A load factor based mean-variance analysis for fuel diversification

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Fuel diversification implies the selection of a mix of generation technologies for long-term electricity generation. The goal is to strike a good balance between reduced costs and reduced risk. The method of analysis that has been advocated and adopted for such studies is the mean-variance portfolio analysis pioneered by Markowitz (1959). However the standard mean-variance methodology, does not account for the ability of various fuels/technologies to adapt to varying loads. Such analysis often provides results that are easily dismissed by regulators and practitioners as unacceptable, since load cycles play critical roles in fuel selection. To account for such issues and still retain the convenience and elegance of the mean-variance approach, we propose a variant of the mean-variance analysis using the decomposition of the load into various types and utilizing the load factors of each load type. We also present examples using real data for the state of Indiana and demonstrate the ability of the model in providing useful insights.

1. Introduction

Fuel diversification implies the selection of a mix of electric generation technologies in a fashion that strikes a good balance between reduced cost and reduced risk. A long-term perspective as well as a short-term perspective can be taken on the fuel diversification problem. In a short-term perspective, the decision maker is limited to selecting power sources from existing alternatives. The construction of new generation plants and the associated fixed costs are justifiably ignored. The short-term problem translates in most instances to a scheduling problem. On the other hand the long-term perspective on fuel diversity seeks insights that can help decision-making involved in the selection of new power plants. The long-term problem can be thought of as a resource-planning problem. Our focus is on the long-term perspective.

Long-term fuel diversity has recently gained the attention of state regulators and federal policy makers. It has been argued (see Costello (2005)) that fuel diversity has the potential to advance several socially desirable objectives such as (a) lower long-term prices (b) lower price risk (c) less dependency on foreign sources of energy (d) higher power reliability and (e) a cleaner environment. Organizations like the National Association of Regulatory Utility Commissioners (NARUC) and the National Regulatory Research Institute (NRRI) have become strong advocates of fuel diversification. At the NRRI/NARUC Commissioners only summit in January 2005, it has been noted in Costello (2005) that commissioners identified fuel diversity in electric generation as one of the top four issues in the next 12 to 18 months. Following this, several state regulatory bodies have initiated a formal study of long-term fuel diversification in their states.

However, it has also been recognized by commissions that the major problem in conducting a study of long-term fuel diversity is the absence of a formal, balanced and well-accepted approach. Given the long-term nature of the problem, portfolio optimization techniques developed in finance become a natural tool. A popular briefing paper from NRRI advocates the use of mean-variance based portfolio optimization for the computation of a good balance between lower expected price and lower risk. Several state regulators, including the Indiana Utility Regulatory

Commission, have attempted to pursue analysis on these lines.

The mean-variance portfolio optimization approach considers variance as the measure of risk. One first begins with an estimate of the means, variances and covariances of per unit generation costs incurred in using various technology/fuel combinations. The fixed costs and deterministic operating expenses of setting up the generation unit contribute to the expected cost. The fuel costs and operating costs that are not deterministic affect the mean costs as well as the variances. Then an optimization problem that seeks a combination of technology/fuel types is set up to minimize total variance for a given expected cost. The solution of this optimization problem can be traced as a frontier in a mean-variance plot, for various values of expected cost. A rational choice of fuel mix would then be the solution corresponding to any point on this frontier, called the efficient frontier. The exact point depends on the decision maker's risk preference.

Estimation of means, variances and covariances can be done using historical prices and investment data. A mean-variance analysis is quite straightforward from there. In such analysis, the impossibility of enumerating and determining probabilities of major events like disruptive events or technological breakthroughs, lead to scenario analysis. Under scenario analysis, one first plots the mean-variance frontier using currently available historical data. For each possible major event that the decision maker is interested in, another relevant mean variance frontier is constructed to provide a subjective comparison.

Though the elegance and intuitive clarity of the mean-variance analysis is appealing, results obtained by such an analysis are often dismissed by regulators and practitioners as unacceptable. The unacceptability is due to a multitude of mis-alignments the results have with their intuition and experience. Either the intuition and experience that they have acquired are inaccurate or the model fails to capture a significant aspect of the underlying problem. We argue that it is the latter and differences caused arise due to the failure to account for the natural variation of the load.

For example, a very often pointed issue on the results of standard portfolio analysis based fuel diversification studies is the very low investment in natural gas based generation. Natural gas based generation infrastructure costs are low, but the fuel costs are considerably higher than other options such as coal based technologies. Hence looking at the rationale driving the mean-variance analysis, it is understandable that long-term reliance on natural gas is kept low. However, this would be a bad decision. Demand is seldom constant and usually has a very short period of peak demand. Investing in a large infrastructure that can serve this peak demand would be a waste of resources due to the low utilization. Natural gas would be a wonderful candidate for satisfying such high demand since the construction costs are low and variable fuel costs are incurred only during the short peak time. The ignorance of such fluctuations in demand decreases the reliance on natural gas, which is not necessarily a good thing.

Section 2 briefly discusses relevant literature. In section 3 we develop a variant of the mean-variance approach that removes this deficiency while retaining the elegance and simplicity of the mean-variance approach. Section 4 describes the data that we use for our fuel diversification studies in Indiana. Finally section 5 presents exhaustive analysis of long-term fuel diversity for the state of Indiana, using our model.

2. Related Literature

Several papers and reports use standard mean-variance analysis for identifying optimal fuel mixes for electric generation. We discuss only a representative set in this section.

A popular briefing paper (Costello (2005)) from the National Regulatory Research Institute describes recent trends in the regulatory circles on long-term fuel diversification. Portfolio analysis is strongly advocated as the analysis methodology for such studies. An overview of the mean-variance analysis is also provided in the context of electric generation.

Humphreys and McClain (1998) introduce a portfolio method for choosing efficient energy mixes given a national goal is to minimize the risk to domestic economy from energy price shocks, using time-varying variances and covariances estimated with generalized autoregressive conditional heteroskedastic (GARCH) models. The results suggest that electric utility industry is operating close to the minimum variance position, but overall energy consumption in the U.S. is far from efficient.

Awerbuch and Berger (2003) introduce the mean-variance portfolio theory as a means to evaluate the development of both current and projected efficient European Union generating mixes to enhance energy security objectives. The analysis reflects the risk of the relevant generating cost attributes: fuel, operation and maintenance (O&M) and construction period costs and illustrates the portfolio effects of different generating mixes. It also introduces preliminary findings on the effects of including renewable energy sources in the typical mixes of conventional fuel types.

A study by DeLaquil et al. (2005) applies the mean-variance portfolio method similar to what presented by Awerbuch and Berger (2003). The method is used for an analysis of electricity generation planning for the Commonwealth of Virginia. The analysis examines renewable energy portfolios that could be included in Renewable Portfolio Standard (RPS). The results show the optimized RPS generating mixes significantly reduce electricity cost-risk while slightly increasing cost.

Krey and Zweifel (2006) use the seemingly unrelated regression estimation (SURE) method to obtain time-invariant covariance matrices as input to find efficient generating mixes for Switzerland and the United States. Results suggest that the maximum expected return portfolio for Switzerland would contain more reliance on nuclear and solar power and less reliance on hydropower. By contrast, the minimum variance mixes would contain more nuclear and hydropower. For the U.S., the maximum expected return would contain more coal and wind, and the minimum variance mixes will rely on coal, nuclear, oil and wind together. Results indicate that natural gas does not play any role in the determination of generating mixes in the U.S.

Bar-Lev and Katz (1976) apply the mean-variance approach to the fossil fuel procurement problem to determine how efficiently the U.S. utility industry uses of scarce resources. To assure long-range supply of fossil fuel, electric utility companies sign long-term contracts with price adjustment clauses of 10 to 20 years covering 70-80% of their expected needs, and buy the rest on spot. The authors generate efficient frontiers of fuel mixes, which minimize the expected increase of fuel cost for a given risk. The results show that while utilities are efficiently diversified, their portfolios are characterized by both high return and high risk. The authors suggest that regulation causes the electric utilities to behave in a risky manner.

Yu (2003) presents a short-term market risk model based on mean-variance analysis. The author includes practical constraints such as transaction costs and wheeling contracting, resulting in a mixed integer-programming model. A case study illustrates the successful application of the method and gives an interesting observation; the Markowitz mean-variance efficient frontier is neither smooth nor concave mainly due to the effect of constraints such as the minimum production levels and fixed costs.

3. Model Formulation

We first provide a brief overview of load duration curves, load factors and capacity factors before describing our model.

3.1 Load duration curves, Load factors and Capacity factors.

A load-duration curve illustrates the distribution of demand for power. Power requirement is plotted against time, indicating the amount of power that is needed for the amount of time plotted on the horizontal axis. Figure 1, shows a typical load duration curve. The curve is usually divided into three regions corresponding to peak periods of very high demand for short amounts of times, cycling periods with moderate demands for longer periods and base periods of low demand that always exists. Though it is very common to consider three types of periods, peak, cycle and base, any number of period types can be considered. It is a common practice to approximate the load duration curve using a non-increasing step function. In this case (Figure 2) the different load regions become rectangles.

A plant's utilization is measured by the capacity factor whereas the entire systems utilization is measured by the load factor. Capacity Factor (CF) is defined as the ratio of the electrical energy produced by a generating unit for the period of time to the electrical energy that could have been produced at full power operation. On the other hand the Load Factor (LF) is defined as the ratio of the energy produced by the entire generating system (with one or more generating units) in a certain period and the theoretical maximum of each load type that it could have produced.

$$LF = \frac{energy\, produced}{peakload * time\, period}, \quad 0 \le LF \le 1$$

$$CF = \frac{energy\;\; produced}{capacity * time\;\; period}, \quad 0 \le CF \le 1$$

For example, consider three different load types (peak, cycle and base) and two generation units (generator 1 and 2) each with capacity 150 MW. Say the load duration curve is given as in Figure 1 and its approximation as in Figure 2. The three load factors are LF_1=1.0 for base, LF_2=0.9 for cycling load and LF_3=0.25 for peaking load. If generator 1 is always used before generator 2, then the capacity factors are CF_1=0.97 for generator 1 and CF_2=0.47 for generator 2.

3.2 Model formulation

Let the number of different technologies available for electricity generation be *I*. Each technology has a particular fuel source. It is allowed that two different technologies can have the same fuel source. We segment the load duration curve into *L* load types with load factors given by $LF_1 > LF_2 > \cdots > LF_L$. For each technology, the existing capacity is taken as U_i expressed in MWh for *i*=1,…,*I*. The variable cost of fuel for technology *i*, is V_i and is expressed in \$/MWh. The mean and variance of V_i is estimated from available data and is taken as (μ_i, σ_i^2). Covariances obviously exist between different fuels and σ_{ij} will denote the covariance between fuel *i* and fuel *j*. The variable operations and maintenance costs for technology *i* are denoted by OM_i.

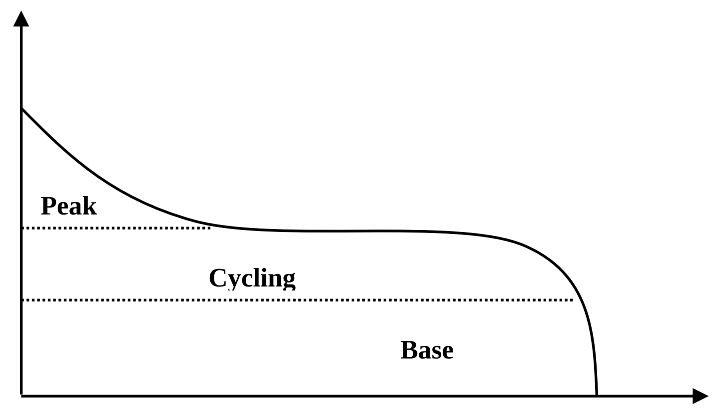

Figure 1. Load duration curves to demonstrate load factor calculations

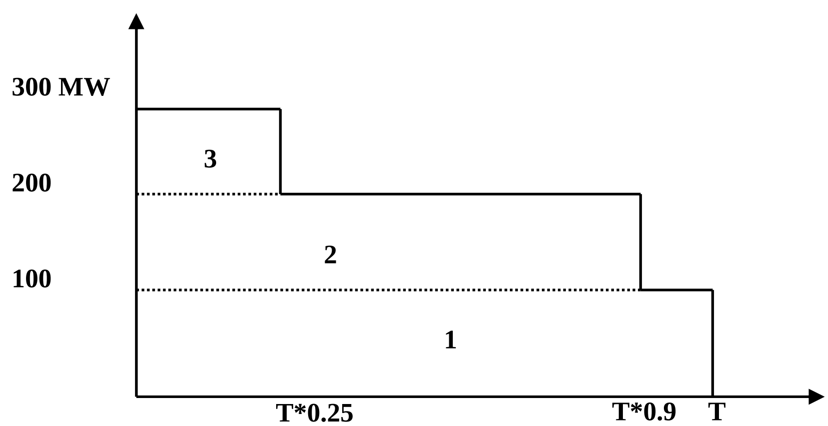

Figure 2. Load duration curve, linearly

For the sake of long-term planning, apart from the question of how much energy existing technologies should produce, we are also interested in guidance on the construction of new plants. To this extent, we differentiate power production from existing and new plants. We let F_i be the total fixed costs associated with technology *i* expressed in $/MWh. Demand for power is divided into the demand for different load types D_l expressed in MWh.

Let us denote the energy (MWh) produced using existing plants based on technology *i* for meeting demand type *l* by ye_{il}. Correspondingly the energy from new plants will be denoted by yn_{il}. Our objective is to choose yn_{il} and ye_{il} so as to strike a good balance between low expected costs and low variance of cost. For a risk aversion parameter $\beta \in [0,\infty)$, the problem at hand can then be stated as follows.

$$Minimize \quad \left[\sum_{i=1}^{I}\sum_{l=1}^{L}\left(\frac{Fn_i}{LF_{il}} yn_{il} + (OM_i + V_i)(ye_{il} + yn_{il})\right)\right] + \beta * \left[\sum_{i=1}^{I}\sum_{j=1}^{I}\sum_{l=1}^{L}\Big(\sigma_{ij}(ye_{il} + yn_{il})(ye_{jl} + yn_{jl})\Big)\right]$$

with the following constraints,

Existing capacity constraint,

$$\sum_{l \in L} \frac{ye_{il}}{LF_{il}} \quad \leq \quad U_i \quad , \quad for\ i = 1,\ldots,I \qquad (1)$$

Demand satisfaction constraint,

$$\sum_{i \in I} ye_{il} + \sum_{i \in I} yn_{il} \quad = \quad D_l \quad , \quad for\ l = 1,\ldots,L \qquad (2)$$

Non-negativity constraint,

$$\begin{aligned} ye_{il} &\geq 0 \quad , \quad for\ i = 1,\ldots,I; l = 1,\ldots,L \\ yn_{il} &\geq 0 \quad , \quad for\ i = 1,\ldots,I; l = 1,\ldots,L \end{aligned} \qquad (3)$$

4. Parameter Estimations

4.1 Cost data

As determined by the Energy Information Administration (EIA), average fuel costs for generating units powered by coal, residual fuel[1] and natural gas are shown in Table 1. Fuel cost for nuclear power, according to the World Nuclear Association, is shown in Table 2. Table 2 also shows annual fixed costs, F_i, and variable O&M costs, OM_i. Fixed O&M costs have been converted to dollars per unit energy, $/GWh, by dividing by the number of hours in a year, 8760. Table 2 shows cost estimates for fixed and variable O&M, as well as fuel costs.

Table 1. Average costs including taxes of fossil-fuel receipts at electric generating plants in 2005

Unit	Coal	Residual Fuel	Natural Gas
Nominal[2] dollars per million Btu	1.54	7.12	8.20
Nominal dollars per MWh[3]	15.77114	72.91592	83.9762

Source: Table 9.10. Cost of Fossil-Fuel Receipts at Electric Generating Plants, *August 2006 Monthly Energy Review*, EIA.

4.2 Fuel cost covariance estimates

Historical Indiana electric power sector fuel prices (1970 through 2002) for coal, oil and natural gas in dollars per million Btu and approximate heat rates in Btu per kWh were used to calculate approximate fuel prices in dollars per MWh. Since Indiana does not have any commercial

[1] Residual fuel costs are used to represent fuel oil costs.
[2] Unadjusted for inflation
[3] Converted by using 10241×10^{-3} million Btu per MWh, approximate heat rate for fossil fuel plants for electricity, Annual Energy Review 2005, EIA.

nuclear facilities geographically located in the state, but does have a nuclear station in Michigan (D. C. Cook) that primarily serves Indiana load, Michigan nuclear fuel prices were used. The resulting price series were used for estimating fuel price covariance for the electric sector, shown in Table 3.

Table 2. Costs for electricity generation technologies

Technology	Fixed Costs[4] F_i		Variable O&M[5] OM_i		Fuel Cost V_i	
	million $/MW	million $/GWh	$/MWh	million $/GWh	$/MWh	million $/GWh
Coal	1.249	0.14258	4.18	0.00418	15.77	0.01577
Oil	0.584	0.06667	1.88	0.00188	72.92	0.07292
Natural Gas	0.385	0.04395	2.89	0.00289	83.98	0.08398
Nuclear	2.014	0.22991	12.7[6]	0.01270	5.20[7]	0.00520

Table 3. Fuel price covariance estimates for the electric sector, Indiana (prices in million$/GWh)

	Coal	Oil	Gas	Nuclear
Coal	**0.00001877226**	0.00006815061	0.00004736821	0.00000653022
Oil	0.00006815061	**0.00037299100**	0.00021565344	0.00002063233
Gas	0.00004736821	0.00021565344	**0.00018436456**	0.00001697626
Nuclear	0.00000653022	0.00002063233	0.00001697626	**0.00000363517**

The fuel price variance for nuclear generation is very small, reflecting the historical stability of the price of nuclear fuel. This does not adequately reflect the risks associated with nuclear generation, particularly the risk associated with the need for large capital expenditures when equipment must be repaired or replaced. In order to capture this variance, an additional variance term was derived based on the actual maintenance expenditures of the D. C. Cook nuclear plant. Unlike fuel price variance, the variance associated with maintenance expenses should not be correlated between different units using the same fuel. That is, while an increase in the price of natural gas will have a similar effect on all natural gas fired units, the need to replace a steam generator at one nuclear unit is unlikely to have a corresponding cost risk at another nuclear unit. Thus, the covariance matrix has been expanded by an additional row and column, with nuclear being separated into existing nuclear (the D. C. Cook station) and new (presently non-existing) nuclear. The diagonal variance terms for both existing and new nuclear facilities are identical (0.000381804) and based on a combination of fuel price variance and maintenance cost variance. The covariance terms for both existing and new nuclear with the other fuels are the same as those shown in Table 3. The covariance term between existing nuclear and new nuclear is simply the nuclear fuel price variance (0.00000363517) in Table 3.

[4] Table 38. Cost and Performance Characteristics of New Central Station Electricity Generating Technologies, Assumptions to the Annual Energy Outlook 2006, Energy Information Administration.

[5] Table 38. Cost and Performance Characteristics of New Central Station Electricity Generating Technologies, Assumptions to the Annual Energy Outlook 2006, Energy Information Administration. Variable O&M values for scrubbed coal new, conventional gas/oil comb cycle, advanced combustion turbine, and advanced nuclear were chosen to represent those for coal, oil, natural gas, and nuclear technologies respectively.

[6] U.S. nuclear industry non-fuel O&M costs, Nuclear Energy Institute, 2005.

[7] Table 1. Average US nuclear production costs, 1981-2003, “The New Economics of Nuclear Power,” World Nuclear Association, 2006.

4.3 Existing capacity

Generating capacity levels for existing units in Indiana were combined for each energy resource and are shown in Table 4. All existing generating capacity in the model is located in Indiana except for the D.C. Cook nuclear plant.

Table 4. Existing Generation Capacity for Indiana by Energy (Fuel) Sources[8]

Energy Source	Total Summer Capacity (MW)	Production Capacity (GWh)
Coal[9]	16005.4	140207.304
Oil	481.6	4218.816
Gas	4559.7	39942.972
Nuclear	1674.4	14667.744
Water[10]	63.68	559.4136
Total	22784.96	

Source: Existing Electric Generating Units in the United States, 2004, Form EIA-860 Database, Annual Electric Generator Report, EIA.

4.4 Electricity requirements

The model runs are performed using an estimated load for the year 2020. The estimated load was derived by increasing the actual hourly Indiana electricity demand in 2003 using expected growth rates developed for Indiana by the State Utility Forecasting Group. By analyzing the load duration curve for the historical demand, the load was then assigned to each of the three types mentioned previously. Table 5 shows the total energy requirements for each load type in the model year, 2020. The resulting load factors for each load type are shown in Table 6.

Table 5. Indiana Forecast Electricity Requirements by Load Type

	Forecast Requirements (GWh)			
Projected Year	Baseload	Cycling	Peaking	Total
2020	142953.4594	8311.1096	7185.0004	158450

Source: Rardin et al. (2005), Figure 3-1. Indiana Electricity Requirements in GWh (Historical, Current and Previous Forecasts), Indiana Electricity Projections: The 2005 Forecast Summary, State Utility Forecasting Group, Purdue University.

Table 6. Load Factors by Load Type

Load Year	Base	Cycling	Peak
2003	.9594	.4276	.0811

[8] Energy sources include Bituminous (BIT), Sub-bituminous (SUB), Natural Gas (NG), Nuclear (NUC), Distilled Fuel Oil (DFO), and Water (WAT).
[9] Coal represents both BIT and SUB generating units.
[10] For the time being, water resources are not considered in the model.

5. Results and Discussion

5.1 Model validation

This section shows the results of attempts to verify that the model behaves in a manner that is consistent and explainable. In order to accomplish this, the model was run under a number of scenarios where an individual parameter was changed. The model results were then compared to the base case (no parameter changes) to observe any changes to the results.

5.2 Base scenario

The results for the base scenario, with all fuel costs and variances as described previously, are shown in Figure 3. The plot shows the efficient frontier, with the cost on the vertical axis and the variance on the horizontal. Therefore, points to the right have a greater risk than points on the left. The value of beta indicates the importance of reducing risk: zero indicates that cost is minimized and risk is ignored, while infinity indicates that risk is minimized and cost is ignored. Thus, higher values of beta mean greater risk aversion, with a willingness to pay a higher cost. The production cost and standard deviation for selected values of beta are shown.

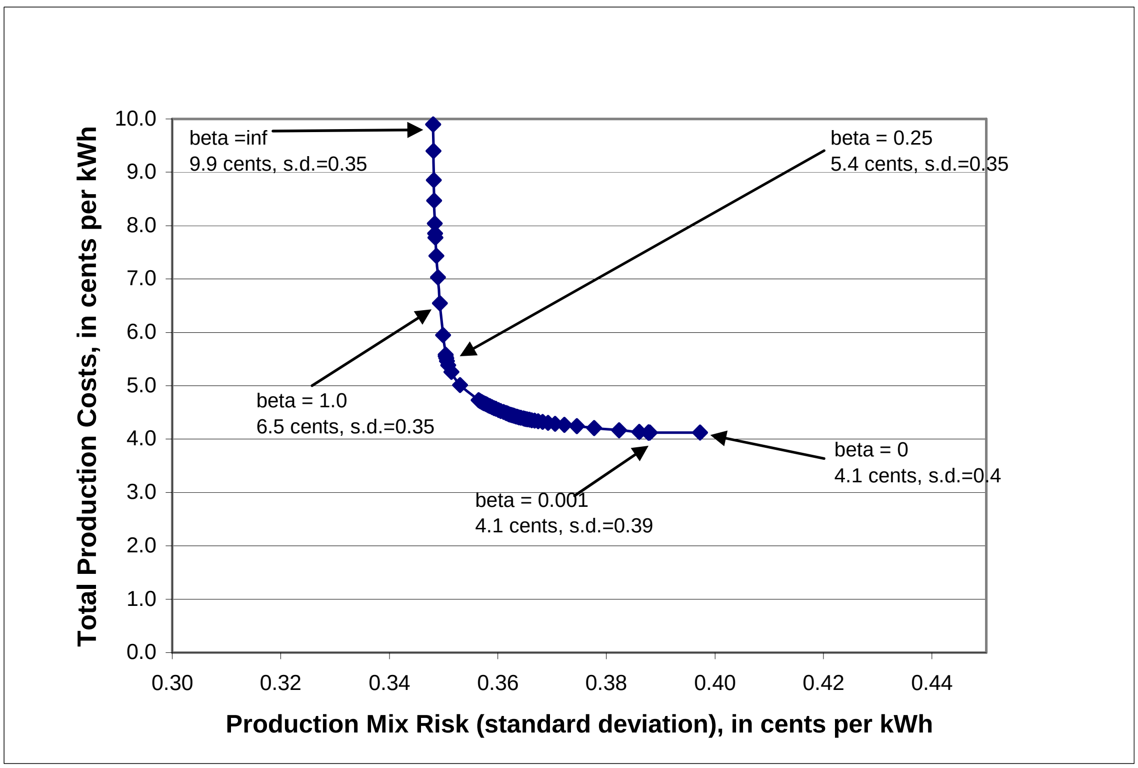

Figure 3. Base case cost-risk efficient frontier

For low levels of risk aversion (beta = 0), coal is the dominant source of energy (providing 83 percent), largely from existing units. The existing nuclear unit provides 9 percent of the energy, while natural gas and oil provide 7 percent and 1 percent, respectively. Some new natural gas-fired generation is added for peaking purposes. For an extreme level of risk aversion (beta = infinity), less coal (77 percent) and nuclear (8 percent) are used, while more energy is provided by natural gas (12 percent) and oil (4 percent). Furthermore, the nuclear generation is split between existing and new sources, in order to take advantage of the diversity between them.

5.3 Extreme variance scenario

In order to test the model behavior, a scenario was run with extremely high coal price variance (thirty times the value in the base scenario). The mean price of coal was not changed, nor were the prices and variances for other fuels. Figure 4 shows the efficient frontier with the same selected values of beta as were shown previously. For beta equal to zero (absolute cost minimization with no risk aversion), the production cost is the same (4.1 cents per kWh), while the standard deviation is dramatically higher (1.92 vs. 0.4). The sources of energy generation are exactly the same as in the base scenario. This makes intuitive sense, since the only difference between the scenarios is the variance of coal, which has no effect on the optimal mix for beta = 0. As beta increases even slightly, the risk declines rapidly and the cost increases dramatically. This is a result of the model using less of the high variance coal and toward higher cost alternatives. At the opposite end of the spectrum (beta = infinity), only 13 percent of energy is provided by coal. There is a substantial increase in the use of other sources: oil (19 percent), natural gas (40 percent) and nuclear (28 percent). Again, this result could be expected as the model looks to mitigate risk at any cost. Both the final cost (16.6 cents per kWh) and standard deviation (0.75) are higher than in the base scenario.

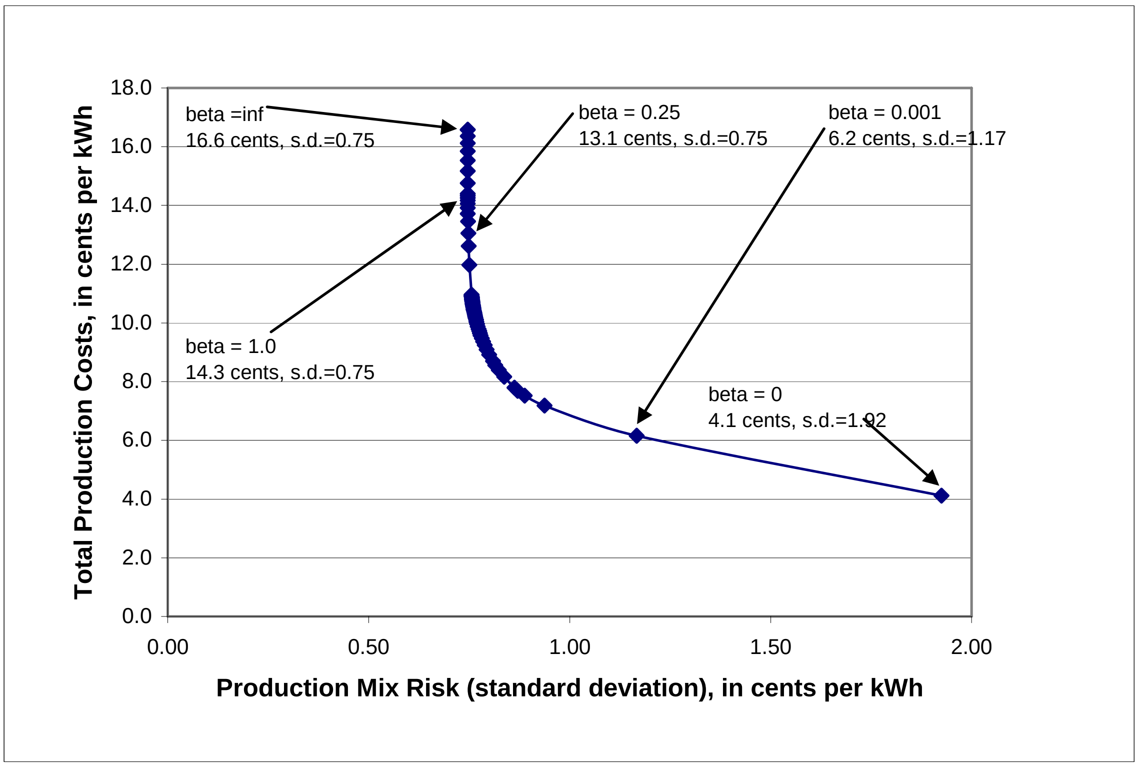

Figure 4. Extreme coal variance cost-risk efficient frontier

5.4 Extreme fuel cost scenario

An additional test of the model involves a scenario was run with extremely high coal prices. In this scenario, the mean coal price of coal was increased by a factor of ten, while the variance was not changed from the base scenario. The prices and variances for other fuels were the same as in the base scenario. Figure 5 shows the efficient frontier with the same selected values of beta as were shown previously. For beta equal to infinity, the standard deviation is the same as the base scenario (0.35), while the total cost is dramatically higher (21.2 vs. 9.9). The sources of energy generation are exactly the same as in the base scenario. Again, this makes intuitive sense, since the only difference between the scenarios is the price of coal, which has no effect on the optimal mix for beta = infinity (the objective is to minimize risk at any cost). For beta = 0, much less of the high cost coal is used (10 percent), with natural gas picking up much of the slack (79 percent).

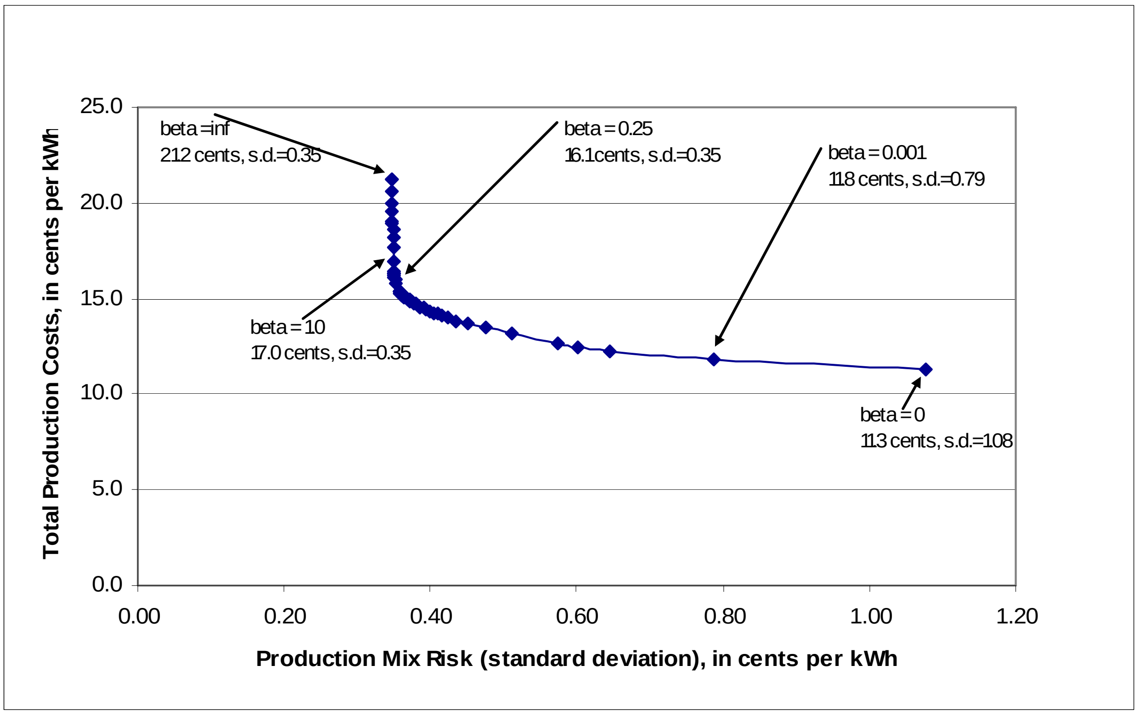

Figure 5. Extreme coal price cost-risk efficient frontier

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