# Mid-Semester Memo

# Introduction

This memo explores my locational marginal price (LMP) prediction exploration and process and my lifecycle analysis (LCA) of all candidate options for our energy portfolio. In the interest of transparency, I have compiled my code for public reference on GitHub at <https://github.com/rmoglen/EnergyDevelopment_Policy>.

# Locational Marginal Price (LMP) Prediction

## Sources

ERCOT’s 2018 Long-Term System Assessment (LTSA) report [5] was central in guiding my LMP predictions, specifically the data presented in its Figure I.1, duplicated in Appendix C. Figure I.1 in the LSTA was generated by a survey of ERCOT stakeholders who concluded that the key drivers for the ERCOT grid were Texas economic conditions, natural gas prices, capital costs for renewable energy, environmental regulations, and weather conditions, followed by several less significant drivers. Therefore, I selected natural gas prices, Texas GDP, and renewable energy capital costs as predictors in my model, along with year, load zone, season, and peak versus off peak timing. Table A in Appendix A summarizes the data I used in my model and their sources. I used publicly available data primarily from the EIA and ERCOT to build my model and predict LMPs.

## Scenarios

ERCOT’s 2018 LTSA report [5] also provided guidance on scenarios likely to impact the ERCOT grid and thus future prices. Two of the scenarios it discusses are (1) High Economic Growth and (2) High Renewable Penetration. My third scenario was (3) the Base Case. Forecasts for the next 20 years for all my predictors were available except for renewables capital costs, which I extrapolated by fitting an exponential model to the available data.

(1) the Base Case was predicted using the available forecasts data from Table A. For (2) the High Economic Growth scenario, EIA provides its own predictions of natural gas prices under high economic growth, and ERCOT describes an annual Texas GDP increase of 2.2% rather than the 1.4% in the base case. Again, future LMPs were predicted using forecasts as predictors, this time with 2.2% GDP growth and High Economic Growth conditions gas prices in place of the base case numbers. For (3) the High Renewable Penetration, it was assumed that this adoption was driven by lower renewable energy costs, so forecasted renewable energy capital costs were multiplied by a discount factor (assumed to be 0.9). Future LMPs were once more predicted using the forecast data from Table A, with the substitution of the discounted renewable energy capital cost forecasts.

## Aggregation

Historical LMPs were aggregated by season (“summer” as April through October and “non-summer” as the rest of the year) and “peak” (hours 8 through 23 in the summer and 1 and 24 in the non-summer) and off-peak the rest of the time. In the summer, the price peak is largely temperature-driven. In the non-summer, “peak” refers to the nighttime hours associated with West-Texas Congestion. This aggregation was done both because the financial models that will use the LMP predictions as inputs will likely not need a finer temporal resolution and because the forecast data available was generally only at 1 year temporal resolution, making finer prediction difficult and likely inaccurate. Historical LMPs in each of the time-categories (summer peak, summer off-peak, non-summer peak, and non-summer off-peak) were averaged by median value in that year. Therefore, my model predicts the median LMP in each load zone, each year from 2020-2039, in each of the four time-categories. I predict the median LMP, rather than mean LMP, because the price distribution is so heavily skewed; in the financial models, my LMP predictions are used as “typical” price forecasts, and in this case the median is more representative. If a prediction of future LMP volatility is requested, a prediction of upper tail risk, such as the 90th percentile LMP each year, could be generated in a similar manner to the median LMP prediction model below.

## Model

I used linear regression to fit a model to LMPs from 2011 to 2019. I then applied this model to 2020 to 2039 to predict future LMPs. My model is of the following form:

The resulting model is summarized in Appendix B. Figure 1 displays both historic averaged LMPs and forecasts under the three scenarios explored. In all three cases, the predicted LMPs stay within the range of historic values. Under the base case and cheaper renewables scenarios, prices decrease only slightly over time, and perform quite similarly. Under the high GDP growth scenario, prices increase slightly over time.

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| Chart, line chart  Description automatically generated |
| Figure 1: Linear Model LMP Predictions in Austin |

## ERCOT Price Model

Some validation of price predictions can be achieved through corroboration from the ERCOT price model. Figure 2 shows the results of running the ERCOT Price model under the same three scenarios applied to my linear model: a base case, a high economic growth case, and a low-cost renewables case. Table 1 shows the specific inputs used to model these three scenarios.

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| Table 1: ERCOT Price Model Inputs | | | |
|  | **Base Case** | **High Econ. Growth** | **Low-Cost Renewables** |
| Natural Gas | Natural Gas-Med | Natural Gas-High | Natural Gas-Med |
| Renewable | Renewable-Med | Renewable-Med | Renewable-Low |
| Policy | Status Quo | Status Quo | Status Quo |
| Peak % | 0.75% | 0.95% | 0.75% |
| Off Peak % | 0.20% | 0.30% | 0.20% |

In Figure 2, the ERCOT Price Model predictions show some similarities to the results received with my linear model. Notably, the magnitude of the predictions is uniformly higher in Figure 2 than Figure 1. This is due largely to my decision to model median LMPs, as compared to the ERCOT Price model’s mean predictions. As previously discussed, my decision was driven by the skewness of the price distribution. However, assuming the approximate shape of the price distribution remains the same over time, the trend of prices in Figures 1 and 2 can be directly compared, if not their exact magnitude. In both Figures 1 and 2, the high economic growth scenario exhibits the highest long-term price predictions. It is possible that this effect would be magnified if I selected higher peak and off-peak percentages as inputs to the ERCOT Price Model; engineering judgement was all that guided the selection of the current values. In both Figures 1 and 2, the base scenario and low-cost renewables displayed relatively flat prices over prediction horizon, with the low-cost renewable scenario displaying the lowest price predictions. Overall, while my linear model and the ERCOT Price model display differences in magnitude and modest difference in pattern, the similarities in overall trend (over time and relative to each other) helps corroborate my linear model.

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| Figure 2: ERCOT Price Model LMP Average Predictions |

## Model Limitations

My linear model depends heavily on the accuracy of natural gas and renewable capital costs predictions, as well as GDP predictions. This recalls the modeling adage: “garbage in equals garbage out.” While I certainly would not call the forecasts used “garbage” it is worth nothing that the predictive accuracy of the model is limited by the accuracy of its inputs. However, the entities from which the inputs are sourced, the EIA, ERCOT, and the US Bureau of Economic Development, are well respected and therefore their forecasts can reasonably be trusted. Furthermore, lacking any alternative, the use of such forecasts is necessary to the modeling process.

Another limitation of the linear model I have selected is its simplicity. It is a linear function of drivers known to be important in determining ERCOT prices, but neglects factors such as planned transmission projects, substantial policy changes, and generation mix. These more qualitative or reactive factors cannot be directly incorporated to the structure of the linear model. Moreover, the model is trained on the years 2011 to 2019, and so significant deviation from the norms of these years (for example a pandemic) would not be included in the model’s predictive range. Nevertheless, the linear model has the advantage of being easily interpretable and transparent. Appendix B notes each predictor’s coefficient and level of significance, making it much clearer than the ERCOT price model. It is also easily updated or modified if more predictors become available to us for modeling purposes. For example, after the election and depending on its result, our team plans to incorporate the possibility of a carbon tax, something we evaluate as more likely under a Biden administration.

# Lifecycle Analysis (LCA)

A Lifecycle analysis (LCA) was performed to analyze the emissions and water use generated by the candidate natural gas plants in our portfolio, as well as the water use for renewable energies in our portfolio. The LCA for each generation source is composed of three parts: first the capacity factor is calculated, then plant’s net generation is computed, and finally the total emissions are calculated using the generation and the per-MWh rate of emissions or water use.

## CCGT Analysis

The first step in the life cycle analysis of the CCGTs in both Houston in San Antonio was computing their capacity factors. The Houston build offers three candidate turbines, each with their respective heat rates, while the San Antonio site requires analysis of only one turbine. These sites and their respective options are summarized in Table 1 below. The capacity factor of each of these potential projects was assumed to be the average hypothetical capacity factor for the years 2011 to 2019, computed by comparing the turbine’s marginal cost to the LMP in the plant’s location. This implicitly assumes that the plant’s capacity factor for 2011 to 2019 would be the same as from 2020 to 2039. While certainly a simplification, given the coarse aggregation of forecasts (LMP and gas prices) for 2020 to 2039, calculating the capacity factor using these values would fail to capture a gas plant’s ability to spin up and down quickly in response to LMPs. The time resolution of the forecast data is significantly coarse than a gas plant’s spin up time, which is a large part of how natural gas plants stay profitable. It was therefore deemed preferable to extrapolate each turbine’s capacity factor based on 2011 to 2019 gas prices and LMPs.

The capacity factor is the average percentage of time intervals where the LMP exceeds the turbine’s marginal cost. The marginal cost for each turbine was computed using equation (1):

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|  | (1) |

The annual total emissions were then estimated using equation (2). Note that there are 8760 hours in a year. These results are shown in Table 2. Note that two values for NOx are reported for the San Antonio plant in Tables 1 and 2, for before and after the SCR is added in 2021 as required by the Clean Air Act.

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|  | | | | | | | | (2) |
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| Table 1: CCGT Life Cycle Analysis Emissions Rate | | | | | | | | |
| **Turbine** | **Location** | **Capacity Factor**  **(2011-2019)** | **Heat Rate (BTU/ kWh)** | **Capacity (MW)** | **NOx**  **(lb/ MMBTU)** | **SO2**  **(lb/ MMBTU)** | **CO2-eq**  **(lb/ MMBTU)** | |
| GE 7FA.05 | Houston | 26.7% | 6800 | 600 | 0.0228 | 0.00074 | 117 | |
| Mitsubishi 501J | Houston | 31.4% | 6400 | 460 | 0.0228 | 0.00074 | 117 | |
| Mitsubishi 501GAC | Houston | 34.4% | 6200 | 405 | 0.0228 | 0.00074 | 117 | |
| GE 207FA.04 | San Antonio | 10.5% | 8840 [2] | 942 | 0.15 / 0.0228\* | 0.00074 | 117 | |
| \* Emissions rates before and after the SCR is added in 2021 as required by the Clean Air Act | | | | | | | | |

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| Table 2: CCGT Life Cycle Analysis Annual Emissions | | | | | | | |
| **Turbine** | **Location** | **Capacity Factor**  **(2011-2019)** | **Heat Rate (BTU/ kWh)** | **Capacity (MW)** | **NOx**  **(s.t./year)** | **SO2**  **(s.t./year)** | **CO2-eq**  **(s.t./year)** |
| GE 7FA.05 | Houston | 26.7% | 6800 | 600 | 108.79 | 3.53 | 558253.43 |
| Mitsubishi 501J | Houston | 31.4% | 6400 | 460 | 92.32 | 3.00 | 473726.22 |
| Mitsubishi 501GAC | Houston | 34.4% | 6200 | 405 | 86.26 | 2.80 | 442654.75 |
| GE 207FA.04 | San Antonio | 10.5% | 8840 [2] | 942 | 574.46/ 87.32\* | 2.83 | 448076.78 |
| \* Emissions before and after the SCR is added in 2021 as required by the Clean Air Act | | | | | | | |

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|  | (3) |

Equation (3) can be used to compute water consumption and withdrawal for the candidate CCGT. In this case, [3] as referenced for the consumption and withdrawal rates per MWh for our candidate turbines. [3] lists water rates for several CCGT configurations; the recirculating cooling rates were used in this analysis. Table 3 presents the annual water consumption and usage for the candidate turbines.

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| Table 3: CCGT Life Cycle Analysis Water Consumption and Withdrawal [3] | | | | | | | |
| **Turbine** | **Location** | **Capacity Factor** | **Capacity (MW)** | **Water Consumption\*** | | **Water Withdrawal\*** | |
| **(2011-2019)** | **(gal/MWh)** | **(10^6 gal/year)** | **(gal/MWh)** | **(10^6 gal/year)** |
| GE 7FA.05 | Houston | 26.70% | 600 | 200 | 280.67 | 250 | 350.84 |
| Mitsubishi 501J | Houston | 31.40% | 460 | 200 | 253.06 | 250 | 316.32 |
| Mitsubishi 501GAC | Houston | 34.40% | 405 | 200 | 244.09 | 250 | 305.11 |
| GE 207FA.04 | San Antonio | 10.50% | 942 | 200 | 173.29 | 250 | 216.61 |
| \* Assumed recirculating cooling (cooling towers) | | | | | | | |

## Renewables Analysis

The renewables Life Cycle Analysis is conducted similarly to the CCGT Life Cycle Analysis. Using the values provided in the case study for the seasonal capacity factors, the annual weighted capacity factor was calculated, presented in Table 4. Then, using theCO2-eq emissions rates for each source’s production provided in [4], the annual CO2-eq emission rate was calculated using equation (3).

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| Table 4: Renewables Life Cycle Analysis [4] | | | | | | |
| **Development** | **Source** | **Capacity Factor** | **Capacity** | **Project Area** | **CO2-eq** | |
| **(MW)** | **(acres)** | **(g CO2-eq/kWh)** | **(kg CO2-eq/yr)** |
| Big Sky | Solar | 0.328 | 250 | 8000 | 55 | 39.48 |
| XIT Ranch | Onshore Wind | 0.495 | 250 | 38000 | 13 | 14.10 |
| Lavaca | Coastal Wind | 0.484 | 200 | 20000 | 13 | 11.02 |
| Lavaca | Coastal Wind | 0.446 | 150 | 20000 | 13 | 7.62 |

# References

1. 7F.04 Gas Turbine. (2020). Retrieved 26 October 2020, from <https://www.ge.com/power/gas/gas-turbines/7f-04>
2. eGrid. (2018). Retrieved 26 October 2020, from <https://www.epa.gov/egrid/download-data>
3. Macknick, et al. (2012). Environ. Res. Lett
4. National Renewable Energy Laboratory. (2013). *Life Cycle Greenhouse Gas Emissions from Electricity Generation*. Retrieved from <https://www.nrel.gov/docs/fy13osti/57187.pdf>
5. ERCOT Public. (2018). *2018 Long-term System Assessment for the ERCOT Region*. Retrieved from http://www.ercot.com/content/wcm/lists/144927/2018\_LTSA\_Report.pdf

# Appendix A: Data Sources

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| Table A: Data Sources | | | | |
| **Name** | **Source** | **Notes** | **Date Range** | **Time Resolution Downloaded** |
| Historical SPP | [ERCOT](http://mis.ercot.com/misapp/GetReports.do?reportTypeId=13061&reportTitle=Historical%20RTM%20Load%20Zone%20and%20Hub%20Prices&showHTMLView=&mimicKey) |  | 2011-2019 | 15 minutes |
| Historical Temperature | [NOAA](https://www.ncdc.noaa.gov/cdo-web/datatools/lcd) | Houston Airport | 2011-2020 | 1 hour |
| Temperature Forecasts | [USGS](http://regclim.coas.oregonstate.edu/visualization/rccv/states-counties/) | Texas-wide Used, Mean Model Used | 2020-2099 | 10 years |
| US Natural Gas Price Forecasts | [EIA](https://www.eia.gov/outlooks/aeo/data/browser/#/?id=13-AEO2018&cases=ref2018&sourcekey=0) | Industrial Used | 2016-2050 | 1 year |
| Historical US Natural Gas Price | [EIA](https://www.eia.gov/dnav/ng/hist/n3035us3A.htm) | Monthly available, Industrial Used | 1997-2019 | 1 year |
| Historical and Forecasted Peak and Annual Demand | [ERCOT](http://www.ercot.com/content/wcm/lists/114580/2017_Long-Term_Hourly_Peak_Demand_and_Energy_Forecast.pdf) | Extrapolate for 2027-2039, not yet included in model | 2007-2026 | 1 year |
| Historical Texas GDP | [US Bureau of Economic Development](https://fred.stlouisfed.org/series/TXNGSP) |  | 1997-2019 | 1 year |
| Texas GDP Forecasts | [ERCOT](http://www.ercot.com/content/wcm/lists/144927/2018_LTSA_Report.pdf) | Growth rate applied to 2019 GDP | 1.4% growth (normal), 2.2% (high) | 1 year |
| Capacity-Weighted Average Renewable Costs | [EIA](https://www.eia.gov/electricity/generatorcosts/) | Extrapolate exponentially for years outside range, past and future | 2013-2018 | 1 year |

# Appendix B: LMP Model Summary

Call:

lm(formula = Price ~ Year + category + Zone + NG\_Price + GDP +

Solar\_PV\_Cost + Onshore\_Wind\_Cost, data = training\_data)

Residuals:

Min 1Q Median 3Q Max

-4.1783 -0.7047 -0.1300 0.6750 8.3850

Coefficients:

Estimate Std. Error t value Pr(>|t|)

(Intercept) 3.103e+03 3.747e+02 8.281 1.20e-15 \*\*\*

Year -1.550e+00 1.866e-01 -8.308 9.79e-16 \*\*\*

categorynon-summer peak -2.368e+00 1.632e-01 -14.510 < 2e-16 \*\*\*

categorysummer off-peak -1.913e+00 1.632e-01 -11.723 < 2e-16 \*\*\*

categorysummer peak 5.843e+00 1.632e-01 35.808 < 2e-16 \*\*\*

ZoneHB\_HOUSTON 5.061e-01 3.065e-01 1.651 0.099325 .

ZoneHB\_HUBAVG -5.944e-02 3.065e-01 -0.194 0.846296

ZoneHB\_NORTH 4.819e-02 3.065e-01 0.157 0.875117

ZoneHB\_PAN -2.310e+00 6.970e-01 -3.314 0.000988 \*\*\*

ZoneHB\_SOUTH 2.040e-01 3.065e-01 0.666 0.505928

ZoneHB\_WEST -4.525e-01 3.065e-01 -1.476 0.140490

ZoneLZ\_AEN 2.593e-01 3.065e-01 0.846 0.397947

ZoneLZ\_CPS 4.303e-01 3.065e-01 1.404 0.160996

ZoneLZ\_HOUSTON 5.972e-01 3.065e-01 1.949 0.051923 .

ZoneLZ\_LCRA 2.594e-01 3.065e-01 0.846 0.397694

ZoneLZ\_NORTH 1.503e-01 3.065e-01 0.490 0.624133

ZoneLZ\_RAYBN 2.969e-01 3.065e-01 0.969 0.333104

ZoneLZ\_SOUTH 3.749e-01 3.065e-01 1.223 0.221898

ZoneLZ\_WEST 5.083e-01 3.065e-01 1.659 0.097853 .

NG\_Price 4.700e+00 1.332e-01 35.297 < 2e-16 \*\*\*

GDP 1.360e-05 2.199e-06 6.187 1.31e-09 \*\*\*

Solar\_PV\_Cost -1.857e-03 3.694e-04 -5.028 6.99e-07 \*\*\*

Onshore\_Wind\_Cost 3.491e-03 1.456e-03 2.397 0.016901 \*

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Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.3 on 485 degrees of freedom

Multiple R-squared: 0.9364, Adjusted R-squared: 0.9335

F-statistic: 324.5 on 22 and 485 DF, p-value: < 2.2e-16

# Appendix C: ERCOT Key Drivers

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| Figure I.1: Summary of Survey Results, Key Drivers [5] |