ERCOT Energy Portfolio Optimization

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Abstract

The Texas electricity market is currently undergoing rapid change in several key areas. These changes are rewriting the way Texas electricity providers plan for future demand and handle ever growing uncertainties. This paper develops a framework to model the uncertaintiy within the cost structure of building new power generating production facilities. We use Monte Carlo simulation to model the Levelized Cost of Electricity with a multivariate normal error term embeded in each energy source cost equation. This allows us to develop a covariance structure between the different energy sources which can be fed into a quadratic programing model to determine an optimal mix (portfolio) of energy supplies which minimize the variability of the price of energy in the Texas electricity market while at the same time keeping costs low for residential and commercial users.

Over the past several decades the Texas electricity market has seen large changes in several key areas. Many of these changes have been slow and predictable while others have been quick and hard to imagine. The unimaginable situations are where modeling solutions often fail unless a robust mechanism is embedded within the model to account for large variations across interconnected situations.

This paper will develop a Quadratic Program to determine an optimal mix (portfolio) of energy supplies which minimize the variability of the price of energy in the Texas electricity market. I will use the “Modern Portfolio Theory”, introduced by Harry Markowitz (1952) to help gain insight into this problem. The two central themes of Marowitz theory are,

- to maximize return for any level of risk;
- risk can be reduced by creating a diversified portfolio of unrelated assets.

In the context of this paper, we can reformulate Marowitz idea to developed an optimized portfolio of energy sources that can be used to help determine the directions for future investments in new electricity production facilities in the State of Texas. When used in electric power system optimization modeling, Merlin and Back (1975) note that we are interested in both minimizing expected cost and minimizing risk. This is a multi-objective optimization problem and there is always a trade-off between these two objectives.

Currently, the approach that has most often been employed to determine the optimal portfolio of energy sources has been to evaluate the Levelized Cost of Electricity (LCOE) across all energy sources of interest. This allows us to normalize the costs of energy sources so a direct comparison can be made. Without this normalization it is unclear what is meant by comparing the cost of generation electricity using coal with the cost of generating electricity using wind. Once the levelized costs have been determined they can be plugged into an optimization model to determine the ideal portfolio of energy sources. LCOE calculations are generally computed as point source estimates of costs (U.S. Energy Information Admin. (EIA), U.S. Department of Energy (DOE), The National Renewable Energy Lab (NREL), LAZARD, and Sandia National Lab). If uncertainty is incorporated in the LCOE calculations at all, it is usually obtained by varying one parameter while holding all other parameters constant, ie. varying the cost of fuel to determine the upper and lower bound on LCOE when fuel costs fluctuate. This approach to incorporating uncertainty within the LCOE structure is lacking in a few areas. It is possible, and indeed likely, that multiple parameters are varying simultaneously. These fluctuations will be missed entirely by hold them constant. In addition, it is possible for many of the energy sources to have interdependence. In other words, the costs of fuel between combustion cycle natural gas, peaking natural gas, and coal are likely to move in directions which are related, either positively or negatively. These relationships have been omitted in previous studies. Our paper seeks to fill this void by using Monte Carlo simulation to model the Levelized Cost of Electricity with a multivariate normal error term embedded in each energy source cost equation. This allows us to develop a covariance structure between the different energy sources which can be used to determine an optimal portfolio of energy supplies that minimize the variability of the price of energy in the Texas electricity market while at the same time keeping costs low for residential and commercial users.

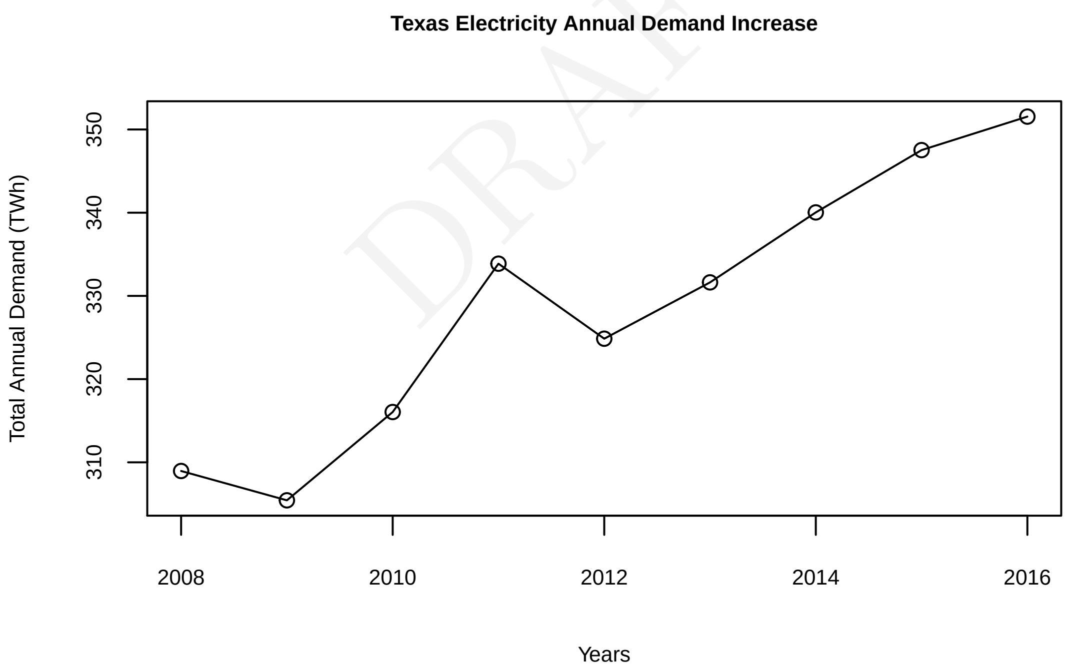
Section 1 provides a brief background on the structure and management of the Texas electricity market. In addition, there are many challanges facing electricity prividers and these challanges have the potiential to reshape the energy market ladscape, several of these situations will be explored in this section. Section 2 will detail the Monte Carlo simulation approach to modeling LCOE and detail how the covariance structure is developed. Section 3 details the optimization model used and the model constraints employed. Section 4 provides results and discussion. Section 5 concludes.

1 Background

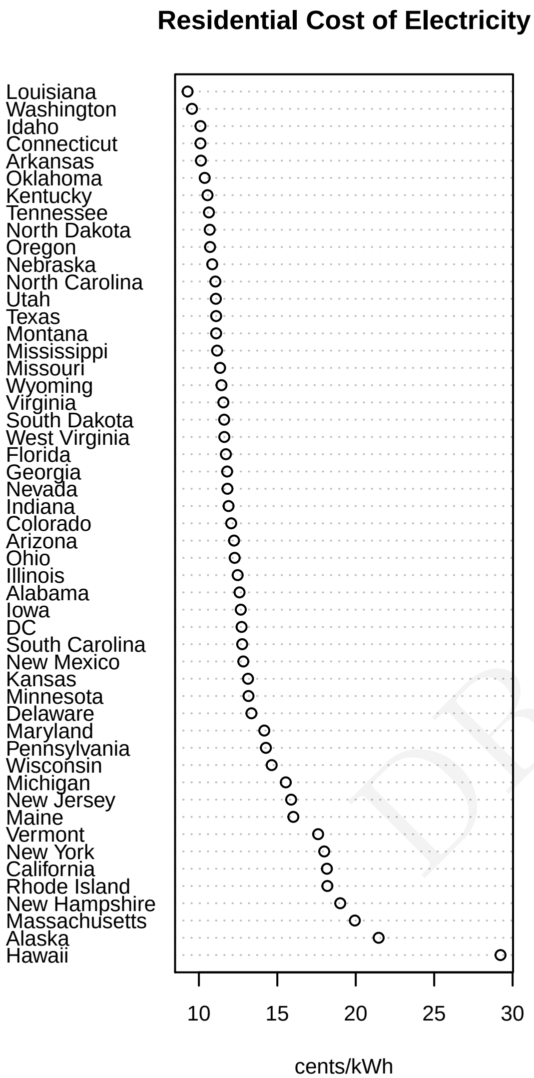
The Texas electrcity grid is managed by The Electric Reliability Council of Texas (ERCOT). ERCOT has a long and diverse history that reaches back to the start of World War II (WWII). The precursor to ERCOT was formed during the start of WWII (1951) when several Texas utilities banded together to form an interconnection that sent power from disparate locations in the state to the gulf coast to aid in the war effort. The utilities recognized the stability the interconnection provided and after the war ended the utilities decided to remain connected. They established two monitoring stations, one in the northern part of Texas and one in the south. This group of interconnected utilities became known as the Texas Interconnected System (TIS). The North American Electric Reliability Council (NERC) was formed in 1968 and was charged with ensuring the reliability of the North American bulk power system. As a result of the formation of NERC, TIS was motivated to form ERCOT in 1970 to comply with NERC regulations. ERCOT is a membership-based 501(c)(4) nonprofit corporation, governed by a board of directors and subject to oversight by the Public Utility Commission of Texas and the Texas Legislature. ERCOT currently manages the flow of electric power to 24 million Texas customers representing about 90 percent of the state's electric load.

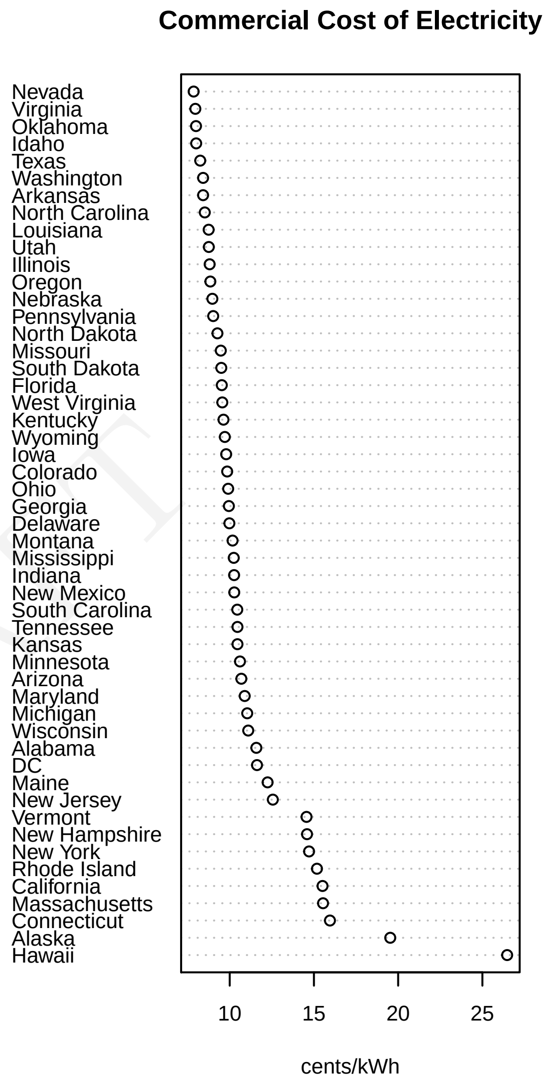
One of the many challenges facing EROCT, while considering how best to design the electricity grid of the future, is the uncertainty in demand. Demand uncertainties can emerge from many locations, including increases in population and business development, changes in state and federal regulation, structural changes that stem from new technologies, such as electric vehicles which require grid power for recharge, and the ever present weather uncertainties. Of these demand shifters, population increase and demand shocks from electric vehicles stand poised to present the greatest challenge for ERCOT. Power used tomorrow needs to be provision for today.

The State of Texas has enjoyed rapid increases in population and remains at the top of the list as one of the fastest growing states in the union. Families are attracted to the state by high wages and low cost of living. At the same time, Texas has developed a business friendly regulatory environment which has attracted both large corporations and small businesses alike. From an economic standpoint this has propelled Texas to the front of the line as a leader in economic growth and development. With this growth in population and business, the demand for electricity has progressively increased and these increases need to be accommodated for Texas to continue to be successful.



Despite increases in demand for electricity, Texas has maintained some of the lowest costs per kilowatt-hour for both residential and commercial use. Maintaining low costs on the supply side is essential to the ability of electricity producers to maintain low costs on the consumer side. Maintaining low cost of service presents a unique challenge for producers who are tasked with meeting the current demands for electricity and planning for future demand increases.





Electric vehicles, while representing less than one percent market share today, have the potential, in the future, to stress the electricity grid to the point of failure. It is projected that electric vehicles will make up 65% of new light duty vehicle sales by the year 2050. The demands on the power grid from these electric vehicles will be non-trivial. Each new electric vehicle, assuming current technology, adds the equivalent of one new house to the electricity grid landscape. This demand increase needs to be considered today so that grid capacity can be available when needed in the future.

2 Monte Carlo Simulation and Covariance Model

The ability of ERCOT to meet growing electricity demands is predicated on two main considerations; accurate forecasting of future needs, and accurate cost estimates for generating units. While both of these areas have the potential to inject substantial levels of uncertainty, the main focus of this paper is to model the uncertainty related to costs. Measuring costs is generally thought to be the first step toward the understanding of an optimal electricity mix. To this end, we will estimate the Levelized Cost of Electricity (LCOE) using Monte Carlo simulation for six electricity sources; coal, combustion cycle natural gas, peaking natural gas, nuclear, wind, and solar.

The most reliable estimates of future Levelized costs have be modeled by the U.S. Energy Information Administration (EIA) and the LAZARD Investment Group. Both of these estimates fail to incorporate robust modeling of uncertainty and neither estimate contains information related to the covariance structure between the energy source profiles.

Since the electricity industry has been heavily regulated there exists detailed historical information related to the cost structures of power generating technologies. We use this historical cost information to identify a candidate statistical distribution to model various parameters used to calculate the LCOE.

The Levelized Cost of Electricity formula used in this study follows:

$$
\begin{aligned}
LCOE &= \frac{P + OM_F}{8760 \cdot C_f} + F_c \cdot Q + OM_v \\
P &= C_c \left[i + \frac{i}{(i+1)^n - 1} \right]
\end{aligned}
$$

where,

P is the yearly payment on capital costs.

OM_F is the fixed costs.

8760 is the number of hours in a year.

C_f is the capacity factor.

F_c is the fuel cost.

Q is the heat rate of the plant.

OM_v is the variable costs.

C_c is the capital cost of building the generation plant or station.

i is the interest rate.

n is the number of payments, assumed to be the lifetime of the plant.

To calculate the LCOE we preformed the following steps:

- determine distributional choice by historical data on costs across energy sources (statistical distributions used in the Monte Carlo simulation are presented in Figure 1).
- Collate point source data from EIA and LAZARD LCOE reports. Use the data to establish boundary conditions for the chosen distributions.
- Draw LCOE Cost Parameters (10,000) from statistical distributions to calculate mean LCOE.

Summary statistics from the Monte Carlo study are presented in Table 1. When

Inputs	Coal	Natural Gas - CC	Natural Gas - Peaking	Nuclear	Wind	Solar - PV
Capital Cost ($/KW)	Log Normal	Log Normal	Triangular	Log Normal	Normal	Log Normal
Interest Rate (%, yr)	Triangular	Triangular	Triangular	Constant	Constant	Constant
Loan Term (yrs)	Constant	Constant	Constant	Constant	Constant	Constant
Fixed Cost OM ($/KW/yr)	Normal	Triangular	Log Normal	Normal	Triangular	Normal
Fuel Cost ($/MMBtu)	Normal	Triangular	Triangular	Constant	NA	NA
Heat Rate (Btu/KWh)	Normal	Normal	Normal	Normal	NA	NA
Variable Cost OM ($/MWh)	Normal	Normal	Log Normal	Triangular	Log Normal	NA
Capacity Factor (%)	Constant	Triangular	Normal	Normal	Constant	Normal

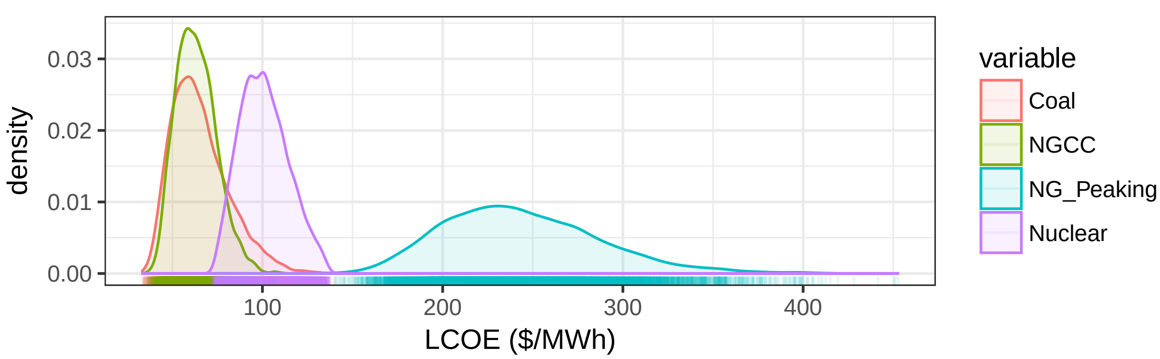
Figure 1:

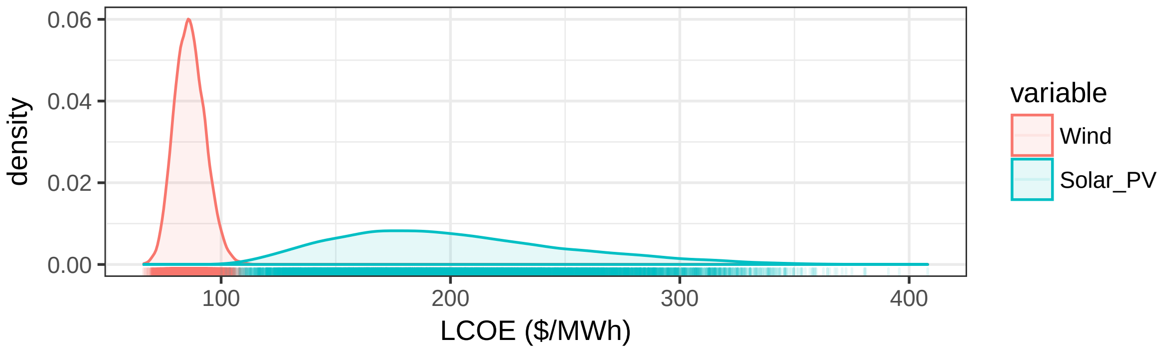
compared to the point source estimates from EIA and LAZARD, the results from the Monte Carlo study are comparable. However, the minimum and maximum values from our Monte Carlo study are greater in magnitude, representing the greater uncertainty in the cost parameters when drawing random variables from a distribution.

Table 1: Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Max
Coal	10,000	65.511	15.923	33.392	145.185
NGCC	10,000	63.301	11.154	36.009	117.525
NG_Peaking	10,000	243.703	43.161	128.065	452.628
Nuclear	10,000	100.916	13.262	71.238	140.292
Wind	10,000	86.433	6.644	66.249	117.402
Solar_PV	10,000	201.289	49.519	100.199	408.096

A density plot of the Monte Carlo derived distributions of energy sources is provided below.





With the simulated LCOE results in hand we can now turn our attention to developing the covariance structure that will be used to model the cross-correlations between energy sources. To develop the covariance structure we use the multivariate normal distribution. This process is as follows:

- take random draws (10,000) from the Multivariate Normal Distribution (MVN) to construct a correlated error term across all energy source LCOE's.
- add the correlated error terms to each LCOE source.

This gives the following LCOE with the correlated error term embedded:

$$LCOE_{\varepsilon_i} = LCOE_i + \varepsilon_i \text{ where } \varepsilon \sim \mathcal{N}_p(\mu, \Sigma)$$

3 Optimization Model

To determine an optimal portfolio of energy supplies which minimize the variability of the price of energy we will use a quadratic programming model. The optimization model takes the following form:

$$\min(\mathbf{x\Sigma x}') \text{ subject to: constraints}$$

where,

$\mathbf{x}$ is a vector of energy sources (1,...,6),

i indexes over the sources (1,...,6),

x_i is the power provisioned from resource i [TWh],

c_i is the expected cost of resource i in 2022 [million USD/TWh],

c_{max} is the maximum expected cost [million USD/TWh],

d is the total ERCOT energy demand in 2022 [TWh],

Σ is the variance-covariance of resource i's cost [million USD/TWh].

The constraints are taken from several sources. The estimated demand for electricity on the ERCOT grid in 2022 is 385 TWh. This estimate is applied as the minimum level of electricity generation required. For ERCOT to maintain low residential and commercial electricity rates the maximum expected cost of the electricity profile should be less than 100 million USD/TWh.

Technical constraints on electricity generation are taken from various sources including, (Marrero et al. 2015), (Awerbuch and Berger 2003), (Awerbuch and Yang 2007), and (Marrero and Ramos-Real 2010).

A full list of constraints used in the model are as follows:

$$\begin{bmatrix} \sum_{i=1}^{6} x_i \geqslant d_{385} \text{ 2022 Energy Demand} \\ \frac{\sum_{i=1}^{6} c_i x_i}{\sum_{i=1}^{6} x_i} \leqslant c_{max_{100}} \text{ maximum expected cost} \\ x_i \geqslant 0, \ \forall i \text{ non - negativity} \end{bmatrix} \begin{bmatrix} \text{Solar}_{pv} \leqslant 7\% \\ Wind \leqslant 25\% \\ NG_{peaking} \geqslant 10\% \\ x_1 = NG_{cc} \leqslant 90\% \\ x_2 = Coal \leqslant 90\% \\ x_3 = Nuclear \leqslant 90\% \\ \sum_{i=1}^{3} x_i \geqslant 60\% \end{bmatrix}$$

4 Results and Discussions

The output from the quadratic program is listed in Figure 2. According to the model, the optimal portfolio of energy supplies which minimize the variability of the price of energy in the Texas electricity market are: 14.45% coal, 29% combustion cycle natural gas, 10% peaking natural gas, 20.14% nuclear, 25% wind, and 1.4% solar. These values make sense when we consider the high variance on peaking natural gas and solar. The constraint on peaking natural gas is active which suggests the amount would be lower, but peaking gas is required since this source is brought online when peak demand exceeds available baseline capacity. The constraint on wind is also active. When we relax the constraint on wind the amount of wind in the portfolio increases. This suggests wind is a viable and desirable energy source in the Texas market.

The variance-covariance shown in Figure 2 list two different scenarios. The first shows the covariance matrix where we have allowed cross-correlations between the energy sources. In the second covariance matrix all covariance is set to zero. We notice there is not much change between the two scenarios but this could be due

With seed= 12345										
Q1 w/ vcov	id	source	percent	vcov matrix	Coal	NGCC	NG_Peaking	Nuclear	Wind	Solar_PV
coal	1	55.638586	14.451581	Coal	251.1977117	-0.8574479	2.318398	0.6466162	1.2734792	4.2576218
natural_gas_cc	2	111.672017	29.005719	NGCC	-0.8574479	124.4080090	5.086962	2.0653877	-0.5982139	4.0523558
natural_gas_peaking	3	38.500000	10.000000	NG_Peaking	2.3183977	5.0869622	1958.544699	1.1294195	2.2372874	14.3966414
nuclear	4	77.542357	20.140872	Nuclear	0.6466162	2.0653877	1.129419	176.0786624	2.1279467	-0.5545507
wind	5	96.250000	25.000000	Wind	1.2734792	-0.5982139	2.237287	2.1279467	43.8762257	1.0086051
solar	6	5.397041	1.401829	Solar_PV	4.2576218	4.0523558	14.396641	-0.5545507	1.0086051	2384.2161112
Q w/o vcov	id	source	percent	vcov matrix	Coal	NGCC	NG_Peaking	Nuclear	Wind	Solar_PV
coal	1	54.986405	14.282183	Coal	251.1977	0.000	0.000	0.0000	0.00000	0.000
natural_gas_cc	2	111.025482	28.837788	NGCC	0.0000	124.408	0.000	0.0000	0.00000	0.000
natural_gas_peaking	3	38.500000	10.000000	NG_Peaking	0.0000	0.000	1958.545	0.0000	0.00000	0.000
nuclear	4	78.444821	20.375278	Nuclear	0.0000	0.000	0.000	176.0787	0.00000	0.000
wind	5	96.250000	25.000000	Wind	0.0000	0.000	0.000	0.0000	43.87623	0.000
solar	6	5.793292	1.504751	Solar_PV	0.0000	0.000	0.000	0.0000	0.00000	2384.216
with seed= 123										
Q1 w/ vcov										
	id	source	percent	vcov matrix	Coal	NGCC	NG_Peaking	Nuclear	Wind	Solar_PV
coal	1	54.732629	14.216267	Coal	254.2681389	-0.9083444	1.843315	3.998742	1.064627	5.272965
natural_gas_cc	2	110.125665	28.604069	NGCC	-0.9083444	129.8986558	-3.634986	1.427547	1.356694	-3.414447
natural_gas_peaking	3	38.500000	10.000000	NG_Peaking	1.8433148	-3.6349862	1870.958434	-3.327918	1.430276	-31.254010
nuclear	4	79.445819	20.635278	Nuclear	3.9987420	1.4275474	-3.327918	175.262036	1.135800	9.771821
wind	5	96.250000	25.000000	Wind	1.0646272	1.3566943	1.430276	1.135800	43.766321	8.254088
solar	6	5.945887	1.544386	Solar_PV	5.2729654	-3.4144473	-31.254010	9.771821	8.254088	2364.510594
Q w/o vcov										
	id	source	percent	vcov matrix	Coal	NGCC	NG_Peaking	Nuclear	Wind	Solar_PV
coal	1	55.417048	14.394038	Coal	254.2681	0.0000	0.000	0.000	0.00000	0.000
natural_gas_cc	2	108.475254	28.175391	NGCC	0.0000	129.8987	0.000	0.000	0.00000	0.000
natural_gas_peaking	3	38.500000	10.000000	NG_Peaking	0.0000	0.0000	1870.958	0.000	0.00000	0.000
nuclear	4	80.398414	20.882705	Nuclear	0.0000	0.0000	0.000	175.262	0.00000	0.000
wind	5	96.250000	25.000000	Wind	0.0000	0.0000	0.000	0.000	43.76632	0.000
solar	6	5.959284	1.547866	Solar_PV	0.0000	0.0000	0.000	0.000	0.00000	2364.511

Figure 2:

to inadequate development of the covariance structure. To more properly develop the covariance structure we will need to bootstrap the variance-covariance matrix to obtain a structure more representative of the population. However, we do detect a small change between the two portfolios and when considering large costs, a small percentage change equals a large cost difference.

5 Conclusions

Understanding the cost structure of different energy sources in the Texas electricity market is critical to the ability of electricity producers to properly determine the appropriate mix of energy sources to satisfy future demand. This study developed a cost system which allowed more uncertainty to enter the Levelized Cost of Electricity equation through the use of Monte Carlo simulation. By drawing random variables from pre-specified statistical distributions we have allowed the parameters that enter the LCOE equations to vary. Modeling the LCOE equations in this fashion more realistically captures the variation across all parameters. We have also developed a framework to allow cross-correlations between energy sources, a critical component to more fully understand the optimal portfolio of electricity sources. The goal of determining an optimal portfolio is to minimize variation and minimize costs. Without a proper modeling of the variations within the cost structure we are in danger of reaching false conclusions.

This study is a first step in the development of a more comprehensive model of uncertainty that lives within the cost structures of energy production. More work is needed to better develop this framework. Bootstrapping the variance-covariance matrix is needed to better represent the population covariance structure. This study omits all costs associated with carbon sequestration, a large omission but an omission that was necessary to develop a baseline model. Future studies need to incorporate a cost structure for carbon abatement. This study used national level data for the cost parameter boundary conditions. While some regional specific information was available most parameters were aggregated on a national level. To more fully represent the Texas electricity market future studies should enrich the LCOE calculations with more regional specific data.

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