



A Load Factor Based Mean-Variance Analysis for Fuel Diversification

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Outline

- Introduction
- Model formulation
- Parameter estimates
- Results and discussion
- Future work



Introduction

- Fuel diversification: the selection of a mix of electric generation technologies in a way that strikes a good balance between reduced cost and reduced risk.
- Short-term perspective: scheduling problem
- Long-term perspective: resource planning



Benefits of Fuel Diversity

See Costello (2005)

- Lower long-term prices and price risk
- Less dependency on foreign sources of energy
- Higher power reliability and a cleaner environment

Impact: may cause different strategic decisions to be made

- When reviewing a generation resource plan for a **utility** in isolation or when compared to what the policy decision may be when considering the **statewide** or a **regional** perspective



Fuel Diversity Advocates

- National Association of Regulatory Utility Commissioners (NARUC)
- National Regulatory Research Institute (NRRI)
- Commissioners identified fuel diversity in electric generation as one of the top issues (see Costello (2005))



Mean-variance for Fuel Diversification

- Risk: high fuel price and variability; variance as the measure of risk
- Probable cause: reliance on inadequate mix of fuel sources or generation technologies
- Impact of exposure: future high fuel and externalities costs resulting in increase and variability of unit cost of electricity



Approach for Fuel Diversification

- Estimate of the means, variances and covariances of per unit generation costs using various technologies/fuels from historical data
- Deterministic fixed and operating costs versus non-deterministic fuel and operating costs
- Optimization traces solutions (mixes) as frontier in mean-variance plot; exact points correspond to risk preferences



Issue with Direct Mean- variance Analysis

- Results obtained often dismissed by practitioners
- Important aspect of the underlying problem: investment in generation assets pays off by utilizations which depend on variation of the load
- Natural gas generation infrastructure costs are low; fuel costs considerably high...



Related Literature

- Costello (2005)
- Markowitz (1959)
- Humphreys and McClain (1998)
- Awerbuch and Berger (2003)
- DeLaquil et al. (2005)
- Krey and Zweifel (2006)
- Bar-Lev and Katz (1976)
- Yu (2003)

still counting...



Model Formulation

- Load duration curve illustrates the distribution of demand for electricity, power requirement plotted against time
- Capacity factor (CF) measures a plant utilization
- Load factor (LF) measures the entire system utilization



Load Factor Based Model

$$\text{Load Factor} = \frac{\text{energy produced}}{\text{peak load} * \text{time period}}$$

- Low LF means large variations occur in the load, whereas high LF for small
- LF unity implies constant load curve through the period
- Reflects how generation plants are dispatched to cover load duration
- Generating system can have one or more units
- Used as factor to **scale** fixed costs for the system; thus, more realistic consideration of investment payoffs



Power Production Mix

- A portfolio is a mix of power generation plants, e.g., a mix of production by fuel sources or plant technologies to provide the best means of hedging future risks, assuming risk reduction is achieved by diversification of production mix.



Optimization Model

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

(Fixed costs terms)

(Variable costs terms)

(Covariance terms)

Assumptions:

- Existing generation capacity has sunk costs
- Future demand by load types are known
- No upper bounds for building new generation capacity

β = cost reduction versus variance tradeoff

- How much decrease in \$ costs the investor would be willing to trade for one unit increase of risk



Optimization Model

$$\sum_{i=1,\dots,I} ye_{il} + \sum_{i=1,\dots,I} yn_{il} = D_l, \quad \text{for } l=1,\dots,L$$

$$\sum_{l=1,\dots,L} \frac{ye_{il}}{LF_{il}} \leq U_i, \quad \text{for } i=1,\dots,I$$

$$ye_{il} \geq 0, \quad \text{for } i=1,\dots,I; l=1,\dots,L$$

$$yn_{il} \geq 0, \quad \text{for } i=1,\dots,I; l=1,\dots,L$$

Constraints

- Demand by load types must be met by existing and/or new generation capacity
- Existing capacity by fuel types/technologies) each has upper bound
- Non negativity



Data

- Cost attributes: expected investment costs, fuel costs, variable O&M costs, --expressed in \$/Watt*hour--
- Historical hourly load and future projection factor
- Load by types, predetermined by specific cutoffs
- Covariance between fuel costs is source of variability, estimated from historical data
- Existing capacity in Indiana by fuel sources



Variance as Measure of Risk

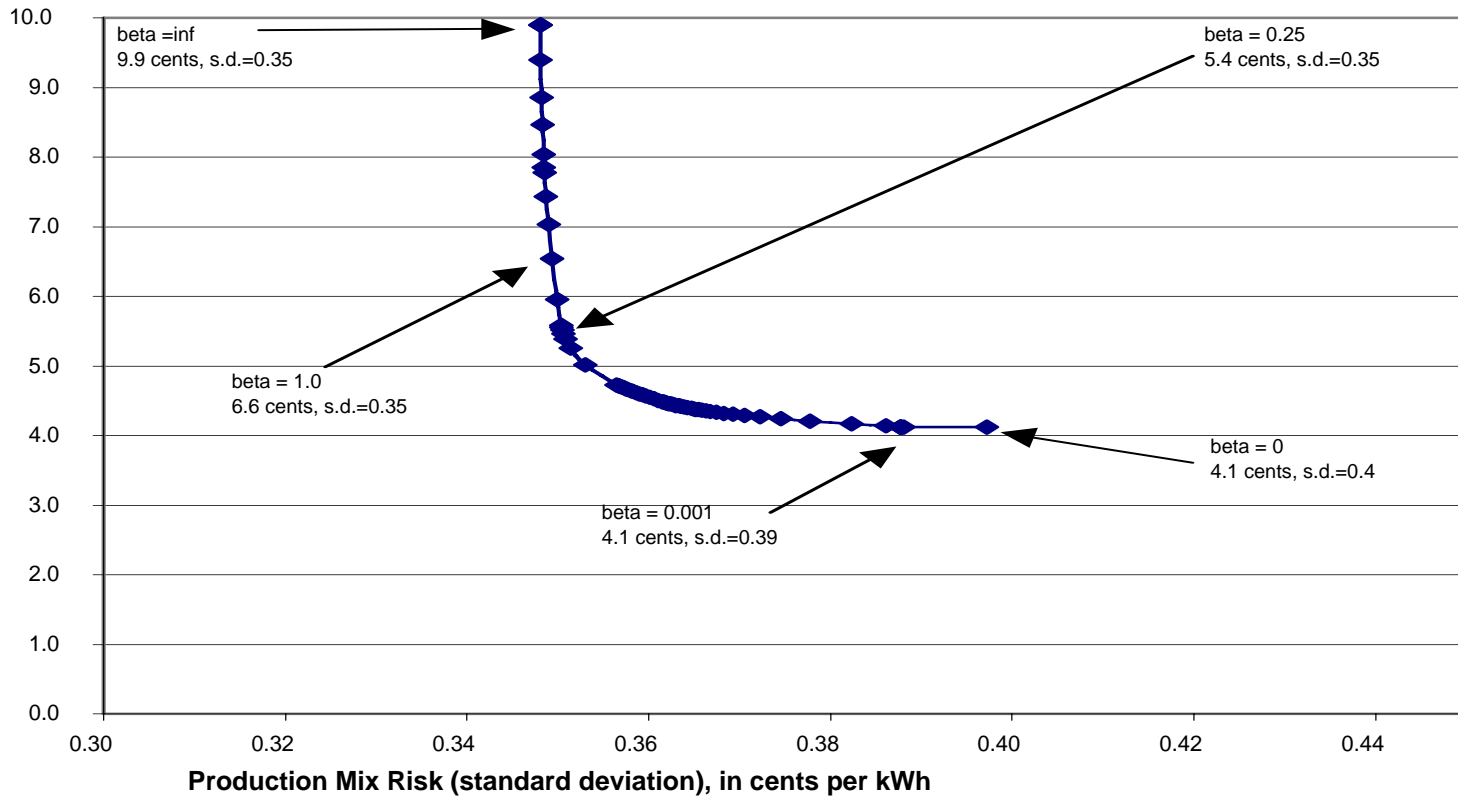
Fuel costs' variance rankings, from least to most volatile: nuclear, coal, natural gas, oil.

Table 1. Fuel Price Covariance Estimates for the Electric Sector, Indiana (Prices in million \$ per GWh)

| | Coal | Oil | Gas | Nuclear (MI) |
|---------|----------------------|----------------------|----------------------|----------------------|
| 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 |



Base Scenario



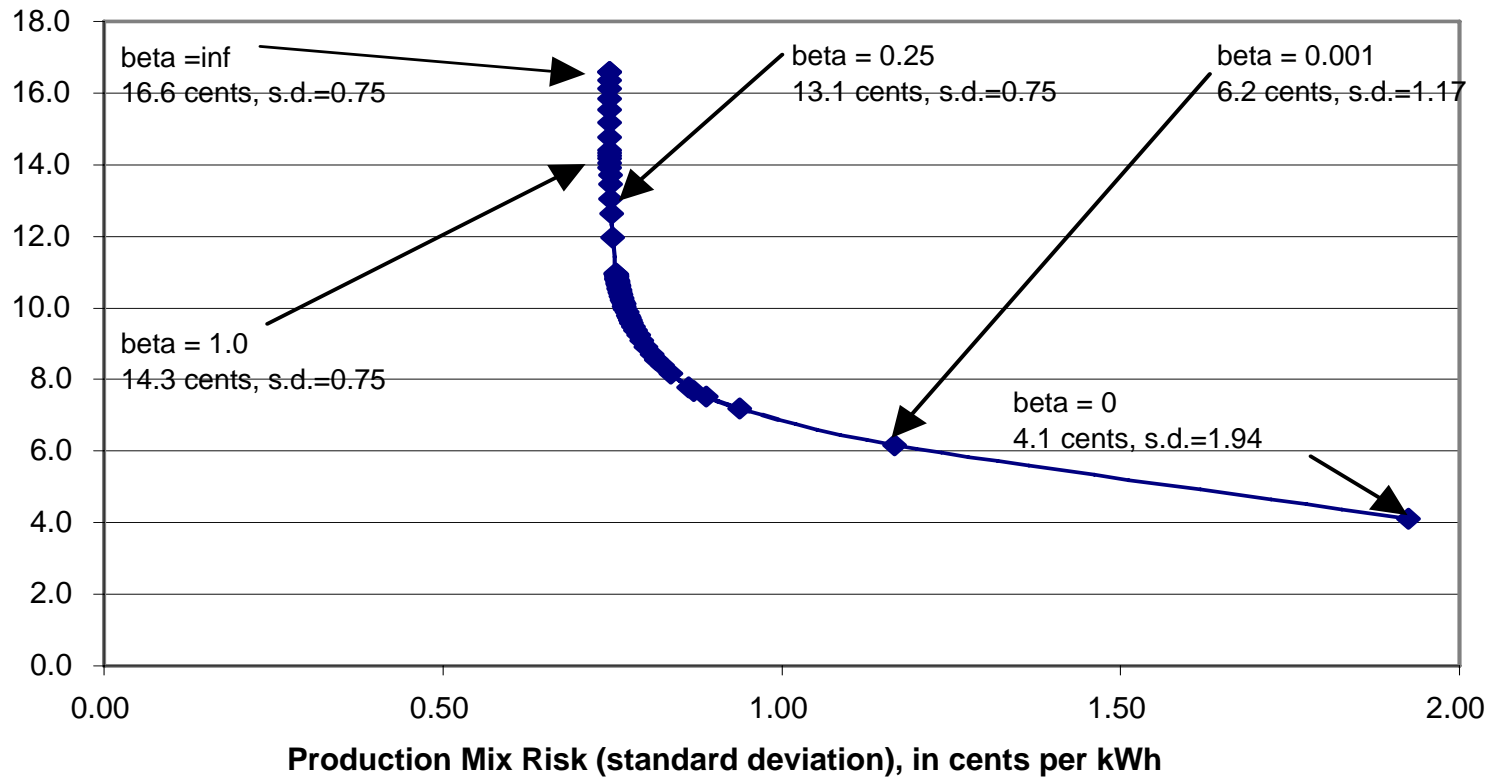


Base Scenario

- What we saw:
 - From $\beta=0$ (risk neutral) to the $\beta=\text{inf}$ (most risk averse), there is an increase in production from oil and gas-fired units so as to reduce variance. There is a drop of production from coal units (83 to 80%). Increase for natural gas (7 to 8%). Increase for oil (1 to 4%). Thus, an increase of total production costs from 4.1 to 9.9 cents/kWh



Scenario 1: extreme coal price variance (x30)



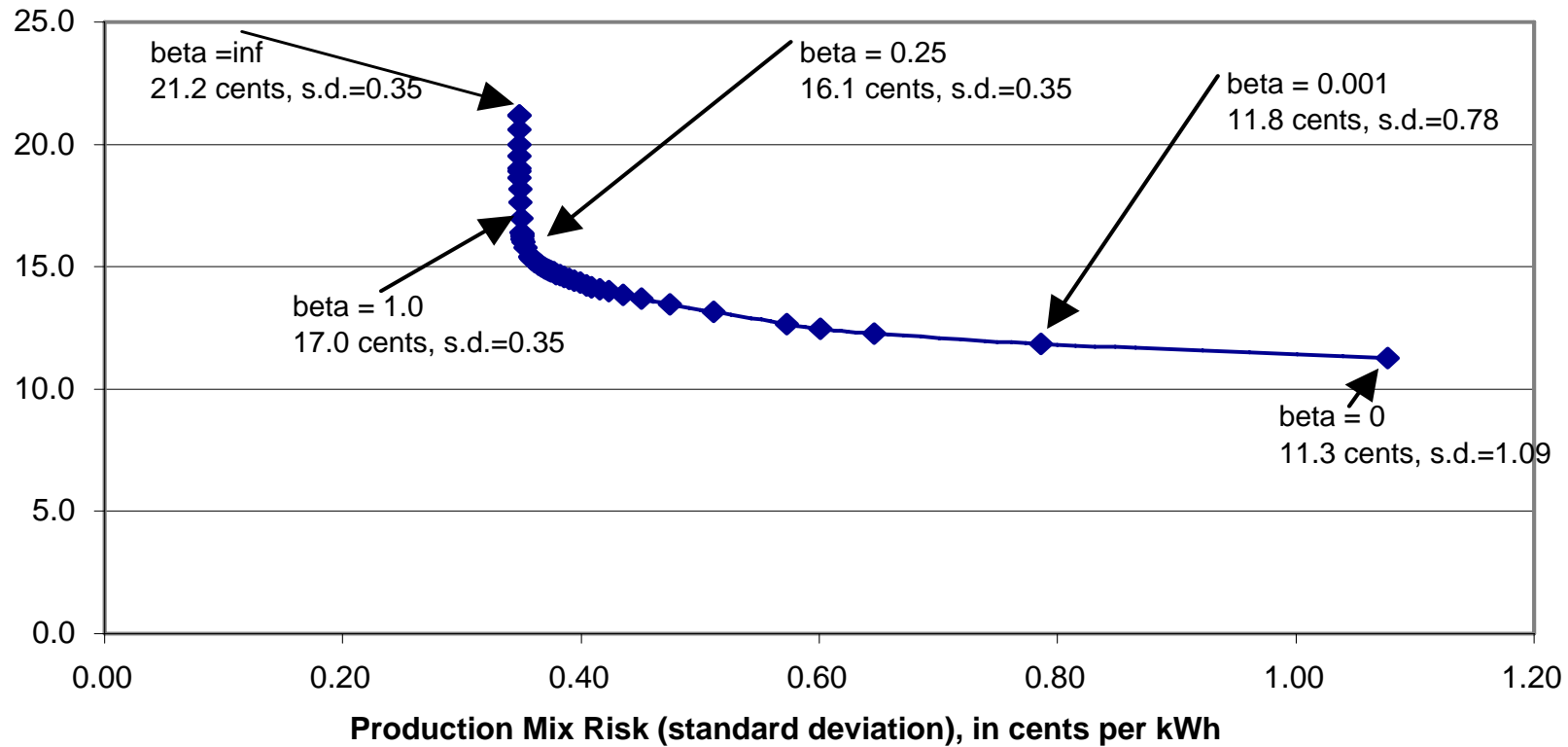


Scenario 1: extreme coal price variance

- What we saw:
 - As expected for coal having 30 times higher variance, the production from coal sharply decreases as we become more risk averse. At $\beta=\text{inf}$ only 13% of energy is provided by coal. The model simply backs away production from coal with high variance fuel costs, instead uses more higher cost alternatives.
 - As a result, substantial increase in uses of oil (19%), natural gas (40%), and nuclear (28%).
 - At $\beta=0$ the mix of generation and the cost are the same as in the base case, but the variance is higher.



Scenario 2: extreme fuel cost (coal price increases 10 times)



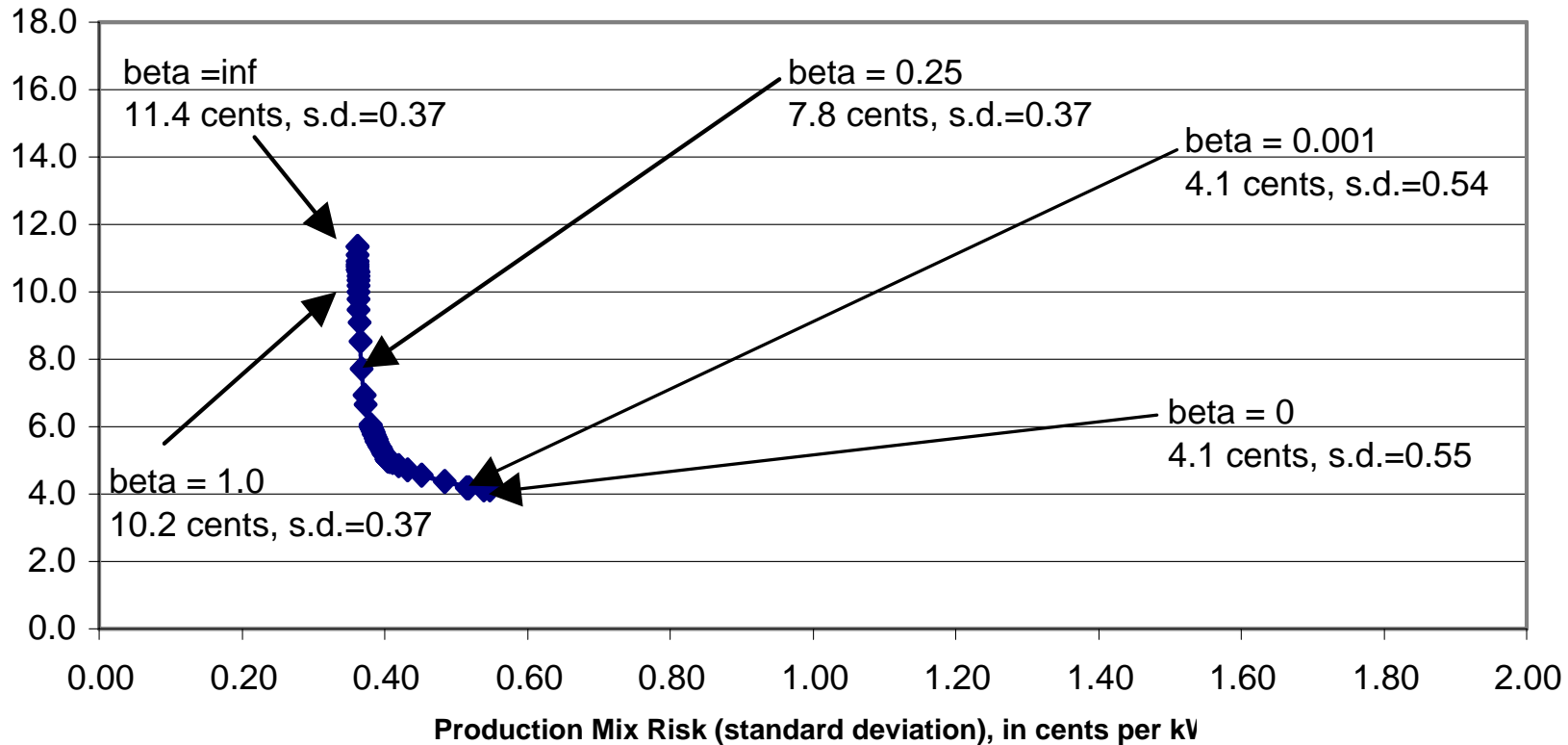


Scenario 2: extreme fuel cost (coal price increases 10 times)

- What we saw:
 - For $\beta=\text{inf}$ the mix of generation and the variance are exactly the same as in the base scenario. The only difference is the price of coal, which has no effect on the optimal mix.
 - For $\beta=0$, much less of the high cost coal is used (10%) with natural gas picking up much of the slack (79%). This results in a much higher cost and variance when compared to the base case.



Scenario 3: extreme natural gas price variance (x30)





Scenario 3: extreme natural gas price variance

- What we saw:
 - Similar results to the high coal price variance scenario. For $\beta=0$, the generation mix and the cost are the same as in the base scenario, while the variance increases.
 - For $\beta=\text{inf}$, production from natural gas drops from 7% to less than 1%. The drop in production is made up in oil (1% to 4%) and coal (83% to 87%).



Conclusion

- Load Factor-based optimization model is a tool to generate costs-risk efficient frontiers, which could be used in analyzing strategic planning for least-cost production.
- Model ran with other varying input assumptions like coal and gas variance, and found the model to behave intuitively.
- Extreme scenarios perform as expected and tend to validate the method.

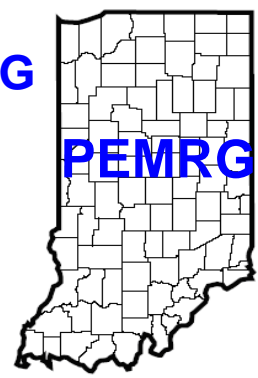


Current and Future Work

- Will include renewable resources or emissions controls
 - Wind
 - Solar
 - Biomass
 - Possibly emissions limits and/or availability factors
- Zero-start scenarios
- Want to choose and run more realistic scenarios
- Technologies
 - Simple cycle combustion gas turbine
 - Combined cycle combustion gas turbine
 - Internal combustion engine
 - Pulverized coal, fluidized-bed combustion, and integrated gas combined-cycle



Questions or Comments?



Thank you