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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.

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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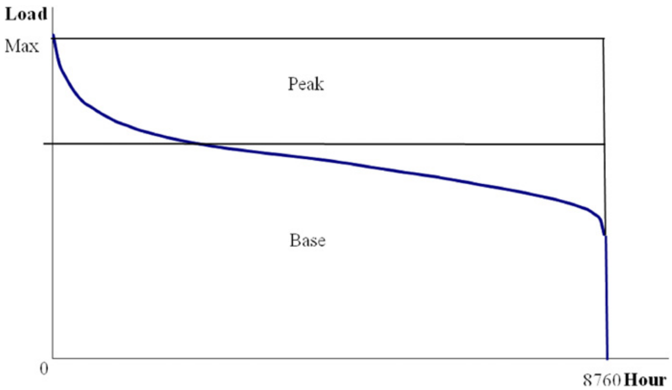

Fig. 1. Load duration curve.

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 $A=\{[a_0,a_1], [a_1,a_2], \ldots, [a_{N-1},a_N]\}$. 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 ith component of the vector indicates the energy production of the ith 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 ith component of the vector indicates the existing capacity of the ith 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 ith component corresponding to the fixed cost for the ith 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 ith component corresponding to the variable costs for the ith 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 $\boldsymbol{\Omega}$ 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

$$\underset{\substack{a_0,a_1,\ldots,a_N \\ x_{[a_0,a_1]},\ldots,x_{[a_{N-1},a_N]} \\ y_{[a_0,a_1]},\ldots,y_{[a_{N-1},a_N]}}}{\text{minimize}} \sum_{n=1}^{N} (x_{[a_{n-1},a_n]}+y_{[a_{n-1},a_n]})^t \Omega \Sigma_{n=1}^{N} (x_{[a_{n-1},a_n]}+y_{[a_{n-1},a_n]})$$