Essays on Power System Economics

Dissertation

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Abstract

Chapter 1: Optimizing Transmission from Distant Wind Farms

We explore the optimal size of the transmission line from distant wind farms, modeling the tradeoff between transmission cost and benefit from delivered wind power. We also examine the benefit of connecting a second wind farm, requiring additional transmission, in order to increase output smoothness. Since a wind farm has a low capacity factor, the transmission line would not be heavily loaded, on average; depending on the time profile of generation, for wind farms with capacity factor of 29-34%, profit is maximized for a line that is about ¾ of the nameplate capacity of the wind farm. Although wind generation is inexpensive at a good site, transmitting wind power over 1,000 miles (about the distance from Wyoming to Los Angeles) doubles the delivered cost of power. As the price for power rises, the optimal capacity of transmission increases. Connecting wind farms lowers delivered cost when the wind farms are close, despite the high correlation of output over time. Imposing a penalty for failing to deliver minimum contracted supply leads to connecting more distant wind farms.

Chapter 2: The optimal baseload generation portfolio under CO2 regulation and fuel price uncertainties

We solve for the power generation portfolio that minimizes cost and variability among existing and near-term baseload technologies under scenarios that vary the carbon tax, fuel prices, capital cost and CO_2 capture cost. The variability of fuel prices and uncertainty of CO_2 regulation favor technologies with low variable cost and low CO_2 emission. The qualitative results are expected; stringent CO_2 regulation cost leads to more technology with little carbon emissions, such as nuclear and IGCC CCS, while penalizing coal. However, the variability of fuel prices and the correlation among fuel prices are the principal attributes shaping the optimal portfolio mix. We also model a Bayesian approach that allows the planner to express his belief on the future cost of power generation technology.

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Chapter 1

Optimizing Transmission from Distant Wind Farms

1. Introduction

California and 29 other states have renewable portfolio standards (RPS) that will require importing electricity generated by wind from distant locations. A long transmission line increases cost significantly since its capacity factor is approximately the same as the wind farms it serves, unless storage or some fast ramping technology fills in the gaps left by wind generation. We explore issues surrounding importing wind electricity from distant wind farms, including: the delivered cost of power, considering both generation and transmission, the cost of the transmission line, when to pool the output of two wind farms to send over a single transmission line, and what additional distance would the owner be willing to go for a better wind site in order to minimize the cost of delivered power.

Wind energy is the cheapest available renewable at good wind sites. Since no fuel is required, generation cost depends largely on the investment in the wind farm and the wind characteristics (described by the capacity factor). Assuming $1,915/kW for the cost of the wind farm, annual operations and maintenance (O&M) costs of $11.50/kW-yr, variable O&M cost of $5.5/MWh, a blended capital cost of 10.4%, and a 20 year life time for the turbine, generation costs at the wind farm are around $76/MWh, $66/MWh, $59/MWh, $56/MWh, and $53/MWh, respectively, for the wind farms with capacity factors of 35%, 40%, 45%, 47.5%, and 50%, respectively.

Wind is the fastest growing renewable energy, adding 8,558 MW of capacity in 2008, 60% more than the amount added in 2007 (Wiser and Bolinger, 2009). Total wind capacity in 2008 was 25,369 MW, about 2.2% of U.S. total generation nameplate capacity.

Good wind sites (class 4-6 with average wind speed 7.0-8.0 m/s at 50 m height (AWEA, 2008)), accounting for 6% of the U.S. land, could supply 1.5 times current U.S. electricity demand (DOE, 2007). However, transmission is a key barrier for wind power development, since good wind sites are generally remote from load centers (DOE, 2008a). The low capacity factor of a wind turbine, added to the remoteness of good wind sites, makes transmission a major cost component. Denholm and Sioshansi (2008) note that transmission costs can be lowered by operating the transmission line at capacity through storage or fast ramping generation at the wind farm. Whether this co-location lowers the delivered cost of electricity depends on the site characteristics and other factors.

Low utilization of a long transmission line could double the cost of delivered wind power, since a wind turbine's capacity factor is only 20-50%. Using actual generation data from wind farms, we model the optimal capacity of a transmission line connecting a wind farm to a distant load. We show that the cost of delivered power is lowered by sizing the transmission line to less than the capacity of the wind farm.

We assume the wind farm is large enough to require its own transmission line without sharing the cost with another wind farm or load in a different location. While we know of no example of a wind farm building its own transmission, T. Boon Pickens proposed to do this. If 1,000 MW were to be sent 1,000 miles or more, available capacity in short, existing lines would not be helpful. We also extend the model to two wind farms, trading off the additional transmission needed to connect the farms against the less correlated output. The relationship between wind output correlation and distance is modeled using the wind data from UWIG (2007). Finally, we model the effect of charging wind farms for failing to provide the minimum supply requirement.

2. Model

2.1 One Wind Farm Model

In this model, a wind farm is large enough to require its own high voltage DC transmission line to the load. The project consists of the wind farm and transmission line. We formulate the model as the owner of the wind farm and transmission line seeking to maximize profit. However, in this case the objective function is equivalent to seeking to maximize social welfare, as explained below.

The general form of the objective function for optimizing the capacities of the transmission line is:

$$\underset{0 \le s \le 1}{MAX} \ NPV = \sum_{j=1}^{40} \sum_{i=1}^{N} \frac{p_{ji}}{(1+r)^j} \min[q_{ji}, sK] - aC(sK) - WC_1 - \frac{WC_2}{(1+r)^{20}}$$

K = capacity of the wind farms (MW)

s = transmission capacity normalized by total capacity of the wind farm (called "transmission capacity factor")

a = length of the transmission line (mile)

$C(sK)$ = cost per mile of sK MW transmission line built in year 0

i = i^{th} hour in a year

j = j^{th} year (from 1^{st} – 40^{th})

N = 8,760 hours in a year

p_{ji} = the expected price of wind power ($/MWh) in year j at hour i

q_{ji} = the expected delivered wind power (MWh) in year j at hour i

r = the discount rate

WC_1 = cost of the wind turbines built in year 0

WC_2 = cost of the wind turbines built in year 20

The lifetimes of the transmission line and wind turbine are assumed to be 40 and 20 years respectively. Thus, the turbines must be replaced in year 20. We also assume that construction is instantaneous for both transmission and turbines.

Transmission investment has economies of scale over the relevant range; the cost per MW decreases as capacity of the line increases (Weiss and Spiewak, 1999). Line capacity is defined as the “thermal capacity” in megawatts (MW) (Baldick and Kahn (1993)). The transmission line cost is $C(q)$ per mile, where q is the capacity of the line. $C(q)$ is increasing and concave, $C'(q) \geq 0$ and $C''(q) \leq 0$.

We assume no line loss (delivered power equals the injected amount) and the wind distribution (output) is the same in all years.

According to Barradale (2008), about 76% of wind power is purchased via a long term power purchasing agreement (PPA) that specifies a fixed price or price adjusted by inflation. Electricity price paid to the wind farm is assumed to be constant over time and unrelated to the quantity of wind power supplied. Thus, whether the owner seeks to maximize profit or a public authority seeks to maximize social welfare, the goal is to maximize the benefit of delivered wind power by optimizing the size of the transmission line.

Given these assumptions, the variables q_i and P are used instead of q_{ji} and p_{ji} to represent the constant annual output and fixed price. The optimization problem is simplified as follow.

$$\underset{0\le s\le 1}{MAX}\ NPV = P\left(\sum_{j=1}^{40}\frac{1}{(1+r)^j}\right)\sum_{i=1}^{N}\left(\min[q_i, sK]\right) - aC(sK) - WC_1 - \frac{WC_2}{(1+r)^{20}}$$

Let $\sum_{j=1}^{40}\frac{1}{(1+r)^j} = \beta$, $\sum_{i=1}^{N}\left(\min[q_i, sK]\right) = Q(s,K)$ and $WC_1 + \frac{WC_2}{(1+r)^{20}} = WC$.

The above objective function can be written as;

$$\underset{0\le s\le 1}{MAX}\ NPV = \beta PQ(s,K) - aC(sK) - WC$$

The optimal transmission capacity is determined by the tradeoff between the incremental revenue from delivering additional electricity and the incremental cost of the capacity increase. The optimization problems is solved numerically by using the search algorithm to find the maximum point over the range of feasible transmission capacity; $0 \le s \le 1$.

2.2 Two Wind Farms Model

The model with two wind farms assumes a branch line of “*b*” miles connecting farm 2 to farm 1, which is connected to the customer with a main line of “*a*” miles. If the two farms are so distant that it is cheaper to connect each to the customer, the previous model applies.

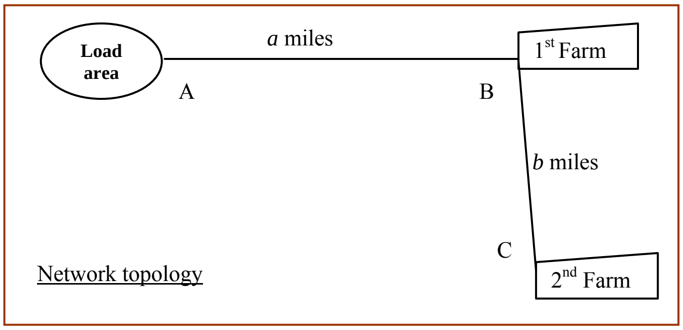

Figure 1: Simplified network topology of the model with 2 wind farms

This model explores the effect of output correlation on the optimal transmission capacity. The basic one-farm model assumptions are retained and the two farms have the same capacity. (K MW). The investor chooses the optimal size of both transmission lines to maximize profit. The objective function is:

$$\underset{0\le s_1\le 2,\ 0\le s_2\le 1}{MAX}\ NPV = P\beta\sum_{i=1}^{N} q_i(s_1,s_2,K) - aC(s_1K) - bC(s_2K) - WC_{11} - WC_{12} - \frac{WC_{21}+WC_{22}}{(1+r)^{20}}$$

s_1 = the transmission capacity factor (main line)

s_2 = the transmission capacity factor (branch line)

$aC(s_1K)$ = cost of a miles main transmission line capacity s_1K MW built in year 0

$bC(s_2K)$ =cost of b miles branch transmission line capacity s_2K MW built in year 0

WC_{11} and WC_{12} = cost of 1st and 2nd wind farms built in year 0

WC_{21} and WC_{22} = cost of 1st and 2nd wind farms built in year 20

$q_i(s_1,s_2,K)$ = the expected delivered wind power at hour i from both wind farms

Note that $q_i(s_1,s_2,K) = q_{1i}(s_1,K) + q_{2i}(s_2,K)$ where $q_i(s_1,s_2,K) \le s_1K$. $q_{1i}(s_1,K)$ is the power generated by the 1st farm. $q_{2i}(s_2,K)$ is the delivered power from the 2nd farm such that $q_{2i}(s_2,K) \le s_2K$.

Let $\sum_{i=1}^{N} q_i(s_1,s_2,K) = Q(s_1,s_2,K)$ and $WC_{11} + WC_{12} + \frac{WC_{21}+WC_{22}}{(1+r)^{20}} = WC$. The objective function can be formulated as;

$$\underset{s1,s2}{MAX}\ NPV = \beta PQ(s_1,s_2,K) - aC(s_1K) - bC(s_2K) - WC$$

The optimization problem is solved numerically by evaluating the objective function over a two-dimensional grid of s_1 and s_2 values.

3. Data and variables

1. Wind data

We use hourly wind power generation data from four Northeastern U.S. wind farms covering January-June and assume the July-December data are similar. The data are shown in figure 1. The data were normalized so that the maximum output (the nameplate capacity) was equal to 1. Descriptive statistics and output correlation & distance between farms are shown in the tables below.

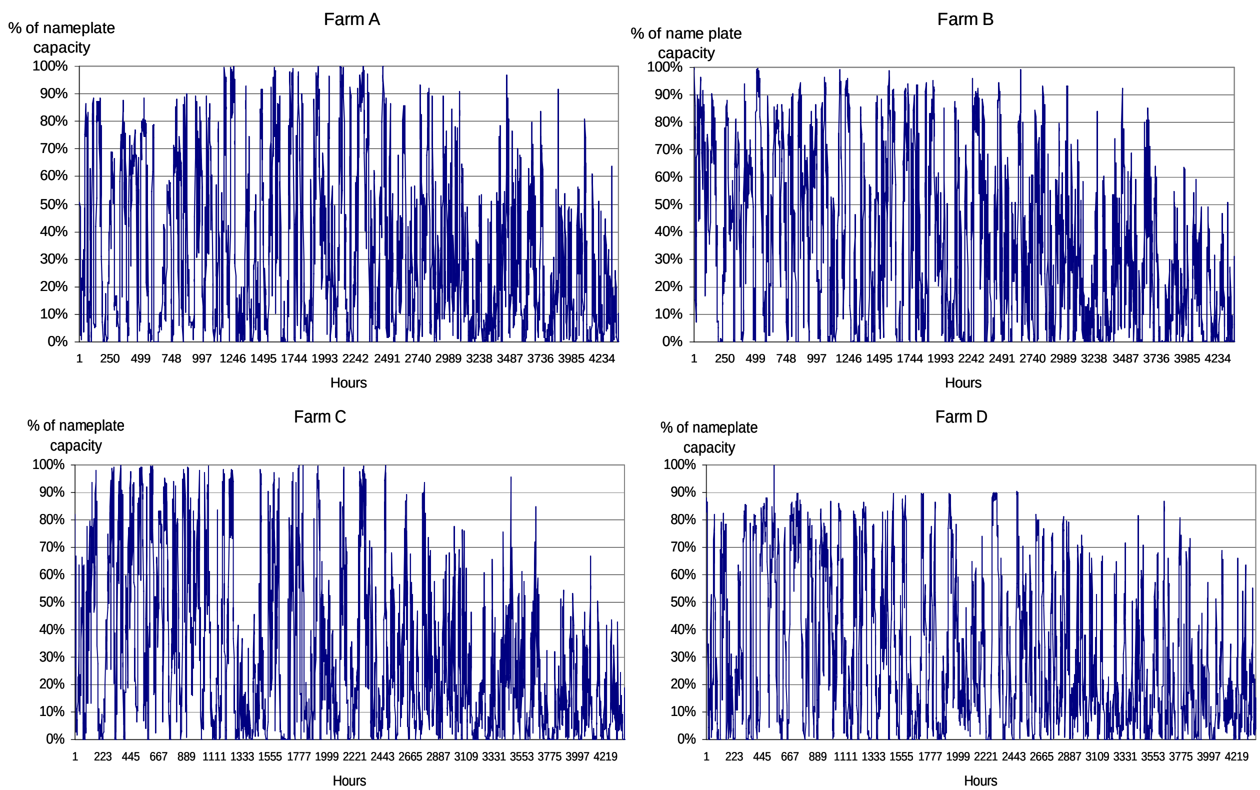

Figure 2: Hourly distribution of wind power

Wind farm	Capacity factor (%)	Variance
A	32.73	0.0840
B	34.73	0.0871
C	29.92	0.0821
D	29.77	0.0738

Table 1: Descriptive statistics of the wind farm output

Farm	A	B	C	D
A	1.0	0.77	0.69	0.35
B	56	1.0	0.71	0.46
C	19	63	1.0	0.36
D	219	250	200	1.0

Note: correlations are shown on and above the diagonal and distances are shown below the diagonal.

Table 2: Output correlation and distance between farms (mile)

q_i, $Q(s,K)$, $q_i(s_1,s_2,K)$ and $Q(s_1,s_2,K)$ are derived from this actual wind data.

2. Financial variable

   The discount rate in this model is 10.4% (20% equity at 20% and 80% debt at 8%).

3. Transmission cost data and estimation

   The cost of a transmission line varies with distance and terrain, but the greatest uncertainty concerns regulatory delay and the cost of acquiring the land. To reflect this uncertainty, we perform a sensitivity analysis with cost varying between 20% and 180% of the base cost in the next section. We use DOE (2002) data to estimate the transmission line cost function. The data are adjusted to reflect the current cost of DC transmission construction[1].

The functional form of the cost function is; $cost\ per\ mile = e^{\alpha} MW^{\beta}$. The coefficient β indicates how much cost increases as the line capacity increases by 1%; elasticity with respect to line capacity. By using a log-log transformation, the transmission line cost function is estimated as a log-linear function of transmission capacity (*MW*). The transmission line cost, as a function of capacity is estimated using ordinary least square (OLS); see Appendix A. As expected, the estimated result displays economies of scale of transmission line investment.

$$cost\ per\ mile = e^{10.55415} MW^{0.5759}$$

[1] The reported cost for high voltage transmission line covers a wide range (ISO-NE, 2007). If the cost of the transmission line were half or twice the cost we assume, the cost of the transmission would be halved or doubled assuming the capacity of the line is fixed.

The regression equation has R^2 = 0.94 and all parameters are statistically significant. The t-statistics for the constant and the parameter of *MW* are 35.31 and 10.24 respectively.

4. Wind turbine cost

Costs of new wind turbines have risen and then fallen in the past few years; we use $1,915/kW as the installed cost of a wind farm (Wiser and Bolinger, 2009), $11.5/KW-year fixed O&M cost and $5.5/MWh variable O&M cost (Wind Deployment System (WinDS) model (DOE, 2008b)).

5. Electricity price

The electricity price in this study is the real hourly electricity price paid to the owner of the wind farm and transmission. Since the wind farm operator has little control over when the turbines generate electricity, we assume that she receives the average price for the year for each MWh. We assume that the delivered price paid to the wind farm investor is $160/MWh included all federal and state subsidies. In addition, for simplicity, we assume the electricity price over the next forty years is constant, after adjusting for inflation.

4. Results

4.1 Results for One Wind Farm

We focus on delivering wind power over a distance of 1,000 miles, about the distance from Wyoming to Los Angeles; California's renewable portfolio standard will require large amounts of wind energy from distant sites. For a 1,000 mile long transmission line, the optimal transmission capacity, utilization rate, profit and delivered output for the four wind farms are shown in Appendix C, Table C1. The optimal capacity is 74 - 79% of the wind farms' capacity. As expected, among the four wind farms, those with higher capacity factors have higher optimal transmission capacity, profit and delivered output, with lower delivered power cost.

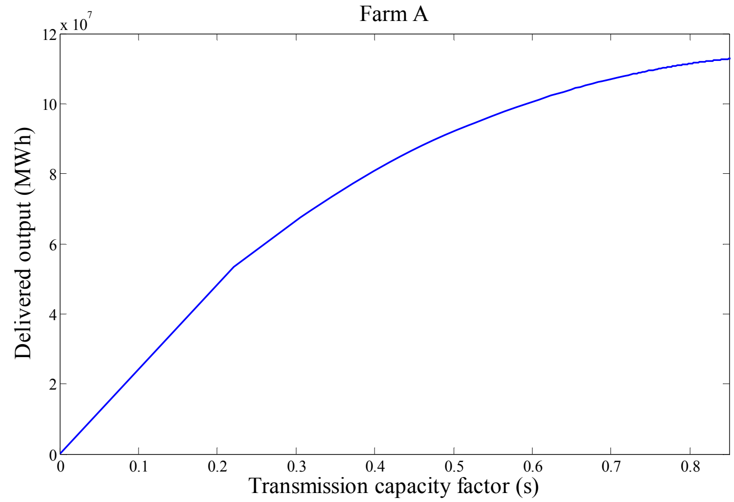

Figure 3: Transmission capacity and delivered output

Figure 3 shows the relationship between the capacity of the transmission line and the delivered wind power of Farm A. The slope of the curve represents the marginal benefit of transmission capacity. As transmission capacity increases, marginal benefit decreases since the turbine's output is at full capacity for only a few hours per year. Farm A's optimal transmission capacity is 79% of the farm's capacity, but the transmission line delivers 97% of the wind power generated. Adding 21 percentage points to transmission capacity increases delivered output by only 3 percentage points.

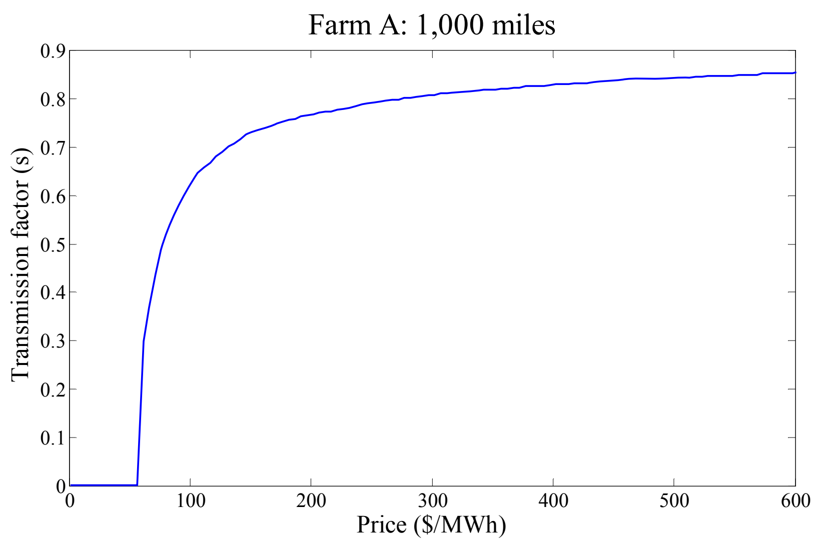

Figure 4: Price vs. transmission capacity factor (*s*)

Figure 4 shows the relationship between price and transmission capacity (*s*) of farm A derived from the first order condition. The first order condition shows the optimal capacity decision, even when profit is negative, although the investor would not build the wind farm and transmission for a negative return. At price below $55/MWh, the optimal capacity is zero. Optimal transmission capacity and delivered power rise rapidly as price goes from $55 to 200/MWh due to economies of scale in transmission investment and the initial high marginal benefit of the transmission line (as seen in Figure 3). The scale economies are essentially exhausted and virtually almost all of the generated power is being delivered by the time a $300 price is reached; higher prices would increase transmission capacity little.

As price rises, the value of the delivered electricity rises, increasing the value of transmission capacity; almost all of the generated power is being delivered by the time a $300 price is reached. The supply curve is shown in Figure 5.

The delivered cost of wind power (transmission cost included) ranges from $144 to 169/MWh for these 4 wind farms. Since the generation cost is $78 to 92/MWh, transmission is 44-46% of the total cost; see Appendix C, Table C1. Note that the price paid to the investor is $160/MWh.

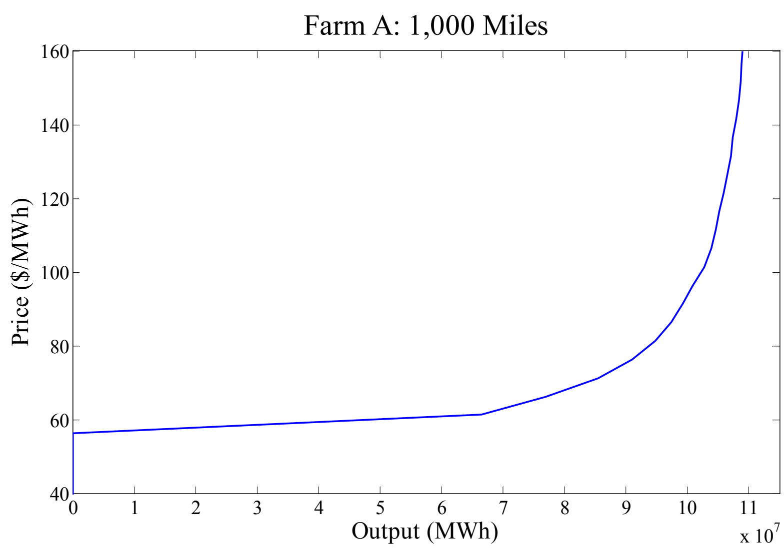

Figure 5: The supply curve

The output distribution of a wind farm also affects the optimal transmission capacity.[2] In order to test the effect of the distribution, all 4 wind farms' output data are modified to have a 50%capacity factor. As shown in Appendix C Table C2, the optimal

[2] Consider two wind farms with 30% capacity factor, if the turbine produced at 100% of capacity 30% of the time and zero capacity the rest, the optimal transmission capacity would be 100%; if it produced at 30% of capacity 100% of the time, the optimal transmission capacity would be 30%.

transmission capacity, profit and delivered output of farms A, B and C are about the same. However, Farm D has the lowest transmission capacity and the highest profit, since it has less output distributed in the 80-100% of nameplate capacity range. As a result, farm D faces less trade-off between transmission capacity and loss of high level output. In addition, the farm with lower output standard deviation tends to have lower optimal transmission capacity.

	Transmission capacity factor (s)	Transmission cost $	Additional transmission cost $	Additional revenue $	Decrease in profit $
A	0.7880	1.785×10^9	2.626×10^8	1.248×10^8	1.378×10^8
B	0.8075	1.810×10^9	2.373×10^8	0.946×10^8	1.427×10^8
C	0.7747	1.767×10^9	2.799×10^8	1.534×10^8	1.265×10^8
D	0.7388	1.720×10^9	3.276×10^8	1.049×10^8	2.227×10^8

Table 3: Implication of increasing transmission to 100% of wind farm capacity

Table 3 shows profit reduction in present value term when the transmission line is expanded from the profit maximizing capacity to the wind farm's nameplate capacity. Profit reduction is calculated as the difference between the additional cost of building the line at full capacity and revenue from additional delivered wind power (in present value); expanding the line to full capacity costs $127 to $223 millions. Although it may seem wasteful to spill some of the power generated by the wind farm, beyond the optimal transmission capacity, the incremental cost of increasing transmission capacity is greater than the value of the additional power delivered. For example, building a line at full capacity for Farm A increases the cost of the line by 15% while delivering only 3% of additional power.

The best wind sites are distant from load and so there is a tradeoff between lower generation cost and lower transmission cost. Figure 6 shows the delivered cost of power from wind farms with capacity factors of 35% and 50% as a function of the distance of the wind farm from load. For a 50% capacity factor wind farm, the delivered cost of power doubles when it is just over 1,063 miles away. For a 35% capacity wind farm, the delivered cost of power is doubled when the wind farm is just under 1,000 miles away.

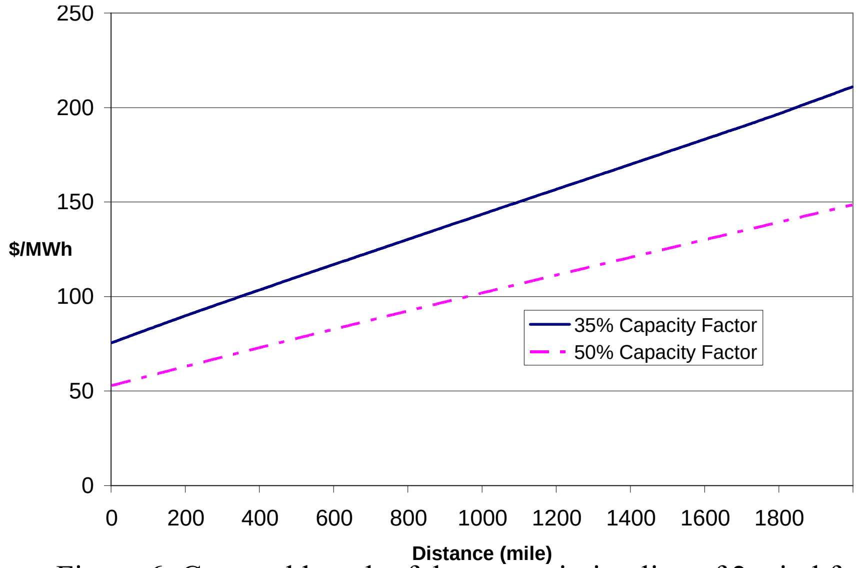

Figure 6: Cost and length of the transmission line of 2 wind farm sites

A more interesting interpretation of the figure is to see how much further you would be willing to go to get power from a 50% capacity factor wind farm compared to a 35% capacity factor wind farm. At a cost of delivered power of $100/MWh, a 35% capacity wind farm could be 300 miles away while a 50% capacity wind farm could be 1,000 miles away. Thus, if a 35% capacity factor wind farm were located 300 miles away, the customer would be willing to go up to an additional 700 miles. For any delivered cost of electricity, the horizontal difference between the two lines is the additional distance a customer would be willing to go to get to a wind farm with capacity factor 50% rather than 35%. Since much of the USA has a minimally acceptable wind site within 300 miles, they would not find it attractive to go to the best continental wind sites in the upper Midwest.

To ensure reliability, power systems must satisfy an N – 1 criterion. The variability of wind output puts an additional burden on the generation system. The cheapest way of meeting the N – 1 criterion is by using spinning reserve; this reserve can also ramp up and down to fill the gaps in wind generation. As reported by CAISO (2008), the total cost of ancillary services per MWh in 2008 (monthly average) is from $0.42-1.92/MWh. This cost includes spinning reserve, non spinning reserve and regulation. The cost of spinning reserve alone is about $0.15-0.67$/MWh. Thus, the cost of purchasing spinning reserve would add less than 1% to the cost of delivered power.

Sensitivity analysis

We perform 4 sensitivity analyses: transmission cost vs. optimal capacity, the optimal transmission capacity vs. length of the line, transmission capacity vs. the discount rate, and profit vs. the discount rate. Other parameters are assumed to stay at former levels.

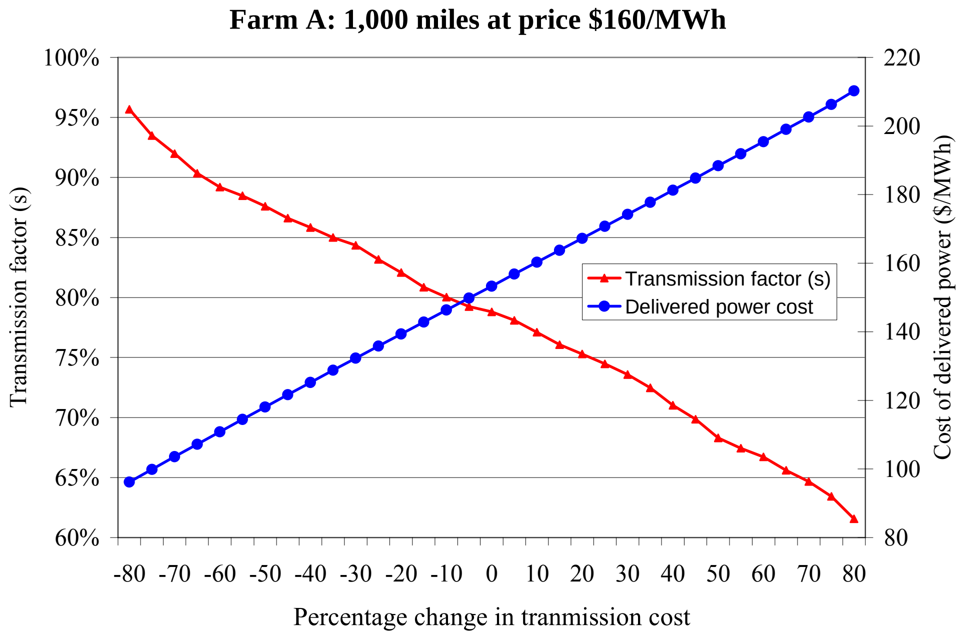

Figure 7: Transmission cost and optimal line capacity of farm A

Transmission cost and optimal capacity

The optimal transmission capacity is solved for transmission cost varying plus or minus 80% of the base line. When the transmission line costs 80% less than the base case, the optimal size of the transmission line is 96% of the wind farm capacity and the cost of delivered power is $96/MWh. When the transmission line costs 80% more than the base case, the optimal capacity of the transmission line is 62% of the wind farm capacity and the cost of delivered power is $210/MWh. The base case values have the transmission line at 79% of the capacity of the wind farm with a delivered cost of $149/MWh.

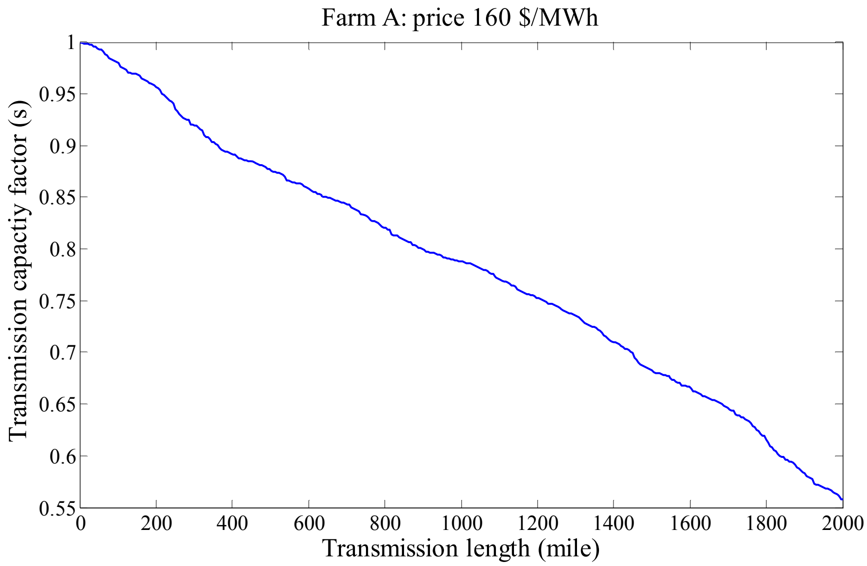

Figure 8: Optimal transmission capacity and transmission length of farm A

Transmission capacity and length: Transmission cost increases with the length of the line. Figure 7 can be interpreted as showing the effects of shortening the line to 200 miles or lengthening it to 1,800 miles. As transmission cost increases, the optimal capacity of the transmission line relative to the wind farm capacity decreases for a given power price, as shown in Figure 8. A longer transmission line results in lower delivered output.

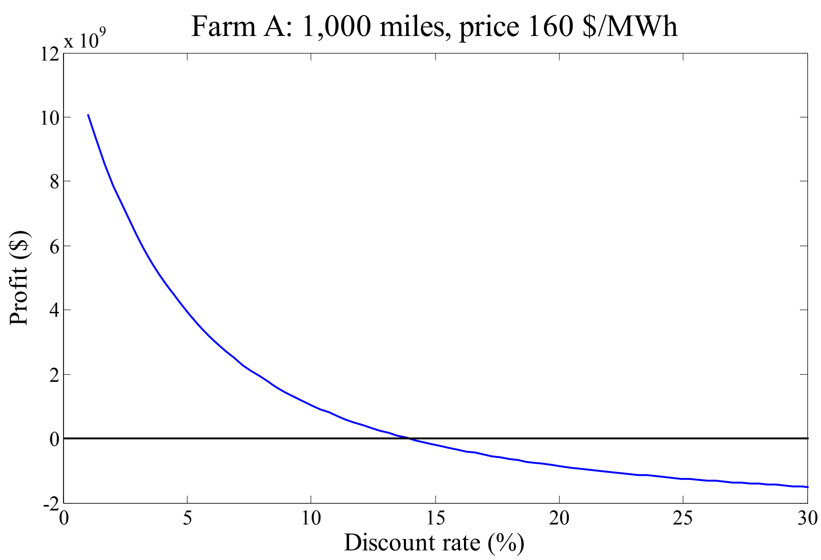

Figure 9: Profit and discount rate of farm A

Profit and a discount rate: Profit steadily decreases as the discount rate increases. As shown in Figure 9, the IRR (Internal Rate of Return) of this project is around 14% at a $160/MWh price (the discount rate giving zero NPV).

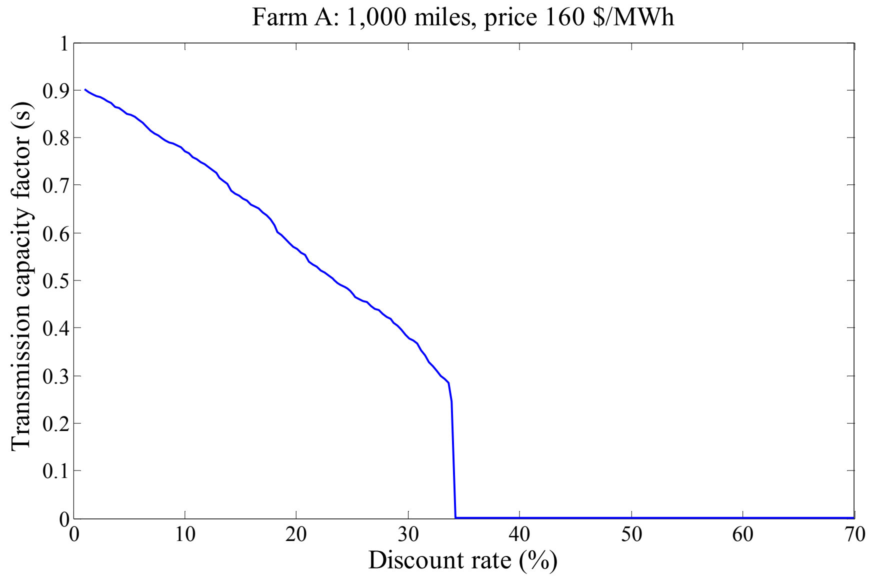

Figure 10: Optimal transmission capacity and discount rate of farm A

Transmission capacity and discount rate: Increasing the cost of capital (equity and loans) increases the cost of the transmission line. Figure 10 shows that the capacity of the line declines as the discount rate increases.

4.2 Results for Two Wind Farms

The data from 4 wind farms is used to maximize profit when two wind farms share the same central transmission line. By bundling 2 wind farms, the capacity of the main transmission line is almost double compared with the one wind farm case and so the transmission line can take advantage of economies of scale at this level (see Appendix C Table C3 for detail). The correlation between outputs of wind farms generally decreases as the farms are more distant. Here we investigate connecting wind farms that are more distant, trading off the cost of the additional transmission against the lower correlation of output. We examine each of the 12 possible pairs. Note that the pair AB means that the main transmission line goes to A, with a secondary line to B. The results from AB and BA are similar. The model is solved under 3 scenarios.

- Scenario 1: a = 1,000 miles and b = the actual distance between farms

- Scenario 2: a = 1,000 miles and b = the distance calculated from the estimated relationship between correlation and distance (Appendix B). Farm A is paired with a fictitious wind farm whose capacity factor is the same as A where the correlation between the outputs of the two wind farms is calculated from the estimated correlation-distance relationship.
- Scenario 3: This scenario has the same configuration as scenario 2 but imposes a penalty per MWh when the delivered power from the wind farms falls below a minimum requirement level.

In scenario 1, the total cost of wind power (both generation and transmission cost included) ranges from $134 to 153/MWh, taking advantage of the economies of scale in transmission. The cost of generation ranges from $80 to 92/MWh, approximately the same as the one wind farm model. Transmission cost still accounts for more than one third of the delivered wind power cost.

When the second wind farm is close to the first, the output from the two wind farms are highly correlated. The second wind farm would help lower the delivered cost of electricity through economies of scale of transmission but this cost saving must be traded off against the length of the connecting transmission line.

In addition, when the length of the second transmission line is shorter, the capacity of the line (s_2) is higher. A shorter line translates to lower cost, which makes a slightly higher capacity more profitable. In addition, like the one wind farm model, capacity factor is the key factor that determines profit from the project.

Given the correlation-distance relationship, in scenario 2, we vary the correlation over the relevant range, calculate the implied distance, and then optimize the capacity of the transmission line to maximize profit. Farm A is paired with a wind farm of the same capacity, but we vary the distance (and thus the output correlation) between the two farms. The simulated data used in scenario 2 are random numbers generated with the specific correlation with farm A and have capacity factor 30%.

While the correlation of output from two wind farms decreases with the distance between them, the correlation also varies with terrain and wind direction. The pair of wind farms with lower correlation tends to have higher utilization rate of the main transmission line. This can be considered as the effect of output smoothing by aggregating wind farms with low output correlation. The transmission line is used more efficiently when output is smoother (see Appendix C Table C4 for detail). If the system needs the smoother wind power output, more money is needed to invest in longer transmission.

Lower output correlation implies lower transmission capacity and higher transmission (main line) utilization rate. Without a price premium for smoothed output, the shorter distance between farms is more profitable than a low correlation. Thus, for this distance-correlation relationship, investors would want to build wind farms close together, despite the high correlation of their outputs. Thus, the optimal distance between wind farms is zero, as long as the second farm has the same capacity factor as the first.

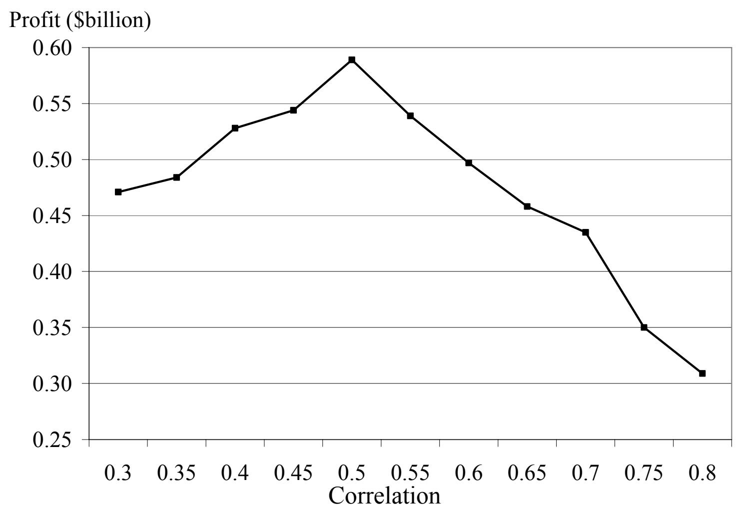

Figure 11: Profit at penalty $160/MWh with minimum delivery requirement 400 MW

Scenario 3 analyzes the effect of imposing a minimum output requirement of 400 MW (20% of the total nameplate capacity) by the buyer. If the wind farm cannot fulfill this requirement, it has to buy power from other generators or pay the buyer the financial penalty. This cost is defined as an imbalance price. In addition, this imbalance price is assumed to be higher than or equal to the price paid to the wind farm.

As expected, the pair with lower correlation has lower imbalance output. As shown in Appendix C Table C5, the imbalance output (the amount in MWh that cannot meet the requirement) increases steadily as the correlation between wind farms' output increases. In addition, the result from this scenario shows the different investment decision from scenario 2. In scenario 2 without the minimum output requirement penalty, the wind farm projects with high output correlation and short transmission line are more profitable. Imposing the minimum requirement increases the optimal distance between wind farms, resulting in an optimal output correlation in the range 0.4 – 0.6, as shown in Figure 11.

5. Conclusion

This analysis illustrates the complications with deciding where to site wind farms, trading off the lower cost of better wind potential against transmission cost, how large a transmission line to build, and where to locate a second wind farm if it is to be connected to the load with the same transmission line. The results are based on actual data with some extensions. The wind farm capacity factors, costs of transmission, and correlation among wind farms are unique to each location; an analysis of a specific location could be optimized using the methods presented here.

Since a 1,000 mile transmission line roughly doubles the delivered cost of power, decreasing the variability of generation at the wind farm lowers power costs. However, two connected wind farms only raise the capacity factor slightly. Imposing a minimum requirement penalty leads to changes that increase firm output, although raising the generation cost.

For a wind farm with a 1,000 mile transmission line, about the distance from Wyoming to Southern California, the intermittency and low capacity factor of wind farms increases the cost of transmission significantly. We find that the delivered cost of power and optimal capacity of the transmission line increase with the price paid for the power, and decrease with the wind farm's capacity factor, the distance from load, and the discount rate.

For a delivered price of \$160/MWh, the optimal capacity of the transmission line is 74-79%; only 3% of generated power is wasted for this transmission line. When two wind farms are bundled, economies of scale in transmission increase the optimal capacity of the transmission line and lower the cost of delivered power. When we examine the distance between wind farms, trading off lower output correlation with greater distance between farms, we find that closer farms have the lowest cost of delivered power.

However, when there is a penalty for failing to deliver a minimum amount of power, the distant wind farms become more profitable.

Appendix A: Transmission cost function estimation

The data used for transmission cost function estimation are from DOE (2002) which is the cost data from 1995 study. The data are adjusted by the factor of 3. We need to adjust the data that makes the approximation close to the current cost range of transmission line. The factor of 3 gives the estimated transmission within the range of the observed transmission project cost. The transmission cost data is the limitation in this model. The cost data at different thermal capacity from the same source is necessary for estimating the cost function. In the future, when more appropriate cost data is available, the approach here can be applied. In addition, the actual cost of the DC line, if available, is an alternative for the study.

$$\ln(cost) = 10.55415 + 0.5759*\ln(MW)$$

Variable	Coefficient	Std. Error	t-Statistic	Prob.
constant	10.55415	0.298873	35.31313	0.0000
ln(*MW*)	0.575873	0.056237	10.24006	0.0000
R-squared	0.937421	F-statistic		104.8589
Adjusted R-squared	0.928481	Prob(F-statistic)		0.000018
S.E. of regression	0.194477	Log likelihood		3.097459
Sum squared resid	0.264748	Durbin-Watson stat		1.814451

Table 1: Transmission cost function estimation result

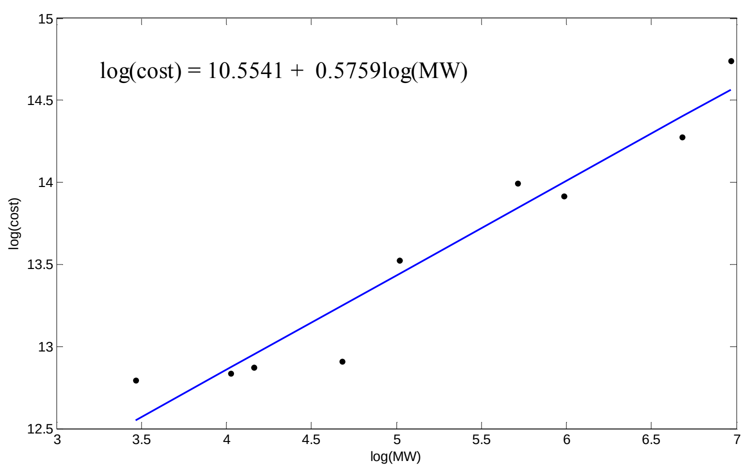

Figure 1: Estimated transmission cost vs. actual cost (log-linear)

Appendix B: Relationship between distance and wind-output correlation

We use the wind speed data from 9 wind speed observation sites in Colorado (UWIG, 2007) to estimate the relationship between distance and correlation. There are 3,909 hourly wind speed observations used for correlation coefficient estimation. According to Manwell et al (2002), wind power (*P*) per area (*A*) is the function of the wind speed (*V*) and air density (ρ).

$$\frac{P}{A} = \frac{1}{2}\rho V^3$$

Note that we used the same data source as DOE (2005) but we set some wind speed observations that are lower than the cut-in speed or higher than the cut-out speed to be 0. The cut-in speed and the cut-out speed [3] of the wind turbine is 4.5 m/s and 30 m/s respectively (Gipe, 2004). We calculate the correlations coefficients of the cubic wind speed (V^3) among the wind speed observation sites. Given that other variables in the formula (*A* and ρ) held constant, the correlation coefficients calculated V^3 are the estimated correlation coefficients of wind power among the wind sites.

Various models of distance and correlation are estimated including linear, quadratic and linear-log (correlation is a function of ln(*distance*)). Ordinary Least Square (OLS) is used for the estimation. The linear-log model used by DOE (2005) is more suitable than the linear and quadratic models.

Note that in Figure B1 (right) some observations are deviate far from the estimated line, for example, close wind stations with low correlation. This could be due to terrain such as a ridge between the nearby locations.

[3] From Gipe (2004), cut-in wind speed is the wind speed that a wind turbine starts to generate power. The wind turbine cannot generate power if the wind speed is lower than the cut-in level. Cut-out wind speed is the wind speed at which the wind turbine stops generating electricity in order to protect the equipment from an excessive wind speed. The wind turbine cannot generate power if the wind speed is higher than the cut-out level.

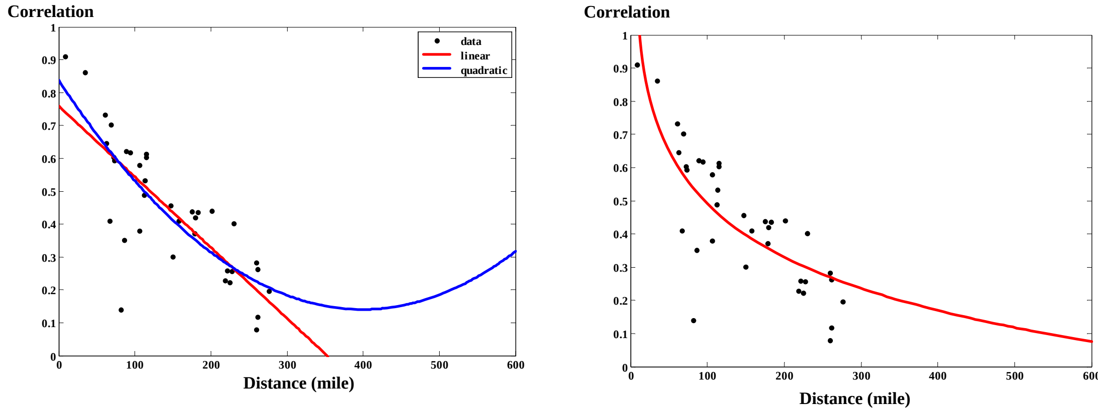

Figure B1: Linear and quadratic models (left) and linear-log model (right)

The linear-log model, *correlation* = *a* + *b**ln(*distance*), seems best for this study. The shape of the curve is similar to the curve from NREL (2007).

Correlation = 1.557018 – 0.231544*ln(*distance*)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
constant	1.557018	0.145054	10.73408	0.0000
ln(*distance*)	-0.231544	0.029868	-7.752362	0.0000
R-squared	0.638679	F-statistic		60.09911
Adjusted R-squared	0.628052	Prob(F-statistic)		0.000000
S.E. of regression	0.123475	Durbin-Watson stat		1.446861
Sum squared residual	0.518366	Log likelihood		25.24887

Table B1: Correlation and distance estimation result

Appendix C: Computation results

Farm	Capacity factor	Trans. factor (s)	Trans. utilization	Profit	Cost $/MWh	$/MWh (turbine)	Delivery (MWh)	Delivery/ Generation
A	32.73 %	0.7880	40.22%	1.75×10^8	153.31	82.24	1.11×10^8	97.10%
B	34.73 %	0.8075	42.00%	4.43×10^8	144.20	77.78	1.19×10^8	97.93%
C	29.92 %	0.7747	37.02%	-2.05×10^8	168.68	91.99	1.01×10^8	96.11%
D	29.77 %	0.7388	39.11%	-1.28×10^8	165.35	91.31	1.01×10^8	97.32%

Table C1: 1,000 mile transmission line at price $160/MWh

Farm	Standard deviation	Trans. factor (s)	Trans. utilization	Profit	Cost $/MWh	$/MWh (turbine)	Delivery (MWh)	Delivery/ Generation
A	0.2472	0.9135	54.39%	3.39×10^8	77.45	53.10	1.74×10^8	99.64%
B	0.2594	0.9117	54.56%	3.40×10^8	77.33	53.04	1.74×10^8	99.77%
C	0.2337	0.9212	53.95%	3.39×10^8	77.55	53.09	1.74×10^8	99.66%
D	0.2231	0.8817	56.44%	3.42×10^8	76.84	53.02	1.74×10^8	99.79%

Table C2: 1,000 mile transmission line with 50% adjusted capacity factor farm at price $160/MWh

Pair	Corr. (mile)	Trans (s_1) utilization,%	Trans (s_2)	Profit	Cost $/MWh	Cost $/MWh (turbine)	Delivery (MWh)	Delivery/ Generation
AB	0.7665 (56)	1.6330 (40.61)	0.8952	1.50×10^9	132.69	79.57	2.32×10^8	98.78 %
BA		1.6326 (40.61)	0.8988	1.50×10^9	132.71	79.58	2.32×10^8	98.85 %
AC	0.6919 (19)	1.5586 (39.22)	0.9864	0.95×10^9	141.08	86.33	2.14×10^8	97.83 %
CA		1.5587 (41.32)	0.9925	0.95×10^9	141.09	86.33	2.14×10^8	97.83 %
AD	0.3471 (219)	1.4013 (43.32)	0.8124	0.69×10^9	146.18	86.93	2.13×10^8	97.74 %
DA		1.3984 (43.32)	0.8829	0.69×10^9	146.65	87.01	2.13×10^8	97.71 %
BC	0.7074 (63)	1.5641 (40.36)	0.9382	1.12×10^9	138.40	83.59	2.11×10^8	98.05 %
CB		1.5678 (40.29)	0.9196	1.13×10^9	138.37	83.55	2.21×10^8	98.06 %
BD	0.3552 (250)	1.4073 (44.50)	0.7929	0.89×10^9	142.79	84.25	2.19×10^8	97.88 %
DB		1.4141 (44.33)	0.8649	0.87×10^9	143.27	84.18	2.20×10^8	97.87 %
CD	0.4572 (200)	1.4159 (40.80)	0.8038	0.33×10^9	153.12	91.34	2.02×10^8	97.49 %
DC		1.3981 (41.21)	0.8980	0.30×10^9	153.66	91.59	2.02×10^8	97.21 %

Table C3: 1,000 mile main transmission line and actual distance between farms at price $160/MWh

Pair	Corr. (mile)	Trans (s_1) utilization, %	Trans (s_2)	Profit	Cost $/MWh	Cost $/MWh (turbine)	Delivery (MWh)	Delivery/ Generation
A, A30	0.30 (227)	1.1865 (51.70)	0.5799	1.07 x 10^9	138.81	86.03	2.15 x 10^8	98.28 %
A, A35	0.35 (184)	1.1948 (51.13)	0.5769	1.10 x 10^9	138.25	86.38	2.14 x 10^8	98.26 %
A, A40	0.40 (147)	1.2105 (50.64)	0.5771	1.16 x 10^9	137.07	86.07	2.15 x 10^8	98.36 %
A, A45	0.45 (119)	1.2180 (50.34)	0.5980	1.20 x 10^9	136.37	86.07	2.15 x 10^8	98.32 %
A, A50	0.50 (96)	1.2493 (49.53)	0.6459	1.27 x 10^9	135.23	85.27	2.17 x 10^8	98.28 %
A, A55	0.55 (77)	1.2503 (49.13)	0.6186	1.25 x 10^9	135.57	85.90	2.15 x 10^8	98.43 %
A, A60	0.60 (62)	1.2585 (48.75)	0.6224	1.24 x 10^9	135.45	86.00	2.15 x 10^8	98.35 %
A, A65	0.65 (50)	1.2716 (48.22)	0.6382	124 x 10^9	135.47	86.06	2.15 x 10^8	98.30 %
A, A70	0.70 (40)	1.2952 (47.49)	0.6323	1.26 x 10^9	135.21	85.78	2.16 x 10^8	98.44 %
A, A75	0.75 (33)	1.3240 (48.04)	0.6689	1.23 x 10^9	135.82	85.89	2.15 x 10^8	98.49 %
A, A80	0.80 (26)	1.3314 (46.07)	0.6769	1.22 x 10^9	135.95	86.03	2.15 x 10^8	98.32 %

Table C4: Farm A paired with farms at different correlation (capacity factor 30%) with 1,000 mile main transmission line and the distance between farms calculated from relationship in Appendix B at price = $160/MWh

Pair	Corr. (mile)	Profit @ penalty $160/MWh	Profit @ penalty $180/MWh	Profit @ penalty $200/MWh	Imbalance (MWh)	Delivery (MWh)	Imbalance / Delivery (%)
A, A30	0.30 (227)	4.71×10^8	3.95×10^8	3.20×10^8	1.60×10^7	2.15×10^8	7.44%
A, A35	0.35 (184)	4.84×10^8	4.08×10^8	3.31×10^8	1.63×10^7	2.14×10^8	7.61%
A, A40	0.40 (147)	5.28×10^8	4.49×10^8	3.70×10^8	1.68×10^7	2.15×10^8	7.81%
A, A45	0.45 (119)	5.44×10^8	4.62×10^8	3.81×10^8	1.73×10^7	2.15×10^8	8.06%
A, A50	0.50 (96)	5.89×10^8	5.05×10^8	4.20×10^8	1.79×10^7	2.17×10^8	8.28%
A, A55	0.55 (77)	5.39×10^8	4.52×10^8	3.64×10^8	1.86×10^7	2.15×10^8	8.63%
A, A60	0.60 (62)	4.97×10^8	4.04×10^8	3.10×10^8	1.98×10^7	2.15×10^8	9.21%
A, A65	0.65 (50)	4.58×10^8	3.60×10^8	2.62×10^8	2.08×10^7	2.15×10^8	9.68%
A, A70	0.70 (40)	4.35×10^8	3.52×10^8	2.51×10^8	2.14×10^7	2.16×10^8	9.92%
A, A75	0.75 (33)	3.50×10^8	2.40×10^8	1.30×10^8	2.33×10^7	2.15×10^8	10.81%
A, A80	0.80 (26)	3.09×10^8	1.96×10^8	0.83×10^8	2.41×10^7	2.15×10^8	11.20%

Table C5: Farm A paired with farms at different correlation (capacity factor 30%) with 1,000 mile main transmission line and the distance between farms calculated from relationship in Appendix B at price = $160/MWh with 400 MW delivery requirement

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Chapter 2

The optimal baseload generation portfolio under CO2 regulation and fuel price uncertainties

Introduction

NERC (North American Electric Reliability Corporation) predicts that many regions in the US will need significant investment in electricity generation in the near future (NERC, 2009). Electricity suppliers face difficult decision concerning which technology to invest. New generation plants are capital intensive and have a long lead time. Once a plant is built, capital becomes sunk and the plant/technology will be locked in for 20-60 years. Uncertainty about environmental regulation and variability in fuel price during the plant's lifetime make the decision difficult.

According to Awerbuch (2003), traditional power system planning attempts to minimize cost of power generation while risk factors are not taken into account explicitly. In the next few decades, the power sector will face many challenges especially the tighter environmental regulation on green house gas emission. Future cost of CO_2 regulation is uncertain.

While choosing the best technology for each plant is important, choosing a portfolio of technologies/fuels is more important in managing risks in an uncertain world. A natural gas combined cycle (NGCC) generator may have the lowest expected cost but the observed past volatility in gas price suggests that a portfolio of 100% NGCC is likely to have higher variability than a portfolio of different technologies. An optimal portfolio can have the dominated technology if it has negative correlation with other technologies leading to lower variance portfolio.

The expected cost and cost variability of the generation assets portfolio depend on the mix of generation technologies in the portfolio. Each generation asset (technology) has a different risk and cost profile. Even if a single fuel-technology choice had lower cost and variability than all others, the variability of the portfolio would be greater than one with a mix of technologies/fuels (a more conventional way of stating this that it would be imprudent to have only one type of asset in the system). Thus, the planner has to choose the mix of fuel-technology plants that optimizes cost and risk of the generation asset.

The mean-variance portfolio model is a tool that can formulate the efficient trade-off between risk and return. This model has been widely used in the finance field. This study applies the mean-variance portfolio theory to a model that optimizes the technology portfolio for the power system. In this study, we derive the optimal portfolio frontier by focusing mainly on the variability in the fuel markets and the range of prices that could be imposed on CO_2 emissions. Whether the regulation is in the form of a carbon tax or a cap and trade system, there will be a market clearing price for a ton of CO_2 emissions. We refer to this as the CO_2 prices. The model constructs optimal portfolios assuming scenarios with a range of CO_2 price, fuel prices, capital cost and the cost of carbon capture and storage (CCS). In addition, the study uses the mean variance portfolio model with a Bayesian technique that allows decision makers to input their beliefs about the likelihood of each scenario.

Literature review

The mean-variance portfolio model was developed by Markowitz (1952). The model assumes the mean and variance of the portfolio are the two factors that matter to the investor. The investor is assumed to love 'return' and avoid 'risk' (variance). Investor's utility is a function of wealth derived in term of return (r) from investment. By assuming a normal distribution of asset return and using a Taylor's series expansion, the expected utility function can be derived as the function of mean return and variance (Huang and Litzenberger, 1988).

$$E[U(r)] = U(E[r]) + \frac{1}{2}U''(E[r])\sigma_r^2$$

The expected utility function is an increasing function of mean (return) and decreasing function of risk (variance); the utility function is concave where $U'(\cdot) \geq 0$ and $U''(\cdot) \leq 0$. Thus, in order to maximize the expected utility, the investor chooses the portfolio that yields the highest return at the given variance (standard deviation) or the portfolio with the lowest variance at the given return.

The optimization of the mean-variance portfolio model is shown below. The investor chooses the portfolio weight of each asset that minimizes the portfolio variance given the specific value of portfolio return.

$$\text{Min } \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N} w_i w_j \sigma_{ij}$$

Subject to: $\sum_{i=1}^{N} w_i = 1$ and $\sum_{i=1}^{N} w_i r_i = \mu$

w_i is the portfolio weight of asset *i* (N assets in total). σ_{ij} is the covariance of asset *i* and *j* . r_i is the return of asset *i*. μ is the target return of the portfolio (constant). The optimization problem can also be written in the matrix form.

$$\underset{\mathbf{w}}{\text{Min}} \ \frac{1}{2}\mathbf{w}'\Sigma\mathbf{w}$$

Subject to: $\mathbf{w}'\mathbf{1} = 1$ and $\mathbf{w}'R = \mu$

Σ is the covariance matrix of asset return where the diagonal elements represent variance of the asset and the off-diagonal terms represent covariance between assets. $\mathbf{w}$ is the Nx1 vector of portfolio weight. R is the Nx1 vector of asset return. $\mathbf{1}$ is Nx1 vector of one.

The model is made operational by assuming the return and variance can be estimated from recent market data. In effect, this narrows the theory and it is operational as short term within the model. The mean-variance portfolio model uses the historical movement in asset return to formulate the optimal portfolio. This approach may not support the investor's belief about the future return. Black and Litterman (1991) and (1992) (thereafter "BL") apply the Bayesian statistical theory to the conventional mean-variance portfolio model. This model enables an investor to express his belief on the future asset return.

In order to accommodate the individual's view in portfolio formulation, BL use the market equilibrium portfolio as the neutral starting point. The individual can express his subjective view or belief on the asset return which can be different from the equilibrium return. (BL use the term "view" to represent the posterior belief on the asset's return). Using Bayesian statistical theory, we can estimate the posterior asset return and covariance matrix given the individual belief using the following formulation.

Posterior return: $R_{bl} = \left[\Sigma^{-1} + P'\Omega^{-1}P\right]^{-1}\left[\Sigma^{-1}\Pi + P'\Omega^{-1}Q\right]$

Covariance matrix: $\Sigma_{bl} = \Sigma + (\Sigma^{-1} + P'\Omega^{-1}P)^{-1}$

Σ is the covariance matrix of prior asset return (NxN matrix), P is the matrix (KxN) represented the assets in the posterior belief, K is the number of assets expressed in the posterior belief, Ω is the covariance of posterior belief (KxK matrix), Π is the equilibrium return (Nx1 vector) and Q is the posterior belief vector (Kx1). The proof of the above formulation is presented in Satchell and Scrowcroft (2000).

The confidence level of the individual's belief is represented by the covariance matrix of belief (Ω) where $\Omega = (\frac{1}{c} - 1)P\Sigma P$ (Meucci, 2005). $c \in (0,1]$ indicates the level of confidence; *c* close to 0 means low confidence and *c* close to 1 means high confidence. High variance indicates low confidence in belief. Note that the variance of return is the sum of prior variance and variance of the posterior belief.

Many studies have attempted to apply the mean-variance portfolio theory to the energy and electric utility sector. Bar-Lev and Katz (1976) did the pioneer study applying the model to find the optimal fossil fuel mix for a power utility. "Return" of the fossil fuel is defined as Btu[4]/$; the inverse of the fuel cost. The standard deviation is calculated from the inverse of the fuel cost data. However, the model is incorrectly defined such that return and weight do not match according to the theory[5].

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[4] Btu or British thermal unit is the unit of energy used for measuring the heat content.
[5] From the mean-variance portfolio theory, return = $\frac{\text{payoff of asset } i \text{ (\$)}}{\text{money invested in asset } i \text{ (\$)}}$ and weight $= \frac{\text{money invested in asset } i \text{ (\$)}}{\text{total investment (\$)}}$. The denominator (cost of asset *i*) from 'return' and denominator (money

Other studies repeating Bar-Lev and Katz (1976)'s mistake include Humphreys and McClain (1998) for U.S. fossil fuel portfolio, Awerbuch and Berger (2003) and Awerbuch (2006) for power generation technology portfolio.

Alternatively, Doherty et al. (2005) uses the risk-cost framework instead of risk-return to solve for the efficient generation portfolio for Ireland in 2020. Under the risk-cost framework, the definition of cost and weight are consistent. However, they do not explain the theoretical framework under the mean-variance portfolio theory.

Roques et al. (2006) applies the mean-variance portfolio theory to solve the optimal technology portfolio for the private investors incorporating electricity, fuel and CO_2 price risks. Historical prices of electricity, fuel and CO_2 in UK are used for the study. Return is defined as the net present value (NPV) per GW of generation capacity. NPV is calculated from electricity sale revenue (using spot electricity price) and generation cost. The simulated CO_2 tax with the average of £40/ton and standard deviation of 10 is included in power generation cost.

Our study uses the risk-cost framework to analyze the power generation technology portfolio. Our definition of cost is the cost of electricity generation per MWh. This study aims to find the efficient risk-cost portfolio such that the portfolio has the lowest variance (standard deviation) at the given level of cost.

This study goes further in reinterpreting the mean-variance portfolio theory for an electricity investment decision. We calculate power generation cost (levelized cost of electricity) using the cost components such as capital cost, economic lifetime, capacity factor, discount rate, historical fuel price, operation and maintenance costs and CO_2 price. This approach gives flexibility in power generation cost calculation and scenario formulation.

The contribution of this study includes the analysis of the optimal portfolio under different scenarios on generation cost components such as fuel cost and CO_2 price. The analysis on capital cost of the plant is also included in the study. The possible range of capital cost is tested in order to examine the effect on the optimal portfolio. Our study

invested in asset *i*) from 'weight' match each other. If return on fuel is defined as $\frac{\text{Btu}}{\text{money paid for fuel } i \text{ (\$)}}$, the correct weight must be $\frac{\text{money paid for fuel } i \text{ (\$)}}{\text{total payment on all fuel (\$)}}$ because Btu is the payoff from investing in fuel *i*.

explains the theoretical formulation of the risk-cost framework under the mean-variance portfolio theory which is not presented in the previous studies. In addition, we show an example applying the Bayesian analysis to formulate the optimal power generation portfolio given the investor's belief on cost.

Model

The first step is to solve for the efficient power generation technology-fuel frontier. Having defined the efficient frontier, the planner must decide which combination of risk/cost is preferred. Rather than suggest an optimal risk/cost ratio, we finesse this choice and show the optimal portfolio for all risk/cost ratios on the efficiency frontier. The optimal portfolio depends on the planner's preference regarding to the tradeoff between cost and variation in cost.

The model here is focused on the baseload[6] generation that produces 75-85% of power during a year. It accounts for the majority of investment and utilities' expenditure.

<u>Power generation portfolio</u>

The model for analyzing the optimal power generation portfolio is modified from the conventional mean-variance portfolio model where the individual maximizes his utility (wealth) by selecting the portfolio that has the lowest variance given the return. For the application to the power generation portfolio, the convention model is adjusted such that the optimal portfolio has the lowest variance given the expected cost of the portfolio. Another important difference is that the low transactions cost of financial markets means that the individual can rearrange her portfolio to the optimal one. Electricity generators are illiquid and there are high transactions costs for rearranging the generation mix.

The utility function is concave and strictly increasing in wealth. The expected utility function is a decreasing function of both cost and variance. Let *V* be the value or

[6] According to Energy Information Administration (EIA), the baseload (demand) is "the minimum amount of electric power delivered or required over a given period of time at a steady rate" (EIA, http://www.eia.doe.gov/glossary/glossary_b.htm).

benefit from electricity which is assumed to be constant and independent of electricity cost (C). Thus, the utility function from electricity consumption is a function of the net value; $\mathrm{U}(V - C)$. Applying Taylor's series approximation around V-$\mathrm{E}[C]$, we can derive the expected utility function which is a decreasing function in both cost and variance.

$$U(V-C) \;=\; U(V-E[C]) + U'(V-E[C])(V-C-V+E[C]) + \frac{1}{2}U''(V-E[C])((V-C-V+E[C])^2 + R_3$$

$$= \; U(V - E[C]) \; + U'(V - E[C])(E[C] - C) + \frac{1}{2}U''(V - E[C])(E[C] - C)^2 + R_3$$

$$E[U(V-C)] \;= U(V-E[C]) \; + U'(V-E[C])E[(E[C]-C)] + \frac{1}{2}U''(V-E[C])E[(E[C]-C)^2] + E[R_3]$$

$$= \; U(V-E[C]) \; + \frac{1}{2}U''(V - E[C])\sigma_C^2$$

$$= U(V - E[C]) - \frac{1}{2}\beta\sigma_C^2$$

R_3 is the higher degree terms from Taylor's approximation and $E[R_3] = 0$ from the normal distribution assumption. $U''(V - E[C]) < 0$ (from concavity); β is the positive constant. Since the utility function is a decreasing function in cost (C), the expected utility function is decreasing in the expected cost (E[C]) and variance of cost (σ_{C}^2). Thus, the planner chooses the optimal portfolio which has the lowest variance given the cost of the portfolio. Note that there is no theoretical derivation of the expected utility function using cost and variance in the previous studies which use the risk-cost framework.

Baseload generation technology portfolio

The optimization approach for the baseload generation portfolio is similar to the conventional mean-variance portfolio. Additional constraints require that the weight of each technology is greater than zero.

$$\text{Min } \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N} w_i w_j \sigma_{ij}$$

$$\text{Subject to: } \sum_{i=1}^{N} w_i = 1$$

$$\sum_{i=1}^{N} w_i c_i = \mu$$

$$w_i \geq 0 \quad \text{for all } i$$

There are N baseload technologies with the respective cost (c_i) and weight (w_i) for i = 1-N. σ_{ij} is the covariance between generation cost of technology i and j. μ is the positive constant representing the given cost level.

All portfolios considered are assumed to satisfy baseload electricity demand. In other words, all portfolios generate the same amount of electricity. Given that all portfolios yield the same output, the optimal portfolio is the one that has the efficient tradeoff between cost and variance.

The Bayesian analysis or BL model can be applied to the baseload generation portfolio model directly. The generation cost calculated from the baseline model is used as the neutral starting point (BL model uses an equilibrium return as the starting point). An individual can express a belief on power generation cost of one or more baseload technologies. The belief can be expressed as an absolute belief (i.e. return of asset A is expected to be at 14%) or the relative belief (i.e. return of asset A is expected to be higher than asset B by 2%).

The baseload generation portfolio in this study includes 7 technologies. The current technologies which already operate commercially include nuclear, PC (pulverized coal), NGCC (Natural Gas Combined Cycle). The prospective future technologies include IGCC (Integrated Gasification Combined Cycle), IGCC with CCS (Carbon Capture and Storage), PC with CCS and NGCC with CCS. The detail on power generation cost data and assumption on the cost is presented in the appendix.

Results

The mean-variance portfolio model for baseload power generation technology evaluates technologies with different characteristics. Nuclear has high capital cost and relatively low fuel costs, giving it low variance. PC, IGCC, IGCC CCS and PC CCS are technologies with somewhat lower capital cost. NGCC and NGCC CCS are the technologies with relatively low capital cost and high variable cost; mainly fuel cost.

Nuclear emits zero CO_2 in the generation process. PC and IGCC are technologies with high CO_2 emission per MWh. NGCC emits around half of CO_2 per MWh compared with PC. IGCC and NGCC with CCS capture most of the CO_2 in the power generation process. In this section, we formulate the optimal mean-variance portfolio under various scenarios of CO_2 price, fuel price structure, capital cost and CCS cost.

1. The baseline model

The baseline model uses the fuel price data from 1990-2009. The optimal portfolios are formulated under 2 scenarios of CO_2 prices; \$20 and 40/ton of CO_2. The first 2 models (B1 and B2) include 3 current baseload technologies; nuclear, PC (pulverized coal) and NGCC (Natural Gas Combined Cycle). Models B3 and B4 include these 3 current technologies and prospective future technologies including IGCC (Integrated Gasification Combined Cycle) and PC, NGCC and IGCC with CCS (Carbon Capture and Storage).

- B1: Portfolio of 3 current technologies under \$20/ton CO_2 price

	Cost/MWh	S.D.
Nuclear	106.75	2.20
PC	73.42	5.53
NGCC	59.82	14.03

	Nuclear	PC	NGCC
Nuclear	1.00	0.11	-0.02
PC	0.11	1.00	0.05
NGCC	-0.02	0.05	1.00

Table 1: Cost/standard deviation (left) and the correlation matrix (right)

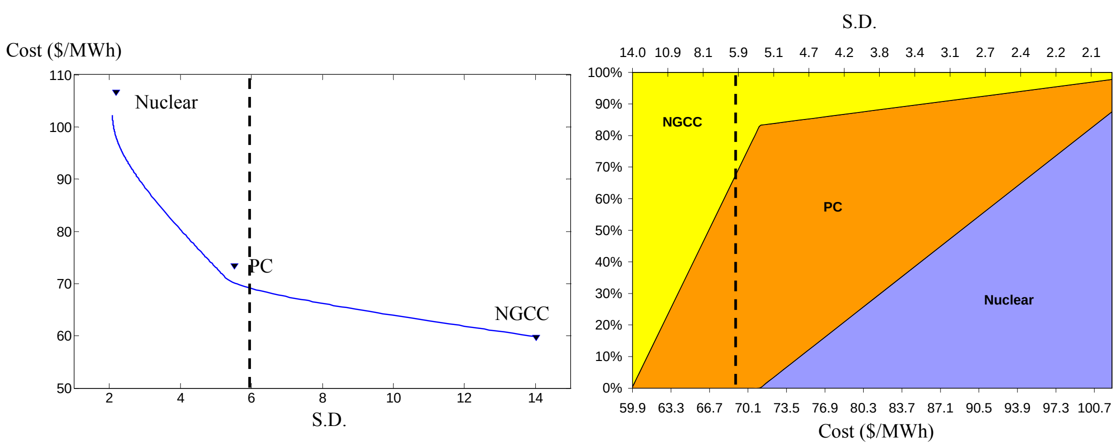


Figure 1: The efficient frontier (left) and technology mix along the frontier (right)

The left hand side of figure 1 shows the efficient frontier. The right hand side shows the composition of the optimal portfolio for each cost-standard deviation. For example a standard deviation of 6 corresponds to a cost of \$68/MWh. The optimal portfolio consists of 65% PC and 35% NGCC while the efficient frontier on the left hand sides shows cost-standard deviation; it does not identify the composition of the portfolio.

In the first scenario, the CO_2 regulation cost is set at \$20/ton with standard deviation of 5. NGCC is the lowest cost technology but has the highest standard deviation. The opposite is true for nuclear. Thus, the lowest cost portfolio is 100% NGCC having high standard deviation at 14. Minimizing the standard deviation leads to a portfolio dominated by nuclear with some PC and a tiny share of NGCC. Low correlation between NGCC and nuclear leads to a small share of NGCC that lowers the variance of a portfolio when the share of nuclear increases. PC and nuclear dominate portfolios on the efficient portfolio as the standard deviation decreases. At a portfolio cost around 80/MWh with standard deviation 4, the portfolio consists of 25% nuclear, 55% PC and 20% NGCC.

- B2: Portfolio of 3 current technologies under \$40/ton CO_2 price

	Cost/MWh	S.D.
Nuclear	106.75	2.20
PC	93.42	5.53
NGCC	68.82	14.03

	Nuclear	PC	NGCC
Nuclear	1.00	0.11	-0.02
PC	0.11	1.00	0.05
NGCC	-0.02	0.05	1.00

Table 2: Cost/standard deviation (left) and the correlation matrix (right)

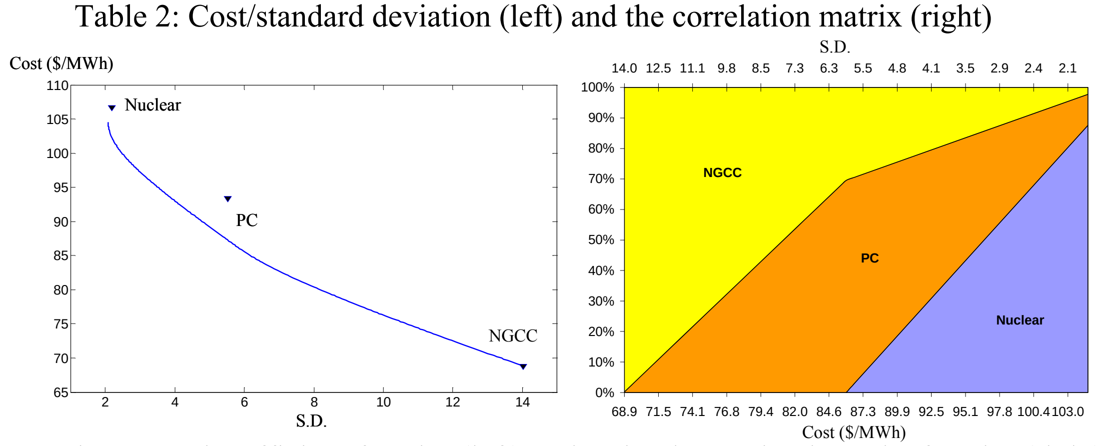


Figure 2: The efficient frontier (left) and technology mix along the frontier (right)

In the second scenario, CO_2 emission charge is at \$40/ton. Nuclear is not affected by this charge; higher CO_2 price increases the generation cost of NGCC slightly and that of coal much more. The cost range of the efficient portfolio shifts from \$60 – 100/MWh in the previous scenario to \$69 – 104/MWh due to higher CO_2 price charged to all fossil fuel plants. NGCC has a more significant role gaining higher share especially in the first half of the efficient frontier at the expense of PC because of its lower CO_2 emission. The cost difference between coal and gas increases from \$13.6 to 24.6/MWh due to an increase in CO_2 price. Nuclear has a role similar to that is in the previous model. At a cost of \$80/MWh with standard deviation 8, the portfolio consists of 60% NGCC and 40% PC.

- B3: Portfolio 7 technologies under \$20/ton CO_2 price

	\$/MWh	S.D.
Nuclear	106.75	2.20
PC	73.42	5.53
PC CCS	101.68	4.17
IGCC	78.01	5.25
IGCC CCS	89.98	3.54
NGCC	59.82	14.03
NGCC CCS	71.46	19.23

	Nuclear	PC	PC CCS	IGCC	IGCC CCS	NGCC	NGCC CCS
Nuclear	1.00	0.11	0.23	0.10	0.26	-0.02	-0.03
PC	0.11	1.00	0.43	0.98	0.48	0.05	-0.07
PC CCS	0.23	0.43	1.00	0.41	0.85	-0.05	-0.03
IGCC	0.10	0.98	0.41	1.00	0.52	0.02	-0.11
IGCC CCS	0.26	0.48	0.85	0.52	1.00	-0.05	-0.04
NGCC	-0.02	0.05	-0.05	0.02	-0.05	1.00	0.98
NGCC CCS	-0.03	-0.07	-0.03	-0.11	-0.04	0.98	1.00

Table 3: Cost/standard deviation (left) and the correlation matrix (right)

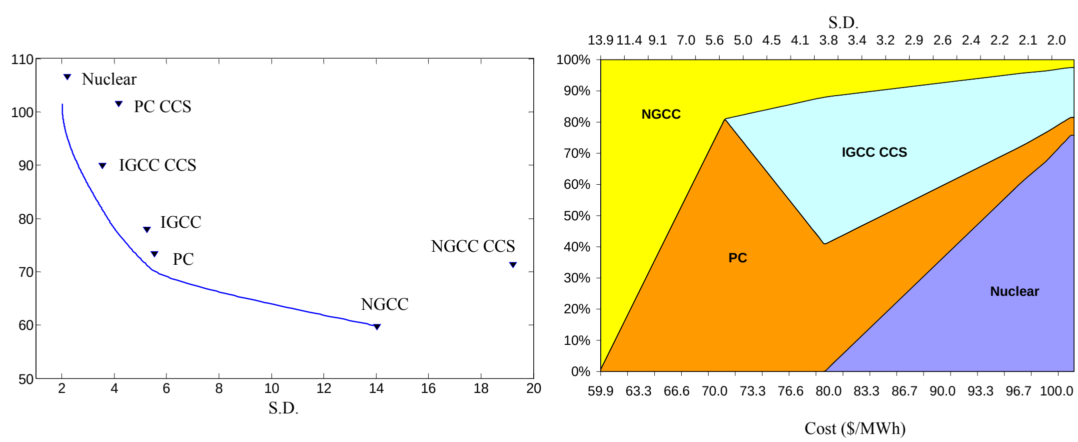


Figure 3: The efficient frontier (left) and technology mix along the frontier (right)

In the 3rd scenario, 4 prospective future baseload technologies, IGCC, IGCC, NGCC and PC with CCS are included in the portfolio. Nuclear is the highest cost technology followed by PC CCS. NGCC and PC have significant share in the part of the efficient portfolio frontier where portfolio cost is low and cost variation is high. For the higher cost portfolio, IGCC CCS starts to gain significant share. Although cost of IGCC CCS is high, its volatility is lower than PC since there is volatility in future CO_2 price. The volatility in CO_2 price increases the overall volatility of fossil fuel plants cost.

IGCC, NGCC CCS and PC CCS have no role in the optimal portfolio. IGCC has higher cost and just lower volatility than PC. As a result, IGCC without CCS is a dominated technology in our analysis. Also the cost of PC CCS is too high although its volatility is less than PC. NGCC CCS is the second lowest cost technology but has the highest volatility. NGCC CCS has higher volatility than NGCC because it uses more natural gas due to higher heat rate. Thus, the volatility in natural gas price has more impact on volatility of NGCC CCS generation cost. When forcing the portfolio to have lower variance, more nuclear is required for the system. The lowest standard deviation portfolio has about 70% nuclear capacity; its standard deviation of 2.0 is less than nuclear's (also the portfolio cost) due to the covariance of PC, IGCC CCS and NGCC with nuclear. At $80/MWh portfolio cost with standard deviation 3.8, the optimal portfolio consists of 5% Nuclear, 35% PC, 45% IGCC CCS and 15% NGCC.

- B4: Portfolio of 7 technologies under $40/ton CO_2 price

	$/MWh	S.D.
Nuclear	106.75	2.20
PC	93.42	5.53
PC CCS	103.68	4.17
IGCC	96.01	5.25
IGCC CCS	91.78	3.54
NGCC	68.82	14.03
NGCC CCS	72.36	19.23

	Nuclear	PC	PC CCS	IGCC	IGCC CCS	NGCC	NGCC CCS
Nuclear	1.00	0.11	0.23	0.10	0.26	-0.02	-0.03
PC	0.11	1.00	0.43	0.98	0.48	0.05	-0.07
PC CCS	0.23	0.43	1.00	0.41	0.85	-0.05	-0.03
IGCC	0.10	0.98	0.41	1.00	0.52	0.02	-0.11
IGCC CCS	0.26	0.48	0.85	0.52	1.00	-0.05	-0.04
NGCC	-0.02	0.05	-0.05	0.02	-0.05	1.00	0.98
NGCC CCS	-0.03	-0.07	-0.03	-0.11	-0.04	0.98	1.00

Table 4: Cost/standard deviation (left) and the correlation matrix (right)

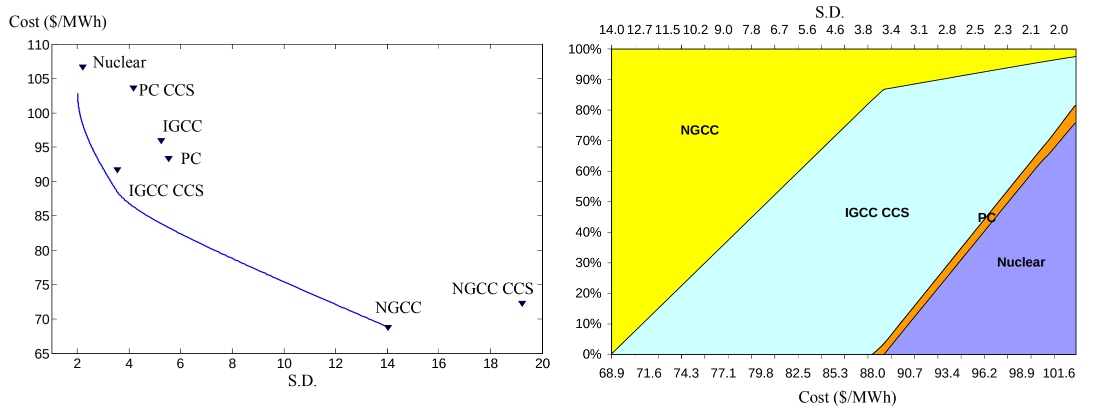


Figure 4: The efficient frontier (left) and technology mix along the frontier (right)

In the 4th scenario with \$40/ton of CO_2 price (figure 4), cost of technology with high CO_2 emission such as PC and IGCC increase significantly. NGCC is still the lowest cost due to low CO_2 emission per MWh. IGCC CCS replaces most of PC and some nuclear from the previous scenario (B3). Share of PC decreases significantly due to increase in cost from higher CO_2 price. Nuclear again reduces portfolio variation but has less significant role than the previous scenario. Like the previous scenario, there is no share of IGCC, PC CCS and NGCC CCS in the optimal portfolio. At a cost of \$80/MWh with standard deviation around 5.2, the optimal portfolio consists of 45% IGCC CCS and 55% NGCC.

From the 4 scenarios in the baseline model, we can see that each generation technology has different characteristic in term of cost and variation in cost. The nuclear plant has high capital cost but low variable cost. Generation cost from nuclear does not vary in high magnitude when uranium or operation cost change. Nuclear plays the same role in all 4 scenarios to reduce the overall portfolio variation. However, because nuclear is the highest cost technology more nuclear generation results in higher cost but lower variation portfolio.

PC is the technology with moderate cost and cost variation. Emission of CO_2 per unit of power generation from PC is the highest among all technology. IGCC is also the coal based technology with the high amount of CO_2 emission. Cost of PC and IGCC are highly sensitive to CO_2 price and some of the cost variation of these 2 technologies is attributed to the variation in CO_2 price. PC CCS is another coal technology that emits small amount of CO_2. However, its cost is significantly higher than IGCC CCS with about the same variation. Like IGCC, PC CCS is the dominated technology in this analysis and has no share in the optimal portfolio.

NGCC is the low cost and high variance technology. NGCC has the high portion of fuel cost in total generation cost; its generation cost is highly affected by the change in natural gas price. NGCC can help lowering the portfolio cost in exchange for higher variation. The CO_2 price also increases the cost of NGCC but in lower magnitude than PC and IGCC. NGCC CCS is another natural gas turbine technology with carbon capture facility. Its cost is lower than some technologies but its variation is the highest. Note that NGCC CCS uses higher amount of natural gas than NGCC due to its higher heat rate.

Technology shares along the efficient portfolio frontier are similar across these 4 scenarios. NGCC has a high share at the low cost-high variation portion of the frontier. On the other hand, nuclear gains share at the high cost-low variation portion. PC and IGCC CCS have some share along the frontier with the highest around the middle part of the efficient set depending on the CO_2 price.

When comparing portfolios with CO_2 prices of \$20 and \$40/ton, significant change can be observed especially from shares of the fossil fuel technology; NGCC, PC and IGCC CCS. NGCC gains significant share when the system moves toward higher CO_2 price. It replaces most PC and some nuclear. When we introduce IGCC CCS in the 3rd and 4th scenarios, IGCC CCS seems to replace the share of PC rather than NGCC. Shape of NGCC share is about the same after including IGCC CCS which can be seen by comparing 1st with 3rd and 2nd with 4th scenarios.

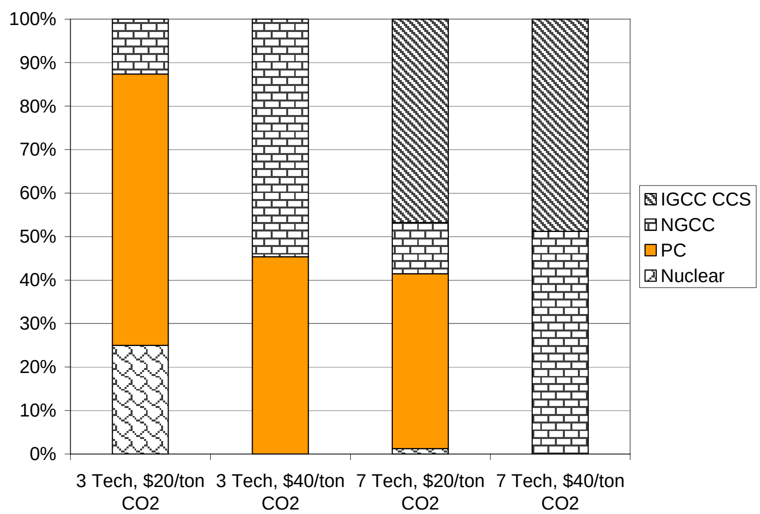


Figure 5: Generation mix at \$80/MWh

When comparing all 4 scenarios and fixing the portfolio cost at \$80/MWh, as seen from Figure 5, the generation mixes are significantly different under the 2 CO_2 prices. For example, at a portfolio cost of \$80/MWh, the 3-technology portfolio has about 25% nuclear in \$20/MWh CO_2 price scenario but it has no nuclear when CO_2 regulation cost increases to \$40/MWh. As new technologies are introduced to the 7-technology portfolio, at \$20/ton CO_2 price, shares of NGCC is about the same but all shares of PC and some nuclear are replaced by IGCC CCS. Also, at \$40/ton CO_2 all PC is replaced by IGCC CCS. The change in portfolio mix is mainly due to the shift in portfolio cost and the replacement of some nuclear and PC by IGCC CCS.

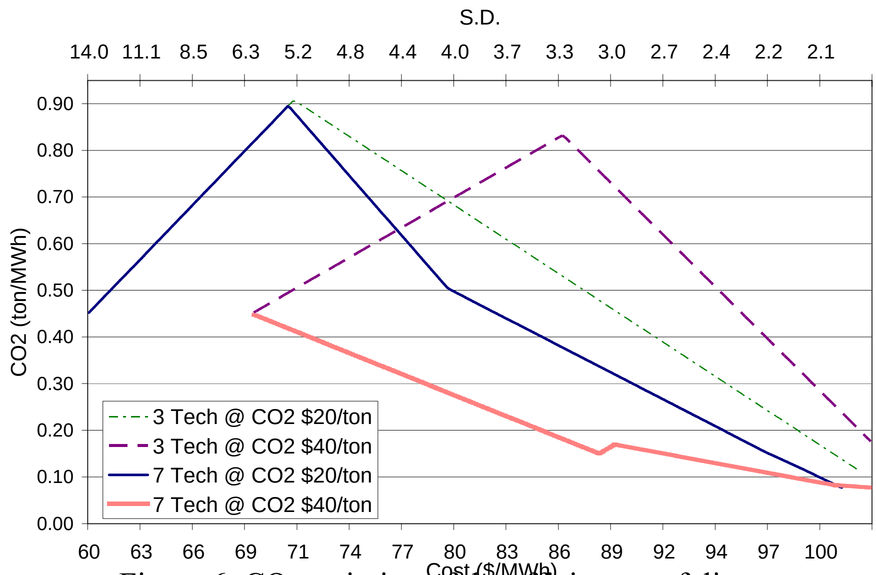


Figure 6: CO_2 emission of the efficient portfolio

Figure 6 shows the amount of CO_2 emission per MWh of the efficient portfolios of the 3 and 7 technologies options under \$20 and \$40/ton of CO_2 prices. Under \$20/ton CO_2 price for 3 and 7-technology portfolios, the amount of CO_2 increases at the beginning due to the portfolio mix between NGCC and PC and reaches the peak at the portfolio with the highest share of PC (as shown in Figure 2 and 4). When moving toward the higher cost portfolio, nuclear and IGCC CCS (for 7-technology model) gain higher share resulting in the reduction of CO_2 emission. Under \$20/ton CO_2 price, portfolios with 3 and 7 technologies have similar pattern of CO_2 emission, it declines after reaching the peak, but the 7-technology portfolios perform better in lowering CO_2 emission at the same level of cost and variation.

In contrast, under \$40/ton CO_2 price, the patterns of CO_2 emission between 3 and 7 technology portfolios are significantly different. CO_2 emission under 3-technology portfolio increases at the beginning and decreases as the portfolio moves to higher cost and lower variance section. Unlike 3 technology portfolio, CO_2 emission of 7 technology portfolio decreases steadily due to higher share of IGCC CCS and nuclear as the portfolio moves to higher cost and lower variance. As seen from the graph, introduction of IGCC CCS helps lowering the CO_2 emission at the given level of cost and variation compared with the portfolio of current baseload technology.

The results from the baseline model indicate that some technologies such as PC CCS and NGCC CCS are the dominated technologies in the optimal portfolio. These technologies have higher cost than conventional technology but are insensitive to an increase in CO_2 price. The following analysis examines the change in portfolio mix if significantly higher CO_2 prices are imposed to the generator.

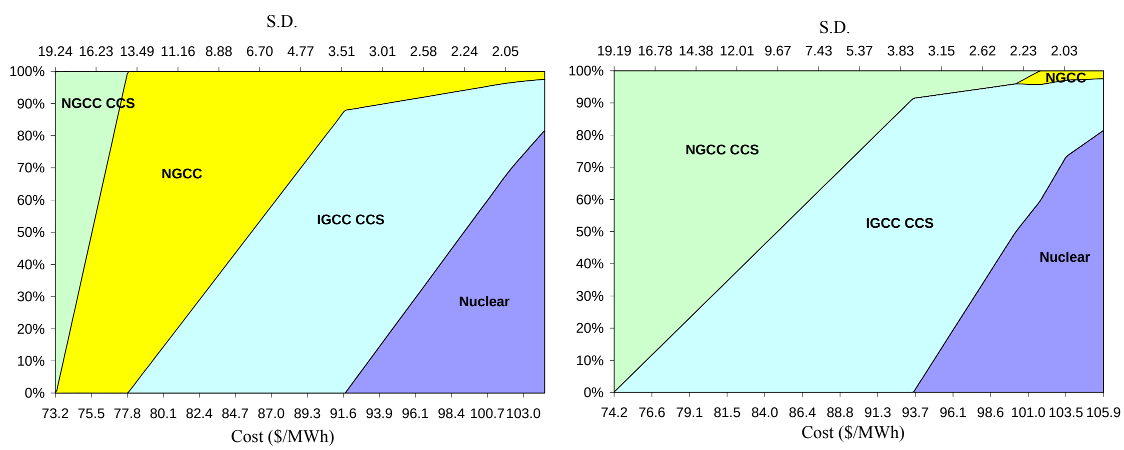


Figure 7: Portfolio of the baseline model with \$60 (left) and \$80/ton CO_2 (right)

Figure 7 shows the portfolio mix when CO_2 prices increase to \$60 and \$80/ton. When CO_2 prices are \$60-80/ton, generation costs of all coal technology without CCS increase to a level higher than nuclear. PC which almost disappears from the scenario with \$40/ton CO_2 is not in the optimal portfolio. NGCC CCS becomes the lowest cost technology with the highest variation.

The shares of IGCC CCS and nuclear are similar to the baseline model with \$40/ton CO_2 price. The obvious change is between NGCC CCS and NGCC. When higher CO_2 prices are imposed, NGCC CCS has a large share in the optimal portfolio with low cost-high variation similar to the role of NGCC in the baseline model. There are some shares of NGCC under \$60/ton CO_2 price but at \$80/ton it almost disappears from the optimal portfolio. When \$100/ton CO_2 price is applied, the result is almost the same as the model with \$80/ton CO_2 price.

2. Analysis of the fuel price structure

In this analysis, we divide the time period from 1990-2009 into 2 parts. Each one represents a different structure of fuel price movement. The period from 1990-1999 represents the structure where fuel prices were stable (less volatile) called "the stable price period". The period from 2000- Jun 2009 represents the structure with high gas price and volatility called "the volatile price period". The figure below shows the movement of real fuel price (in 2008 dollar) from 1990- Jun 2009.

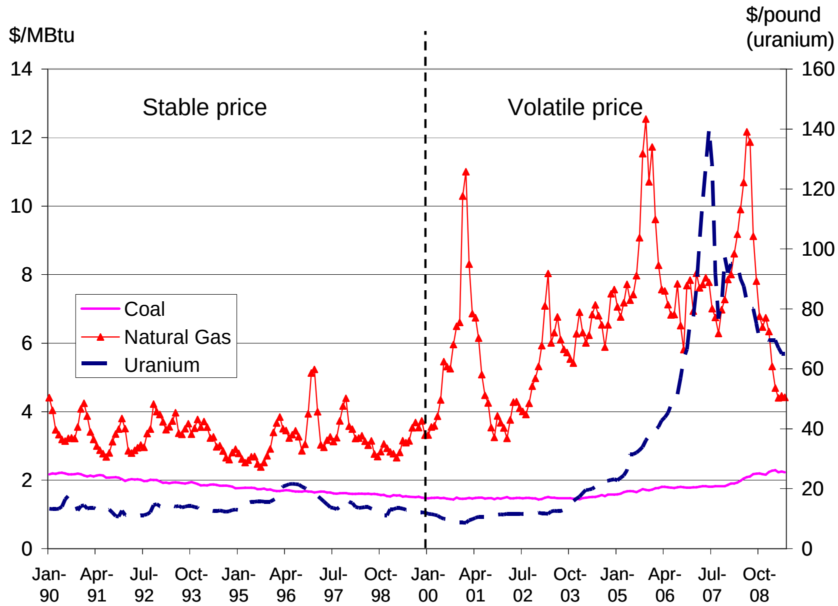


Figure 8: Real fuel price movement from 1990-Jun 2009

1990-1999			
	Uranium	Coal	Gas
Uranium	1.00	-0.21	0.23
Coal	-0.21	1.00	0.10
Gas	0.23	0.10	1.00
Mean	14.31	1.82	3.29
S.D.	2.56	0.22	0.51

2000-Jun 2009			
	Uranium	Coal	Gas
Uranium	1.00	0.78	0.42
Coal	0.78	1.00	0.35
Gas	0.42	0.35	1.00
Mean	38.62	1.67	6.65
S.D.	33.39	0.24	2.07

Table 5: Correlation coefficients of fuel prices in 2 price structures

From table 5, the correlation coefficients of fuel prices differ in the 2 periods. In the 'stable price' structure, prices of all fuels are stable (low standard deviation). The correlation coefficient between uranium and natural gas is positive but those with coal price are negative. In the 'volatile price' structure, all fuel prices are positively correlated. Uranium price has the highest fluctuation and increases sharply during the volatile price period. Note that although uranium has the highest standard deviation, the nuclear power generation process uses small amount of uranium per MWh resulting in low standard deviation of nuclear generation cost.

The model includes the same set of 7 technologies as in the baseline model. The optimal portfolio frontier is solved separately for each fuel price structure under CO_2 prices of $20 and 40/ton. Note that the correlation coefficient of the fuel cost and that of the total generation cost may not represent the same structure of correlation. The generation cost includes other cost components such as O&M and CO_2 regulation cost.

- Stable price period (1990-1999) at $20/ton CO_2 price

	$/MWh	S.D.
Nuclear	107.32	2.03
PC	73.62	5.16
PC CCS	102.49	4.23
IGCC	78.43	4.73
IGCC CCS	90.69	3.28
NGCC	50.23	4.14
NGCC CCS	57.35	4.80

	Nuclear	PC	PC CCS	IGCC	IGCC CCS	NGCC	NGCC CCS
Nuclear	1.00	-0.23	-0.44	-0.26	-0.40	0.13	0.10
PC	-0.23	1.00	0.55	0.97	0.46	0.32	0.04
PC CCS	-0.44	0.55	1.00	0.57	0.83	0.16	0.25
IGCC	-0.26	0.97	0.57	1.00	0.55	0.28	0.03
IGCC CCS	-0.40	0.46	0.83	0.55	1.00	0.09	0.26
NGCC	0.13	0.32	0.16	0.28	0.09	1.00	0.81
NGCC CCS	0.10	0.04	0.25	0.03	0.26	0.81	1.00

Table 6: Cost/standard deviation (left) and the correlation matrix (right)

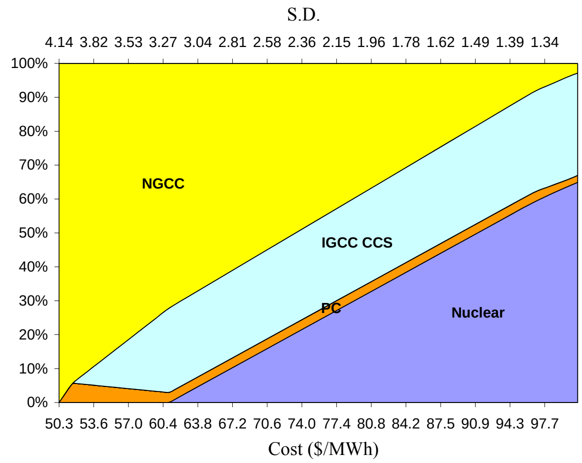


Figure 9: Technology mix along the efficient frontier

The optimal portfolio in this scenario is dominated by NGCC. Cost difference between NGCC and other technologies is large. In addition, standard deviation of NGCC cost is not relatively high. This is due to the stable movement of the natural gas price in this period. Note that PC and IGCC have high standard deviation partially due to the volatility of the simulated CO_2 price. The capacity share of PC is small and there is no share of IGCC in the optimal portfolio. The share of IGCC CCS is stable; about 25-30% along the efficient frontier. Like other scenarios portfolio, nuclear dominates the technology mix in the higher cost and lower variation portion of the efficient frontier. The largest share of nuclear on the efficient portfolio is around 60%. In this scenario, it seems that the change in portfolio mix along the frontier is mainly between NGCC and nuclear, since share of IGCC CCS and PC are quite stable. At portfolio cost $80/MWh, the optimal portfolio consists of 35% nuclear, 2% PC, 23% IGCC CCS and 40% NGCC.

- Stable price period (1990-1999) at $40/ton CO_2 price

	$/MWh	S.D.
Nuclear	107.32	2.03
PC	93.62	5.16
PC CCS	104.49	4.23
IGCC	96.43	4.73
IGCC CCS	92.49	3.28
NGCC	59.23	4.14
NGCC CCS	58.25	4.80

	Nuclear	PC	PC CCS	IGCC	IGCC CCS	NGCC	NGCC CCS
Nuclear	1.00	-0.23	-0.44	-0.26	-0.40	0.13	0.10
PC	-0.23	1.00	0.55	0.97	0.46	0.32	0.04
PC CCS	-0.44	0.55	1.00	0.57	0.83	0.16	0.25
IGCC	-0.26	0.97	0.57	1.00	0.55	0.28	0.03
IGCC CCS	-0.40	0.46	0.83	0.55	1.00	0.09	0.26
NGCC	0.13	0.32	0.16	0.28	0.09	1.00	0.81
NGCC CCS	0.10	0.04	0.25	0.03	0.26	0.81	1.00

Table 7: Cost/standard deviation (left) and the correlation matrix (right)

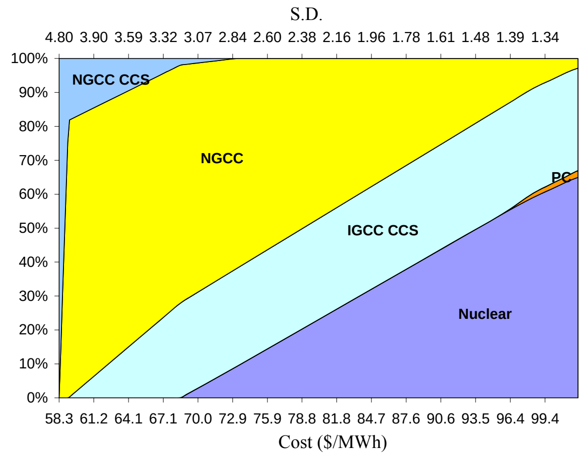


Figure 10: Technology mix along the efficient frontier

The optimal portfolio in this case is similar to the previous one except that the range of the efficient frontier is shifted due to the higher CO_2 charge. NGCC still dominates in this scenario because it has low cost, moderate volatility and low CO_2 emission. In addition there are some shares of NGCC CCS at the lower portion of the frontier. NGCC CCS has just lower cost than NGCC with slightly higher volatility. The share of IGCC CCS is quite stable along the frontier. It increases steadily from the low cost portfolio and becomes constant at around 25-30%. At cost $80/MWh, the optimal portfolio consists of 25% nuclear, 30% IGCC CCS and 45% NGCC.

This $20/ton increase in CO_2 price does not significantly change the results in the 'stable price' scenario. Only NGCC CCS appears in the optimal portfolio when higher CO_2 price is charged. The key technologies are NGCC, IGCC CCS and Nuclear. NGCC and NGCC CCS account for large percentage in the low cost and high variation part of the efficient frontier. Similarly, nuclear dominates the high cost and low variance portfolios.

- Volatile price period (2000-2009) at \$20/ton CO_2 price

	\$/MWh	S.D.
Nuclear	106.16	2.22
PC	72.53	5.41
PC CCS	100.46	4.25
IGCC	76.94	5.05
IGCC CCS	89.01	3.82
NGCC	69.62	13.96
NGCC CCS	86.20	17.88

	Nuclear	PC	PC CCS	IGCC	IGCC CCS	NGCC	NGCC CCS
Nuclear	1.00	0.35	0.66	0.32	0.67	0.30	0.35
PC	0.35	1.00	0.43	0.97	0.48	0.17	0.07
PC CCS	0.66	0.43	1.00	0.38	0.83	0.23	0.29
IGCC	0.32	0.97	0.38	1.00	0.52	0.17	0.07
IGCC CCS	0.67	0.48	0.83	0.52	1.00	0.23	0.28
NGCC	0.30	0.17	0.23	0.17	0.23	1.00	0.98
NGCC CCS	0.35	0.07	0.29	0.07	0.28	0.98	1.00

Table 8: Cost/standard deviation (left) and the correlation matrix (right)

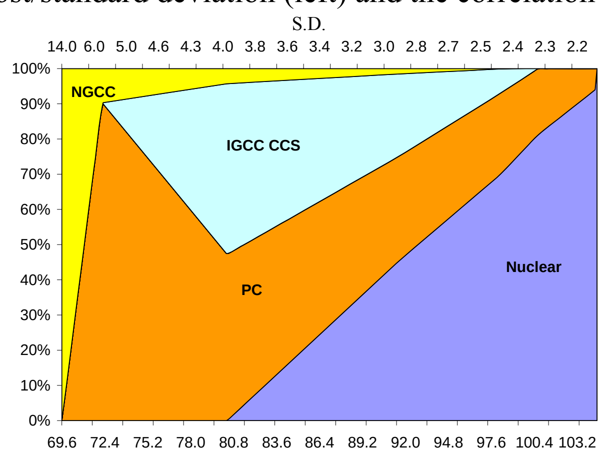


Figure 11: Technology mix along the efficient frontier

In this scenario, the technologies that dominates the optimal portfolio are PC and nuclear. Natural gas price in this case is high and volatile. Although, NGCC is still the lowest cost technology but the cost difference between NGCC and other technology is smaller than the previous scenario. Shares of NGCC are high for a short portion of the efficient frontier and decrease sharply. PC dominates most of the low cost/high variance part of the efficient portfolios. IGCC CCS gains significant share in the middle portion of the efficient frontier with the highest share around 45%. Like other scenarios, nuclear plays a key role in the high cost portion of the portfolio frontier. There are no share of IGCC, PC CCS and NGCC CCS in the optimal portfolio. At cost \$80/MWh, the optimal portfolio consists of 45% IGCC CCS, 50% PC and 5% NGCC.

- Volatile price period (2000-2009) at \$40/ton CO_2 price

	\$/MWh	S.D.
Nuclear	106.16	2.22
PC	92.53	5.41
PC CCS	102.46	4.25
IGCC	94.94	5.05
IGCC CCS	90.81	3.82
NGCC	78.62	13.96
NGCC CCS	87.10	17.88

	Nuclear	PC	PC CCS	IGCC	IGCC CCS	NGCC	NGCC CCS
Nuclear	1.00	0.35	0.66	0.32	0.67	0.30	0.35
PC	0.35	1.00	0.43	0.97	0.48	0.17	0.07
PC CCS	0.66	0.43	1.00	0.38	0.83	0.23	0.29
IGCC	0.32	0.97	0.38	1.00	0.52	0.17	0.07
IGCC CCS	0.67	0.48	0.83	0.52	1.00	0.23	0.28
NGCC	0.30	0.17	0.23	0.17	0.23	1.00	0.98
NGCC CCS	0.35	0.07	0.29	0.07	0.28	0.98	1.00

Table 9: Cost/standard deviation (left) and the correlation matrix (right)

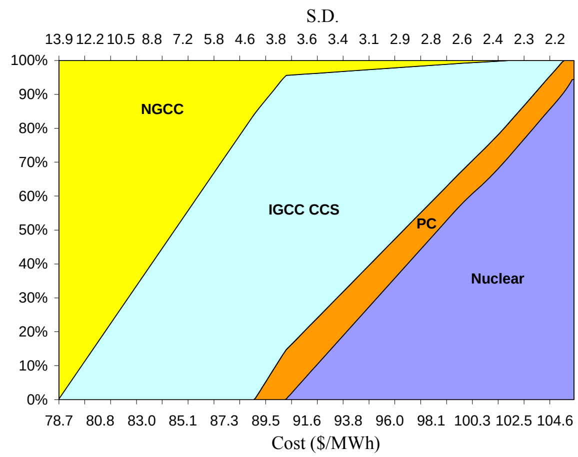


Figure 12: Technology mix along the efficient frontier

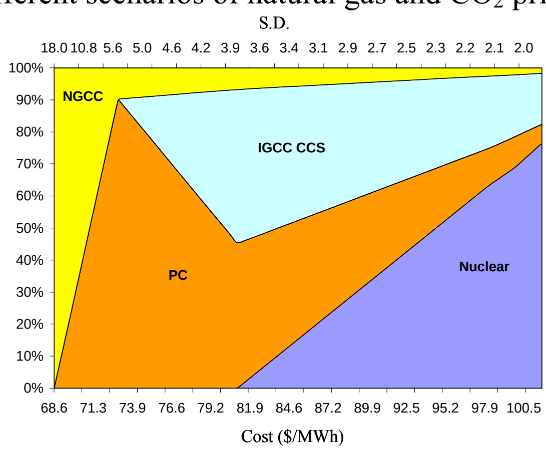
In this scenario, IGCC CCS dominates the optimal technology mix portfolio especially in the middle part of the efficient frontier. NGCC is still the lowest cost technology and the gap of generation cost with PC and IGCC is larger due to higher CO_2 price. NGCC gains more shares in the low cost portion of the portfolio than the previous scenario due to low CO_2 price. IGCC CCS has significant influence along the frontier. This is due to cost advantage over PC and IGCC when higher CO_2 regulation cost is charged. At cost \$80/MWh, the optimal portfolio consists of 20 % IGCC CCS and 80% NGCC.

This analysis shows that the period of the historical fuel cost to be used in the analysis can determine the result. The planner can choose the period which he believes best represents the future structure. The components that account for these differences are the expected generation cost, variation and correlation of the cost between technologies.

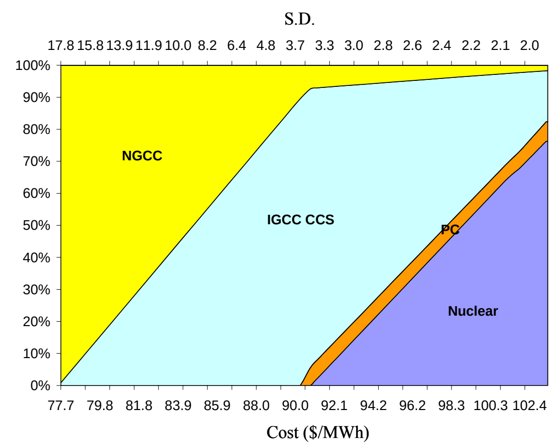
3. Analysis of expected future fuel price

The baseline model used the expected power generation cost calculated from the historical fuel cost data. In this analysis, we assume that the distribution of future fuel cost is the same as the historical distribution during 1990-2009. The efficient portfolio frontier is formulated under different values for the natural gas and coal prices.

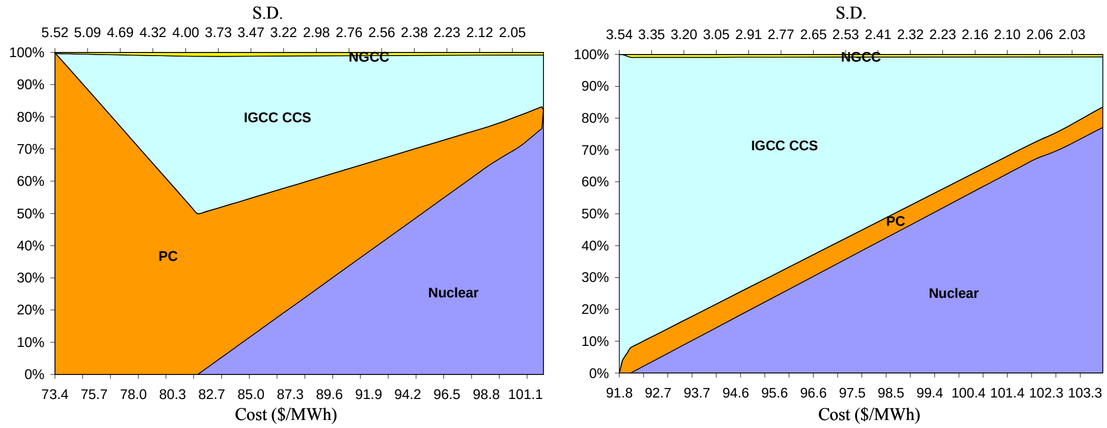
The expected price of natural gas in the baseline model is \$4.8/Mcf (Million cubic feet). The expected future price of natural gas used in this analysis is \$6 and \$10/Mcf. The Annual Energy Outlook 2010 by EIA (2009) forecasts the price of natural gas for the electric power sector to be at the range from \$6 – \$9/Mcf (2008 dollars) during the next 25 years. At \$20/ton CO_2 price, NGCC costs are \$68.6 and \$97.5/MWh for natural gas prices at \$6 and 10\$/Mcf respectively. In addition, at \$40/ton CO_2 price, the costs of NGCC are \$77.6 and \$106.5/MWh for natural gas price at \$6 and 10\$/Mcf respectively. Figure 13 below shows the technology mix along the efficient portfolio frontier under different scenarios of natural gas and CO_2 prices.



a) \$6/Mcf and \$20/ton CO_2 price



b) \$6/Mcf and \$40/ton CO_2 price



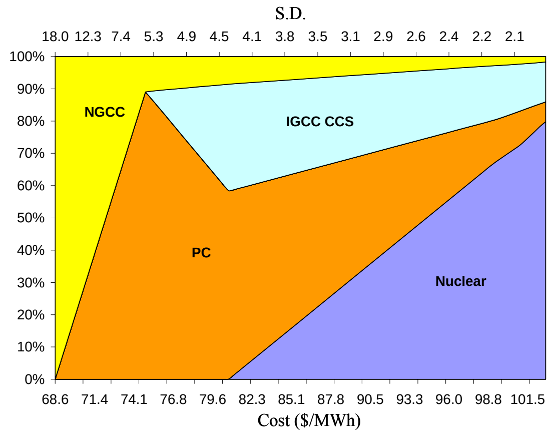
c) \$10/Mcf and \$20/ton CO_2 price d) \$10/Mcf and \$40/ton CO_2 price

Figure 13: Optimal portfolio mix under different natural gas and CO_2 price

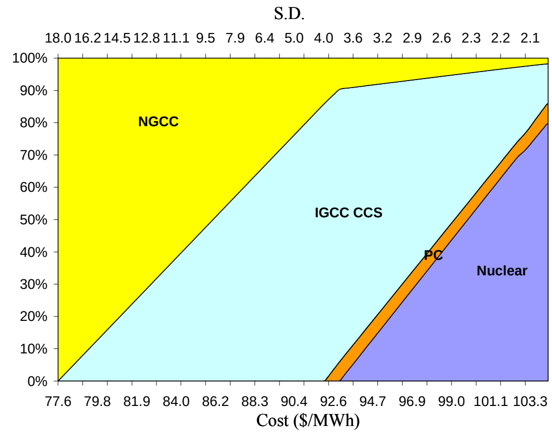
Since the fuel cost accounts for large portion of power generation from NGCC, an increase in fuel cost affects the total generation cost significantly. When the natural gas price is at \$6/Mcf, NGCC has a significant share when portfolio variance is high but, its share decreases sharply compared with the baseline model as we lower portfolio standard deviation.

As the price of natural gas increases to \$10/Mcf, there is almost no NGCC in the optimal portfolio; the share is less than 1%. At low CO_2 price, the efficient portfolio mainly consists of PC, IGCC CCS and nuclear. However, when CO_2 price is high, IGCC CCS and nuclear dominate the portfolio. Note that the optimal portfolio mix is the same when natural gas price is at \$16/Mcf; it is the dominated technology since NGCC has high cost and high volatility.

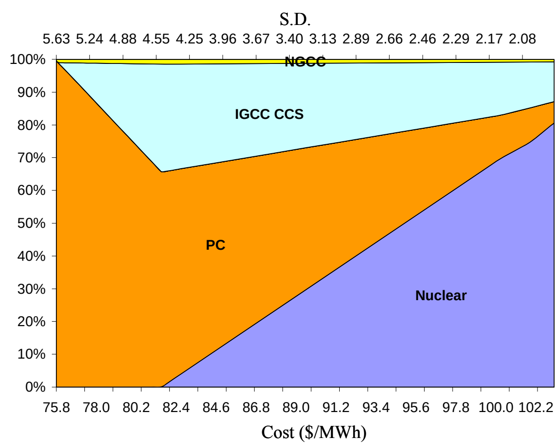
Figure 14 shows the optimal technology mix of the efficient portfolio at \$2/Mbtu coal and \$10/Mcf natural gas. Note that the baseline price of coal is at \$1.7/Mbtu and the forecast coal price in EIA (2009) is around \$2/Mbtu over the next 25 years.



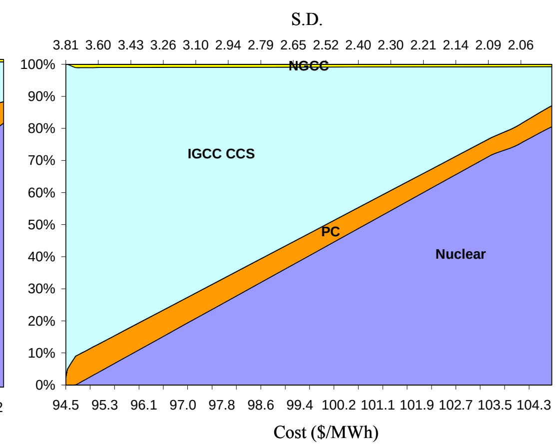
a) Gas at $6/Mcf and CO_2 at $20/ton



b) Gas at $6/Mcf and CO_2 at $40/ton



c) Gas at $10/Mcf and CO_2 at $20/ton



d) Gas at $10/Mcf and CO_2 at $40/ton

Figure 14: Optimal portfolio mix at $2/Mbtu coal price and $6 and 10/Mcf gas price

With $2/Mbtu coal price and $6/Mcf natural gas price, the optimal portfolio mix is similar to the baseline model but when gas price is at $10/Mcf, the optimal technology mix is different. Especially, when CO_2 price is at $20/ton, PC dominates the portfolio frontier at low cost and high variance portion and the high cost and low variance portion is dominated by nuclear. However, when cost of CO_2 is higher, the optimal technology mix is similar to Figure 13 (d) where IGCC CCS and nuclear dominates the whole efficient portfolio.

The decision rule to choose the optimal technology mix of the planner or utility can be based on the marginal rate of substitution (MRS) between cost and variation in cost. Theoretically, the selection of the optimal portfolio depends on the utility function of the planner. In this study, the decision rule is simplified such that the planner decides the MRS between cost and variation and chooses the portfolio that satisfies that condition. For example, the MRS of $5/MWh/S.D. can be interpreted that the planner is willing to increase power generation cost by $5/MWh for the reduction of 1 standard deviation of the portfolio.

MRS	$/MWh	SD	Nuclear	PC	PC CCS	IGCC	IGCC CCS	NGCC	NGCC CCS
3	70.27	5.48	0.0%	76.8%	0.0%	0.0%	0.0%	23.2%	0.0%
4	70.65	5.37	0.0%	79.7%	0.0%	0.0%	0.0%	20.3%	0.0%
5	72.58	4.97	0.0%	73.1%	0.0%	0.0%	9.4%	17.6%	0.0%
6	76.50	4.26	0.0%	55.1%	0.0%	0.0%	30.5%	14.4%	0.0%
7	78.50	3.95	0.0%	45.9%	0.0%	0.0%	41.2%	12.8%	0.0%
8	80.80	3.65	4.1%	38.8%	0.0%	0.0%	45.6%	11.4%	0.0%
9	86.28	3.00	23.4%	29.6%	0.0%	0.0%	38.1%	9.0%	0.0%
10	89.09	2.71	33.2%	24.8%	0.0%	0.0%	34.2%	7.8%	0.0%

Table 10: Optimal portfolio mix at different MRS

Table 10 shows the optimal portfolio under the baseline model with $20/ton of CO_2 price at different MRS. As the MRS increases, the optimal portfolio moves toward the lower variance portfolio (also with higher cost). In other words, higher MRS means more risk aversion. Given the marginal rate of substitution (MRS), the optimal technology mix can vary significantly depending on the scenario on generation cost as shown in figure 15.

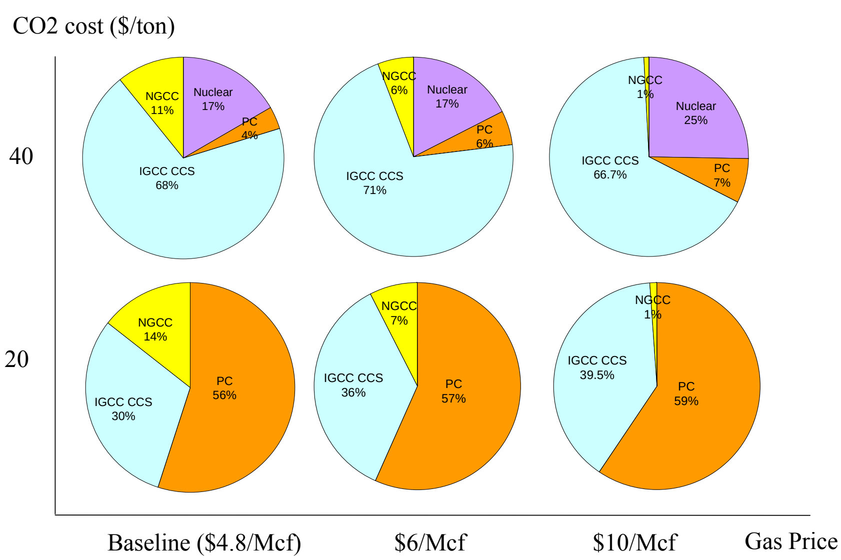


Figure 15: The optimal portfolio mix at the MRS of $5/MWh/S.D.

The scenario of fuel and CO_2 price that the planner uses for deciding the technology mix and the actual event could be different. Although demand grows every year but the new generation capacity could not change the overall technology mix significantly. The selected portfolio could have different cost and variation if the referred scenario does not happen.

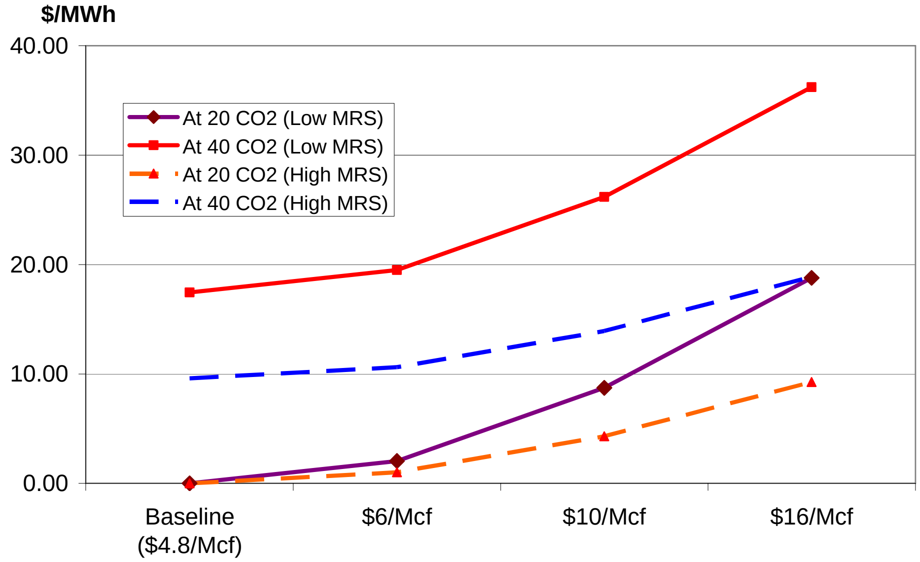


Figure 16: Regret graph from decision at the baseline cost at the MRS of $3 and $8/MWh/S.D.

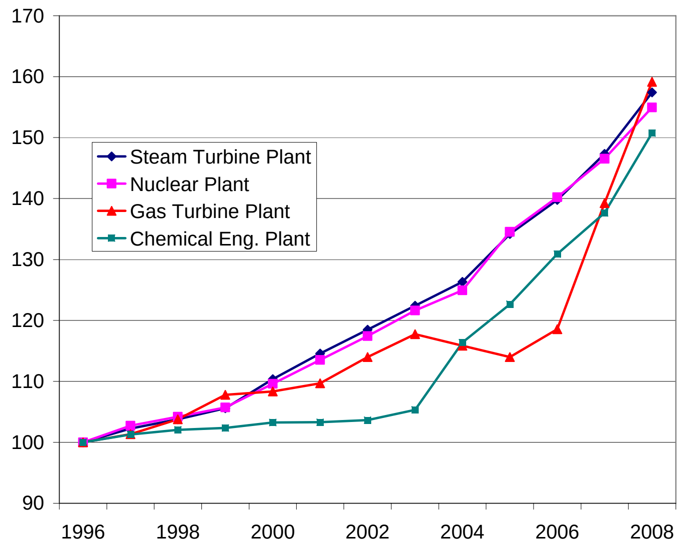
We define the term 'regret' as the change in portfolio cost if the planned scenario does not occur. Positive regret means that the portfolio cost is higher when another scenario occurs. Figure 16 shows the regret graph of the portfolio mix based on the decision at the baseline scenario with $20/ton CO_2 price. The figure shows results from 2 MRS; $3 and $8/MWh/S.D. If the planner is concerned more about variance (at $8/S.D.), the portfolio has higher cost but lower standard deviation and less 'regret' than at $3/S.D. In addition, there are more shares of IGCC CCS and nuclear under MRS $8/S.D. which reduces the impact of unexpected higher CO_2 price and natural gas cost.

4. Analysis of the capital cost

Various published reports show different capital cost for each technology. The actual capital cost especially for the future technology is generally unobservable. Manufacturing and construction of the power plant require similar resources for example steel, cement and labor. Figure 17 shows the construction cost index (Handy-Whitman

Index) of 3 power plant technologies including nuclear, steam turbine and gas turbine power plant and chemical engineering plant index.

Currently there are not many IGCC plants operating and the capital cost is uncertain. However, an IGCC plant is a combination of a chemical plant (a gasification unit) and power plant (a gas turbine). The chemical engineering plant index and gas turbine index together can represent IGCC plant construction cost index.



Data source: Handy-Whitman index and Chemical Engineering (2003, 2009)

Figure 17: Power plant related construction cost index (1996=100)

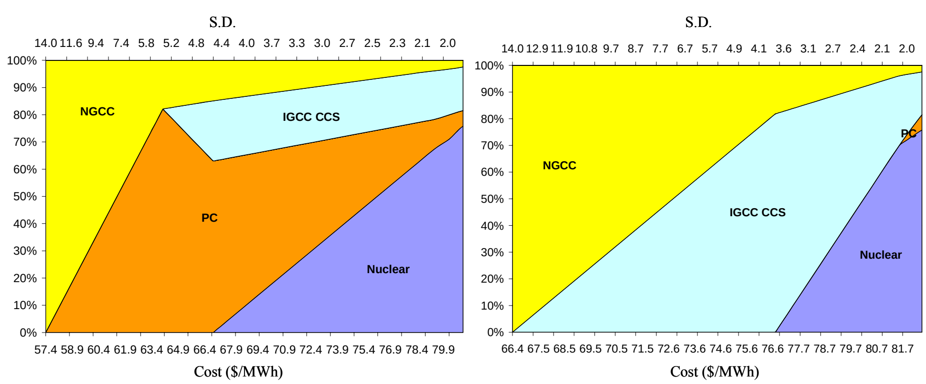
Over the 12 years from 1996-2008 the 3 indices are almost identical. The anomalous gas turbines during 2004-2005 can be explained by the precipitous drop in demand for these plants. Chupka and Basheda (2007) discussed recent increase in utility construction costs. Various index, other than four index shown in Figure 17, such as labor, steel/metal, manufacturing and heavy construction cost increase altogether. Since construction of all power plant types uses common resources, we can imply that cost generally move up and down together.

In this section, we test how the portfolio mix along the efficient frontier changes when the capital cost changes. We impose a ± 30% change in capital cost for each technology. Note that the percentage change in power generation cost ($/MWh) of each technology is not the same since some technologies are more capital intensive. A ± 30% change in capital cost changes the generation cost of nuclear by ± 22%; for PC, IGCC and IGCC CCS, the change is ± 11-14%. For NGCC and NGCC CCS, the cost changes only by ± 4-8% since capital cost accounts for a smaller proportion than other technologies.

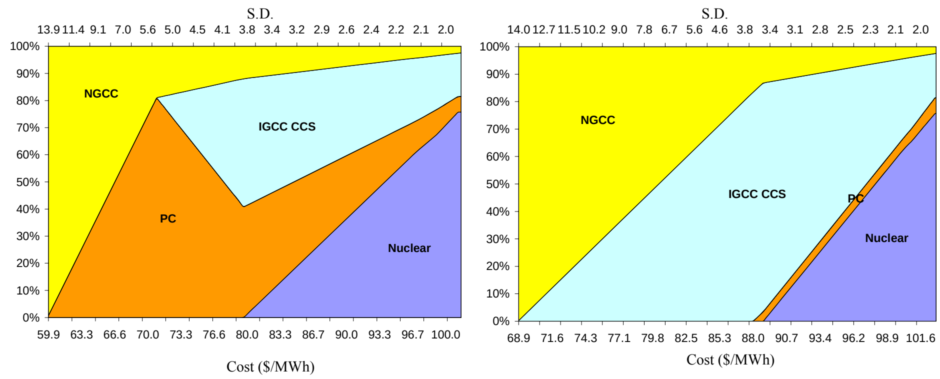
Cost ($/MWh)	$20/ton CO_2			$40/ton CO_2		
	Baseline	-30%	+30%	Baseline	-30%	+30%
Nuclear	106.75	83.41	130.10	106.75	83.41	130.10
PC	73.42	65.48	81.36	93.42	85.48	101.36
PC CCS	101.68	88.52	114.84	103.68	90.52	116.84
IGCC	78.01	68.82	87.20	96.01	86.82	105.20
IGCC CCS	89.98	77.24	102.72	91.78	79.04	104.52
NGCC	59.82	57.43	62.22	68.82	66.43	71.22
NGCC CCS	71.46	65.80	77.12	72.36	66.70	78.02

Table 11: Generation cost as capital cost varies

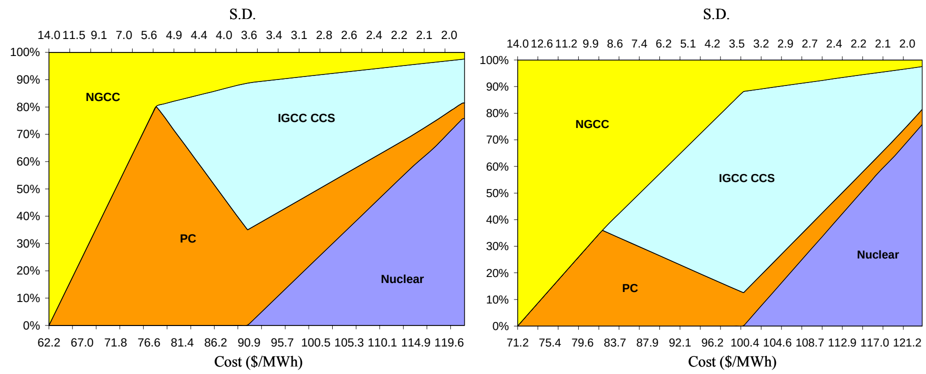
The efficient portfolio mix of these of the tested scenario is shown in figure 18. The ranges of the efficient portfolio are different due to the change in capital cost. The role of each technology mix along the frontier is similar to the baseline model. In addition, the significant change only occurs between PC and IGCC CCS. Shape of NGCC and nuclear portfolio mix does not change from the baseline scenario.



a) Capital cost decreases 30%



b) Baseline capital cost



c) Capital cost increases 30%

Figure 18: Efficient portfolio mix at \$20 (left) and \$40/ton CO_2 (right)

Figure 19 below shows the share of all technologies along the efficient frontier. In order to compare 2 scenarios, in each figure the efficient frontier is normalized to be on the same horizontal axis. At \$20/ton CO_2 price, the change in technology mix occurs mainly with IGCC CCS and PC. When capital cost increases, some of PC share is replaced by IGCC CCS. The opposite occurs when capital cost increases. At \$40/ton CO_2 price, when the capital cost decreases most of PC share is replaced by IGCC CCS and NGCC. There is almost no share of PC when capital decreases by 30%. Also, when capital cost increases, the change is opposite.

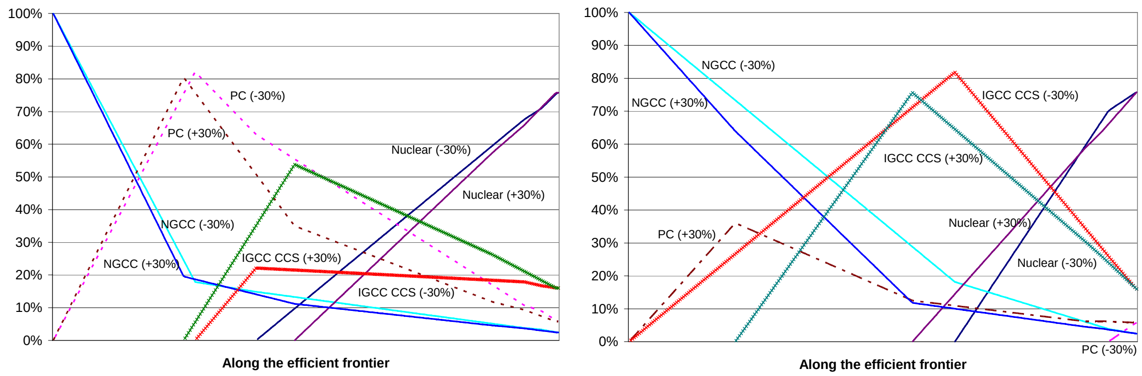
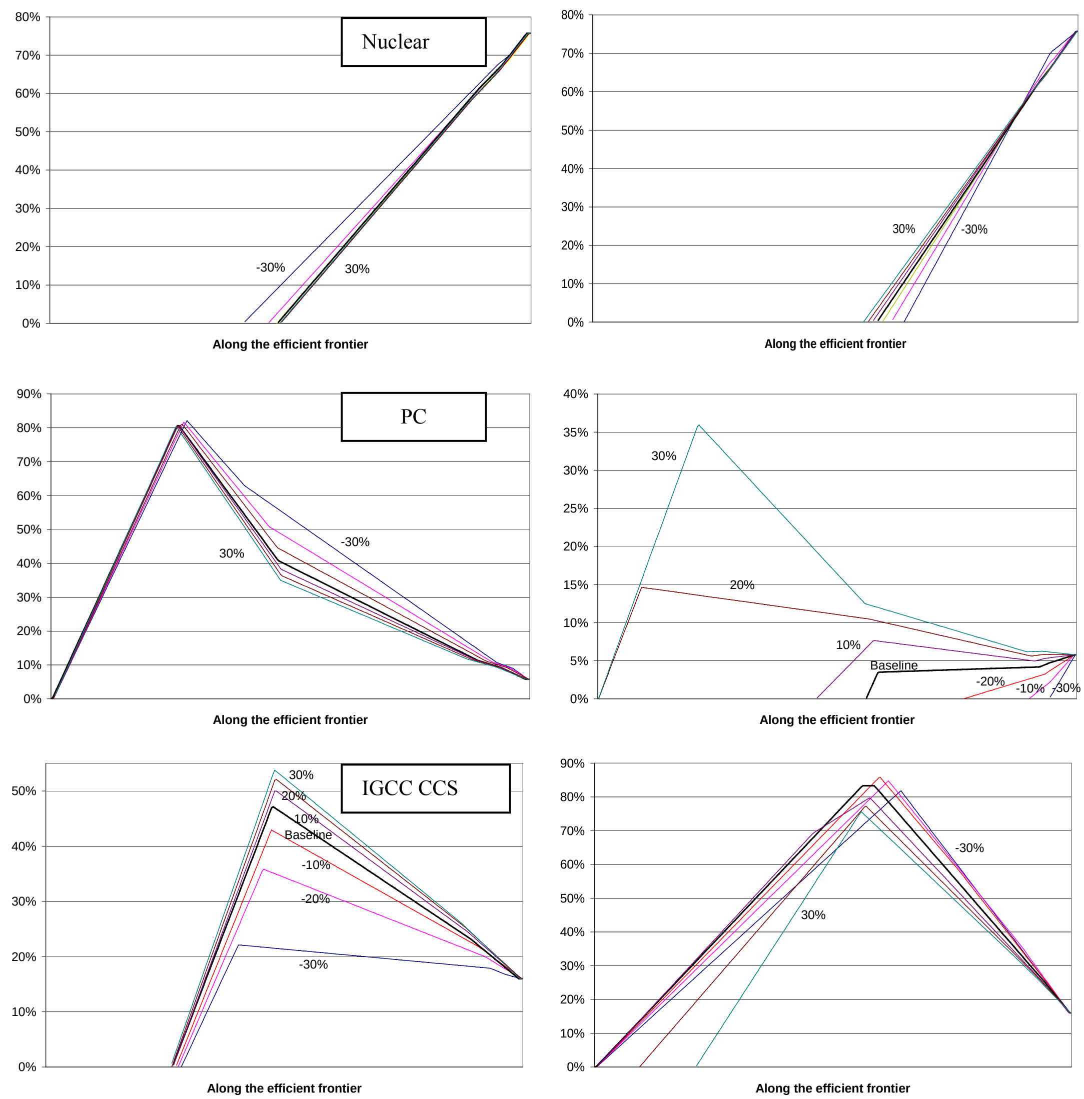


Figure 19: Portfolio at ±30% change in capital cost at \$20 (left) and \$40/ton CO_2 price



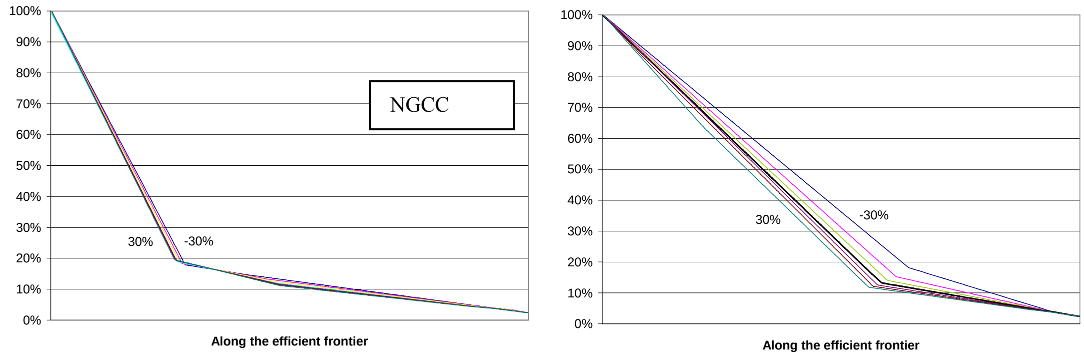


Figure 20: Share of each technology under changes in capital cost at \$20 (left) and \$40/ton CO_2 price (right)

The analysis shows that when all capital cost moves together there is no significant change in the pattern of the portfolio mix. There are significant changes between some technologies, PC and IGCC CCS. These 2 technologies are the technologies in the middle portion of the efficient frontier. With moderate change at ±30%, there is no change in the cost order of the technology at the boundary.

However, as shown in figure 21, when the change is more extreme for example at 50% decrease in capital cost, portfolio mix changes significantly. In this case, nuclear is not the highest cost technology and the gap between NGCC and NGCC CCS cost is smaller. At \$20/ton CO_2 price, PC and nuclear dominate most part of the portfolio and there is only small share of IGCC CCS. When CO_2 price increases, nuclear dominates the portfolio since cost of all fossil fuel technology is higher. Also, NGCC CCS replaces NGCC at the low cost and high volatility portfolios.

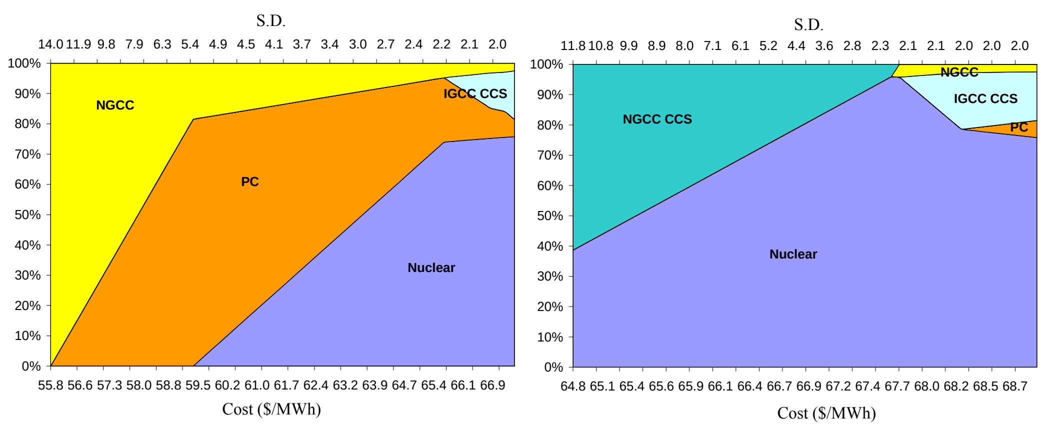


Figure 21: Mix at 50% capital cost decreases at \$20 (left) and \$40/ton CO_2 price (right)

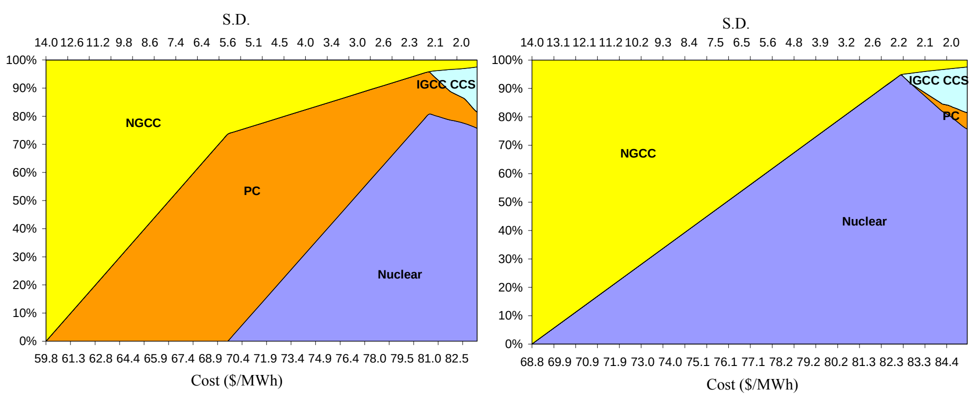
In the previous analysis, the efficient portfolio is formulated under the same percentage change in capital cost for all technologies. In this analysis, we assume a change in capital cost of specific technologies relative to the baseline value. Since the capital cost has the range of possible value, we perform a sensitivity analysis at ± 30% capital cost range for nuclear, IGCC and IGCC CCS.

– Analysis of nuclear capital cost

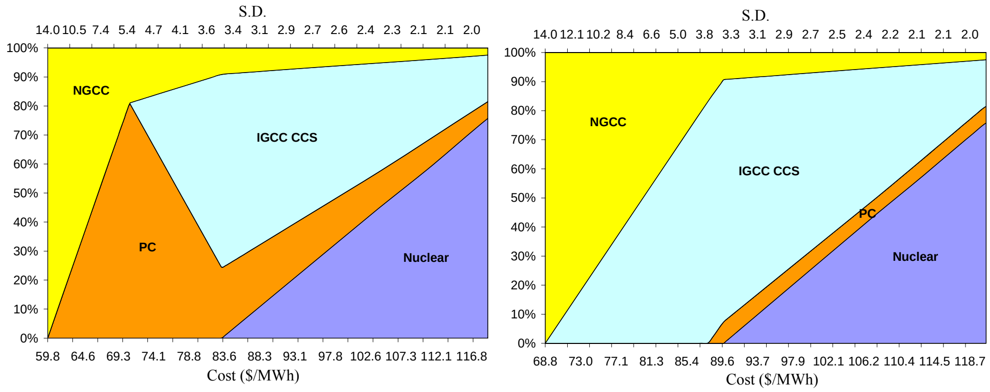
We perform another analysis where only nuclear capital cost changes ±30% from the baseline value. Table 12 shows the generation cost from nuclear from different percentages change in the capital cost.

Change in capital cost	Nuclear cost ($/MWh)	% Change in generation cost
-30%	83.41	-22%
-20%	91.19	-15%
-10%	98.97	-7%
Baseline	106.75	-
10%	114.54	7%
20%	122.32	15%
30%	130.10	22%

Table 12: Generation cost of nuclear at different capital cost levels



a) 30% decrease in nuclear capital cost



b) 30% increase in nuclear capital cost

Figure 22: Portfolio at different nuclear capital cost at \$20 (left) and \$40/ton CO_2 (right)

Under low nuclear capital cost scenario, the share of nuclear replaces the share of IGCC CCS compared with the baseline model. Some shares of IGCC CCS are also replaced by PC and NGCC. When CO_2 price is high, NGCC and nuclear are the only dominant technologies; IGCC CCS does not play a significant role as in the baseline model. For high nuclear cost scenario, the shape of the portfolio is similar to the baseline model with extended range of the efficient frontier.

With carbon costs at \$20-\$40/ton, IGCC CCS and nuclear are direct competitor. Low nuclear costs crowd out IGCC CCS and vice versa. Figure 23 and figure 24 show share of nuclear and IGCC CCS in all scenarios. Shares of nuclear and IGCC CCS change in the opposite direction as the capital cost of nuclear changes. IGCC CCS has lowered share in the optimal portfolio when nuclear cost is lower.

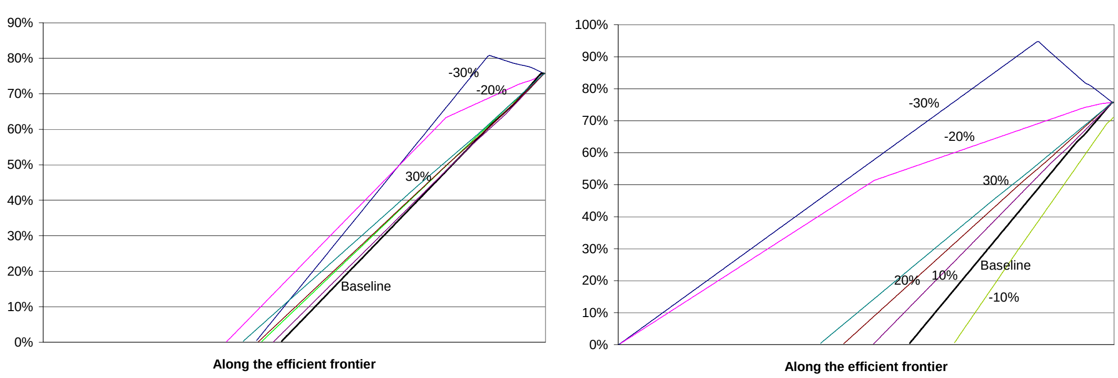


Figure 23: Nuclear share along the efficient frontier at different levels of nuclear capital cost with \$20 (left) and \$40/ton CO_2 (right)

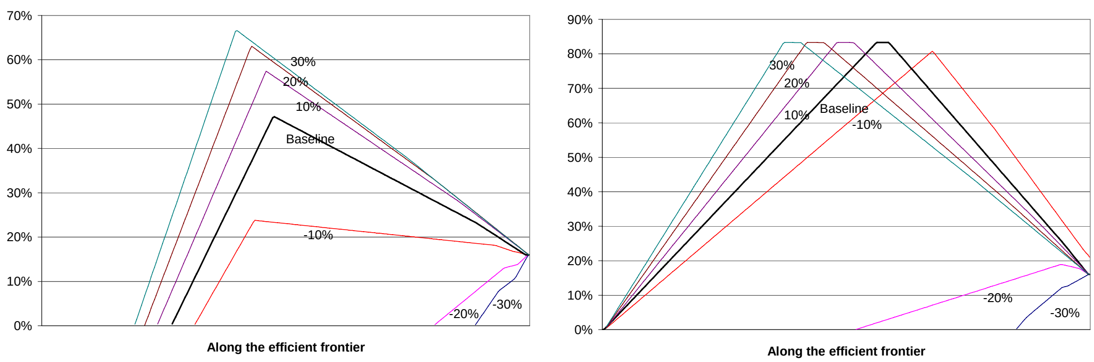


Figure 24: IGCC CCS share along the efficient frontier at different levels of nuclear capital cost with \$20 (left) and \$40/ton CO_2 (right)

– Analysis of IGCC and IGCC CCS total plant cost

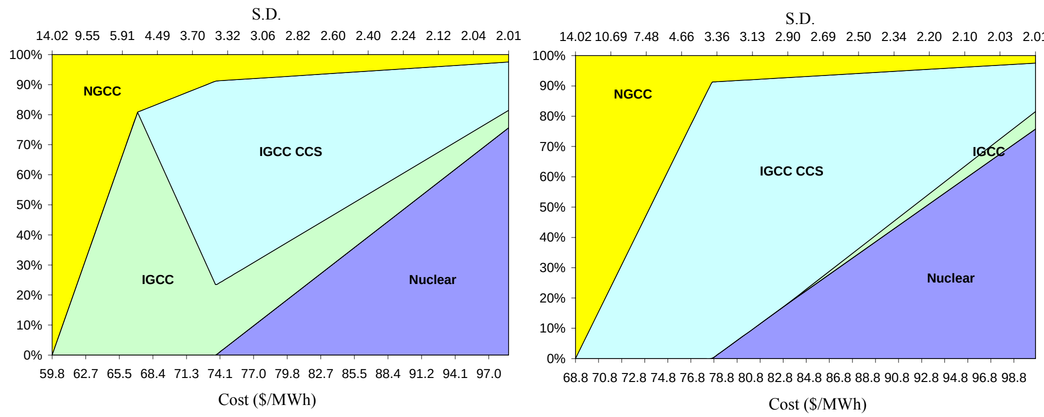
We analyze the change in the share of IGCC and IGCC CCS when capital cost of both technology changes. Since IGCC and IGCC CCS have almost the same facility except the CCS unit, we assume the same percentage change of both technologies in each case. Capital costs of other technology are assumed to be at the baseline level. The test percentage change is between ± 30% of the baseline value. Table 13 below shows the change in generation cost at different levels of change in capital cost.

Change in capital cost	\$20/ton CO_2		\$40/ton CO_2	
	IGCC	IGCC CCS	IGCC	IGCC CCS
-30%	68.82 (-12%)	77.24 (-14%)	86.82 (-10%)	79.04 (-14%)
-20%	71.88 (-8%)	81.48 (-9%)	89.88 (-6%)	83.28 (-9%)
-10%	74.94 (-4%)	85.73 (-5%)	92.94 (-3%)	87.53 (-5%)
Baseline	78.01	89.98	96.01	91.78
10%	81.07 (4%)	94.22 (5%)	99.07 (3%)	96.02 (5%)
20%	84.13 (8%)	98.47 (9%)	102.13 (6%)	100.27 (9%)
30%	87.2 (12%)	102.72(14%)	105.2 (10%)	104.52 (14%)

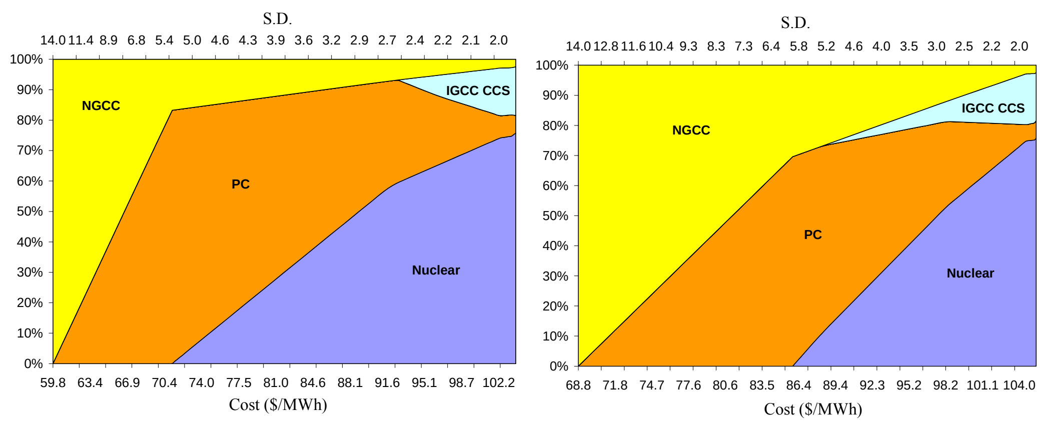
Note: percentage change in total generation cost in the parenthesis

Table 13: Cost/MWh at different capital cost of IGCC and IGCC CCS

From the baseline model, the result shows that the share of IGCC CCS increases significantly when moving from \$20 to \$40/ton CO_2 price. Cost of IGCC CCS becomes more competitive compared with other fossil fuel technology especially PC.



a) IGCC/ IGCC CCS capital cost decreases by 30%



b) IGCC/ IGCC CCS capital cost increases by 30%

Figure 25: Efficient portfolio mix at different levels of IGCC and IGCC CCS capital cost at \$20 (left) and \$40/ton CO_2 price

Figure 26 shows the share of IGCC CCS along the efficient portfolio frontier at 2 levels of CO_2 price. Note that at each level of CO_2 price, the range of the efficient frontier is approximately the same for all scenarios of IGCC cost since there is no change in the cost of NGCC and nuclear which at the high and low end of the frontier. At \$20/ton CO_2 price, the share of IGCC increases steadily as the capital cost lowered; it replaces PC and there is no significant change in NGCC share. However as the capital cost increases, especially from 20-30%, the share of IGCC CCS almost disappears from the efficient portfolio.

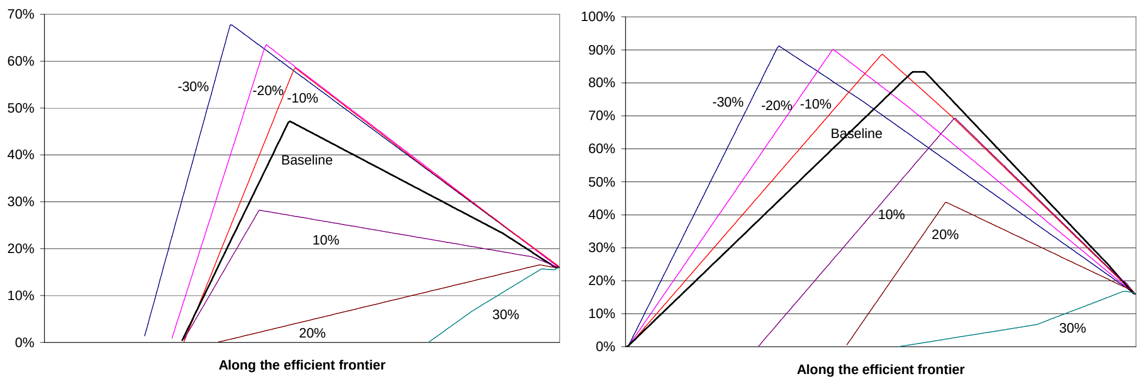


Figure 26: IGCC CCS share along the efficient frontier at different levels of capital cost with \$20 (left) and \$40/ton CO_2 (right)

When CO_2 price increases to \$40/ton, IGCC CCS plays a more significant role. From the baseline model, IGCC CCS replaces most of PC share when higher CO_2 price is imposed. When capital cost decreases, IGCC CCS starts to replace some of NGCC share in the optimal portfolio with no significant change in nuclear share. However, when capital cost increases, the share of IGCC CCS is replaced by NGCC and PC because IGCC CCS is more expensive. Especially, when the capital cost increases by 30% (or 14% increase in total generation cost), there is almost no share of IGCC CCS in the optimal portfolio.

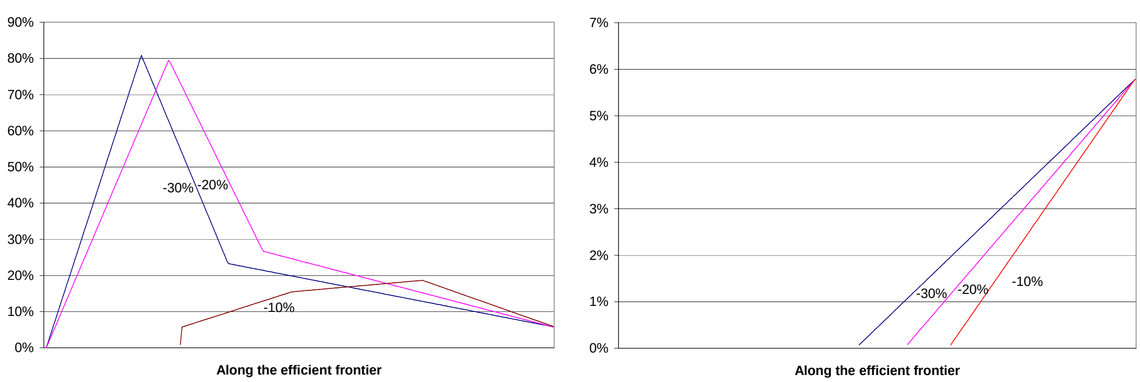


Figure 27: IGCC share along the efficient frontier at different levels of capital cost with \$20 (left) and \$40/ton CO_2 (right)

IGCC is the dominated technology under the baseline model; there is no share of IGCC in the optimal portfolio. When capital cost of IGCC is lowered by 20% (or 9% decreases in total generation cost), IGCC becomes more competitive and replaces the share of PC in the optimal portfolio. Under \$20/ton CO_2 price, IGCC replaces all PC in the optimal portfolio; it acts like PC under the baseline model. When CO_2 price increases to \$40/ton, it also replaces the tiny share of PC since the efficient portfolio is dominated by NGCC, IGCC CCS and nuclear.

5. Sensitivity analysis of the CCS cost

In this analysis, we formulate 4 different scenarios of CO_2 prices and CCS cost. CO_2 prices are low (\$20/ton) and high (\$40/ton). The CCS cost includes capture and transportation and storage (T&S) costs. In this analysis, we assume no change in the capture cost. The focus is on the uncertainty of T&S cost. We formulate 2 scenarios of T&S cost; high and low. According to EPRI (2008), cost for CO_2 transportation and storage (T&S) for IGCC CCS with different types of coal and gasification technology is in the range of \$8.90 – 10.90/MWh. We set the baseline cost for CO_2 T&S at \$10/MWh in the baseline model. The scenario with high CCS cost has the CO_2 T&S cost at \$20/MWh.

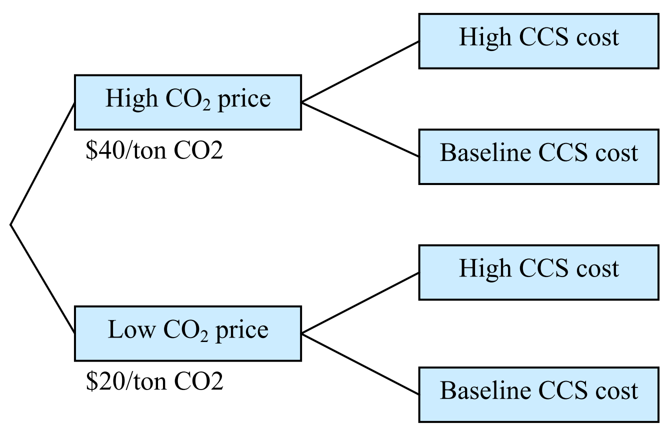
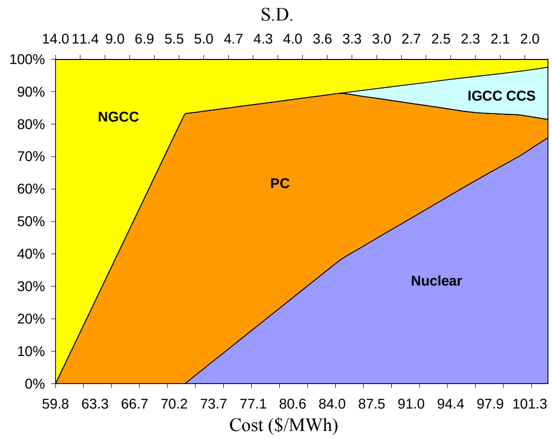
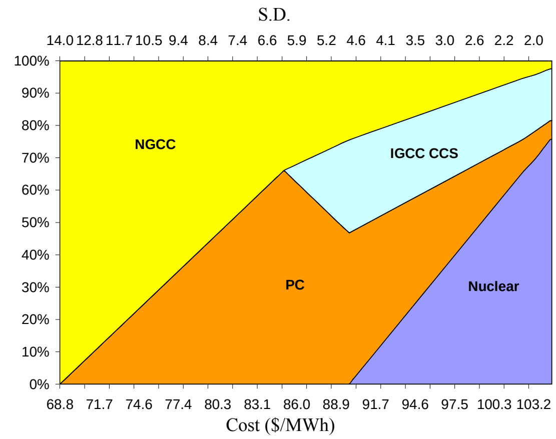


Figure 28: Scenario analysis on CCS cost

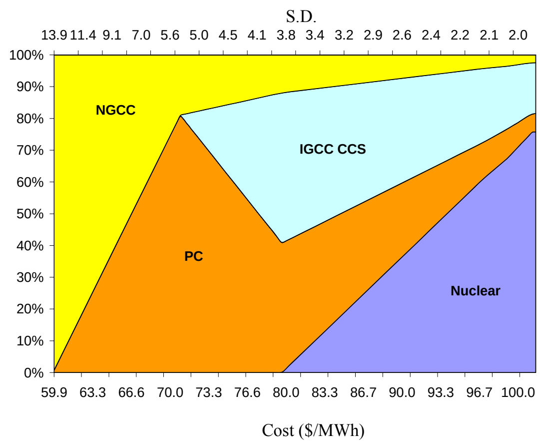
The results from the scenarios with baseline CCS cost at 20 and 40 \$/ton CO_2 prices are presented in the previous section scenarios B3 and B4. Figure 29 shows the technology mix of the portfolio on the efficient frontier under 4 scenarios.



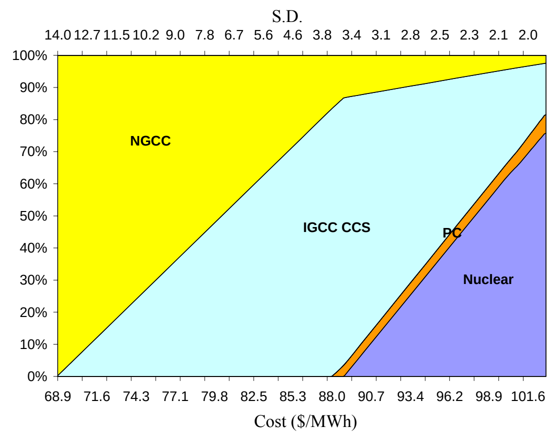
(a) High CCS and Low CO_2 price



(b) High CCS and High CO_2 price



(c) Baseline CCS and Low CO_2 price



(d) Baseline CCS and High CO_2 price

Figure 29: Technology portfolios on the efficient frontier in 4 scenarios

Cost of CCS and CO_2 are the important factors in this analysis. The optimal portfolio changes significantly across these 4 scenarios. In the high CCS cost scenarios, Figure 29a and b, share of IGCC CCS is small in both $20 and 40/ton of CO_2 prices. When price of CO_2 is low (at $20/ton), PC has a large share in the portfolios especially when cost of CCS is high, figure 29a. When price of CO_2 increases to $40/ton, share of PC decreases and is mostly replaced by NGCC.

When we compare models with low CO_2 price at different CCS cost, shares of NGCC along the efficient frontier change significantly. Large share of PC is replaced by IGCC CCS. Some share of nuclear is also replaced. In figure 29a and c, the efficient frontiers have about the same range in term of cost and standard deviation. It can be obviously seen that the share of nuclear decreases significantly as CCS cost decreases. In addition, IGCC CCS gains higher share in the high cost and low variation portion of the efficient frontier.

From figure 29d, low CCS cost and high CO_2 price, NGCC, IGCC CCS and nuclear play a significant role in the optimal portfolio. NGCC and IGCC CCS dominate portfolios in the first half of the efficient frontier (low cost/high variation). In the second half of the efficient frontier (high cost/low variation), IGCC CCS and nuclear have significant share in the portfolios with small share of PC.

5. Bayesian analysis of power generation portfolio (applied BL model)

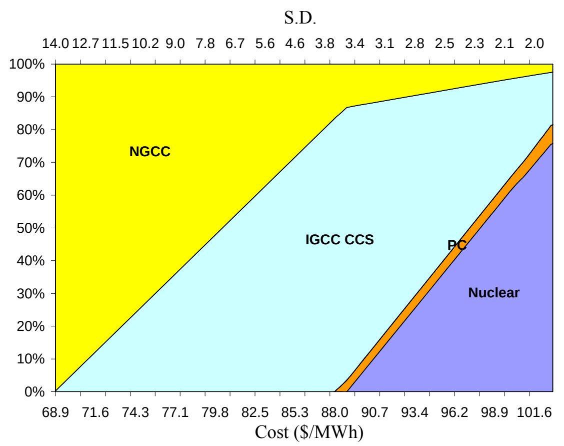
From the baseline model, we apply the Bayesian analysis to formulate the optimal baseload generation portfolio. In this section, we show an example of the expression of the posterior belief on the NGCC cost such that the investor forms his belief after considering the the information on the baseline optimal portfolio mix, generation cost and his expectation on the fuel market.

Example: The investor expects that cost of NGCC under the scenario with $40/ton of CO_2 will increase from $69/MWh to 90$ MWh due to high demand on natural gas. From the baseline model with high CO_2 price, NGCC is the technology that dominates most part of the portfolio. The investor expresses different level of confidence (*c*) of his belief on NGCC cost at the range. The optimal portfolio will be solved for 20, 50 and 80% level of confidence in the posterior belief.

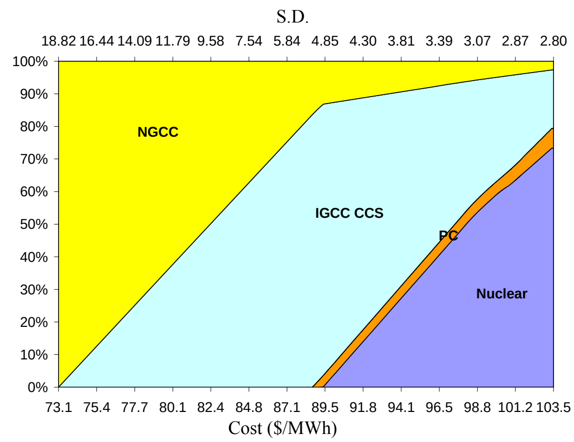
Cost ($/MWh)	Baseline	20% CI	50% CI	80% CI
Nuclear	106.75	106.74	106.72	106.70
PC	93.42	93.51	93.64	93.77
PC CCS	103.68	97.51	97.44	97.37
IGCC	96.01	96.04	96.09	96.14
IGCC CCS	91.78	91.72	91.63	91.55
NGCC	68.82	73.06	79.41	85.76
NGCC CCS	72.36	78.04	86.55	95.07
Posterior belief S.D.	-	28.05	14.03	7.01

Table 14: Power generation cost under different belief’s confidence

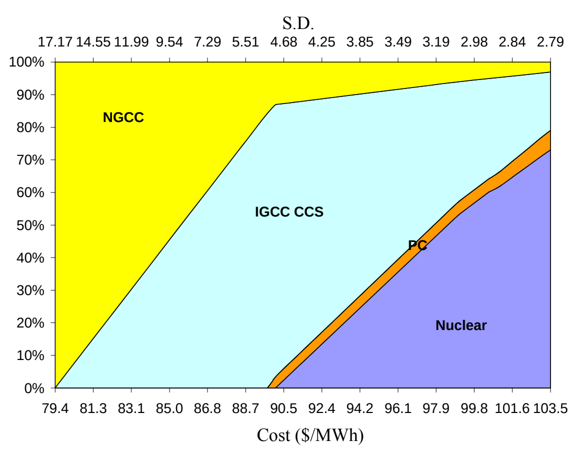
Table 14 shows power generation cost from the baseline model and the model with beliefs at different confidence levels. The value of NGCC cost that the investor expects is \$90/MWh. As confidence grows, the expected cost of NGCC is close to the mean value. For example, at 80% confidence cost of NGCC is \$85.76/MWh. In addition, as shown at the bottom of the table, lower confidence translates to higher belief's standard deviation (variance). Costs of other technology also change when cost of NGCC changes due to the correlation with NGCC cost. However, since the correlation of NGCC and other technologies is low, costs of other technologies do not significantly change.



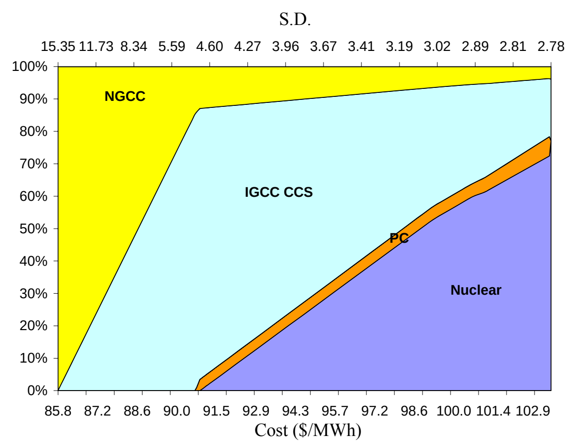
(a) baseline



(b) 20% confidence



(c) 50% confidence



(d) 80% confidence

Figure 30: Optimal portfolios under different view's confidence

From figure 30, the optimal portfolios are solved under different confidence levels in the belief. In this example, cost of NGCC is expected to increase to \$90/MWh. Shapes of the optimal portfolio changes in the direction toward using more NGCC when keeping the portfolio cost fixed because the lower bound of the efficient portfolio frontier cost moves up as NGCC cost increases. Portfolio mix at $90/MWh is shown in figure 31 below.

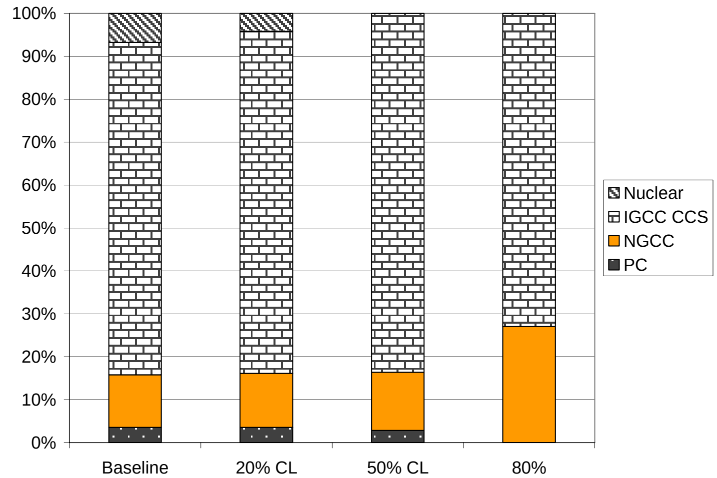


Figure 31: Generation mix at $90/MWh

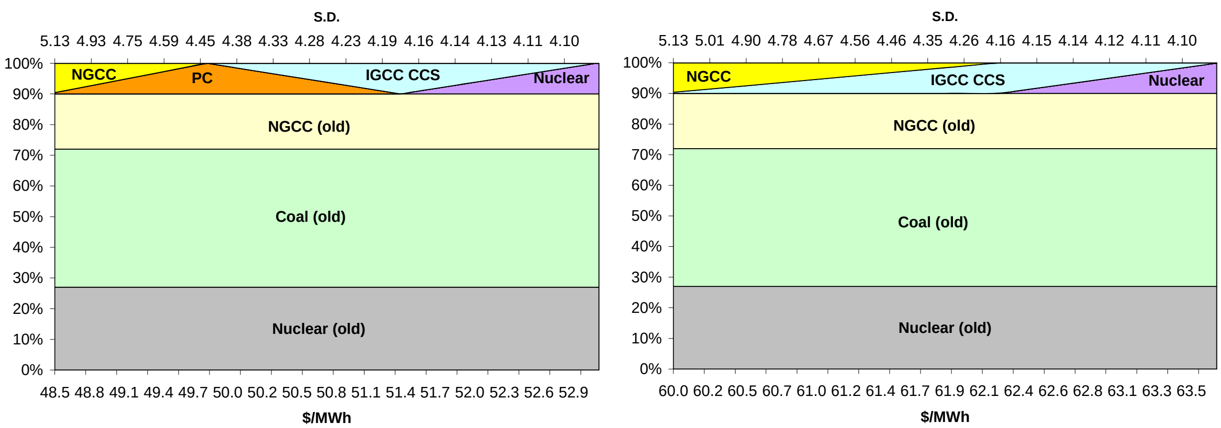
Higher natural gas cost shifts the lower bound cost of the efficient frontier. NGCC cost is significantly higher but it is still the lowest cost technology. It is still the dominant technology in the first half of the efficient frontier. Since this is under $40/ton of CO_2 price, IGCC CCS plays significant role in this scenario. Nuclear and IGCC CCS replaces NGCC shares as NGCC cost increases.

6. Portfolio with existing capacity

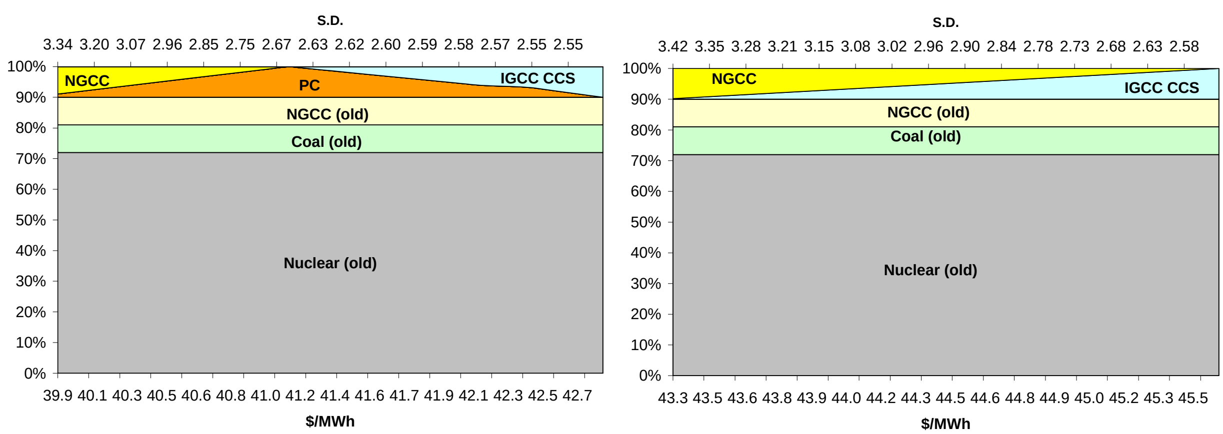
In the previous analysis, we assume all generation capacity in the portfolio is the new capacity. In this section, we relax this assumption by assuming that there is some existing capacity in the portfolio already. The planner's decision is to choose the choice of technology for the additional investment given that there is already existing capacity in the portfolio.

In the model, there are 3 existing baseload capacity including NGCC, PC and nuclear. EIA (2009c) estimates the average annual growth of generation capacity at 0.6% during the next 3 decades; over the 15 year period, the cumulative growth is about 10%. We assume that in the medium term (around 10 – 15 years) the system will need 10% of new capacity. The existing capacity will be 90% of the future portfolio.

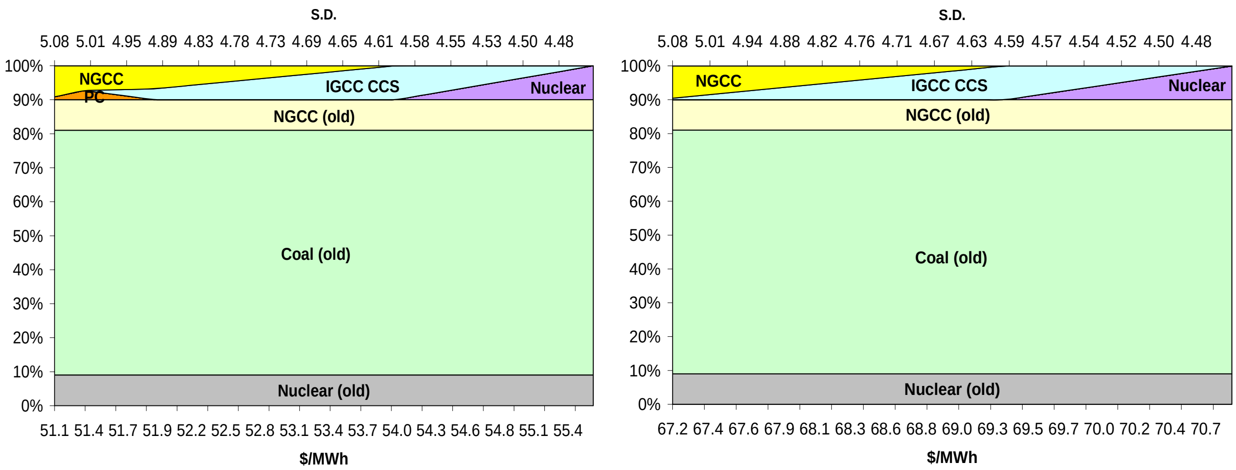
Although the existing capacity is kept constant in the optimization process, the result also depends on the existing mix. The correlation between the existing capacity and the new capacity affects the optimal portfolio mix since the overall portfolio variance calculation includes the weighted variance and covariance from the existing capacity. The weight and variance of the existing capacity are fixed but the weighted covariance with new capacity depends on the weight put on each new generation technology. The cost of existing technology used in the calculation is only the variable cost since the investment was already made. The cost series of the existing capacity are calculated from the variable cost of the existing technology (for nuclear, PC and NGCC) in the baseline model. We assume that variable cost of the existing capacity is 10% higher than the new capacity due to lower efficiency. We will show the result of the optimal portfolio with 4 different mixes of the existing capacity.



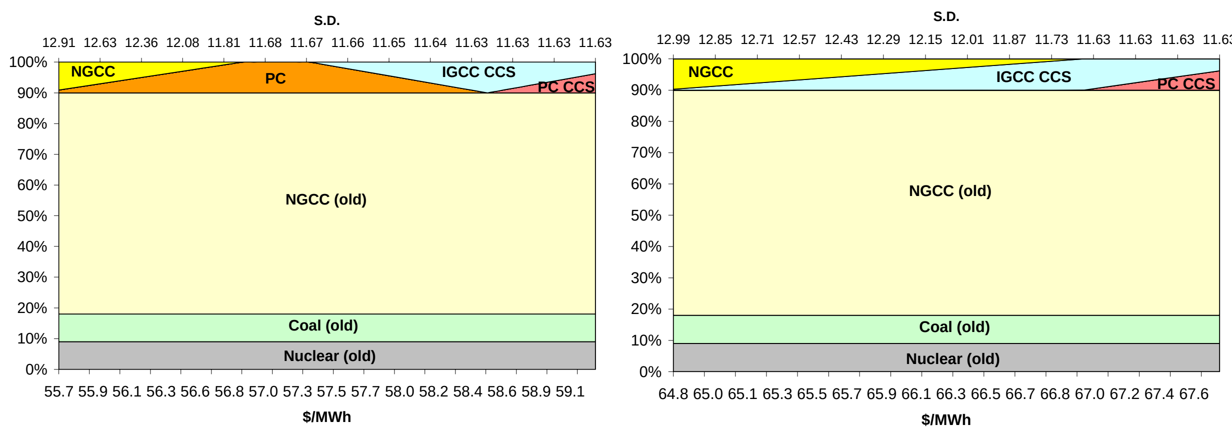
a) Existing capacity with 30% nuclear, 50% PC and 10% NGCC



b) Existing capacity with 80% nuclear, 10% PC and 10% NGCC



c) Existing capacity with 10% nuclear, 80% PC and 10% NGCC



d) Existing capacity with 10% nuclear, 10% PC and 80% NGCC

Figure 32: Portfolio mix with existing capacity with \$20 (left) and \$40/ton CO_2 (right)

The optimal portfolios of the new capacity shown in figure 32 are different due to existing technology mix that varies in each case. However, the pattern of the technology mix is similar to the baseline model. The portfolios with existing technology consisting of 30% nuclear, 50% PC and 20% NGCC (figure 32a) can approximately represent the baseload technology mix in the current US power system. Like the baseline model, NGCC is the dominant technology when portfolio cost is low and variation is high. There are some shares of PC when CO_2 price is low but they disappear when imposing higher CO_2 price. IGCC CCS plays key role when CO_2 price is high. Nuclear dominates high cost and low variation portfolios.

The optimal portfolios with existing capacity having nuclear 80%, PC and NGCC 10% (figure 32b) have no new nuclear capacity in the portfolio. Instead of having nuclear as the technology to reduce portfolio variation, the optimal portfolios have IGCC CCS to play this role. Since nuclear accounts for the majority of the existing portfolio, the weighted covariance of old nuclear with other technology is large especially with the new nuclear capacity. IGCC CCS has the lowest variation among the fossil fuel technology and has lower cost than nuclear. Thus, in order to optimize the portfolio IGCC CCS is selected for the high cost and low variation portfolios.

Similar effect of existing capacity can also be seen from the portfolio with existing 80% PC, 10% nuclear and NGCC (figure 32c). Normally at \$20/ton CO_2 price there are significant PC shares in the portfolio in other cases (also in the baseline model). Since there are significant PC shares in the portfolio, more IGCC CCS and NGCC are selected instead of PC to reduce overall variation. In addition, the mix of IGCC CCS and NGCC can also lower the cost of portfolio; cost of PC is in the range between IGCC CCS and IGCC.

Also, for the case with existing capacity 80% NGCC and 10% PC and nuclear (figure 32d), there is small share of PC CCS instead of nuclear to reduce portfolio variation. The mix of PC CCS and IGCC CCS play the role to reduce portfolio variation in this case where NGCC has large share in the existing capacity. The correlation between NGCC and PC CCS/IGCC CCS are lower than the correlation with nuclear. Including both technologies can give lower portfolio variation than having nuclear while cost of nuclear is in the range between these 2 technologies.

Examples of the optimal portfolio with various existing technology mixes indicate the importance of correlation/covariance of existing capacity and new technology. In general, the portfolio of the additional investment looks similar to the one in the baseline model. However, share of some technologies can be different depending on the mix of existing capacity.

Conclusion

In this study, we present the methodology to apply the mean variance portfolio theory to solve for the optimal power generation portfolio. Rather than choosing a winning technology, we propose power generation planning in term of the portfolio. The baseload generation is the focus of the study because it accounts for most of electricity generation and cost of the power system.

Different technologies play different roles in the portfolio (power system). The nuclear power plant has high capital cost and low variable cost compared with other technologies. The generation cost from nuclear is high but has low variation. In addition, power generation cost from nuclear is not affected by cost of CO_2 regulation. NGCC is the technology with low cost but high variation in cost since the majority of the generation cost of the natural gas plant is fuel cost. Variation in natural gas price significantly affects variation in NGCC generation cost.

We solved the efficient portfolio frontier in term of generation cost and variation in generation cost. Models with different CO_2 prices show significantly different technology mixes along the portfolio frontiers. Since one of the key factors that determines the optimal mix is the order of the cost. Increase in CO_2 price changes the relative cost or order among all technologies. The change in CO_2 pricelargely affects the high CO_2 emission technology such as PC and IGCC. When the CO_2 price increases, NGCC IGCC with CCS replace most of the PC share in the portfolio. The baseline portfolio mix shows that cost of CO_2 at $20/ton is not high enough to encourage investment in clean coal technology (IGCC CCS) which can reduce both cost and variation in cost and importantly CO_2 emission.

In addition, the model is analyzed under different fuel price. The first analysis separate the time period into “stable price” and “volatile price” periods. The results from these 2 periods are different due to differences in average fuel price and correlation structure. The second analysis assumes different scenarios of natural gas price. The result shows that if natural gas price significantly increases from the baseline value, portfolio planned using the baseline cost will impose additional cost in the future. The additional cost can be reduced if the planning is based on more risk aversion preference.

The model is also analyzed with different capital cost levels since most reported cost is in range. Changes in capital cost have more effects on technology with higher capital intensive. The result from model where all technologies capital cost change in the range ±30% shows different portfolio mix from the baseline model but significant change occurs to few technologies such as PC and IGCC CCS. Significant change occurs when the cost order of technology at the boundary of the efficient portfolio (for example NGCC and nuclear) changes.

We also show an example applying the Bayesian analysis to power generation portfolio. This approach has been used in finance so called "Black and Litterman" model. With this model, the investor can express his belief on one or more technology cost with the level of confidence in the belief. We show an example of different confidence levels that can lead to significantly different power generation portfolios.

Our model has limitation in accounting for all types of risk in the power system. Risks, for example power plant outage and other environmental regulations, are not included in the model. However, this study can give portfolio selection criteria and policy implication regarding to investment under uncertainty in CO_2 and fuel prices. Especially, it underlines an importance of planning in term of portfolio. If most of the new generation capacity is NGCC, as most utilities plan today, it could impose significant cost in the future when natural gas price increases from the scenario they plan.

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Appendix

A. Data and Assumptions

The key variable in this study is power generation cost ($/MWh). There are 2 major components of cost; fixed and variable cost. In our study, we assume that all generating capacity in the system is new capacity. To calculate the fixed cost per unit, we need the following data; the total plant cost[7], capacity factor, economic lifetime of the power plan and discount rate. The investment cost that we use is the total plant cost assuming that the power plant is built overnight and all costs are evaluated in the present value term. Total amount of power generated each year is calculated from the capacity factor. Using the annual fixed cost and output, we can find the fixed cost per MWh. The detail on the sources of data is presented later in this section.

To calculate the variable cost, we use the data on fuel price, O&M cost, heat rate and CO_2 emission rate (per MWh). The fuel cost for the fossil fuel plant is calculated from the fuel cost ($/Btu) and heat rate[8] (Btu/kWh). For the nuclear plant, the calculation for fuel cost is different from the fossil fuel power plant. We use the approach in "The Economics of the Nuclear Fuel Cycle", Nuclear Energy Agency (1994) and the nuclear fuel cost calculator from the WISE Uranium project (http://www.wise-uranium.org/index.html). This requires the data on uranium, conversion, enrichment and fabrication prices. In addition, the CO_2 price is the part of the variable cost. Different types of fossil fuel plant emit different amount of CO_2 per MWh. Thus, they have different cost of CO_2 depending on their emission rate. The variable cost per MWh is the sum of fuel, O&M and CO_2 price (for fossil fuel plant). Mean, correlation and the covariance matrix are calculated from the series of generation cost.

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[7] DOE (1999) defines "the total plant cost" as the capital cost including all construction related costs such as equipments, material, labor and contingencies.

[8] According to the definition from Energy Information Administration (EIA), "heat rate is a measure of generating station thermal efficiency commonly stated as Btu per kilowatt hour" (EIA, http://www.eia.doe.gov/glossary/glossary_h.htm).

	Total plant cost [a] ($/kW)	Heat rate [b] (Btu/kWh)	Capacity factor (%)	CO_2 emission [d] (ton/MWh)	Economic life (years)
Nuclear	6,000[e]	NA [c]	90	-	40
PC	1900	9,000	80	1.00	40
PC CCS	3,150	12,500	80	0.10	40
IGCC	2,200	8,850	80	0.90	25
IGCC CCS	3,050	10,700	80	0.09	25
NGCC	550	7,000	80	0.45	25
NGCC CCS	1,300	8,600	80	0.045	25

Table A1: Assumptions on generation cost

Note:

a) The total plant cost is estimated based on many sources for example EPRI (2008), EIA (2008a), NETL (2007) and Synapse (2008). However, currently, investment cost is increasing and there is no consensus on the number especially for nuclear and IGCC plants. The cost used in this study is from the median value of the reported cost.

b) The heat rate data is estimated based on many sources such as EIA (2008b), EPRI (2008), NETL (2007) and IECM (Integrated Environmental Control Model).

c) The heat rate from the nuclear plant is calculated from the approach in "The Economics of the Nuclear Fuel Cycle", Nuclear Energy Agency (1994) and the nuclear fuel cost calculator from the WISE Uranium project (http://www.wise-uranium.org/index.html).

d) The CO_2 emission rate is estimated based on data from eGrid (2006) and EPRI (2008).

e) Nuclear total plant cost reported in Synapse (2008) ranges from $3,600-8,081/kW. Cost at $6,000/kW is selected for the study. It is around the median of the reported range. This cost is higher than other estimate such as EIA (2008b). However, the realized cost of the nuclear plant tends to be higher than the initial estimate. EIA (1994) showed that during 1966-1977 the realized overnight cost of nuclear power plants were 2-3.5 times of the initial estimate.

Fuel cost

The fossil fuel cost data is from EIA (2009a) "Cost of Fossil-Fuel Receipts at Electric Generating Plants". This is the monthly data in $/MBtu unit.

Uranium: Monthly uranium price data is from the Cameco Corp. (http://www.cameco.com/marketing/uranium_prices_and_spot_price/longterm_complete_history/).

O&M cost

The O&M cost data of the existing technology is from EIA (2009b), "Average Power Plant Operating Expenses for Major U.S. Investor-Owned Electric Utilities". The data is from 1995 – 2009. The data from 1990-1994 is estimated by using the average growth rate. The O&M cost for IGCC and IGCC CCS are estimated from EPRI (2008).

CO_2 price

The CO_2 regulation price in our study is the simulated data with a certain mean and variance. The CO_2 price is simulated from normal distribution with mean $20 and 40/ton with standard deviation 5. The study by Roques et al. (2007) simulated the CO_2 price at mean of ₤40/ton and standard deviation of 10.

B. Generation technology portfolio: All load types

The first step in analyzing portfolio for all load types is to categorize technology from load serving characteristic and derive power generation cost. Previous studies do not take into account the load curve and capacity factor of the plants serving different load portions. For example, a baseload plant has a higher capacity factor than the plants serving the intermediate load or peak load.

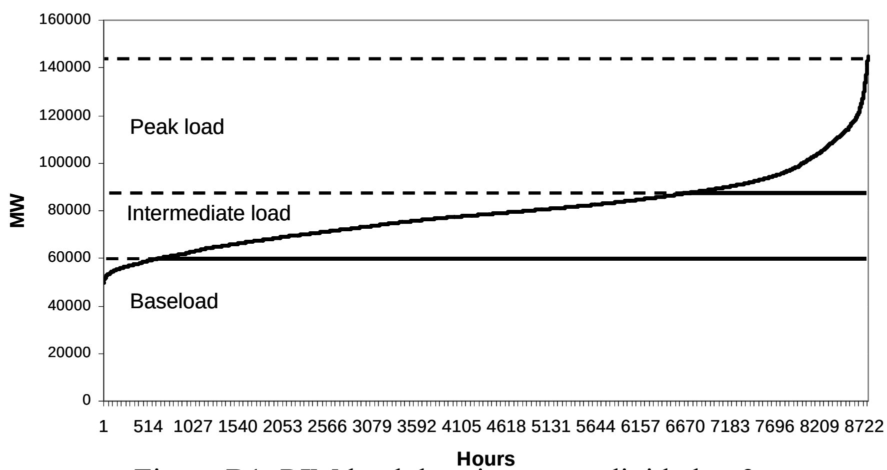


Figure B1: PJM load duration curve divided to 3 parts

From figure B1, the load duration curve is divided into 3 types of load; baseload, intermediate and peak load. The percentages by amount of power (MWh) of baseload, intermediate and peak load are about 78, 18 and 4% respectively. In addition, the shares in terms of capacity (MW) of the plants serving each load are 44, 18 and 38% for the base, intermediate and peak load respectively. In addition, we need to define the capacity factor for the technology serving each load. The baseload plant has a capacity factor around 80-90% while those of intermediate and peak load plants are 50-60% and 5-10% respectively. The capacity factor is important for the calculation of the fixed cost per MWh.

To solve the portfolio optimization problem, we set the “load weight” in term of energy (MWh) for each load type. For example, the load weight for the base, intermediate and peak load are 78, 18, and 4% respectively. In each load category, there is a mix of fuel-technology plants serving the load. While each plant has some flexibility, we assume that each plant can only serve the load it was designed for. Nuclear and coal plants serve baseload. (Some old coal plants are also cycled for serving intermediate load.) A natural gas combined cycle (NGCC) serves base and intermediate load. A simple gas turbine (GT) and diesel plants which can be ramped up and down quickly serve peak demand.

Power generation investment has a lumpy nature that may create a discontinuity in portfolio analysis. In this study, power generation capacity is assumed to be perfectly divisible. The planner solves the optimal risk-cost portfolio from the following quadratic programming problem. Additional constraints are imposed on the weight of each load type. In addition, all weights are greater than or equal to zero (similar to a no short sale constraint in the conventional mean-variance portfolio model).

$$\text{Min } \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N} w_i w_j \sigma_{ij}$$

$$\text{Subject to: } \sum_{i=1}^{N} w_i = 1 \quad \text{or } W_B + W_I + W_P = 1$$

$$\sum_{i=1}^{N} w_i c_i = \mu$$

$$\sum_{k}^{n_b} w_{B,k} = W_B$$

$$\sum_{k}^{n_i} w_{I,k} = W_I$$

$$\sum_{k}^{n_p} w_{P,k} = W_P$$

$$w_i \geq 0 \quad \text{for all } I = 1,\ldots,N$$

w_i is the portfolio weight of technology *i* (N technologies in total). μ is a specific value of portfolio cost. σ_{ij} is the covariance of technology *i* and *j*. $N = n_B + n_I + n_P$ where n_B, n_I and n_P are the number of technology serving base, intermediate and peak load respectively. W_B, W_I and W_P are weights in term of energy (MWh) of base, intermediate and peak load respectively.

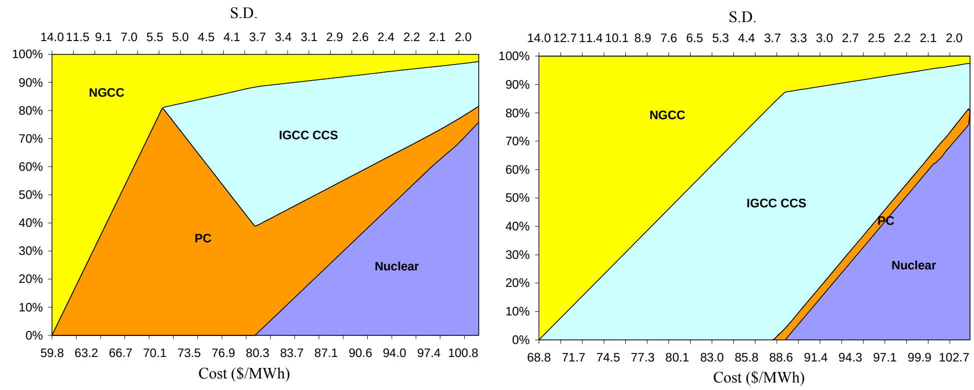
C. Analysis of nuclear plant shutdown

Nuclear plants experienced extensive shutdowns for safety or inspection in the decade of 1970s, since the technology and safety measures were not fully developed. However, we expect that the future nuclear power plant will have less evidence of shutdown for safety because the technology is more developed and improved. In this analysis, we formulate the optimal portfolio under the situation that some capacity of the nuclear power plant is shut down for some periods. The shutdown is not permanent and for maintenance or regulatory inspection.

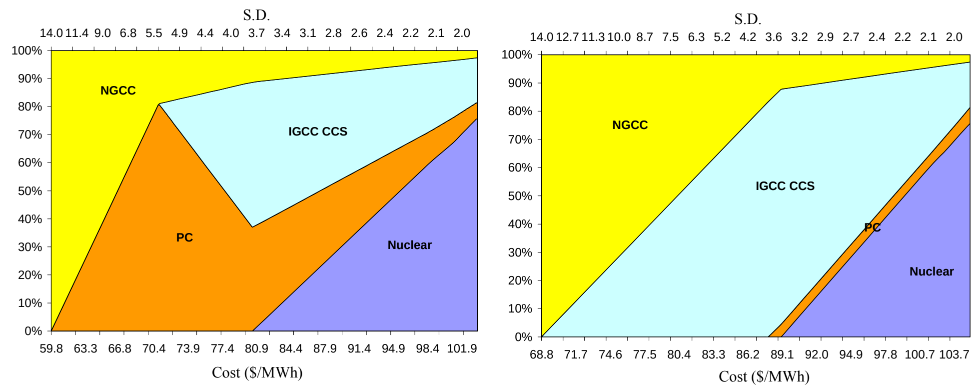
Prior to the decision on the portfolio mix, the planner forms an expectation about the possibility of the shutdown by a certain period of time. We assume that the shutdown affects the overall capacity of the plant. When the plant is shut down, its overall capacity factor decreases. Decrease in capacity factor depends on the length of shutdown; the long period of shutdown leads to low capacity factor. For the nuclear plant that is shut down, the maintenance cost is assumed to be higher than the normal plant. In addition, the variation of the maintenance cost of the shutdown plant is also higher.

In this analysis, we test few cases of nuclear plant shutdown by varying the probability and loss of capacity factor. The probabilities of shutdown are set at 10 and 20% and the loss of capacity is set at 10 and 20%. Note that the baseline assumption sets capacity factor of the nuclear plant at 90%. At 10% probability of shutdown, the expected generation costs from nuclear are \$108.3 and \$109.6/MWh for capacity factor loss 10 and 20% respectively. Also at 20% probability of shutdown, the expected generation costs from nuclear are \$109.7 and \$112.6/MWh for capacity factor loss 10 and 20% respectively. In addition, for all cases the variation of the nuclear plant cost increases due to the change in maintenance cost but not in a high magnitude.

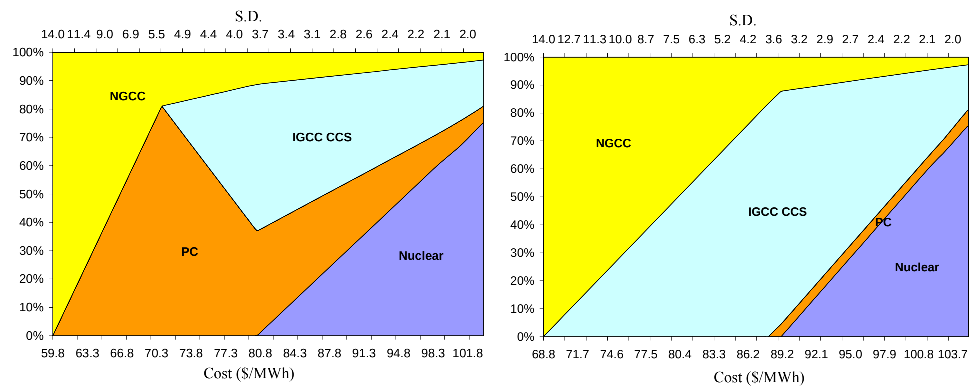
The portfolio mix of each scenario is shown in figure C1. Since the shutdown increases cost of the nuclear plant, it is still the highest cost-lowest variation technology; the variation in cost does not increase significantly. The optimal portfolios from all scenarios look similar to the baseline portfolio.



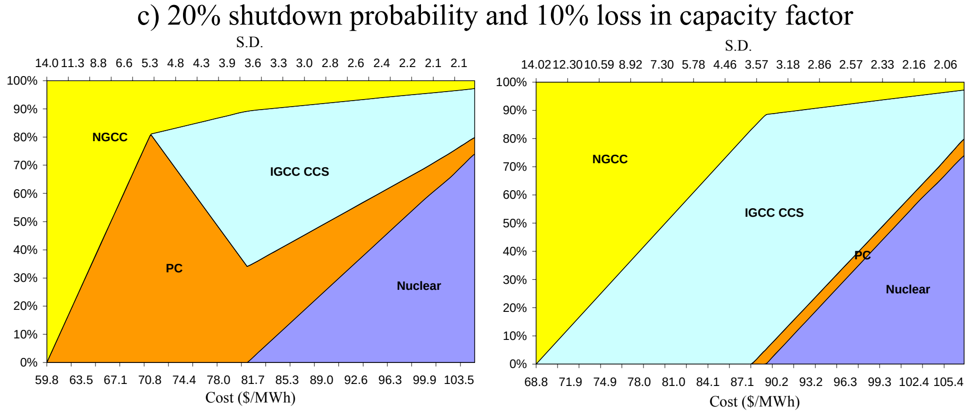
a) 10% shutdown probability and 10% loss in capacity factor



b) 10% shutdown probability and 20% loss in capacity factor



c) 20% shutdown probability and 10% loss in capacity factor



d) 20% shutdown probability and 20% loss in capacity factor

Figure C1: Portfolio mix of all scenario at \$20 (left) and \$40/ton CO_2 (right)

The shapes of portfolio mix along the frontier of all scenarios are similar. Figure C2 shows the plot of the share of nuclear along the efficient frontier by normalizing the frontier on the horizontal axis. At each level of CO_2 price, the line graph shows that there is no significant difference in the share of nuclear along the efficient frontier.

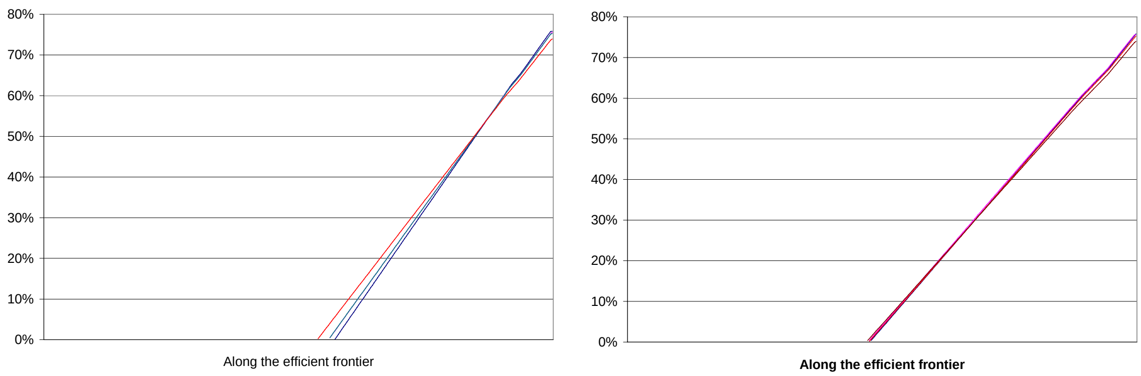


Figure B2: Share of nuclear in all scenarios at \$20 (left) and \$40/ton CO_2 (right)