

Diversification of fuel costs accounting for load variation

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ABSTRACT

A practical mathematical programming model for the strategic fuel diversification problem is presented. The model is designed to consider the tradeoffs between the expected costs of investments in capacity, operating and maintenance costs, average fuel costs, and the variability of fuel costs. In addition, the model is designed to take the load curve into account at a high degree of resolution, while keeping the computational burden at a practical level.

The model is illustrated with a case study for Indiana's power generation system. The model reveals that an effective means of reducing the volatility of the system-level fuel costs is through the reduction of dependence on coal-fired generation with an attendant shift towards nuclear generation. Model results indicate that about a 25% reduction in the standard deviation of the generation costs can be achieved with about a 20–25% increase in average fuel costs. Scenarios that incorporate costs for carbon dioxide emissions or a moratorium on nuclear capacity additions are also presented.

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1. Introduction

Fuel costs are a major source of uncertainty in the cost of electricity generation. Because the prices of alternative fuels are imperfectly correlated, there is an opportunity to manage not only the expectation but also the variability of the cost of generation. That is, by strategically investing in a portfolio of generation capacity that is powered by multiple fuels, a utility or public utility commission can manage the tradeoffs between the expected cost and a measure of the volatility of cost such as its variance. One approach to this problem is a mean–variance analysis of the portfolio of generation capacity. This is similar in spirit to the mean–variance portfolio analysis for investment in financial assets due to Markowitz (1952).

Implementations of mean–variance portfolio analysis to the problem of fuel diversification in electricity generation have often relied on the assumption that the load factor (i.e. the ratio of the energy that is generated over some time period to the maximum amount of energy that could have been generated over the period) of each generating technology is constant (see e.g. Bar-Lev and Katz, 1976). This assumption is inappropriate because power plants are

dispatched to serve varying loads based on a least-cost merit order of technologies. (Other considerations such as ramping rates and minimum up-time and minimum down-time also play a role, but are often ignored for longer term strategic planning.)

The load pattern is often described through the use of a load duration curve as illustrated in Fig. 1. This figure illustrates an annual load duration curve. The horizontal axis corresponds to the hours during the year, but time has been reordered so that the hourly loads (the vertical axis) are in descending order. (The hourly load curve is a step function, whereas the illustrated function is smooth as would be the instantaneous load curve. In practice, hourly load curves are typically used for planning purposes to make data handling more tractable.) Thus, the load duration curve is a monotonically decreasing function of time. Plants with high fixed investment costs and low operating costs are often used for load with small or no variations for extended time periods (e.g. the region labeled Base in Fig. 1), whereas plants with low fixed costs and high operating costs are typically used for load with high variations in shorter time periods (e.g. the region labeled Peak in Fig. 1). Thus, the load factor for a given plant will depend on the part of the load curve that it serves. This is important because if the plant is operated with a higher load factor, then the plant's fixed costs are spread over a larger number of kilowatt-hours, thus lowering the average cost of electricity from that plant.

Most prior work on fuel diversification in electricity generation has used fixed load factors in calculation of the costs. Bar-Lev and

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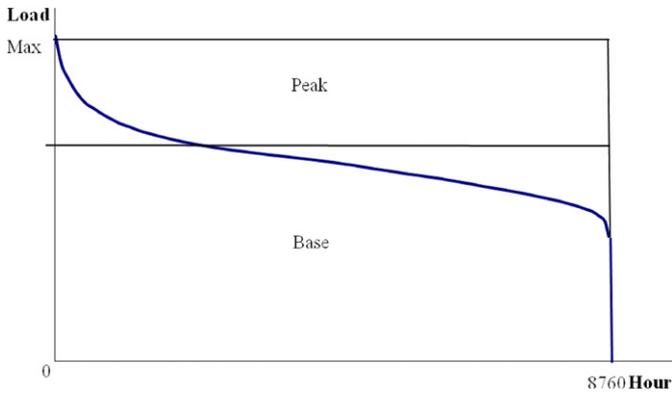


Fig. 1. Load duration curve.

Katz were the first to apply Markowitz’s portfolio theory to the problem of fuel diversification to investigate the tradeoff between expected cost and risk due to fuel price volatility for electric utilities engaging in long-term fuel supply contracts. Other authors (e.g. Humphreys and McClain, 1998; Awerbuch and Berger, 2003; DeLaquil et al., 2005; Krey and Zweifel, 2006) also examined fuel diversification using fixed load factors for generation technologies. Because these analyses do not simultaneously optimize load factor and generation technology portfolio, the resulting portfolios tend to be over specialized with an inadequate mixture of technologies serving the different load segments. An exception to this rule is recent work by Doherty et al. (2006), which determines generation portfolios that optimize plants’ load factors, but does not consider volatility of fuel costs. Another exception is the work by Gotham et al. (2009), which divides the load curve into base load, cycling, and peak segments and optimizes the portfolio of technologies and their dedication to servicing the three segments of the load curve, taking variation of fuel costs into account.

In this paper, the benefit and cost of further subdividing the load curve is assessed. First, it is proved that further subdivision may either decrease the average cost or the variability of cost, and will certainly not increase their appropriately weighted sum. Second, it is argued that this implies that a particular optimal control problem representing the limiting case as the load curve is subdivided ad infinitum is the theoretically ideal model in the sense that no other subdivision results in a lower mean and variance of costs—that is, the optimal control problem defines the efficient mean–variance frontier. Third, a computationally tractable mathematical programming model of the fuel diversification problem that approximates the ideal control problem is given. Fourth, the results of the model with data from the state of Indiana are used to illustrate the benefits of taking the process of subdivision nearly to its limit with only a minor increase in computational effort.

2. Two results regarding load class subdivision

Ruangpattana (2010) and Gotham et al. (2009) proposed a model that removes the one-load factor assumption while retaining the elegance and simplicity of the mean–variance (M–V) approach. Their model has an associated mean–variance frontier that is efficient in the sense that for any point on the frontier, the mean cost cannot be reduced without increasing the variance of cost and vice versa. In addition, any point not on the frontier is either infeasible, or is such that the mean can be reduced without reducing the variance, or the variance can be reduced without reducing the mean. In this paper, it will be shown that if one of

the load classes is subdivided into two load classes, then the resulting M–V frontier will always contain the original frontier, and the new M–V frontier may contain additional points. Geometrically, if this M–V frontier is graphed with the mean cost increasing from bottom to top on the vertical axis and the standard deviation of cost increasing from left to right on the horizontal axis, then the subdivision causes the M–V frontier to shift downward and/or to the left.

To prove this result, it is helpful to restate the model of Gotham et al. in alternative notation. Let $L(a)$ denote the load (MW) at time a , where a is in $[0, 8760]$ for a non-leap year. Following custom, the load curve is non-increasing with maximum load at time 0. The load is divided into n contiguous, non-overlapping intervals that are described by the set $A = \{[a_0, a_1], [a_1, a_2], \dots, [a_{n-1}, a_n]\}$. We refer to these intervals as load classes. The integral of $L(\cdot)$ over the interval $[a_{n-1}, a_n]$ indicates the total demand (MWh) for that load class, and the load factor (the amount of energy demanded for the load class divided by maximum load times the length of the time period) is denoted by

$$L_{[a_{n-1}, a_n]} = \frac{\int_{a_{n-1}}^{a_n} L(a) da}{L(0)(a_n - a_{n-1})}. \tag{1}$$

Generation is distinguished by whether it is existing or new capacity. Generation (MWh) using existing capacity to serve load segment $[a_{n-1}, a_n]$ is denoted by the m -dimensional vector $x_{[a_{n-1}, a_n]}$, where the i th component of the vector indicates the energy production of the i th technology (pulverized coal, natural gas combustion turbine, etc.) dedicated to this load segment in MWhs. Total existing capacity (MWhs) is denoted by the m -dimensional vector U , where the i th component of the vector indicates the existing capacity of the i th technology. (The vector U is stochastic due to forced outages. However, it is treated as deterministic in this problem to maintain the focus on fuel price risk.) Similarly, generation (MWh) to serve load segment $[a_{n-1}, a_n]$ using new capacity is denoted by the m -dimensional vector $y_{[a_{n-1}, a_n]}$. We distinguish existing and new capacity to facilitate the treatment of fixed versus variable costs.

Fixed costs (the sum of levelized capital costs plus fixed operating and maintenance costs) are denoted by the m -dimensional vector F , with the i th component corresponding to the fixed cost for the i th technology. Variable costs (operating and maintenance costs plus the mean fuel costs) for existing capacity are denoted by the m -dimensional vector V_x , with the i th component corresponding to the variable costs for the i th technology. Variable costs for new capacity are denoted by the m -dimensional vector V_y . The final cost element that is needed to formulate the problem is the covariance matrix of the fuel costs, which is denoted by the $m \times m$ matrix Ω that contains the covariance between the fuel costs for technology i and technology j in row i , column j .

Gotham et al. (2009) present two mathematical programming models. One model minimizes the variance of fuel costs subject to an upper limit on the fixed plus expected variable costs. The other minimizes the sum of the fixed and expected variable costs plus the variance of fuel costs scaled by a positive factor, which is related to the level of risk aversion of the decision maker. These models are displayed below with one modification—now we consider the model decision variables to be not only the generation by load class of each of the technologies, but also the end points of the load intervals. The modified model with the objective of minimizing the variance fuel costs is

$$\begin{aligned} & \text{minimize} && \sum_{n=1}^N (x_{[a_{n-1}, a_n]} + y_{[a_{n-1}, a_n]})^t \Omega \Sigma_N^{-1} (x_{[a_{n-1}, a_n]} + y_{[a_{n-1}, a_n]}) \\ & a_0, a_1, \dots, a_N \\ & x_{[a_0, a_1]}, \dots, x_{[a_{n-1}, a_n]} \\ & y_{[a_0, a_1]}, \dots, y_{[a_{n-1}, a_n]} \end{aligned}$$

subject to

$$\begin{aligned} & \sum_{n=1}^N F^t y_{[a_{n-1}, a_n]} (L_{[a_{n-1}, a_n]})^{-1} + \sum_{n=1}^N (V_x^t x_{[a_{n-1}, a_n]} + V_y^t y_{[a_{n-1}, a_n]}) = \mu, \\ & \sum_{n=1}^N x_{[a_{n-1}, a_n]} (L_{[a_{n-1}, a_n]})^{-1} \leq U, \\ & (x_{[a_{n-1}, a_n]} + y_{[a_{n-1}, a_n]})^t \mathbf{1} = \int_{a_{n-1}}^{a_n} L(u) du, \\ & 0 = a_0 \leq a_1 \leq \dots \leq a_N = 8760, \\ & x_{[a_{n-1}, a_n]} \geq 0, y_{[a_{n-1}, a_n]} \geq 0 \text{ for } n = 1, \dots, N, \end{aligned} \tag{2}$$

where $\mathbf{1}$ is an m -dimensional column vector of ones. The modified model with the objective of the weighted sum of the mean of costs and the variance of costs is as follows:

$$\begin{aligned} & \underset{\substack{a_0, a_1, \dots, a_N \\ x_{[a_0, a_1]}, \dots, x_{[a_{n-1}, a_n]} \\ y_{[a_0, a_1]}, \dots, y_{[a_{n-1}, a_n]}}}{\text{minimize}} \sum_{n=1}^N F^t y_{[a_{n-1}, a_n]} (L_{[a_{n-1}, a_n]})^{-1} + \sum_{n=1}^N (V_x^t x_{[a_{n-1}, a_n]} + V_y^t y_{[a_{n-1}, a_n]}) \\ & + \beta \sum_{n=1}^N (x_{[a_{n-1}, a_n]} + y_{[a_{n-1}, a_n]})^t \Omega \sum_{n=1}^N (x_{[a_{n-1}, a_n]} + y_{[a_{n-1}, a_n]}) \end{aligned}$$

subject to

$$\begin{aligned} & \sum_{n=1}^N x_{[a_{n-1}, a_n]} (L_{[a_{n-1}, a_n]})^{-1} \leq U, \\ & (x_{[a_{n-1}, a_n]} + y_{[a_{n-1}, a_n]})^t \mathbf{1} = \int_{a_{n-1}}^{a_n} L(u) du, \\ & 0 = a_0 \leq a_1 \leq \dots \leq a_N = 8760, \\ & x_{[a_{n-1}, a_n]} \geq 0, y_{[a_{n-1}, a_n]} \geq 0 \text{ for } n = 1, \dots, N. \end{aligned} \tag{3}$$

Let (2') and (3') refer to the problems (2) and (3) where the a_n are not model decision variables—that is, they are fixed model parameters. Gotham et al. (2009) proved that for problem (2'), if one of the intervals $[a_{n-1}, a_n]$ is divided into two intervals $[a_{n-1}, b]$ and $[b, a_n]$, where $a_{n-1} < b < a_n$, all of the other intervals are kept the same, and decision variables for existing and new capacity are modified to accommodate these new intervals, then the optimal objective value for the new model will be at most the optimal objective value for (2'). The proof proceeds by constructing a feasible solution for the problem (2') with one of the intervals subdivided. They show that the constructed solution has fuel cost variance equal to the minimum fuel cost variance associated with the optimal solution for (2'). It is straightforward to show in the same way that the optimal objective value for (3') will not increase if one of the intervals is divided into two intervals.

We now consider a similar result for (2). As in Gotham et al. (2009), we assume that we have a globally optimal solution for (2) in hand and consider the problem where there is one more load class. Formally, we have the following.

Theorem 1. Let $P(N)$ denote the problem (2) with N load classes. The optimal objective value of $P(N+1)$ is at most the optimal objective value of $P(N)$.

Proof. Recall that a solution for $P(N)$ includes values not only for $x_{[a_{n-1}, a_n]}$ and $y_{[a_{n-1}, a_n]}$ for $n=1, \dots, N$, but also for a_n , for $n=0, \dots, N$. Starting from an optimal solution to $P(N)$, we can construct a feasible solution for $P(N+1)$ as follows. First, we arbitrarily subdivide one of the load classes prescribed by an optimal solution to $P(N)$ specified by some interval – say $[a_{m-1}, a_m]$ – into two load classes with associated intervals $[a_{m-1}, b]$ and $[b, a_m]$, where b is arbitrarily chosen such that $a_{m-1} < b < a_m$. Using the approach of Gotham et al. (2009), we can then construct a solution for $P(N+1)$ which is feasible and has the same objective value as $P(N)$. (Note that they show that this solution is feasible with respect to all constraints except for $a_{n-1} \leq a_n$ for $n=1, \dots, N$.

Because these constraints are satisfied for any optimal solution to $P(N)$, and because we choose b to be strictly between a_{n-1} and a_n , this constructed solution is feasible with respect to these constraints as well.) Because we can construct a feasible solution to $P(N+1)$ that has the same objective value as $P(N)$, we conclude that optimal objective value of $P(N+1)$ is at most the optimal objective value for $P(N)$. QED.

The following result follows in a similar fashion to the proof of Theorem 1.

Theorem 2. Let $Q(N)$ denote problem (3) with N load classes. The optimal objective value of $Q(N+1)$ is at most the optimal objective value of $Q(N)$.

Proof. Let a globally optimal solution for $Q(N)$ be given. Use the Gotham et al. (2009) method to construct a solution for $Q(N+1)$, and note that the objective value for the constructed solution is again the same as the globally optimal solution for $Q(N)$. Thus, the objective value for the globally optimal solution for $Q(N+1)$ will be at least as low as the objective value for the globally optimal solution for $Q(N)$. QED.

The importance of these two results is that adding load classes will never increase the optimal objective values of $P(N)$ and $Q(N)$. This means that the M–V efficient frontier moves down and/or to the left as the number of load classes is increased. One can imagine a procedure wherein one solves $P(N)$ or $Q(N)$ for successively larger values of N and terminates the process when additional increases in the number of load classes does not change the frontier. Rather than address the technical details of such a procedure, it is useful to observe that neither $P(N)$ nor $Q(N)$ is a convex programming problem, and thus the calculation of a globally optimal solution may be challenging for general $L(\cdot)$. The desire for a practical computational means to find the most efficient frontier, taking into account the load curve leads us to the results in the following section.

3. A reformulation that lends itself to practical computation

The primary reason that (2) and (3) are computationally challenging is due to the fact that the a_n are model decision variables. The goal of this section is to develop a model and computational procedure that is computationally tractable and gets us arbitrarily close to the limiting efficient M–V frontier (e.g. as the number of load classes becomes arbitrarily large). The result that adding load classes never moves a point on the efficient frontier up or to the right suggests one procedure: given N , define a set of load classes corresponding to uniformly spaced intervals (i.e., $a_n = n \times 8760/N$), and solve (2') or (3'), and repeat for successively larger values of N until a satisfactory approximation to the limiting efficient M–V frontier has been found. Unfortunately, because the number of variables appearing in the quadratic term of the objective of these models increases linearly with N , this problem will eventually become computationally intractable due to its size.

To make the computations more efficient, we introduce the following reformulations of (2') and (3') wherein the number of quadratic variables is independent of N . First, consider the following reformulation of (2'). (The load class divisions a_n are exogenous and equally spaced as suggested above in this problem. However, the notation is otherwise unchanged to facilitate comparison with the other models.)

$$\begin{aligned} & \underset{\substack{x_{[a_0, a_1]}, \dots, x_{[a_{n-1}, a_n]} \\ y_{[a_0, a_1]}, \dots, y_{[a_{n-1}, a_n]}}}{\text{minimize}} z^t \Omega z \end{aligned}$$

subject to

$$\begin{aligned} & \sum_{n=1}^N F^t y_{[a_{n-1}, a_n]} (L_{[a_{n-1}, a_n]})^{-1} + \sum_{n=1}^N (V_x^t x_{[a_{n-1}, a_n]} + V_y^t y_{[a_{n-1}, a_n]}) = \mu, \\ & \sum_{n=1}^N x_{[a_{n-1}, a_n]} (L_{[a_{n-1}, a_n]})^{-1} \leq U, \\ & (x_{[a_{n-1}, a_n]} + y_{[a_{n-1}, a_n]})^t \mathbf{1} = \int_{a_{n-1}}^{a_n} L(u) du, \\ & z = \sum_{n=1}^N (x_{[a_{n-1}, a_n]} + y_{[a_{n-1}, a_n]}), \\ & x_{[a_{n-1}, a_n]} \geq 0 \text{ and } y_{[a_{n-1}, a_n]} \geq 0 \text{ for } n = 1, \dots, N. \end{aligned} \tag{4}$$

The simple innovation is to introduce an m -dimensional vector of variables z whose i th component is the sum across load classes of fuel used for generation by the i th technology. With this model, the number of variables that appear in the quadratic objective term is m , independent of N . In addition, the constraints are all linear. As noted in Gill et al. (1981), this is a tractable class of problems that can be solved for fairly large values of N provided that m is not too large. We will demonstrate this later in this paper. However, rather than basing our computations on (4), we base them on the following problem which is analogous to (3’):

$$\begin{aligned} & \underset{\substack{x_{[a_0, a_1]}, \dots, x_{[a_{n-1}, a_n]} \\ y_{[a_0, a_1]}, \dots, y_{[a_{n-1}, a_n]}}}{\text{minimize}} \sum_{n=1}^N F^t y_{[a_{n-1}, a_n]} (L_{[a_{n-1}, a_n]})^{-1} \\ & + \sum_{n=1}^N (V_x^t x_{[a_{n-1}, a_n]} + V_y^t y_{[a_{n-1}, a_n]}) + \beta z^t \Omega z \end{aligned}$$

subject to

$$\begin{aligned} & \sum_{n=1}^N x_{[a_{n-1}, a_n]} (L_{[a_{n-1}, a_n]})^{-1} \leq U, \\ & (x_{[a_{n-1}, a_n]} + y_{[a_{n-1}, a_n]})^t \mathbf{1} = \int_{a_{n-1}}^{a_n} L(u) du, \\ & z = \sum_{n=1}^N (x_{[a_{n-1}, a_n]} + y_{[a_{n-1}, a_n]}), \\ & x_{[a_{n-1}, a_n]} \geq 0 \text{ and } y_{[a_{n-1}, a_n]} \geq 0 \text{ for } n = 1, \dots, N, \end{aligned} \tag{5}$$

where β is a measure of risk aversion as it is in (3). (This risk aversion parameter, β , reflects the weight the decision maker places on variability of costs relative to the mean of costs. A value of zero indicates risk neutrality—i.e. no consideration of cost variability. A very high value for β indicates a near unilateral concern for reducing the variability of costs with little regard for average costs.)

Table 1
Existing generation capacity for Indiana by energy (fuel) sources.
Source: Existing Electric Generating Units in the United States, 2008, Form EIA-860 Database, Annual Electric Generator Report (EIA 2008a).

Energy source	Total summer capacity (MW)
Coal	16,430
Integrated gasification combined cycle	619
Oil	366
Natural gas combustion turbine	3931
Natural gas combined cycle	1148
Nuclear	1655
Hydro	64
Landfill gas	30
Total	24,243

Notes: Capacity for hydro and landfill gas are quite small and have very limited potential for expansion. In addition, existing Hydro capacity is run of river and therefore not dispatchable. For these reasons both hydro and landfill gas are excluded from the analysis reported here. While Wabash Valley Power Association’s Wabash River 1 unit was converted to integrated gasification combined cycle technology in the early 1990s, it is treated as part of the installed coal-fired capacity in the model. The integrated gasification combined cycle capacity listed in the table is for Duke’s Edwardsport facility.

4. Data

This section describes the data that are used in this study and presents numerical results from a case for the state of Indiana. Cost factors and hourly load data are obtained through government reports and utility company filings. The base case scenario expands 2006 demand to 2025 by uniformly scaling up the load curve by a multiplicative factor representing projected demand growth over that period. Existing capacities are taken to be the capacities that were in place in 2008, adjusting for retirements and new construction projects that have been approved by the Indiana Utility Regulatory Commission. Two additional scenarios are considered—one in which costs are imposed for CO₂ emissions and one in which no additions to nuclear capacity are permitted.

4.1. Existing capacity and demand estimates

The analysis reported here is based on national data provided by the Energy Information Administration’s *Assumptions to the Annual Energy Outlook 2009*¹ publication. Generation capacity and historical energy requirements in Indiana are based on figures from the EIA (2008a) and from the State Utility Forecasting Group (Rardin et al. 2005), who in turn obtained data directly from power producers’ filings with the Federal Energy Regulatory Commission. Existing capacity for 2008 is displayed in Table 1. All existing generating capacity in the model is located in Indiana except for the D.C. Cook nuclear plant.

4.2. Cost estimates

Historical Indiana electric power sector fuel prices (1970 through 2007) are obtained from the EIA’s *Electric Power Sector Price and Expenditure Estimates by Source* (EIA, 2008b), and the average fuel costs expressed in 2007 dollars using the Personal Consumption Deflator (BEA, 2010) for generating units powered by coal, residual fuel and natural gas.² These are shown in Table 2. While Indiana does not have any commercial nuclear facilities geographically located in the state, a nuclear station in Michigan (D.C. Cook) primarily serves Indiana load, and hence Michigan nuclear fuel prices were used for the nuclear technology. Table 2 also shows variable operating and maintenance (O&M) costs and annual fixed costs. Fixed capacity costs (\$/MW) have been converted to dollars per unit of energy, \$/MWh, by dividing the annual total by the number of hours in a year (i.e. 8760). Variable O&M and fuel costs are already expressed per unit of energy.

In addition to conventional pulverized coal generation units and simple cycle combustion turbines, all scenarios consider both integrated coal gasification combined cycle (IGCC) and natural gas combined cycle (NGCC) units as possible technologies for new capacity. This allows for an analysis of the impact of the combined cycle technologies that are expected to play a larger role in the future due to their relatively low heat rates.

4.3. Fuel cost variance estimates

The same historical Indiana electric power sector fuel prices used to calculate the average fuel prices were used to calculate fuel price variances and covariances. The fuel price variance for nuclear generation is very small, reflecting the historical stability of the price of nuclear fuel. The resulting fuel price covariance matrix for the electric sector is in Table 3.

¹ See Table 8.2 in EIA (2009).

² The relevant Indiana series are CLEID, DFICD, NGEID, and for Michigan NUEGD, representing historical prices for coal, light oil, natural gas, and nuclear fuel, respectively.

Table 2

Costs for electricity generation technologies (costs in \$/MWh).

Sources: Fixed and Variable O&M Costs are from Table 8.2 Cost and Performance Characteristics of New Central Station Electricity Generating Technologies, Assumptions to the Annual Energy Outlook 2009 (EIA, 2010). Expected fuel costs estimated from 1970–2007 price data in Electric Power Sector Price and Expenditure Estimates by Source (EIA, 2008b).

Technology	Fixed cost		Variable O&M		Fuel cost	
	New	Existing	Existing	New	Existing	New
Pulverized coal (PCoal)	28.2	4.3	4.6	19.7	19.7	
Integrated gasification combined cycle (IGCC)	33.4	2.9	2.9	17.4	17.4	
Oil	9.5	11.8	3.6	113.5	113.5	
Natural gas combustion turbine (NGCT)	8.9	9.2	3.2	54.4	54.4	
Natural gas combined cycle (NGCC)	12.9	2.0	2.0	35.9	35.9	
Nuclear (Nuc)	50.7	0.5	0.5	9.7	9.7	

Table 3

Fuel price covariance estimates for the electric sector, Indiana (prices in \$/MWh). Source: Fuel price covariances estimated from 1970 to 2007 price data in Electric Power Sector Price and Expenditure Estimates by Source (EIA 2008b).

	PCoal	IGCC	Oil	NGCT	NGCC	Nuc
PCoal	43.86	37.83	110.18	66.46	43.81	10.17
IGCC		34.42	97.59	58.87	38.81	9.01
Oil			2289.81	918.43	605.43	-52.23
NGCT				557.27	357.69	-16.97
NGCC					242.16	-11.19
Nuc						10.32

4.4. Electricity requirements

The model runs are performed using an estimated load for the year 2025. The estimated load was derived by increasing the actual hourly Indiana electricity demand in 2006 using expected growth rates obtained from *Indiana Electricity Projections* (Rardin et al., 2005) developed by the State Utility Forecasting Group. By scaling up hourly load in 2006 by a multiplicative constant that makes total load equal to the projected total load for 2025, a new load duration curve can be developed. This results in a total energy requirement of 144,495 GWh and a total capacity requirement of 27,968 MW.

5. Benefits of incorporating a finely subdivided load curve

The principal difference between the model recommended here and the majority of models appearing in the literature is the use of a large number of load classes. Fig. 2 illustrates the impact of increasing the number of load classes on the mean-standard deviation frontier of efficient capacity portfolios. The line labeled “1 Load Factor” in Fig. 2 is obtained by solving the strategic fuel diversification problem with a single average load factor for each generation technology. The line labeled “3 Load Factors” is obtained by solving the strategic fuel diversification problem with three load classes with separate load factors and appropriate fixed and variable costs as is done in Gotham et al. (2009). These load classes are baseload (constituting the lowest 70% of the load curve), peak (constituting the top 10% of the load curve), and cycling (constituting the remaining load). The line labeled “100 Load Factors” is for the model proposed here in which the load has been broken into 100 equally spaced load classes (along the load dimension of the load curve). For each of these divisions of the load curve, the problem (5) was solved repeatedly for a range of values of the risk aversion parameter β to generate the mean/standard deviation efficient frontier that appears in the figure. Three points associated with representative values of β ($\beta=0.003$, $\beta=0.007$, and $\beta=0.016$) are indicated on each of the three frontiers to

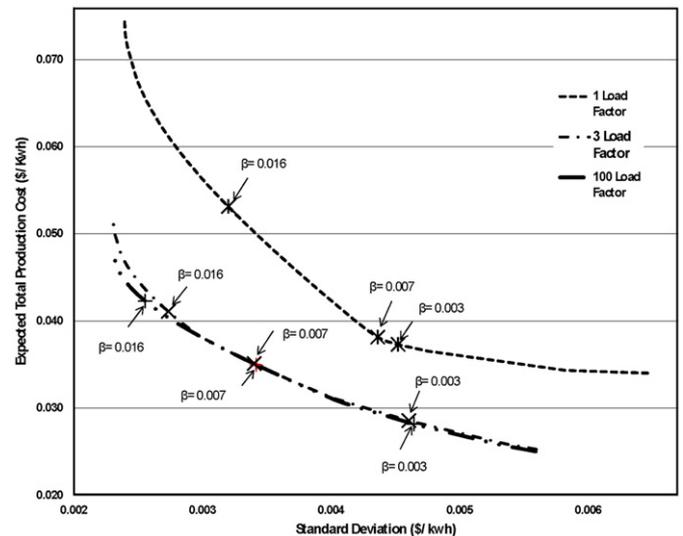


Fig. 2. Cost mean/standard deviation efficient frontier for alternative divisions of the load curve.

allow the reader to follow how choices for agents with the same level of risk aversion shift as the number of load curve divisions changes. (These specific levels of the risk aversion parameter were chosen to allow more detailed focus on how the generation mix changes as risk aversion increases. A value of $\beta=0.003$ yields a generation mix similar to the existing situation with about 84% of generation provided by coal. The higher levels of $\beta=0.007$, and $\beta=0.016$ are sufficiently larger as to result in substantial shifts in the generation mix.)

Fig. 2 illustrates that the efficient frontier (and each of the three points associated with the representative values of the risk aversion parameter) shifts downward (towards lower mean cost) and to the left (towards lower variance of cost) as the number of load classes increases. For the Indiana data used for this illustration, breaking the load into three classes appears to shift the frontier most of the way to the frontier with one hundred load classes. Further subdivision of the load curve does not appear to have an impact. (The model was solved for one thousand load classes, and there was no impact on the efficient frontier relative to the efficient frontier based on one hundred load classes.) This result is specific to the data used for Indiana. Other data may result in a more gradual shift towards the limiting efficient frontier.

6. Model results

This section presents the results for three policy scenarios: a base case that is based on no policy changes relative to 2006,

a carbon cost case that assesses additional costs of \$45.37 per ton of CO₂ for fossil fuel generating technologies, and a “no new nuclear” case that excludes the possibility of expansion of nuclear generating capacity. (This level of carbon costs is the 2025 cost of carbon dioxide emissions assumed in EIA (2009) for their Base case.) The base case serves as the basis for comparison for the other scenarios. All of these results are produced from the model formulated in (5) using one hundred load classes as in the previous section.

6.1. Base scenario

Table 4 provides the detailed portfolios for each of the three representative values of the risk aversion parameter highlighted in Fig. 2. These are grouped by fuel type (coal, oil, natural gas, and nuclear), within fuel type by technology (e.g. pulverized coal and IGCC for coal and NGCT and NGCC for natural gas), and within technology by existing versus new capacity. For each capacity classification (fuel/technology/existing or new), energy production, capacity and load factor are all indicated.

To begin, consider the lower level of β ($=0.003$). For existing pulverized coal, the existing capacity of just over 16 GW is used with an average load factor of over 67% to generate just under 97,000 GWh of energy. No new pulverized coal capacity is added. Existing IGCC capacity of about 0.6 GW is used to generate about 5400 GWh of energy at a load factor of 100%. Over 2 GW of new IGCC capacity is added, generating over 19,000 GWh of energy, again with a load factor of 100%. The 366 MW of existing oil fired capacity is used to generate about 2 GWh of energy at a capacity factor of less than five one hundredths of a percent, reflecting the usefulness of this existing capacity for serving extreme peak loads despite its high variable cost. No new oil-fired capacity is installed. Existing natural gas capacity, about 3.9 GW of combustion turbine and 1.1 GW of combined cycle, are used to generate 176 GWh and about 8000 GWh of energy, respectively, with respective average load factors of about 0.5% and over 79%, emphasizing the greater variable cost efficiency of the combined cycle technology. New natural gas combustion turbine capacity of about 1.6 GW is added to generate about 340 GWh of energy with an average load factor of about 2.4%. No new NGCC capacity is added. The addition of NGCT in preference to NGCC underscores the value of that technology for serving peak load due to its low capital cost. Finally for this base case, the existing nuclear capacity of 1655 MW is fully utilized to produce about 14,500 GWh of energy with a capacity factor of 100%. As in every case, the total energy produced is 144,495 GWh, and the total capacity (i.e. peak load) is just under 28 GW. No new nuclear capacity is added. The expected cost is about \$4.1 billion, the standard deviation of costs due to variations in fuel prices is about \$671 million, and the risk-adjusted cost, the objective in (5), is a bit over \$5.4 billion. On a per kWh basis, the expected cost of generation is \$0.028, with a standard deviation of \$0.0046.

Moving across the columns of Table 4, the aversion to risk rises, and the total energy fueled by coal drops substantially with the gap being filled primarily by nuclear generation. While no new nuclear capacity is installed in the base case, nuclear capacity roughly triples and quintuples as we increase risk aversion (β) from 0.003 to 0.007 to 0.016. While the full existing coal capacity is used in the intermediate risk aversion case, but at a lower average load factor (47% versus 68% in the base case), existing capacity is not fully utilized in the high risk aversion level. The other changes in capacity and utilization are relatively minor. The minor amount of oil capacity is fully utilized in the base case, but mothballed in the cases with higher risk aversion. There is also a modest decline in natural

Table 4

Base case results for three levels of risk aversion.

Technology	Risk aversion (β)		
	0.003	0.007	0.016
Pcoal existing energy (GWh)	96,927	66,965	39,943
Pcoal existing capacity (MW)	16,429 ^a	16,429 ^a	16,025
Pcoal existing average load factor	67	47	28
Pcoal new energy	0	0	0
Pcoal new capacity	0	0	0
Pcoal new average load factor	0	0	0
IGCC existing energy	5422	5422	5418
IGCC existing capacity	619 ^a	619 ^a	619 ^a
IGCC existing average load factor	100	100	100
IGCC new energy	19,132	18,527	18,781
IGCC new capacity	2184	2115	2144
IGCC new average load factor	100	100	100
Total coal energy	121,482	90,914	64,142
Total coal capacity	19,233	19,163	18,788
Oil existing energy	2	0	0
Oil existing capacity	366 ^a	0	0
Oil existing average load factor	0	0	0
Oil new energy	0	0	0
Oil new capacity	0	0	0
Oil new average load factor	0	0	0
Total oil energy	2	0	0
Total oil capacity	366	0	0
NGCT existing energy	176	225	956
NGCT existing capacity	3931 ^a	2485	111
NGCT existing average load factor	1	1	99
NGCT new energy	340	0	0
NGCT new capacity	1636	0	0
NGCT new average load factor	2	0	0
NGCC existing energy	7996	8049	5466
NGCC existing capacity	1148 ^a	1148 ^a	630
NGCC existing average load factor	80	80	99
NGCC new energy	0	0	0
NGCC new capacity	0	0	0
NGCC new average load factor	0	0	0
Total gas energy	8512	8274	6422
Total gas capacity	6714	3633	741
Nuclear existing energy	14,500	14,500	14,500
Nuclear existing capacity	1655 ^a	1655 ^a	1655 ^a
Nuclear existing average load factor	100	100	100
Nuclear new energy	0	30,808	59,431
Nuclear new capacity	0	3517	6785
Nuclear new average load factor	0	100	100
Total nuclear energy	14,500	45,307	73,930
Total nuclear capacity	1655	5172	8440
Total energy (GWh)	144,495	144,495	144,495
Total capacity (MW)	27,968	27,968	27,968
Expected total cost (million \$)	4070	5053	6111
Variance of cost (million \$)	450,645	244,118	136,502
S.D. of cost (million \$)	671	494	369
Risk adjusted cost	5422	6762	8295
Expected unit cost (\$/kWh)	0.02817	0.03497	0.04229
Unit S.D. of cost (\$/kWh)	0.00465	0.00342	0.00256

^a Denotes existing capacity that is fully utilized.

gas-fired capacity, coming primarily from idling of existing capacity and the elimination of new combustion turbine capacity. The shifts in generation shares are illustrated graphically in Fig. 3. The expected costs increase by about \$1 billion as risk aversion moves from 0.003 to 0.007 and again from 0.007 to 0.016. Risk adjusted costs increase even more – by about \$1.3 billion from 0.003 to 0.007 and by about \$1.5 billion from 0.007 to 0.016. On a per kWh basis, the expected cost of generation increases from \$0.028 to \$0.035 to \$0.042, while the standard deviation of cost decreases from \$0.0046 to \$0.0034 to \$0.0026.

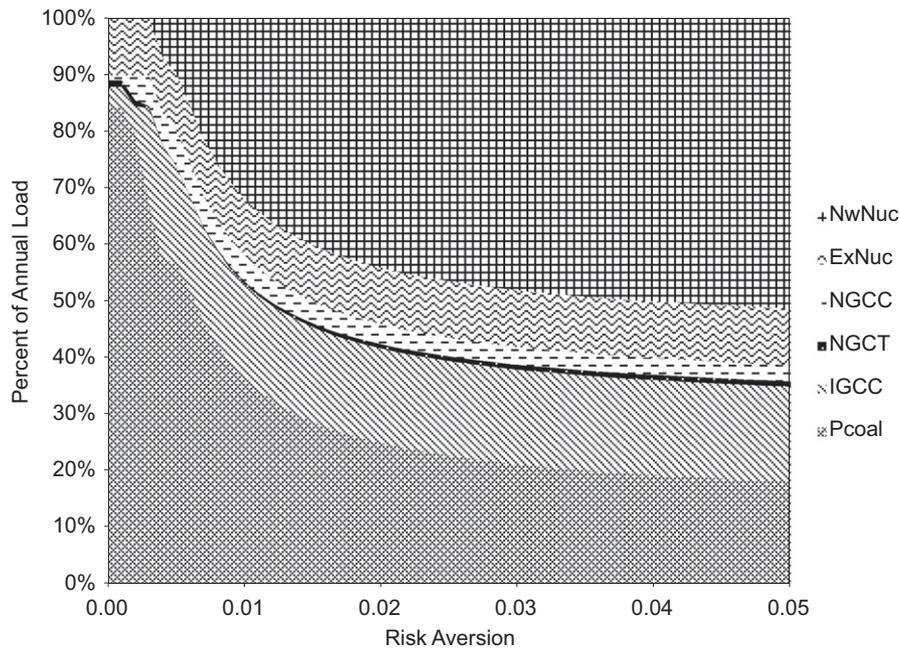


Fig. 3. Capacity shares as risk aversion increases.

6.2. Carbon dioxide emission costs

To simulate the impact of imposing carbon dioxide control legislation, we adjust the expected cost of generation fired by fossil fuel in proportion to emissions (see results in Table 5). With a carbon dioxide emission cost of \$45.37/ton,³ generation shifts away from fossil fuels dramatically. Energy from coal-fired plants drops by about 80%, oil-fired generation is eliminated, and natural gas-fired generation declines modestly, regardless of the level of risk aversion. To pick up the slack, nuclear capacity expands dramatically, adding new capacity equal to about six times existing capacity.

The total expected cost rises dramatically relative to the base case at the lower level of risk aversion, increasing by a factor of two. With carbon dioxide emission costs of the magnitude used for this scenario, the impact of increasing risk aversion across the range $\beta=0.003$ to $\beta=0.016$ on the generation is small. This is because in a world with significant carbon costs, there are limited effective options besides nuclear. (Renewables such as wind and conservation have not been included in this illustration. Given the challenges associated with dispatching intermittent generation, further work will be needed to incorporate wind in the model. While it would be relatively straightforward to incorporate price responsive demand for electricity that has not been done here because our primary focus is on illustrating the approach to incorporating detailed load data in the planning problem.) Because the generation portfolio is stable across the range of risk aversion levels considered, the expected costs and standard deviations of costs are also quite stable with expected costs in the range \$0.056–0.057 per kWh and the standard deviation of costs on the order of \$0.0025.

6.3. Nuclear moratorium

Given the importance of nuclear capacity additions in both the base case at high risk aversion and in the case with carbon dioxide

emission costs at all risk aversion levels, another scenario considered here focuses on determining the strategy when no new nuclear capacity can be built by 2025. In the base case with the low level of risk aversion, no new nuclear capacity is added. Thus if additions to nuclear capacity are disallowed, there is no change to that case. However as risk aversion increases, there are few attractive options for diversifying the fuel price risk. Thus, coal-fired generation decreases only modestly, while gas-fired generation increases by roughly an equal amount. Due to these modest shifts in generation, the level of expected cost increases only about 9% in going from $\beta=0.003$ to 0.007 or 11% from $\beta=0.007$ to 0.016. However, the reduction in fuel price variability is not near as much as it is in the base case, and hence the risk-adjusted costs are higher at the higher levels of risk aversion.

7. Conclusions

A practical mathematical programming model for the strategic fuel diversification problem was presented. The model considers the tradeoffs between expected costs of investment in capacity, operating and maintenance costs, average fuel costs, and the variability of fuel costs. In addition, the model incorporates the load curve at a high degree of resolution, while keeping the computational burden at a practical level. This type of analysis should serve as one input to regulatory commissions' decision-making process as they consider requests for approval of new generation capacity for inclusion in a utility's rate base. The formulation presented here removes one area of potential concern regarding the evaluation of the tradeoffs involved in fuel diversification. It allows direct incorporation of the load curve at an arbitrary level of refinement, thus removing concerns regarding whether a sufficient number of load classes has been used and whether the locations of the divisions between load classes are appropriate.

The model was illustrated with a case study for Indiana's power generation system. The model reveals that an effective means of reducing the volatility of the system-level fuel costs is through the reduction of dependence on coal-fired generation with an attendant shift towards nuclear generation. Model results

³ This is the 2025 cost of carbon dioxide emissions assumed in EIA (2009) for their Basic case.

Table 5
Results for carbon cost and no nuclear scenarios for three levels of risk aversion.

Risk aversion (β) Technology	Carbon cost \$45.37/ton			No new nuclear		
	0.003	0.007	0.016	0.003	0.007	0.016
Pcoal existing energy (GWh)	19,712	21,140	22,584	96,927	79,154	63,357
Pcoal existing capacity (MW)	13,416	13,434	13,426	16,429 ^a	16,429 ^a	16,429 ^a
Pcoal existing average load factor	17	18	19	67	55	44
Pcoal new energy	0	0	0	0	0	0
Pcoal new capacity	0	0	0	0	0	0
Pcoal new average load factor	0	0	0	0	0	0
IGCC existing energy	4927	4935	4955	5422	5422	5422
IGCC existing capacity	619 ^a	619 ^a	619 ^a	619 ^a	619 ^a	619 ^a
IGCC existing average load factor	91	91	91	100	100	100
IGCC new energy	0	0	0	19,132	34,180	48,709
IGCC new capacity	0	0	0	2184	3902	5560
IGCC new average load factor	0	0	0	100	100	100
Total coal energy	24,639	26,075	27,539	121,482	118,756	117,489
Total coal capacity	14,035	14,053	14,045	19,233	20,950	22,609
Oil existing energy	0	0	0	2	1	0
Oil existing capacity	0	0	0	366 ^a	284	0
Oil existing average load factor	0	0	0	0	0	0
Oil new energy	0	0	0	0	0	0
Oil new capacity	0	0	0	0	0	0
Oil new average load factor	0	0	0	0	0	0
Total oil energy	0	0	0	2	1	0
Total oil capacity	0	0	0	366	284	0
NGCT existing energy	0	0	421	176	1185	2799
NGCT existing capacity	0	0	56	3931	3931	2556
NGCT existing average load factor	0	0	87	1	3	13
NGCT new energy	0	0	0	340	0	0
NGCT new capacity	0	0	0	1636	0	0
NGCT new average load factor	0	0	0	2	0	0
NGCC existing energy	8216	6932	5436	7996	10,054	9707
NGCC existing capacity	1148 ^a	1148 ^a	1148 ^a	1148 ^a	1148 ^a	1148 ^a
NGCC existing average load factor	82	69	54	80	100	97
NGCC new energy	0	0	0	0	0	0
NGCC new capacity	0	0	0	0	0	0
NGCC new average load factor	0	0	0	0	0	0
Total gas energy	8216	6932	5857	8512	11,238	12,506
Total gas capacity	1148	1148	1203	6714	5078	3704
Nuclear existing energy	14,500	14,500	14,500	14,500	14,500	14,500
Nuclear existing capacity	1655 ^a	1655 ^a	1655 ^a	1655 ^a	1655 ^a	1655 ^a
Nuclear existing average load factor	100	100	100	100	100	100
Nuclear new energy	97,140	96,989	96,600	0	0	0
Nuclear new capacity	11,131	11,112	11,064	0	0	0
Nuclear new average load factor	100	100	100	0	0	0
Total nuclear energy	111,640	111,488	111,099	14,500	14,500	14,500
Total nuclear capacity	12,786	12,767	12,720	1655	1655	1655
Total energy (GWh)	144,495	144,495	144,495	144,495	144,495	144,495
Total capacity (MW)	27,968	27,968	27,968	27,968	27,968	27,968
Expected total cost (million \$)	8146	8160	8187	4070	4448	4940
Variance of cost (million \$)	133,778	131,324	128,941	450,645	356,225	306,276
S.D. of cost (million \$)	366	362	359	671	597	553
Risk adjusted cost	8548	9079	10,250	5422	6942	9840
Expected unit cost (\$/kWh)	0.05638	0.05647	0.05666	0.02817	0.03078	0.03419
Unit S.D. of cost (\$/kWh)	0.00253	0.00251	0.00249	0.00465	0.00413	0.00383

^a Denotes existing capacity that is fully utilized.

indicate that reductions in the standard deviation of the generation costs on the order of one quarter can be achieved with an increase in average fuel costs on the order of 20–25%. As pointed out by a reviewer, this is a fairly high cost to pay for reducing fuel price variability, suggesting that perhaps other mechanisms not included in the model such as using financial instruments and contracting to reduce fuel price volatility could play a useful role.

Scenarios incorporating costs for carbon dioxide emissions or a moratorium on nuclear capacity additions were also considered. The strategic response to carbon costs is to reduce fossil fuel-fired generation and rapidly ramp up nuclear generation capacity. The

strategic response to a moratorium on new nuclear capacity is to continue to operate the system with little change, recognizing that the opportunities for reducing the variability of fuel costs are greatly hampered by the moratorium.

The analysis of the Indiana case presented here focuses entirely on risks associated with fuel prices and is backward looking in terms of its view of the future prospects for price variability. Risks associated with uncertainties regarding capital costs or risks associated with catastrophic accidents are ignored as are the risks associated with policy uncertainties. The backward looking nature of the assessment of fuel price uncertainty

does not account for possible shifts in the distribution in the future due to discovery of new sources of supply such as shale gas. Another shortcoming of the Indiana case study is the lack of inclusion of emerging technologies for generation such as wind and solar power. Incorporating these technologies in the analysis will require modification of the approach due to their intermittent nature. Future extensions of this work will incorporate intermittent generation resources and include a more comprehensive assessment of the risks that need to be managed.

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