THE IMPACT OF DECARBONIZED ELECTRICITY ON THE ADOPTION OF ELECTRIC VEHICLES IN TEXAS

by

Xinwei Li

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Thesis Committee:
Assistant Professor Jeremiah X. Johnson, Advisor
Professor John M. DeCicco, Co-Advisor

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Abstract

Transportation electrification is increasingly playing an important role in reducing greenhouse gas (GHG) emissions since electricity GHG intensity have dropped greatly in recent years. However, current evaluations on battery electric vehicles rarely consider the impact of this change in the electric sector. This research investigates how decarbonizing electricity would affect the environmental performance and economic competitiveness of the battery electric vehicle by integrating an economic dispatch power system model with a passenger car comparison model. In power system modeling, accounting for 258 strategies, I derive collective mitigation cost curves with Matlab to identify the least-cost strategies for Texas to meet the mass-based emission targets of EPA's Clean Power Plan (CPP) from 2022 to 2030. The model outputs, indicating capacity additions and retirements under each scenario, was used to estimate changes to generation mix, carbon emissions, and production costs for the electric grid in each model year. In the passenger car model, I compile recent studies on the technology progress and cost projection of vehicle technologies to identify their capital costs and efficiency in 2030. The result shows that, the capital costs and the GHG emissions of the electric vehicle will largely decrease, making it more attractive in the market. However, the risk of the increased electricity rates from electric grid upgrading may weaken the market competitive position of electric vehicles.

Acknowledgements

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1 Introduction

In 2016, greenhouse gas (GHG) emissions from transportation accounts for 36% of the total emissions in the United States, overtaking electricity generation as the largest source (US EIA, 2017a). On the other hand, Electric sector CO2 emissions have dropped greatly in recent years, declining at an average rate of 2.8 percent per year over 2007-2015 (DeCicco, 2016). Therefore, vehicle electrification is playing more promising and important role in sustainable transportation.

Well-to-wheel emissions of electric vehicles largely depend on the carbon intensity of the electricity sources. Many studies have shown that battery electric vehicles could contribute to reducing transportation-related greenhouse gas emissions, offering some emissions savings even with today's fossil-fuel-dominated electricity supply mix (Sioshansi, 2010; Donateo, 2014; Tamayao, 2015). However, current evaluations on battery electric vehicles rarely consider the impact of the ongoing decarbonization in the electric sector to the environmental performance and economic competitiveness of the battery electric vehicle. Therefore, it is very important to conduct a more comprehensive analysis of EVs by expanding the boundary to electric sector under an ever-cleaner grid.

This study aims to investigate how a decarbonized electric grid in the service area of ERCOT under EPA Clean Power Plan scenario) would affect the environmental and economic performance of the battery electric vehicle by combining an economic dispatch power system model and a passenger car comparison model.

2 Research Algorithm

In general, the research consists of three phases: power system modeling, mitigation cost curve derivation and electric vehicles competitiveness analysis. Figure 1 shows the overall research algorithm.

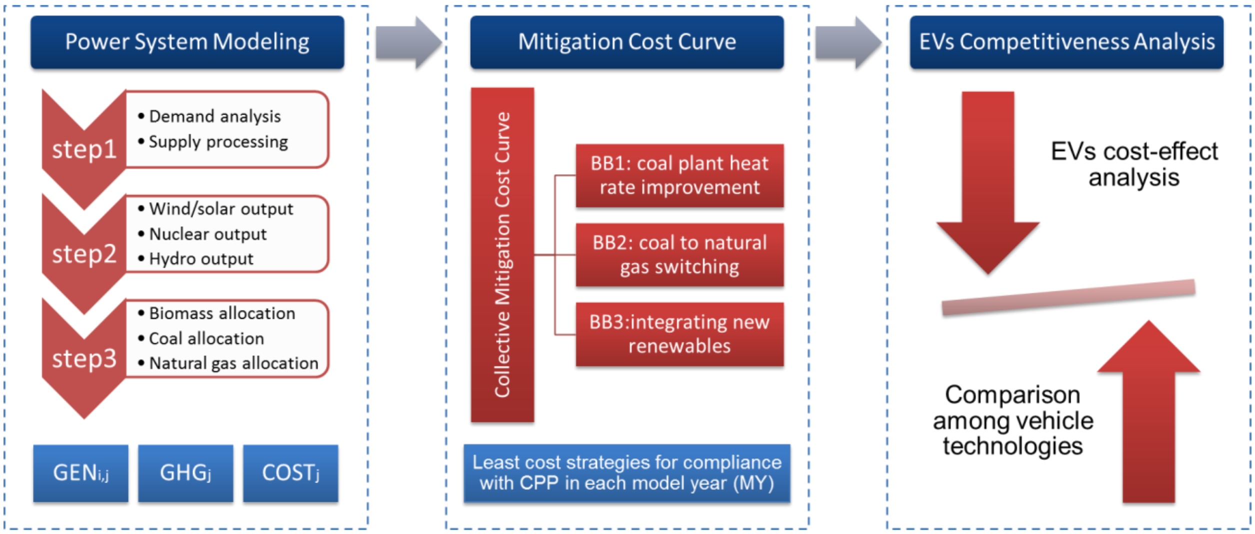


Figure 1. Research Algorithm Overview

First, I employ high-resolution data to build a linear economic dispatch model with Matlab, for estimating generations, GHG emissions, and production costs of coal, natural gas, and biomass plants in the power system under different scenarios. Second, I use the power system model to derive the collective mitigation cost curves, covering all available strategies, to comply with CPP. Referring to the emissions goal for each model year, I identify the least cost strategies, and forecast the generation profiles of the power system under CPP scenario. Finally, using the results from power system modeling for CPP scenario, I conduct a cost-effect analysis to investigate the impacts of the change in power system to the costs and GHG mitigations of EVs, and compare with other vehicle technologies.

3 Power System Modeling

3.1 Modeling Subject

My power system model develops for the electric grid in the Electric Reliability Council of Texas (ERCOT) service area. ERCOT is the independent system operator (ISO) for Texas, covering approximately 75% of the land area in Texas and providing about 90% of Texas electric load (ERCOT, 2016a). Figure 2 shows the geographic boundary of the ERCOT region.

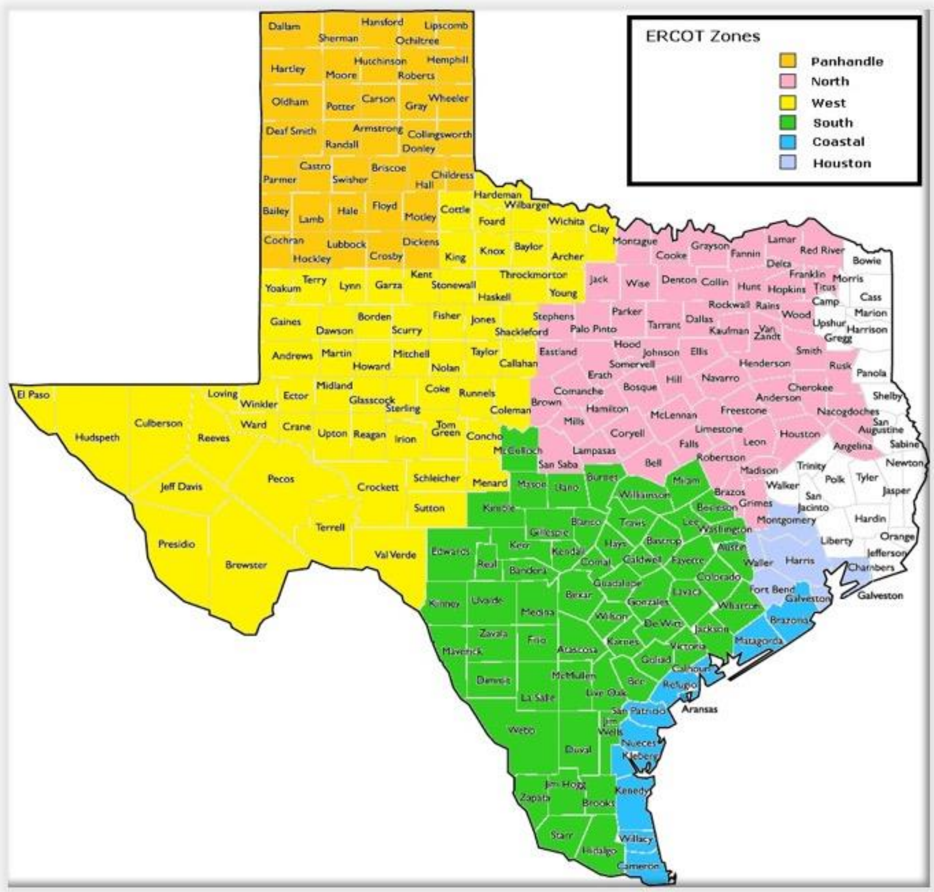


Figure 2. Geographic boundary of ERCOT zones (ERCOT, 2016b)

Two advantages make Texas an attracting place for modeling. First, the electric grid in Texas is independent with low import rates, and suffers few transmission constraints. More importantly, Texas has plentiful energy potential with large amounts of fossil fuel resources such as oil, gas, coal and uranium, as well as even more renewable resources such as wind, solar and biomass.

The wind, solar and biomass potential in Texas is equal to 4,330 quadrillion British Thermal Units (BTUs) per year, or about 400 times the amount of energy our State uses per year (SECO, 2006).

ERCOT has two characteristics, which are important for model build-up. First, it is an energy-only market, which means there is no capacity value for the electricity generated in that region. Moreover, the market is totally deregulated, which means that the generation for each unit is determined by its bidding price (or dispatch cost) and the native load.

3.2 Data and Methods

Figure 3 shows the process to build the power system model, which comprises three steps.

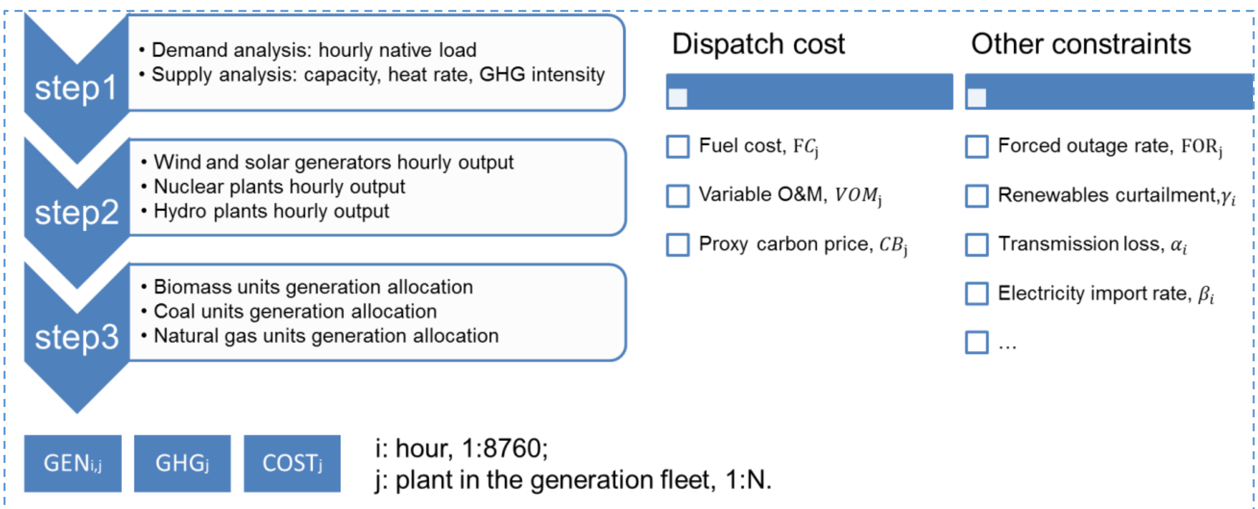


Figure 3. Power System Model Overview

First, I investigate the hourly native demand for each model year, and compile the operational information such as nameplate capacity, heat rate (the efficiency of fuel burning), and GHG intensity of each supplier in ERCOT generation fleet from several databases. Then, I identify the hourly output from all non-dispatchable resources including wind, solar, nuclear and hydro plants for each model year. Finally, I allocate the generation among all dispatchable resources according to their dispatch costs, which consist of fuel costs, and variable operation and maintenance (O&M) costs in the base case, adding proxy carbon prices in other cases (this will be further illustrated in chapter 4.2). I also consider several constraints including the forced outage rate (FOR) for each unit, grid-wide renewable curtailment (curtailment of wind and solar resources typically occurs because of transmission congestion or lack of transmission access), transmission and distribution losses, and electricity import from other interconnections.

3.2.1 Demand and Supply Analysis

Hourly native demand by ERCOT control area is available for the entire year. Data in 2012 and 2015 is obtained from the historical records (ERCOT, 2012, 2015). Hourly demand forecast for 2017-2026 is taken from ERCOT Long-Term Hourly Peak Demand and Energy Forecast (ERCOT, 2016c). Hourly demand for 2027-2030 is forecasted by extrapolating beyond the demand level of 2026 with the average monthly growth rate from ERCOT's forecasts for 2017-2026. To account for the difference between the native demand and the generation required in ERCOT, I assume a constant transmission and distribution loss as 7.2%, and a constant import rate as 0.55% for each hour's native demand. Then, the generation required to be met by all sources is calculated with Equation 1.

$$GA_i = \frac{Demand_i}{(1-\alpha)*(1+\beta)} \quad (1)$$

where GA_i (MW) is the generation required to be met by all sources for each hour, $Demand_i$ (MW) is the hourly native demand in ERCOT, α (%)is the transmission and distribution loss and β (%) is the import rate.

The operational information of suppliers is compiled from several databases by matching the DOE/EIA ORIS plant or facility code. Fuel type, prime mover type, nameplate capacity, heat rate, and GHG intensity are compiled from the Emissions & Generation Resource Integrated Database (eGRID) (US EPA, 2012), Clean Power Plan Final Rule Technical Documents (US EPA, 2015), and EIA Form-860 (US EIA, 2012). Information on forced outage rate for each type of electric technology is assumed based on several technical reports for ERCOT region (ERCOT, 2016; Texas RE, 2016). Table 1 shows the forced outage rates by unit technology type used in the model.

Table 1. Forced Outage Rates by Technology Type

Technology Type	Forced Outage Rate (%)
Coal	7.50%
Lignite	7.11%
Natural Gas Combined Cycle, NGCC	4.58%
Natural Gas Combustion Turbine, NGCT	10.17%
Natural Gas Steam Turbine, NGST	10.17%
Biomass	3.00%
Oil	10.78%

For historical model years, fuel cost of each fossil unit is matched from EIA Form-923 (US EIA, 2012), and fuel cost of biomass plants is assumed at a uniformed level across Texas (US EIA, 2015). For future model years, price forecasts of Henrry Hub natural gas, steam coal and other fuels are referred to the EIA Annual Energy Outlook (US EIA, 2017). Variable O&M cost for each existing or expansion technology is assumed according to the value that ERCOT used in a study on their transmission planning for 2012-2032 (ERCOT, 2013). Table 2 shows the fuel costs assumptions in this research.

Table 2. Fuel Costs by Fuel Type (2015$/MMBtu)

Model Year	Coal	Lignite	Natural Gas	Oil	Biomass
2012	$2.08	$2.60	$3.14	$24.04	$1.55
2015	$2.25	$2.25	$2.63	$15.08	$2.70
2022	$2.30	$2.30	$4.20	$18.14	$2.70
2023	$2.30	$2.30	$4.23	$18.46	$2.70
2024	$2.30	$2.30	$4.36	$18.78	$2.70
2025	$2.30	$2.30	$4.45	$19.25	$2.70
2026	$2.30	$2.30	$4.59	$19.60	$2.70
2027	$2.29	$2.29	$4.70	$19.80	$2.70
2028	$2.28	$2.28	$4.81	$19.82	$2.70
2029	$2.27	$2.27	$4.90	$20.07	$2.70
2030	$2.27	$2.27	$4.94	$20.50	$2.70

3.2.2 Non-Dispatchable Resources Analysis

The second step is to analysis the hourly outputs of all the non-dispatchable sources including wind, solar, nuclear and hydro plants for each model year, and then subtract from the hourly generation required to calculate the generation to be fulfilled by dispatchable sources. For model years 2012 and 2015, the hourly wind, nuclear and hydro outputs are obtained from ERCOT datasets (ERCOT, 2014, 2015; ERCOT, 2015). Due to low penetration of solar generation before 2015, I do not consider the hourly contribution from solar in historical years. For future years, hourly outputs from nuclear and hydro are assumed constant at the 2015 level, while those from wind and solar is forecasted based on the penetrations of the wind and solar for each model year. Wind and solar curtailment rate in ERCOT region is assumed as 3.7% in 2012, and 0.5% in 2015 and beyond (US DOE, 2014). Then, the generation required to be met by dispatchable sources is calculated with Equation 2.

$$GD_i = GA_i - Hyd_i - Nuc_i - (Wd_i - S_i) * (1 - \omega) \quad (2)$$

where GD_i (MW) is the generation required to be met by dispatchable sources for each hour, Hyd_i is the hourly output from hydro plants, Nuc_i is the hourly output from nuclear plants, Wd_i is the hourly output from wind plants, S_i is the hourly output from hydro plants, and ω is the wind and solar curtailment rate.

3.2.3 Economic Dispatch Allocation

The generation allocation among coal, natural gas, and biomass plants is determined with an economic dispatch model, which relies on linear programing to determine the least-cost generators for the entire power system. The problem is solved chronologically in hourly intervals across the whole year. The economic dispatch model minimizes the generation cost for each hour, by determining the dispatch order in the fleet according to their dispatch costs, and identifying the least-cost generators. The dispatch cost for each unit is influenced by its heat rate, fuel price, variable O&M cost, and other factors. Constraints to the optimization include matching supply to demand for each hourly intervals, unit output limit (min/max load), and generator availability (impacted by forced outage rate). The general principal of the economic dispatch model can be expressed with Equation 3 to Equation 7.

Minimize $C_{\mathrm{total}} = \sum_{i=1}^{8784} \sum_{j=1}^{N} C_j \ (GEN_{i,j})$ (3)

Subject to $GD_i - \sum_1^{\mathrm{N}} \mathrm{GEN_{i,j}} = 0$ (4)

$$GENmin_{i,j} \leq GEN_{i,j} \leq \mathrm{Capacity_j} * \mathrm{FOR_j} \quad (5)$$

$$C_j = FC_j + VOM_j + CB_j * CI_j \quad (6)$$

$$FC_j = FP_j * HR_j/1000 \quad (7)$$

where C_{total} ($/yr) is the annual total generation cost for the power system, j is the generation unit in the fleet, C_j ($/MWh) is the dispatch cost for each unit, $GEN_{i,j}$ (MW) is the allocated generation for each unit in each hour, Capacity_j (MW) is the nameplate capacity for each unit, FOR_j is the forced outage rate for each unit, FC_j ($/MWh) and VOM_j ($/MWh) are the fuel cost and variable O&M cost, CB_j ($/tons CO_2) is the proxy carbon price, CI_j (tons CO_2/MWh), FP_j ($/MM BTUs) is the fuel price, and HR_j (BTUs/kWh) is the heat rate.

Then, the annual generation GEN_j, production cost $GOST_j$, and GHG emissions GHG_j for each unit are calculated with Equation 8 to Equation 3.

$$GEN_j = \sum_{i=1}^{8760} G_j * GEN_{i,j} \tag{8}$$

$$GOST_j = \sum_{i=1}^{8760} (FC_j + VOM_j) * GEN_{i,j} \tag{9}$$

$$GHG_j = \sum_{i=1}^{8784} CI_j * GEN_{i,j} \tag{4}$$

3.3 ERCOT 2012 Test Results

The power system model can be used for any model year in ERCOT, and different system characteristics in different years under different scenarios will give different outputs of generation allocations, production costs, and GHG emissions. This section shows the results of the test for ERCOT 2012. The Matlab calculation algorithm for ERCOT 2012 is shown in Appendix 1.

Figure 4. ERCOT 2012 Hourly Generation Profile shows the estimated generation profile by fuel type on hourly basis in ERCOT for the entire year of 2012. Nuclear, coal and efficient natural gas (most NGCC) units form the bulk of the baseload, while inefficient natural gas (most natural

gas combustion/steam turbine) units undertake the rest of the demand.

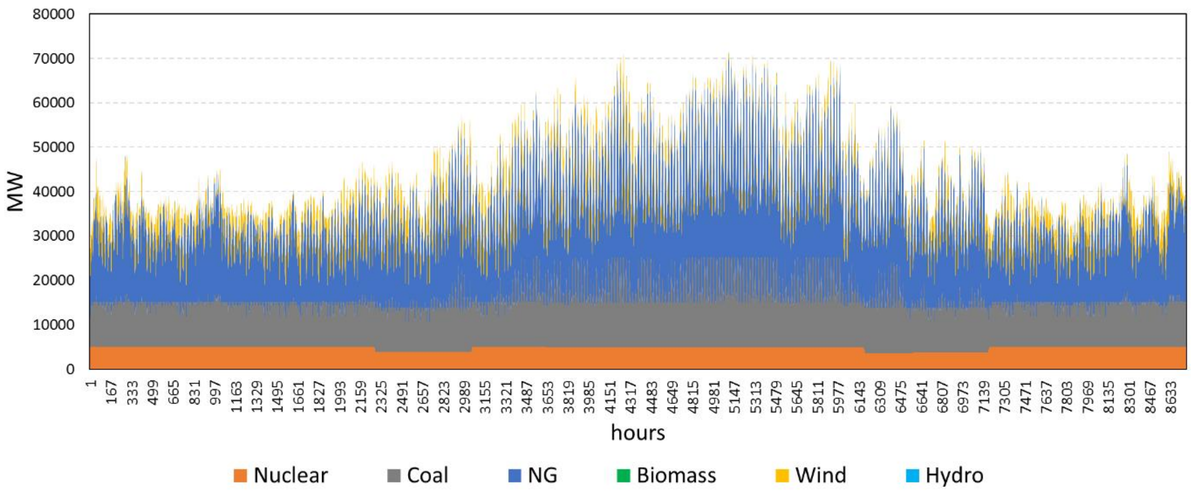


Figure 4. ERCOT 2012 Hourly Generation Profile

Table 3 summarizes the generation mix. Natural gas is the biggest source of electricity with a share of 55%, followed by coal with 31%. Nuclear and wind contribute to 13% and 9% of total generation.

Table 3. ERCOT 2012 Generation Mix

Fuel type	GEN (TWh)	Share (%)
Natural Gas	178	51%
Coal	99	29%
Wind	30	8.6%
Biomass	0.46	0.13%
Hydro	0.11	0.03%
Nuclear	41	12%

Figure 5 and Figure 6 present the distributions of marginal GHG intensity and the Locational Marginal Pricing (LMP) across the year, indicating that the dirtiest marginal generators, along with the most expensive electricity occur during the afternoon of summer months when most inefficient natural gas combustion/steam turbine units are at the margin.

t/MWh	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1:00:00	0.6210	0.6195	0.5661	0.6475	0.6463	0.5024	0.5388	0.5380	0.5010	0.6652	0.7298	0.6198
2:00:00	0.6462	0.5855	0.6003	0.5756	0.5973	0.4559	0.4225	0.5310	0.4726	0.7137	0.7259	0.5988
3:00:00	0.6707	0.6526	0.6217	0.6257	0.6197	0.4597	0.4546	0.5619	0.5240	0.7664	0.7509	0.5157
4:00:00	0.5987	0.7071	0.6449	0.7024	0.5932	0.4712	0.4293	0.5407	0.5016	0.7097	0.7002	0.4992
5:00:00	0.5505	0.6409	0.7457	0.6562	0.5689	0.5276	0.4366	0.4584	0.4799	0.5959	0.6778	0.6503
6:00:00	0.6196	0.5888	0.5964	0.5110	0.6173	0.4485	0.5146	0.6261	0.5884	0.5690	0.6034	0.4972
7:00:00	0.5216	0.5126	0.4744	0.4262	0.6268	0.5084	0.5583	0.6918	0.5327	0.4183	0.5153	0.5024
8:00:00	0.5562	0.5112	0.4718	0.4476	0.4798	0.5018	0.5758	0.5013	0.5088	0.4291	0.6138	0.5629
9:00:00	0.4814	0.5406	0.5334	0.4702	0.5404	0.6041	0.5833	0.6629	0.5811	0.5537	0.4948	0.4957
10:00:00	0.4752	0.4765	0.5230	0.4568	0.5403	0.7514	0.8271	0.9242	0.7515	0.5130	0.4214	0.5090
11:00:00	0.4253	0.4245	0.4974	0.4622	0.6463	0.7756	1.0080	0.9071	0.7648	0.6248	0.4720	0.4839
12:00:00	0.4713	0.5024	0.4959	0.5139	0.7105	0.8989	0.7971	0.8445	0.8534	0.5554	0.4529	0.4822
13:00:00	0.4686	0.4987	0.4288	0.6524	0.7712	0.9122	0.7515	0.8719	0.8101	0.6284	0.4850	0.5352
14:00:00	0.5274	0.5026	0.4713	0.6253	0.8603	0.8777	0.7774	0.8060	0.8505	0.6767	0.4121	0.4799
15:00:00	0.5384	0.5157	0.4500	0.6067	0.8597	0.8205	0.8899	0.7957	0.8689	0.7007	0.5039	0.4850
16:00:00	0.5198	0.5320	0.4730	0.6313	0.7322	0.8651	0.8592	0.8370	0.8362	0.7440	0.4929	0.5033
17:00:00	0.5276	0.5572	0.5066	0.5908	0.7697	0.8526	0.9114	0.8696	0.9283	0.7542	0.4767	0.5516
18:00:00	0.4767	0.4302	0.4775	0.5176	0.8498	0.8675	0.7668	0.8232	0.8552	0.5881	0.4791	0.5013
19:00:00	0.5059	0.4653	0.4888	0.6694	0.7338	0.8136	0.8059	0.7781	0.8161	0.6793	0.5100	0.4716
20:00:00	0.5803	0.4924	0.4727	0.6816	0.7828	0.8116	0.9187	0.8751	0.8237	0.5741	0.5326	0.5359
21:00:00	0.5294	0.4969	0.4984	0.5929	0.6313	0.7925	0.8902	0.9073	0.7441	0.5870	0.4432	0.5114
22:00:00	0.5393	0.4567	0.5130	0.4868	0.5565	0.7289	0.7281	0.8219	0.6619	0.5522	0.4947	0.5364
23:00:00	0.4976	0.4491	0.5447	0.4203	0.5050	0.6532	0.6581	0.6321	0.5382	0.4858	0.4447	0.5076
0:00:00	0.5206	0.6131	0.6935	0.7230	0.4980	0.5164	0.5556	0.5447	0.4878	0.5953	0.6493	0.4659

Red: dirty electricity **Green**: cleaner electricity

Figure 5. ERCOT 2012 marginal GHG intensity distribution

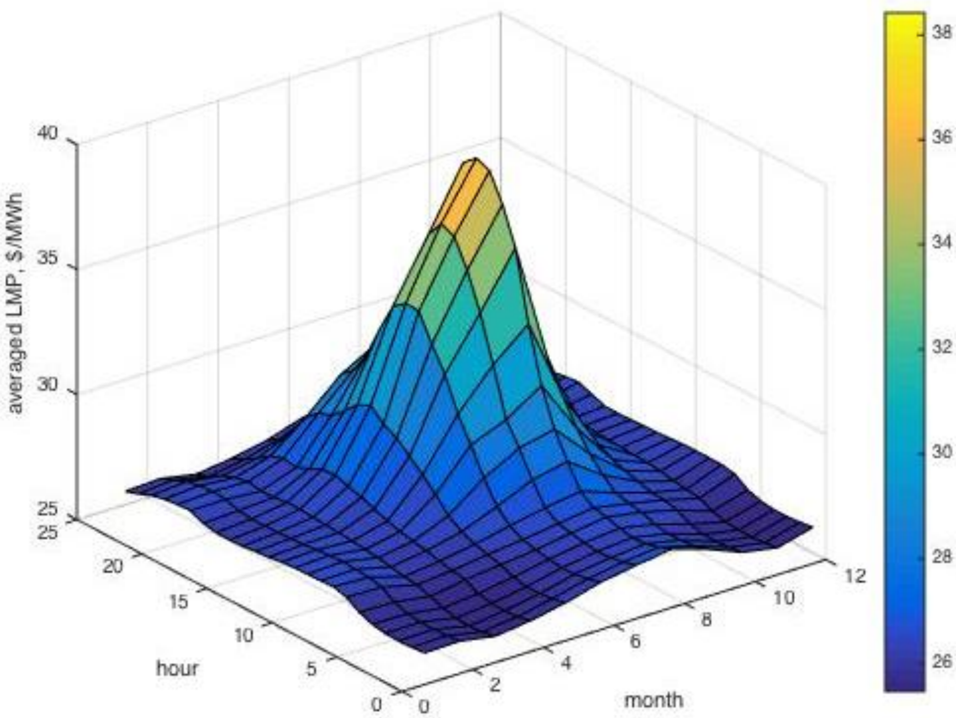


Figure 6. ERCOT 2012 Locational Marginal Pricing (LMP) distribution

Figure 7. ERCOT 2012 average daily GHG intensity and LMPFigure 7 shows the average daily patterns of GHG intensity and LMP of the marginal unit. The GHG intensity ranges from 0.5 tons CO_2/MWh to 0.7 tons CO_2/MWh, with an average value of 0.65 CO_2/MWh. The electricity generation cost ranges from 25.5 \$/MWh to 30.0 \$/MWh, with average rate of \$29.6 during peak hours (hour 14-18), and 26.0 \$/MWh during off-peak hours (hour 2-5).

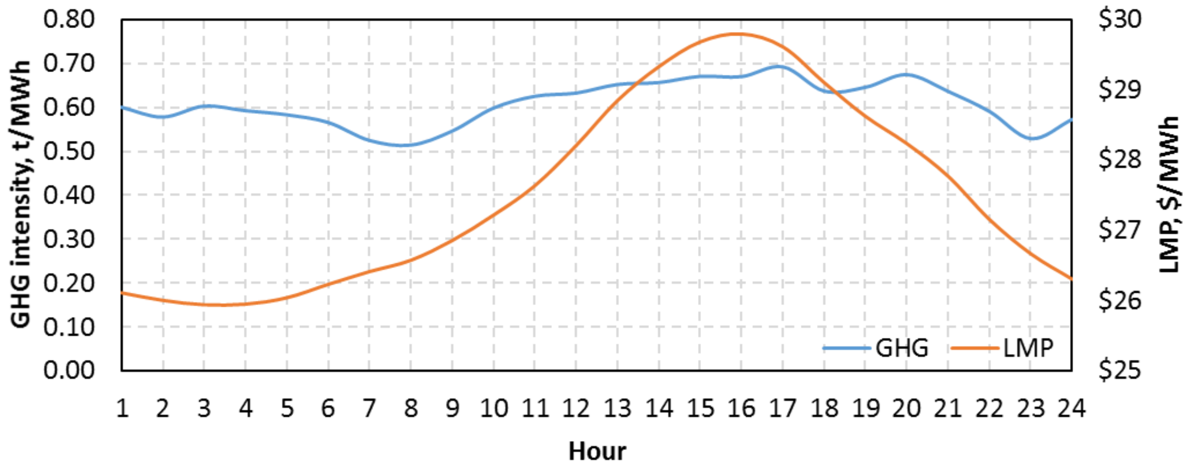


Figure 7. ERCOT 2012 average daily GHG intensity and LMP

4 Mitigation Cost Curve

In this chapter, I derive the mitigation cost curves for compliance with the EPA Clean Power Plan (CPP), and then investigate how the grid will be look like in terms of generation mix and production costs under the CPP scenario.

4.1 Scenario Definition

The Clean Power Plan is the first-ever national standard that address carbon pollution from power plants in the United States (US EPA, 2016). EPA establishes interim and final carbon dioxide emission performance goals from 2022-2030 for existing fossil fuel-fired electric steam generating units, and natural gas-fired combined cycle generating units beyond the 2012 base year level. The statewide goals can be chosen as either rate-based (lb/MWh), or mass-based (short tons of CO_2). In CPP, EPA determines that the best system of emissions reduction (BSER) consists of the following three building blocks:

- Building Block 1 - reducing the carbon intensity of electricity generation by improving the heat rate of existing coal-fired power plants.
- Building Block 2 -substituting increased electricity generation from lower-emitting existing natural gas plants for reduced generation from higher-emitting coal-fired power plants.
- Building Block 3 - substituting increased electricity generation from new zero emitting renewable energy sources (like wind and solar) for reduced generation from existing coal-fired power plants.

In this research, I choose to use the mass-based goals, and calculate the goals for ERCOT region according to the method illustrated in CPP Technical Support Document for statewide emission performance rate and goal computation (US EPA, 2015). For comparison, I also estimate the GHG emissions in a business as usual (BAU) scenario, which assumes that ERCOT generation fleet is unchanged (except for very few ordinary retirements) since 2015. The GHG emissions in the BAU scenario and the mass-based goals of CPP are compared in Figure 8. The difference between the two lines represents the mitigation required for compliance to CPP.

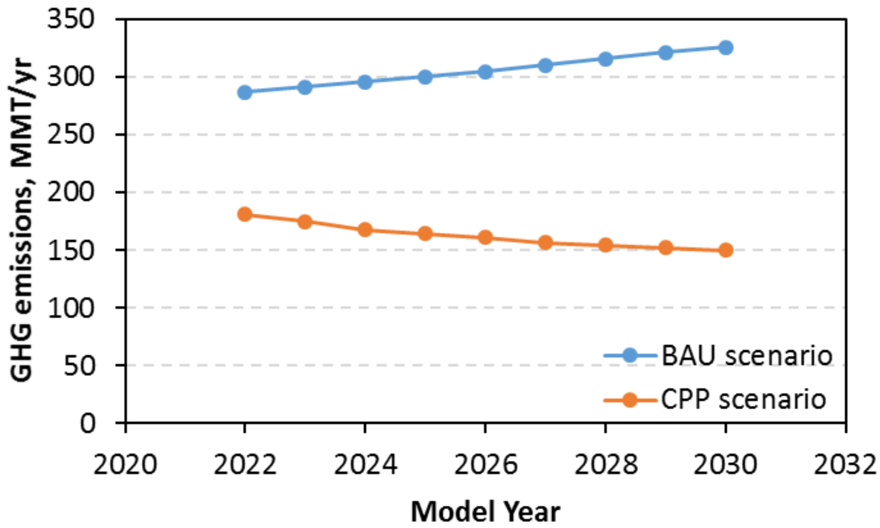


Figure 8. Comparison of GHG emissions in BAU and CPP scenarios in ERCOT region

4.2 Data and Methods

To derive the collective mitigation cost curves, I estimate the mitigation cost and capacity for each strategy within the category of the three building blocks: improving coal plant efficiency, switching from coal to natural gas, or integrating more renewables. The methods for mitigation cost and capacity calculation are different across the three building blocks.

4.2.1 Coal Plant Heat Rate Improvement

Improving the efficiency of existing coal plants will reduce the GHG intensity of the electricity generated by coal. EPA requires a heat rate improvement of 2.3% for Texas Interconnection, and assumes the cost for retrofit as 100,000 \$/MW. Then, the mitigation cost and capacity for coal plant heat rate improvement $\text{Mcost}_{1,\text{j}}$ (\$/ton CO_2) and $\text{Mcap}_{1,j}$ (ton CO_2) are calculated with Equation 11 to Equation 14.

$$Mcost_{1,j} = \frac{Capitalinvest_{1,j} - Fuelsavings_{1,j}}{Mcap_{1,j}} \tag{5}$$

$$Capitalinvest_{1,j} = 100000\,\$/MW * Capacity_j * CRF \tag{6}$$

$$Fuelsavings_{1,j} = 2.3\% * HR_j * GEN_j * FP_j/1000 \tag{7}$$

$$Mcap_{1,j} = 2.3\% * HR_j * GEN_{i,j} * \frac{Coal}{2000}/1000 \tag{8}$$

where $Capitalinvest_{1,j}$ ($) is the capital investment for coal plant retrofit, CRF is the capital recovery rate assumed as 11.75%, $Fuelsavings_{1,j}$ ($) is the fuel savings due to higher efficiency, and $Coal$ (lb CO_2/MM BTUs) is the GHG intensity of coal, which is 214.3 for Subbituminous coal and 215.4 for lignite.

An example of the Matlab calculation algorithm for heat rate improvement in model year 2022 is shown in Appendix 2.

4.2.2 Coal to Natural Gas Switching

Switching generation from existing coal plants to existing natural gas plants will reduce the total GHG emissions of the entire power system. However, most natural gas plants ranks higher than the coal plants in the original dispatch order since natural gas is a more expensive fuel type. Therefore, I apply a series of proxy carbon prices *CB* = 1:30 $/ tons CO_2 to model the switching process and identify the least-cost switching options. The proxy carbon prices only affect the dispatch costs, and do not change the generation costs for each unit. The mitigation cost and capacity for coal to natural gas switching $\mathrm{Mcost}_{2,\mathrm{CB}}$ ($/ton CO_2) and $\mathrm{Mcap}_{2,CB}$ (ton CO_2) are calculated with Equation 15 and Equation 16.

$$Mcost_{2,j} = \frac{COST_{CB} - COST_0}{GHG_{CB} - GHG_0} \tag{15}$$

$$Mcap_{2,CB} = GHG_{CB} - GHG_0 \tag{16}$$

An example of Matlab calculation algorithm for coal to natural gas switching in model year 2022 is shown in Appendix 3.

4.2.3 New Renewables Integration

Integrating new renewable projects, and increasing the share of the electricity generation by renewables will decrease the GHG emissions of the whole power system. The mitigation capacity from new wind and solar projects is determined by their potentials to generating electricity. The mitigation cost through increasing renewables largely depend on the capital investment required.

The mitigation cost for new wind or solar project $Mcost_{3,k}$ (\$/ton CO_2) is calculated as the capital investments with incentives $Capitalinvest_{3,k}$ (\$/MWh) minus the value of the electricity they offset $Evalue_{3,k}$ (\$/MWh), then divided by the GHG intensity of the electricity they offset $GHGoff_{3,k}$ (ton CO_2/MWh), as shown in Equation 17.

$$Mcost_{3,k} = \frac{Capitalinvest_{3,k} - Evalue_{3,k}}{GHGoff_{3,k}} \tag{17}$$

The mitigation capacity for new wind or solar project $Mcap_{3,k}$ (\$/ton CO_2) is calculated as the product of their generation potential $GEN_{3,k}$ (MWh/yr) and the GHG intensity of the electricity they offset $GHGoff_{3,k}$ (t/MWh), which is shown in Equation 18.

$$Mcap_{3,k} = GEN_{3,k} * GHGoff_{3,k} \tag{18}$$

The capital investment for each renewable project is calculated as the levelized cost of electricity (LCOE) with incentives. LCOE represents the per-kilowatthour cost (in real dollars) of building and operating a generating plant over an assumed financial life and duty cycle, which is often cited as a convenient summary measure of the overall competiveness of different generating technologies. Key inputs to calculating LCOE include capital costs, fuel costs, fixed and variable O&M costs, financing costs, and an assumed utilization rate for the plant. For solar and wind generation that have no fuel costs and relatively small variable O&M costs, LCOE changes in rough proportion to the estimated capital cost of generation capacity. The availability of various incentives, including state or federal tax credits, can also impact the calculation of LCOE.

U.S. federal renewable incentives includes accelerated depreciation, production tax credit (PTC) and investment tax credit (ITC). Depreciation is a measure of how much of an asset's value has been “used up.” Businesses are allowed to depreciate their capital investments by writing off the expenditures, deducting these costs from profits before paying corporate taxes. An accelerated tax depreciation schedule is an advantage, due to the time value of money. In the U.S., renewable energy systems can be depreciated on using a MACRS (Modified Accelerated Cost Recovery System) depreciation schedule. In this research, all wind and solar projects follow the depreciation schedule as “MACRS + 50% Bonus”, which means 84% net present value tax savings at 10% discount rate.

Production Tax Credit (PTC) is a 10-year subsidy provided to certain renewables (adjusted for inflation) in the U.S. The first-year PTC incentives for wind and solar projects are shown in Appendix 4. I assume 2% inflation rate with 20-year project life (PTCs is received for first 10 years). Then LCOE with PTCs and depreciation can be calculated with Equation 19 to 21.

$$LCOE = \frac{(FCR * Capital\ costs + FOM)}{Annual\ Generaion} - PV_{PTC} + VOM + Fuel \qquad (19)$$

$$FCR = \frac{0.1*(1+0.1)^{20}}{(1+0.1)^{20}-1} * \frac{1-(T*84\%)}{(1-T)} \tag{20}$$

$$PV_{PTC} = \frac{\sum_{t=1}^{20} \frac{PTC_t}{(1+0.02)^t}}{\sum_{t=1}^{20} \frac{Annual\ Generation_t}{(1+0.02)^t}} \tag{21}$$

where PV_{PTC} is the present value of the production tax credit ($/MWh), PTC_t is the value of the production tax credit in Year t ($), $Annual\ Generation_t$ is the annual generation in Year t (MWh). FCR is fixed charge rate (%), which represents the before-tax annual revenue required to cover costs and achieve desired after-tax return. T is the effective corporate tax rate (%), which is 35% in this research since Texas has no state corporate tax.

Investment Tax Credit (ITC) is a U.S. incentive, based on the investment cost of a renewable project. The ITC incentives for wind and solar projects are shown in Appendix 4. In this research, I assume 95% of the project costs qualify for claim, and the incentive is claimed in the year commercial operations begin. Then LCOE with ITCs and depreciation can be calculated with Equation 22 to 23.

$$LCOE = \frac{(FCR*Capital\ costs*(1-ITC*95\%)+FOM)}{Annual\ Generaion} + VOM + Fuel \tag{22}$$

$$FCR = \frac{0.1*(1+0.1)^{20}}{(1+0.1)^{20}-1} * \frac{1-(T*84\%*\left(1-\frac{ITC*95\%}{2}\right))}{(1-T)} \tag{23}$$

The identification of potential renewable projects in ERCOT region, and the calculation of LCOE with incentives are explained for wind and solar respectively. For each renewable project, the ultimate LCOE is determined with a lower value of LCOE w/ ITC and that w/ PTC. The assumptions on the capital costs and fixed O&M costs of wind and solar for LCOE calculation are also listed in Appendix 4.

Potential wind projects identification

The information for identifying the potential wind projects is from a study by AWS Truepower on wind generation patterns simulation for the ECORT area (AWS Truepower, 2012). In that study, AWS Truepower (AWST) was engaged by the ERCOT to provide 15 years of wind power data for 84 existing wind sites, 11 queue sites (under construction), 130 hypothetical sites (onshore large wind > 100 kW), and three offshore sites. Based on those data, the wind sites distribution in ERCOT region is shown in Figure 9. Their study also provides the hourly generation profile for the 130 hypothetical onshore sites across an entire year. I abstract all their hypothetical onshore and offshore wind sites as the potential wind projects in my study. The total capacity of hypothetical onshore wind is 17.9 GW, and that of offshore wind is 1.5 GW. The hourly generation profile for the three offshore sites are estimated by using the National Renewable Energy Laboratory (NREL) System Advisor Model (SAM).

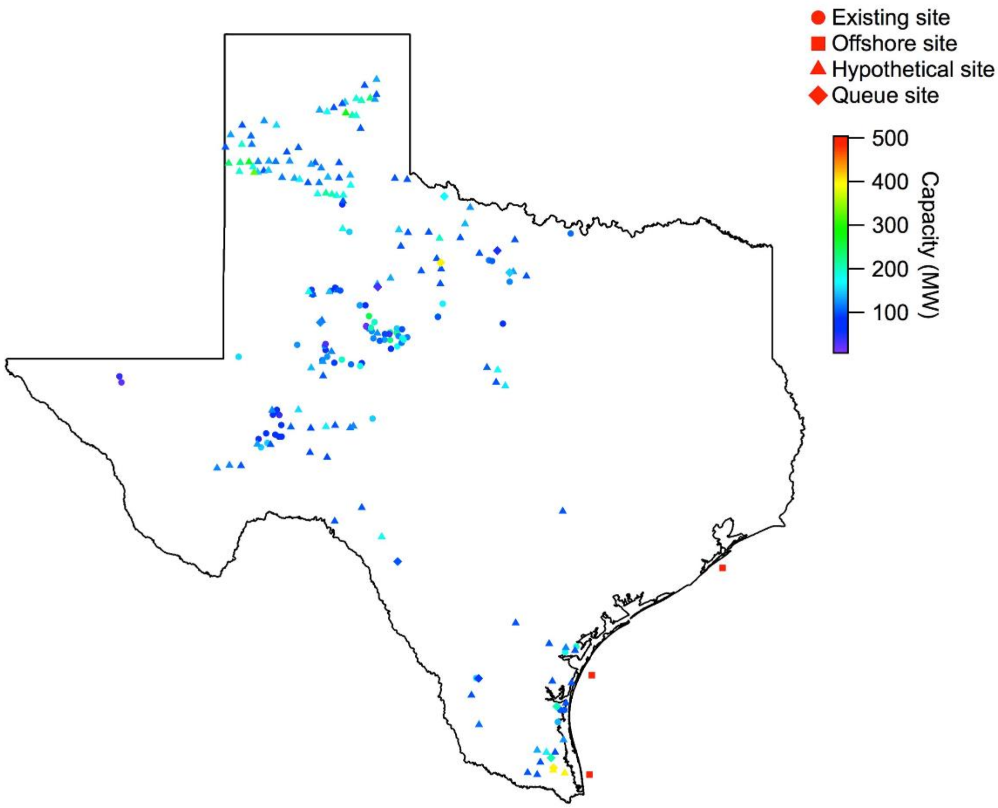


Figure 9. Capacity and geographical locations of all wind sites in Texas

LCOE calculation for the potential wind projects

The results of LCOE calculation vary with different start years of the wind projects operation. Table 4. Financial Parameters for wind projects LCOE CalculationTable 4 lists the intermediate results of financial parameters for LCOE calculation of the wind projects for all the model years.

Table 4. Financial Parameters for wind projects LCOE Calculation

Year	PTC_1	PV_{PTC}	FCR	ITC	FCR w/ ITC
2015	$23.00	$17.90	12.76%	30%	13.51%
2022-2030	$0.00	$0.00	12.76%	0%	12.76%

Potential solar projects identification and LCOE calculation

I use the NREL System Advisor Model (SAM) to identify the potential solar project in Texas. To describe the renewable energy resource and weather conditions at a project location, SAM requires a weather data file. In this research, I choose the weather data file from the list provided by SAM, and test all the locations in Texas on the list. Finally, I identify 78 sites for utility solar PV projects, and generate the annual estimates of their energy production. The total capacity of the PV projects is 1560 MW.

LCOE calculation for the potential solar projects

Calculating LCOE for the potential solar projects follows the same method as explained for wind projects. Table 5 lists the intermediate results of financial parameters for LCOE calculation of the solar PV projects in all model years.

Table 5. Financial Parameters for solar projects LCOE Calculation

Year	PTC_1	PV_{PTC}	FCR	ITC	FCR w/. ITC
2015	$23.00	$17.90	12.76%	30%	13.51%
2022-2030	$0.00	$0.00	12.76%	10%	13.01%

4.3 Collective Mitigation Cost Curve

Ranking the mitigation costs from small to large among all strategies across the three building blocks, and accumulating the mitigation capacity of each strategy, the collective mitigation cost curve is derived. Figure 10 shows the collective mitigation cost curve for model year 2022. The cheapest strategies are coal to natural gas switching, followed by several onshore wind and coal plant retrofit. Solar and offshore wind are the most expensive options. Referring to the information provided in in Figure 8 of Chapter 4.1, the mitigation required in 2022 is calculated as 106 MMT. Therefore, all coal to gas switching projects, 36 onshore wind projects, and 10 coal plant retrofit projects are selected.

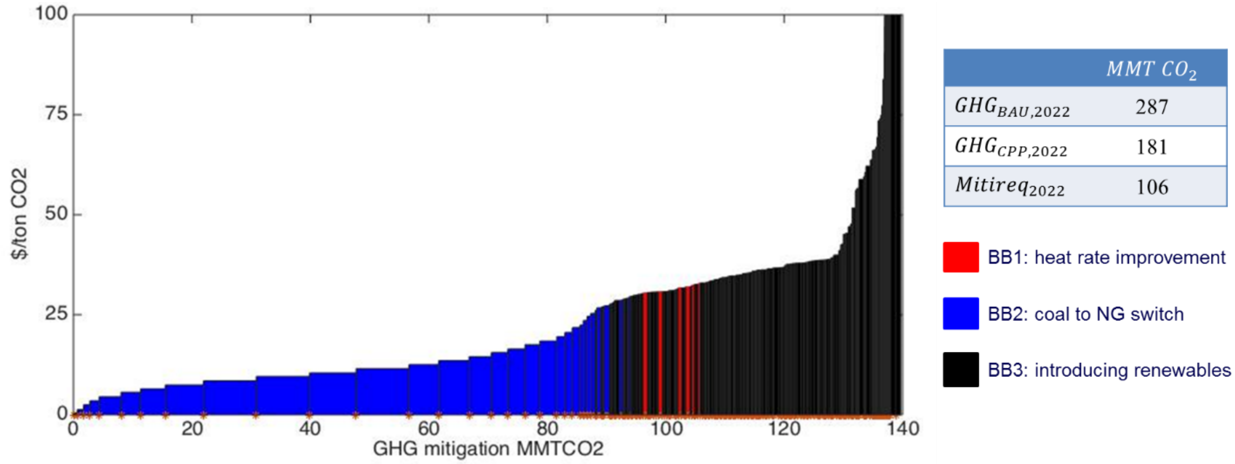


Figure 10. Collective mitigation cost curve for MY2022

4.4 ERCOT 2030 Forecasts

I repeat the process of deriving the collective mitigation cost curve, and identifying the least-cost strategies for compliance with the GHG emission goals from 2022 to 2030. Since this is a long-term forecast, the production capacity of the whole fleet should also change with the peak summer demand along the years. To maintain the reliability of the grid, I include new natural gas units into the grid to the point that the reserve margin of 13.4% is always satisfied. According to EPA regulation of greenhouse gas emissions for new power plants (US EPA, 2015), the heat rate of the new natural gas units is 8547 BTUs/kWh, and the GHG emission rate is 0.5 matric tons/MWh.

The final generation profile in 2030 is forecasted as shown in Figure 11, and summarized in

Table 6. The share of natural gas generation will increase to 60%, wind and solar will undertake about 23%, and coal will decrease to 17%.

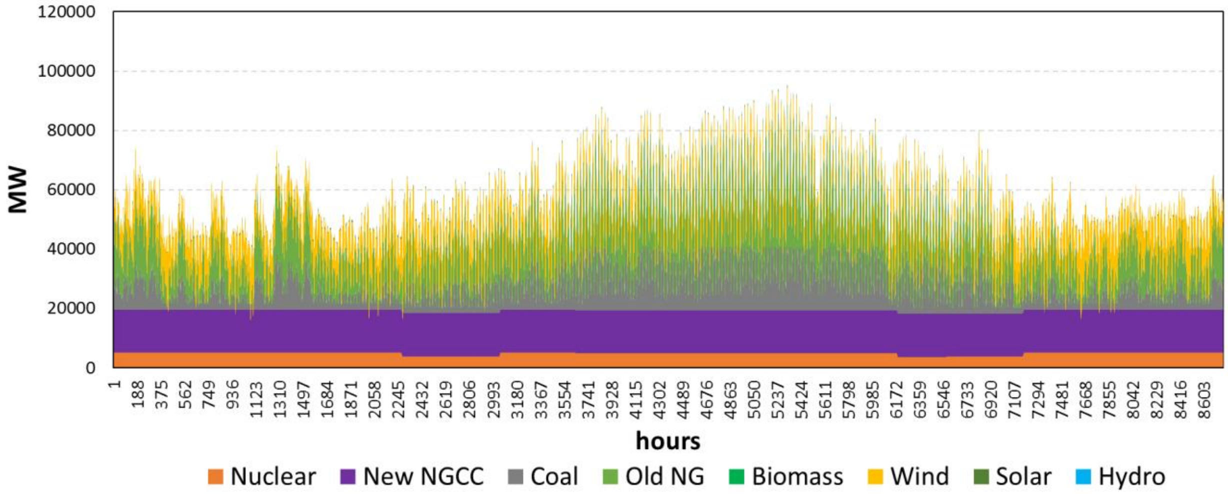


Figure 11. ERCOT 2030 hourly generation profile

Table 6. ERCOT 2030 Generation Mix Forecast

Fuel type	GEN (TWh)	Share (%)
New natural gas	127	29%
Old natural gas	137	31%
Coal	76	17%
Wind	96	22%
Solar	1.97	0.45%
Biomass	1.15	0.26%
Hydro	0.11	0.03%

Figure 12 shows the LMP distributions in model year 2012 and 2030. Due to a higher penetration of renewable sources, LMP in 2030 is has a higher fluctuation with a range from 24.54 $/MWh to 72.30 $/MWh. The average LMP in 2030 also increases with more coal to natural gas switching.

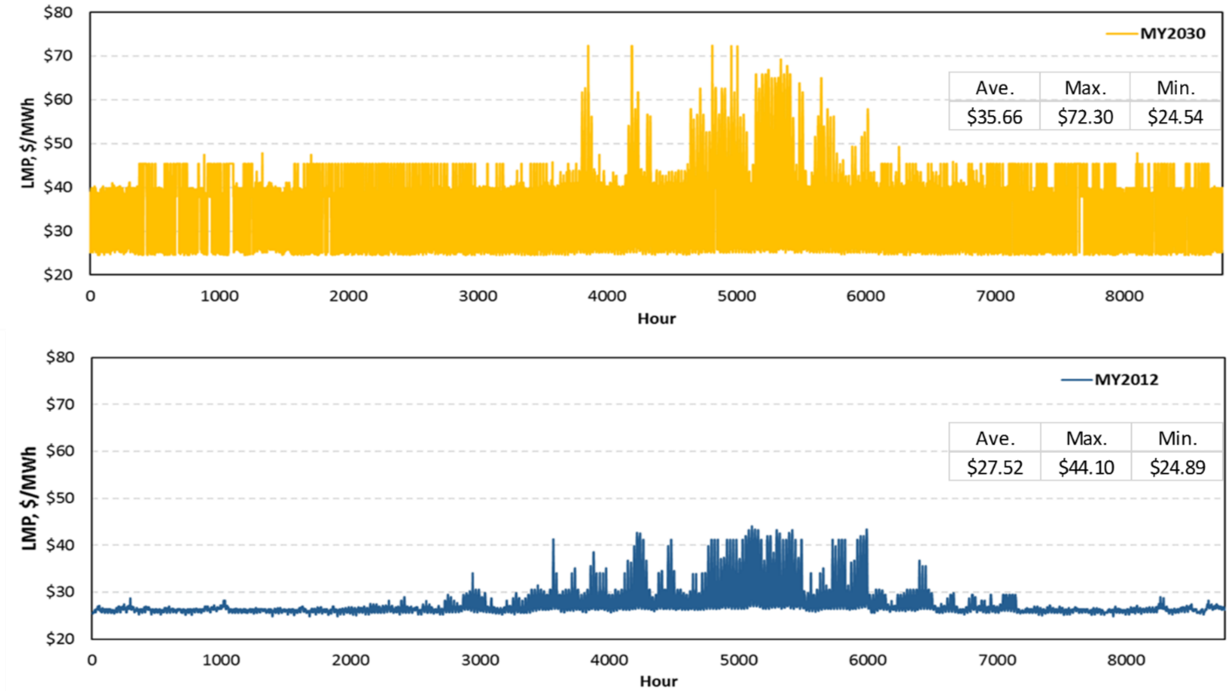


Figure 12. LMP Comparison for Model Year 2012 and 2030

Table 7 summarizes the change of LMP and GHG intensity from 2012 to 2030 under CPP scenario. The GHG intensity of the grid decreases 15% from grid update, while the average LMP increases 30%.

Table 7. GHG intensity and LMP Comparison in 2012 and 2030

Parameters	2012	2030
Generation (TWh)	349	439
GHG intensity (tons/MWh)	0.5724	0.4855
Ave. LMP ($/MWh)	$27.52	$35.66
Max. LMP ($/MWh)	$44.10	$72.30
Min. LMP ($/MWh)	$24.89	$24.54

5 Electric Vehicles Competitiveness

This chapter examines the impacts of the changing electric grid to the competitiveness of electric vehicles in the passenger car market by comparing the 2012 historical and 2030 projected total costs and the GHG emissions of electric vehicles (EV) with those of internal combustion engine vehicles (ICEV), non-plug-in hybrid electric vehicles (HEV), and fuel cell vehicles (FCV). Vehicle prices and vehicle efficiency improvement are estimated base on a technological cost analysis from National Research Council (NRC)'s study on different vehicle technologies through 2050 (NRC, 2013). Fuel prices is from EIA's forecasts (US EIA, 2017), while electricity prices is from the results of LMP estimates in chapter 4.

5.1 Electric Vehicles Use-Phase Impact Analysis

This section analyzes the influence of the changing electric grid on the annual GHG emissions and fuel costs of electric vehicles. The GHG emissions in the use phase of electric vehicles will decrease if charged with a cleaner electricity, while the fuel costs will increase due to a higher electricity rates. As technology progress goes on, the benefits from the improvement of electric vehicles efficiency will be amplified in terms of GHG mitigations, but be offset in terms of fuel cost savings. Table 8 summarizes the efficiency, costs and GHG emissions in the use phase of the electric vehicles in 2012 and 2030. I assume that the annual vehicle traveled (VMT) stay unchanged as 10,358 miles/yr, and the electricity rates as the average LMP. With the double benefits from vehicle efficiency improvement and electricity decarbonization, the annual GHG emissions from running electric vehicles in 2030 is 34% lower than that in 2012. However, the fuel savings from a higher vehicle efficiency cannot make up the fuel cost increase driven by a higher electricity rates.

Table 8. EV efficiency, fuel costs, and GHG emissions change from 2012 to 2030

	2012	2030
EV efficiency, miles/kWh	3.63	4.64
Electricity rates, $/MWh	$27.52	$35.66
Annual fuel cost, 2015$/yr	$79	$80
Annual GHG emissions, tons CO2/yr	1.64	1.08

To test the sensitivity of fuel costs to different charging times, I recalculate the fuel costs with the maximum and minimum LMPs of the electricity. The result is shown in Figure 13. Although fuel costs can be as high as $160/year if the vehicle is always charged at peak hours, fuel costs savings is available in 2030 with appropriate charging strategies.

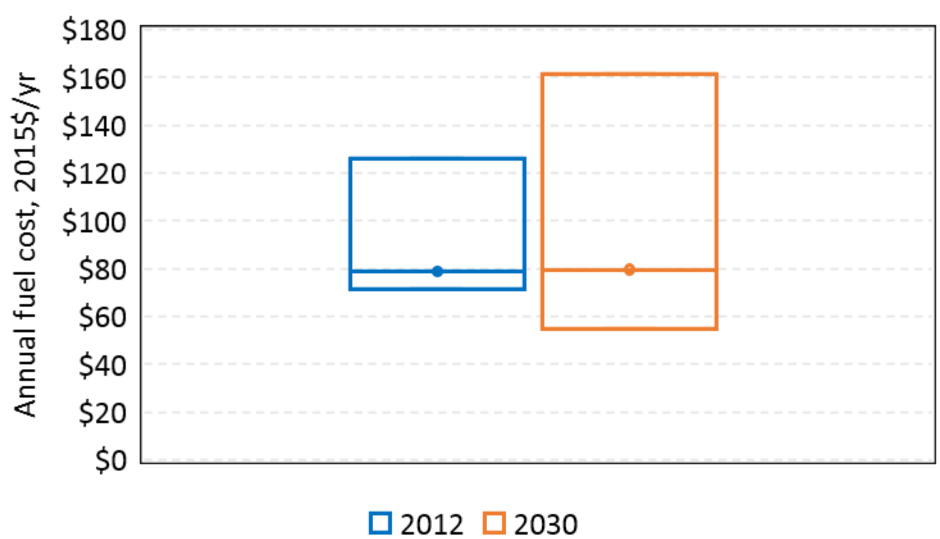
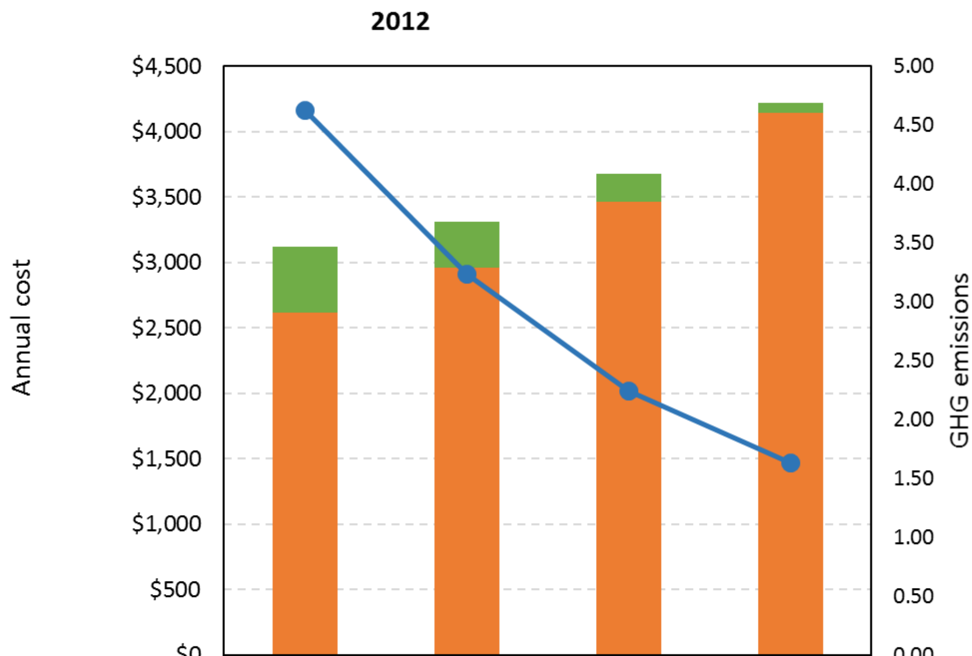


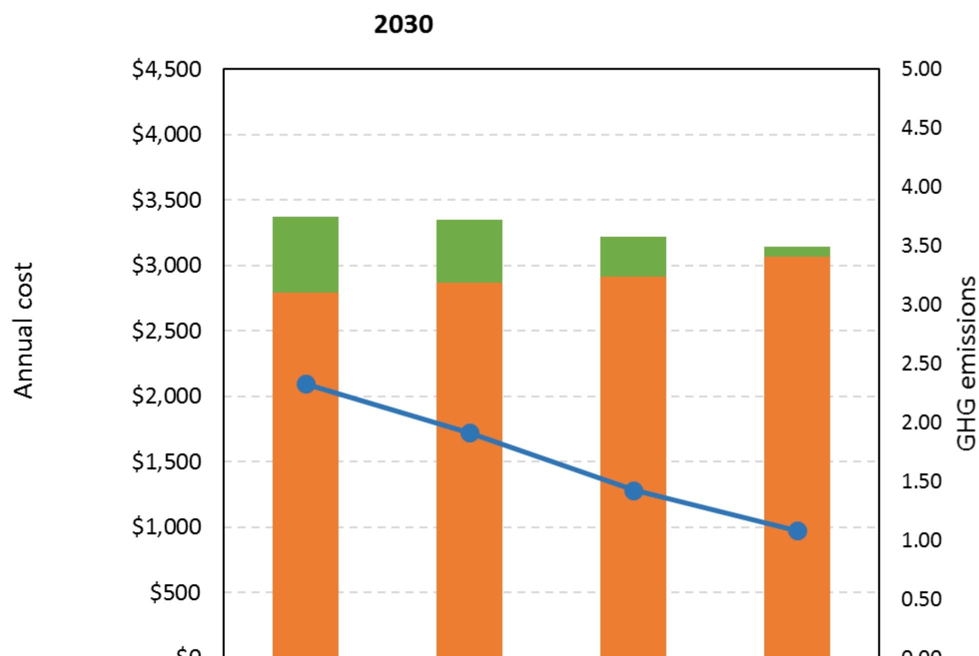
Figure 13. Annual fuel cost change for EVs

5.2 Vehicle Technologies Comparison

To figure out the change of competitive position of electric vehicles in the car market from 2012 to 2030, I compare the annual vehicle and fuel costs (at average LMP charging scenario), and GHG emissions of electric vehicles with other vehicle technologies. Figure 14 illustrates that the annual capital cost of electric vehicles (note as BEV) in 2030 will decrease by more than \$1000/year, but the annual fuel cost will increase due to a higher electricity rates even if vehicle efficiency improves. Overall, electric vehicles will be more competitive in future passenger car market. The annual GHG emissions will decrease by 0.6 tons/year with a cleaner electricity, but its GHG mitigation potential is not as much as that of other technologies.



	ICEV	HEV	FCV	BEV
Annual fuel cost, 2015$/yr	$503	$352	$210	$79
Annualized vehicle cost, 2015$/yr	$2,616	$2,960	$3,465	$4,142
Annual GHG emissions, tons CO2/yr	4.63	3.24	2.25	1.64



	ICEV	HEV	FCV	BEV
Annual fuel cost, 2015$/yr	$577	$474	$304	$80
Annualized vehicle cost, 2015$/yr	$2,796	$2,874	$2,916	$3,067
Annual GHG emissions, tons CO2/yr	2.33	1.91	1.42	1.08

Figure 14. Annual fuel and vehicle costs and GHG emissions comparison

Figure 15 plots the change in annual total costs of different vehicle technologies against their GHG emissions from 2012 to 2030. This chart illustrates how gasoline vehicles (ICEVs and HEVs) could catch up with EVs and FCVs in environmental performance as measured by GHG emissions, and how EVs and FCVs could become more price competitive in 2030.

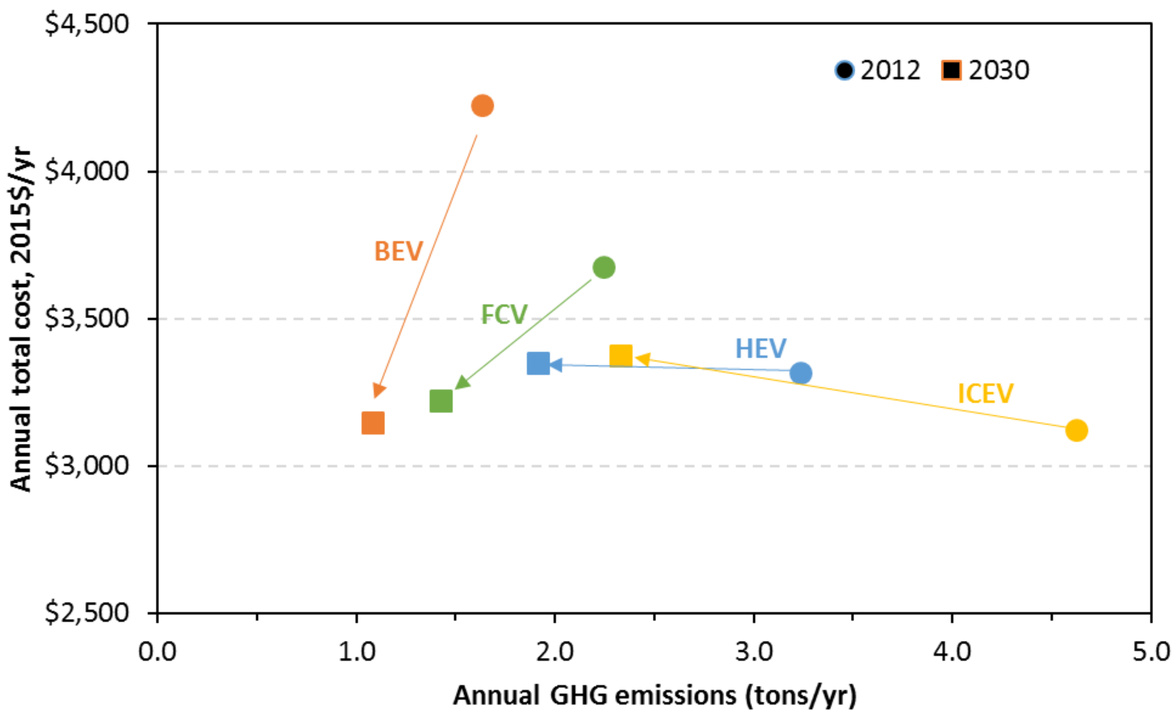


Figure 15. Annual total cost against greenhouse gas emissions

6 Conclusions and Future Opportunities

This research focuses on investigating how a decarbonized electric grid will influence the adoption of the electric vehicles in Texas under EPA's Clean Power Plan (CPP) from year 2012 to 2030. By incorporating several EIA/EPA datasets, with the demand forecasts in the service region of the Electric Reliability Council of Texas (ERCOT), a linear economic dispatch power system is built with high resolution. By deriving the collective mitigation costs covering 258 strategies within the category of the three building blocks, the least cost strategies are identified for compliance with the CPP. By analyzing the cost and benefit of using electric vehicles with the results of power system modeling under CPP scenario, and comparing with other vehicle technologies, the competitive position of electric vehicles in the car market is recognized.

The results of the power system modeling demonstrate that, for ERCOT in 2012, natural gas is the main source of electricity, and the baseload is comprised of nuclear, coal and NGCC. The overall GHG intensity of the electricity is 0.5724 tons CO2/MWh, and the average production costs is $27.52/MWh in 2012. The results of the mitigation cost curve shows that coal to gas switching is the cheapest strategy, followed by the competition between coal plant heat rate improvement and onshore wind. Solar PV and offshore wind are among the most expensive options, which indicates a relatively low penetration of solar in the forecast of generation mix in 2030 under the CPP scenario. To comply with the mass-based goal, the production costs will increase to $35.66/MWh for the ultimate ERCOT electric grid in 2030, but the GHG intensity will decrease to 0.4855 tons CO2/MWh.

The results of EV competitiveness analysis demonstrate that the plug-in electric vehicles will be more competitive in future passenger car market with a better environmental performance in terms of GHG emissions, and a lower a large decrease in the capital cost as the technology progress goes on from 2012 to 2030. However, the risk of the increased electricity rates from electric grid upgrading may weaken the market competitiveness of the plug-in EVs, especially during peak hours. The results also show that the GHG emissions in the use phase of electric vehicles will decrease as the electricity becomes cleaner, but not as much as that for other technologies during the same period.

Further work is needed to address the limitations of the research. Power system model could be further optimized by considering more operational constraints of the generators, and the difference in natural gas spot prices across the state. The assessment could be more comprehensive if includes the cost and benefit from vehicle to grid or grid to vehicle, with considerations of different charging strategies and additional equipment required.

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Appendix

Appendix 1 Matlab code for ERCOT 2012 test

```
clc;clear;

% Import Native Demand for 2012 & Wind output 2012, MW
Demand12 = xlsread('Input_dem.xlsx','Native Load','A1:A8760'); % Input hourly
demand for 2012
Wind12 = xlsread('Input_dem.xlsx','Wind Output','A1:A8760'); % Input wind
output 2012, estimated with 2014 data
Hydro = xlsread('Input_dem.xlsx','Hydro','A1:A8760'); % Input hourly hydro
output, constant across 2012-2030
Nuclear = xlsread('Input_dem.xlsx','Nuclear','A1:A8760'); % Input hourly
nuclear output, constant across 2012-2030

% Import ERCOT fleet data, operating cost parameters
Fleet12 = xlsread('Input_Sup.xlsx','Fossil12','A2:H160');
Fuelpri = xlsread('Input_Sup.xlsx','Dispatch cost','C39:N46'); % Fuel price
for each kind of fuel in 2012, 2015, 2022-2030, 2015$/MMBtu
VOMcost = xlsread('Input_Sup.xlsx','Dispatch cost','C50:N66'); % VOM for each
kind of plant in 2012, 2015, 2022-2030, 2015$/MMBtu

% Grid Parameters
WDcurtailrate = [0.037 0.005 0.005 0.005 0.005 0.005 0.005 0.005 0.005 0.005
0.005]; % Wind curtailment rate for 2012, 2015, 2022-2030, %
TDlossrate = 0.072; % Transmission & distribution loss rate
Importrate = 0.0055; % Import rate

% Load to be met by dispatchable sources
Dspload12 = Demand12/(1+Importrate)/(1-TDlossrate) - Hydro - Nuclear -
Wind12*(1-WDcurtailrate(1)); % Dispatchable load for 2012, no solar
n = size(Dspload12,1);

% Dispatch cost for 2012 fleet
n12 = size(Fleet12,1);
m1 = size(Fuelpri,1);
% Fuel cost match
for i = 1 : n12
  for j = 1 : m1
      if Fleet12(i,2) == Fuelpri(j,1)
         Fleet12(i,9) = Fuelpri(j,2); % Fuel price in 2012($/MMbtu)
         break;
      end
  end
Fleet12(i,10)= Fleet12(i,6)*Fleet12(i,9)/1000; % Fuel Cost ($/MWh)
 end

% VOM match
m2 = size(VOMcost,1);
for i = 1 : n12
  for j = 1 : m2
      if Fleet12(i,3) == VOMcost(j,1)
         Fleet12(i,11) = VOMcost(j,2); % VOM cost in 2012($/MWh)
         break;
```

```
      end
    end
    Fleet12(i,12)= Fleet12(i,11)+ Fleet12(i,10); % dispatch cost ($/MWh)
end

Fleetsort12 = sortrows(Fleet12,12);
for i = 1 : n12
   Fleetsort12(i,13) = i;
end

% marginal plant and generation
Plant_id = zeros(n,2);
for j = 1 : n
  capacity_temp = 0;
  for i = 1 : n12
    capacity_last = capacity_temp;
    capacity_temp = capacity_temp + Fleetsort12(i,5);
    if capacity_temp >= Dspload12(j,1);
      Plant_id(j,1) = i;
      Plant_id(j,2) = Dspload12(j,1) - capacity_last;
      break;
    end
  end
end

% Annual generation, emission, production cost
for i = 1 : n12
  Fleetsort12(i,14)=0;
  for j = 1 : n
    if Fleetsort12(i,13) < Plant_id(j,1)
       Fleetsort12(i,14) = Fleetsort12(i,14) +  Fleetsort12(i,5);
    elseif Fleetsort12(i,13) == Plant_id(j,1)
       Fleetsort12(i,14) = Fleetsort12(i,14) +  Plant_id(j,2); % annual
generation (MWh)
    end
    Fleetsort12(i,15) = Fleetsort12(i,14)*Fleetsort12(i,7); % annual emission
(tons)
    Fleetsort12(i,16) = Fleetsort12(i,14)*Fleetsort12(i,12); % annual
production cost ($)
    SumGEN12 = sum(Fleetsort12(:,14)); % total annual generation (MWh)
    SumGHG12 = sum(Fleetsort12(:,15)); % total annual emission (tons)
    SumCOST12 = sum(Fleetsort12(:,16)); % total annual production cost ($)
  end
end

Gen_hour = zeros(n12,8760);
for i = 1 : n12
   for j = 1: n
      if i < Plant_id(j,1)
         Gen_hour(i,j) = Fleetsort12(i,5);
      elseif i == Plant_id(j,1)
         Gen_hour(i,j) = Plant_id(j,2);
      else
          Gen_hour(i,j) = 0;
      end
   end
```

```
end
Gen_T = [Fleetsort12(:,1) Fleetsort12(:,2) Gen_hour];
Gen12 = Gen_T';

% Fleet and Fleetsort match
 for i = 1 : n12
     for j = 1 : n12
       if Fleet12(i,1) == Fleetsort12(j,1)
           Fleet12(i,13) = Fleetsort12(j,13); % rank of the plant
           Fleet12(i,14) = Fleetsort12(j,14); % annual generation (Mwh)
           Fleet12(i,15) = Fleetsort12(j,15); % annual emission (tons)
           Fleet12(i,16) = Fleetsort12(j,16); % annual production cost ($)
           break;
        end
     end
  end

Output_mrg = zeros(n,5);
for i = 1: n
   Output_mrg(i,1) = Dspload12(i,1);
   Output_mrg(i,2) = Plant_id(i,1);
   Output_mrg(i,3) = Plant_id(i,2);
   Output_mrg(i,4) = Fleetsort12(Plant_id(i,1),12);
   Output_mrg(i,5) = Fleetsort12(Plant_id(i,1),7);

end

Output_mix = [Demand12 Dspload12 Wind12 Nuclear Hydro];

xlswrite('Output_MY12.xlsx',Output_mrg,'Marginal','B2:F8761');
xlswrite('Output_MY12.xlsx',Output_mix,'Mix','A2:E8761');
xlswrite('Output_MY12.xlsx',Fleet12,'Fleet','A2:P151');
xlswrite('Output_MY12.xlsx',Gen12,'GEN12','B1:EU8762');
```

Appendix 2 Matlab code of mitigation cost and capacity calculation for BB1 in 2022

```
MY22bef;
% ======================================================= %
  % BB1: Coal plant heat rate improvement
% ======================================================= %

improverate = 0.023;
improvecost = 100; $/kW
CRF = 0.1175; % with 10% discount rate & 20 years

SUB_id = find(Fleet220(:,2)==21);
SUB = 214.3; % GHG intensity of SUB, lbs CO2/MMBtu
Fleet220(SUB_id,17) =  Fleet220(SUB_id,6)*(1-improverate); % New HR
Fleet220(SUB_id,18) =
Fleet220(SUB_id,6)*improverate.*Fleet220(SUB_id,14)/1000*SUB/2000; % GHG
mitigation (tons CO2)
Fleet220(SUB_id,19) =
Fleet220(SUB_id,6)*improverate.*Fleet220(SUB_id,14)/1000*Fuelpri(1,4); % Fuel
savings ($)
```

```
Fleet220(SUB_id,20) =  Fleet220(SUB_id,5)*improvecost*1000*CRF; % Capital
cost ($)
Fleet220(SUB_id,21) =  (Fleet220(SUB_id,20)-
Fleet220(SUB_id,19))./Fleet220(SUB_id,18); % Mitigation cost ($/ton)

LIG_id = find(Fleet220(:,2)==22);
LIG = 215.4; % GHG intensity of LIG, lbs CO2/MMBtu
Fleet220(LIG_id,17) =  Fleet220(LIG_id,6)*(1-improverate); % New HR
Fleet220(LIG_id,18) =
Fleet220(LIG_id,6)*improverate.*Fleet220(LIG_id,14)/1000*LIG/2000; % GHG
mitigation (tons CO2)
Fleet220(LIG_id,19) =
Fleet220(LIG_id,6)*improverate.*Fleet220(LIG_id,14)/1000*Fuelpri(2,4); % Fuel
savings ($)
Fleet220(LIG_id,20) =  Fleet220(LIG_id,5)*improvecost.*1000*CRF; % Capital
cost ($)
Fleet220(LIG_id,21) =  (Fleet220(LIG_id,20)-
Fleet220(LIG_id,19))./Fleet220(LIG_id,18); % Mitigation cost ($/ton)

Coal_id = find(Fleet220(:,2)==21 | Fleet220(:,2)==22);
c = length(Coal_id);
Coal_plant22 = zeros(c,3);
for i = 1:c
    Coal_plant22(i,1) = Fleet220(Coal_id(i,1),1);
    Coal_plant22(i,2) = Fleet220(Coal_id(i,1),21); % Mitigation cost ($/ton)
    Coal_plant22(i,3) = Fleet220(Coal_id(i,1),18)/1000000; % GHG mitigation
(MMT CO2)
end

xlswrite('Output_MC22.xlsx',Coal_plant22,'BB1','A2:C17');
```

Appendix 3 Matlab code of mitigation cost and capacity calculation for BB2 in 2022

```
MY22bef;
% ===================================================== %
  % BB2: coal to natural gas switch (proxy CO2 price)
% ===================================================== %
Fleet2 = xlsread('Input_Sup.xlsx','Fossil22','A2:H160');

% Dispatch cost for 2022 fleet
n220 = size(Fleet2,1);
m1 = size(Fuelpri,1);
% Fuel cost match
for i = 1 : n220
  for j = 1 : m1
      if Fleet2(i,2) == Fuelpri(j,1)
         Fleet2(i,9) = Fuelpri(j,4); % Fuel price in 2022($/MMbtu)
         break;
      end
  end
Fleet2(i,10)= Fleet2(i,6)*Fleet2(i,9)/1000; % Fuel Cost ($/MWh)
 end

% VOM match
m2 = size(VOMcost,1);
```

```
for i = 1 : n220
  for j = 1 : m2
      if Fleet2(i,3) == VOMcost(j,1)
         Fleet2(i,11) = VOMcost(j,4); % VOM cost in 2022($/MMbtu)
         break;
      end
  end
  Fleet2(i,12)= Fleet2(i,11)+ Fleet2(i,10); % dispatch cost ($/Mwh)
end

carbonprice = 1:30; % $/ton
l = length(carbonprice);
for c = 1: l
  Fleet2(:,13) = Fleet2(:,12) + carbonprice(c) * Fleet2(:,7); % CO2 cost
$/MWh
  Fleetsort2 = sortrows(Fleet2,13);
  for i = 1 : n220
     Fleetsort2(i,14) = i;
  end
  % marginal plant and generation
    Plant_id = zeros(n,2);
    for j = 1 : n
      capacity_temp = 0;
      for i = 1 : n220
        capacity_last = capacity_temp;
        capacity_temp = capacity_temp + Fleetsort2(i,5);
        if capacity_temp >= Dspload22(j,1);
           Plant_id(j,1) = i;
           Plant_id(j,2) = Dspload22(j,1) - capacity_last;
           break;
        end
      end
    end

  % Annual generation, emission, production cost
    for i = 1 : n220
      Fleetsort2(i,15)=0;
      for j = 1 : n
        if Fleetsort2(i,14) < Plant_id(j,1)
           Fleetsort2(i,15) = Fleetsort2(i,15) +  Fleetsort2(i,5);
        elseif Fleetsort2(i,14) == Plant_id(j,1)
           Fleetsort2(i,15) = Fleetsort2(i,15) +  Plant_id(j,2); % annual
generation (Mwh)
        end
      end
      Fleetsort2(i,16) = Fleetsort2(i,15)*Fleetsort2(i,7); % annual emission
(tons)
      Fleetsort2(i,17) = Fleetsort2(i,15)*Fleetsort2(i,12); % annual
production cost ($)
    end

   % Fleet2 and Fleet2sort match
 for i = 1 : n220
     for j = 1 : n220
       if Fleet2(i,1) == Fleetsort2(j,1)
           Fleet2(i,14) = Fleetsort2(j,14); % rank of the plant
           Fleet2(i,15) = Fleetsort2(j,15); % annual generation (Mwh)
```

```
            Fleet2(i,16) = Fleetsort2(j,16); % annual emission (tons)
            Fleet2(i,17) = Fleetsort2(j,17); % annual production cost ($)
            break;
         end
      end
 end
   GEN(:,c) = Fleet2(:,15);
   GHG(:,c) = Fleet2(:,16);
   COST(:,c) = Fleet2(:,17);
end

sumGEN = sum(GEN);
sumGEN22 = sumGEN';
sumGHG = sum(GHG);
sumGHG22 = sumGHG';
sumCOST = sum(COST);
sumCOST22 = sumCOST';

Coal_NG22 = [sumCOST22 sumGHG22];

xlswrite('Output_MC22.xlsx',Coal_NG22,'BB2','B2:C31');
xlswrite('Output_MC22.xlsx',SumCOST220,'BB2','B1');
xlswrite('Output_MC22.xlsx',SumGHG220,'BB2','C1');
```

Appendix 4 Costs and incentives assumptions for renewable projects

Table 9. Onshore wind (large wind, >100kW) costs and incentives

Model Year	Installed cost	Fixed O&M	PTC1		ITC/Grant Value
	(2015$/kW$_{AC}$)	(2015$/kW$_{AC}$-yr)	(real $/kWh)	2015$/kWh	
2015	$1,690	$9	$0.0230	$0.0230	30%
2016	$1,690	$9	$0.0230	$0.0227	24%
2017	$1,690	$9	$0.0184	$0.0178	18%
2018	$1,690	$9	$0.0138	$0.0131	12%
2019	$1,690	$9	$0.0092	$0.0085	0%
2020	$1,690	$9	$0.0000	$0.0000	0%
2021	$1,690	$9	$0.0000	$0.0000	0%
2022	$1,690	$9	$0.0000	$0.0000	0%
2023	$1,690	$9	$0.0000	$0.0000	0%
2024	$1,690	$9	$0.0000	$0.0000	0%
2025	$1,690	$9	$0.0000	$0.0000	0%
2026	$1,690	$9	$0.0000	$0.0000	0%
2027	$1,690	$9	$0.0000	$0.0000	0%
2028	$1,690	$9	$0.0000	$0.0000	0%
2029	$1,690	$9	$0.0000	$0.0000	0%
2030	$1,690	$9	$0.0000	$0.0000	0%

Table 10. Offshore wind costs and incentives

Model Year	Installed cost	Fixed O&M	PTC1		ITC/Grant Value
	(2015$/kW$_{AC}$)	(2015$/kW$_{AC}$-yr)	(real $/kWh)	2015 $/kWh	
2015	$5,747	$69	$0.0230	$0.0230	30%
2016	$5,575	$67	$0.0230	$0.0227	24%
2017	$5,408	$65	$0.0184	$0.0178	18%
2018	$5,245	$63	$0.0138	$0.0131	12%
2019	$5,088	$61	$0.0092	$0.0085	0%
2020	$4,935	$59	$0.0000	$0.0000	0%
2021	$4,787	$57	$0.0000	$0.0000	0%
2022	$4,644	$56	$0.0000	$0.0000	0%
2023	$4,504	$54	$0.0000	$0.0000	0%
2024	$4,369	$52	$0.0000	$0.0000	0%
2025	$4,238	$51	$0.0000	$0.0000	0%
2026	$4,111	$49	$0.0000	$0.0000	0%
2027	$4,000	$48	$0.0000	$0.0000	0%
2028	$4,000	$48	$0.0000	$0.0000	0%

2029	$4,000	$48	$0.0000	$0.0000	0%
2030	$4,000	$48	$0.0000	$0.0000	0%

Table 11. Solar PV costs and incentives

Model Year	Installed cost	Fixed O&M	PTC[1]		ITC/Grant Value
	(2015$/kWAC)	(2015$/kWAC-yr)	($/kWh)	(2015$/kWh)	
2015	$2,700	$16	$0.0230	$0.0230	30%
2016	$2,241	$16	$0.0230	$0.0227	30%
2017	$1,860	$16	$0.0000	$0.0000	30%
2018	$1,544	$16	$0.0000	$0.0000	30%
2019	$1,281	$16	$0.0000	$0.0000	30%
2020	$1,064	$16	$0.0000	$0.0000	26%
2021	$1,000	$16	$0.0000	$0.0000	22%
2022	$1,000	$16	$0.0000	$0.0000	10%
2023	$1,000	$16	$0.0000	$0.0000	10%
2024	$1,000	$16	$0.0000	$0.0000	10%
2025	$1,000	$16	$0.0000	$0.0000	10%
2026	$1,000	$16	$0.0000	$0.0000	10%
2027	$1,000	$16	$0.0000	$0.0000	10%
2028	$1,000	$16	$0.0000	$0.0000	10%
2029	$1,000	$16	$0.0000	$0.0000	10%
2030	$1,000	$16	$0.0000	$0.0000	10%