ERCOT Energy Portfolio Optimization

Matthew Aaron Looney

12/04/2017

Goal of this Research

- 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 in 1952.
- Model Energy Costs using Monte Carlo Simulation.
- 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.

Background

- **My study is focused exclusively on the Texas Electric Grid.**
- The Texas Grid is managed by The Electric Reliability Council of Texas (ERCOT).
- 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) manages the flow of electric power to 24 million Texas customers – representing about 90 percent of the state's electric load.**
- ERCOT schedules power on an electric grid that connects more than 46,500 miles of transmission lines and 570+ generation units.

Current ERCOT Service Area

Figure 1:

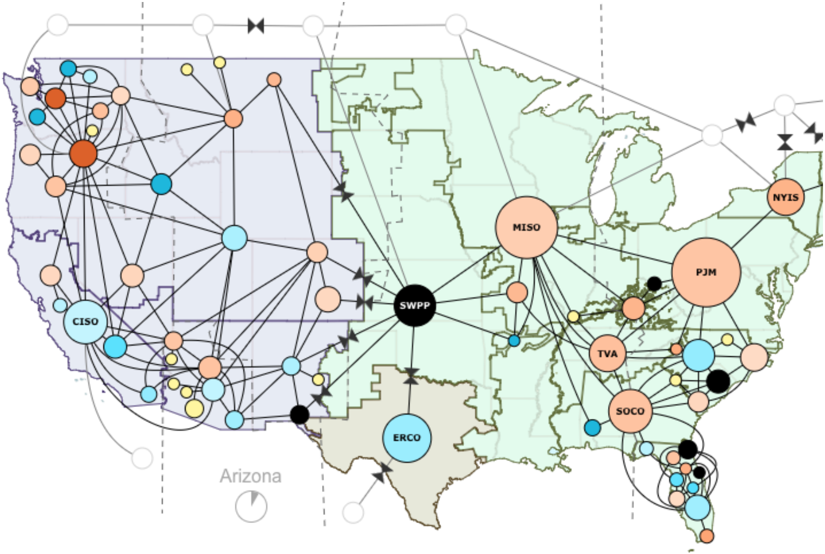
Changing Texas Electric Market

ERCOT is currently undergoing rapid change in several key areas.

- Demand Increase
- Structural Change
- Changes in Regulatory environment
- Change in ERCOT's Service Territory
- Weather Uncertainty

United States Power Grid

- Western Interconnection, ERCOT, Eastern Interconnection



Demand Increase - Historical Source Data (%)

Table 1: Historical Energy Source Mix in Percentage

Fuel Types	Biomass	Natural_Gas	Gas-CC	Coal	Nuclear	Wind
2008_(%)		43.0		37.1	13.2	4.9
2009_(%)		42.1		36.6	13.6	6.2
2010_(%)		38.2		39.5	13.1	7.8
2011_(%)		40.4		39.0	11.9	8.5
2012_(%)		44.6		33.8	11.8	9.2
2013_(%)		40.5		37.2	11.6	9.9
2014_(%)		41.1		36.0	11.6	10.6
2015_(%)		48.3		28.1	11.3	11.7
2016_(%)		43.7		28.8	12.0	15.1
2017_(%)_10	0.15	5.02	34.62	31.87	10.40	17.21

Gas CC - Combined Cycle Natural Gas
2017 data is incomplete.

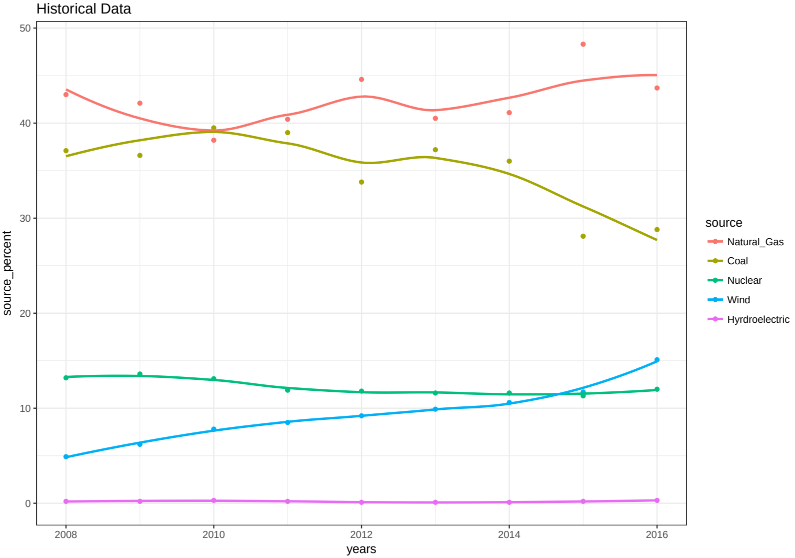
Demand Increase - Historical Source Data (%)

Table 2: Historical Energy Source Mix in Percentage

Fuel Types	Solar	Water	Net_DC_BLT	Other	Total_TWh
2008_(%)		0.2000		1.6000	308.9595
2009_(%)		0.2000		1.3000	305.4322
2010_(%)		0.3000		1.1000	316.0463
2011_(%)		0.2000		0.2000	333.8748
2012_(%)		0.1000	0.2000	0.3000	324.8597
2013_(%)		0.1000	0.5000	0.3000	331.6241
2014_(%)		0.1000	0.4000	0.3000	340.0334
2015_(%)		0.2000	0.1000	0.3000	347.5229
2016_(%)	0.2000	0.3000	-0.2000	0.2000	351.5478
2017_(%)_10	0.6400	0.2600	-0.1900	0.0100	302.1717

Other - includes petroleum coke, landfill gas, biomass solids, biomas gases, and any unknown fuel.
A positive value in the 'Net DC/BLT' row indicates import of power, negative indicates export.
2017 data is incomplete.

Demand Increase - Historical Source Data Plot



Demand Increse - Forcasted

- ERCOT Generated Model for Peak Summer Demand

Peak Demand and Energy Forecast Summary

Year	Summer Peak Demand (MW)	Energy (TWh)
2017	72,934	356
2018	74,149	362
2019	75,588	371
2020	76,510	376
2021	77,417	380
2022	78,377	385
2023	79,348	389
2024	80,315	393
2025	81,261	398
2026	82,286	417

Structural Change

Energy source portfolio changes

- More Wind and Solar sources online
- More Natural Gas integration
- Coal plant retirement schedules

Demand Shifters

- Electric vehicles have less than 1% market share today
- The future will look very different
- The electricity demands from electric vehicles on the power grid will be non-trivial
- Turns out the future is hard to predict, BUT future demands need to be provisioned for today.

Changes in Regulatory Environment

Electricity Market Reform

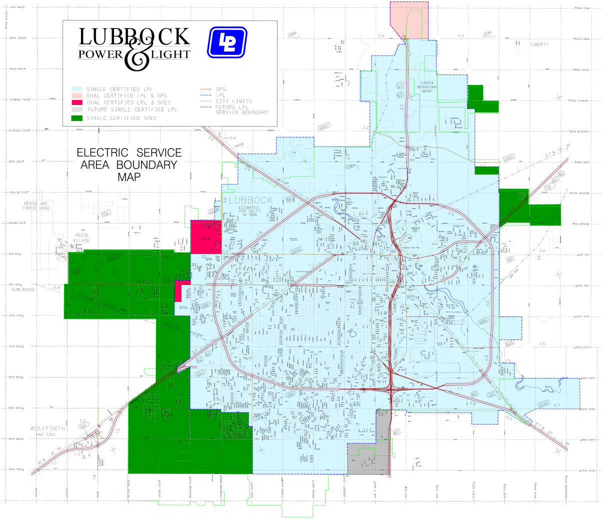
- Move away from vertically integrated electricity markets
- Move toward Investor Owned Utilities (IOU's)
- Development of Spot Market and Day Ahead Transaction Markets
- More sophisticated Cost Plus Pricing Models

Changes in Environmental Regulations

- Move toward renewable energy sources
- Move away from Nuclear and Coal
- Carbon Price Modeling

Change in ERCOT's Service Territory

- Lubbock will add 600 MW of demand load



Weather Uncertainty

- Texas summers are always hot!!! and getting hotter???

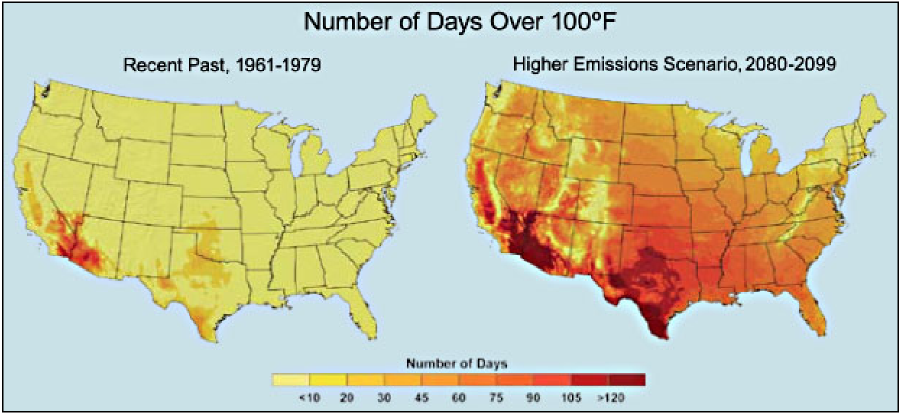


Figure 5:

Optimization Model

Quadratic Programing Model - General Formula

$$\min_{x_i} \frac{1}{2} x_i' H x_i + f' \text{ subject to } \begin{cases} Ax_i \leqslant b, \\ Aeqx = beq, \\ x_i \geqslant 0 \end{cases}$$

Strategy

How have energy portfolios been modeled in the past?

- Measuring costs is the first step to the understanding of electricity mix.
- A common and useful measure to compare different electricity generating technologies is the Levelized Cost of Electricity (LCOE).
- LCOE calculations are generally computed as point source estimates of costs. (U.S. Energy Information Admin. (EIA), DOE, National Renewable Energy Lab, LAZARD, Sandia National Lab)
- The calculation of the LCOE is based on the equivalence of the present value of the sum of discounted revenues and the present value of the sum of discounted costs (see for instance, Marrero and Ramos-Real, 2010).

Strategy

Levelized Cost of Electricity Formula

$$LCOE = \frac{P + OM_F}{8760 \cdot C_f} + F_c \cdot Q + OM_v$$

$$P = C_c \left[i + \frac{i}{(i+1)^n - 1} \right]$$

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.

Strategy

My Approach in this Study

1. Calculate LCOE by Monte Carlo Simulation.
   - Draw LCOE Cost Parameters from various statistical distributions.
   - Distributional choice is determined by historical data on costs across energy sources.
   - Collate point source data from EIA and LAZARD LCOE reports. Use the data to establish boundary conditions for the chosen distributions.

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

Strategy

My Approach in this Study

2. Take random draws from the Multivariate Normal Distribution to construct a correlated error term across all energy source LCOE's.
    - Since most studies focus on point source estimates, little work has been done to evaluate the covariance structure between energy sources. Some correlation is assumed to exist within costs and interest rates. Using the MVN distribution allows us to model the unknown correlations across energy sources.

$$\varepsilon \sim \mathcal{N}_p(\mu, \Sigma)$$

$$LCOE_{\varepsilon_i} = LCOE_i + \varepsilon_i$$

Strategy

My Approach in this Study

3. Use the Expected $LCOE_{\varepsilon_i}$ cost estimates from the Monte Carlo study along with the uncovered variance-covariance matrix to minimize the risk, (using a Quadratic Programming Model) of obtaining energy while satisfying the defined constraints.

Optimization Model

Model and Notation

$$\min \sum_{i=1}^{6} (\Sigma x_i)^2 \text{ subject to: constraints}$$

Variable	Description	Value or Dimensions
i	Index over the sources (1,…6)	-
x_i	Power provisioned from resource i [TWh]	-
c_i	Expected cost of resource i in 2022, [million USD/TWh]	-
c_{max}	Maximum expected cost [million USD/TWh]	100
d	Total ERCOT energy demand in 2022 [TWh]	385
Σ	Variance-Covariance of resource i's cost [million USD/TWh]	-

Figure 6:

Optimization Model

General Constraints

- 2022 Energy Demand

$$\sum_{i=1}^{6} x_i \geqslant d$$

- Maximum Expected Cost

$$\frac{\sum_{i=1}^{6} c_i x_i}{\sum_{i=1}^{6} x_i} \leqslant c_{max}$$

- Non-negativity

$$x_i \geqslant 0,\ \forall i$$

Optimization Model

Technical Constraints

- from Marrero, et al (2015); Awerbuch and Berger (2003); Awerbuch and Yang (2007); Marrero and Ramos-Real (2010)

$$Solar_{PV} \leqslant 7\%$$
$$Wind \leqslant 25\%$$
$$NG_{Peaking} \geqslant 10\%$$

$$\left.\begin{aligned} x_1 &= NG_{cc} \leqslant 90\% \\ x_2 &= Coal \leqslant 90\% \\ x_3 &= Nuclear \leqslant 90\% \end{aligned}\right\} UpperLimit$$

$$\left.\sum_{i=1}^{3} x_i \geqslant 60\%\right\} LowerLimit$$

Optimization Model

Practical Implementation in R

- Using “quadprog” algorithm
- the algorithm expects the following format

$$\min \left(\frac{1}{2} b' D b - d' b \right) \text{ s.t. } A' b \geqslant b$$

$$d_{vec} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} dim[1X6]$$

$$b_{vec} = \begin{bmatrix} d & 0 & 0 & 0 & 0 & 0 & 0 & 0 & d.6 & d.9 & d.9 & d.9 & d.07 & d.25 & d.1 \end{bmatrix} \mathrm{dim}[1X15]$$

Figure 7:

Optimization Model

Practical Implementation in R

$$A = \begin{bmatrix} -1 & -1 & -1 & -1 & -1 & -1 \\ c_1 - c_{max} & c_2 - c_{max} & c_3 - c_{max} & c_4 - c_{max} & c_5 - c_{max} & c_6 - c_{max} \\ -1 & 0 & 0 & 0 & 0 & 0 \\ 0 & -1 & 0 & 0 & 0 & 0 \\ 0 & 0 & -1 & 0 & 0 & 0 \\ 0 & 0 & 0 & -1 & 0 & 0 \\ 0 & 0 & 0 & 0 & -1 & 0 \\ 0 & 0 & 0 & 0 & 0 & -1 \\ -1 & -1 & 0 & -1 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & -1 & 0 & 0 & 0 \end{bmatrix} \dim[15X6]$$

$$D = \Sigma \dim[6X6]$$

Results

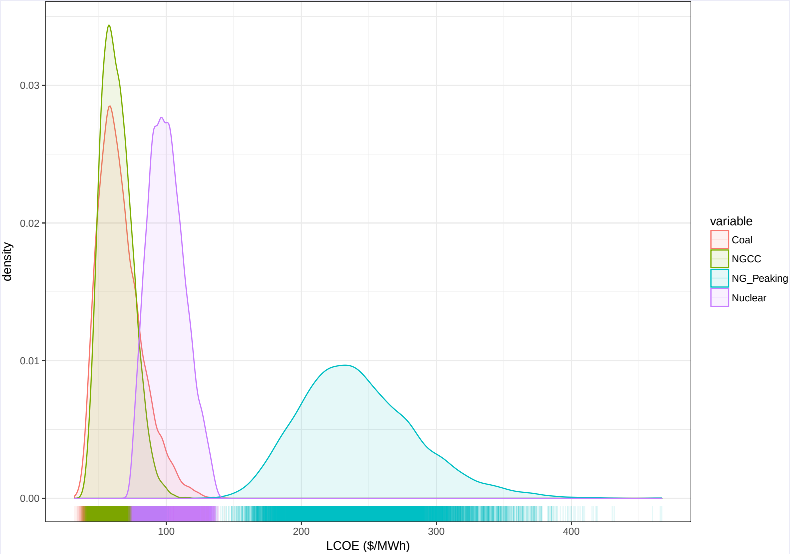
Summary Statistics from Monte Carlo Study

Table 3: Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Max
Coal	10,000	65.579	15.947	33.446	139.497
NGCC	10,000	63.214	11.134	35.320	115.209
NG_Peaking	10,000	243.180	43.505	129.175	475.980
Nuclear	10,000	100.830	13.301	72.219	138.894
Wind	10,000	86.447	6.678	67.177	119.814
Solar_PV	10,000	201.187	48.394	104.108	394.782

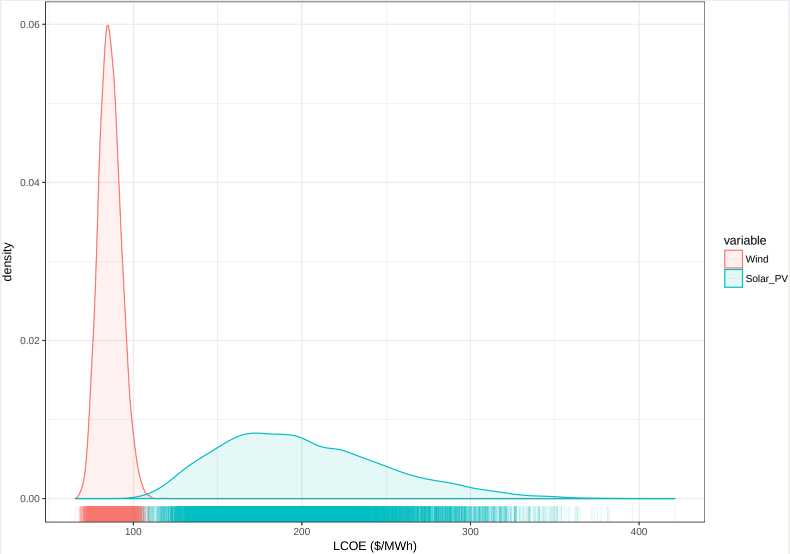
Results

Density Plots from Monte Carlo Study



Results

Density Plots from Monte Carlo Study



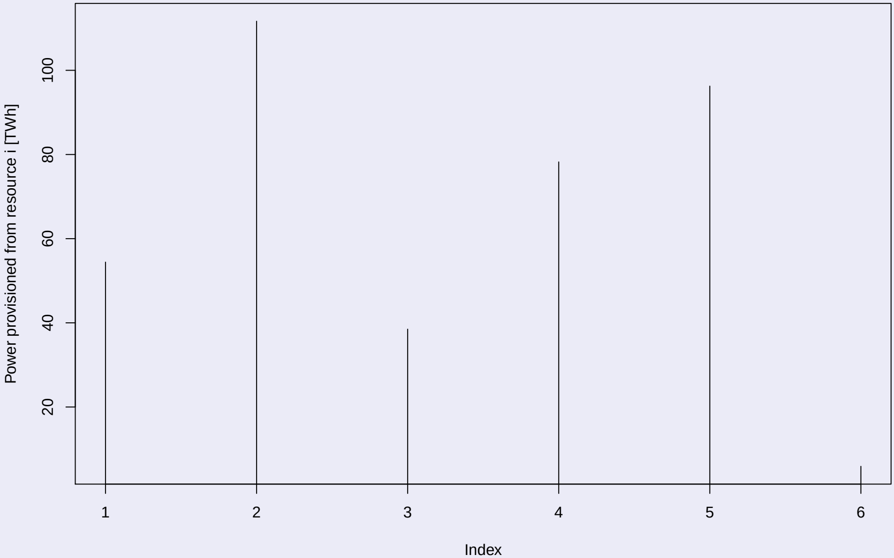
Results

Output from Quadratic Program

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

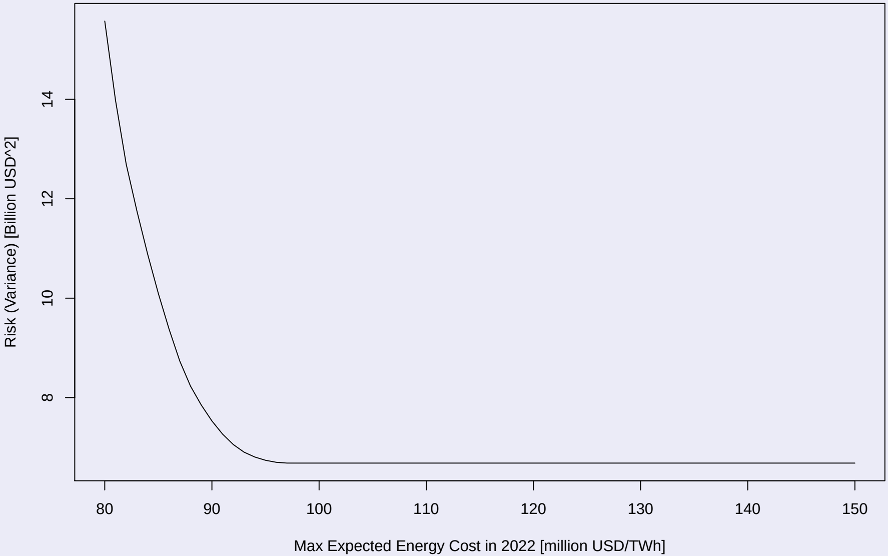
Results

Histogram Plot of Quadratic Program Optimization



Results

Risk Plot of Quadratic Program Optimization



What next

Directions for Future Research

- Bootstrap the variance-covariance matrix.
- Enrich the LCOE calculations with additional parameters and better data.
- Model the variance-covariance using SUR.
- Model the LCOE using ARCH/GARCH modeling.