**Final Scientific/Technical Report
COVER PAGE**

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Project Title: Techno-economic Modeling of the Integration of 20% Wind and Large-scale Energy Storage in ERCOT by 2030

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ACCOMPLISHMENTS

Project Objective: This study's objective is to examine interrelated technical and economic avenues for the Electric Reliability Council of Texas (ERCOT) grid to incorporate up to and over 20% wind generation by 2030. Our specific interests are to look at the factors that will affect the implementation of both high level of wind power penetration (> 20% generation) and installation of large scale storage.

Project Goals: The overall project goal is to understand the economic and technical considerations for operating an electric grid in a reliable manner as more wind power capacity is installed and as more wind energy is generated within the grid. The subgoals of the project are to understand the role that large scale energy storage technologies, such as compressed air energy storage, can technically and economically play in the context of ERCOT. Figure 1 graphically represents the overall goals and concept of the project.

Figure 1. Flow chart for integrating the economic screening curve with ERCOT historical generation data and ancillary services to estimate the value of storage. The same framework will then be used to project the future value of storage as more wind power (up to 20% total MWh in ERCOT) is simulated for integration into ERCOT.

Goal Status: This project is complete. See below for more detail according to subheadings.

The following sections describe the work completed for each SOPO task of the project

Results for Task 1.1: Add storage system parameters to aggregate cost supply curve models based upon hourly generation in ERCOT

Table 1 provides parameters used to specify CAES systems when included in the unit-specific database. These costs inherently get included in to the aggregate supply cost curve for ERCOT when simulating the unit-commitment model used in this report to understand the role of storage technologies in ERCOT with 20% wind generation. There are two existing large-scale CAES facilities that provide a basis for parameter specifications. A facility in Huntorf, Germany can output 290 MW for up to 2 hours while a facility in McIntosh, Alabama can generate 110 MW over 26 hours [Ridge, 2005]. To fall within the range of these output capacities and capacity-to-energy ratios, CAES scenarios are modeled with 200 MW output capacity for up to 8 hours (1,600 MWh energy storage capacity). As discussed in the later sections describing simulation results, we use multiple such CAES units for enough total CAES capacity to make a substantial impact on ERCOT dispatch.

The ratio of input-to-output capacity is 25% at Huntorf and 62.5% at McIntosh, so 50% is chosen for the present analysis (100 MW input capacity) [Ridge, 2005]. McIntosh and Huntorf heat rates are 4.51 and 6.05 MMBTU/MWh, respectively, so a slightly lower 4.1 MMBTU/MWh is used as a basis and randomized to prevent identical performance [Ridge, 2005]. CO₂ emissions rate and heat rate have a direct relationship, so the linear relationship between these quantities across ERCOT facilities is used to determine a CO₂ emissions rate of 0.237 tCO₂/MWh for a facility having a 4.1 MMBTU/MWh heat rate [USEPA, 2010]. Minimum capacities are 50% of maximum to reflect relatively inefficient operation of CAES turbomachinery at low load. Since combusted natural gas adds energy to the system in addition to that stored during air compression, the output-to-input efficiency is 1.25 in this analysis. Recent work by Fertig and Apt uses a larger output/input efficiency, but those authors also assume a lower 3.8 MMBTU/MWh heat rate [Fertig & Apt, 2011].

CAES systems are expected to have rapid ramping capabilities, so ramp rates reflect the ability to ramp from 0% to 100% load within one 15-minute time interval. The required storage level at the start of each day is 30% of capacity, Non-fuel/CO₂ VOM costs of \$3/MWh are assessed for operation of turbomachinery, pollution controls, and operation of the air storage cavern. Startup costs and minimum up/down time are assumed equal to those of OCGT units.

Table 1. Energy storage system parameters reflect typical values of current and future CAES designs.

Parameter (units)	Value
Maximum output capacity (MW)	200
Minimum output capacity (MW)	100
Heat rate (MMBTU/MWh)	4.10
CO ₂ emissions rate (tCO ₂ /MWh)	0.236
Output ramp limit up/down (MW/min)	13.3
Maximum input capacity (MW)	100
Minimum input capacity (MW)	50
Input ramp limit up/down (MW/min)	6.67
Output/input efficiency	1.25
Energy storage capacity (MWh)	1,600
Day-starting stored energy level (MWh)	480
Minimum up/down time for input and output (hr)	1
Non-fuel/CO ₂ VOM cost for input and output (\$/MWh)	3
Startup cost for input and output (\$/startup)	1,000

Results for Task 2.1: Using historic ERCOT data for price and wind power, correlate AS costs to wind integration

Because there is a 5-6 year history of significant quantities of wind generation in ERCOT, our tactic for Task 2.1 was to analyze the historical data for trends in ancillary service (AS) costs, procurements, and/or deployments that relate to increased wind power capacity and/or wind power generation. In seeking the data needed for this analysis, we were unable to obtain actual deployments of any ancillary services except for the non-spinning reserve service (NSRS) that ERCOT uses to address generation shortages at time scales of 30 minutes. Generators providing NSRS must meet their submitted generation capacity within 30 minutes. Due to the natural variability in load forecasts, the variability at time scales < 5 minutes is not significantly different when integrating wind power into the grid. However, at longer time scales (e.g. 30 minutes), wind power can have significant influence on varying from the forecasted net load (net load = load – wind power). Thus, our analysis focuses primarily on the procurement and deployment of NSRS as a governing factor for handling increased wind power in ERCOT.

Figure 2 shows the increase from 2005 to 2010 of the amount of installed wind capacity in the ERCOT grid. The rapid increase in wind capacity from 2005-2009 provides the context for exploring if wind power integration necessitated increased AS deployments occurred during this time.

Growth of Wind Capacity in ERCOT

Figure 2. Using three different data sets, wind capacity in the ERCOT grid has increased from 1.3 GW in 2005 to nearly 10 GW in 2010.

In order to get a better understanding of how ancillary services (AS) and wind have played a role in the current electric grid, we looked at the ERCOT AS of non-spinning reserve deployments over the last several years. We developed programs to cross reference the deployment information with generation data from ERCOT that is delineated by generator type (e.g. NG combined cycle, coal steam turbine, etc.). By looking at the times when non-spinning ancillary services were deployed, rather than simply procured to be on call, we can determine if at those times wind generation decreased and if so what type of generators increased output to compensate. ***Upon completion of our analysis, we determined that there is no discernible influence of wind power on historical deployments of NSRS in ERCOT.*** However, this does not necessarily mean that NSRS will not be deployed due to wind power variations in the future, particularly if total wind power accounts for 20% of ERCOT annual generation.

We now discuss our analysis of the historical ERCOT data and NSRS (or NS-AS: non-spinning ancillary service) deployments.

Figure 3 - Figure 6 show the results of our NSRS analysis as related to wind power. We plot information for all 18 events in 2010 for which NSRS were deployed. ERCOT reports generation data per unit type by MWh per 15-minute interval, and the cumulative aggregation of the change in generation from one interval to the next are those data plotted these figures.

Figure 3 plots all NSRS (or NS-AS) deployments in 2010 along with the change in net output from different types of generators on the ERCOT grid. Each deployment last for several 15-minute dispatch intervals, and the deployments as plotted in

Figure 3 sequentially from left to right (but do not specifically relate to the time of the year or day when NSRS was deployed. From

Figure 3, it is difficult to determine a pattern of ramping for any one type of prime mover and fuel combination during NSRS deployment.

Figure 4 shows that natural gas combustion turbines (NG-GT) are the primary responders during deployment of non-spinning ancillary services (NS-AS). This result is not surprising given that natural gas turbines have fast start-up and ramping times.

Figure 3. When looking at all generator types separately it is hard to discern conclusive patterns regarding what types of generation units are serving non-spinning ancillary services (NS-AS) as many generator types show a change in net MW levels during NS-AS deployments.

Figure 4. The cumulative generation (MWh) required for deployed NS-AS (deployed in MW) changes over several time intervals along with the cumulative change in MWh per type of power plants. NG combustion turbines (NG-GT) account for a majority of the total fleet change in total generation (“all generator types”) during NSRS (or non-spinning ancillary service, NS-AS) deployment.

Figure 5 plots the same concept as Figure 4, but indicates the cumulative change in MWh from wind turbines during NS-AS deployments in 2010. It appears that wind generation was ramping by significant amount only during a few of the 18 events in 2010 when NS-AS were deployed. The same non-spinning reserve service deployment data are plotted in Figure 6 according to the dispatch interval during the day that the AS was deployed.

Figure 5. By plotting the cumulative generation (MWh) required for deployed NS-AS over the several intervals, along with the cumulative change in MWh per type of wind generators, we see that wind generation is usually of a much smaller magnitude than the requested NS-AS generation. ERCOT reports generation data per unit type by MWh per 15-minute interval, and the cumulative aggregation of the change in generation from one interval to the next are those data plotted above.

Figure 6. The same data of Figure 4 are plotted except they are plotted with respect (x-axis) to the time period of the day in which the NS-AS were deployed (e.g. there are 96 intervals during one day). NS-AS in 2010 were deployed mostly from the hours of 2 pm to 8pm, or peak hours of the day. ERCOT reports generation data per unit type by MWh per 15-minute interval, and the cumulative aggregation of the change in generation from one interval to the next are those data plotted above.

From inspecting Figure 3 - Figure 6 we see that the total sum of generation is often on a decreasing trend during NS-AS deployments in 2010. Usually the interval generation change starts as an increase and ends while the overall ramping of the grid is negative by the time NS-AS deployment has ceased. However, only in some cases does the total change in grid generation seem to map well to the non-spinning deployment (e.g. positive net generation to match to positive net NS-AS requirements). This lack of correlation between needing more generation for NS-AS and negative overall ramping for the grid could indicate that a significant quantity of the non-spin deployments are negative loads, or what ERCOT calls “loads that are capable of being interrupted” within 30 minutes and staying interrupted for at least 1 hr. If interruptible loads were actually interrupted to serve NS-AS, then the NS-AS would not need *more* generation because load has been shed. However, there is zero MW of planned “Loads acting as Resources” capacity to serve the non-spin ancillary service of ERCOT (from ERCOT’s Capacity, Demand, and Reserves report for 2009).

The cumulative increase in grid generation is mostly positive for intervals 55-65 (1:45 pm to 4:15 pm) and primarily negative for intervals greater than 65 (after 4:15 pm). This pattern corresponds to the overall need for increased generation leading up to the peak power demand time of the day (near 5 to 6 pm). After this peak time, the total demand on the grid is typically dropping such that the *net ramping of the overall grid may still be negative during NS-AS deployments* if the planned day-ahead generation for ERCOT is less than the actual demand. In other words, after peak demand, ERCOT may have planned for a decrease in demand of 2000 MW from 6 pm to 7 pm, but the real demand only decreased 500 MW during that time. Thus, NS-AS may have been called after all other ancillary services were used to serve load.

Next, we investigated specific historical contingency events in ERCOT to analyze how a known wind die-off event impacted the electric grid. After initial inspection of the event on February 26 of 2008, the wind power output started to drop off several hours before non-spinning ancillary services were called upon. In addition, in this particular event problems with wind output were not the only issues. In fact, an under-predicted load increase during the early afternoon as well as unavailability of generators that were counted as available in the ERCOT operational planning process also contributed to the contingency event.

We have revisited our previous analysis of occurrences of the deployment of non-spinning reserve service (NSRS) ancillary services to also look at *the 2 hours prior to* the actual NSRS deployment in order to see if there were any irregularities in wind power output. These figures show what the types of generators were doing 2 hours before and after the deployment occurred. It seems that NG generators are really the ones changing their output during these times, as seen in Figure 7. Wind output is very constant across the times, as seen in the second figure below. The last figure allows you to see that the change in output from wind is very small compared to the change in all other generators.

Figure 7. The same plot as in Figure 4, but including 2 hours of intervals before the deployment of NS-AS. The cumulative generation (MWh) required for deployed NS-AS (deployed in MW) changes over several time intervals along with the cumulative change in MWh per type of power plants. NG generation accounts for a majority of the total fleet change in total generation (“all generator types”) during NSRS (or non-spinning ancillary service, NS-AS) deployment.

Figure 8. The same plot as Figure 5, but including 2 hours of intervals before NS-AS deployment. By plotting the cumulative generation (MWh) required for deployed NS-AS over the several intervals, along with the cumulative change in MWh per type of wind generators, we see that wind generation is usually of a much smaller magnitude than the requested NS-AS generation. ERCOT reports generation data per unit type by MWh per 15-minute interval, and the cumulative aggregation of the change in generation from one interval to the next are those data plotted above.

The project team investigated the relationship between the time of day and time of year when non-spinning ancillary services were deployed in 2010 (see Figure 9 and Figure 10). Most of the 2010 NSAS deployments occurred in the afternoon between 2 pm and 6 pm, with 6 of 18 deployments during August. Since West Texas wind production is typically lowest in the afternoon and in summer, this suggests that wind is not a significant issue in most of these NSAS deployments. In other words, ERCOT would normally not expect to rely on much wind power capacity on summer afternoons.

Figure 9. Each blue line represents a day in 2010 when NSAS were deployed, the height of the line indicated the magnitude of the deployment in MW. Out of the 18 days when NSAS were deployed, 6 of these occurred in August, the peak demand month in ERCOT.

Figure 10. In this illustration we can see that most of the 18 NSAS deployments occur in the latter parts of the day, which is indicated on the vertical axis (as a reference interval 64 is 4 pm). In this figure, each blue bar represents one of the days NSAS were deployed in 2010; the horizontal length represents the amount of time it was deployed and the height represents the time of day it was deployed.

Comparing month ancillary services procurement data with wind generation/capacity

In addition to our analysis of specific times and dates for non-spinning reserve deployments, we completed a more long term analysis related to AS procurements in ERCOT. We organized the following hourly data for 2005-2010 to compare on a monthly basis:

- Total wind generation (MWh) in ERCOT
- Average daily wind generation (MWh) in ERCOT
- Installed wind capacity (MW) in ERCOT
- ERCOT system requirement (MW) for the following ancillary services:
 - Regulation Down
 - Regulation Up
 - Responsive Reserves
 - Non-Spinning Reserves
- ERCOT amount procured (MW) for the following ancillary services:
 - Regulation Down
 - Regulation Up
 - Responsive Reserves
 - Non-Spinning Reserves
- ERCOT price (\$) for the following ancillary services:
 - Regulation Down
 - Regulation Up
 - Responsive Reserves
 - Non-Spinning Reserves

The compiling of these various data sets enabled us to determine if the increase in wind generation over the past several years caused the operators of the ERCOT grid to increase the amount of ancillary services procured. We also used these data to recreate the historical procurements for ERCOT AS such that we could project future AS procurements for our simulation of the future 20% wind and storage scenarios. After much effort, we were unable to match ERCOT's historical AS procurements. In addition, the range of values for the non-spinning reserves, the most relevant AS for the wind and storage scenarios, at peak demand hours does not vary more than approximately 1,000 MW. Thus, as discussed here, our simulations of future scenarios assumed the maximum NSRS procurements allowed by current ERCOT protocols to explore the 'best case' scenario for our simulated use of compressed air energy storage to interact and operate within ERCOT.

Figure 11 shows the increase from 2005 to 2010 of the amount of installed wind capacity in the ERCOT grid along with the total monthly wind generation. Over time, even as wind capacity installation slowed after 2008, the total amount of wind generation still did increase due to small investments in transmission and better load and wind forecasting. Also, a significant portion of the post-2008 wind farm installations occurred in southern coastal regions of Texas where the wind patterns peak closed to the middle of the day and transmission constraints are relatively insignificant.

Growth of Wind Energy in ERCOT

Figure 11. Over the past several years, the amount of wind installed and the corresponding wind generation have continued to increase in the ERCOT grid. A seasonal trend is apparent in the highs and lows of the wind generation, shown in orange.

Figure 12 - Figure 15 plot the procurement of the various AS in ERCOT versus wind generation and wind capacity in ERCOT. Both visual and statistical analyses do not indicate that the procurement of AS changed significantly from 2005 through late 2010 as a function of wind power capacity. However, there is possibly a relationship between the NSRS procurements and the actual generation of wind power in ERCOT (see Figure 15). Starting in 2008, ERCOT began procuring NSRS as a function of what they call “net load uncertainty”. As discussed next, the project team spent a considerable amount of time investigating this trend for potential patterns related to wind forecast and generation uncertainty and variability. In principle, these patterns could guide procurements of NSRS for a future 20% wind and storage scenario for simulations of Tasks 1.2, 2.2, 4.2 and 5.2. Ultimately, we did not find a pattern and could not replicate ERCOT procurements (for reasons discussed next).

Relationship of Wind Energy and Ancillary Services in ERCOT

Figure 12. Since 2005, the amount of Regulation Up and Regulation down procured, shown in red and green respectively, does not significantly change as either more wind capacity was installed or more wind power was generated.

Figure 13. The amount of Responsive Reserve Service (RRS), often termed spinning-reserve, has been nearly constant since 2005. This is anticipated because the ERCOT requirement for RRS is set at 2300MW per hour, which is equal to an outage from the largest generator on the ERCOT grid. Even though it is expected that responsive reserve could play a role in responding to wind events, ERCOT does not take wind energy into account when determining the amount of responsive reserve to procure.

Figure 14. Non-spinning reserve service (NSRS) is the only one of the four ancillary services that shows significant variation over time (as aggregated on monthly basis), however, a general trend in NSRS requirements (here, requirements = procurements) is unclear.

Figure 15. There seems to be a trend visible between highs in wind generation (MWh) and highs in NSRS requirements (here, requirements = procurements). Much of this NSRS trend was driving by changes in ERCOT guidelines that included the net load forecast as a factor for procuring NSRS.

Replication of ERCOT NSRS ancillary service procurements

I. Introduction to the Non-Spinning Reserve Service (NSRS) Requirement

A. Goal and Definition of NSRS requirement

NSRS requirement is procured to cope with the possibilities that the net load increases faster than online generation can ramp over extended periods, to restore spinning reserves after a large unit trips, or to compensate for large load forecasting errors. (The net load is defined as the ERCOT load minus estimated total wind power of WGRs.) Furthermore, increasing the penetration level of wind power might increase the risk of not providing sufficient generation to the grid when wind does not blow as much as forecasted. In particular, wind generally blows strongly during off-peak hours when the load is generally lower, but wind blows weakly during on-peak hours when the load is generally higher, and has episodes of wind die-off.

To comply with above mentioned requirements, NSRS is defined as resources that can respond within thirty minutes or loads that can be interrupted within thirty minutes, and the reduced load should last at least one hour. The NSRS can be procured from on-line or off-line generation resources. The ERCOT determines the amount of NSRS so that the combination of NSRS and Regulation Up requirement will cover 95% of the observed net load uncertainty (ERCOT 2011). In our application, we will follow ERCOT methodologies for determining NSRS and compare our estimated NSRS and actual NSRS. This work will be a stepping stone for estimating the future NSRS as the penetration level of wind power increases.

B. Equations for the NSRS

As mentioned above, the net load at time t is defined as the load at time t minus the total wind power at time t :

$$\text{Net Load}_t = \text{Load}_t - \text{Wind Power}_t \quad (1)$$

The net load can be forecasted using the forecasted load and forecasted wind power as:

$$\text{Net Load Forecast}_t = \text{Load Forecast}_t - \text{Wind Power Forecast}_t \quad (2)$$

When the observed net load is bigger than the forecasted net load because of a sudden loss of generating capacity, because of large forecast errors for load or wind, or because of insufficient regulation amounts, the NSRS is required to cover the net load forecast errors. The NSRS requirements should be the positive amount to be purchased to compensate for insufficient generation. Therefore, the net load uncertainty can be defined as:

$$\text{Net Load Uncertainty}_t = \text{Net Load}_t - \text{Net Load Forecast}_t \quad (3)$$

Considering (1) and (2), the net load uncertainty in (3) can also be defined as

$$\text{Net Load Uncertainty}_t = (\text{Load}_t - \text{Wind}_t) - (\text{Load Forecast}_t - \text{Wind Forecast}_t) \quad (4)$$

$$=(\text{Load}_t - \text{Load Forecast}_t) - (\text{Wind}_t - \text{Wind Forecast}_t) \quad (5)$$

As shown in (3), if the uncertainty is defined as the measurement minus the forecast, the net load uncertainty is rewritten as:

$$\text{Net Load Uncertainty}_t = \text{Load Uncertainty}_t - \text{Wind Uncertainty}_t \quad (6)$$

In here, the net load uncertainty is defined as the load uncertainty minus the wind uncertainty. Equation (6) corresponds to the goal of NSRS since it will cover both insufficient power situations: under-forecasted load and over-forecasted wind power.

II. Overall Process of Calculating the NSRS Requirement

Three important sets of data are required to calculate the NSRS requirement. First, we need the 95th percentile of net load uncertainty for the surveyed days, which are the 30 days prior to the upcoming month and days of the same month in the previous year. Second, the averaged Regulation Up requirement for the upcoming month is required. Third, the average net load uncertainty should be calculated; however, only the negative averaged net load uncertainty, which corresponds to the over-forecasted net load, is required. (The rationale for this procedure is not entirely clear.)

In brief, three sets of data are combined to calculate the NSRS. The second data set, the averaged Regulation Up requirement, is subtracted from the first data set, the 95th percentile of net load uncertainty. Then, the third data set, the negative averaged net load uncertainty, is added back to the previous result. Lastly, the final value is limited by the upper bound and the lower bound.

It should be noted that the 95th percentile and averaged data are calculated using the data for each four hour block in each upcoming month. The detailed explanation for the four hour block is as follows.

A. Hour-Block Characterization

In our application, we used data that are averaged between the starting-time and ending-time. Then, data can be tagged with their ending-time as shown in Table 2.

Table 2. Tag description for an Hour-Block

Starting Time	Ending Time	Hour Tag
00:00	01:00	1
01:00	02:00	2
...	...	...
22:00	23:00	23
23:00	00:00 (Next Day)	0

Furthermore, four consecutive hourly data sets can be classified into six four hour blocks by the hour tags as shown in Table 3.

Table 3. Hour-Block Classification

Block Number	Starting Time	Ending Time	Tags
1	22:00	2:00	23, 0, 1, 2
2	02:00	06:00	3, 4, 5, 6
3	06:00	10:00	7,8,9,10
4	10:00	14:00	11, 12,13,14
5	14:00	18:00	15,16,17,18
6	18:00	22:00	19,20,21,22

It is worth noting that the 95th percentile of the net load uncertainty, averaged Regulation Up requirements, and averaged net load uncertainty are calculated over each block. This means that every block has three 95th percentile values associated with it.

B. 95th Percentile of Net Load Uncertainty

ERCOT decides the 95th percentile of the hourly net load uncertainty from the 30 days prior to the upcoming month and the same month of the previous year. In order to calculate the net load uncertainty, we used the aggregated WGR forecast in the Current Operation Plans (COP), which is forecasted at 16:00 in the day-ahead. (The time that the forecast is issued varies every year. See further discussion below.) In this process, the amount of curtailed wind power resulting from the down balancing instructions is added back to the observed aggregated Wind Generation resource (WGR) output in order to determine the total WGR outputs before curtailing the wind power. Moreover, the load forecasting is obtained from the Mid-Term Load Forecast (MTLF).

C. Average Regulation Up Requirements

The average Regulation Up is calculated by averaging the procured Regulation Up requirements over every block during every month. Then, as mentioned above, the ERCOT subtracts the average Regulation Up requirement for each hour block from the calculated 95th percentile of net load uncertainty for each hour block. Table 4 shows the data structure for a month with 31 days.

Table 4. Data Dimensions for Regulation Up Requirements

Hour Block	Days					Total Dimension	Averaged Data
	1	2	...	30	31		
1	[4X1]	[4X1]	[4X1]	[4X1]	[4X1]	[4X31]	[1X1]
2	[4X1]	[4X1]	[4X1]	[4X1]	[4X1]	[4X31]	[1X1]
...	[4X1]	[4X1]	[4X1]	[4X1]	[4X1]	[4X31]	[1X1]
5	[4X1]	[4X1]	[4X1]	[4X1]	[4X1]	[4X31]	[1X1]
6	[4X1]	[4X1]	[4X1]	[4X1]	[4X1]	[4X31]	[1X1]

D. Average Net load Uncertainty

Similar to the averaged Regulation Up requirement, the net load uncertainty is averaged for every hour block per month. However, only the negative averaged Regulation Up requirement, which corresponds to the over-forecasted net load, is added back to the 95th percentile of the net load uncertainty. The sample net load uncertainty for a certain hour-block is sorted in descending order and plotted in Figure 16. The red dot on the left represents the 95th percentile net load uncertainty, and the other red dot represents the average net load uncertainty. Since the average net load uncertainty in Figure 16 is positive, it is not included into the NSRS calculation.

Figure 16. Sorted Net Load Uncertainty

The adjusted value could be negative if the Regulation Up requirement and averaged net load uncertainty are large, so it is important that the adjusted 95th percentile net load uncertainty should not be negative. Furthermore, for on-peak hours (hour tags from 7 to 22), ERCOT also set a floor on the NSRS so that minimum NSRS is equal to the capacity of the largest unit. The

capacity of the largest unit was 1,375 MW in 2011 and 1,354 MW in 2012. In addition, the NSRS is not allowed to exceed 2,000 MW. This upper bound is different every month.

III. Result of replicating NSRS requirement

Table 5 shows the columns of all data required to calculate the NSRS. The last two columns show the actual average net load uncertainty and actual NSRS. First, wind power is adjusted by adding the curtailed wind power. In this case, the amount of curtailed wind power is zero. Then, the time series of net load uncertainty is calculated by using load, load forecast, adjusted wind power, and wind power forecast. The 95th percentile of net load uncertainty is calculated for every hour block. The averaged Regulation Up is subtracted from it, and the average net load uncertainty is added to it. It should be noted that the actual average Regulation Up is given.

All our estimated average net load uncertainties are positive, so they are not considered. On the contrary, all actual average net load uncertainties are negative. This discrepancy might cause the mismatch between the actual NSRS and estimated NSRS.

Table 5. NSRS Calculation. All units are MW.

Ending Time	Load	Load Forecast	Wind Power	Curtailment	Adjusted Wind Power	Wind Power Forecast at 16:00	95 th Net Load	Average Reg Up	Estimated Average Net Load Uncertainty	Estimated NSRS	Actual Average Net load Uncertainty	Actual NSRS
11/1/10 1:00	26289.77	24618.00	4120.13	0.00	4120.13	3124.70	1834.48	590.00	314.85	1244.48	-341.00	984.00
11/1/10 2:00	25162.33	23456.00	3828.40	0.00	3828.40	4045.70	1834.48	590.00	314.85	1244.48	-341.00	984.00
11/1/10 3:00	24614.18	23088.00	3547.87	0.00	3547.87	3827.20	2247.25	810.00	268.11	1437.25	-70.00	861.00
11/1/10 4:00	24460.32	22869.00	3227.67	0.00	3227.67	3506.10	2247.25	810.00	268.11	1437.25	-70.00	861.00
11/1/10 5:00	25001.28	23295.00	2737.97	0.00	2737.97	3259.20	2247.25	810.00	268.11	1437.25	-70.00	861.00
11/1/10 6:00	26900.50	25045.00	2549.15	0.00	2549.15	2824.00	2247.25	810.00	268.11	1437.25	-70.00	861.00
11/1/10 7:00	30354.22	28425.00	3140.92	0.00	3140.92	2576.30	2118.24	758.75	44.99	1359.49	-101.00	1354.00
11/1/10 8:00	32229.50	29975.00	3586.78	0.00	3586.78	2779.60	2118.24	758.75	44.99	1359.49	-101.00	1354.00
11/1/10 9:00	32119.08	30149.00	3286.73	0.00	3286.73	2830.30	2118.24	758.75	44.99	1359.49	-101.00	1354.00
11/1/10 10:00	33170.12	31479.00	2187.72	0.00	2187.72	2230.20	2118.24	758.75	44.99	1359.49	-101.00	1354.00
11/1/10 11:00	34461.72	32291.00	2044.72	0.00	2044.72	1708.90	2524.81	872.50	41.96	1652.32	-844.00	1354.00
11/1/10 12:00	35713.00	33598.00	2098.47	0.00	2098.47	1661.50	2524.81	872.50	41.96	1652.32	-844.00	1354.00
11/1/10 13:00	36899.58	34843.00	1825.20	0.00	1825.20	1468.70	2524.81	872.50	41.96	1652.32	-844.00	1354.00
11/1/10 14:00	38196.98	36232.00	1657.17	0.00	1657.17	1406.30	2524.81	872.50	41.96	1652.32	-844.00	1354.00
11/1/10 15:00	39171.00	37021.00	2058.08	0.00	2058.08	1583.80	3341.33	996.25	506.04	2000.00	-1178.00	1453.00
11/1/10 16:00	39769.22	37887.00	2338.65	0.00	2338.65	1808.80	3341.33	996.25	506.04	2000.00	-1178.00	1453.00
11/1/10 17:00	40111.97	38208.00	2728.20	0.00	2728.20	2034.80	3341.33	996.25	506.04	2000.00	-1178.00	1453.00
11/1/10 18:00	39519.48	37549.00	3099.77	0.00	3099.77	2224.80	3341.33	996.25	506.04	2000.00	-1178.00	1453.00
11/1/10 19:00	39160.92	36883.00	3139.87	0.00	3139.87	2509.70	2109.16	888.75	349.42	1220.42	-814.00	1627.00
11/1/10 20:00	39787.13	37051.00	3193.53	0.00	3193.53	2840.20	2109.16	888.75	349.42	1220.42	-814.00	1627.00
11/1/10 21:00	38493.03	36231.00	3362.75	0.00	3362.75	3411.80	2109.16	888.75	349.42	1220.42	-814.00	1627.00
11/1/10 22:00	36409.88	34374.00	3177.00	0.00	3177.00	4060.30	2109.16	888.75	349.42	1220.42	-814.00	1627.00
11/1/10 23:00	33283.13	31847.00	3178.20	0.00	3178.20	4495.30	1834.48	590.00	314.85	1244.48	-341.00	984.00
11/2/10 0:00	29771.83	28680.00	3343.73	0.00	3343.73	4146.40	1834.48	590.00	314.85	1244.48	-341.00	984.00

Finally, the estimated and actual NSRS in November 2010 are plotted in Figure 17. We can see that the pattern of NSRS is similar, but the estimated NSRS is shifted up, because the positive average net load uncertainty is not subtracted. It is also observed that the estimated value is limited by the upper bound, 2,000 MW during on-peak hours.

Figure 17. NSRS Procurement in November 2010 (comparison of actual NSRS procurement and our calculated estimate).

IV. Change of Methodologies for NSRS

As mentioned above, ERCOT has recently changed methodologies for procuring NSRS. The three representative cases from 2009 to 2011 are compared in Table 6. First, the time to issue the wind power forecast has been changed from 16:00 to 24:00 since 2011. From 2010, the set of historical data has been changed to reflect seasonal trends of wind power. Furthermore, the average net load uncertainty has been added to respond to the over-forecasted net load, which might cause to excessive procurement of NSRS since 2010.

In addition, the upper and lower bounds have been applied since 2010. These bounds were most likely introduced due to the fact that as the penetration level of wind power increases, the size of forecast errors for over-forecasted cases might also increase. This will increase the 95th percentile of the net load uncertainty and also increase the amount of the NSRS requirement more than necessary. Therefore, the upper bound has been introduced to limit the NSRS. Similarly, the lower bound has been introduced to respond to the under-forecasted cases.

Table 6. Changes of Methodologies for NSRS

Year	2009	2010	2011
Time to issue the wind power forecasts	16:00	16:00	24:00 (midnight)
Used Historical Data	Net load uncertainty for the last 90 days	Net load uncertainty from the previous 30 days and from the same upcoming month of the previous year.	Net load uncertainty from the previous 30 days and from the same upcoming month of the previous year.
Over-forecasted Net Load Adjustment	NA	Add average net load uncertainty when it is over-forecasted.	Add average net load uncertainty when it is over-forecasted.
Floor	NA	Largest unit during on-peak hours.	Largest unit during on-peak hours.
Ceiling	NA	2000 MW	1500 MW

V. Summary and Conclusion

In this application, we estimate the NSRS using the given data by following the ERCOT methodologies for determining ancillary service requirements. However, our estimation does not match the actual NSRS. There are a few reasons for the mismatch. First, the curtailment data might be inaccurate since it does not come from down balancing instructions. Second, the exact date when methodologies were changed is unclear to us. Third, the wind power forecasting data could differ depending on the issuing companies and dates.

In addition, the methodologies for NSRS have been changed to respond to the wind power efficiently. Even though increasing the penetration level of wind power can affect the amount of NSRS requirements, the upper and lower bounds will bias the function between them. Therefore, it might be difficult to extract the trend of NSRS from the trend of the penetration levels of wind power.

Results for Task 3.1: Using nodal pricing structure, correlate congestion cost, wind variability, and uncertainty

This task was officially removed from the scope of work after awarding of the project.

Results for Task 4.1: Incorporate models of proposed policies for CO₂ emissions reductions

Previous work by the project PIs and students has simulated the operation of the ERCOT market under the constraint of increasing CO₂ emissions penalties (Cohen et al., 2011, Cohen et al., 2012). As there is no U.S. or Texas legislation for internalizing the cost of CO₂ emissions, we do not use specific policies to model decreased CO₂ emissions. The addition of a CO₂ emissions penalty is included in the unit commitment model used to simulate the role of CAES to assist the ERCOT grid in 20% wind generation scenarios. Thus, our “minimum CO₂” scenarios are defined by increased CO₂ emissions penalties.

Figure 18 and Figure 19 show results from previous work that informed the team as to the impact of CO₂ prices, or emissions penalties, on ERCOT unit dispatch and total grid CO₂ emissions (Cohen et al., 2011). At historical fuel prices (e.g. natural gas prices \$5-\$7 per MMBtu) baseload generation in ERCOT begins to shift from coal to natural gas at CO₂ prices > \$40/tCO₂. As the price CO₂ prices moves to \$100/tCO₂ (assuming the existing ERCOT grid), we can expect a reduction of total grid CO₂ emissions of 30 MtCO₂/yr, or 15%. A reduction of 15% of 2005-2010 CO₂ emissions by 2020 (our assumed future year for 20% wind power) is comparable to what we can expect from any legislation mandating a reduction in CO₂ emissions. We chose internalized CO₂ prices for simulating the unit-commitment model based upon the results presented here, as well as other similar studies.

Figure 18. The amount of generation from each type of prime mover and fuel in ERCOT as a function of internalized CO₂ emissions penalty. Each columns represents generation by plant type for ERCOT at a specified CO₂ price in a business as usual (BAU) scenario where no power plants have CO₂ capture (Cohen et al., 2011).

Figure 19. CO₂ emissions in an ERCOT BAU scenario decrease approximately 30 MtCO₂/yr as CO₂ price increases to \$100/tCO₂. Most of the reduction occurs above > \$40/tCO₂ (Cohen et al., 2011). A natural gas price of \$6.60/MMBtu was assumed for these results to match historical data (Cohen et al., 2011). NOTE: The “FLEX Profit” and “CCS Base” cases assume various rules for coal-fired power plants that have CO₂ capture facilities. “GB” = Great Britain electric grid.

Results for Task 5.1: Model wind power forecasting uncertainty at multiple time scales

Wind and grid generation data organization:

During the course of this project, we received high resolution 4-second interval data on seven ERCOT grid operational metrics: wind generation, ERCOT total load, ERCOT total generation, the automatic control generator signal of total regulation deployment, grid frequency, area control error, and non-conforming load. We need to be able to compare this high-resolution data to other data sets that are on 5-minute, 15-minute, and/or hourly intervals. Thus, we spent considerable effort in organizing the data into a usable database.

When we received the data files from ERCOT, they were .txt files with all the data stored in rows, separated by a space or comma. Also, the data was polled on average every 4 seconds, instead of actually being polled at 4 seconds. This meant we needed to reformat the data and then re-index the time series on a true 4 second interval. Since the data was not in a standard row/column format as is required for a .csv file, we were unable to use the data in its current form. Each row contained the same data in the following format: Column_Header, Date Time, Data. The first step was to reformat the data using a custom written C++ program.

In order to compare our existing wind generation data to the data provided by ERCOT, the data needed to be reformatted. The original ERCOT data files were comma-separated but in .txt files. The main problem was all the data were stored in rows instead of a more standard columnar layout. Data polling consistency was also an issue as the data were polled on a 4-second average, but not a constant 4-seconds. This forced a reformatting of the data and then re-indexing of the time series on a true 4-second interval. Since the data was not in a standard row/column format, we were unable to use the data in its current form. Each row contained the same data in the following format: Column_Header, Date Time, Data. The first step was to reformat the data using a custom written C++ program.

The purpose of the C++ program was to reformat the data into a standard .csv format, but with a .txt file extension so we could then process the data through MATLAB. Since .csv is actually just a formatted .txt file, the extension was inconsequential so long as the data was separated by commas. The C++ program takes the original .txt file (input file) and scans each row in order to write the data into memory. The first scan of the input file results in the program collecting all of the column headers so it knows how many data columns to expect. The second pass then begins collecting all of the dates and times in order to use them as the index for each row. If the program encountered a date and time it had seen before, it would only write the data into memory rather than duplicating the date and time. This was an important step as the input file contained on average 7 column headers that were generally polled at the same time. This means that 7 unique data points were collected each time they polled the grid data.

In some cases the data for all 7 data points were polled together, in some cases only certain data were polled at various intervals. The program needed to be capable of capturing all unique dates and times to make sure no data was lost in the conversion. Upon further analysis of the input files, we realized there were a number of duplicate data points in the input files that would need

to be removed. Since this was a job best suited to MATLAB, the C++ program was written to capture all duplicate data points. The C++ program also allowed for leap years and removes daylight saving time from the final comma separated .txt file (output file). The purpose of removing daylight saving time was to allow for the comparison of our data with other data sets in standard time. The C++ program does not modify the actual data at all, it only changes the dates and times by 1 hour to remove daylight saving time. Once all data from the input file is captured, the C++ code writes the data from memory, one line at a time, into the output file and saves it as a .txt. After this step, the data is imported into MATLAB in order to adjust the time series and remove the duplicate data points.

After importing the data into MATLAB, the dates and times were converted to numerical values to allow MATLAB to re-index them. MATLAB converts the year, month, day, hour, minute, and second into one numerical value. From here we needed to remove the duplicate data points; this was accomplished with a third-party (freely distributed) function called “Consolidator”. Consolidator takes duplicate data points and averages them together. Next, the data were interpolated using the interp1 function specifying a piecewise cubic Hermite or “p-chip” interpolation. This interpolation gave us new data on 4- second intervals. Finally, the data was combined back together and written to a .csv file with another third-party function (freely distributed) called “Cell2CSV”. Once all this was accomplished the data were available for analysis.

In the final data set there are multiple month-sized gaps of missing data marked as “NaN” or “Not-a-Number.” The reason for this is that the original ERCOT data was also missing, so there were no data to interpolate with. The interpolation function needed a beginning and ending data point to interpolate with and in these instances there was either no beginning or no ending data point because the gaps occurred at the start or end of the year.

Analysis of wind forecasting error

In coordination with ERCOT, the project team obtained several important datasets that allowed us to analyze the relationship between forecast and actual load as well as forecast and actual wind generation. We analyzed these relationships in order to find indicators that lead to the deployment of ancillary services and models of net load forecasting. In doing this, we discovered how these various relationships have changed over time as more wind energy has been added to the electric grid.

An important part of this analysis includes determining which forecast to utilize. For instance, the dataset we obtained for the wind generation forecast includes forecasts that are made every hour of the day (from late-June 2009 through November 2010). There are 48 separate forecasts that correspond to the forecast for each of the next 48 hours. In other words, there are multiple overlapping forecasts.

We decided to make use of two different types of forecasts, each for a particular purpose. First, since ERCOT operates on a day-ahead basis where the initial procurement of ancillary services as well as settling of the balancing energy market is set around 8am a day ahead of time, we decided to first look at the forecast for every day that was created at around 8am the previous

day. An example of this type of forecast would be for the 24 hours of January 2, 2009, the forecasted wind and load would have been created at 8am on January 1, 2009. The dataset we procured for wind forecast was based on the ERCOT zonal market with data for all dates from June 25, 2009 to Dec 2, 2010. One last note is that we actually organized the forecast data so that we could analyze the day-ahead forecast based on any hour (1am to 12 midnight) of the previous day. The second forecast we want to look at is a rolling forecast that is based on always being created a certain number of hours ahead. An example of this is the forecast that is always one hour ahead of the time for which it is forecasting. By comparing these ‘rolling’ forecasts we can understand how the forecast accuracy changes as the forecasts go from 48 hours ahead to 1 hour ahead.

Wind uncertainty results using 24 hour day-ahead forecast made at 8am

Figure 20 shows the relationship between the forecasted wind generation and the actual wind generation. In the figure, any data point above the black line represents when actual wind generation exceeded the wind forecast, while below the line is when the wind forecast exceeded the actual wind generation. We can immediately see that there are many more instances when the wind forecast exceeded the actual wind generation. This illustration shows us that over-forecasting is more prominent. Also, we can see that above a 6000 MW wind forecast, there is nearly no under-forecasting occurring, meaning that at times when there is high wind generation, the forecasted generation is always over predicting the wind generation. We can also see from Figure 20 that there is an approximate 6,000 MW ceiling on the actual wind generation, which is presumably related to transmission constraints from west Texas wind farms to east/central Texas load centers.

Figure 20. Comparison of the 24 hour day-ahead wind forecast (created at 8am on the day-ahead) to the actual wind generation for the ERCOT electric grid.

Figure 21 indicates interesting trends when looking at the wind forecast error, which is defined as the wind generation forecast (MW) minus actual wind generation (MW). In Figure 21, zero on the y-axis represents when actual wind generation is equal to the forecasted wind generation and the black line represents when actual wind generation was zero. Also, as seen by the red line, there is a near linear relationship happening that clearly shows how the forecast error tends toward larger over-forecasting at times of higher expected wind output. Both of these figures led us to explore if this relationship is related to wind curtailment (due to transmission constraints).

It is known that curtailment occurs in the ERCOT electric grid when the wind generation in the rural northwest region exceeds the capacity of the transmission lines to the more populous south and eastern part of ERCOT. During these times, ERCOT instructs wind producers to reduce their generation in order to maintain a safe level of flow over the transmission system. We expect that curtailment causes the data pattern in the more non-linear upper right portion of Figure 20 as well as more over-forecasting than under-forecasting (or more positive wind forecast errors as seen in Figure 21).

Figure 21. Wind forecast error (wind forecast – actual wind generation) versus wind forecast. The black line represents when the actual wind generation is equal to zero.

Figure 22 provides an understanding of the distribution of the wind forecast error. This histogram shows that there are relatively few instances when under-forecasting of 1,000 MW or greater occur (represented by values of less than -1,000 MW), but there are significantly more instances when over forecasting of 1,000 MW or more occur. We also see that the average forecast error is 555 MW (over forecast) with a standard deviation of 1110 MW. Once again we believe that part of this average over estimate in the forecast is a result of wind being curtailed because of the lack of adequate transmission capacity.

Figure 22. Histogram of the wind forecast error (wind forecast – actual wind generation) for wind forecasts and wind generation from June 25, 2009 to December 2, 2010.

Lastly, we investigate the percent error of the wind power forecast defined as “% forecast error = ((wind forecast-actual wind generation)/(wind forecast))” as seen in Figure 23. We find that there is some positive bias near 30% at the high MW ranges of forecasted wind. Also, there are many instances where 0-3000 MW is forecasted, and the actual wind output is near 0 MW (represented here by 100% forecast error). Once ERCOT forecasts $\geq 3,000$ MW, ERCOT never produces double the forecasted amount (represented by the y-axis value of -100% on the graph). Obviously this gets physically difficult the higher the forecast – i.e. if the wind power forecast is 6,000 MW, it is impossible to generate twice as much wind as a forecasted if there is only 9,000 MW of installed capacity.

Figure 23. Percent wind forecast error versus the forecasted wind. (Note that this is a slightly zoomed in figure that is omitting all data < -200%).

Wind forecast uncertainty from 'rolling' wind power forecasts

We analyzed a second type of wind forecast that we term the 'rolling' forecasts. These forecasts can be based on the predicted wind output at some constant specified number of hours ahead (e.g. the forecasted wind power that is always "x" hours ahead, where x can be from 1 to 48 hours). We arranged the data to show all 48 rolling forecasts (one data set for each incremental hour-ahead from 1 hour-ahead to 48 hours-ahead). We calculated the average forecast error for each as well as the standard deviation of the forecast error (see Figure 24 and Figure 25, respectively). As expected, the average error decreases as the forecasts move from 48 hours ahead to 4 hours ahead. There is an unexpected increase in the average error from 4 hours ahead to 1 hour ahead; however, the standard deviation does continue to decrease throughout from 48 hours ahead to 1 hour ahead. The average forecast error for the 1 hour ahead rolling forecast was 603 MW with a standard deviation of 888 MW.

Figure 26 shows the percent forecast error with respect to the actual wind generation. Percent forecast error is defined as: $\% \text{ forecast error (MW)} = (\text{forecast wind} - \text{actual wind}) / (\text{actual wind})$. Once again, as expected we see a percent forecast error that gets more accurate as the forecast time gets closer to real time. The fact that the percent forecast error continues to decrease between 4 hours ahead and 1 hour ahead indicates that with respect to the actual wind generation the forecast does continue to get more accurate as the forecast time gets closer to the real time.

Figure 24. The average forecast error based on the amount of time ahead the forecast was made. The results from the 1-48 hr ahead rolling forecast analysis show a mean error of around -600 MW for each hour. Forecast error (MW) = (forecast wind –actual wind generation).

Figure 25. The standard deviation of the average forecast error (= std dev. [forecast wind –actual wind]).

Figure 26. The results from the 1-48 hr ahead rolling forecast analysis show a mean % forecast error relative to the actual wind generation that gets more accurate as the forecast time gets closer to real time.
 $\% \text{ forecast error (MW)} = (\text{forecast wind} - \text{actual wind}) / (\text{actual wind})$.

Analysis of forecast error considering ERCOT Estimated Curtailment Data

We expected that part of the reason that there seems to be a consistent over forecasting behavior is that there is wind power curtailment occurring during times of high wind generation. Curtailment occurs because the available transmission capacity is not able to safely handle all the available wind generation. Based on the two types of forecast discussed above, we found an average forecast error of between 550 and 600 MW every hour of the day. Based on data analyzed by the National Renewable Energy Laboratory (NREL), the average annual wind curtailment in 2009 was 16%. ERCOT reported that 18.8 TWh of wind energy was generated in 2009, which would mean that approximately 3.6 TWh of wind was curtailed. Dividing by 8760, the number of hours per year, we can estimate a simple average 409 MW of constant wind curtailment at all times. Obviously wind curtailment does not occur at a constant amount each hour. However, this average amount of curtailment could represent a large percentage of the wind forecast error shown previously.

In order to quantify the role curtailment played in the difference between the forecasted wind generation and the actual wind generation, we obtained a dataset of estimated wind curtailment every hour from January 1, 2008 to October 31, 2010. This wind curtailment data are data as reported by the wind generators to the ERCOT independent market monitor. Thus, these data are not direct measurements but are considered a rough estimate. However, using these data provides a good step toward understanding the impact that curtailment has on wind generation. The curtailment data was graciously provided by Daniel Jones of Potomac Economics, director of the ERCOT Independent Market Monitor.

Figure 27 and Figure 28 illustrate the effect of correcting the wind generation for curtailment and comparing this adjusted wind generation to the forecasted wind generation. This analysis was done using the 1 hour ahead rolling forecast (theoretically the most accurate forecast). Table 7 lists the statistics for the comparison of wind forecast and wind generation both before and after the correction for curtailment. Correcting for wind power curtailment has a significant impact on the forecast error. The average error drops from 603 MW to 377 MW, also the sum of all the forecast errors drops from a little over 7 million MW to only 4.3 million MW.

Table 7. Statistics of wind forecasting errors for actual wind generation and adjusted wind generation that includes the addition of estimated wind power curtailment correction (for data covering the time period January 1, 2008 to October 31, 2010).

	Actual Wind Generation	Adjusted Wind Generation = Wind Generation + Curtailment
Average Forecast Error (MW)	603	377
Standard Deviation of Forecast Error (MW)	886	773
Sum of Forecast Error (MW)	7,082,031	4,319,831
% Forecast Error	48	41
Absolute Forecast Error (MW)	802	658
Absolute % Forecast Error	57	30

The following figures also help illustrate how curtailment affects wind generation. In Figure 27 (a) and (b) we see that when we correct the wind generation for curtailment (the “adjusted wind generation”) the trend between the adjusted wind generation and forecasted wind generation is much more linear. All the data in blue represent times when curtailment did not occur; these data are also shown independently in Figure 28 (a). All data in red represent times when curtailment did occur (at any amount); these data are shown independently in Figure 28 (b). Clearly wind power curtailment occurs at times of high wind output.

The major result from these figures is the difference between Figure 27 (a) and Figure 27 (b). Figure 27 (a) plots adjusted wind output that *assumes curtailment did not occur* and thus the wind forecasts appear much more accurate as indicated by the red points lying closer to the black line (data on the black line represent an exact forecast of the wind generation).

Figure 27. (a) Adjusted wind generation versus wind forecast (corrected by including wind curtailment). (b) Wind generation versus wind forecast (wind curtailment is not included).

Figure 28. Wind generation versus wind forecast (only non-curtailed times). (b) Wind generation versus wind forecast (only curtailed times).

Background on 2020 projections for ERCOT load and wind generation

Scaling 2010 wind and load to a future year with 20% total wind generation

The team used data from ERCOT's long term forecast for total ERCOT load for a future 2019/2020 scenario with 20% total wind generation. The 2010 actual load data were then scaled with a month-specific scaling factor so that we could estimate 15-minute load for any week of the future 2020 year. In this way, we can account for the anticipation that load in February is anticipated to increase at a slower rate than load in July, for example. .

The projected 2020 hourly wind generation was based upon 2010 actual potential wind defined as "actual wind generation + wind curtailments" (obtained from the ERCOT market monitor, Potomac Economics). The reported wind generation curtailment was added to actual 2010 wind generation as we are assuming that there will be no appreciable transmission constraints in 2020 due to the construction of the Competitive Renewable Energy Zone (CREZ) transmission lines that is ongoing as of the writing of this report. The 2010 potential wind generation was scaled up by a constant factor until total wind generation equaled 20% of the total projected 2020 ERCOT load.

It is important to understand these seasonal load patterns and how they have been changing over time as total demand has increased because it is the "net load = load – wind" generation that dictates the need for dispatchable generation, including storage energy systems. Figure 29 and Figure 30 demonstrate the changing trends of monthly load in ERCOT. Figure 29 shows the total MWh of load for each month from 2005-2010 and also a projected monthly load in a future year (2019/2020) for which we can assume is the year that 20% of generation will come from wind power. One can clearly see the seasonal load patterns and how monthly load drops rather quickly from September to November. Also, Figure 29 and Figure 30 show how it is not straightforward to assume that more load will exist in each month of the year even if more load is anticipated for the entire year. However, it is important to note that the total ERCOT generation from 2005 to 2010 did not increase substantially from 2005-2010, but there was a significant increase from 2009 to 2010. Also note that 2006 and 2010 (the years with highest total load) were appreciably hot years in Texas.

Figure 29. The monthly load (MWh) in ERCOT from 2005-2010 and a future year where it is assumed that the monthly loads are equal to a future projected annual load (362 TWh from ERCOT) multiplied by the % of annual load for each month averaged over 2005-2010.

Figure 30. The % of annual load for each month from 2005 to 2010. Interesting patterns emerge such as the Fall months having a decreasing % of annual generation over time even as total annual load was approximately constant.

For simulating the unit-commitment model used to analyze our 20% wind scenarios, we created 15-minute interval load (“All Gen”) and wind generation (“Wind Gen”) data for each of our 4 weeks representing a ‘typical’ week for each season in ERCOT. We now describe this scaling procedure where we derived two monthly scaling factors: one for load and one for wind generation. Both the ‘All Gen’ and ‘Wind Gen’ monthly scale factors are used as multipliers applied to their respective 2009-2010 15-minute historical values to calculate the 2020 ‘All Gen’ and ‘Wind Gen’ every 15 minutes. Thus, we are scaling actual data from 2009-2010 up to levels projected for 2020, and we simulate the future projected year of 2020.

We used the following data sets for projecting 2020 ERCOT wind generation and load:

- 15min ERCOT actual wind generation [MW] (possess data from 2008-2011, data source = ERCOT GenByFuel from ERCOT planning and operations information website)
- 15min ERCOT estimated wind curtailment [MW] (possess data from 1/1/2008 2:15am to 10/31/2010 23:15pm, data source = Potomac Economics)
- 15min ERCOT total generation, which will be used as a load estimate [MW] (possess data from 2008-2011, data source = ERCOT GenByFuel – from ERCOT planning and operations information website)
- Monthly ERCOT installed wind capacity [MW] (possess data from Jan 2005 through Jun 2012, data source = ERCOT’s monthly system planning reports available on ERCOT website)
- Hourly ERCOT forecasted load [MW] (possess data from Mar 2011 to Feb 2032, data source = ERCOT Long Term Study)

Step 1: Calculating the Monthly Load Scale-Up Factors to estimate 2020 load

We use the 2009:2010 15-min total generation (in MW) data for each month from November 2009 through October 2010 to calculate the total monthly generation (in MWh) for 2009-2010, as seen in Equation (7).

$$\text{2009/2010 ERCOT Generation}_{\text{month}} \text{ (MWh)} = \frac{\sum_{i=1}^{\text{N intervals/month}} \text{Total Generation}_i \text{ (MW)}}{4 \left(\frac{15 - \text{min intervals}}{\text{hour}} \right)} \quad (7)$$

Similarly as in Equation (7), using the ERCOT Long Term Study which forecasts the hourly load (in MW) in 2020, we calculate the month totals for the estimated 2020 total generation, in MWh. After calculating both the November 2009 - October 2010 and 2020 monthly totals, we can determine the “Monthly Load Scale-Up Factors” by taking the ratio of total generation for each month of 2020 and 2009-2010 as in Equation (8).

$$\text{Load ScaleUp Factor}_{\text{month}} = \frac{\text{2020 ERCOT Projected Generation (MWh)}_{\text{month}}}{\text{2009/2010 ERCOT Generation (MWh)}_{\text{month}}} \quad (8)$$

Therefore, to estimate 2020 monthly 15-minute generation (or ERCOT load), we multiply each month's load scale factor to all of the 2009:2010 15min total generation data in a given month.

Step 2: Calculating the Wind Generation Potential

Since the goal is to scale up the pre-curtailed (before curtailment occurs) wind generation, the first step is to add the actual 2009/2010 wind generation with the estimated wind curtailment for every 15 minute interval to calculate the wind generation potential (pre-curtailed wind gen), as seen in Equation (9). Since our available data for wind curtailment ends on October 31, 2010, we used data from November 2009 through October 2010 which represents a full continuous year available data. We also use the 15min total generation from the same dates (November 2009 through October 2010).

$$\text{WindGen Potential (MW)}_i = \text{Actual WindGen (MW)}_i + \text{Wind Curtailment (MW)}_i \quad (9)$$

Step 3: Calculating the Monthly Wind Scale-Up Factors to estimate 2020 wind power

The last step is to determine monthly wind scale up factors in a similar manner as for ERCOT load. Using the November 2009 – October 2010 15-min wind generation potential, we calculate the total monthly MWh of wind energy produced. This is done using the same concept as described for total generation in Equation (7) but using the 2009:2010 wind generation potential that was calculated in Equation (9). Using the known installed wind capacity for each month from November 2009 – October 2010, we calculate the monthly wind capacity factor as shown in Equation (10).

$$\text{Wind Capacity Factor}_{\text{month}} = \frac{\text{WindGen Potential}_{\text{month}} \text{ (MWh)}}{\text{Wind Capacity}_{\text{month}} \text{ (MW)} \cdot \frac{\text{days}}{\text{month}} \cdot \frac{24 \text{ hours}}{\text{day}}} \quad (10)$$

Once each month's wind capacity factor is known, the annual capacity factor can be calculated. In order to take into account for the facts that months have different numbers of days and installed wind capacity changes over time, we calculate the weighted average annual capacity factor as shown in Equation (11).

$$\text{Wind Capacity Factor}_{\text{annual}} = \frac{\sum_{i=1}^{12 \text{ months}} (\text{days}_i \cdot \text{Wind Capacity Factor}_i)}{365 \text{ days}} \quad (11)$$

Next, we must estimate the amount of wind generation over the entire 2020 year that equates to 20% of total ERCOT load. First, using the 15-min scaled up load for 2020, which was estimated just after Equation (8), we take 20% of the total estimated 2020 annual energy production as the estimate of total 2020 annual wind energy production. Then, using the estimated 2020 total wind production and the estimated 2020 annual wind capacity factor, from Equation (11), we calculate the installed wind capacity required in 2020 to achieve 20% of total generation from wind (see Equation (12)).

$$\text{Wind Capacity}_{2020} (\text{MW}) = \frac{20\% \cdot 2020 \text{ ERCOT Projected Generation}_{2020} (\text{MWh})}{\text{Wind Capacity Factor}_{\text{annual}} \cdot 8760 \text{ hours} / \text{year}} \quad (12)$$

Using the estimated 2020 wind capacity we calculate the total wind generation in each month of 2020. To do this, we assume that each month's wind capacity factor in 2020 is equivalent to that of the same month as we calculated for November 2009 – October 2010 (see Equation (13)).

$$\text{Wind Generation}_{\text{month},2020} (\text{MWh}) = \text{Wind Capacity}_{2020} (\text{MW}) \cdot \text{Wind Capacity Factor}_{\text{month}} \cdot N \text{ days} / \text{month} \cdot 24 \text{ hr} / \text{day} \quad (13)$$

Finally, in order to calculate the monthly wind scale-up factors, simply divide the estimated 2020 total monthly wind generation by the total wind generation in each month of November 2009 – October 2010 (see Equation (14)).

$$\text{Wind ScaleUp Factor}_{\text{month}} = \frac{\text{Wind Generation (MWh)}_{\text{month},2020}}{\text{Wind Potential Generation (MWh)}_{\text{month},2009/2010}} \quad (14)$$

The final step for estimating 15-minute wind generation in 2020 is to multiply each month's wind scale factor to all of the 2009:2010 15min wind potential generation data for a given month. This method calculates new 2020 wind generation for every 15-min interval as needed for the unit commitment model. For all of our unit commitment model simulations, we use the same scaled-up 2020 15-min wind generation data. Table 8 and Table 9 summarize results from the wind and load scaling procedure as described in Equations (7)-(14).

Table 8. A summary of the 2009/2010 data used to scale ERCOT wind generation and load to 2020.

Month-Year	Wind Generation (MWh)	Load Scale Up Factor	Wind Capacity Factor (%)	Wind Scale Up Factor
Jan-10	2,127,607	1.23	32.1%	3.36
Feb-10	1,679,980	1.19	28.0%	3.36
Mar-10	2,941,476	1.34	43.4%	3.29
Apr-10	2,933,913	1.36	44.7%	3.29
May-10	2,335,464	1.32	34.4%	3.29
Jun-10	2,477,794	1.23	36.9%	3.21
Jul-10	1,776,973	1.30	25.6%	3.21
Aug-10	1,578,271	1.19	22.8%	3.21
Sep-10	1,546,414	1.30	23.1%	3.21
Oct-10	1,835,051	1.34	26.1%	3.16
Nov-09	1,807,487	1.42	28.2%	3.36
Dec-09	1,723,730	1.25	26.0%	3.36
Total	24,764,160			

Table 9. A summary of the 2020 projected ERCOT wind generation and load used in the unit commitment model simulations.

Month-Year	Forecasted Load (MWh)	Estimated Wind Generation (MWh)	Wind Capacity Factor (%)
Jan-20	31,690,696	7,146,778	32.1%
Feb-20	27,809,914	5,643,168	28.0%
Mar-20	29,211,491	9,662,785	43.4%
Apr-20	28,911,508	9,637,940	44.7%
May-20	35,530,321	7,672,029	34.4%
Jun-20	38,759,505	7,964,857	36.9%
Jul-20	41,608,418	5,712,073	25.6%
Aug-20	42,192,048	5,073,346	22.8%
Sep-20	37,134,286	4,970,940	23.1%
Oct-20	31,988,714	5,805,301	26.1%
Nov-20	29,025,349	6,071,473	28.2%
Dec-20	31,891,838	5,790,128	26.0%
Total	405,754,088	81,150,818	

A summary of values from estimating 2020 ERCOT wind generation and load are:

- Weighted Average Annual Capacity Factor Nov2009-Oct2010 = 30.9%
- Estimated 2020 Total ERCOT Wind Energy Generation = 81,150,818 MWh
- Estimated 2020 Total ERCOT Energy Generation = 405,754,088 MWh
- Estimated 2020 Wind Capacity = 29,949 MW
- % of Total Generation from Wind in 2020 = 20%

The unit commitment model optimizes all non-wind generators on the ERCOT electric grid such that they meet the “net load” on ERCOT as defined in Equation (15).

$$\text{Net Load (MW)} = \text{Total Load (MW)} - \text{Wind Generation (MW)} \quad (15)$$

To fulfill research Tasks 1.2, 2.2, 4.2, and 5.2 we chose four individual weeks to represent each season of the year. We simulate the unit commitment model for these four weeks for each Task while using alternative assumptions to understand the role of grid storage systems. We chose the specific weeks as those that have a relatively ‘normal’ load pattern in the 2009/2010 data that we scaled to 2020. However, as seen in Figure 32 - Figure 37, the net load shows various patterns, and there are instances (in low load months) in which wind generation is greater than all other generation.

Figure 31 - Figure 38 below show the actual 2010 and estimated 2020 total load (when 20% of total electricity is from wind power), wind generation and net load for the four weeks selected to represent each season. It is clear from these figures that the scaled increase in wind generation between 2010 and 2020 significantly reduces net load (red line) and increases the amount of ramping capacity the non-wind generators will have to reach.

Another important concept illustrated by these figures is that the net-load is more volatile than the total load. This volatility is visible in the increase in the magnitude of the primary fluctuations between high to low net load as well as in the increase in amount of secondary fluctuations (small spikes and valleys). The increased slopes as well as the increase in amount of narrow spikes and valleys necessitate in the need for more generators that have the necessary ramping capabilities being used more often.

Looking at the projected 2020 load, net load, and wind generation, it is clear that at times the net load reaches significantly lower values in 2020 compared to 2010 in all seasons except summer. Such a low net load may interfere with the desire of base load power plants like nuclear and coal as well as any combined heat and power plants to maintain maximum output. Historically, ERCOT nuclear and coal power plant operators do not vary (by a significant amount) their daily electricity output. However, with significantly lower net load, it is expected that these types of power plants would have to be more flexible in their operation.

Figure 31. Actual 2010 ERCOT load, wind generation, and net load for the *Winter week* simulated using the unit commitment model for Tasks 1.2, 2.2, 4.2, and 5.2.

Figure 32. Projected 2020 ERCOT load, wind generation, and net load for the *Winter week* simulated using the unit commitment model for Tasks 1.2, 2.2, 4.2, and 5.2.

Figure 33. Actual 2010 ERCOT load, wind generation, and net load for the *Spring week* simulated using the unit commitment model for Tasks 1.2, 2.2, 4.2, and 5.2.

Figure 34. Projected 2020 ERCOT load, wind generation, and net load for the *Spring week* simulated using the unit commitment model for Tasks 1.2, 2.2, 4.2, and 5.2.

Figure 35. Actual 2010 ERCOT load, wind generation, and net load for the *Summer week* simulated using the unit commitment model for Tasks 1.2, 2.2, 4.2, and 5.2.

Figure 36. Projected 2020 ERCOT load, wind generation, and net load for the *Summer week* simulated using the unit commitment model for Tasks 1.2, 2.2, 4.2, and 5.2.

Figure 37. Actual 2010 ERCOT load, wind generation, and net load for the *Fall week* simulated using the unit commitment model for Tasks 1.2, 2.2, 4.2, and 5.2.

Figure 38. Projected 2020 ERCOT load, wind generation, and net load for the *Fall week* simulated using the unit commitment model for Tasks 1.2, 2.2, 4.2, and 5.2.

Background the unit commitment model used for assessing the role of storage with 20% wind in ERCOT

Description of unit commitment electricity system model used for scenario simulations

The model employed for our scenario analysis is a mixed integer linear program (MILP) created using the GAMS modeling language. A detailed model description is contained in the 2012 Ph.D. dissertation of Stuart Cohen, and while a student, Dr. Cohen contributed his MILP simulation program for the project. Dr. Cohen's dissertation description of the MILP model is included as Appendix A to this report, and many plant-level model characteristics are described in other prior work (Cohen, 2012, Cohen et al., 2012). Given generating unit performance parameters, net electricity demand (demand minus wind production), and AS requirements, the model minimizes the cost of electricity dispatch across the fleet. While the general framework is suitable for any electricity system, the model characteristics are tailored for ERCOT.

The model mimics ERCOT by optimizing electricity dispatch *one day at a time* in two stages: 1) an hourly forward market optimization determines which units are online and which are procured for AS, and 2) a 15-minute real-time market determines power output and input to storage systems (modeled as compressed air energy storage). The model does not perform AS deployments because we did not model stochastic events that necessitate AS. However, the model implements the ERCOT penalty function for supply/demand imbalances, so AS deployment needs can be inferred from the frequency of imbalances and associated cost penalties.

The objective function includes operating costs for all generating unit types, which include hydroelectric, biomass, nuclear, coal, natural gas combined cycle (NGCC), natural gas steam boilers (NGBLR), open-cycle gas turbine (OCGT), natural gas internal combustion (NGIC) units, and compressed air energy storage (CAES) systems. Capital costs are not included in electricity dispatch optimization. Fossil-fueled units have fuel, variable operation and maintenance (VOM), and CO₂ emissions costs if applicable. Non-fossil facilities have VOM costs. The model can model coal-fired facilities with CO₂ capture as having additional VOM costs including solvent makeup to offset degradation and volatility losses, caustic sodium hydroxide for thermal solvent reclaiming, reclaimer waste disposal, additional water use for CO₂ capture, CO₂ transport and storage, and ramping the capture load. However, for the purposes of this project, we did not run any simulations with CO₂ capture such that we could focus on the interplay between more wind power and storage. CAES facilities have VOM costs for energy input and output along with fuel and CO₂ costs during output because natural gas is burned to preheat the compressed air before expansion through a turbine (Ridge, 2005). Startup costs are included for all units. There are no direct costs for AS procurements, but indirect costs exist if capacity reserved for AS requires more expensive units to meet electricity demand.

Electricity supply/demand balance is enforced while allowing imbalances that are penalized by up to \$4500/MWh. The four ERCOT AS markets are included in the model. Regulation up and down (RU, RD) service primarily provides frequency response, and requirements vary by month, hour, and ERCOT wind generating capacity (ERCOT, 2011). Responsive reserve service (RRS)

is always 2,800 MW (the ERCOT-specified value as of April 1, 2012 increased from the previous value of 2,300 MW in the latest ERCOT documentation) to ensure enough available online capacity to respond to the largest possible single outage (ERCOT, 2011). Online and offline units can provide non-spinning reserve service (NSRS), which makes quick-starting capacity available for major outage events. NSRS varies by month and hour with the uncertainty in ERCOT net demand (demand minus wind generation) (ERCOT, 2011).

Power generation units are constrained by minimum and maximum load, minimum up/down time, and ramp rate limits. AS offers are limited to 5 min. ramping capability for RU/RD, 10 min. for RRS, and 30 min. for NSRS. Electrical output and AS procurements must also remain within minimum and maximum capacity limits. The model also assumes that combined heat and power (CHP) units operate continuously at maximum output because ERCOT CHP facilities are typically built to satisfy constant heat and process loads at industrial facilities. *This CHP assumption turns out to be highly influential in our results indicating that a 20% wind scenario in ERCOT makes it apparent that industrial cogeneration and wind will interplay in new ways (e.g. either CHP will not be able to export as much electricity to the grid, demand might have to increase in low demand months, wind will need to be curtailed, or various combinations). We discuss these findings in the results for each simulation task in the following sections.*

CAES facilities can provide “up” AS (RU, RRS, and NSRS) with capacity to increase output or decrease input to storage, and RD can be provided by capacity to decrease output or increase input. A flow balance constraint tracks stored energy and accounts for the round-trip efficiency of energy input to output. A daily storage system set point is also required to be consistent with the daily cycling optimization procedure, *so storage system operation is only truly optimal within each day.*

The model represents many detailed electricity system operating behaviors, but a few limitations are worth noting. Transmission is not included, so the model implicitly assumes no transmission constraints in ERCOT are binding. Performance parameters are constant across operating ranges to maintain model linearity and tractability. While marginal values, or dual variables, for energy supply and AS requirement constraints provide shadow prices for electricity and AS, the lack of explicitly modeling offer/bid behavior prevents these prices from corresponding to those in the actual ERCOT market. However, we are able to infer the value of storage systems for acting in the ERCOT AS market.

Estimating Ancillary Service Requirements for 2020

For detailed explanations of how ancillary service procurements are calculated for the unit commitment model, see Appendix A. This section summarizes the AS concepts.

Responsive Reserve Service (RRS)

The amount of Responsive Reserve Service (RRS), also known as spinning reserves, is kept as a constant at 2,800 MW for all dispatch intervals in all seasons. This constant value is consistent with what ERCOT currently requires. In 2012, ERCOT set the RRS value to 2,800 MW. Previously, the RRS value was set at a constant 2,300 MW, and had been set at that lower

constant value for the last several years. That past 2,300 MW RRS procurement was set to exceed the greatest possible single-facility outage within ERCOT, currently 2,300 MW, the capacity of the South Texas Project nuclear facility.

Regulation Up and Regulation Down

Regulation Up (RU) and Regulation Down (RD) services are procured to respond within 5 minutes to discrepancies between expected and actual demand. The quantity of RU and RegDown required varies throughout the day and year and depends on current demand uncertainty, historical regulation deployments, and installed wind capacity. We use tables that ERCOT also uses to estimate additional RU and RD requirements from more wind capacity. These tables originate from report by General Electric that provides a “Wind Adjustment Factor” for RU and RD for a given month and hour of the day for that month. Then this factor is multiplied by the amount of added wind capacity in GW to calculate the additional amount of RU or RD required in 2020.

The 2020 wind capacity that we assume in ERCOT is 29,949 MW. This 2020 installed wind capacity is scaled up from the 2010 installed ERCOT wind capacity for the weeks we simulated as follows:

- Winter: Feb 15-21, 2010, Wind Cap = 8916 (21,033 MW added wind capacity for 2020)
- Spring: Apr 12-18, 2010 , Wind Cap = 9317 (20,632 MW added wind capacity for 2020)
- Summer: Aug 9-15, 2010, Wind Cap = 9317 (20, 632 MW added wind capacity for 2020)
- Fall: Oct 18-24, 2010, Wind Cap = 9467 (20,482 MW added wind capacity for 2020)

Non-Spinning Reserve Service (NSRS)

The procurement of Non-Spinning Reserve Service (NSRS), also known as non-spinning reserves, in ERCOT is a relatively complicated procedure involving the calculation of the 95th percentile of net-load uncertainty based on the data from the previous month of the same year and the same month of the previous year. There are also certain ceilings, floors and additions that are then applied to this value. During this project, we spent considerable effort in attempting to duplicate ERCOT’s NSRS procurement procedure, and we discussed our efforts in a previous section of this report (see section “Replication of ERCOT NSRS ancillary service procurements” under results for Task 2.1).

For the purposes of our model, we decided to select a constant value for the NSRS requirement equal to the current (2012) ceiling value of 2,000 MW. The unit commitment model uses the net load uncertainty as input which is the combination of NSRS and RU. Based on the ERCOT protocols NSRS + RRS must be able to cover 95% of the uncertainties from the net load.

Summary of Simulation Scenarios for Tasks 1.2, 2.2, 4.2, and 5.2

Using our unit commitment model of the ERCOT electric grid, we completed 96 simulations that each model a unique set of conditions that help us to understand the role of wind and storage systems (specifically compressed air energy storage, CAES) in ERCOT. For the purposes of

completing Tasks 1.2, 2.2, 4.2 and 5.2, the following parameters were varied for each task (a more detailed explanation follows):

- A. Season (dates used for each season are in parenthesis)
 - 1. Winter (Feb 15-21)
 - 2. Spring (Apr 12-18)
 - 3. Summer (Aug 9-15)
 - 4. Fall (Oct 18-24)
- B. Capacity Investment Option (names used in results figures are in parenthesis)
 - 1. 5,900 MW Thermal Only (Thermal)
 - 2. 2,780 MW Energy Storage with some Thermal (Store CapLim)
 - 3. 7,900 MW Energy Storage with more Thermal (Store NoCap)
- C. Natural Gas Price (names used in results figures are in parenthesis)
 - 1. \$3 per MMBTU (\$3 NG)
 - 2. \$4.91 per MMBTU (\$5 NG)
 - 3. \$8 per MMBTU (\$8 NG)

Season Scenarios

As previously described (see Appendix A), the unit commitment model optimizes one day at a time over a one week period. Therefore, one week was selected as representative of the expected conditions for each season (see Figure 32 - Figure 37). Each week is considered to start at the interval ending 12:15 am on Monday and end at the interval ending 12 midnight on Sunday.

Capacity Investment Scenarios

Based on population growth and an expected increase in per capita energy demand, the total installed capacity required to meet the maximum combination of total load, regulation up, responsive reserve service, and non-spinning reserve service is significantly larger than the available capacity in the ERCOT grid today. After scaling up 2009/2010 generation and ancillary service requirements to 2020 levels, we calculate a maximum required capacity (excluding wind generators) by summing the net load, and required regulation up, responsive reserve, and non-spinning reserves during every 15 minute interval of the year 2020. We calculated a ***maximum required dispatchable capacity of 82,421 MW*** on July 16, 2020 at 3pm.

This ‘dispatchable’ capacity represents an estimate of the non-wind generation needed in our future 2020 ERCOT scenario. Since ERCOT currently has only 79,642 MW of non-wind capacity, a minimum of 2,779 MW will need to be installed between now and 2020. So, we assume that between now and 2020 several new power plants will be built in order to ensure that ERCOT has adequate capacity available. This additional required capacity was selected as a parameter that we vary (slightly) in order to simulate how the electric grid would operate if different combinations of new power plants, including energy storage, were to be constructed and online by 2020.

Three different capacity investment options are assumed to have occurred over the time period from 2010 to 2020 (2020 being the year we assume 20% wind generation). ***The first investment capacity option***, used as a base case, assumes installation of 4,000 MW of combined cycle, and 1,900 MW of open cycle natural gas thermal generators with no energy storage. Based on ERCOT's published planned future installations, these 5,900 MW represent all the additional thermal generators currently scheduled to be available in 2020 in the ERCOT electric grid. We label this scenario "**thermal**" as it invests only in thermal generators.

The second capacity investment option assumes the installation of only 2,000 MW of compressed air energy storage and 800 MW of combined cycle natural gas thermal generators. This second option is just enough capacity to meet the max demand that we estimate for 2020. Therefore, this option is labeled as "capacity limited" (**StoreCapLim**). ***The third, and final, capacity investment option*** includes the same amount of combined cycle and open cycle natural gas thermal generators as the first investment option (5,900 MW) and the same amount of compressed air energy storage as the "capacity limited" option (2,000 MW). Similar to option StoreCapLim, this third option incorporates the same amount of energy storage but includes much more total capacity than is needed to meet the maximum demand; therefore, this option is considered "not capacity limited" (**StoreNoCap**).

The StoreCapLim scenario is intended to simulate what could happen when storage must be used at times of extremely high electricity demand when no other power is available, while StoreNoCap represents what could happen when storage is available but there is adequate thermal capacity to meet the highest demand.

Table 10. Three different capacity investment scenarios for ERCOT from 2010 to 2020 enable us to have varied insights into how effective storage systems can be for ERCOT with 20% wind.

Grid Investment Scenario	New energy storage (CAES) from 2010 to 2020 (MW)	New NGCC from 2010 to 2020 (MW)	New NG turbine from 2010 to 2020 (MW)
Thermal:			
Thermal Capacity Only	0	4,000	1,900
StoreCapLim:			
Storage + limited thermal capacity	2,000	800	0
StoreNoCap:			
Storage + planned thermal capacity	2,000	4,000	1,900

Natural Gas Price Scenarios

The price of natural gas has fluctuated by an order of magnitude over the last decade. From over \$12 in June of 2008 to as low as \$2.26 in April of 2012, the uncertainty of the price of natural gas is an important factor in the operation of the electric grid and perhaps even more so in the ERCOT electric grid that currently has 64% natural gas by capacity. For this report, we used three different natural gas prices in order to capture a range of possible unit commitment scenarios in ERCOT. A low value of \$3 per MMBTU and high value of \$8 per MMBTU are used to bound the solution. A value of \$4.91 (“\$5”) per MMBTU was used as a ‘likely’ future scenario.

Project Task Scenarios and “Base Case”

For each four project research tasks (1.2, 2.2, 4.2, and 5.2), we use a base case for comparison that includes capacity option 1 (no energy storage), all three natural gas prices, and all four seasons. This yields a total of 12 simulations.

For **Task 1.2**, the model is modified so that any energy storage will only be able to operate in the energy-only electricity market by engaging in price arbitrage (storing cheaper energy at low demand and selling more costly energy at high demand) but not in the ancillary services market.

For **Task 2.2** the model is adjusted so that CAES energy storage facilities will only be able to operate in the ancillary services market and not in the energy market. Then, for **Task 4.2** energy storage is allowed to participate in both the arbitrage and ancillary services market and it is up to the optimization model to determine what is best for energy storage to do. In reality, this is the likely scenario because the nature of energy storage is such that it can profit from both markets. For Tasks 1.2, 2.2, and 4.2 we simulate both storage capacity investment options (StoreCapLim and StoreNoCap) as well as all three natural gas prices and all four seasons. This combination yields a total of 72 unique simulations for these three tasks.

Lastly, for **Task 5.2** we modify the model to include a high CO₂ tax penalty to simulate what could happen under strict carbon regulations. For this task, all three capacity investment options are used, as well as all four seasons, but only the \$4.91 natural gas price is selected for this task. Therefore, for this task we run a total of 12 unique simulations.

A chart that illustrates the details of these simulations as well as gives them each a unique identifying number can be found in Appendix B.

Explanation of some Limiting Factors for Unit Commitment Model

Even though we ran 24 simulations for each Task X.2, our results are limited by a few key concepts, all of which affect the represented operational flexibility of generators within our model of the ERCOT electric grid. As we will see, these limiting assumptions on thermal generator flexibility add additional constraints on the generators in terms of how they can respond, or ramp, quickly, to changes in net load. In reality, there will be procedures that can be implemented by ERCOT and generation units to alleviate some ‘problems’ that we simulate to occur (e.g. negative prices). Further, our modeling assumptions make the optimization procedure more computationally difficult.

Our major assumptions for interpreting unit commitment simulation results are:

- CHP capacity factor: We considered all CHP facilities to have capacity factor of 100% and always be running at their max capacity. This is not necessarily realistic and probably contributes to much of our negative price results while making the numerical optimization more difficult especially during times of low net load. By leaving this simple CHP assumption, we can focus on the dynamics of our scenarios that are designed to understand how storage systems can play with higher wind generation in ERCOT.
- Minimum up and down times for thermal generators: The occurrences of low net loads during the Winter, Spring and Fall seasons contributed to several oversupply conditions in which more electricity is scheduled (and generated) than is needed for the forecasted load. This oversupply is largely caused by the lack of flexibility in thermal generation to turn on and off to follow the net load, and negative market prices occur. Furthermore, when we simulate higher natural gas prices, we are finding that an increased amount of coal dispatch (due to relatively lower operating costs) leads to more oversupply and still negative market prices. This effect from low ramping flexibility competes against the more intuitive effect of increasing electricity prices along with increasing natural gas prices, and it sometimes drives the electricity price down in a non-monotonic manner (with respect to increasing NG price). As we discuss, we believe this relates to having more committed capacity that has slower ramp rates (e.g. nuclear, coal) that is less able to adjust to changes in net load at very low net load.
- No simulation of actual deployment of ancillary services: While the unit commitment model determines which generators will be used for procurements of ancillary services, it does not actually model the deployment of these ancillary services. A simulation of deployments would help reduce oversupply and undersupply effects as well as allow for additional ramping capabilities. The deployment of ancillary service would also affect

the price of electricity at the times of deployment. Currently in our day-ahead procurement unit commitment model, the electricity price is affected by oversupply and undersupply penalties, and these penalties would not necessarily be incurred if ancillary services were deployed as would happen in a full real-time market simulation. The deployment of ancillary services could therefore lead to a more smoothly fluctuating electricity price that might not result in the sudden price spikes that we simulate due to inability of the available generators to ramp quickly enough to match net load. For this reason, we have calculated generator revenues using the electricity prices found by the 'raw' unit commitment model as well as by using adjusted electricity prices where negative prices are set to zero and the positive price outliers are removed and smoothed out through interpolation.

- No wind power curtailment: Since we assumed the estimated 2020 wind power to be a given, we did not allow one additional source of flexibility that could help alleviate issues with oversupply and ramp constraints: wind power curtailment. Our model does not account for the ability to curtail wind generation, which is a currently a normal occurrence in the ERCOT grid. Primarily done because of transmission constraints, wind curtailment could also be used as a form of interruptible load in times of low net load and inflexibility of committed thermal generation units. Much like the constraint on CHP plants, the lack of wind curtailment increases the magnitude and occurrences of oversupply, leading to high instances of negative prices.

Commentary on Creating the Adjusted Electricity Price

Due to the assumptions and model limitations discussed in the previous section, most notably the lack of flexibility of CHP plants, not including deployments of ancillary services, and not allowing for wind curtailment, we can expect deviations from our model output in simulating historical situations. These limitations in particular will cause the occurrence of an oversupply or undersupply of electricity as well as a penalty price with each. However, in order to eliminate all negative and unrealistically high prices that would result from incurring the oversupply or undersupply penalty we set all negative prices to zero and removed any high prices that are greater than two standard deviations away from a rolling average. We expect that this adjusted electricity price will better reflect reality but will still have significant error. However, even though the adjusted electricity price is still not ideal, it will remove the large positive and negative price spikes and allow us to calculate much more realistic revenues from electricity sales. *Thus, throughout this report we refer to what is an adjusted electricity price or electricity price with outliers removed.*

Comparing unit-commitment model simulation of 2010 to actual 2010 ERCOT dispatch

Before discussing the numerous simulations that were completed to analyze the various tasks of this project, we present results for comparing the accuracy of our unit-commitment model. For this test the actual 2010 data (load, wind gen, ancillary service requirements, and generator fleet) from the four selected weeks (one for each season) was used to run the optimization model. The results from these simulations are then compared to what actually happened in 2010.

Comparison of Generation by Fuel Type:

Figure 39 - Figure 46 below show the generation by fuel type for each season showing both what actually happened in the selected weeks of 2010 and what the model finds as its solution. The first noticeable difference is what happens with nuclear in winter, spring, and fall. In these three seasons the actual level of nuclear output was much more constant throughout the week as compared to the model output.

The other noticeable difference is the level of power output from coal plants. In winter, spring, and fall the model predicts coal output to be much less than actual coal generation, and in the summer the model predicts coal to ramp up and down much more than it actually does. Much of this difference is attributed to how we model combined heat and power (CHP) plants. As was explained previously, the model assumes that all CHP plants are always running at their maximum output, but looking at what actually happened in 2010 it is clear this did not actually occur. Looking specifically at the NGCC CHP plants, the actual level of NGCC in winter, spring, and fall during the times of low net load reached levels below the combined capacity of all NGCC CHP plants. However, all seasons do show similar levels of generation at the switch from NGCC to OCGT.

Although the CHP requirement may be causing deviation from what actually occurs, we chose to keep this requirement until we can better analyze the actual activity of CHP facilities in order to better model their actions. In light of results and comparisons in Figure 39 - Figure 46, it is most relevant to consider the results of our simulations in comparison to themselves, and not to actual ERCOT dispatch. Because of this, we chose to run the several (100) simulation variations to test the sensitivity of the model to different circumstances that are relevant for understanding the role of storage in the ERCOT grid.

Figure 39. 2010 Winter actual generation by fuel type.

Figure 40. 2010 Winter simulated generation by fuel type.

Figure 41. 2010 Spring actual generation by fuel type.

Figure 42. 2010 Spring simulated generation by fuel type.

Figure 43. 2010 Summer actual generation by fuel type.

Figure 44. 2010 Summer simulated generation by fuel type.

Figure 45. 2010 Fall actual generation by fuel type.

Figure 46. 2010 Fall simulated generation by fuel type.

Comparison of Electricity Prices:

Figure 47- Figure 54 show the real-time market electricity price for each season showing both what actually happened in the selected weeks of 2010 and what the model finds as its solution. In all four seasons the adjusted electricity price that is predicted from the model is flatter than that of reality; the highs and lows are less pronounced resulting in a narrower range of prices.

Another noticeable difference is that the model predicts more \$0 per MWh behavior during times of low net load. Once again, the role of CHP plants may be important at these times in the model by driving prices down since they are required to be running at maximum capacity. Thus, the difference between on-peak and off-peak prices is much lower in the model predicted prices than in the historical data.

Although the model predicts prices that are narrower, they do follow the same trends of the actual prices. Peaks and valleys in the price occur simultaneously with peaks and valley in the net load. The more minimal fluctuation of the model predicted prices should serve to keep any estimates of revenues and profits as conservative estimates.

In light of results and comparisons in Figure 47 - Figure 54, it is most relevant to consider the results of our simulations in comparison to themselves, and not to actual ERCOT dispatch.

Figure 47. 2010 Winter actual market electricity prices.

Figure 48. 2010 Winter simulated market adjusted electricity prices.

Figure 49. 2010 Spring actual market electricity prices.

Figure 50. 2010 Spring simulated market adjusted electricity prices.

Figure 51. 2010 Summer actual market electricity prices.

Figure 52. 2010 Summer simulated market adjusted electricity prices.

Figure 53. 2010 Fall actual market electricity prices.

Figure 54. 2010 Fall simulated market adjusted electricity prices.

Results for Task 1.2: Simulate investment and operation scenarios storage with arbitrage only

Committed generation (gross output, TWh) – Arbitrage Only

Figure 55 graphs the electricity output in the ERCOT market grouped by fuel type. In these simulations wind output is a user specified parameter and is assumed given for each dispatch interval. As will be seen in all tasks, wind output accounts for around 30% of total electricity generation in winter and spring, 10% in summer, and 20% in fall. Once again it is important to point out that all CHP facilities will be generating at the same level (100% output) for all simulations and all tasks, so there will be no variation in the output from these facilities (brown to purple).

Changing the natural gas price from \$3 to \$4.91 per MMBTU has a significant effect on the Coal and natural gas combined cycle (NGCC) generators. At \$3 per MMBTU very little coal power is being utilized, instead it is less costly to run NGCC plants. Jumping to \$4.91 per MMBTU causes a large increase in coal power output in favor of NGCC. The next jump to \$8 per MMBTU does not result in as significant an increase in coal output. This trend will be visible in all the other Tasks as well.

Although the electricity output from storage (CAES) is very small with respect to the output from many of the other generator types, CAES does account for around 1% of total electricity supply from some weeks. In fact there are several occurrences during these various weeks when output from CAES is at its maximum of 2000 MW. So although it seems insignificant, the available capacity of CAES (2000 MW) is much smaller than the available capacity of most other generator types; therefore 1% is a significant level and the same order of magnitude as the output from Hydro, Biomass, Coal CHP, NGBLR, OCGT, and NGIC generators. In these simulations the capacity factor for the CAES facilities is between 10-20% with the highest values occurring in the summer.

Figure 55. Electricity generation (TWh) for each season per type of generator.

Ancillary service procurements – Arbitrage Only

Figure 56 illustrates the procurements, in GWh, of all the ‘up’ ancillary services, namely Regulation Up (RU), Responsive Reserve Service (RRS) and Non-Spinning Reserve Service (NSRS) grouped by generator and fuel type. Once again, this model does not simulate the dispatching of these ancillary services; therefore, in times of undersupply a penalty cost is incurred and the undersupply is allowed to occur. From these figures it is evident that faster ramping and primarily natural gas plants (NGCC and OCGT) are procured for these ancillary services. However, what is not evident is that RU is almost entirely comprised of the faster OCGT, RRS is mostly procured from NGCC and OCGT, and NSRS utilizes mostly NGCC and NGBLR. It is expected that the faster ramping OCGT plants would be used for the faster responding RU service.

Figure 57 illustrates that regulation down (RD) is supplied by mostly NGCC, OCGT, and Hydro. From Figure 57 it is also evident that the increase in the price of natural gas causes a minor shift toward using Coal instead of NGCC. This trend is also evident in the RRS procurements (not shown individually).

Since *for this specific research task*, storage was limited to only participating in the arbitrage market, no storage was used for these ancillary services.

Figure 56. Procurements of all “up” ancillary services, by generator type.

Figure 57. Procurements of “down” ancillary services, by generator type.

Total ERCOT CO₂ emissions – Arbitrage Only

Figure 58 shows the CO₂ emissions grouped by fuel type in tons of CO₂. In all four seasons, the increase in natural gas prices causes the utilization of more coal power and less NGCC which results in higher CO₂ emissions. It is also clear based on the scale of the y-axis that CO₂ emissions are highest in the summer when more generators are required to be online to meet the demand requirement.

The 2000 MW of modeled CAES generation does not appreciably affect total ERCOT emissions.

Figure 58. ERCOT generator CO₂ emissions for each season, listed by generator type.

Total ERCOT operating costs – Arbitrage Only

Figure 59 presents the total operating costs (\$ million) for each simulation broken down by the contributions from each fuel type. In ERCOT, the marginal electricity price is set by natural gas generators, and thus, we expect that higher natural gas prices should result in higher overall operating costs because of the increase in the fuel costs of all natural gas-fired facilities. This expectation is confirmed by the figures below where it is clear that increasing natural gas price causes an increase in the total operating costs. The magnitude of the costs is also shown to be greater in the summer when more total generation must be online to meet the greater electricity demand.

Also evident from Figure 59 is a decrease in total operating costs for the StoreNoCap investment case (7,900 MW of new capacity from 2010 to 2020). Although the reduction is small, the addition of CAES in the StoreNoCap case results in a slightly lower and more optimum overall cost. The restriction of total installed capacity in the StoreCapLim (2,800 MW of new capacity from 2010 to 2020) cases indicates that installing more NG power plants will compete differently with CAES depending upon the NG price: at higher NG prices CAES produces contributes more generation to the grid but the overall operating cost of the grid is higher.

Figure 59. Operating costs increase with natural gas price, and are higher in the limited installed capacity (“CapLim”) scenario.

Total ERCOT electricity prices – Arbitrage Only

Figure 60 shows the trends in the adjusted electricity price (\$/MWh, with price outliers removed) for all seasons and all capacity investment options relative to the increasing price of natural gas. Just as we expect that the total operating cost would increase with increasing natural gas price, we also expect that the electricity price for a particular season and capacity option will increase when that price for natural gas increases. This trend is evident in Figure 60.

We can also see that the electricity prices in summer are typically higher than the other seasons while winter typically has the lowest electricity prices. Once again this is the expected trend based on historical data. So even though the real time 15 minute electricity price may not match what has happened historically, the average prices over a week's relative to the other average prices do follow the expected trends.

In comparing the investment case scenarios, it is interesting to note that the capacity limited, CapLim, scenario (with only 2,800 MW installed a capacity (2,000 MW is CAES) from 2010 to 2020) shows lower prices compared to the base Thermal only scenario in all seasons except for summer. This indicates that CAES can lower the average electricity price when the grid needs much less than its maximum capacity for generation.

Figure 60. ERCOT average wholesale electricity price (adjusted by removing negative prices and positive price outliers) for each season and investment scenario, listed as a function of natural gas price.

Total ERCOT dispatch costs – Arbitrage Only

Similarly to Figure 59 for Total Operating Cost, the Total Dispatch Cost for all arbitrage only simulations illustrates the increase in costs resulting from an increase in the price of natural gas (see Figure 61). Within each group of four seasonal simulations, the difference in the costs is due mostly to the different total MWh output requirement, as we can see that summer is always significantly higher.

Comparing the costs of the three different investment options, there is an increase in costs evident for the CapLim case. This result is expected since this is the capacity investment option with limited new capacity (2,800 MW versus 5,900 MW for Thermal baseline and 7,900 the NoCap scenario). With a more limited capacity the CapLim cases have to utilize the higher priced inefficient generators in the electric grid more often than the other cases would. The increase in costs for the CapLim case could also be partially contributed to the occurrence of more oversupply and undersupply of energy. During times of high demand, the CapLim option may be more limited in what generators are available to increase output and therefore have to incur more undersupply cost penalties. Similar events could occur for oversupply because of the more limited nature of the CapLim case.

Also evident in this Figure 61 is a decrease in total dispatch cost for the NoCap investment case. The decrease is most evident in spring and winter. Compared to the Thermal case, the addition of CAES in the NoCap case results in a slightly lower overall cost.

Figure 61. Total ERCOT dispatch costs for each investment scenario and NG price.

Results for Task 2.2: Simulate investment and operation scenarios with AS

Committed generation (gross output, TWh) – Ancillary Services Only

Figure 62 graphs the electricity output in the ERCOT market grouped by fuel type. Unlike the previous Task, CAES has zero gross output since it can only participate in the ancillary services market. Thus, there is little to explain in this figure for the ramifications of storage.

It is once again clear that changing the natural gas price from \$3 to \$4.91 per MMBTU has a significant effect on the Coal and NGCC generators. At \$3 per MMBTU very little coal power is being utilized, except in the summer when the larger demand dictates the use of some coal power. Jumping to \$4.91 per MMBTU causes a large increase in coal power output in favor of NGCC. The next jump to \$8 per MMBTU does not result in as significant an increase in coal output.

Figure 62. Electricity generation (TWh) for each season per type of generator.

Ancillary service procurements – Ancillary Services Only

Figure 63 illustrates the procurements of all the ‘up’ ancillary services, namely Regulation Up (RU), Responsive Reserve Service (RRS) and Non-Spinning Reserve Service (NSRS) grouped by fuel type in GWh. From these figures it is evident that faster ramping and primarily natural gas plants (NGCC and OCGT) are procured for these ancillary services. It is also evident that CAES is utilized to supply more than 20% of the total ‘up’ ancillary services.

Regulation Up (RU) is still primarily supplied by the faster responding OCGT. However, when available, CAES supplies between 30-40% of the RU. CAES also supplies around 20% of the RRS and 5% of the NSRS. Clearly CAES is a useful asset for supplying ancillary services.

In these simulations, since the CAES facility was not actively charging or discharging (by assumption of this task CAES could not engage in the energy market) and maintain a low level of stored energy, it did not supply any of the regulation down (RD), as seen in Figure 64. RD is still supplied by mostly NGCC, OCGT, and Hydro.

Notes on AS:

- Reg Down is mostly Hydro, NGCC, and OCGT with a little NGIC, Coal, or Nuclear, when available storage accounts for 0% of Reg Down because storage is not charging at is at a low level, summer has more NGCC and less OCGT
- Reg Up is mostly OCGT’s, and when storage is included it accounts for around 30-40% of Reg Up (larger % in summer)
- RRS is primarily NGCC and OCGT, when storage is available it accounts for around 20% of RRS
- NSRS is primarily NGCC, some NGBLR and Coal, when available storage accounts for around 5% of NSRS, summer has significantly more NGBLR and less NGCC

Figure 63. Procurements of all “up” ancillary services, by generator type.

Figure 64. Procurements of “down” ancillary services, by generator type.

Total ERCOT CO₂ emissions – Ancillary Services Only

Figure 65 shows the CO₂ emission grouped by fuel type in tons of CO₂. Once again, in all four seasons, the increase in natural gas prices causes the utilization of more coal power and less NGCC which results in higher CO₂ emissions. It is also clear based on the scale of the y-axis that CO₂ emissions are highest in the summer when more generators are required to be online to meet the demand requirement. Clearly minimizing the use of coal-fueled facilities will result in less CO₂ emissions.

In these simulations, since CAES is not allowed to participate in the arbitrage market, CAES does not actually generate any electricity for the grid and therefore there are no CO₂ emissions associated with CAES and CAES is not able to affect grid-scale emissions.

Figure 65. ERCOT generator CO₂ emissions for each season, listed by generator type.

Total ERCOT operating costs – Ancillary Services Only

Figure 66 displays the total ERCOT operating costs for each simulation broken down by the contributions from each fuel type in millions of dollars. Once again these simulations confirm the prediction that increasing natural gas price causes an increase in the total operating costs. The magnitude of the costs is also shown to be greater in the summer when more total generation must be online to meet the greater electricity demand.

Also evident in these figures is a decrease in total operating costs for the NoCap investment case. In this Task, the Thermal case has the highest costs followed by the CapLim and then NoCap cases. The addition of CAES in the CapLim and NoCap cases results in a slightly lower and more optimum overall cost even when CAES can only perform ancillary services. Of course, these results only consider operating costs, and not capital costs.

Figure 66. Operating costs increase with natural gas price, and are lower in the limited installed capacity (“CapLim”) scenario than the base “Thermal” scenario (opposite cost trend as Task 1.2 when CAES could only perform arbitrage).

Total ERCOT electricity prices – Ancillary Services Only

Figure 67. ERCOT average wholesale electricity price (adjusted by removing negative prices and positive price outliers) for each season and investment scenario, listed as a function of natural gas price.

Total ERCOT dispatch costs – Ancillary Services Only

Similarly to the figure for Total Operating Cost shown previously, the Total Dispatch Cost for all ancillary service-only simulations illustrates the increase in costs resulting from an increase in the price of natural gas. Within each group of four seasonal simulations, the difference in the costs is due mostly to the different total MWh requirement, as we can see that summer is always significantly higher.

Unlike the previous Task 1.2, there is very little noticeable difference in the total dispatch costs between the three different investment cases. However, there is a slight decrease in total dispatch cost for the NoCap investment case, for all seasons, compared to the Thermal (base) case. This decreasing cost trend could be because there is more total installed capacity in the NoCap case (7,900 MW more from 2010 to 2020 of NG and CAES) versus the Thermal case (5,900 MW more of NG generation).

Figure 68. Total ERCOT dispatch costs for each investment scenario and NG price.

Results for Task 3.2: Simulate investment in transmission

This task was officially removed from the scope of work after awarding of the project.

Results for Task 4.2: Simulate 1.2, 2.2, 3.2 to minimize CO₂ emissions

After consideration, this task was deemed insufficiently distinct from Task 5.2 and ill-defined such that the team could not formulate a structured problem that would be informative for considering only CO₂ emissions and not economic costs. All results that consider CO₂ constraints and pricing are discussed in the results for Task 5.2. Results presented in this section describe simulations that assume CAES storage can operate in both ERCOT's energy market (perform arbitrage) and ancillary services market (AS).

For this task, we instead decided to run similar simulations to those of the previous two Tasks, but allow the energy storage facilities to participate in both the arbitrage and ancillary services markets. In reality, an energy storage facility would most likely want to participate in both markets in an effort to maximize revenues. For this task, the optimization model allows the CAES facilities to participate in one or both markets however necessary to minimize the total operating grid costs. It is anticipated that this additional flexibility will allow for a more optimum solution and would therefore be better than the arbitrage only and ancillary services only Tasks.

Committed generation (gross output, TWh) – Arbitrage and Ancillary Services

Figure 69 graphs the electricity output in the ERCOT market grouped by fuel type in TWh. These simulations also show the important effect of changing the natural gas price from \$3 to \$4.91 per MMBTU. At \$3 per MMBTU very little coal power is being utilized, instead it is less costly to run natural gas combined cycle (NGCC) plants. Jumping to \$4.91 per MMBTU causes a large increase in coal power output in favor of NGCC. The next jump to \$8 per MMBTU does not result in as significant an increase in coal output.

Although the electricity output from storage (CAES) is very small with respect to the output from many of the other generator types, CAES does account for around 1-1.7% of total electricity supply. Although it seems insignificant, the available capacity of CAES (2000 MW) is much smaller than the available capacity of most other generator types; therefore this is a significant level and the same order of magnitude as the output from Hydro, Biomass, Coal CHP, NGBLR, OCGT, and NGIC generators.

For each of the seasons the MWh output from CAES for this task is greater than that of the arbitrage only Task 1.2. The ability of the storage facility to participate in both markets allows it increase its capacity factor to between 20-25%. This most realistic scenario for CAES enables higher utilization of storage as compared to if it is restricted to only serving in the energy market (e.g. arbitrage only).

Figure 69. Electricity generation (TWh) for each season per type of generator.

Ancillary service procurements – Arbitrage and Ancillary Services

Figure 70 illustrates the procurements of all the ‘up’ ancillary services, namely Regulation Up (RU), Responsive Reserve Service (RRS) and Non-Spinning Reserve Service (NSRS) grouped by fuel type in GWh. From these figures it is evident that faster ramping and primarily natural gas plants (NGCC and OCGT) are procured for these ancillary services. It is also evident that CAES is utilized to supply between 10-15% of the total ‘up’ ancillary services. This is a smaller percentage of ‘up’ ancillary services served by CAES as compared to Task 2.2 when CAES could only provide AS.

Regulation Up (RU) is still primarily supplied by the faster responding OCGT. However, when available, CAES supplies between 10-20% of the RU. CAES also supplies around 10-15% of the RRS and 1-1.5% of the NSRS. These percentages are slightly lower than those of the ancillary services only Task; however, in these simulations CAES also supplied 10-20% of the Regulation Down (RD).

The generation (MWh) and AS procurement results for Task 4.2 indicate that CAES storage systems should have multiple benefits for operating within ERCOT with 20% annual generation from wind. Overall, in these simulations CAES satisfies less of the ancillary service requirements than that of the ancillary service only Task. However, in combination with the amount of energy supplied in the arbitrage market, allowing storage to participate in both arbitrage and ancillary services markets should yield more profit for the energy storage facilities.

Notes on AS:

- Reg Down is mostly Hydro, NGCC, and OCGT with a little NGIC, Coal, or Nuclear, when available storage accounts for 10-20% of Reg Down (5-10% in summer)
- Reg Up is mostly OCGT's, when storage is included it accounts for around 10-15% of Reg Up (15-20% in summer)
- RRS is primarily NGCC and OCGT, when storage is available it accounts for around 10-15% of RRS
- NSRS is primarily NGCC, some NGBLR and Coal, when available storage accounts for around 1-1.5% of NSRS, summer has significantly more NGBLR and less NGCC also has up to 5% from storage

Figure 70. Procurements of all “up” ancillary services, by generator type.

Figure 71. Procurements of “down” ancillary services, by generator type.

Total ERCOT CO₂ emissions – Arbitrage and Ancillary Services

Figure 72 shows the CO₂ emission grouped by fuel type in tons of CO₂. Once again, in all four seasons, the increase in natural gas prices causes the utilization of more coal power and less NGCC which results in higher CO₂ emissions. It is also clear based on the scale of the y-axis that CO₂ emissions are highest in the summer when more generators are required to be online to meet the demand requirement. Clearly minimizing the use of coal-fueled facilities will result in less CO₂ emissions.

Figure 72. ERCOT generator CO₂ emissions for each season, listed by generator type.

Total ERCOT operating costs – Arbitrage and Ancillary Services

Figure 73 displays the total operating costs for each simulation broken down by the contributions from each fuel type in millions of dollars. Once again these simulations confirm the expected trend that increasing natural gas price causes an increase in the total operating costs. The magnitude of the costs is also shown to be greater in the summer when more total generation must be online to meet the greater electricity demand.

Also evident in Figure 73 is a decrease in total operating costs for the NoCap investment case. Although the reduction is small, the addition of CAES in the NoCap case results in a slightly lower and more optimum overall cost.

What is also of note is that the total operating costs are approximately the same for the Thermal (base) and Store CapLim investment cases, but the capital costs of installing the new capacity might be quite similar also (or possibly lower of the Store CapLim scenario). The Thermal scenario assumes installation of 4,000 MW of NGCC and 1,900 MW of OCGT, whereas the CapLim scenario assumes only 2,000 MW of CAES and 800 MW of OCGT. *Thus, if 2,000 MW of CAES has a lower capital cost than (4,000 MW NGCC + 1,100 MW OCGT), it could be a more overall efficient investment option for ERCOT.*

Figure 73. Operating costs increase with natural gas price, and are *similar* in the limited installed capacity (“CapLim”) scenario than the base “Thermal” scenario (balancing cost trends as in Tasks 1.2 and 2.2).

Total ERCOT electricity prices – Arbitrage and Ancillary Services

Figure 74 shows average wholesale ERCOT grid prices for our simulations allowing CAES to engage in both energy price arbitrage and the AS market. The price trends are similar as the results for Tasks 1.2 and 2.2. For this task, one might expect that the average prices are higher for the CapLim investment case that represents the least amount of new installed capacity into the grid, and this is the case more so than the prices estimated in Tasks 1.2 and 2.2. However, as we have stated regarding assumptions of the unit-commitment model, because it does not dispatch AS, we do not estimate fully realistic prices, and we adjust them to remove some inconsistencies.

Figure 74. ERCOT average wholesale electricity price (adjusted by removing negative prices and positive price outliers) for each season and investment scenario, listed as a function of natural gas price.

Total ERCOT dispatch costs – Arbitrage and Ancillary Services

Similarly to the Figure 73 for Total Operating Cost shown previously, the Total Dispatch Cost for these simulations illustrates the increase in costs resulting from an increase in the price of natural gas (see Figure 75). Within each group of four seasonal simulations, the difference in the costs is due mostly to the different total MWh requirement, as we can see that summer is always significantly higher.

Comparing the three costs of the three different investment options, there is a very small increase in costs evident for the CapLim case. As was discussed in the arbitrage only Task 2.2, this increase could be a result of the greater use of less efficient generators (because of less total installed capacity) or of incurring more oversupply and undersupply penalties.

Also evident in Figure 75 is a decrease in total dispatch cost for the NoCap investment case. The decrease is most evident in spring and winter. Compared to the Thermal case, the addition of CAES in the NoCap case results in a slightly lower and more optimum overall cost, with the tradeoff being the higher capital costs of installing that much more capacity.

Figure 75. Total ERCOT dispatch costs for each investment scenario and NG price.

Results for Task 5.2: Simulate ERCOT system with minimum costs and CO₂ constraints

For simplicity, we only compare a ‘base case’ NG price simulation with and without CO₂ prices to understand how CAES plays a role if there is an emissions penalty price in ERCOT. Thus, all simulation results for Task 5.2 assume \$4.91/MMBtu NG price, but we still consider the three different capital investment cases.

Committed generation (gross output, TWh) – High CO₂ Price

Figure 76 graphs the electricity output in the ERCOT market grouped by fuel type in TWh. These simulations show the important effect of changing the CO₂ price from \$0 to \$80 per ton of CO₂. At \$0 per ton a large amount of coal power is being utilized, while at \$80 per ton coal power output is zero in all seasons except summer and is replaced by NGCC. The higher summer demand necessitates some coal capacity to be used even though such a high price is incurred from the CO₂ emissions.

Although the electricity output from storage (CAES) is very small with respect to the output from many of the other generator types, CAES does account for around 1-1.5% of total electricity supply over the various weeks. Although this quantity of generation seems insignificant, the available capacity of CAES (2000 MW) is much smaller than the available capacity of most other generator types; therefore this is a significant level and the same order of magnitude as the output from Hydro, Biomass, Coal CHP, NGBLR, OCGT, and NGIC generators. CAES also provide significant quantities of ancillary services.

Figure 76. Electricity generation (TWh) for each season per type of generator.

Ancillary service procurements – High CO₂ Price

Figure 77 illustrates the procurements of all the ‘up’ ancillary services, namely Regulation Up (RU), Responsive Reserve Service (RRS) and Non-Spinning Reserve Service (NSRS) grouped by fuel type in GWh. From these figures it is evident that faster ramping and primarily natural gas plants (NGCC and OCGT) are procured for these ancillary services. CAES is utilized to supply between 10-12% of the total ‘up’ ancillary services.

Regulation Up (RU) is still primarily supplied by the faster responding OCGT. However, when available, CAES supplies between 10-23% of the RU. CAES also supplies around 10-15% of the RRS and 1-3% of the NSRS. In these CO₂ emissions penalty simulations CAES also supplied 4-12% of the Regulation Down (RD) (see Figure 78).

Figure 77. Procurements of all “up” ancillary services, by generator type.

Figure 78. Procurements of “down” ancillary services, by generator type.

Total ERCOT CO₂ emissions – High CO₂ Price

The coal power plants play the dominant part in the overall CO₂ emissions. In these simulations, the increase in cost of CO₂ emissions leads to a major reduction in use of coal-fired power plants. This reduction in use of coal plants leads to a significant reduction in the total CO₂ emissions, as seen in Figure 79. It is also clear based on the scale of the y-axis that CO₂ emissions are highest in the summer when more generators are required to be online to meet the demand requirement. Clearly minimizing the use of coal-fueled facilities will result in less CO₂ emissions.

Table 11 shows the reductions in CO₂ emissions for each season and investment case. The minimum reductions are 20% in the Spring and Summer, with closer to 30% emissions reduction in the Winter and Fall. Thus, we could expect annual emissions to be more than 20% below a our baseline case that *already assumes 20% wind generation with no CO₂ emissions*.

Table 11. The percentage (%) reduction in CO₂ emissions for each investment case and season assuming the \$4.91/MMBtu natural gas price.

	Winter	Spring	Summer	Fall	Average for Cap Investment Option
\$5 NG Thermal	28	18	20	33	25
\$5 NG Store CapLim	27	17	18	31	23
\$5 NG Store NoCap	32	26	22	34	29
Average for Season	29	20	20	33

Figure 79. ERCOT generator CO₂ emissions for each season, listed by generator type.

Total ERCOT operating costs – High CO₂ Price

Figure 80 displays the total operating costs for each simulation broken down by the contributions from each fuel type in millions of dollars. Clearly the additional costs associated with CO₂ emissions increases the weekly total operating costs. Even in the winter and summer when the use of coal plants is removed, the added cost of CO₂ emissions from the various types of natural gas-fired facilities results in a much higher total cost. In fact, in all seasons the total operating costs for the \$80 per ton CO₂ simulations is nearly double that of the \$0 per ton CO₂ simulations. The magnitude of the costs is also shown to be greater in the summer when more total generation must be online to meet the greater electricity demand.

Figure 80 also shows a decrease in total operating costs for the NoCap investment case (e.g. higher total capital investment of more capacity). Although the reduction is small, the addition of CAES in the NoCap case results in a slightly lower and more optimum overall cost.

Figure 80. ERCOT grid operating costs approximately double when including a price of CO₂ at \$80/tCO₂. Generally, more installed capacity, CAES or NG, helps decrease operating costs.

Total ERCOT electricity prices – High CO₂ Price

Due to the 80 \$/tCO₂ emissions penalty, our ERCOT wholesale electricity prices are estimated 30-40 \$/MWh higher for winter, spring, and fall and approximately 55 \$/MWh higher in the summer. In analyzing the price trends between investment cases, there is generally little difference. For winter, the pure NG investment “Thermal” case is cheaper than the investment cases with CAES, and this phenomenon is largely driven by the low net loads caused by our constraints on forcing CHP plants to operate.

Figure 81. ERCOT average wholesale electricity price (adjusted by removing negative prices and positive price outliers) for each season and investment scenario, listed as a function of natural gas price.

Total ERCOT dispatch costs – High CO₂ Price

Similarly to Figure 80 for Total Operating Cost shown previously, the Total Dispatch Cost for these simulations illustrates the increase in costs resulting from an increase in the price of CO₂ (see Figure 82). Within each group of four seasonal simulations, the difference in the costs is due mostly to the different total MWh requirement, as we can see that summer is always significantly higher. The emissions penalty of 80 \$/tCO₂ effectively makes total winter, spring, and fall dispatch costs approximately equal to dispatch costs in the summer when there is no emissions penalty.

Figure 82 also shows a slight decrease in total dispatch cost for the NoCap investment case. The decrease is most evident in spring and winter. Compared to the Thermal case, the addition of CAES in the NoCap case results in a slightly lower and more optimum overall dispatch cost, again, with the tradeoff of higher capital costs of installing the higher total MW of capacity.

Figure 82. Total ERCOT dispatch costs for each investment scenario and NG price.

Select unit-commitment model results of generator dispatch

In this section we show some example model results that are representative of the core information supporting the summarized weekly results of previous sections.

Effects of Increasing NG Price: summer, Store NoCap investment case

Comparing Generation By Fuel Type

Figure 83 - Figure 85 illustrate the effect of increasing the natural gas price for a given season (summer) and capacity investment option (Store NoCap). These results are for the summer week with the NoCap investment option and natural gas prices of \$3, \$4.91, and \$8 per MMBTU. The impact of the natural gas price is clear as we see a significant increase in the use of electricity from coal-fired power plants as the NG price increases. This result was evident in all four seasons.

Figure 83. Real Time Electricity Generation by Fuel Type (Summer, Thermal, \$3 NG).

Figure 84. Real Time Electricity Generation by Fuel Type (Summer, Thermal, \$4.91 NG).

Figure 85. Real Time Electricity Generation by Fuel Type (Summer, Thermal, \$8 NG).

Shown next are a set of figures for the four ancillary services that illustrate which fuel types are being used for each. In the case of regulation down, we see an increased use of coal with increasing natural gas price. However, for regulation up, there is no change in use of coal; and for both RRS and NSRS coal use actually decreases with increasing NG price. This decrease may be a result of having less coal-fired generation available for these ancillary services since more coal is being used in the energy market.

Comparing Regulation Down (RD)

Figure 86. Real Time Regulation Down by Fuel Type (Summer, Thermal, \$3 NG).

Figure 87. Real Time Regulation Down by Fuel Type (Summer, Thermal, \$4.91 NG).

Figure 88. Real Time Regulation Down by Fuel Type (Summer, Thermal, \$8 NG).

Comparing Regulation Up (RU)

Figure 89. Real Time Regulation Up by Fuel Type (Summer, Thermal, \$3 NG).

Figure 90. Real Time Regulation Up by Fuel Type (Summer, Thermal, \$4.91 NG).

Figure 91. Real Time Regulation Up by Fuel Type (Summer, Thermal, \$8 NG).

Comparing Responsive Reserve Service (RRS)

Figure 92. Real Time RRS by Fuel Type (Summer, Thermal, \$3 NG).

Figure 93. Real Time RRS by Fuel Type (Summer, Thermal, \$4.91 NG).

Figure 94. Real Time RRS by Fuel Type (Summer, Thermal, \$8 NG).

Comparing Non-Spinning Reserve Service (NSRS)

Figure 95. Real Time NSRS by Fuel Type (Summer, Thermal, \$3 NG).

Figure 96. Real Time NSRS by Fuel Type (Summer, Thermal, \$4.91 NG).

Figure 97. Real Time NSRS by Fuel Type (Summer, Thermal, \$8 NG).

Comparing grid operation between the Base (Thermal) Case with no CAES storage to the most likely case (NoCap) with CAES storage

Out of the various simulations we anticipate that the most likely future simulations that could occur and contain energy storage would be those for each season that use the \$4.91 per MMBTU natural gas price and the capacity investment option NoCap where all planned thermal generators are built with the addition of 2,000 MW of CAES that is allowed to participate in both the arbitrage (Arb) and ancillary services markets (AS). The following figures illustrate the changes in generation by fuel type and ancillary service procurements by fuel type that occur between the base case (\$4.91 NG price with Thermal option) and the “most likely” case (\$4.91 with NoCap option and Arb & AS case).

Comparing Generation By Fuel Type

Figure 98- Figure 105 show the generation by fuel type for each season and for both the base case (Thermal) and most likely case (\$4.91 NG with NoCap option and Arb & AS case). Even though input to and output from CAES only shows up as small slivers in the stacked plots (bright green is when CAES is generating electricity and bright yellow is when CAES is storing electricity), it does play an important role. We can see that in all season input to CAES (bright yellow) is reducing energy oversupply (most evident in winter) and output from CAES (bright green) is shaving off the peaks. The peak shaving behavior reduced energy undersupply and reduced the need for fast ramping generation. Thus, in any situations of very low net load caused by high wind generation in a “20% wind scenario”, the CAES facilities will benefit the most.

Figure 98. Real Time Electricity Generation by Fuel Type (**Winter**, Thermal, \$4.91 NG, No CAES).

Figure 99. Real Time Electricity Generation by Fuel Type (**Winter**, NoCap, \$4.91 NG, CAES Arb & AS).

Figure 100. Real Time Electricity Generation by Fuel Type (**Spring**, Thermal, \$4.91 NG, No CAES).

Figure 101. Real Time Electricity Generation by Fuel Type (**Spring**, NoCap, \$4.91 NG, CAES Arb & AS).

Figure 102. Real Time Electricity Generation by Fuel Type (**Summer**, Thermal, \$4.91 NG, No CAES).

Figure 103. Real Time Electricity Generation by Fuel Type (**Summer**, NoCap, \$4.91 NG, CAES Arb & AS).

Figure 104. Real Time Electricity Generation by Fuel Type (**Fall**, Thermal, \$4.91 NG, No CAES).

Figure 105. Real Time Electricity Generation by Fuel Type (**Fall**, NoCap, \$4.91 NG, CAES Arb & AS).

Comparing Ancillary Service Procurements By Fuel Type (*Fall* only)

Figure 106 - Figure 113 show the generation by fuel type for the *Fall* season only season for both the base case (Thermal) and most likely case (\$4.91 NG with NoCap option and CAES Arb & AS case). We can see that for regulation down, regulation up, and RRS services, CAES replace a significant portion of the procurements compared to the base thermal case. CAES accounts for approximately 12% of RD, 14% of RU, and 13% of RRS (only 1% of NSRS). The ancillary service procurements for the other seasons show similar results.

It should also be pointed out that regulation up is often over procured resulting in under procurement of both RRS and NSRS. The procurement of both RRS and NSRS is defined such that the combination of each with regulation up must meet a minimum requirement. In the case of RRS the minimum requirement is just the sum of the RU and RRS requirements, while in the case of NSRS the minimum requirement is based on NSRS + RU meeting 955 of the net load uncertainties.

Figure 106. Regulation Down by Fuel Type (Fall, Thermal, \$4.91 NG, No CAES).

Figure 107. Regulation Down by Fuel Type (Fall, NoCap, \$4.91 NG, CAES Arb & AS).

Figure 108. Regulation Up by Fuel Type (Fall, Thermal, \$4.91 NG, No CAES).

Figure 109. Regulation Up by Fuel Type (Fall, NoCap, \$4.91 NG, CAES Arb & AS).

Figure 110. RRS by Fuel Type (Fall, Thermal, \$4.91 NG, No CAES).

Figure 111. RRS by Fuel Type (Fall, NoCap, \$4.91 NG, Arb & AS).

Figure 112. NSRS by Fuel Type (Fall, Thermal, \$4.91 NG, No CAES).

Figure 113. NSRS by Fuel Type (Fall, NoCap, \$4.91 NG, CAES Arb & AS).

Conclusions and Takeaways on Comparison of simulated results for different scenarios and tasks

Overall conclusions

The complexity of the ERCOT electric grid and our attempt to model it resulted in several useful conclusions. First the importance of the natural gas price clearly affects the output levels of Coal and NGCC power plants and in turn affects total CO₂ emissions. Our model shows that the change from \$3 to \$4.91 per MMBTU yields a significant move toward use of more Coal and less NGCC. The additional increase to \$8 per MMBTU did not further increase Coal use to a similar extent. The average adjusted electricity price for a selected week and capacity investment option increased as the natural gas price increased. This expected behavior is a result of an increase in the costs of the marginal generator (which is typically a natural gas-fired power plant).

Additionally, including a high price for CO₂ emissions similarly stimulated a move toward NGCC and away from Coal generators. The additional costs incurred when the \$80 per ton of CO₂ price was enforced resulted in significantly higher average market electricity prices. As expected the action to reduce CO₂ emissions would come at a significant cost to consumers.

The model consistently under predicts the range between high and low daily fluctuations of the electricity price for the actual 2010 weeks selected. Due in part to the previously noted limitations regarding how the model constrains combined heat and power facilities, how ancillary services are not dispatched, and how wind is not allowed to be curtailed, the magnitude of the electricity price fluctuation is narrowed. However, by adjusting the electricity price to remove large negative and large positive values that result from incurring a price penalty for oversupply and undersupply of energy, we can get a reasonable estimate that does follow the same trend as the actual electricity prices.

Net load in the 2020 weeks was significantly lower than the same 2010 weeks. Along with the CHP requirement, this low net load caused more difficulty in the numerical code optimizing for a solution, witnessed by the occurrences of oversupplies of electricity. Furthermore, oversupply was a key indicator to how well and how quickly the simulations were able to solve. Oversupply seems to be worst in winter, followed by Spring, then Fall, with Summer having virtually no oversupply. This is consistent with the frequency and magnitude of low net load occurrences in those seasons.

Also, the simulations for Task 1.2 using CAES for “arbitrage only” worsened the effects on oversupply, especially during the CapLim Capacity cases. Allowing storage to participate in the AS market likely frees up other fast ramping open cycle gas turbine that could keep up better with net load. In all cases, storage under the NoCap condition reduced the amount of oversupply from the base condition (for the same season and the same NG price). This indicates that the charging operation enabled more grid flexibility to remove load during times of low net load.

The amount of undersupply is 2 orders of magnitude smaller than oversupply. Undersupply is worst during the winter most likely because of the sharp peaks where even the fastest reacting

units cannot ramp up then down fast enough. In most cases, storage with the CapLim condition reduced the amount of undersupply while storage with NoCap usually increased the amount of undersupply.

The three capacity investment cases yielded similar results with the most notable difference coming from the total operating costs and total dispatch costs. In nearly all simulations, adding energy storage in the NoCap option resulted in lower operating and lower dispatch costs. There is simply more total capacity in the grid, including NGCC, OCGT, and CAES, to follow the net load and enable an overall cheaper unit-commitment solution. Our results indicate that when energy storage was allowed to participate in the arbitrage market it tended to replace open cycle gas turbines, which are typically the most expensive types of generators, and thus provide a lower cost solution.

It was also clear that allowing energy storage to participate in both the arbitrage and ancillary service (AS) market yielded a more optimum solution. Surprisingly, the results from the arbitrage and AS case showed more energy from storage being generated into the arbitrage market than in the arbitrage only case. And the amounts of AS supplied by energy storage in the arbitrage and AS case was only slightly less than the AS only case. Our results indicate that allowing energy storage to optimize how it operates in both markets simultaneously will result in larger revenues for the energy storage facility and cheaper operating costs for the grid overall.

Additionally, when allowed to participate in the AS market, energy storage tended to be utilized more in the faster reacting regulation up, regulation down and responsive reserve services. The ability to provide these faster services makes CAES energy storage more valuable to the electric grid operator since the only other generators that can supply these services are typically very expensive open cycle gas turbines.

It is evident that a future with over 30 GW wind capacity in ERCOT and 20% annual generation will have a significant new impact on the operation of the electric grid. Specifically, the increase in slope and frequency of spikes in the net load as well as the increase in occurrences of very low net load would result in a grid that is possibly more difficult to control and where existing thermal generation units will be competing for less dispatchable load. The presence of more dispatchable and fast reacting generators would help the grid operator compensate for the increased ramping requirements.

Using the current expected operating costs of a compressed air energy storage (CAES) facility, our analysis showed open cycle gas turbines (OCGT) being replaced in both the arbitrage and ancillary services markets by CAES facilities, which indicates that the operating costs of CAES are less than that of their OCGT counterparts. Thus, the difference in capital costs between CAES and OCGTs needs to be investigated to determine total profitability of each. Compressed air energy storage could help provide the fast reacting services required in both the arbitrage and ancillary services markets at an overall cost that may be less than that of current OCGTs.

Effect of CAES being able to operate in Ancillary Services Market

- **Coal and nuclear commitment can be heavily impacted by ability of CAES to operate in AS market, particularly during low net load situations**
 - In comparing the results of total generation (TWh) among the scenarios, and in times of low net load, when CAES is allowed to operate by selling AS, nuclear and coal tend to generate more electricity. Compare the Winter and Spring results for generation (Figure 55, Figure 62, Figure 69, and Figure 76) in the StoreCapLim investment scenario. When CAES is restricted to only selling energy, “arbitrage only”, the limited installed capacity assumed for ERCOT in the StoreCapLim scenario forces coal and/or nuclear plants to generate less electricity at NG prices of \$5 and \$8 per MMBtu. We reason this is because the ramping needs for following the fast net load changes in Winter and Spring are faster than what nuclear and coal plants can (or would be willing to) operate.
 - In comparing the up regulation per generator types (Figure 56, Figure 63, and Figure 70), we see that there is a significant quantity of AS served by CAES when NG prices are 5 or 8 \$/MMBtu: over 20% when CAES is restricted to only provide AS as in Task 2.2, and near 10% of up regulation when CAES can provide both sell energy and AS).
 - If more OCGT or NGCC are installed (e.g. StoreNoCap investment scenario), then these generators are capable of ramping to serve the net load changes, and the baseload coal and nuclear power plants can operate more fully.

Notes on additional work:

None.

i. Significant results, including major findings, developments or conclusions (positive or negative)

- We have good data to create a statistical relationship between 1-hour ahead wind forecasts and actual wind output even assuming no wind curtailment occurs due to transmission constraints (our assumption for future 20% wind).

ii. Key outcomes, milestones and other achievements

- As specified in the proposal, two workshops/conferences were sponsored using funds with this project. Both conferences addressed one or more topics related to the project scope including renewable (e.g. wind) energy integrated into the electric grid and CO₂ emissions associated with electric grid operation.

Workshop 1:

As planned, a workshop was held on June 10, 2010 for nearly 100 interested stakeholders. The workshop brought together various protagonists in the integration of wind into the electricity system in the context of greenhouse reductions, including wind farm developers, environmental advocates, grid operators, utility representatives, regulators, and subject matter experts. Further details, including presentations, can be obtained from:

http://lifelong.engr.utexas.edu/shortcourse.cfm?course_num=1292. Approximately 35 invitees were sponsored with grant funds. There were a total of approximately 95 attendees, and the discussion provided useful input into the issues that must be considered for wind integration at high penetration levels.

Additional participation of students in related work in 2010:

A forum about the role of natural gas as a back-up power provider for intermittent sources in ERCOT was held August 12, 2010. Participants in the panel included analysts, power companies, production companies, experts and environmental advocates. The audience included more than 125 attendees that included regulators, subject matter experts, entrepreneurs, investors, academics, industry and self-selected clean energy enthusiasts. A master's thesis of related work (by Chioke Harris, M.S. in mechanical engineering) was completed, evaluating the role of storage to handle intermittencies for the Austin Energy service area.

Workshop 2:

The funds from this project assisted in promoting and organizing the Second Annual Austin Electricity Conference, in conjunction with the McComb's School of Business.

Federal Energy Regulatory Commission Chairman Jon Wellinghoff and EPA Region 6 Administrator Al Armendariz were among the participants in the Second Annual Austin Electricity Conference, held at the AT&T Hotel and Conference Center on April 4th and 5th.

The conference was an invitation-only affair, bringing together scholars, industry representatives and policymakers each spring to address cutting edge issues in the energy industry. This year's conference theme was "Climate Change, Clean Energy and Electricity;" last year's conference focused on the "Smart Grid."

This year's conference included academic participants from Stanford University, the University of Minnesota, and University of California at Berkeley, among others, as well as environmental groups like the Natural Resources Defense Council and the Environmental Defense Fund. Also represented were companies and governmental organizations including ERCOT, the Texas Public Utility Commission, Oncor, AEP, Austin Energy, CallISO, Calpine, among others.

University of Texas panelists included David Spence of the McCombs School of Business, David Adelman of the University of Texas School of Law, Ross Baldick of the Cockrell School of Engineering, and Varun Rai of the LBJ School of Public Affairs.

During the first day, conference participants focused on renewable energy, including an exploration of the effects of state renewable portfolio standards as drivers of investment in renewable energy, as well as an examination of the problems of integrating renewable sources (such as wind generation) into the electric grid. The second day focused on the future role of traditional electricity sources, such as natural gas.

The 2012 conference was co-sponsored by the UT Law School's Energy Center, the McCombs School of Business' Energy Management and Innovation Center, the Cockrell School of Engineering, and the LBJ School of Public Affairs, as well as the Pecan Street Project and the University of Texas Energy Institute. The [conference website](#) contains a complete list of conference participants, as well as photos and the full conference agenda.

Publications / Presentations/Travel:

Three relevant papers to the project were presented at the American Society of Mechanical Engineering's (ASME) Fourth International Conference on Sustainability in Phoenix, AZ, in May 2010. These papers represented some of the preliminary work evaluating the role of renewable power and storage in ERCOT and the Austin area.

A paper was presented at the "Energy, Sustainability and Climate Change" conference at the University of Florida Conference Center, Gainesville, Florida, February 26-28, 2010. This paper presented basic concepts in the "augmented screening curve" approach in adding wind power to a cost supply curve for the ERCOT generation capacity.

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Appendix A

Electricity System Optimization Unit Commitment Model

1.1 Model Formulation

1.1.1 ERCOT Market Protocols

ERCOT market protocols are discussed first to provide context for ERCOT-specific model characteristics. ERCOT operates markets for electricity to meet consumer demand as well as ancillary services to ensure grid reliability. Market participants submit electricity and ancillary service offers to ERCOT, and ERCOT finds the combination of generation resources that minimizes the cost of supplying electricity and ancillary services. Consumer electricity demand can be accurately forecast a day ahead based on weather and economic conditions, so ERCOT plans hourly electricity supply in a day-ahead market then reconciles any discrepancy between planned and actual demand every 5 minutes in a real-time market. The day-ahead market determines which units will be online in each hour, and prices paid to generators are 15-minute averages of real-time market settlements.

Ancillary service requirements are specified by ERCOT and can change with market conditions at ERCOT discretion. For instance, increased wind capacity in ERCOT has altered the method for calculating some ancillary service requirements [ERCOT, 2011a]. There are four ancillary service markets in ERCOT. Regulation Up (RU) and Regulation Down (RD) services are procured to respond within 5 minutes to discrepancies between expected and actual demand [ERCOT, 2011a]. The quantity of RU and RD required varies throughout the day and year and depends on current demand uncertainty, historical regulation deployments, and installed wind capacity [ERCOT, 2011a]. Responsive Reserve Service (RRS), commonly called spinning reserves, must be provided by online units or load (demand) resources capable of responding within 10 minutes [ERCOT, 2011a]. Total RRS procurements must exceed the greatest possible single-facility outage within ERCOT, currently 2,300

MW, the capacity of the South Texas Project nuclear facility [ERCOT, 2011a]. Non-Spinning Reserve Service (NSRS) can be provided by online or offline units and must be able to respond within 30 minutes. The quantity of NSRS required in each hour depends on the RU procurement and demand uncertainty [ERCOT, 2011a]. All AS procurements are co-optimized with electricity in the day-ahead market.

1.1.2 Model Structure

The structure of the grid-level model reflects ERCOT operating procedures (Fig. 1.1). Input parameters describe the cost and performance specifications of generating units as well as the market conditions and electricity system requirements. After defining plant operating variables, objective and constraint equations describe the operating characteristics that govern power, CO₂ capture, and electricity systems.

The model uses a two-stage optimization in each day to mimic the ERCOT market. A day-ahead forward market optimization uses an hourly time step, τ^{FW} , and the resulting unit commitments and ancillary service procurements are fixed before determining generator output in the real-time market optimization. If the grid contains energy storage systems, the input to energy storage systems is also determined in the real-time optimization. The real-time market optimization uses a 15-minute time step, τ^{RT} . Though ERCOT currently optimizes its real-time market in 5 minute intervals, settlement prices for electricity load and generation are averages over 15 minutes, so a 15 minute time interval is assumed sufficient to characterize electricity market behavior. After performing the real-time optimization for the current day, the solution informs initial conditions for the following day, and the process repeats for the desired number of days.

The model represents the day-ahead and real-time markets generally so that their time intervals can be set to any length as long as $\tau^{RT} \leq \tau^{FW}$. The day-

ahead market is also implemented as a generalized forward market so that the overall time length could be shorter or longer than one day. The length of the forward planning period, L^{FW} , is set to 96 real-time intervals to represent a day-ahead market with 15-minute real-time market intervals, but a longer length could be specified given sufficient computational resources to solve the unit commitment problem over longer time scales. Unfortunately, the nature of mixed-integer problems and solving algorithms makes computation time difficult to estimate strictly from problem size. In addition to better representing ERCOT procedures, the two-stage approach reduces computation time by optimizing many integer variables on a coarser time step before solving for remaining integer and continuous variables on a shorter time step. If desired, the two-stage process could be bypassed and all variables optimized on a single time scale by setting τ^{FW} to the desired time interval and bypassing the real-time market optimization.

The model optimizes AS procurements but does not perform AS deployments, which are executed in ERCOT in response to discrepancies in planned and actual electricity demand, wind generation, and unplanned transmission and generation outages. Modeling the manner in which AS are deployed is outside of the scope of this work. Instead, the model assesses a large cost penalty to any imbalances between electricity supply and demand, and the existence of these penalties indicates when AS deployments would likely be required. The frequency of these cost penalties indicates the need for AS deployments under a given set of input conditions.

1.1.3 Required Input Information

1.1.3.1 Generating Units

Extensive input data are required to fully characterize the generating unit fleet. The model is built to consider several types of electricity generating facilities, includ-

Figure 1.1: The model structure mimics the two-stage operating procedure used by ERCOT.

ing coal-fired plants with and without CO₂ capture, nuclear power plants, natural gas-based plants (combined-cycle NGCC, open-cycle OCGT, steam boiler NGBLR, and internal combustion NGIC), oil-fired plants, biomass-based facilities, and hydroelectric turbines. Hydroelectric turbines are not given pumped storage capabilities, but pumped hydroelectric units could be included using the energy storage system specifications discussed later in this section. Instead of representing wind turbines as generating units, wind production is subtracted from input electricity demand, and all other facilities are optimized in response to the resulting net electricity demand. Thermal generation facilities can also be designated as CHP units. CHP facilities are typically designed to meet near-constant heat and process loads, so these systems are assumed to operate continuously at their maximum electrical output regardless of operating costs. Interruptible load systems can also be included but are only permitted to provide RRS and NSRS per ERCOT restrictions. The model also includes a generic framework for energy storage systems so that a variety of storage system types could be examined.

Table 1.1 lists the input parameters required for all generating units. Plant names must be unique for each plant and are used as elements p within set $\mathbb{P}$. Plant type is used to appropriately assign costs and constraints for p within a set of each plant type. The boolean CHP flag is also used to identify facilities in the set of CHP facilities $\mathbb{M}$, which must operate continuously at maximum output, $\bar{x}_p$. If a particular parameter is not applicable for a unit, such as CO₂ emissions rate for carbon-free electricity sources, the quantity is set to zero in the generating unit database.

Explicit limits on the minimum and maximum of each type AS provision are not needed. Minimum AS provision is zero because a facility could use all available capacity to meet electricity demand, leaving none for AS. Maximum AS provision is

Table 1.1: The following input parameters are required for each generating unit.

Parameter (Units)	Symbol
Plant name	p
Plant type	n/a
Non fuel or CO ₂ base plant VOM cost (\$/MWh)	OM_p^b
Heat rate (MMBTU/MWh)	H_p^b
CO ₂ emissions rate (tCO ₂ /MWh)	R_p^b
Base plant startup cost (\$/startup)	$S_p^{b,u}$
Base plant shutdown cost (\$/shutdown)	$S_p^{b,d}$
Minimum output (MW)	$\underline{x}_p$
Maximum output (MW)	$\bar{x}_p$
Base plant ramp limit up (MW/min)	$\delta_p^{b,u}$
Base plant ramp limit down (MW/min)	$\delta_p^{b,d}$
Base plant minimum up time (hr)	$\Theta_p^{b,u}$
Base plant minimum down time (hr)	$\Theta_p^{b,d}$
Base plant initial up time (hr)	$\Theta_p^{b,u,0}$
Base plant initial down time (hr)	$\Theta_p^{b,d,0}$
CHP flag (1=yes, 0=no)	n/a

constrained by ramp rates and the combination of energy and AS provided in the current time period.

For each facility with a CO₂ capture system, several additional parameters are required to determine the energy requirement for CO₂ capture, CO₂ removal rate, and solvent storage capabilities if applicable. Minimum and maximum load, ramp rate limits, startup/shutdown costs, and minimum up/down time for the absorber and stripper are also specified. Parameters required of all CO₂ capture systems are listed in Table 1.2, and parameters specific to solvent storage systems are found in Table 1.3. Similar to plant type and the CHP flag, the CO₂ capture indicator is used to appropriately assign costs and constraints to p within the set of capture facilities $\mathbb{C}$.

Additional parameters are required to define CO₂ capture costs and constraints. These parameters, listed in Table 1.4, are assumed constant across all capture facilities, but making them plant-specific is possible by adding them to the generating unit database and modifying the parameter import code.

No additional input parameters are required to model interruptible load; facilities are represented using constraints discussed in Section 1.1.7. However, energy storage systems require constraints on power input systems that are analogous to those on power output. Thus, minimum and maximum capacity, ramp rate, and minimum up and down time must be specified for input power systems. For some storage systems, like batteries, these parameters are likely the same for input and output because power flows both ways in the same equipment. However, for systems such as pumped hydroelectric storage or CAES, power input devices (pumps, compressors) and power output devices (turbines) could have different capacities and operating characteristics. For all types of storage, a round-trip efficiency of energy

Table 1.2: The following input parameters are required for each unit with CO₂ capture.

Parameter (Units)	Symbol
CO ₂ capture indicator (1=yes, 0=no)	n/a
Absorber minimum load (fractional)	$\underline{y}_p^a$
Stripper minimum load (fractional)	$\underline{y}_p^s$
Design CO ₂ removal (fractional)	F_p
Stripping/compression energy requirement (MWh/tCO ₂)	E_p^s
Absorption energy requirement (MWh/tCO ₂)	E_p^a
Absorber ramp rate up (load fraction/min)	$\delta_p^{a,u}$
Absorber ramp rate down (load fraction/min)	$\delta_p^{a,d}$
Stripping/compression ramp rate up (load fraction/min)	$\delta_p^{s,u}$
Stripping/compression ramp rate down (load fraction/min)	$\delta_p^{s,d}$
LP steam fraction for stripping (fractional)	f_p^{Steam}
Absorber startup cost (\$/startup)	$S_p^{a,u}$
Absorber shutdown cost (\$/startup)	$S_p^{a,d}$
Stripper startup cost (\$/startup)	$S_p^{s,u}$
Stripper shutdown cost (\$/startup)	$S_p^{s,d}$
Absorber minimum up time (hr)	$\Theta_p^{a,u}$
Absorber minimum down time (hr)	$\Theta_p^{a,d}$
Absorber initial up time (hr)	$\Theta_p^{a,u,0}$
Absorber initial down time (hr)	$\Theta_p^{a,d,0}$
Stripping/compression minimum up time (hr)	$\Theta_p^{s,u}$
Stripping/compression minimum down time (hr)	$\Theta_p^{s,d}$
Stripping/compression initial up time (hr)	$\Theta_p^{s,u,0}$
Stripping/compression initial down time (hr)	$\Theta_p^{s,d,0}$
CO ₂ transport and storage cost (\$/tCO ₂)	$C_p^{T/S}$

Table 1.3: The following input parameters are required for each unit with CO₂ capture that has a solvent storage system.

Parameter (Units)	Symbol
Solvent storage tank size (m^3)	ψ_p
Design CO ₂ carrying capacity (mol solvent/mol CO ₂)	Ω_p
Day-starting CO ₂ quantity in rich storage tank (tCO ₂)	l_p^0

Table 1.4: The following input parameters are held constant for all units with CO₂ capture.

Parameter (units)	Symbol
Minimum mass flow in LP turbine	Z_{min}^{Turb}
Fractional efficiency point penalty of ramping stripping/compression systems 0–100% (MW _e for ramp/MW _{th} heat input)	$\hat{\eta}^s$
Fractional efficiency point penalty of ramping absorption systems 0–100% (MW _e for ramp/MW _{th} heat input)	$\hat{\eta}^a$
Solvent price (\$/kg)	P^{Solv}
Total solvent degradation rate (kg/tCO ₂ stripped)	D
Solvent degradation rate from thermal effects (kg/tCO ₂ stripped)	D^{th}
Caustic NaOH price (\$/kg)	$P^{Caustic}$
Water fraction in the reclaimer	w^R
Waste disposal price (\$/kg waste)	P^{Waste}
Water price (\$/m ³)	P^{Water}
Additional water use for capture (m ³ /MW gross capacity)	w
Solution density (kg/m ³ solution)	ρ
Solvent molecular weight (kg/kmol)	M^{Solv}
Stripping/compression equipment oversizing fraction	f^{Equip}

output from storage per energy input to storage, η^{es} , must also be specified along with the storage capacity limit, $\bar{v}_p$. A daily set point for the storage system, v_p^0 , is also required when using one day for the forward market planning period. Energy storage parameters are listed in Table 1.5.

Table 1.5: The following input parameters are required for all energy storage units.

Parameter (Units)	Symbol
Minimum input capacity (MW)	$\underline{x}_p^{IN}$
Maximum input capacity (MW)	$\bar{x}_p^{IN}$
Output/input efficiency	η^{es}
Energy storage capacity (MWh)	$\bar{v}_p$
Day-starting stored energy level (MWh)	v_p^0
Input ramp limit up (MW/min)	$\delta_p^{IN,u}$
Input ramp limit down (MW/min)	$\delta_p^{IN,d}$

1.1.3.2 Electricity System

The model imports total ERCOT electricity demand, L_t , as well as data for electricity production from wind, W_t , in each time period. The difference $L_t - W_t$ is the net electricity demand, L_t^{net} , that all other facilities must satisfy.

To determine ancillary service requirements in each time period, RU and RD requirements (RU_t, RD_t) are imported for each hour. ERCOT calculates RU_t and RD_t as a function of total wind-based generating capacity in the grid, $\bar{W}$, so this adjustment is performed to ensure regulation requirements are appropriate for the assumed wind capacity. Tables 1.6 and 1.7 show these adjustment factors, which vary by month and hour. The RRS requirement, RRS , is always 2,300 MW as stated above. An hourly net load uncertainty, σ_t^L , is required to determine the necessary quantity of NSRS in each time interval, and the parameter f^{NLU} is used in NSRS

constraints as discussed in Section 1.1.11. ERCOT requires that offers in each AS market be no greater than the amount of capacity that could be supplied to (or removed from) the electricity market in a specified period of time, κ . For RU and RD, $\kappa^{RU} = \kappa^{RD} = 5$ minutes; for RRS, $\kappa^{RRS} = 10$ minutes; and for NSRS, $\kappa^{NSRS} = 30$ minutes. RRS offers by generating units (but not load) are also restricted to $f^{RRS,Gen} = 20\%$ of maximum output capacity, and interruptible load systems cannot provide more than $f^{RRS,Load} = 50\%$ of the 2,300 MW RRS requirement.

Fuel prices for coal, natural gas, oil, and biomass (P^{Coal} , P^{NG} , P^{Oil} , and P^{Bio}) are necessary for fuel cost calculations. The CO₂ price, P^{CO_2} , is nonzero when examining a policy to reduce CO₂ emissions. Fuel and CO₂ prices are kept constant throughout the simulation time period in this analysis. Variable fuel prices would be straightforward to implement, but constant values are assumed sufficient for the days-to-weeks time scales simulated. Furthermore, assuming constant annual prices would still yield important insights into the operation of electricity systems with flexible CO₂ capture. An estimated average annual electricity price is also required to calculate CO₂ capture ramping costs. Table 1.8 summarizes the input parameters necessary to define electricity system constraints and market conditions.

Rather than require strict equality between electricity supply and demand, the model allows supply/demand imbalances in both the day-ahead and real-time optimizations but penalizes any imbalances using the same procedure as ERCOT. Any oversupply or undersupply of electricity in the day-ahead market is penalized by $\Gamma^{FW} = \$5,000,000/\text{MWh}$ [ERCOT, 2010]. This hefty penalty does not influence real-time electricity prices; it primarily serves to ensure economical unit commitment. An oversupply penalty in the day-ahead market indicates that net demand is exceeded due primarily to uncontrollable supply such as wind and fixed output from

Table 1.6: The following factors adjust regulation up requirements by the stated quantity per 1,000 MW additional wind capacity.

	Month											
	1	2	3	4	5	6	7	8	9	10	11	12
0	7.8	6.1	0.3	7.2	3.5	3.0	1.3	9.4	2.0	7.9	9.2	5.7
1	6.5	6.7	6.1	1.1	8.9	5.8	7.4	9.5	7.2	5.7	3.4	7.3
2	7.0	6.9	2.4	8.8	2.3	8.6	6.2	4.4	6.3	9.9	1.1	2.6
3	3.3	9.4	3.4	3.9	3.0	7.6	2.8	5.4	2.4	5.4	7.2	4.0
4	6.0	6.0	6.0	4.5	3.6	5.4	6.5	9.0	5.5	9.9	3.9	3.9
5	8.3	5.2	7.2	3.8	2.9	6.0	1.7	1.7	6.6	9.9	6.6	1.7
6	5.6	6.9	3.9	3.5	6.1	8.6	8.9	8.4	5.0	2.6	3.8	8.0
7	9.3	6.3	5.8	6.5	3.0	9.5	3.3	9.6	3.9	3.4	0.1	2.0
8	9.2	2.4	6.0	7.4	0.0	5.5	1.7	7.9	4.0	7.9	1.9	8.3
9	9.3	2.7	7.6	5.3	6.7	0.2	5.6	6.7	0.6	6.6	5.6	7.9
10	8.3	3.0	7.2	7.0	9.1	8.1	9.6	7.2	4.2	0.7	7.6	2.5
11	1.4	4.5	5.9	0.2	7.9	3.5	4.8	0.3	4.2	9.7	4.3	3.6
12	9.9	1.8	0.6	7.1	1.9	8.0	0.3	5.8	8.2	8.6	9.1	3.6
13	4.1	4.3	9.3	6.1	2.5	5.4	1.0	7.6	7.7	2.4	3.8	3.4
14	0.9	1.6	1.6	5.8	1.7	5.1	9.8	1.4	2.9	3.3	1.4	2.8
15	8.2	9.6	1.5	9.2	8.8	9.4	8.8	5.4	8.8	2.8	3.4	1.1
16	5.1	0.5	5.6	5.5	1.8	7.6	7.5	7.2	5.4	9.4	5.0	3.5
17	5.1	1.0	0.0	8.2	0.1	5.4	4.4	9.1	7.4	0.7	9.7	7.4
18	4.0	4.0	8.2	5.8	8.9	6.0	3.2	6.5	7.2	7.2	2.0	5.1
19	7.4	3.1	0.6	2.9	6.6	7.1	3.6	9.4	1.6	6.4	5.7	3.0
20	9.9	6.2	5.8	5.3	4.0	2.6	8.3	2.1	6.4	2.3	8.2	1.5
21	3.3	9.0	8.8	0.7	5.4	9.1	5.7	1.6	1.5	6.3	8.5	4.3
22	5.8	1.2	7.2	8.2	2.8	7.2	9.9	4.7	5.8	1.4	8.8	2.4
23	0.5	5.8	4.3	4.1	1.2	7.6	9.7	9.3	1.4	7.7	0.6	5.7

Table 1.7: The following factors adjust regulation down requirements by the stated quantity per 1,000 MW additional wind capacity.

	Month											
	1	2	3	4	5	6	7	8	9	10	11	12
0	8.7	6.6	0.6	0.9	5.6	2.6	9.0	8.1	2.9	2.9	3.5	5.7
1	9.9	0.6	4.1	4.4	2.1	7.3	1.1	7.3	4.5	1.2	4.5	1.6
2	2.4	5.8	5.3	5.7	9.9	7.5	4.0	6.9	8.3	4.4	8.5	5.9
3	5.7	6.9	1.0	5.7	8.6	9.9	1.1	4.1	1.5	0.6	3.7	6.2
4	8.2	9.8	8.8	3.4	2.8	7.4	5.3	9.4	9.2	4.0	1.7	8.8
5	9.2	1.9	5.7	7.9	0.6	1.9	7.4	9.9	1.3	5.9	5.7	1.6
6	7.0	1.6	8.9	2.0	3.8	5.5	2.3	7.6	5.0	0.7	8.7	2.3
7	6.3	1.1	1.9	4.7	2.1	3.9	2.1	4.3	3.5	1.4	7.5	5.1
8	0.4	7.3	0.3	5.8	5.0	9.4	3.0	8.6	7.5	6.0	4.4	9.6
9	1.6	3.8	1.3	7.4	4.9	9.3	7.3	4.9	3.2	7.2	6.2	2.4
10	2.6	1.3	2.3	4.5	6.8	8.3	0.9	8.0	7.9	5.4	9.2	4.9
11	4.1	2.5	7.4	9.9	1.4	8.1	3.3	6.6	5.6	9.0	5.0	4.0
12	4.3	2.3	3.5	7.5	1.5	0.3	6.8	9.3	2.8	7.4	8.2	3.6
13	1.7	9.3	7.5	6.7	1.5	8.8	6.9	8.3	5.7	3.8	3.8	3.0
14	2.3	9.7	4.2	0.8	5.4	1.4	4.8	3.0	6.5	6.4	6.7	0.4
15	3.4	2.8	2.1	8.8	9.0	9.0	4.4	7.0	4.1	1.2	8.7	8.0
16	2.0	4.3	5.0	4.2	1.7	3.2	3.1	5.3	3.6	9.2	3.4	6.9
17	4.4	4.0	8.9	2.6	9.3	2.0	7.5	2.3	2.3	3.7	2.1	1.5
18	5.9	7.7	5.9	5.3	3.9	5.6	3.0	5.3	8.3	7.6	3.5	6.4
19	9.9	1.4	6.1	3.2	7.7	1.5	8.5	4.9	7.8	7.8	1.3	7.4
20	5.1	9.5	1.4	4.5	3.8	5.1	1.7	0.6	7.8	9.0	7.9	0.1
21	1.6	6.8	1.0	8.6	7.6	9.4	5.2	4.6	0.7	0.6	5.3	5.3
22	7.6	3.7	1.5	3.6	8.9	9.1	5.2	9.1	4.6	6.4	4.3	4.1
23	0.7	7.5	6.1	2.3	1.3	5.5	3.8	6.5	3.9	1.6	3.4	7.9

Table 1.8: The following input parameters are required to specify electricity system constraints and market conditions.

Parameter (Units)	Symbol
Electricity demand (MW)	L_t
Wind production (MW)	W_t
Net electricity load (MW)	L_t^{net}
Regulation down requirement (MW)	RU_t
Regulation up requirement (MW)	RU_t
Responsive reserves requirement (MW)	RRS
Net demand uncertainty (MW)	σ_t^L
Fraction of net demand uncertainty (fractional)	f^{NLU}
Required response time for regulation up (min)	κ^{RU}
Required response time for regulation down (min)	κ^{RD}
Required response time for responsive reserves (min)	κ^{RRS}
Required response time for non-spinning reserves (min)	κ^{NSRS}
Maximum capacity fraction allowed for RRS (fractional)	$f^{RRS,Gen}$
Maximum fraction of RRS that can be met by interruptible load (fractional)	$f^{RRS,Load}$
Coal price (\$/MMBTU)	P^{Coal}
Natural gas price (\$/MMBTU)	P^{NG}
Oil price (\$/MMBTU)	P^{Oil}
Biomass price (\$/MMBTU)	P^{Bio}
CO ₂ price (\$/tCO ₂)	P^{CO_2}
Estimated average electricity price (\$/MWh)	$P^{e,avg}$

Figure 1.2: ERCOT assesses a penalty for electricity undersupply that increases with supply deficiency towards the market maximum electricity price.

CHP facilities. Undersupply in the day-ahead market means the grid has insufficient capacity available to meet demand. The real-time market penalty for oversupply is $\Gamma^{O,RT} = \$250/\text{MWh}$, and the penalty for undersupply, $\Gamma_g^{U,RT}$, increases with the supply deficiency until reaching the market maximum electricity price of $\$3,000/\text{MWh}$ ¹ above 50 MW undersupply (Fig. 1.2) [ERCOT, 2010]. The subscript index g represents the segment on Fig. 1.2.

1.1.4 Decision Variables

For each time period in the day-ahead and real-time markets, the model must find optimal electrical output, $x_{p,t}$, and procured AS quantities; $ru_{p,t}$, $rd_{p,t}$, $rrs_{p,t}$, and $nsrs_{p,t}$; for each power generation facility. To allow NSRS procurements by offline facilities, $nsrs_{p,t}$ has two components, NSRS procured when online, $nsrs_{p,t}^{on}$, and NSRS procured when offline, $nsrs_{p,t}^{off}$. The model must also determine the optimal

¹As of August 1, 2012, the market maximum electricity price is $\$4,500/\text{MWh}$. This market change could be incorporated into future analysis by modifying undersupply penalties appropriately.

commitment status, $u_{p,t}^b$, (on or off) in the day-ahead optimization, and commitment variables are used to specify binary startup and shutdown variables, $on_{p,t}^b$ and $off_{p,t}^b$. Energy storage facilities must also optimize storage level, $v_{p,t}$, and electrical input, $x_{p,t}^{IN}$, along with commitment, startup, and shutdown status for power input systems, $u_{p,t}^{IN}$, $on_{p,t}^{IN}$, and $off_{p,t}^{IN}$. Facilities with CO₂ capture must also determine absorption and stripping load, $y_{p,t}^a$ and $y_{p,t}^s$, along with the on/off status of CO₂ capture systems, $u_{p,t}^a$ and $u_{p,t}^s$, and when they undergo startup or shutdown, $on_{p,t}^a$, $on_{p,t}^s$, $off_{p,t}^a$ and $off_{p,t}^s$. Load change variables for absorption and stripping systems in either direction (up or down), $\Delta_{p,t}^{a,u}$, $\Delta_{p,t}^{a,d}$, $\Delta_{p,t}^{s,u}$, and $\Delta_{p,t}^{s,d}$, are also required to define CO₂ capture ramping costs. If the CO₂ capture system utilizes solvent storage, a variable for the amount of CO₂ stored in rich solvent, $l_{p,t}$, is used to govern solvent storage operation. Lastly, to allow penalized imbalances in electricity supply and demand, slack variables for oversupply quantity, z_t^O , and undersupply quantity, $z_{t,g}^U$, are defined.

All commitment, startup, and shutdown variables are binary. All output, input, AS procurement, capture load, storage level, load change, and supply/demand imbalance variables are defined as positive. Table 1.9 reviews the subscripts used as index sets, and all decision variables are summarized in Tables 1.10 and 1.11.

Structurally, the model is defined with one time set with elements in each of the real-time market time intervals. In the forward market optimization, variables are fixed across each day-ahead time interval using constraints. This implementation eliminates the need to compose two sets of each constraint type within the model. If desired, a reformulation could utilize unique time indices for each market.

1.1.5 Objective Function

The model seeks to minimize the total cost of electricity dispatch, TC , across all units and time periods within the day being optimized. Variables are defined

Table 1.9: The following subscripts are used to index decision variables within their sets.

Subscript	Description
t	Time index
p	Plant index
g	Index of segments on electricity undersupply penalty curve

Table 1.10: The following variables describe power systems, energy storage systems, and electricity supply/demand imbalances.

Variable (Units)	Symbol
Gross power output (MW)	$x_{p,t}$
Regulation up procurement (MW)	$ru_{p,t}$
Regulation down procurement (MW)	$rd_{p,t}$
Responsive reserves procurement (MW)	$rrs_{p,t}$
Non-spinning reserves procurement (MW)	$nsrs_{p,t}$
Non-spinning reserves procurement when online (MW)	$nsrs_{p,t}^{on}$
Non-spinning reserves procurement when offline(MW)	$nsrs_{p,t}^{off}$
Base plant commitment status (1=on, 0=off)	$u_{p,t}^b$
Base plant startup indicator for base plant (1=yes, 0=no)	$on_{p,t}^b$
Base plant shutdown indicator for base plant (1=yes, 0=no)	$off_{p,t}^b$
Power input to storage (MW)	$x_{p,t}^{IN}$
Stored energy level (MWh)	$v_{p,t}$
Input system commitment status (1=on, 0=off)	$u_{p,t}^{IN}$
Input system startup indicator for base plant (1=yes, 0=no)	$on_{p,t}^{IN}$
Input system shutdown indicator for base plant (1=yes, 0=no)	$off_{p,t}^{IN}$
Quantity oversupply (MW)	z_t^O
Quantity undersupply (MW)	$z_{t,g}^U$

Table 1.11: The following variables describe CO₂ capture system operation.

Variable (Units)	Symbol
Absorption system load (fractional)	$y_{p,t}^a$
Stripping/compression system load (fractional)	$y_{p,t}^s$
Absorption system commitment status (1=on, 0=off)	$u_{p,t}^a$
Stripping/compression system commitment status (1=on, 0=off)	$u_{p,t}^s$
Absorption system startup indicator for base plant (1=yes, 0=no)	$on_{p,t}^a$
Stripping/compression system startup indicator for base plant (1=yes, 0=no)	$on_{p,t}^s$
Absorption system shutdown indicator for base plant (1=yes, 0=no)	$off_{p,t}^a$
Stripping/compression system shutdown indicator for base plant (1=yes, 0=no)	$off_{p,t}^s$
Absorption load change up (fractional)	$\Delta_{p,t}^{a,u}$
Absorption load change down (fractional)	$\Delta_{p,t}^{a,d}$
Stripping/compression load change up (fractional)	$\Delta_{p,t}^{s,u}$
Stripping/compression load change down (fractional)	$\Delta_{p,t}^{s,d}$
Quantity of CO ₂ in rich solvent storage tank (tCO ₂)	$l_{p,t}$

across many days, so the objective function for each daily optimization is restricted between the first and last time interval of the day, m and k , to prevent erroneous assignment of variables in future days. The general form of the objective function is defined for the day-ahead market in Eqn. 1.1 and the real-time market in Eqn. 1.2. Separate objective functions are required because supply/demand imbalance penalties represented by the second and third terms differ between markets. Power plant cost functions, $C_{p,t}$, are the same for both markets.

$$TC = \sum_{p,m \leq t \leq k} C_{p,t} + \sum_{m \leq t \leq k} \Gamma^{FW} z_t^O + \sum_{g,m \leq t \leq k} \Gamma^{FW} z_{t,g}^U \quad (1.1)$$

$$TC = \sum_{p,m \leq t \leq k} C_{p,t} + \sum_{m \leq t \leq k} \Gamma^{O,RT} z_t^O + \sum_{g,m \leq t \leq k} \Gamma_g^{U,RT} z_{t,g}^U \quad (1.2)$$

Startup and shutdown costs can be assessed for all units, and the framework also includes the ability to assess startup costs for CO₂ capture and energy storage input systems. Startup and shutdown costs, $C_{p,t}^{SUP}$ and $C_{p,t}^{SDown}$, for all possible components are calculated using Eqns. 1.3 and 1.4.

$$C_{p,t}^{SUP} = S_p^{b,u} on_{p,t}^b + S_p^{a,u} on_{p,t}^a + S_p^{s,u} on_{p,t}^s \quad (1.3)$$

$$C_{p,t}^{SDown} = S_p^{b,d} off_{p,t}^b + S_p^{a,d} off_{p,t}^a + S_p^{s,d} off_{p,t}^s \quad (1.4)$$

For thermal generating units without CO₂ capture fueled by coal, natural gas, oil, and biomass, $C_{p,t}$ is composed of fuel costs, $C_{p,t}^{Fuel}$, CO₂ emissions costs, $C_{p,t}^{CO_2}$, and additional VOM costs, $C_{p,t}^{b,O\&M}$ (Eqns. 1.5–1.7). Fuel costs are assessed with the fuel price appropriate for each unit type. If biomass is assumed carbon neutral, CO₂

emissions costs can be neglected by setting the emissions rate, R_p^b , to zero in input parameters. Nuclear and hydroelectric facilities are assigned a total VOM cost, so operating costs are calculated using Eqn. 1.7 only.

$$C_{p,t}^{Fuel} = P^{Fuel} H_p^b x_{p,t} \tau^{RT} \quad (1.5)$$

$$C_{p,t}^{CO_2} = P^{CO_2} R_p^b x_{p,t} \tau^{RT} \quad (1.6)$$

$$C_{p,t}^{b,O\&M} = OM_p^b x_{p,t} \tau^{RT} \quad (1.7)$$

Operating costs at energy storage facilities are defined generally to include any fuel and CO₂ emissions costs when there is net electrical output (Eqns. 1.5 and 1.6). Though some energy storage systems such as batteries and pumped hydroelectric facilities have no fuel or CO₂ emissions costs, CAES facilities typically burn natural gas to heat the compressed air when generating electricity, so these costs are included for generality. VOM costs for energy storage facilities, $C_{p,t}^{Stor,O\&M}$, also include a modification to Eqn. 1.7 that assesses VOM costs when electricity is input to storage (Eqn. 1.8).

$$C_{p,t}^{Stor,O\&M} = OM_p^b (x_{p,t} + x_{p,t}^{IN}) \tau^{RT} \quad (1.8)$$

For coal-fired facilities with CO₂ capture, fuel and base plant VOM costs are assessed using Eqns. 1.5 and 1.7. No changes are required because these equations use gross output before subtracting CO₂ capture energy requirements rather than net electrical output available to meet electricity demand. CO₂ emissions costs, $C_{p,t}^{Capt,CO_2}$,

account for the quantity of CO₂ removed by absorption systems (Eqn. 1.9). Additional costs are again assessed for the following: solvent makeup to offset degradation and volatility losses, $C_{p,t}^{Solv}$; caustic sodium hydroxide (NaOH) for thermal solvent reclaiming, $C_{p,t}^{Caustic}$; reclaimer waste disposal, $C_{p,t}^{Waste}$; additional water use for CO₂ capture, $C_{p,t}^{CapWat}$; CO₂ transport and storage, $C_{p,t}^{T/S}$; and ramping the capture load, $C_{p,t}^{CapRamp}$. These costs are calculated using (Eqns. 1.10–1.15).

$$C_{p,t}^{Capt,CO_2} = P^{CO_2} (R_p^b x_{p,t} - R_p^b \bar{x}_p F_p y_{p,t}^a) \tau^{RT} \quad (1.9)$$

$$C_{p,t}^{Solv} = P^{Solv} R_p^b F_p \bar{x}_p ((D - D^{th}) y_{p,t}^s + D^{th}) \tau^{RT} \quad (1.10)$$

$$C_{p,t}^{Caustic} = P^{Caustic} R_p^b F_p \bar{x}_p D^{Caustic} y_{p,t}^s \tau^{RT} \quad (1.11)$$

$$C_{p,t}^{Waste} = \frac{P^{Waste} R_p^b F_p \bar{x}_p [D^{th} + (D^{Caustic} + D - D^{th}) y_{p,t}^s] \tau^{RT}}{1 - w^R} \quad (1.12)$$

$$C_{p,t}^{CapWat} = P^{Water} w \bar{x}_p \frac{1}{2} (y_{p,t}^s + y_{p,t}^a) \tau^{RT} \quad (1.13)$$

$$C_{p,t}^{T/S} = P_p^{T/S} R_p^b F_p \bar{x}_p y_{p,t}^s \tau^{RT} \quad (1.14)$$

$$C_{p,t}^{CapRamp} = P^{e,avg} \tau^{RT} \bar{x}_p \frac{1}{\eta_p^b} \left(\Delta_{p,t}^{a,u} \hat{\eta}^{a,u} + \Delta_{p,t}^{a,d} \hat{\eta}^{a,d} + \Delta_{p,t}^{s,u} \hat{\eta}^{s,u} + \Delta_{p,t}^{s,d} \hat{\eta}^{s,d} \right) \quad (1.15)$$

There are typically no direct costs for AS procurements, though there are opportunity costs if the AS procurement prevents the use of low-cost supply and

requires more expensive units to meet electricity demand. The facility is contracted to have capacity available without necessarily needing to deploy that capacity. However, to prevent the model from grossly over-procuring AS, costs on the order of 10^{-5} \$/MW are assessed for each. To ensure the model properly prioritizes the each service entailing an output increase (RU, RRS, NSRS), AS costs are placed in the order $\text{NSRS} < \text{RRS} < \text{RU}$. Since interruptible load facilities can only provide RRS and NSRS, these facilities are essentially costless in the model. Additional operating costs could be specified for interruptible load to represent lost revenue from reducing electricity demand, but estimating these costs is outside the scope of this work. Market prices for AS in ERCOT are determined by settlement of AS offers provided by generating units. Future work could use bid data to ascertain the opportunity costs of AS provision to ERCOT generating units, but this procedure was not performed for the present analysis.

1.1.6 Power System Constraints

Within each optimization, all constraints are defined only between the first interval, m , and the last interval, k , in a given optimization period. All simulations optimize one day at a time, so $m - k = 96$ fifteen-minute intervals.

Power system constraints that bound gross power output capacity, define startup and shutdown indication variables, and enforce minimum runtime and downtime are shown in Eqns. 1.16–1.24.

$$\forall \{t|m \leq t \leq k\}, \underline{x}_p u_{p,t}^b \leq x_{p,t} \leq \bar{x}_p u_{p,t}^b \quad (1.16)$$

$$\forall \{t|t > 1, m \leq t \leq k\}, on_{p,t}^b \geq u_{p,t}^b - u_{p,t-1}^b \quad (1.17)$$

$$\forall \{t|t > 1, m \leq t \leq k\}, \text{off}_{p,t}^b \geq u_{p,t-1}^b - u_{p,t}^b \quad (1.18)$$

$$\forall \{t|1 \leq t \leq \Theta_p^{b,u,0}, m \leq t \leq k\}, u_{p,t}^b = 1 \quad (1.19)$$

$$\forall \{t|\Theta_p^{b,u,0} \leq t \leq T - \Theta_p^{b,u} + 2, m \leq t \leq k\}, \sum_{t'=t}^{t+\Theta_p^{b,u}-1} u_{p,t'}^b \geq \Theta_p^{b,u}(u_{p,t}^b - u_{p,t-1}^b) \quad (1.20)$$

$$\forall \{t|T - \Theta_p^{b,u} + 2 \leq t \leq T, m \leq t \leq k\}, \sum_{t'=t}^T u_{p,t'}^b \geq (T - t + 1)(u_{p,t}^b - u_{p,t-1}^b) \quad (1.21)$$

$$\forall \{t|1 \leq t \leq \Theta_p^{b,d,0}, m \leq t \leq k\}, u_{p,t}^b = 0 \quad (1.22)$$

$$\forall \{t|\Theta_p^{b,d,0} \leq t \leq T - \Theta_p^{b,d} + 2, m \leq t \leq k\}, \sum_{t'=t}^{t+\Theta_p^{b,d}-1} (1 - u_{p,t'}^b) \geq \Theta_p^{b,d}(u_{p,t-1}^b - u_{p,t}^b) \quad (1.23)$$

$$\forall \{t|T - \Theta_p^{b,d} + 2 \leq t \leq T, m \leq t \leq k\}, \sum_{t'=t}^T (1 - u_{p,t'}^b) \geq (T - t + 1)(u_{p,t-1}^b - u_{p,t}^b) \quad (1.24)$$

Separate ramp rate constraints are required for the real-time market (Eqns. 1.25 and 1.26) and forward (day-ahead) market (Eqns. 1.27 and 1.28) due to model construction, and a special modification is required for the first interval in the forward market (Eqns. 1.29 and 1.30). The model uses the 15-minute real-time market interval in both optimizations while fixing variables across each hour in the day-ahead market

optimization, so allowable output changes each hour in the day-ahead market must be four times that allowed in each 15 minutes in the real-time market. Equations 1.29 and 1.30 are the exception, where the real-time market allowable ramp is used for the first hour in each day-ahead market optimization. Initially, several simulations using a generating unit-specific data set had difficulty finding feasible solutions because first-hour ramps from the forward market optimization could not be achieved in the real-time optimization. The additional term applying only in the first interval of each forward market optimization eliminates these infeasibilities with minimal impact on operational realism.

$$\forall \{t|t > 1, m \leq t \leq k\}, x_{p,t} - x_{p,t-1} \leq 60\tau^{RT} \delta_p^{b,u} u_{p,t-1}^b + (1 - u_{p,t-1}^b) \underline{x}_p \quad (1.25)$$

$$\forall \{t|t > 1, m \leq t \leq k\}, x_{p,t-1} - x_{p,t} \leq 60\tau^{RT} \delta_p^{b,d} u_{p,t}^b + (1 - u_{p,t}^b) \underline{x}_p \quad (1.26)$$

$$\forall \{t|t > 1, m+1 \leq t \leq k\}, x_{p,t} - x_{p,t-1} \leq 60\tau^{FW} \delta_p^{b,u} u_{p,t-1}^b + (1 - u_{p,t-1}^b) \underline{x}_p \quad (1.27)$$

$$\forall \{t|t > 1, m+1 \leq t \leq k\}, x_{p,t-1} - x_{p,t} \leq 60\tau^{FW} \delta_p^{b,d} u_{p,t}^b + (1 - u_{p,t}^b) \underline{x}_p \quad (1.28)$$

$$\forall \{t|t > 1, t = m\}, x_{p,t} - x_{p,t-1} \leq 60\tau^{RT} \delta_p^{b,u} u_{p,t-1}^b + (1 - u_{p,t-1}^b) \underline{x}_p \quad (1.29)$$

$$\forall \{t|t > 1, t = m\}, x_{p,t-1} - x_{p,t} \leq 60\tau^{RT} \delta_p^{b,d} u_{p,t}^b + (1 - u_{p,t}^b) \underline{x}_p \quad (1.30)$$

AS offers are limited by plant ramping capability as specified by ERCOT [ERCOT, 2009]. RU and RD offers must not exceed the $\kappa^{RU} = \kappa^{RD} = 5$ -minute ramping capability of a facility (Eqns. 1.31 and 1.32). RRS cannot exceed the $\kappa^{RRS} = 10$ -minute up ramping capability of a facility less any RU procurements (Eqn. 1.33). ERCOT also limits RRS procurement to $f^{RRS,Gen} = 20\%$ of maximum output capacity for generation resources (not interruptible load) (Eqn. 1.34). Committed NSRS cannot exceed the $\kappa^{NSRS} = 30$ -minute up ramping capability less any RU and RRS procurements (Eqn. 1.35). NSRS procured by an uncommitted (off) facility cannot exceed its maximum output capacity (Eqn. 1.36). If an uncommitted unit were deployed for NSRS, it would need to supply at least its minimum output capacity. However, ERCOT does not explicitly constrain the minimum NSRS offer by offline units, so no such constraint is included.

$$\forall \{t|m \leq t \leq k\}, ru_{p,t} \leq \kappa^{RU} \delta_p^{b,u} u_{p,t}^b \quad (1.31)$$

$$\forall \{t|m \leq t \leq k\}, rd_{p,t} \leq \kappa^{RD} \delta_p^{b,d} u_{p,t}^b \quad (1.32)$$

$$\forall \{t|m \leq t \leq k\}, rrs_{p,t} \leq \kappa^{RRS} \delta_p^{b,u} u_{p,t}^b - ru_{p,t} \quad (1.33)$$

$$\forall \{t|m \leq t \leq k\}, rrs_{p,t} \leq f^{RRS,Gen} \bar{x}_p \quad (1.34)$$

$$\forall \{t|m \leq t \leq k\}, nsrs_{p,t}^{on} \leq \kappa^{NSRS} \delta_p^{b,u} u_{p,t}^b - rrs_{p,t} - ru_{p,t} \quad (1.35)$$

$$\forall \{t|m \leq t \leq k\}, nsrs_{p,t}^{off} \leq \bar{x}_p (1 - u_{p,t}^b) \quad (1.36)$$

The sum of electricity output and all AS requiring an output increase (RU, RRS, NSRS when committed) must not exceed the maximum power output capacity (Eqn. 1.37), and output minus procured RD must exceed the minimum output capacity (Eqn. 1.38). These constraints ensure generation facilities do not offer any energy or ancillary services they cannot provide within capacity limitations. If all capacity is utilized for electricity output, no AS can be procured. Generally, AS procurements reduce the range of available electrical output.

$$\forall \{t|m \leq t \leq k\}, ru_{p,t} + rrs_{p,t} + nsrs_{p,t}^{on} \leq \bar{x}_p u_{p,t}^b - x_{p,t} \quad (1.37)$$

$$\forall \{t|m \leq t \leq k\}, rd_{p,t} \leq x_{p,t} - \underline{x}_p u_{p,t}^b \quad (1.38)$$

1.1.7 CHP and Interruptible Load Constraints

For all CHP facilities, $p \in \mathbb{M}$, gross electrical output is fixed to maximum capacity, $x_{p,t} = \bar{x}_p$. Doing so prevents also the facility from providing any RU, RRS, and NSRS by Eqn. 1.37, and RD variables are fixed to 0 for CHP facilities assumed to be firm supply and unavailable to provide any grid reliability services.

Interruptible load facilities must have a nonzero output capacity to allow RRS or NSRS provision. However, these facilities must not provide any output in the model because load is interrupted only when necessary for AS deployments, which are not modeled. To represent interruptible load facilities, all output variables are fixed to 0 ($x_{p,t} = 0$), all commitment variables are fixed to 1 ($u_{p,t}^b = 1$), and $\underline{x}_p$ must be 0. These constraints ensure capacity limits (Eqn. 1.16) are satisfied while RRS can be procured from interruptible load by Eqns. 1.33 and 1.37. ERCOT does not allow interruptible load to provide regulation service, so $ru_{p,t}$ and $rd_{p,t}$ are also fixed

to 0 for interruptible load facilities.

1.1.8 Energy Storage System Constraints

Energy storage systems can provide any AS and either supply electricity from storage or increase demand with input to storage. Input systems have minimum/maximum load, startup/shutdown indication, ramp rate, and minimum up/down time constraints that are analogous to the corresponding base plant constraints (Eqns. 1.16–1.30) with variable and parameter substitutions as indicated in Table 1.12.

Table 1.12: Analogous energy storage system constraints are produced by making the following substitutions in Eqs. 1.16–1.30.

Variable or parameter in Eqs. 1.16–1.30	Substitution for energy storage systems
$u_{p,t}^b$	$u_{p,t}^{IN}$
$on_{p,t}^b$	$on_{p,t}^{IN}$
$off_{p,t}^{fb}$	$off_{p,t}^{IN}$
$x_{p,t}$	$x_{p,t}^{IN}$
$\underline{x}_p$	$\underline{x}_p^{IN}$
$\overline{x}_p$	$\overline{x}_p^{IN}$
$\delta_p^{b,u}$	$\delta_p^{IN,u}$
$\delta_p^{b,d}$	$\delta_p^{IN,d}$
$\Theta_p^{b,u,0}$	$\Theta_p^{IN,u,0}$
$\Theta_p^{b,u}$	$\Theta_p^{IN,u}$
$\Theta_p^{b,d,0}$	$\Theta_p^{IN,d,0}$
$\Theta_p^{b,d}$	$\Theta_p^{IN,d}$

Equation 1.39 is the flow balance for stored energy, which calculates stored energy in each time interval, $v_{p,t}$, as the sum of the previous stored energy level, $v_{p,t-1}$, energy output, and energy input. Energy input is multiplied by the output-to-input efficiency to account for energy losses in the storage-retrieval cycle. The

efficiency parameter, η^{es} , depends on the energy storage system type. Though this round-trip efficiency should eliminate any cost incentive to operate both input and output systems simultaneously, Eqn. 1.40 is included in the model to ensure independent operation. Equation 1.41 specifies the maximum energy storage capacity. In addition, energy storage level must be specified at the beginning of each forward market planning period, which is one day in the present work. Without doing so, an energy storage facility would have no incentive to reserve stored energy for future days because the model prevents facilities from planning ahead of the current optimization period. Utilities with large-scale storage systems might seek optimal operation over longer time periods. The model formulation can consider longer forward market planning periods, but day-ahead planning is used exclusively to ensure reasonable computation time. Results are expected to be nearly optimal for storage systems sized primarily to leverage diurnal variations in energy and ancillary service demand and prices.

$$\forall \{t|t > 1, m \leq t \leq k\}, v_{p,t} = v_{p,t-1} - x_{p,t}\tau^{RT} + \eta^{es}x_{p,t}^{IN}\tau^{RT} \quad (1.39)$$

$$\forall \{t|m \leq t \leq k\}, u_{p,t} + u_{p,t}^{IN} \leq 1 \quad (1.40)$$

$$\forall t, v_{p,t} \leq \bar{v}_p \quad (1.41)$$

AS offer limitations with energy storage account for the fact that ramping input systems down is akin to ramping output systems up, and vice versa. Equations 1.42–1.45 redefine the AS offer limitations for energy storage systems to account for input system ramp rates when the facility is storing energy. Constraints

also ensure that combined energy output and AS procurements fall within the input capacity range when a facility is storing energy. Equations 1.46 and 1.47 thus redefine Eqns. 1.37 and 1.38 for energy storage systems so that combined energy input and RD procurement does not exceed maximum input capacity, and energy input less combined RU, RRS, and NSRS exceeds minimum input capacity. Additional constraints (Eqns. 1.48 and 1.49) also account for the duration-limited nature of energy storage, ensuring that RU, RRS, and NSRS cannot be procured when there is insufficient stored energy, and RD cannot be procured if there is insufficient available storage capacity. At the writing of this dissertation, ERCOT had not incorporated such constraints for energy storage systems into its market protocols, so the duration-limited nature of energy storage is not explicitly represented in ERCOT operations. These constraints are included for operational realism even though they do not match ERCOT procedures.

$$\forall \{t|m \leq t \leq k\}, ru_{p,t} \leq \kappa^{RU}(\delta_p^{b,u}u_{p,t}^b + \delta_p^{IN,d}u_{p,t}^{IN}) \quad (1.42)$$

$$\forall \{t|m \leq t \leq k\}, rd_{p,t} \leq \kappa^{RD}(\delta_p^{b,d}u_{p,t}^b + \delta_p^{IN,u}u_{p,t}^{IN}) \quad (1.43)$$

$$\forall \{t|m \leq t \leq k\}, rrs_{p,t} \leq \kappa^{RRS}(\delta_p^{b,u}u_{p,t}^b + \delta_p^{IN,d}u_{p,t}^{IN}) - ru_{p,t} \quad (1.44)$$

$$\forall \{t|m \leq t \leq k\}, nsrs_{p,t}^{on} \leq \kappa^{NSRS}(\delta_p^{b,u}u_{p,t}^b + \delta_p^{IN,d}u_{p,t}^{IN}) - rrs_{p,t} - ru_{p,t} \quad (1.45)$$

$$\forall \{t|m \leq t \leq k\}, ru_{p,t} + rrs_{p,t} + nsrs_{p,t}^{on} \leq (\bar{x}_p u_{p,t}^b - x_{p,t}) + (x_{p,t}^{IN} - \underline{x}_p u_{p,t}^{IN}) \quad (1.46)$$

$$\forall \{t|m \leq t \leq k\}, rd_{p,t} \leq (x_{p,t} - \bar{x}_p u_{p,t}^b) + (\bar{x}_p^{IN} u_{p,t}^{IN} - x_{p,t}^{IN}) \quad (1.47)$$

$$\forall \{t|t > 1, m \leq t \leq k\}, (x_{p,t} + ru_{p,t} + rrs_{p,t} + nsrs_{p,t}^{on})\tau^{RT} \leq v_{p,t} \quad (1.48)$$

$$\forall \{t|t > 1, m \leq t \leq k\}, (x_{p,t}^{IN} + rd_{p,t})\tau^{RT} \leq \bar{v}_p - v_{p,t} \quad (1.49)$$

1.1.9 CO₂ Capture System Constraints

Minimum load, startup/shutdown indication, ramp rate, and minimum up/down time constraints for CO₂ capture are analogous to corresponding base plant constraints (Eqns. 1.16–1.30) with variable and parameter substitutions as indicated in Table 1.13. Equations 1.50 and 1.51 redefine CO₂ capture load change variables for indices used in the unit commitment model.

$$\forall \{t|t > 1, m \leq t \leq k\}, \Delta_{p,t}^u \geq y_{p,t} - y_{p,t-1} \quad (1.50)$$

$$\forall \{t|t > 1, m \leq t \leq k\}, \Delta_{p,t}^d \geq y_{p,t-1} - y_{p,t} \quad (1.51)$$

When modeling an inflexible CO₂ capture system, absorber and stripper load must equal fractional base plant load (Eqn. 1.52), and specified minimum capture load must equal minimum fractional base plant load.

$$\forall \{t|m \leq t \leq k\}, y_{p,t}^a = y_{p,t}^s = \frac{x_{p,t}}{\bar{x}_p} \quad (1.52)$$

Table 1.13: Analogous CO₂ capture system constraints are produced by making the following substitutions in the left hand side of Eqn. 1.16 and Eqs. 1.17–1.30.

Variable or parameter	Substitution for absorption systems	Substitution for stripping systems
$u_{p,t}^b$	$u_{p,t}^a$	$u_{p,t}^s$
$on_{p,t}^b$	$on_{p,t}^a$	$on_{p,t}^s$
$off_{p,t}^b$	$off_{p,t}^a$	$off_{p,t}^s$
$x_{p,t}$	$y_{p,t}^a$	$y_{p,t}^a$
$\underline{x}_p$	$\underline{y}_p^a$	$\underline{y}_p^s$
$\delta_p^{b,u}$	$\delta_p^{a,u}$	$\delta_p^{s,u}$
$\delta_p^{b,d}$	$\delta_p^{a,d}$	$\delta_p^{s,d}$
$\Theta_p^{b,u,0}$	$\Theta_p^{a,u,0}$	$\Theta_p^{s,u,0}$
$\Theta_p^{b,u}$	$\Theta_p^{a,u}$	$\Theta_p^{s,u}$
$\Theta_p^{b,d,0}$	$\Theta_p^{a,d,0}$	$\Theta_p^{s,d,0}$
$\Theta_p^{b,d}$	$\Theta_p^{a,d}$	$\Theta_p^{s,d}$

Absorber and stripper load must be equal for a venting-only flexible CO₂ capture system, but capture load can be below fractional base plant load (Eqns. 1.53 and 1.54).

$$\forall \{t|m \leq t \leq k\}, y_{p,t}^a = y_{p,t}^s \quad (1.53)$$

$$\forall \{t|m \leq t \leq k\}, y_{p,t}^a \leq \min \left(u_{p,t}^a, \frac{x_{p,t}}{\bar{x}_p} \right) \quad (1.54)$$

With solvent storage, absorber and stripper load are decoupled. Absorber load is limited by available flue gas (Eqn. 1.54), and maximum stripper load is constrained by steam availability (Eqn. 1.55) and equipment size (Eqn. 1.56). Equations 1.57 and 1.58 redefine the stored CO₂ flow balance and CO₂ storage capacity limits for the

unit commitment model. Similar to energy storage systems, the model requires a set point for the quantity of CO₂ stored in rich solvent at the beginning of each day.

$$\forall \{t|m \leq t \leq k\}, y_{p,t}^s \leq \frac{1 - Z_{min}^{Turb}}{f_p^{Steam}} \frac{x_{p,t}}{\bar{x}_p} \quad (1.55)$$

$$\forall \{t|m \leq t \leq k\}, y_{p,t}^s \leq f^{Equip} u_{p,t}^s \quad (1.56)$$

$$\forall \{t|t > 1, m \leq t \leq k\}, l_{p,t} = l_{p,t-1} + \tau^{RT} R_p^b \bar{x}_p F_p (y_{p,t}^a - y_{p,t}^s) \quad (1.57)$$

$$\forall \{t|m \leq t \leq k\}, l_{p,t} \leq \bar{l}_p \quad (1.58)$$

The presence of CO₂ capture systems impacts AS offer limitations at a facility. If CO₂ capture systems are inflexible, both minimum and maximum net electrical output is reduced, so the net ramp rate at a facility should reflect CO₂ capture energy requirements. Equations 1.59–1.62 redefine AS offer limitations for an inflexible capture facility, where the factor within parentheses uses CO₂ capture energy requirements, E_p^a and E_p^s , base plant emissions rate, R_p^b , and design CO₂ removal, F_p , to calculate the ratio of net to gross power output. Equations 1.63 and 1.64 similarly redefine the constraints restricting total energy and AS procurements for inflexible CO₂ capture facilities.

$$\forall \{t|m \leq t \leq k\}, ru_{p,t} \leq \kappa^{RU} \delta_p^{b,u} u_{p,t}^b (1 - (E_p^a + E_p^s) R_p^b F_p) \quad (1.59)$$

$$\forall \{t|m \leq t \leq k\}, rd_{p,t} \leq \kappa^{RD} \delta_p^{b,d} u_{p,t}^b (1 - (E_p^a + E_p^s) R_p^b F_p) \quad (1.60)$$

$$\forall \{t|m \leq t \leq k\}, rrs_{p,t} \leq \kappa^{RRS} \delta_p^{b,u} u_{p,t}^b (1 - (E_p^a + E_p^s) R_p^b F_p) - ru_{p,t} \quad (1.61)$$

$$\forall \{t|m \leq t \leq k\}, nsrs_{p,t}^{on} \leq \kappa^{NSRS} \delta_p^{b,u} u_{p,t}^b (1 - (E_p^a + E_p^s) R_p^b F_p) - rrs_{p,t} - ru_{p,t} \quad (1.62)$$

$$\forall \{t|m \leq t \leq k\}, ru_{p,t} + rrs_{p,t} + nsrs_{p,t}^{on} \leq (\bar{x}_p u_{p,t}^b - x_{p,t}) (1 - (E_p^a + E_p^s) R_p^b F_p) \quad (1.63)$$

$$\forall \{t|m \leq t \leq k\}, rd_{p,t} \leq (x_{p,t} - \underline{x}_p u_{p,t}^b) (1 - (E_p^a + E_p^s) R_p^b F_p) \quad (1.64)$$

Conversely, flexible CO₂ capture systems enhance ramping capabilities. Capture system load could decrease while base plant load increases, producing a larger net up ramp rate and greater ability to offer RU, RRS, and NSRS. Even at maximum power system plant load, RU, RRS, and NSRS could be offered given the ability to ramp down CO₂ capture systems. RD offer limits also increase because the facility could ramp capture systems up while decreasing base plant load or decrease minimum base plant load using the energy requirement for capture. Thus, capture system load and ramp rate play a role in AS offer limits and the total quantity of energy and AS the facility can provide. Equations 1.65–1.70 again recast Eqns. 1.31–1.33, 1.35, 1.37, and 1.38 for flexible CO₂ capture facilities. The two additional terms in each AS offer limit represent the supplemental ramping capability provided by flexible capture systems. The quantities $E_p^s R_p^b F_p$ and $E_p^a R_p^b F_p$ again represent the fractional energy requirement for capture, and $\bar{x}_p$ scales the CO₂ capture ramp rates in fractional load per minute to the appropriate MW/min net ramp rate. Additional terms in Eqn. 1.69

account for the RU, RRS, and NSRS offer capacity provided by the capacity to ramp down or turn off capture systems. The additional terms in Eqn. 1.70 similarly represent the available capacity to ramp capture systems up and reduce net electrical output.

$$\begin{aligned} \forall \{t|m \leq t \leq k\}, ru_{p,t} \leq \kappa^{RU} (& \delta_p^{b,u} u_{p,t}^b + E_p^s R_p^b F_p \bar{x}_p \delta_p^{s,d} u_{p,t}^s \\ & + E_p^a R_p^b F_p \bar{x}_p \delta_p^{a,d} u_{p,t}^a) \end{aligned} \quad (1.65)$$

$$\begin{aligned} \forall \{t|m \leq t \leq k\}, rd_{p,t} \leq \kappa^{RD} (& \delta_p^{b,d} u_{p,t}^b + E_p^s R_p^b F_p \bar{x}_p \delta_p^{s,u} u_{p,t}^s \\ & + E_p^a R_p^b F_p \bar{x}_p \delta_p^{a,u} u_{p,t}^a) \end{aligned} \quad (1.66)$$

$$\begin{aligned} \forall \{t|m \leq t \leq k\}, rrs_{p,t} \leq \kappa^{RRS} (& \delta_p^{b,u} u_{p,t}^b + E_p^s R_p^b F_p \bar{x}_p \delta_p^{s,d} u_{p,t}^s \\ & + E_p^a R_p^b F_p \bar{x}_p \delta_p^{a,d} u_{p,t}^a) - ru_{p,t} \end{aligned} \quad (1.67)$$

$$\begin{aligned} \forall \{t|m \leq t \leq k\}, nsrs_{p,t}^{on} \leq \kappa^{NSRS} (& \delta_p^{b,u} u_{p,t}^b + E_p^s R_p^b F_p \bar{x}_p \delta_p^{s,d} u_{p,t}^s \\ & + E_p^a R_p^b F_p \bar{x}_p \delta_p^{a,d} u_{p,t}^a) \\ & - rrs_{p,t} - ru_{p,t} \end{aligned} \quad (1.68)$$

$$\begin{aligned} \forall \{t|m \leq t \leq k\}, ru_{p,t} + rrs_{p,t} + nsrs_{p,t}^{on} \leq & (\bar{x}_p u_{p,t}^b - x_{p,t}) + E_p^s R_p^b F_p \bar{x}_p (y_{p,t}^s - \underline{y}_p u_{p,t}^s) \\ & + E_p^a R_p^b F_p \bar{x}_p (y_{p,t}^a - \underline{y}_p u_{p,t}^a) \end{aligned} \quad (1.69)$$

$$\begin{aligned} \forall \{t|m \leq t \leq k\}, rd_{p,t} \leq & (x_{p,t} - \underline{x}_p u_{p,t}^b) + E_p^s R_p^b F_p \bar{x}_p (f^{Equip} u_{p,t}^s - y_{p,t}^s) \\ & + E_p^a R_p^b F_p \bar{x}_p (u_{p,t}^a - y_{p,t}^a) \end{aligned} \quad (1.70)$$

1.1.10 Fixing Variables Across Forward Market Intervals

As discussed in Section 1.1.4, using a common time index for both the day-ahead and real-time optimization requires constraints in the forward market to fix variables across each forward market time interval (1 hour). This constraint for $x_{p,t}$ is shown in Eqn. 1.71. Analogous constraints are defined in the forward market model for the following variables: $x_{p,t}^{IN}$, $ru_{p,t}$, $rd_{p,t}$, $rrs_{p,t}$, $nsrs_{p,t}^{on}$, $nsrs_{p,t}^{off}$, $y_{p,t}^a$, $y_{p,t}^s$, $u_{p,t}^b$, $u_{p,t}^{IN}$, $u_{p,t}^a$, and $u_{p,t}^s$. The startup/shutdown indicator variables (*on*, *off*) and CO₂ capture load change variables (Δ) are fixed by commitment variables (u) and capture load (y). Stored energy levels cannot be fixed within a forward market interval with constant input or output in that interval. Likewise, CO₂ levels in a solvent storage system will vary across the forward market interval for any unequal absorber and stripper load.

$$\forall \left\{ t | t \geq 1, m \leq t \leq k, \left((t-1) \bmod \frac{\tau^{FW}}{\tau^{RT}} \right) < \left(\frac{\tau^{FW}}{\tau^{RT}} - 1 \right) \right\}, x_{p,t} = x_{p,t+1} \quad (1.71)$$

1.1.11 Electricity System Constraints

Real-time dispatch is optimized in response to 15-minute net demand data, and day-ahead dispatch is optimized in response to the average electricity load in each 1-hour forward market time interval, so different net demand quantities are used in each optimization to enforce the balance between electricity supply and net demand. Using hourly averages in the day-ahead optimization is expected to most closely approximate actual ERCOT practices. The model was tested using hourly maximum

net demand in the forward market to help ensure enough units are committed to respond to hourly demand variations; however, hourly averages are used exclusively in the present analysis. Future activity could study the effect of net demand forecasting accuracy by using discrepant net demand data for the forward and real-time optimizations. Electricity supply/demand balance is satisfied by Eqns. 1.72 and 1.73. Energy requirements for CO₂ capture are subtracted from the gross output of units with CO₂ capture, and input to energy storage increases net demand. Undersupply and oversupply variables allow slack in the supply/demand balance to ensure model feasibility, but these imbalances are penalized in the objective function (Eqns. 1.1 and 1.2).

$$\begin{aligned}
\forall \{t|m \leq t \leq k\}, L_t^{net,FW} &= \sum_p x_{p,t} - \sum_p x_{p,t}^{IN} \\
&+ \sum_{p \in \mathbb{C}} (x_{p,t} - E_p^s R_p^b F_p \bar{x}_p y_{p,t}^s - E_p^a R_p^b F_p \bar{x}_p y_{p,t}^a) \\
&+ \sum_g z_{t,g}^U - z_t^O
\end{aligned} \tag{1.72}$$

$$\begin{aligned}
\forall \{t|m \leq t \leq k\}, L_t^{net,RT} &= \sum_p x_{p,t} - \sum_p x_{p,t}^{IN} \\
&+ \sum_{p \in \mathbb{C}} (x_{p,t} - E_p^s R_p^b F_p \bar{x}_p y_{p,t}^s - E_p^a R_p^b F_p \bar{x}_p y_{p,t}^a) \\
&+ \sum_g z_{t,g}^U - z_t^O
\end{aligned} \tag{1.73}$$

As the highest-priority AS, regulation up and down procurements must meet or exceed requirements in all hours (Eqns. 1.74 and 1.75). ERCOT requires $RRS = 2,300$ MW at all times, but the model is implemented to establish priority of $RU > RRS > NSRS$, so higher-priority RU can be used for lower-priority RRS if economical

(Eqn. 1.76). In practice, AS offers for each service establish appropriate priorities, but this model does not include an offer-bid settlement process. ERCOT constrains NSRS by requiring the sum of RU and NSRS to cover $f^{NLU} = 95\%$ of the total uncertainty in forecasted net demand, σ_t^L (Eqn. 1.77). Additional terms along with objective penalties establish AS priorities, so $ru_{p,t}$ actually appears twice in this representation of the NSRS constraint. Finally, Eqn. 1.78 invokes the ERCOT protocol limiting the quantity of RRS that can be provided by interruptible load to $f^{RRS,Load} = 50\%$ of the RRS requirement.

$$\forall \{t|m \leq t \leq k\}, \sum_p ru_{p,t} \geq RU_t \quad (1.74)$$

$$\forall \{t|m \leq t \leq k\}, \sum_p rd_{p,t} \geq RD_t \quad (1.75)$$

$$\forall \{t|m \leq t \leq k\}, \sum_p rrs_{p,t} + ru_{p,t} \geq RRS + RU_t \quad (1.76)$$

$$\forall \{t|m \leq t \leq k\}, \sum_p ru_{p,t} + nsrs_{p,t}^{on} + nsrs_{p,t}^{off} + ru_{p,t} + rrs_{p,t} \geq f^{NLU} \sigma_t^L + RRS + RU_t \quad (1.77)$$

$$\forall \{t|m \leq t \leq k\}, \sum_{p \in Load} rrs_{p,t} \leq f^{RRS,Load} RRS \quad (1.78)$$

1.1.12 Details of the Two-Stage Optimization

Time series of electricity demand, wind production, and AS requirements are imported over a span of several days, with the total number of days defined as T/L^{FW} .

The day-ahead and real-time market optimizations are then solved within a loop from intervals m to k in that day, and m to k are updated to the appropriate indices at each iteration. After optimizing the day-ahead market, the following variables are fixed for $m \leq t \leq k$ before real-time market optimization: $u_{p,t}^b$, $u_{p,t}^{IN}$, $on_{p,t}^b$, $off_{p,t}^b$, $on_{p,t}^{IN}$, $off_{p,t}^{IN}$, $ru_{p,t}$, $rd_{p,t}$, $rrs_{p,t}$, $nsrs_{p,t}^{on}$, and $nsrs_{p,t}^{off}$. Commitment of CO₂ capture system components is allowed to change between the forward and real-time markets. After optimizing the real-time market, the following variables are fixed for $m \leq t \leq k$ before solving the forward market optimization for the next day: $x_{p,t}$, $x_{p,t}^{IN}$, $v_{p,t}$, $y_{p,t}^a$, $y_{p,t}^s$, $u_{p,t}^a$, $u_{p,t}^s$, $on_{p,t}^a$, $on_{p,t}^s$, $off_{p,t}^a$, $off_{p,t}^s$, $l_{p,t}$, z_t^O , and $z_{t,g}^U$.

1.1.13 Model Limitations

Though many detailed power and electricity system operating behaviors are represented in this model formulation, there are some limitations that deserve notice. The model does not represent transmission constraints, so it implicitly functions as if no transmission constraints in ERCOT are binding. Transmission constraints can have a significant effect on electricity prices when there are locational supply/demand mismatches, so while the model can be used to demonstrate trends in shadow electricity prices, absolute price values might not be accurate. The addition of transmission constraints could allow future research to determine the value of flexible capture in a transmission-constrained system, but results produced without transmission provide a basis for discussing the value of flexible capture in a grid-level context. An intermediate extension could represent the electricity system as a small number of aggregate nodes, or zones, prior to implementing a full nodal transmission system.

As mentioned in the discussion of the single plant profit maximization model, all power and capture system specifications are kept constant across their operating ranges to preserve model linearity. A nonlinear or piecewise-linear representation of

performance curves would improve the detailed short-term representation of operating behavior, but constant-average performance parameters are assumed sufficient to make conclusions about long-term aggregate performance.

Another common set of constraints in unit commitment modeling accounts for the difference between “hot” and “cold” startups by varying minimum up/down time and the transition between zero and minimum load based on time spent on or offline. These effects are assumed negligible to the aggregate performance of the electricity system, so they are not included in this formulation.

1.2 Power Plant Database Creation

Accurate input data are essential for meaningful modeling results. Generating unit data are often difficult to find because specifications are proprietary. High-resolution generating unit information improves realism; however, model output for a large unit database is more difficult to interpret when verifying proper model functionality. This section describes two power system databases. An aggregated representation of the ERCOT system is used for model testing and demonstration. Then, a generating unit-specific database for ERCOT allows greater accuracy when studying the implications of flexible capture in a least-cost dispatch framework.

1.2.1 Aggregated Ten-Facility Test System

Model testing and demonstration uses an aggregated 10-facility system that roughly approximates the capacity of each plant type in ERCOT, including interruptible load. ERCOT does not currently contain any energy storage systems with hundreds of MW input/output capacity, but a large energy storage system is included in this database for functionality testing. Though parameter specifics were

often varied to test different conditions, Table 1.14 contains the parameter set used in simulations with the aggregated system. Marginal costs for electrical output are also shown with \$1.54/MMBTU coal, \$4/MMBTU natural gas, and \$0/tCO₂ to illustrate the typical dispatch order in ERCOT, where nuclear- and coal-based facilities primarily supply base load and natural gas combined-cycle (NGCC) and open-cycle gas turbines (OCGT) provide intermediate and peak supply. Startup costs are also intended primarily to preserve relative order of startup costs among plant types. Maximum output of thermal, nuclear, and hydroelectric facilities reflects approximate total ERCOT capacity of those plant types. The capacity for interruptible load purposefully exceeds the quantity allowed for RRS provision. Minimum output is set to 30% of the maximum for nuclear- and coal-based facilities and a smaller percentage for gas-based facilities. Ramp rates are also defined to reflect relative ramping capabilities of each plant type, and hydroelectric, load, and storage facilities are effectively given infinite ramp rates (the ability to ramp from minimum to maximum output within one 15-minute time interval). Minimum up and down times echo the greater difficulty of startup and shutdown for nuclear- and coal-based plants relative to gas-based, hydroelectric, and most storage facilities. Ramp rate and minimum up and down times are assumed the same in both directions.

Table 1.15 lists additional parameters used when simulating the energy storage system. Storage input and output capacity are 1,000 MW, and the storage system is given 10 hours of storage, or 10,000 MWh. The energy output-to-input efficiency is set to 90%. The stored energy level must be 5,000 MWh at the start of each day, an arbitrary but sufficient value for initial testing and demonstration. The parameters in Tables 1.14 and 1.15 for the energy storage facility combine best-case specifications across many types of energy storage to ensure the storage system is utilized. Pumped hydroelectric systems can have up to 87% round trip efficiency and large

Table 1.14: An aggregated 10-facility data set is used for model testing and proof-of-concept analysis. (*at \$1.54/MMBTU coal, \$4/MMBTU natural gas, \$0/tCO₂)

Plant	Startup cost (\$/startup)	Base Plant VOM Cost (\$/MWh)	Minimum output (MW)	Maximum output (MW)	Ramp rate up/down (MW/min)	Base plant minimum up/down time (hr)	Marginal generating costs* (\$/MWh)
Nuclear	15,000	17.15	1,380	4,600	50	168	17.15
Hydro	100	24.3	0	200	1000	0.5	24.3
Coal 1	12,000	5	2,100	7,000	140	24	20.4
Coal 2 - capture	12,002	0	1,050	3,500	70	24	20.7
Coal 3 - capture	12,003	5	1,050	3,500	70	24	21.2
NGCC 1	8,000	5	3,125	12,500	375	6	39
NGCC 2	8,001	5	3,125	12,500	375	6	41
OCGT 1	500	5	1,300	26,000	2,600	0.5	45
Load	0	5	0	2,000	200	n/a	0
Storage	0	3	0	1,000	500	0.5	0

storage capacity, but lack of suitable geography and environmental impacts are barriers to new large hydroelectric facilities [APS, 2007]. Efficiencies $>90\%$ are achievable with flywheels and supercapacitors, but energy storage types and batteries are currently impractical at a hundreds of MW scale [APS, 2007]. Since CAES often heats air by natural gas burning before expanding it through a gas turbine, output/input efficiencies are above 100%, but electrical output incurs fuel and possibly CO₂ emissions costs. The unit-specific database described in the next section provides a more realistic representation of energy storage systems.

Table 1.15: The following parameters describe the generic energy storage system used for testing purposes.

Parameter (Units)	Value
Minimum input capacity (MW)	0
Maximum input capacity (MW)	1,000
Output/input efficiency (fractional)	0.9
Energy storage capacity (MWh)	10,000
Day-starting stored energy level (MWh)	5,000
Input system ramp rate up/down (MW/min)	500
Input system minimum up/down time (hr)	0.5

Table 1.16 contains key specifications for the Coal 2 and Coal 3 generation blocks when being tested in a CO₂ capture configuration. Again, a baseline 7m MEA capture system is assumed. Only a small solvent storage system is tested with the aggregated unit dataset.

1.2.2 Unit-Specific Database

1.2.2.1 Power System Specifications

Before creating a database for each ERCOT generating unit, successful simulations were completed with the 10-facility data and semi-aggregated databases with

Table 1.16: The following CO₂ capture parameters are used when simulating the 10-unit data set with CO₂ capture systems.

Parameter (Units)	Value
Absorber/stripper min load (fractional)	0.3
Design CO ₂ removal (fractional)	0.9
Stripping/compression energy requirement (MWh/tCO ₂)	0.239
Absorption energy requirement (MWh/tCO ₂)	0.030
Absorber/stripper ramp rate up/down (load fraction/min)	0.05
LP steam fraction to stripping (fractional)	0.4
CO ₂ transport and storage cost (\$/tCO ₂)	9.69
Solvent storage tank size (m ³)	8,300
Design CO ₂ carrying capacity (molCO ₂ /molMEA)	0.12
Day-starting CO ₂ quantity in rich storage tank (tCO ₂)	164

~40 and ~140 facilities to ensure model solvability within reasonable computation time for larger databases. After favorable results with the ~140-unit database, a unit-specific database for ERCOT was created to produce the most realistic dispatch achievable within model limitations. This section provides key parameters and describes how the database is created.

The unit-specific database is built from a 2010 list of ERCOT generating units containing unit-specific maximum capacity as well as generic plant-type specific values for minimum capacity fraction, ramp rate, minimum up/down time, startup cost, heat rate, CO₂ emissions rate, and non-fuel/CO₂ VOM cost [ERCOT, 2011b]. These data are publicly available as part of a contract between ERCOT and the U.S. Department of Energy (DOE).

The ERCOT database provides both summer and winter maximum capacities; the average is assumed sufficient for this analysis. ERCOT-provided values for minimum capacity fraction, ramp rate, minimum up/down time, startup cost, and

non-fuel/CO₂ VOM cost are used for all units of each plant type; these quantities are shown in Table 1.17. Also listed is the corresponding classification for each plant type within the unit commitment model, which is used for appropriately calculating operating costs and displaying results. Oil-based units make up a negligible portion of ERCOT capacity, so these facilities are not included in the database. Parameters in Table 1.17 were not varied among individual units of each type unless the ERCOT database contained an alternate value for that facility.

All quantities in Table 1.17 are zero for hydroelectric units because hydroelectric dams in ERCOT have negligible costs and operating restrictions. OCGT and internal combustion units have the lowest minimum output, minimum up/down time, and startup costs among fossil-fueled units, followed by NGBLR and NGCC units. Coal- and nuclear-based units have the highest minimum up/down time, but more advanced NGCC units such as F/G/H-Class NGCC units are assigned higher startup costs. In practice, startup costs depend on power plant size. For example, startup costs for coal-based units are proportional to the amount of diesel fuel used to pre-heat the boiler, which rises with plant size. However, absent unit-specific startup cost information, generic startup costs by plant type are considered sufficient to establish priority among unit types and produce realistic dispatch patterns. Shutdown costs are set to 0 for all facilities. Every plant startup will eventually require a shutdown, so the startup cost can be thought to include any shutdown costs. Required initial up and down times are also set to 0 for all units.

Ramp rates on the order of 0.2–0.7% in either direction are assumed for all unit types except OCGT, NGIC, and hydroelectric facilities. ERCOT uses these data for an hourly dispatch model, so these ramp rates appear conservative. Short-term ramp rates could be faster than average hourly ramp rates listed in Table 1.17, but

ERCOT-provided values are used as conservative input specifications in the absence of better data. OCGT, NGIC, and hydroelectric facilities are assumed able to ramp from 0–100% of maximum output capacity within one hour, so ERCOT simply ignores ramp rate limits for these unit types. These unit types could also be expected to ramp from 0–100% within the 15-minute time interval used in the present model, so ramp rates for these unit types are set to 6.7%/min.

ERCOT does not provide a minimum capacity fraction for nuclear facilities because its studies assume constant full-load operation, but the present work will relax this assumption so that nuclear facilities have the option to reduce output or provide regulation down service. Minimum capacity for nuclear facilities is assumed to be 30% of the maximum. Though possibly unrealistic, nuclear VOM costs are only \$4/MWh, so these facilities will only ramp down if the difference between net electricity demand and firm supply from CHP units is less than nuclear-based output capacity. ERCOT also does not specify a startup cost for nuclear facilities since it assumes continuous operation at maximum output. Since the present analysis relaxes this assumption, nuclear units are assigned a \$7,200/startup cost to be reasonably close to startup costs of other large base load facilities.

Generic values for each plant type are sufficient for the parameters discussed above. However, if generic heat rates and CO₂ emissions rates are used, facilities of each plant type with nonzero heat and CO₂ emissions rates will have identical operating costs, which could lead to inaccurate dispatch. This situation also creates “ties” in the optimization procedure, which can increase solution difficulty and complicate results interpretation because dispatch decisions are often arbitrary artifacts of the solver algorithm. The EPA eGRID database provides plant-specific heat rates and CO₂ emissions rates for many facilities in ERCOT; however, it lacks sufficient data to

Table 1.17: The following parameters from an ERCOT database are kept constant for all units of a given type.

ERCOT plant type	Plant type in UC model	Minimum output (fractional)	Minimum down time (hr)	Minimum up time (hr)	Non-fuel/CO ₂ VOM cost (\$/MWh)	Startup cost (\$/startup)	Ramp rate (load fraction/min)
Biomass	Biomass	0.25	6	8	9.5	2,500	0.0054
Coal	Coal	0.48	12	24	5	5,000	0.0026
Hydro	Hydro	0.00	0	0	0	0	non-binding
GSSUP	NGBLR	0.28	8	8	6.5	2,500	0.0054
Non-reheat	NGBLR	0.43	8	8	5	2,500	0.0054
Reheat	NGBLR	0.38	8	8	8	2,500	0.0054
CC-E Class	NGCC	0.24	4	4	3	3,000	0.0066
CC-F Class	NGCC	0.32	4	6	3	10,000	0.0066
CC-LM6000	NGCC	0.36	8	4	5	5,000	0.0066
G&H Class	NGCC	0.63	8	6	2.9	15,000	0.0066
Internal combustion	NGIC	0.20	1	1	3	0	non-binding
Nuclear	Nuclear	-	24	168	4	-	0.0026
CT-E Class	OCGT	0.25	1	1	4	1,000	non-binding
CT-LM6000	OCGT	0.36	1	1	8	2,000	non-binding
LMS100	OCGT	0.70	1	1	3	0	non-binding
Older	OCGT	0.25	1	1	3	0	non-binding

calculate unit-specific performance parameters [USEPA, 2010]. Furthermore, eGRID values are averaged over a calendar year, so heat rates and CO₂ emissions rates for plants with multiple units depend on the relative utilization of each unit, which is not reported. When all units are the same type, equivalent performance across units is often a reasonable assumption, but there is greater uncertainty in unit performance for plants with multiple unit types. To maximize the utilization of the plant-specific information in eGRID while creating the unit-specific database used in the unit commitment model, the following procedures are utilized to specify unit heat rates and CO₂ emissions rates.

Case 1: Performance specifications for the plant appear in both the eGRID and ERCOT databases.

- If all units are the same type, use the eGRID heat rate and CO₂ emissions rate for all units.
- If the plant has units of multiple types, use the following procedures.
 - If generic ERCOT values are within 10% of the eGRID values for one of the unit types, use the eGRID value for that unit type and the generic ERCOT value for all other unit types.
 - If the ERCOT specifications are not within 10% of the eGRID specifications, use ERCOT generic values for all unit types.
 - Heat rate only: If the ERCOT specifications are not within 10% of the eGRID specifications for any unit type and some units are NG internal combustion engines, use eGRID values for non-NGIC units and use ERCOT generic values for NGIC units (eGRID does not list any NGIC units in its ERCOT plant database).

Case 2: Performance specifications for the plant appear do not appear in eGRID (plant might not be listed in eGRID): Use the generic ERCOT values for heat rate and CO₂ emissions rate.

The above procedure ensures all applicable units are assigned a heat rate and CO₂ emissions rate and helps minimize the number of facilities with the same performance characteristics, but several units will still have identical performance and cost. To ensure no units have exactly the same cost and performance, heat rates and CO₂ emissions rates were multiplied by a random number from 0.995–1.005 to differentiate performance with minimal change to parameters. For each unit, the same random number is used for both the heat rate and CO₂ emissions rate to make adjustments in a consistent manner. Rather than isolating units with identical performance, all units with nonzero heat rate and CO₂ emissions rate are adjusted in this manner for consistency.

The ERCOT database does not contain information on which units are CHP unless unit names indicate CHP status. The eGRID database provides CHP status by plant, so all units at plants designated as CHP in eGRID are marked as CHP units in the database used for optimization. There is a large portion of CHP capacity in eGRID not listed in the ERCOT database, but there are also several unnamed Private Use Network (PUN) units in the ERCOT database whose names are withheld in the public version of the ERCOT database. It is assumed that PUN units are on-site units at industrial facilities such as oil refineries and chemical manufacturers, and since units at these facilities are typically CHP units, all PUN units in the ERCOT database are marked as CHP units. The resulting total CHP capacity is similar to that reported in eGRID.

Interruptible load is not included in the unit-specific database for the analysis

Figure 1.3: The completed unit-specific database demonstrates the dominance of natural gas in the 2010 ERCOT fleet, and over 12 GW of capacity is combined heat and power (CHP).

presented within this dissertation. Its inclusion would yield more accurate RRS and NSRS procurements. However, initial testing found that load resources were almost always used for the maximum allowable RRS requirement, significantly limiting the amount of AS provided by other unit types. A primary goal of the present work is to understand the potential role of flexible capture for AS provision, so interruptible load is omitted to provide greater opportunity for flexible capture to provide AS and allow a clearer picture of how different electricity system conditions affect AS provision by flexible capture facilities.

Panel (a) in Fig. 1.3 displays the capacity by plant type in the unit-specific database under 2010 conditions, and Panel (b) shows the portion of capacity designated as CHP. Total capacity is 79.6 GW (omitting wind capacity). CHP facilities are primarily NGCC and OCGT units, but there is also 705 MW of coal-based capacity designated as CHP based on information in the eGRID database.