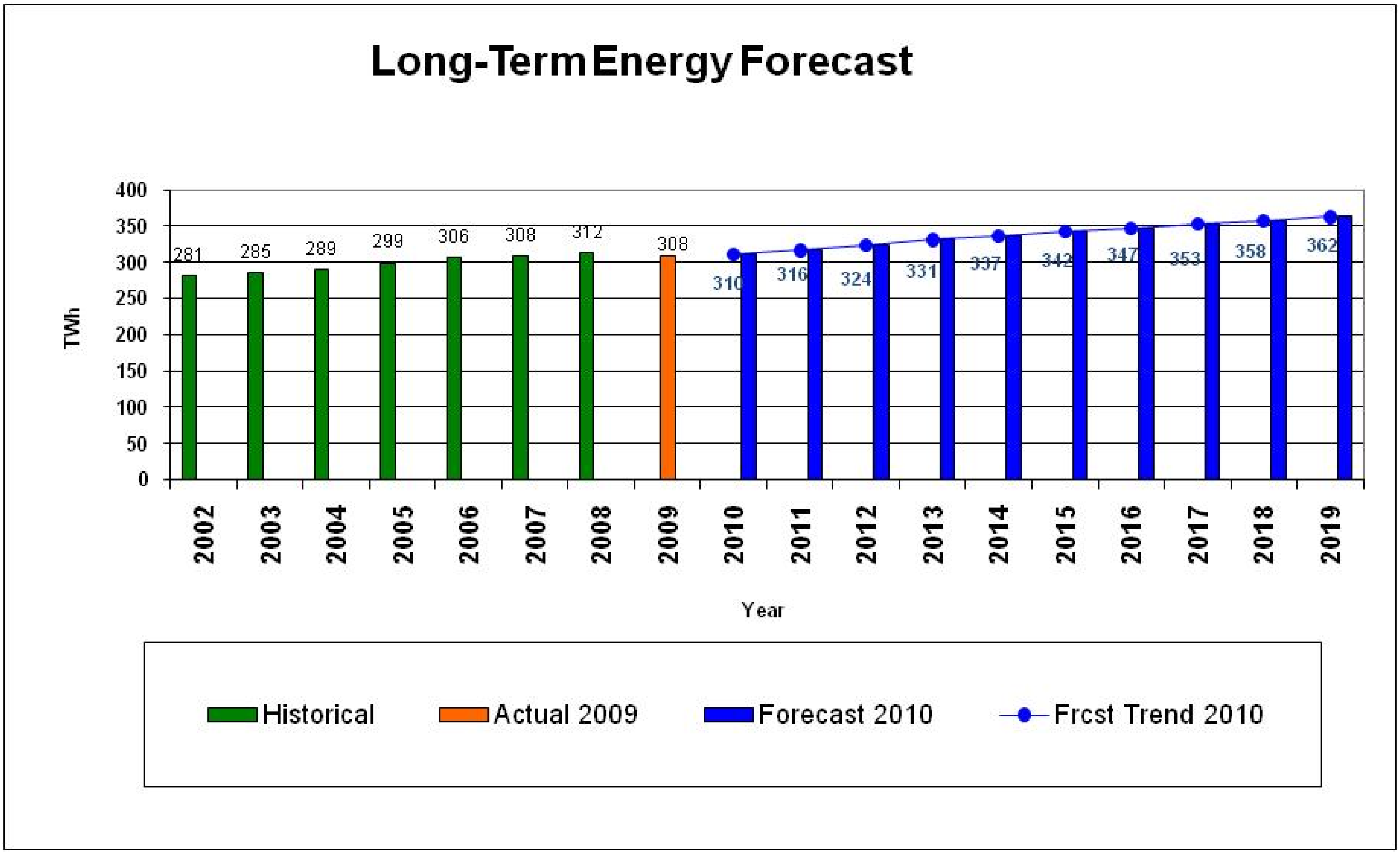


Figure 6 – Historical and Forecast Energy Consumption

Economic Outlook and Factors Driving Peak Demand and Energy

Growth in electricity demand and consumption is closely correlated with three main factors: 1) Weather, 2) Economics, and 3) Demographics. Economic and demographic changes can affect the characteristics of electrical demand in the medium to the long-run. Weather, on the other hand, drives most of the variation in electric demand in the short-run. Thus, since weather also affects the variation in the electric demand in the long-run, long-term forecasting uses historical average weather profiles to indicate the future variation in weather.

In general, the economic variables used in the models throughout the eight weather zones in the ERCOT electric grid, are various forms of employment indicators, such as total non-farm employment and total employed, real personal per-capita personal income, gross domestic product and population. Employment is a measure of the growth in the commercial and industrial areas. Population is a proxy for capturing customer formation, and income addresses overall standard of living which translates into increase in comfort and convenience and in many instances leads directly to an increase in electricity demand. Gross Domestic Product (GDP) is an important measure of economic activity in a country or an area, such as the ERCOT territory. GDP is the synthesis of three sides of the economy: expenditure, output, and income. GDP is thought to capture the overall health of the economy and shows a high correlation with the growth in electricity use. These key factors are driving the lower peak demand and energy consumption forecasts, reflecting the overall state of the economy.

The 2010 forecast is lower than last year's forecast for 2009 due to the slow recovery from the national economic recession that started in December 2007, and developed into a deep recession and financial meltdown at the US and global level. The result has been that growth has slowed to some extent at the state level, here in Texas, which affects the state's outlook for growth in employment, income and GDP. Additionally, there are some shorter term effects, derived from the housing sub-prime loans and the credit liquidity issues, which will prevail over the next two to four years. Ultimately, the economy is forecasted to continue to rebound in 2010.

There has been a deceleration in the Texas employment, and a near-term decline is forecasted. However, Texas will continue to perform better than the US. Even though the decline in housing permits is similar to the US as a whole and existing home sales slowed down considerably, the decline in home prices has been less than everywhere else in the country. Longer-term, growing global energy demand and decreasing energy supply will raise the energy prices, but not to the peak levels seen in 2008.In the long-term the energy forecast is lower than last year's forecast due to a continuing slow recovery.

ERCOT's Peak Demand and Energy Uncertainty

One measure of the uncertainty associated with extreme weather impacts on the peak demands can be obtained by using a more extreme weather profile to obtain the forecasts. ERCOT developed weather profiles that rank at the 90th percentiles of all the temperatures in its hourly temperature database and did the same to develop with the 10th percentile of all temperatures. Strictly speaking these are not confidence bands in the statistical sense, but common use has been to use this term to refer to the results. A more appropriate term would be to use scenarios associated with the 90th percentile temperature distribution or 90th percentile scenario forecasts. ERCOT has also, in the past, run Monte Carlo simulation to assess the effects of extreme temperatures on the peak demands.

For the 2010 LTFM the 90% Confidence Bands were developed and are depicted in the figures below. The high forecast for 2010 is 5.0% higher than the 2010 forecast with an average weather profile.

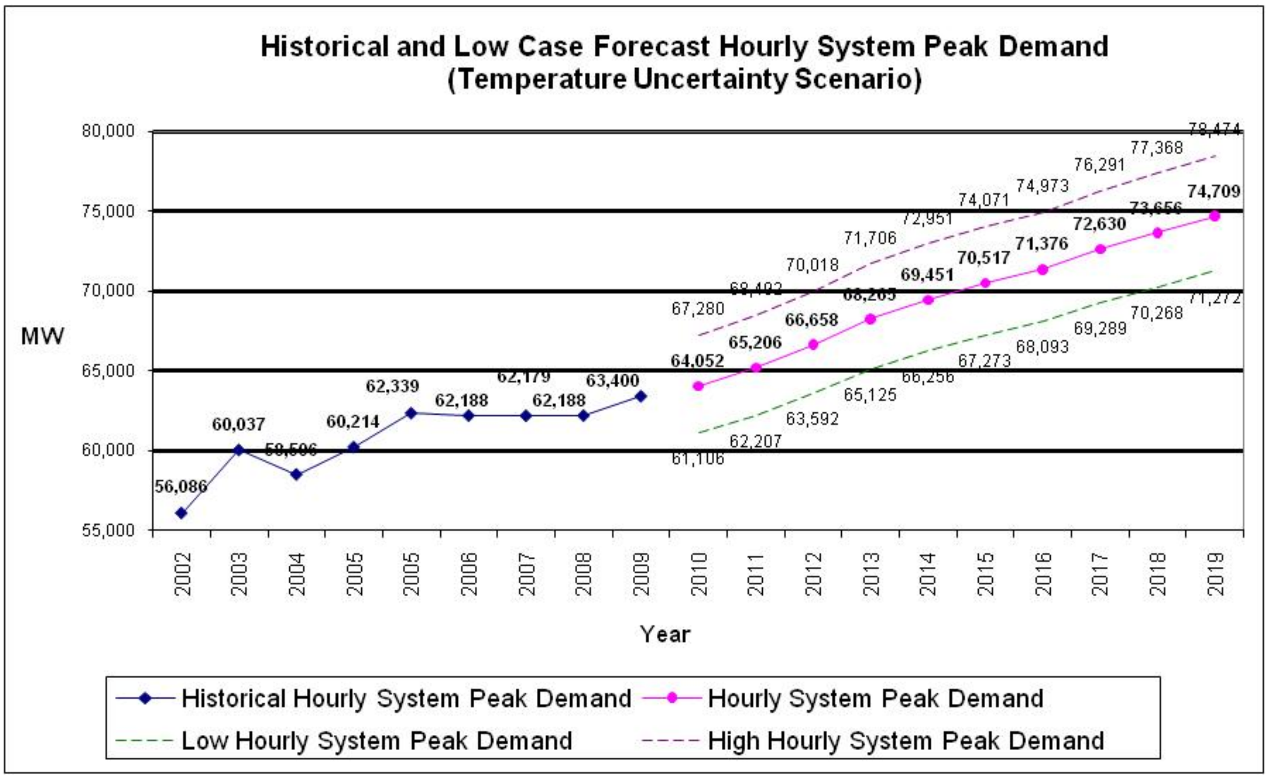


Figure 7 – Historical and Forecast Hourly Peak Demand

Differences with Last Year's Forecast

In the long term, the forecast differs significantly from last year's forecast. Overall, the forecast is lower due to the remaining effects of a national recession that are having an impact on the Texas economy. The forecasting models were recalibrated based on having an additional year of actual data. The figure below shows the two forecasts over the 2010 to 2019 time frame.

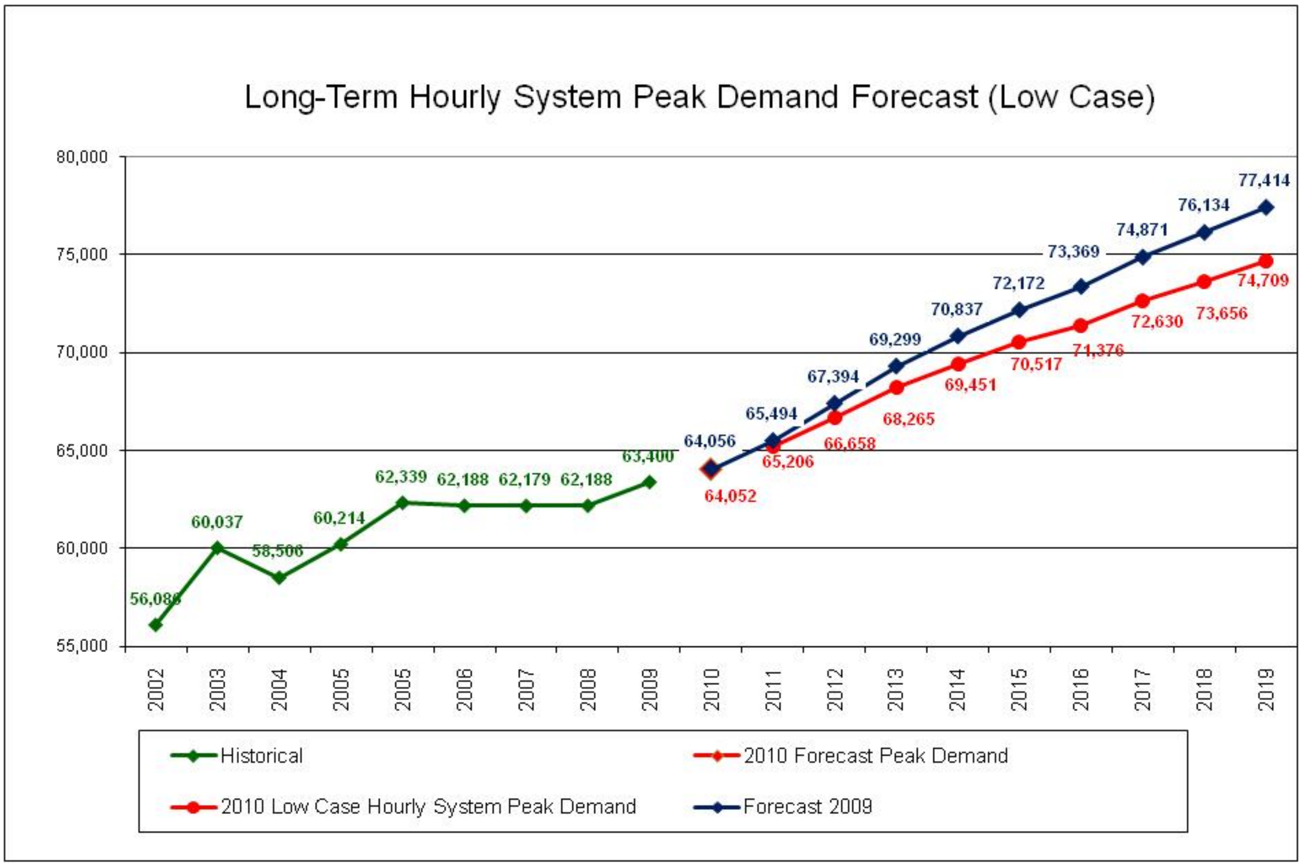


Figure 8 - Comparison of 2009 and 2010 Forecast

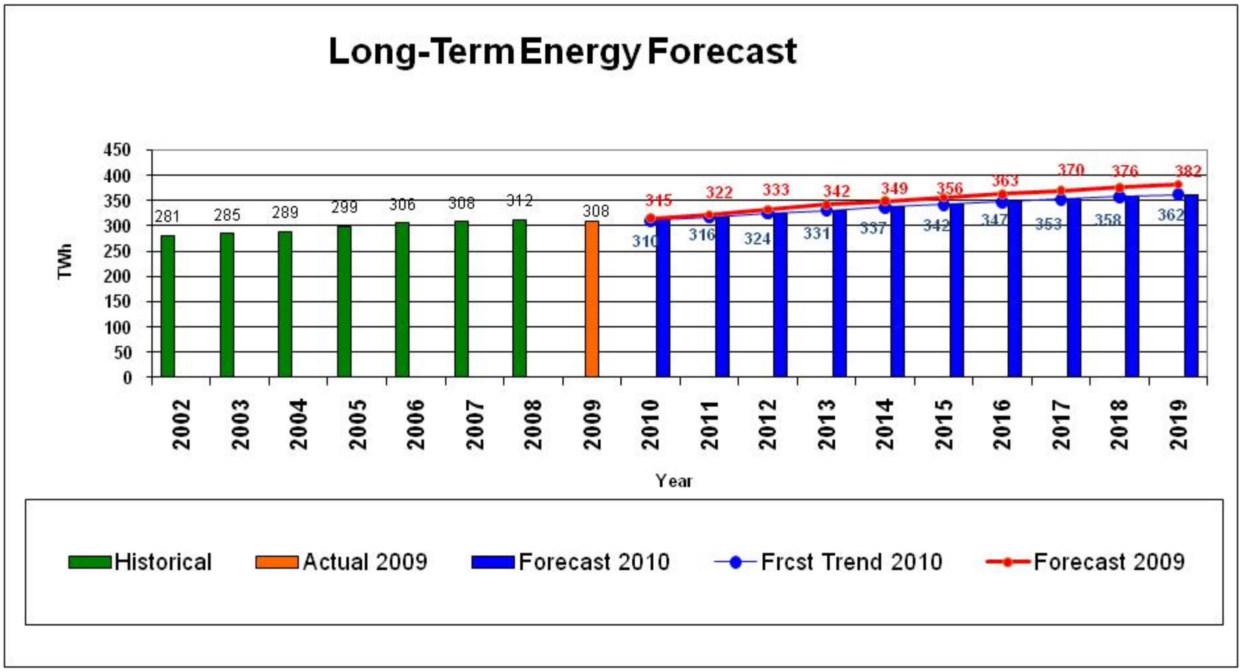


Figure 9 - Comparison of 2009 LTDEF and 2010 LTDEF

ERCOT's Load Shape Forecast

The process used to develop ERCOT's peak demand forecast produces an hourly Load Shape for each weather zone. The hourly load forecast also contributes to the annual system peak demands that are used in the resource adequacy assessment, NERC summer and Long-Term assessments, and other reports.

Figure 10 depicts a representative hourly ERCOT load shape for 2010 to 2015. This load shape is derived using an average weather profile. Because of this, the ERCOT load shapes are basically the same for each forecast year. The upward trend comes from the economic forecasts that drive the energy consumption forecasts. Figures 11, 12, 13 and 14 show a peak day for each season.

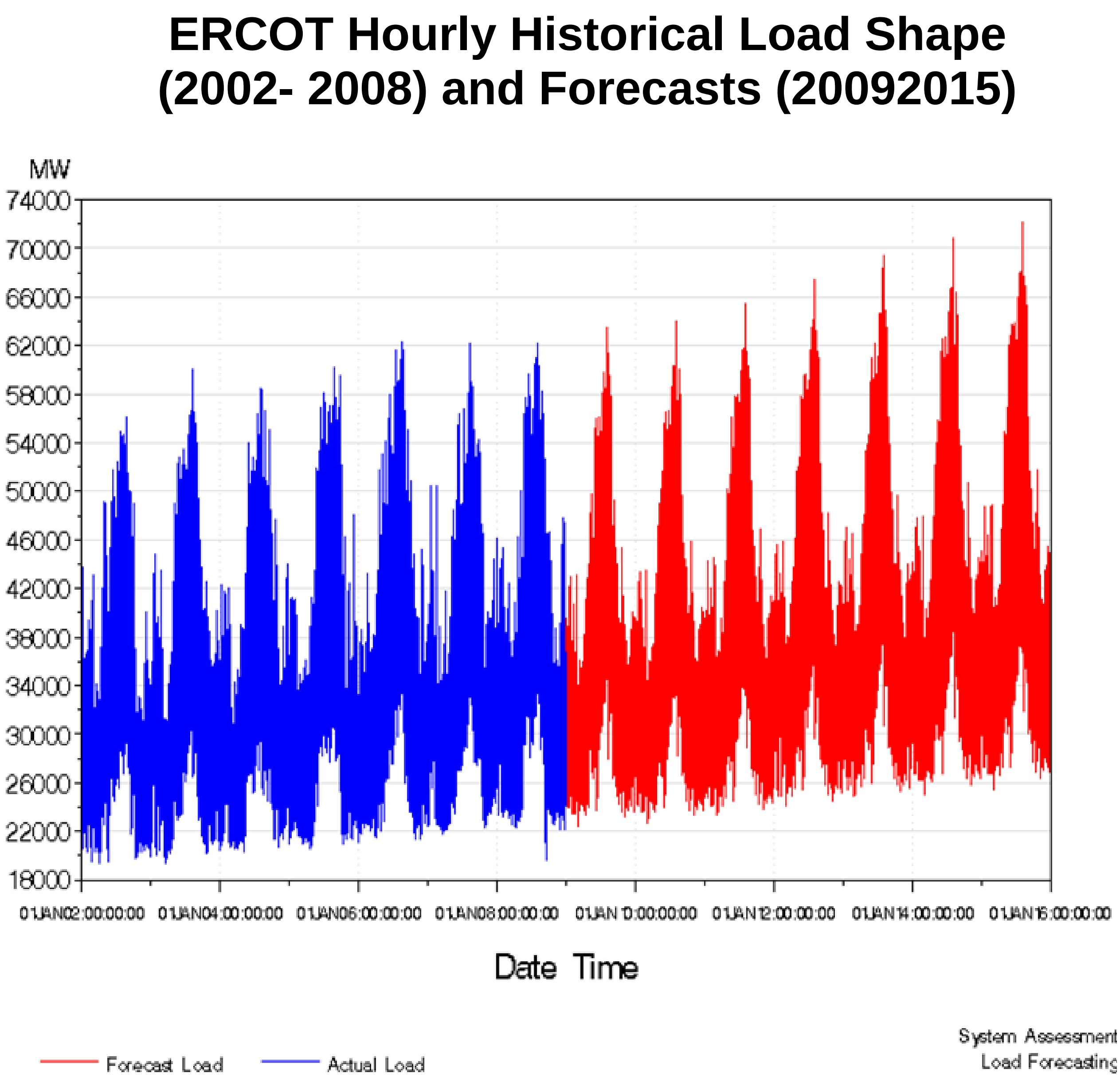


Figure 10 – Hourly Load Forecast and Actual

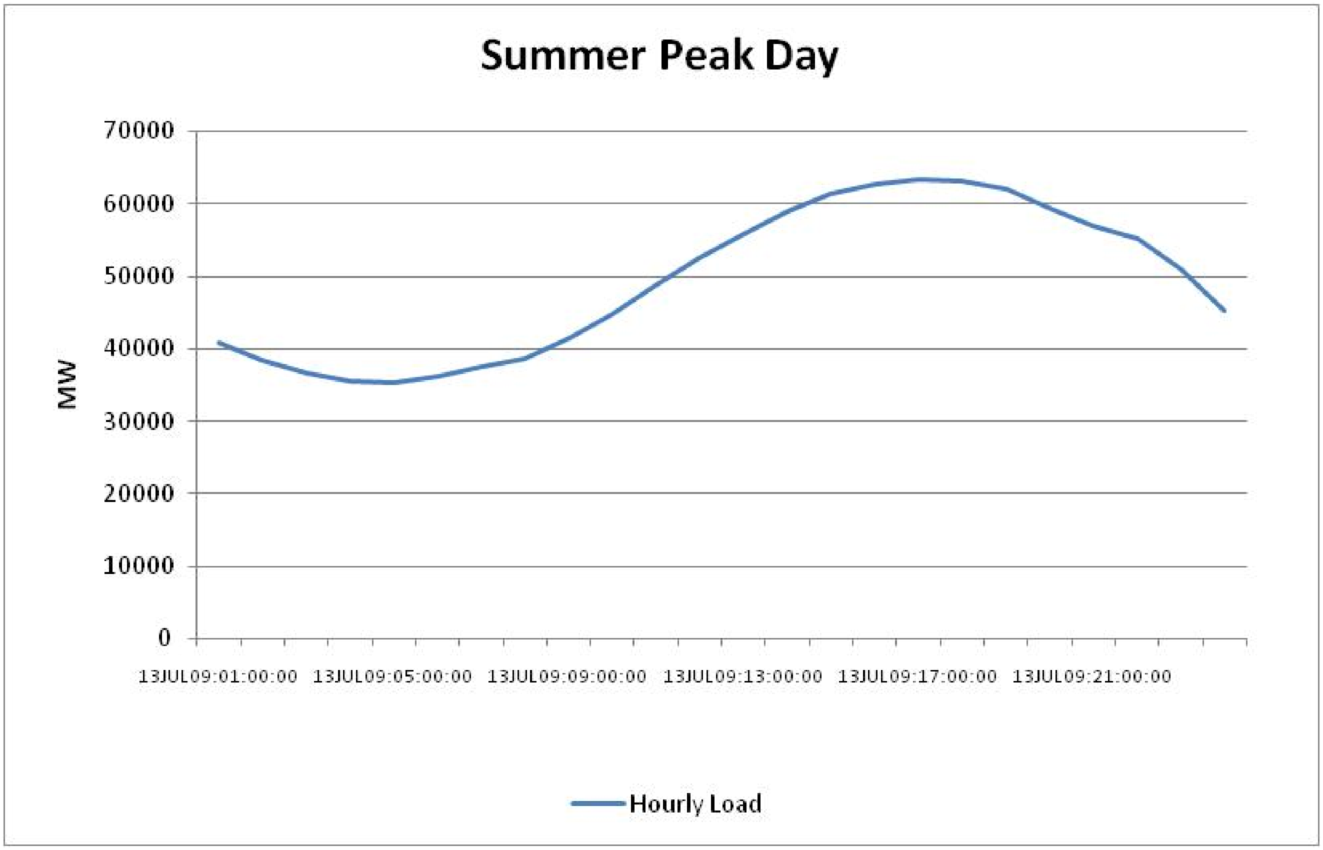


Figure 11 – Summer Peak Day

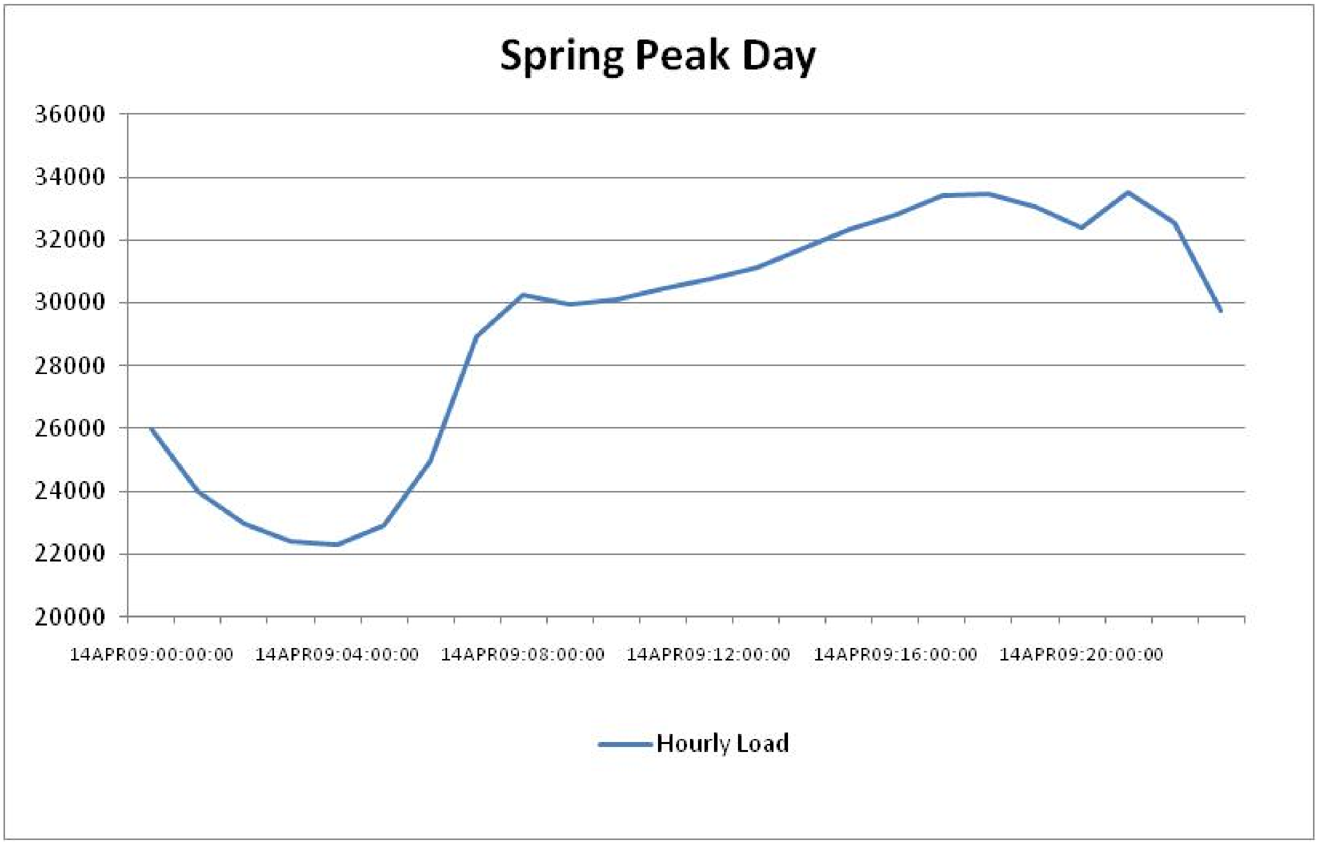


Figure 12 – Spring Peak Day

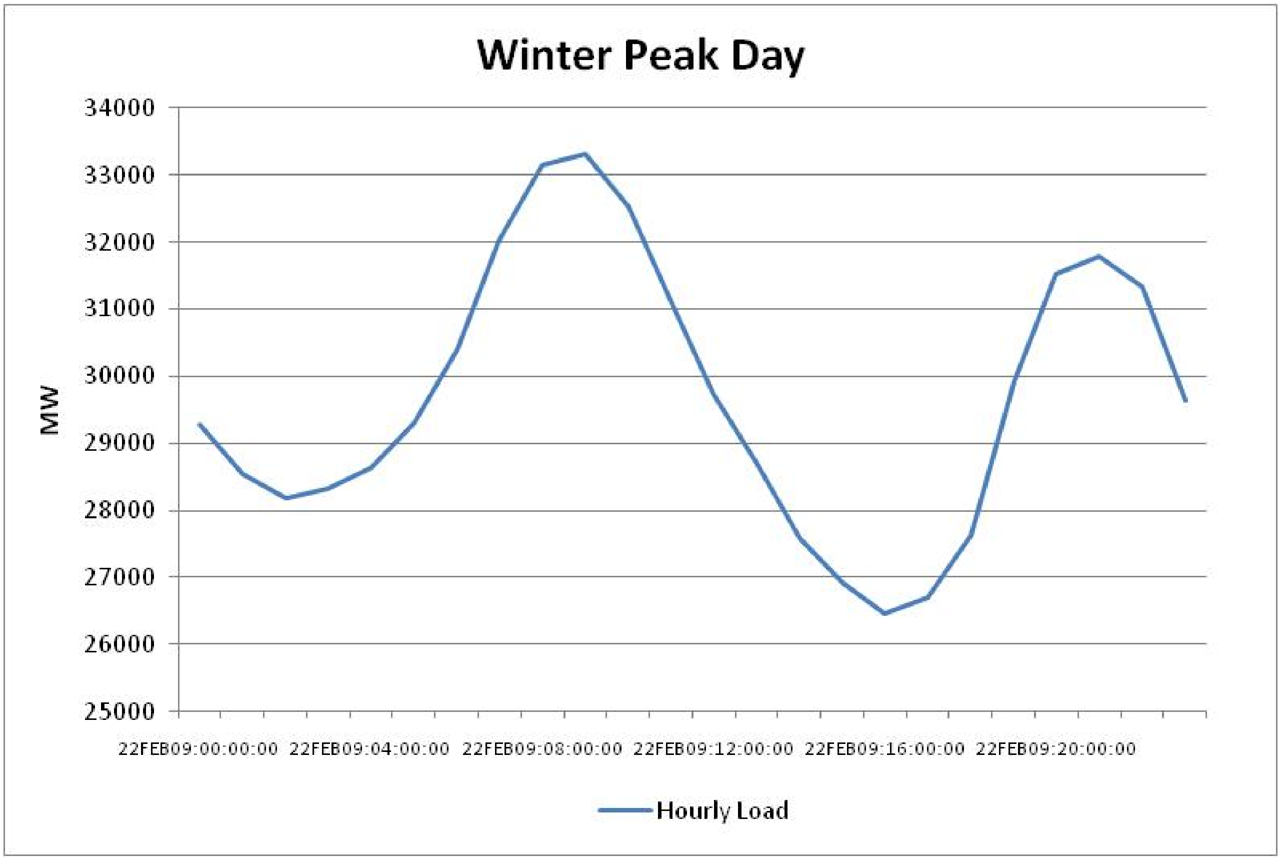


Figure 13 – Winter Peak Day

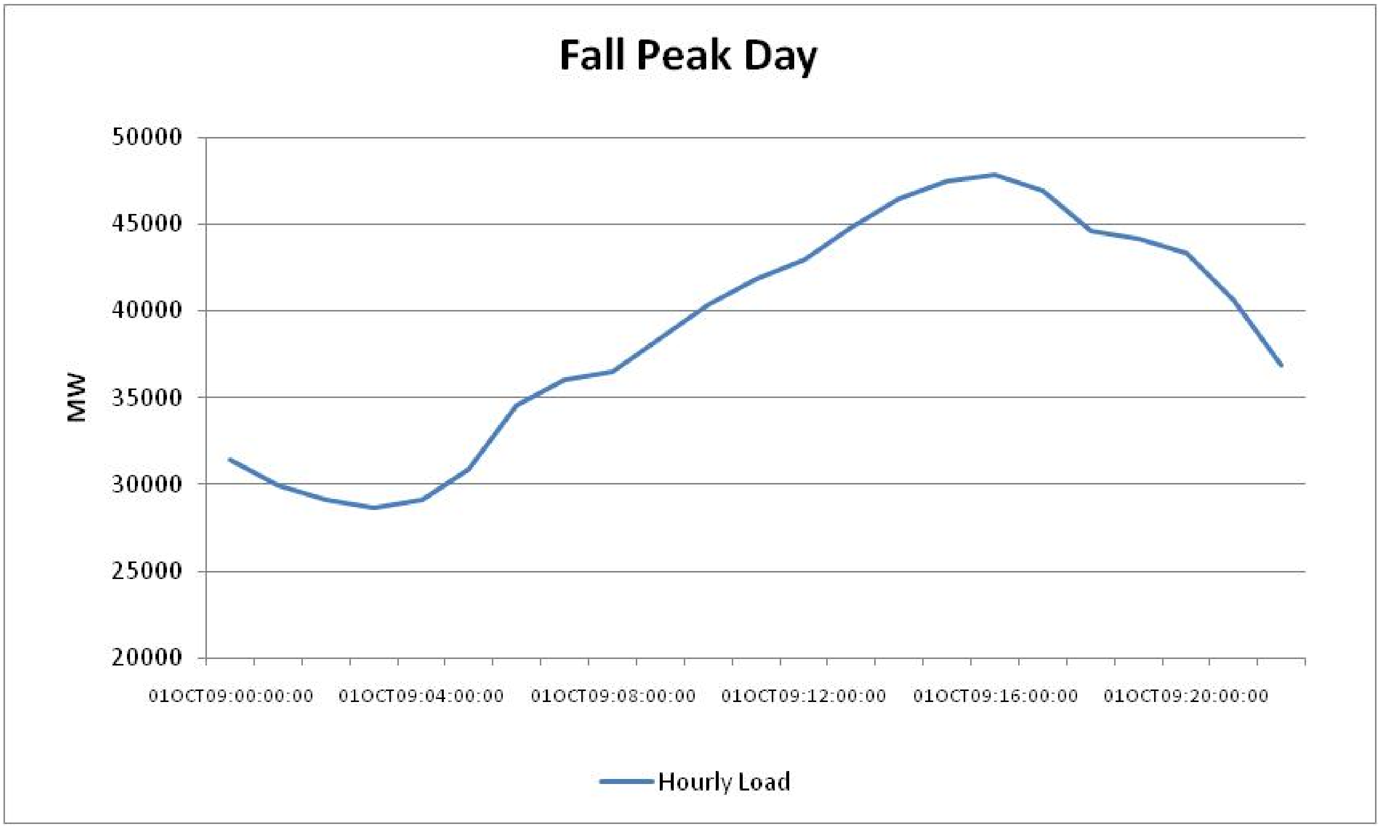


Figure 14 – Fall Peak Day

Texas continues to recover at a very moderate and slow pace. Other recent data are more positive and point to potential for near-term acceleration in the state's economy. The key industries leading the advance are high tech, particularly semiconductor manufacturing, telecom, energy-related equipment, related supplies, and petrochemicals.

Specifically, manufacturing is heating up as the Texas Outlook Survey reported increasing current activity for the sixth straight month in April. Almost every component index is now in positive territory for the first time in nearly two years. Of particular note are the recent strong positive readings for employment and workweek. These indicators are consistent with the employment surveys and show slow but steady job growth for the state for the past six months. Moreover, optimism about the future remains high, as indices for future activity also increased and have now been in positive territory for the past year. Housing around the state is beginning to improve again after a lull since mid-2009. The lack of excess supply in each of the major single-family markets has kept home prices essentially stable throughout this cycle. Not all the news is positive however, as the still unchecked oil spill following the explosion of the Deepwater Horizon offshore oil rig casts a long shadow over the prospects for the local energy industry. Nonetheless, our forecast is that global recovery in energy demand will be more than offset. This will lead to a continuation of the rebound in oil prices and local exploration in such places as Houston and Midland. However, the oil spill will result in higher insurance rates for offshore drilling, new government safety regulations that will also be costly, and European debt turmoil will constrain the advance of oil prices. As a result, less-profitable drilling projects will be postponed or cancelled, affecting the pace of the local recovery.

ERCOT's Peak Demand and Energy Forecast by MSA

There are eight defined weather zones at ERCOT, which approximately correspond to MSAs. The weather zones are: 1) North, 2) North Central, 3) East, 4) Far West, 5) West, 6) South Central, 7) Coastal, and 8) South. The largest MSAs are located in the North Central, South Central and Coastal zones. The Dallas/FW area is in the North-Central zone, Austin and San Antonio areas are contained within the South-Central zone, and Houston is in the Coastal zone.Dallas/FortWorth semiconductor and telecom industries will continue to help the local rebound. For example, capacity utilization at the huge, Richardson TI plant is increasing, driven by the strong global high-tech recovery. Houston's recovery is facing several new hurdles. In addition to the dampening effects of the oil spill on the energy industry, the Obama administration's proposal to cancel the Constellation program could mean the loss of many highly paid engineering and technical jobs. Further, the Continental-United merger will mean fewer local management jobs. However, prospects for local activity of the airline itself remain good as the airport has room for expansion and Houston remains a gateway to Latin America. San Antonio's recovery is on track. The June addition of Tacoma production at the Toyota plant will diversify output and help the company hold onto its small-truck market share. Additionally, the local convention business will continue to expand in 2010, having bucked the national trend in 2009 as total room nights in the first quarter were up nearly 12% compared to the year before. Additions to the stock of hotel rooms raised the metro area total by 20% between 2006 and 2009, enabling the area to compete for larger conventions. Austin will continue to lead the state as strong population gains drive retail spending. Additionally, the tech rebound is lifting the prospects of many small local companies. However, the hiring freeze and UT, owing to state budget issues, will be a drag.

All three areas have been previously affected by substantial slowdowns in nonresidential construction and property markets. This cyclical weakness is most apparent in Dallas and Austin, where office vacancy rates were particularly high and rising. However, the credit crisis has also meant that weakness was emerging on San Antonio and Houston. Further, although service-producing industries had previously offsets declines in manufacturing employment, in the short-term that is no longer the case in these major MSAs.

The forecasts for these major zones vary in terms of near-term economic performance. Longer term, after the current cycle finally ends, the various fundamentals which drive above-average long-term performance of the largest, compared to the U.S as a whole, remain in place. These include above average population growth, relatively lower costs of doing business when contrasted with comparable metropolitan areas elsewhere in the country, energy resources, concentration of high tech companies, and growing transportation and distribution capacity. The forecasts for the smaller zones show an average or below average trend in growth.

The annual forecasts data by weather zone are included in Tables 2 and 3 of Appendix 2.

APPENDIX 1: PEAK DEMAND AND ENERGY CONSUMPTION DATA

A summary of the 2010 Long-Term Forecast Model (LTFM) results is condensed below. This table includes forecast energy, forecast energy for the load shape, the MWh historical values, the coincident and zonal peaks, the diversity, coincident, and load factors and the diversity in % terms. For reference, historical data for 2002-2009 is included. The MW peak is a coincident peak and the zonal peak refers to the aggregate of individual non-coincident peaks. The Energy MWh column, from 2002-2009, contains the forecasted values for that period. The MWh_Hist contains the historical energy consumption for 2002-2009. The following quantities in the table below can be defined as follows (numbers are rounded):

Load Factor: (energy/(peak*number of hours in a year)
Diversity: (Non-Coincident Peak – Coincident Peak)
Diversity Percent: (Diversity Factor/Coincident Peak)
Coincident Factor: (1-Diversity Percent)

Year	Actual/Forecast MWh	MWh Peak	Zonal Peak	Diversity	Coincident Factor	Diversity %	Load Factor
2002	280,750,077	56,086	57,237	1,151	97.99%	2.01%	57.14%
2003	284,960,390	60,036	60,411	375	99.38%	0.62%	54.18%
2004	289,117,029	58,507	59,342	835	98.59%	1.41%	56.41%
2005	299,229,332	60,215	61,393	1,178	98.08%	1.92%	56.73%
2006	305,716,035	62,339	63,372	1,033	98.37%	1.63%	55.98%
2007	307,783,177	62,187	63,686	1,499	97.65%	2.35%	56.50%
2008	312,460,058	62,179	64,394	2,215	96.56%	3.44%	57.36%
2009	308,278,171	63,400	65,142	1,742	97.33%	2.67%	55.51%
2010	310,444,722	64,052	64,558	506	99.22%	0.78%	55.33%
2011	316,194,142	65,206	65,719	513	99.22%	0.78%	55.36%
2012	324,104,991	66,658	67,178	520	99.23%	0.77%	55.50%
2013	330,985,125	68,265	68,725	460	99.33%	0.67%	55.35%
2014	336,564,643	69,451	69,991	540	99.23%	0.77%	55.32%
2015	341,980,635	70,517	71,063	546	99.23%	0.77%	55.36%
2016	347,271,990	71,376	71,927	551	99.23%	0.77%	55.54%
2017	352,584,337	72,630	73,176	546	99.25%	0.75%	55.42%
2018	357,653,548	73,656	74,229	573	99.23%	0.77%	55.43%
2019	362,373,844	74,709	75,200	491	99.35%	0.65%	55.37%
2020	367,079,690	75,526	76,099	573	99.25%	0.75%	55.48%
2021	371,686,335	76,639	77,218	579	99.25%	0.75%	55.36%
2022	375,960,834	77,479	78,063	584	99.25%	0.75%	55.39%
2023	380,426,448	78,406	78,982	576	99.27%	0.73%	55.39%
2024	385,124,827	79,162	79,763	601	99.25%	0.75%	55.54%
2025	389,711,510	80,477	81,077	600	99.26%	0.74%	55.28%

Table 1 – Forecast Results of the 2010 Long-Term Forecast Model

APPENDIX 2: WEATHER ZONE LOAD DATA

Year	North	North Central	East	Far West	West	South Central	Coast	South
2002	1,414	21,061	2,175	1,741	1,644	9,181	14,578	4,292
2003	1,520	22,898	2,319	1,712	1,728	9,685	15,823	4,351
2004	1,496	21,343	2,265	1,572	1,610	9,293	16,611	4,317
2005	1,462	22,634	2,351	1,576	1,592	9,788	16,282	4,530
2006	1,684	23,406	2,432	1,516	1,665	10,311	16,734	4,591
2007	1,486	22,761	2,252	1,544	1,519	10,008	18,228	4,389
2008	1,610	23,364	2,303	1,707	1,615	10,466	16,825	4,289
2009	1,514	23,329	2,314	1,683	1,685	10,712	17,595	4,584
2010	1,427	23,719	2,299	1,700	1,780	10,087	18,488	4,552
2011	1,428	24,037	2,332	1,716	1,796	10,289	18,959	4,650
2012	1,418	24,394	2,367	1,740	1,844	10,553	19,521	4,820
2013	1,413	24,732	2,504	1,778	1,908	10,888	20,025	5,018
2014	1,417	25,005	2,458	1,803	1,952	11,199	20,422	5,194
2015	1,413	25,242	2,492	1,824	1,987	11,398	20,836	5,325
2016	1,405	25,408	2,518	1,838	2,015	11,538	21,227	5,427
2017	1,405	25,829	2,553	1,863	2,047	11,718	21,677	5,539
2018	1,400	26,178	2,584	1,880	2,077	11,861	22,043	5,632
2019	1,398	26,513	2,705	1,898	2,104	11,999	22,377	5,717
2020	1,400	26,827	2,639	1,911	2,127	12,165	22,661	5,796
2021	1,400	27,237	2,673	1,933	2,160	12,301	23,047	5,888
2022	1,397	27,536	2,698	1,948	2,184	12,403	23,354	5,959
2023	1,396	27,924	2,721	1,963	2,202	12,505	23,668	6,027
2024	1,387	28,277	2,736	1,972	2,216	12,577	23,919	6,078
2025	1,397	28,822	2,765	1,990	2,237	12,771	24,320	6,175

Table 2 – Historical and Forecast Coincident Peak Demands by Weather Zone (MW)

Year	North	North Central	East	Far West	West	South Central	Coast	South
2002	7,986	99,090	11,543	9,669	7,580	43,591	79,019	22,273
2003	7,827	99,134	11,746	9,520	7,842	44,191	82,475	22,225
2004	8,067	98,700	11,685	9,502	8,184	44,508	85,690	22,781
2005	8,124	103,439	12,203	9,749	8,388	47,162	86,554	23,610
2006	8,110	105,205	12,323	10,114	8,346	48,986	88,736	23,895
2007	7,959	104,946	12,686	10,201	8,349	49,774	89,811	24,058
2008	8,109	106,527	13,123	10,701	8,633	52,272	88,516	24,579
2009	7,543	103,639	12,200	10,563	8,783	51,722	88,648	25,181
2010	7,913	105,799	12,794	10,440	8,660	51,004	89,946	23,893
2011	7,923	107,218	12,987	10,533	8,745	52,075	92,293	24,426
2012	7,898	109,110	13,207	10,711	9,002	53,575	95,227	25,379
2013	7,873	110,375	13,468	10,919	9,292	55,210	97,474	26,379
2014	7,850	111,444	13,664	11,069	9,488	56,473	99,337	27,246
2015	7,829	112,553	13,860	11,196	9,665	57,550	101,394	27,941
2016	7,814	113,620	14,057	11,313	9,831	58,492	103,581	28,569
2017	7,804	115,201	14,212	11,435	9,966	59,351	105,517	29,104
2018	7,797	116,818	14,394	11,546	10,115	60,107	107,287	29,595
2019	7,787	118,324	14,553	11,655	10,246	60,841	108,922	30,049
2020	7,777	119,920	14,720	11,761	10,371	61,517	110,537	30,477
2021	7,763	121,464	14,874	11,865	10,508	62,178	112,127	30,908
2022	7,754	122,824	15,026	11,958	10,629	62,775	113,688	31,306
2023	7,750	124,544	15,146	12,049	10,723	63,337	115,206	31,672
2024	7,752	126,514	15,278	12,140	10,820	63,890	116,712	32,017
2025	7,739	128,445	15,371	12,218	10,870	64,394	118,287	32,388

Table 3 – Historical and Forecast Energy by Weather Zone (GWh)

APPENDIX 3: METHODOLOGY

A Modified Approach to Long-Term Load And Energy Forecasting: Its Uses In An ISO's Environment For Resource Adequacy And Transmission Planning

Introduction

The main focus of this paper is the benefits of a modified approach to long-term demand and energy forecasting model in an ISO's setting. The forecasts that were produced by a regression model are input into several planning processes that are important in the long-term planning of an electrical grid. The development of this forecasting methodology was designed to address the needs for forecasts in several processes. The load forecasting methodology that was adopted is discussed and its results are outlined. The objective of this methodology is to determine a long-term view of the peak demands that ERCOT (total load served in the ERCOT region including exports across DC ties and excluding private use network loads) can expect to face, in order to secure sufficient resources in the next five to ten years. The discussion covers the success experienced in using this methodology and details of the process involved in producing the forecasts. More specifically, this paper details:

- A methodology developed specifically for ERCOT to meet its specific needs.
- How the methodology chosen has been used to successfully meet ERCOT's planning objectives.

Why it is needed

The development of a long-term trend outlook uses a regression model that forecasts peak demands that are most likely to occur under normal weather conditions to determine the approximate timing for scheduling the building of transmission lines to balance the supply and demand for electric power in the ERCOT electrical grid. The load forecast is an input to the reserve margin calculation. As such, the load forecast is a key component necessary for meeting this objective, which is used to ensure a balanced system.

A resource adequacy assessment begins with the calculation of a reserve margin as,

Reserve margin= ((Resources – Firm Load Forecast)/Firm Load Forecast) *100

This calculation is the foundation of the process for determining the adequacy of the system. The review of resource adequacy is an annual process that ensures that enough resources will be available to meet demand in the medium-to long-term time frame.

The forecast is also used in the medium-range planning of resources by the outage coordinators to schedule plant outages for the next year.

Another aspect of system adequacy, where the load forecast plays an important role, entails performing a load sensitivity assessment. This assessment is related to the risk associated with the volatility of the load due to weather. The 90% approximate forecast limits due to the volatility associated with forecasting the load, using temperatures at the 90th percentile of the distribution, are calculated for the next ten to fifteen years to assess the risks of extreme weather volatility on the peak demands. These load volatility estimates are an input into the loss-of-load-probability studies (LOLP), which are used to determine the target reserve margin.

Reviews of the reserve margin to ensure its adequacy are performed every few years through a LOLP study. In this study, expected load, load forecast error, the load volatility due to weather, generation fleet, maintenance schedules, and unit forced outage rates are input into a unit commitment and dispatch model in order to simulate the interrelationships between these variables over a number of replications. This simulation yields an expected un-served energy value. Then, the target reserve margin is obtained by finding the minimum point of the intersection where the LOLP is the ERCOT/NERC standard of one event every ten years.

Load volatility estimates derived from the load forecast are also used by NERC in the summer and winter reliability assessments. These load forecasts feed into the reporting requirements of FERC 714.

The long-term hourly load forecast by weather zones also serves an important function in performing economic analyses. It is an input to the UPLAN software which determines whether or not to undertake transmission projects.

As described above, the load forecast is a major input to several planning processes. The long-term forecast can affect the adequacy of the system grid. Some of the consequences of load forecast errors and their impact on system adequacy can be:

- Building excessive additional generation capacity and/or transmission facilities
- Inadequate levels of resources and generation leading to blackouts and price spikes
- Sending incorrect signals to the market regarding the value of ancillary payments and energy

Finally, the energy consumption forecast provides the means to determine the annual $/MWh ERCOT fee for the annual budget review, conducted by the Texas PUC.

Availability of methods

There are a wide variety of methods that can be used to forecast system peak and energy consumption. Such methods range from simple trending methods to more complex ones such as end-use forecasting or hybrid end use and econometric techniques, sophisticated Box-Jenkins Transfer function (Dynamic Regression) models and neural network models that can be adapted to produce long-term forecasts

For ERCOT, data requirements were a major determinant of which method was feasible and appropriate to implement. There were specific requirements to be met in terms of the end product. The following describes the specific nature of these data needs.

Forecast Level of Detail

An hourly forecasted load shape by weather zones for the next five to ten years was needed as an input into UPLAN for economic analysis of transmission projects. The hourly loads from the load shape, combined with the results of a monthly energy forecast, were considered a feasible way to produce a system peak forecast for each year in the five-to-ten-year horizon. The system peaks and energy consumption forecasts were thought to be a high priority for this important process as these forecasts could as well be used as inputs into the resource adequacy process.

Load and Weather Data level of Detail

ERCOT Staff decided to produce long-term forecasts for eight major areas in Texas where weather data was available and coincided with the available data appropriate for load analysis. Thus, from ERCOT‘s standpoint, weather zones were the logical choice. In addition, these zones also coincided with the major areas of interest for the analysis of transmission projects. In summary, the total load by weather zone was chosen as meeting the objective of the forecast needs. These forecasts then could be aggregated to a system level.

Economic, Demographic and Price Data Level of Detail

Besides hourly load, ERCOT also secures weather data, economic and demographic data from outside providers. In regard to prices, which are considered an important driver for inclusion in a demand equation, it is not clear as to whether the wholesale prices that ERCOT collects are really the most relevant for a forecasting application, in terms of being the prices ultimately faced by the consumer. Since the wholesale prices are collected on an hourly basis, and retail prices are better reflected by an average over a longer time period, such as a month, wholesale hourly prices do not capture the correlation with the MWh consumption correctly. Several attempts to include market clearing prices of energy (MCPE s) in the forecasting models were made but were unsuccessful. The models obtained showed price to be insignificant or to indicate a nonsensical relationship regarding the direction of the effect of price (wrong sign on the coefficient) and thus should not be included in a long-term demand equation. To make matters more challenging in this respect, an objective and credible forecast of these prices would represent a major accomplishment in itself. Inclusion of a price variable in the forecasting models could potentially provide a means to calculate an unbiased and credible forecast of the price effect on the long-term load response.

Method Selection

There is no single best forecasting method. The choice of a forecasting method in this case was based on the specific circumstances of the situation being faced. Given the requirements at the time, in terms of available data, the capabilities needed of any chosen method, and the intended use of the resulting forecasts, a regression with capabilities of performing a correction for autocorrelated errors was deemed as the most appropriate choice available to meet ERCOT's objectives. This methodology is unique in that it directly and successfully forecasts an hourly load shape using a regression model estimated by seasons. This methodology could potentially be applied to other entities facing similar requirements.

Forecast Process --- General Description

The forecast process starts with the development of regression equations from historical data for demand peaks and energy. These use the following input drivers:

Trend Variables
- Population
- Income
- Economic

Calendar Variables
- Seasonal Variation
- Daily Variation
- Weekly Variation
- Holidays

Weather profiles from actual data that use an average representation of weather not prediction of weather
- Temperature
- Humidity
- Cooling Degree Days (CDD)
- Heating Degree Days (HDD)

The results are forecasts for energy and peak.

The data used to prepare the forecast came from the following sources:

1. Economic Data
   - Economic data obtained from Economy.com
   - Data includes economic and demographic data (such as income, employment, housing permits, GDP, population and migration patterns) for Texas at the state, county, metropolitan statistical areas (MSAs). Some of these data is also available at the national level

2. Weather Data
   - Ten years of weather data obtained from Weather Bank for 20 weather stations

- The data is first weighted by individual weather stations using ERCOT's standard factor, and then for the total system using weights proportional to the load in each weather zone

3. Load Data
   - Settlement load data available on an hourly basis since July 31, 2001
   - Prior to 2001, we have Transmission and Distribution Service Providers (TDSP) hourly data

The weather data is used in the development of weather normalized profiles by weather zone and is accomplished by calculating the normalized temperature profile by weather zone. The weather profiles use the rank-average method which 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 from all years for every 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
5) Use this year's profile to re-sort the median temperatures

A major issue in the preparation of the long-term forecast relates to the variable selection process. The process in this case generally entails performing the following analyses with the following considerations:

- Multiple regression analysis is used to develop the forecasting equations
- Initial selection of variables comes from a variation of the stepwise procedure using a combination of the Least Absolute Shrinkage and Selection Operator (LASSO) and the Least Angle Regression (LAR) to determine those that were the most statistically significant
- A methodical process and pre-specified strategy of selecting a subset of those variables using empirical results and informed judgment
- Variables selected for inclusion had to meet the following: 1) justifiable on a logical basis , 2) historically measurable and 3) must have an available forecast
- Ordinary least squares techniques with models that can selectively include autoregressive error terms, are used to calculate the appropriate coefficients on each variable and to choose the best equations

Load shape and Energy forecasts were developed from monthly energy and hourly load shape equations for each season of the following form:

- The general formulation of the energy equations include the following variables:

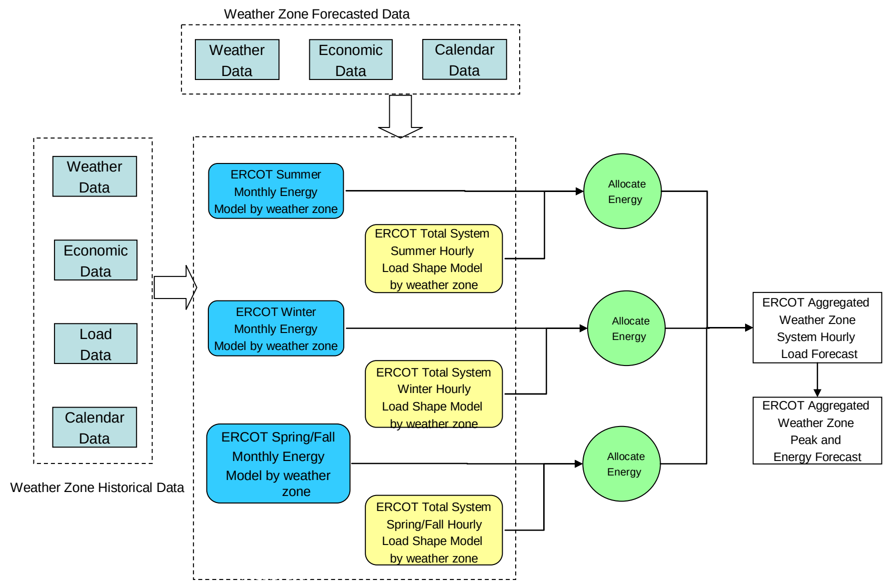
  Energy Month i = f {CDD, HDD, Income, Population, Employment, GDP, Monthly Indicators, AR terms}

- The general formulation of the load shape equations include selected variables from some of the following:

  Load hour i =f {Max Temps, Lagged Temps, Heat Index, Non-Linear Temp Components (square and cube), Temp Gains (diff between daily high and low temps), Temp Build-up, Dew Point, Month*Temp Interactions, CDD, HDD, Hour of Day Indicators, Weekday/Weekend, Holidays, AR terms}

Putting it all together

Weather Zone Forecasting Process



The Weather Zone forecasting process flow is as follows:

1. Obtain weather and economic variables by weather zone (historical and forecast)
2. Develop regression equations by weather zone describing the historical actual:
--Monthly Energy
* Using a different equation for each season
-- Hourly Load Shape
* Using a different equation for each season or a single model for all seasons
3. Incorporate forecasted values of economic and normalized temperatures for 2008-2019 by weather zone into monthly energy equation to produce forecasted monthly energy
4. Incorporate normalized temperatures for 2008-2019 by weather zone into monthly load shape equation to produce forecasted load shape
5. Produce hourly demand forecast by weather zone by fitting forecasted monthly energy under projected hourly load shape

Hourly Forecast

The calculation of an hourly forecast is a result of the process described above and yields the following results:

- The forecasted hourly shape from the load shape equations is scaled to produce the final hourly forecast
  - Each hour's load is scaled so that the amount of energy under the load shape for a month is equal to the amount of energy projected for that month by the energy forecast from the energy equations
  - The percent of a month's energy that is contained in each hour from the load shape equation is maintained
- The peak forecast is the highest hourly load from this final hourly forecast

Mathematical/statistical rigor

(A) Derivation:

There are instances in which the models may require to perform a correction for auto correlated error terms. The mathematical/statistical intricacies of the models are presented below. The peak demand forecasts are obtained by combining the results of two models: an hourly model that forecasts the load shape and a monthly energy forecast which includes economic and demographic variables to determine the long-term trend. The hourly load shape model is of the following form:

$$Y_t = \alpha_o + \sum_{i=1}^{23} \beta_i HR_{i,t} + \sum_{i=1}^{n} \gamma_i W_{i,t-s} + \sum_{i=1}^{n} \Omega_i DT_{i,t} + \sum_{i=1}^{n} \Theta_i WI_{i,t} + \sum_{i=1}^{n} \delta_i SV_{i,t} + \sum_{i=1}^{n} \nu_i \mathrm{E}_{i,t} + \frac{\varepsilon_{i,t}}{\left(1 - \Phi_1 L - \Phi_2 L^2 - \ldots - \Phi_p L^p\right)}$$

Where:

- Y_t is the hourly load (MW)
- $HR_{i,t}$ are hourly indicator variables
- $W_{i,t-s}$ are weather variables and their lags
- $DT_{i,t}$ are day type variables
- $WI_{i,t}$ are weather interaction variables
- $SV_{i,t}$ are sunlight variables
- $E_{i,t}$ are special events variables
- $\varepsilon_{i,t}$ is a random error term
- $\Phi's$ are autocorrelation terms specified with a lag (backshift) operator, $L^s = \mathrm{X}_{t-s}$

This model specified in mathematical form can be generalized as follows:

$$Y_t = \beta_o + \sum_{i=1} \beta_\kappa \mathrm{X}_{\kappa,t} + \frac{\varepsilon_t}{\Phi(L)}$$

Where:

$\beta_o, \beta_1, \ldots, \beta_\kappa$ = coefficients to be estimated

$\mathrm{X}_{K,t} =$ K regressor variables, K=l, …, m

ε_t = a random error term

Φ (L) = an autoregressive structure of order ρ where ρ = 24 or an AR(ρ) process

“ $= \left(1 - \Phi_1 L - \Phi_2 L^2 - \Phi_3 L^3 - \ldots - \Phi_p L^p\right)$

Φ_j = autoregressive coefficients

L^j = Lag operator, $L^j = X_{t-j}$

Thus, the model to be estimated can be derived as follows:

(1) $$\Phi(L)Y_t = \Phi(L)\beta_o + \Phi(L)\sum_{\kappa=1}^{m}\beta_\kappa X_{\kappa,t} + \varepsilon_t$$

Where the constant term $\alpha_o = \Phi(L)\beta_o$.

Expanding the expression on the right hand side,

$$\Phi(L)\sum_{\kappa=1}^{m}\beta_{\kappa,t} = \left(1 - \Phi_1 L - \Phi_2 L^2 - \ldots - \Phi_p L^p\right) - \left(\beta_1 X_{1t} + \beta_2 X_{2t} + \ldots + \beta_m X_{mt}\right)$$

and gathering common terms together we obtain

$$\Phi(L)\sum_{\kappa=1}^{m}\beta_{\kappa,t} = \sum_{\kappa=1}^{m}\beta_\kappa X_{\kappa,t} - [\ \Phi_1 + \Phi_2 + \ldots + \Phi_p\ ] \bullet \sum_{\kappa=1}^{m}\beta_\kappa X_{\kappa,t-p}$$

Or more succinctly,

(2) $$\Phi(L)\sum_{\kappa=1}^{m}\beta_\kappa X_{\kappa,t} - \sum_{j=1}^{p}\Phi_j \sum_{\kappa=1}^{m}\beta_{\kappa,t-j}.$$

The expression on the left hand side of the equation is

$$\Phi(L)Y_t = \left(1 - \Phi_1 L - \Phi_2 L^2 - \ldots - \Phi_p L^p\right)Y_t$$
$$\Phi(L)Y_t = Y_t - \Phi_1 Y_{t-1} - \Phi_2 Y_{t-2} - \ldots - \Phi_p Y_{t-p}$$

Or more compactly stated,

(3) $$\Phi(L)Y_t = Y_t - \sum_{j=1}^{p}\Phi_j Y_{t-j}$$

Substituting (2) and (3) into (1) we get,

$$Y_t - \sum_{j=1}^{p}\Phi_j Y_{t-j} = \gamma_o + \sum_{\kappa=1}^{m}\beta_\kappa X_{\kappa,t} - \sum_{j=1}^{p}\Phi_j \sum_{\kappa=1}^{m}\beta_\kappa X_{\kappa,t-j} + \varepsilon_t$$

or

$$Y_t = \gamma_o + \sum_{j=1}^{p}\Phi_j Y_{t-j} + \sum_{\kappa=1}^{m}\beta_\kappa X_{\kappa,t} - \sum_{j=1}^{p}\sum_{\kappa=1}^{m}\beta_\kappa X_{\kappa,t-j} + \varepsilon_t$$

Where

$$\varepsilon_t = \mu_t - \sum_{j=1}^{p}\Phi_j L^j \mu_{t-j}.$$

(B) Estimation:
In vector notation [1],

$$y_t = x_t'\beta + \mu_t$$

Where $\left(x_t = x_{1t,} x_{2t,} \ldots, x_{Kt} \right)'$

$$\mu_t = \varepsilon_t + \varphi_1 \mu_{t-1} + \varphi_2 \mu_{t-2} + \ldots + \varphi_p \mu_{t-p}$$ [2]

And $\varepsilon_t = N\left(o, \sigma^2\right)$, normally and independently distributed with mean o and variance of σ^2

y_t	=	dependent values
x_t'	=	a column vector of regressor variables
β	=	a column vector of structural parameters

The autoregressive parameter vector, $\varphi = (\varphi_1, \varphi_2, \ldots, \varphi_p)'$ and its variance covariance matrix:

$$\mu = \left(\mu_{1,} \mu_{2,\ldots,} \mu_p\right)' = \Sigma$$
$$\mathrm{E}\left(\mu \mu'\right) = \Sigma \sigma^2 U$$

Since the stepwise-like procedure BACKSTEP is specified for testing the statistical significance of the φ's, the TOEPLITZ matrix is used, with the (i,j)th

element $\gamma_{|i-j|}$ is equal to $R\hat{\varphi} = r$

Where r = $\left(r_1, r_2, \ldots, r_p\right)'$ and r_i is the lag i sample autocorrelation. The matrix [R, r] is treated as sum-of-squares cross products matrix coming from a simple regression using N-K observations, where K = number of estimated parameters.

This method of estimation is known as the Yule-Walker (YW) method. It alternates the estimation of β using generalized least squares (GLS) with the estimation of the φ's using the YW equations applied to the sample autocorrelation function (SA).

The steps are:

1) Form OLS estimates of β.
2) Estimate φ from the SAC function of the OLS residuals using the YW equations.
3) Estimate U from the estimate of φ and Σ from U and the OLS estimate of σ^2.

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[1] This material comes from the SAS Autoreg Procedure in the ETS manual.

[2] SAS parametization computes the signs of the autoregressive parameters reversed from what is presented in most of the literature. The parametization shown here is in agreement with most of the literature.

The second model forecasts the long-term trends in energy consumption (MWh) utilizing economic, demographic, weather, and season variables and possibly autoregressive terms. The form of the model is as follows:

$$Y_t = \beta_o + \sum_{i=1}^{n} \gamma_i CDD_{n,t} + \sum_{i=1}^{n} \Theta_i HDD_{n,t} + \sum_{i=1}^{s} \delta_i \mathrm{E}_{it} + \sum_{i=1}^{11} \alpha_i m_{itit} + \varepsilon_{i,t}$$

Where: Y_t = Monthly energy consumption (MWh)
$CDD_{n,t}$ = Cooling Degree Days (n terms using different basis)
$HDD_{n,t}$ = Heating Degree Days (n terms using different basis)
E_{it} = Economic and Demographic variables
m_{it} = Monthly indicator variables
$\varepsilon_{i,t}$ is a random error term

This model represented in general form is as follows:

$$Y_t = \beta_o + \sum_{i=1}^{p} \beta_\kappa \mathrm{X}_{\kappa,t} + \frac{\varepsilon_{i,t}}{\left(1 - \Phi_1 L - \Phi_2 L^2 - \ldots - \Phi_p L^p\right)}$$

Where,

$\beta_o, \beta_1, \ldots, \beta_p$ =coefficients to be estimated

$\varepsilon_{i,t}$ is a random error term

$\Phi's$ are autocorrelation terms specified with a lag (backshift) operator,

$L^s = \mathrm{X}_{t-s}$

This energy equation is estimated using the Yule-Walker method as described above..

(C) <u>Allocation of Energy Under Load Shape:</u>

Let $Y_{LSi,t} =$ hourly load shape forecast from the first model,

$Y_{\mathrm{E}t} =$ monthly energy forecast from the second model,

Then, the long-term load forecast is obtained as follows:

$$Y_{LSi,t} = Y_{LSj} \cdot \frac{\Sigma Y_{Et}}{\Sigma Y_{LSi}}$$

Where:

Y_{LSj} is the load at hour j, j=1, …,8760

Thus, the annual system peak demand is obtained as,

$$\text{Y peak} = \max \left\{ Y_{LSit\,;}\ i = 1,\ldots 8760; t = 1,\ldots 12 \right\}$$

Conclusions-- Forecast Performance, Results, Findings and Properties

Model validation using actual temperatures in the forecast period – The validation of the model is done by using the actual temperatures experienced during the year, instead of the "50-50 normal profile" temperatures that were used to produce the forecast. The forecasting model is estimated with the same data used in the forecasting process and with the same mix of variables as originally formulated for each equation.

The result of this validation reveals the forecasting error due to the inaccuracy of the model itself and its formulation (misspecification, incorrect functional form, irrelevant variables, lacking important variables, etc) the error in forecasting the independent variables that serve as drivers, except for actual temperatures which reflect the exact temperatures that produced the loads. Thus, this is way to take out the effects of weather to evaluate the accuracy of the model and other input variables.
.
The forecasting model can be used to perform weather scenarios by looking at 90th percentile temperatures (90-10). Thus, it can be used to look at load volatility using the model with a wide variety of weather profiles – including extreme weather profiles.

There are strengths and weaknesses associated with the process described in this paper. They are:

ERCOT's model strengths

- The methodology is statistical and mathematical in nature, but it still allows for judgment to be incorporated into the results by selecting variables that contribute to the generation of a forecast that passes, not only statistical tests, but common sense criteria.
- This approach was implemented in an automated fashion using macro routines in SAS. With so many models to maintain (8 zones * 3 seasons per zone = 24 models total), it is advantageous to have the ability to make changes and produce normal or extreme weather or any other type of forecasts very quickly.
- The chosen methodology remains consistent in the face of changes in the structural pattern of new incoming data. This is an indication of the robustness of the approach and the model.

ERCOT's model weaknesses

- The initial set-up for the infrastructure for using this approach is time consuming and complex.
- The model was developed from a top-down approach analyzing total ERCOT (system) load. Thus, it does not allow analysis at a more disaggregated level such as focusing at the class level, i.e., residential, business commercial, large industrial customers, etc.

An important aspect associated with any forecasting model is the robustness of its forecasts. Another related consideration is whether these forecasts can be considered reliable enough to lend the model some credibility. In this case, there are forecasts produced with a very similar model for 2005, using the same methodology but, with system load data instead of disaggregated data for weather zones. The model presented here aggregates across zones can be used to obtain the system peak. The results produced by the model for 2005 are very similar in terms of the magnitude of the percent forecast errors. The overall error was between 0 and + 0.5%. This pattern of successful forecasting gives this methodology some credibility and shows its robustness.