Efficient frontiers for electricity procurement by an LDC with multiple purchase options

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Abstract

In meeting its retail sales obligations, management of a local distribution company (LDC) must determine the extent to which it should rely on spot markets, forward contracts, and the increasingly popular long-term tolling agreements under which it pays a fee to reserve generator capacity. We address these issues by solving a mathematical programming model to derive the efficient frontier that summarizes the optimal tradeoffs available to the LDC between procurement risk and expected cost. To illustrate the approach, we estimate the expected procurement costs and associated variances that proxy for risk through a spot-price regression for the spot-purchase alternative and a variable-cost regression for the tolling-agreement alternative. The estimated regressions yield the estimates required to determine the efficient frontier. We develop several such frontiers under alternative assumptions as to the forward-contract price and the tolling agreement's capacity payment, and discuss the implications of our results for LDC management.

Keywords: Efficient frontier, Cross hedging; Forward contracts; Tolling agreements; Partial-adjustment model

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1. Introduction

A concomitant of deregulation and related market reforms in the electricity industry in the United States has been the emergence of wholesale electricity spot markets for which highly volatile prices that are at best amenable to imperfect forecasts are the norm. The price volatility and forecast imperfection have two principal sources: (1) the random demand surges that the buyers, notably local distribution companies (LDCs) that must procure electricity to meet customer demand in real time, have to deal with in the face of the generators' upward-sloping electricity supply curve; and (2) random capacity shortages due to unexpected generation or transmission outages that shift the supply curve upwards along a downward-sloping and inelastic electricity demand curve [1 – 3]. Analogous random changes in the price of natural gas, which is both an input into the electricity generation process as well as a competitive energy source, can further exacerbate the electricity spot-price volatility [4 – 5]. If unmitigated, such price volatility can financially ruin an LDC with its obligation to serve at regulated rates unresponsive to wholesale spot market prices. A dramatic case in point is the April 6, 2001 bankruptcy of Pacific Gas and Electric Company (PG&E), one of the largest LDCs in the United States [6 – 10]. Both state and federal governments now endorse the important role of risk management in the energy business [11 – 12].

Recent analyses of an LDC's management of electricity-procurement cost and risk have focused on two procurement alternatives: spot-market purchases and fixed-price forward-contract purchases [13 – 15]. The latter facilitate risk management and mitigate potential market-power abuses by generators, because they reduce an LDC's dependence on the spot markets [16]. LDC management, however, may be reluctant to enter into a long-term forward contract if the

LDC's regulator - and the industry remains subject to partial regulation - can engage in an after-the-fact prudence review that might result in full cost recovery being disallowed [9; 17].

To be sure, legislative actions can minimize the need for and use of after-the-fact prudence reviews. For example, California Assembly Bill (AB) 57 that became law on September 25 2002 directs "the Public Utilities Commission …. to review each electrical corporation's procurement plan in a manner that assures creation of a diversified procurement portfolio, assures just and reasonable electricity rates, provides certainty to the electrical corporation in order to enhance its financial stability and credit worthiness, and eliminates the need, with certain exceptions, for after-the-fact reasonableness reviews of an electrical corporation's prospective electricity procurement performed consistent with an approved procurement plan" (SECTION 1(c)).

On October 24, 2002, the California Public Utilities Commission (CPUC) issued Decision 02-10-062, which implements AB57. The Decision requires the three large utilities, PG&E, Southern California Edison (SCE) and San Diego Gas and Electric (SDGE), to submit procurement plans for the CPUC's approval. A critical element of such plans is the choice among alternative electricity-procurement options. That is, in meeting its down-the-road electricity requirements: To what extent should the LDC rely on spot markets? To what extent should it rely on forward contracts? And to what extent should it rely on the increasingly popular long-term tolling agreements under which the LDC pays a generator a fee to, in effect, reserve some of the generator's capacity?

We address these issues by first solving the mathematical programming model from which one derives the efficient frontier that summarizes the optimal tradeoffs available to LDC management between procurement risk and expected cost, when it can diversify its electricity purchases through electricity spot markets, fixed-price forward contracts, and tolling agreements. We then put empirical meat on these theoretical bones via an application in which we estimate expected procurement costs and the associated variances that proxy for risk. The estimation entails a spot-price regression for the spot-purchase alternative and a variable-cost regression for the tolling-agreement alternative. The estimated regressions yield the parameter estimates required to determine the efficient frontier. We develop several such frontiers under alternative assumptions as to the forward-contract price and the tolling agreement's capacity payment, and discuss the implications of our results for LDC management.

2. The efficient frontier

Consider an LDC that requires a flat power block of a given megawatt (MW) size to be delivered at 100%, 24 hours a day, seven days a week. The LDC has three procurement alternatives for buying the base-load power that will enable it to meet its resale obligation of serving its retail end-users:

(1) Spot-market purchases from a local hub, such as Mid-Columbia (Mid-C) in the state of Washington. Complete reliance on this alternative, however, exposes the LDC to the risk entailed in potentially volatile spot prices.

(2) A fixed-price forward contract offered by a generator such as Calpine or by a marketer/trader such as Morgan Stanley. The contract obligates the seller to physically deliver, and the LDC to accept, power at a fixed price. Relatively less risk verse than the buyer, the seller absorbs the spot-price risk and may charge the LDC a risk premium to ensure the forward contract's profitability [18 – 19].

(3) A tolling agreement offered by a generator. The agreement gives the LDC the right, but not the obligation, to dispatch a generation unit specified by the agreement. The LDC pays the

generator a fixed per kilowatt (kW) payment for having the capacity available at an agreed fuel conversion rate (i.e., the heat rate in British thermal units (Btu) per kilowatt-hour (kWh)). The LDC supplies the fuel used by the generator, typically natural gas, and absorbs the fuel price risk. Since a generation unit's non-fuel variable cost is negligible, the LDC's least-cost operating decision is to dispatch the leased capacity whenever the per megawatt hour (MWh) fuel cost is less than the electricity spot price in $/MWh. The payment per kW is therefore the call-option value of a one kW capacity with a specific heat rate [20 – 21]. The capacity payment is equivalent to a fixed MWh payment for each MWh obtained by the LDC, irrespective of whether that MWh comes from the generator or the spot market. Specifically, the capacity charge per MWh is the capacity payment per kW-month multiplied by 1,000 and divided by the number of hours (e.g., 744 for January) in the month. Least-cost dispatch decisions by the LDC always result in a variable cost per MWh that is lower and less volatile than the spot price, except under the highly unlikely scenario in which the spot price never exceeds the per MWh fuel cost of the tolling agreement.

Denote the average cost and variance per MWh of spot-market purchases by μ_1 and σ_1^2, respectively, with μ_2 and σ_2^2, and μ_3 and σ_3^2, denoting the average costs and variances for a tolling agreement and a fixed-price forward contract, respectively; σ_{ij} denotes the covariance between the purchase costs in the i^{th} option and those in the j^{th}. The average cost for the tolling agreement, $\mu_{2,}$ is the fixed capacity payment per MWh plus the average variable cost per MWh. Hence the associated cost variance, σ_2^2, is the variance of the variable cost per MWh. The latter is necessarily less than σ_1^2, because it is only computed for Min[spot price, per MWh fuel cost]. The forward contract's average cost, μ_3, is its fixed price and therefore the variance is $\sigma_3^2 = 0$. Inasmuch as $\sigma_1^2 > \sigma_2^2 > \sigma_3^2 = 0$, we expect and assume $\mu_1 < \mu_2 < \mu_3$; otherwise a risk-averse management would be inclined to either put all its eggs in the risk-free forward-contract basket when that option is available, or, failing that, reduce exposure to the risk of upward-spiraling spot-market prices via a tolling agreement for which $\mu_1 > \mu_2$.

And we do indeed assume the LDC management to be risk averse, as well as budget conscious in the sense of setting an upper bound on its *expected* procurement cost. Following Markowitz [22] and Woo *et al*. [14], management will seek to determine weights of $w_1 \geq 0$, $w_2 \geq 0$, and $w_3 \geq 0$, for the amount of electricity procured via the spot market, a tolling agreement, and a forward contract. The optimal weights will minimize the variance of its procurement portfolio, subject to its expected procurement-cost constraint. The non-negativity condition on the weights, which sum to unity, is applied to preclude short selling and the excessive risk taking that such implies. Further, since there is a fixed purchase quantity, minimizing the procurement-cost variance per MWh of a portfolio comprising the three electricity procurement alternatives is equivalent to minimizing the total procurement-cost variance.

Let $\mathbf{l} = [1, 1, 1]^{\mathrm{T}}$, $\mathbf{0} = [0, 0, 0]^{\mathrm{T}}$, $\boldsymbol{w}^{\mathrm{T}} = [w_1, w_2, w_3]$, and $\boldsymbol{\mu}^{\mathrm{T}} = [\mu_1, \mu_2, \mu_3]$, and denote by $\boldsymbol{\Omega}$ the positive-definite variance-covariance matrix for the three purchase alternatives. Then, the cost variance of the procurement portfolio is $\sigma^2 = \boldsymbol{w}^{\mathrm{T}}\boldsymbol{\Omega}\boldsymbol{w}$ and its expected cost is $\mu = \boldsymbol{w}^{\mathrm{T}}\boldsymbol{\mu}$, where $\boldsymbol{w}^{\mathrm{T}}\mathbf{l} = 1$. Suppose management places an upper bound of M on the expected procurement cost per MWH that it is willing to incur. Stated formally, management's optimization problem may be written:

$$\underset{\boldsymbol{w}}{\text{Minimize}}\ \sigma^2 = \boldsymbol{w}^{\mathrm{T}}\boldsymbol{\Omega}\boldsymbol{w}$$

Subject to:

$$\boldsymbol{w}^{\mathrm{T}}\boldsymbol{\mu} \leq M$$

$$\boldsymbol{w}^{\mathrm{T}}\mathbf{l} = 1$$

$$\boldsymbol{w} \geq \mathbf{0}.$$

Since $\boldsymbol{\Omega}$ is positive definite and the constraints are linear, the optimal solution to the problem, which can be solved by standard techniques, [22 -23], satisfies the Karoush-Kuhn-Tucker conditions. With $\lambda \geq 0$ a Lagrange multiplier, and $L = \sigma^2 + \lambda[\boldsymbol{w}^{\mathbf{T}}\boldsymbol{\mu} - M]$, an interior solution satisfies $\partial L/\partial \boldsymbol{w} = 0$ and $\boldsymbol{w}^{\mathbf{T}}\boldsymbol{\mu} = M$. It is easily shown that plotting the minimum procurement-cost variance σ^{*2} on the vertical axis and the binding cap of $M = \mu^*$, the expected procurement cost that is co-joined to that variance, on the horizontal axis, describes a downward sloping and strictly convex efficient frontier.

3. An application

3.1 The setting

To show the practicality of the efficient-frontier approach, we consider a hypothetical LDC housed in the Pacific Northwest. We assume that LDC management employs a procurement process that entails the following four steps [17]:

(1) Assess the purchase requirements that will meet the LDC's load obligation;

(2) Assess the procurement alternatives through which the LDC can meet the purchase requirements;

(3) Issue a request for proposal (RFP) to obtain competitive bids for alternatives that are not actively traded in wholesale markets;

(4) Evaluate the bids by considering the tradeoffs of the procurement-cost expectations and cost variances presented by the alternatives, including the default alternative of purchasing from the spot market.

Under this assumed process, management considers purchasing a flat power block for a five-year term. The point of delivery is Mid-C. While standard forward contracts are available in the Mid-C market, at present they are only offered for terms up to three years and are only for the on-peak hours (06:00-22:00, Monday – Saturday), rather than (7x24) delivery. Hence, the LDC follows steps (2) and (3) by issuing an RFP to potential suppliers to submit competitive bids for forward contracts and tolling agreements.

The bid submission can be a sealed-bid auction or an internet-based auction [24]. A forward-contract bid should contain a single fixed-price quote. A tolling-agreement bid should contain a single quote for the capacity payment per kW-month, and state the generation unit's heat rate.

Management then implements step (4), bid evaluation, which requires knowledge of the available optimal tradeoffs between the procurement-cost expectation and the procurement-cost variance presented by the bids, and the default alternative of buying from the spot market. This knowledge is best summarized in an efficient frontier. The LDC management's risk preferences, or the tradeoffs they are willing to accept between, in effect, risk and return, would then determine the optimal point on the frontier [14].

3.2 The spot-price equation and cross hedging

To derive the expected procurement cost and the variance of the spot-purchase alternative, we focus on two specific markets: the spot market for electricity at Mid-C and that for natural gas at Henry Hub, which is the most active spot and futures market in North America. As shown in [15, 18 - 19], LDC management can avail itself of the option to cross hedge between these two markets. This option is available for four principal reasons.

First, as a basic input in electricity generation, the natural-gas price helps to drive electricity prices [4, 25]. Second, local natural-gas spot markets, such as Sumas in the Pacific Northwest, are integrated with Henry Hub [5, 10, 25 - 28]. Third, Henry Hub natural-gas futures contracts currently traded on the New York Mercantile Exchange (NYMEX) are for delivery in the next 72 months, which is a sufficiently long time period to permit cross hedging the five-year price/cost risk. Finally, the NYMEX natural-gas futures market is efficient [29].

Suppose, then, that P_t is the Mid-C electricity spot price on some future day t for which we want to determine the expected procurement cost and that P_{Gt} is the currently unknown Henry Hub natural-gas spot price on that day. Since natural-gas prices help drive electricity prices, we hypothesize that there is a systematic linear relationship, $P_t = \alpha + \beta P_{\mathrm{G}t}$, between these two prices, and that the spot price is also impacted by a normally-distributed random error of ε_t that has a zero mean and finite variance of $\nu^2 > 0$; or:

$$P_t = \alpha + \beta P_{\mathrm{G}t} + \varepsilon_t. \tag{1}$$

Thus, from management's current perspective P_t is random and volatile because both $P_{\mathrm{G}t}$ *and* ε_t are random and potentially volatile.

Cross hedging against the volatility of P_t begins with the current purchase of β MMBtu of natural-gas futures at a price of P_{GF} =\$*F*/MMBtu for each MWh delivered at Mid-C. Then, on future day t, the LDC resells the natural gas bought at P_{GF} at the Henry Hub natural-gas spot price $P_{\mathrm{G}t}$. The *net* spot price for Mid-C electricity, after allowing for the machinations in the natural-gas market and substituting equation (7) for P_t, is therefore:

$$P_{nt} = P_t - \beta(P_{\mathrm{G}t} - P_{\mathrm{GF}}) = \alpha + \beta P_{\mathrm{G}t} + \varepsilon_t - \beta P_{\mathrm{G}t} + \beta P_{\mathrm{GF}} = \alpha + \beta P_{\mathrm{GF}} + \varepsilon_t. \tag{2}$$

The future net spot price, P_{nt}, is thus a function of the known price of P_{GF}. Once values have been determined for α and β, the only uncertainty that remains for management as a result of having cross-hedged is introduced by the random error. Hence, the variance of $\nu^2 > 0$ is the minimum variance that cannot be eliminated by cross hedging. This represents the undiversifiable price risk, while β is the minimum-variance hedge ratio [30].

The preceding analysis implies that when evaluating the spot-market alternative for procuring electricity, it is necessary to incorporate the risk-reducing cross-hedging option and to compute expected procurement costs on the basis of the *net* spot price, rather than on the spot price. Thus, rather than being concerned with the determination of the expected spot price and the spot-price variance, our interest will be in determining the expected net spot price and its necessarily smaller variance.

3.3 Partial adjustment

When the Mid-C market is in equilibrium, the average *equilibrium* price on day t, P_{te}, will equal the spot price. Hence P_{te} will also necessarily satisfy spot-price equation (1); or:

$$P_{te} = \alpha + \beta P_{\mathrm{G}t} + \varepsilon_t. \tag{3}$$

Any Mid-C market equilibrium on day t might therefore be disturbed by both the random changes that occur in the Henry Hub natural-gas market and through the noise factor. The daily and unobservable market equilibrium price may not, however, adjust instantaneously to those random shocks. To capture this possibility, we postulate the observed spot-market price adjustment to be a fraction, γ, of the unobservable required adjustment [31, Chapter 11]. That is:

$$P_t - P_{t\text{-}1} = \gamma(P_{te} - P_{t\text{-}1}). \tag{4}$$

Substituting P_{te} from equation (3) into equation (4) and rearranging terms yields:

$$P_t = \gamma\alpha + \gamma\beta P_{\mathrm{G}t} + (1 - \gamma)P_{t\text{-}1} + \gamma\varepsilon_t. \tag{5}$$

The latter may be more compactly written as:

$$P_t = \theta + \varphi P_{\mathrm{G}t} + \phi P_{t\text{-}1} + \eta_t. \tag{5a}$$

Thus, $\theta = \gamma\alpha$, $\varphi = \gamma\beta$, $\phi = (1 - \gamma)$ and $\eta_t = \gamma\varepsilon_t$.

Using daily data for the Mid-C electricity spot price and the Henry Hub natural-gas spot price, we apply the maximum likelihood (ML) method to estimate equation (5a). The use of ML avoids the potential bias caused by the lagged dependent variable as an explanatory variable in a regression that may have first-order autoregressive (AR(1)) errors. Our choice of estimation method is partly based on our analysis of natural-gas prices [5], which as shown by equation (3) are postulated to impact electricity spot prices and hence the variable costs of the tolling agreement. Whether our chosen estimation method is appropriate is ultimately an empirical issue. Absent AR(1) errors, ordinary least squares (OLS) estimation will yield consistent and asymptotically normal estimates. Should the errors turn out to have a higher AR order, one should use the ML method that would account for such errors. As will be seen in Table 2 below, our chosen estimation method is appropriate. The estimation will yield:

- (q, g, f), the estimates for coefficients (θ, φ, ϕ)
- r, the estimate for the AR(1) parameter;
- the covariance matrix for the coefficient estimates; and
- the mean-squared-error (MSE) of the daily price regression.

We can then infer, say, a and b, the estimates for α and β, from $a = q/(1-f)$ and $b = g/(1-f)$.

3.4 The expected net spot price and its variance

Assuming that no major structural change occurs during the forecast period that might invalidate our regression results, these results, rather than computer simulation as in [21, 32], can be used as the basis for computing the expected net spot price and its variance. The approach thus relies solely on market data and does consider the technical details (e.g., generation plants and transmission capabilities) that may underlie those data. So long as there are historic spot-price data for electricity and natural gas for local delivery at the LDC's service territory, along with natural-gas futures covering the LDC's procurement horizon, and such data are indeed always available in North America, our approach will yield the inputs required for developing the efficient frontiers. Therefore it is a practical and easy-to-implement alternative to the more exotic formulae proffered elsewhere, for example [21, 33 - 34], whose complicated natures are likely to deter application by an LDC's staff, frustrate review by its management, and subsequently invite a regulator's disapproval.

The simplest tack for management to take at this point would be to accept a and b as the actual values of α and β rather than merely their ML point estimates. To capture the uncertainty about the still unknown α and β when computing the expected net spot price and its variance, however, which will be accomplished through equation (2), suppose management adopts an empirical Bayes approach [35 – 36]. The approach has survived the test of time [37 - 39], both because it permits a very useful probabilistic interpretation of sample results in the subjective Bayesian context, and because it becomes especially useful when "data are generated by repeated execution of the same type of random experiment" [39, p. 1].

In particular, we rely on a "somewhat broader interpretation of the term 'empirical Bayes' than is implied in the typical EB sampling scheme", wherein the "parameter ω of a prior distribution … is replaced by any estimate derived from observed data…" [39, p. 14]. In the present context, LDC management uses the estimated regression results from equation (5a) as the basis for formulating a set of probability judgments about α and β of spot-price equation (1). In particular, management behaves "as if" the computed standard error of estimate from equation (5a) permits the derivation of ν^2. It also formulates probability judgments about α and β that are summarized in normal distributions with means of a and b, and assigned variances of s_a^2 and s_b^2. The covariance between α and β is set at s_{ab}. The two variances and the covariance are linear approximations derived from the estimated standard errors and covariance that are computed when equation (5a) is estimated. The approximations use a well-known formula [40, p. 181] for the mean and variance of $Z = g(X, Y)$, where X and Y are random variables. We remark, *en passant*, that we could have used a Bayesian approach in the initial specification of equation (1) and then incorporated equation (4), which is not a statistical statement, but we elected not to do so as we felt it might be a distraction at that point from the general development of the model in a more traditional mode.

Denote by $P_{\mathrm{GF}k}$ the fixed current Henry Hub natural-gas futures price for month k that encompasses day t and denote by E the expectation operator. The Mid-C electricity net spot price on day t in that month will be determined by equation (2). Hence the *expected* net spot price will be given by:

$$\mathrm{E}[P_{nkt}] = \mathrm{E}[\alpha] + \mathrm{E}[\beta]\mathrm{E}[P_{\mathrm{G}kt}] + \mathrm{E}[\varepsilon_{kt}]. \tag{6}$$

Since $\mathrm{E}[\varepsilon_{kt}] = 0$, we have

$$\mathrm{E}[P_{nkt}] = a + bP_{\mathrm{GF}k}. \tag{6a}$$

The variance of P_{nkt} is

$$\mathrm{V}[P_{nkt}] = s_a^{\,2} + (P_{\mathrm{GF}k})^2 s_b^{\,2} + 2P_{\mathrm{GF}k}s_{ab} + s_e^{\,2} \tag{6b}$$

where $s_e^{\,2}$ = estimate of the variance of ε_{kt} = daily price regression errors' unconditional variance divided by $(1\text{-}f)^2$.

Although the *average* net spot price computed for any day t, P_{Akt}, will almost certainly differ from one day to the next, the *expected* net spot price is fixed at $\mathrm{E}[P_{nk}] = \mathrm{E}[P_{nkt}]$ for month k. The variance of the daily net spot price is also independent of t and may be written $\mathrm{V}[P_{nk}] = \mathrm{V}[P_{nkt}]$. The (expected) variance of the daily average net spot price for any month k in which there are N_k days is $\mathrm{V}[P_{Akt}] = \mathrm{V}[P_{nk}]/N_k$. Normally distributed under the Central Limit Theorem, the average net spot price is a good estimate of the mean spot price in the forecast period, and $\{\mathrm{V}[P_{Akt}]\}^{0.5}$ is a good estimate of the standard error of the mean.

It immediately follows that the expected net spot price for a period of K months is:

$$\mu_1 = \Sigma_K \mathrm{E}[P_{nk}]/K. \tag{7a}$$

The variance of the monthly average net spot prices over the same period is:

$$\sigma_1^2 = \Sigma_K \mathrm{V}[P_{Akt}]/K^2. \tag{7b}$$

Equations (7a) and (7b) account for the time value of money because cross-hedging using NYMEX natural gas futures requires paying the futures prices quoted in today's dollars, implying that the expected net spot prices and their variances are also in today's dollars. The expected net spot price and the associated variance yielded by these equations are forecast values developed using the information embodied in the NYMEX natural-gas-futures price data. We do not use the average spot price and variance from a historic sample, because the resulting forecasts assume that the historic price data will repeat themselves in the forecast period. As will be seen in Tables 1 and 3 below, the historic average spot price for a 26-month sample period from July 2001 through August 2003 is \$29.45/MWh, which is \$8.07/MWh less than the forecast price of \$37.52 for the five-year period of November 2003 through October 2008.

The preceding computational steps equally apply to a tolling agreement's cost expectation and variance. Estimating equation (5a), however, requires data for the variable cost per MWh of the agreement, which is described in the next section. The expected cost per MWh is μ_2, the sum of the capacity payment and the expected variable cost per MWh. The computation of the cost variance σ_2^2 follows that of σ_1^2.

Having estimated the net spot-price expectation and variance (μ_1, σ_1^2) and the tolling agreement's cost per MWh expectation and variance (μ_2, σ_2^2), the covariance between the net spot price and the tolling agreement's variable cost per MWh is found from $\sigma_{12} = \rho\sigma_1\sigma_2$, with the correlation coefficient ρ estimated using the same data from the regression analysis. The last piece of data required to develop the efficient frontier is μ_3, the forward contract's fixed price, which becomes available at the conclusion of bid submission in the LDC's RFP process.

4. The data

The sample for our regression analysis contains daily observations on Mid-C on-peak (06:00-22:00, Monday-Saturday) prices, Mid-C off-peak (hours outside the on-peak period) prices, the Sumas (a major delivery point in Pacific Northwest) natural-gas price, and the Henry Hub natural-gas price. The sample period is July 2, 2001 to September 09, 2003. This period was chosen to avoid the electricity and natural-gas price anomalies during the California energy crisis of May 2000 through June 2001 [2-10, 16, 41]. The Mid-C location is chosen because its spot price fluctuates and often falls below the per MWh fuel cost of a relatively new generation unit with a heat rate at or below 8,000 Btu/kWh.

The daily Mid-C price is the weighted average of the on-peak and off-peak prices. Since the on-peak period has 16 hours, the on-peak weight is 2/3 and the off-peak weight is 1/3, for Monday through Saturday. All of Sunday is off-peak.

At an assumed heat rate of 8,000 Btu/kWh, the tolling agreement's daily variable cost per MWh is computed as follows. Based on the historic Mid-C electricity price data and Sumas natural-gas spot-price data, we construct the variable cost per MWh by time-of-day (TOD) period (on-peak vs. off-peak) as Min[electricity spot price by TOD period, fuel cost = heat rate x Sumas natural-gas spot price]. The daily per MWh variable cost is the weighted average of the daily on-peak and off-peak variable costs per MWh.

Table 1 reports the summary statistics of the four daily data series and the Augmented Dickey-Fuller (ADF) statistics for testing whether a series follows a random walk wherein the estimated regression results may be subject to spurious interpretation [42, pp. 465-467]. The summary statistics show that the series are moderately volatile with standard deviations about 40% as large as their means. The mean Mid-C spot electricity price is \$29.45/MWh, which is \$5.45/MWh higher than the \$24.01/MWh variable cost of the tolling agreement. The electricity price is also more volatile with a standard deviation of \$13.6/MWh, which is higher than the \$10.63/MWh standard deviation of the variable cost per MWh. The tolling agreement has a lower mean cost and a smaller standard deviation than does the spot-market alternative because during the sample period, the on-peak Mid-C price was higher than the per MWh fuel cost 68% of the time, and the off-peak Mid-C price 51% of the time.

The mean Henry Hub gas price is \$3.94/MMBtu, which is about \$0.70/MMBtu higher than the \$3.25/MMBtu mean Sumas price for natural gas. Absent economic dispatch, the variable cost per MWh for a tolling agreement based on the mean Sumas natural-gas price would have been \$26.0/MWh. Except for the Sumas natural-gas price series, the ADF statistics reject the null hypothesis that a daily data series follows a random walk, implying that our estimated Mid-C net-spot-price price and tolling-agreement regressions will not be susceptible to spurious interpretation.

The Mid-C price is highly correlated (R = 0.8) with the variable cost per MWh. It is moderately correlated ($R \approx 0.6$) with the two natural-gas prices. The variable cost per MWh is highly correlated with Henry Hub (R = 0.84) and Sumas (R = 0.93) natural-gas prices.

5. Results

5.1 Regressions

Table 2 presents the daily net spot price and variable cost per MWh estimated regression coefficients. To allow for seasonal effects, the estimated regressions include dummy variables to delineate the months of April, May, and June. The estimates give rise to the following observations:

- Both regressions have a good fit. The Mid-C price regression explains 92% of the price variance, and the per MWh variable-cost regression 96%.
- The Henry Hub price is a statistically significant driver of the Mid-C price and the variable cost per MWh. At a Mid-C spot-price equilibrium characterized by equations (3) - (5), each \$1/MMBtu increase in the Henry Hub natural-gas price would raise the Mid-C spot price by the estimated value of the minimum-variance ratio (β in equation (1)) of \$7.8/MWh (= 1.280/(1 - 0.836)). The same \$1/MMBtu increase would raise the equilibrium variable cost per MWh by \$6.58/MWh (= 1.250/(1 - 0.810)), which is less than the \$8/MWh increase *sans* the LDC's economic dispatch of the generation unit in the tolling agreement.
- The positive difference between the two β estimates suggests a long-position in NYMEX gas futures that is (7.8 MMBtu – 6.58 MMBtu) = 1.22 MMBtu per MWh larger under the spot-purchase alternative than the tolling-agreement alternative.
- The highly significant lagged dependent variables support using a partial-adjustment model to explain the daily variations in the Mid-C spot electricity price and the tolling agreement's variable cost per MWh. The estimated coefficient for the lagged Mid-C price is 0.836, implying that it takes six days (= 1/(1 - 0.836)) for the Mid-C price to regain equilibrium after being perturbed by a random shock or a Henry Hub natural-gas price change. The estimated coefficient for the lagged tolling cost per MWh is 0.810, implying that it takes five days (= 1/(1 - 0.810)) for the tolling cost to regain equilibrium after being perturbed by a random shock or a Henry Hub natural-gas price change.

- The Mid-C spot-price regression's errors are not serially correlated, but the per MWh variable-cost regression's errors are mildly so. Since the Mid-C spot-price regression's coefficient estimates in Table 2 are virtually identical to those obtained by OLS, the latter are not reported here. As a final check, we tested for higher-order AR errors and cannot reject the null hypothesis that such are not present for both equations.
- The Mid-C net-spot-price regression has a MSE of \$14.5/MWh, which is almost three times the MSE of \$4.58 for the variable cost per MWh regression, thus confirming that the spot-market-purchase alternative has a much higher undiversifiable risk than the tolling agreement.
- The ADF statistics reject the hypothesis that the regression residuals follow a random walk, so that neither estimated regression is susceptible to spurious interpretation.

5.2 Expectation and variance statistics

Table 3 presents the expectations and variances of the five-year averages of the daily electricity spot prices and per MWh variable costs of a tolling agreement with an assumed heat rate of 8000 Btu/kWh. These statistics are computed using equations (6) – (7b), the regression results in Table 2, and the NYMEX natural gas futures prices settled on October 15, 2003. The covariance estimate is the product of (a) the standard deviation of the five-year average spot-price expectation, (b) the standard deviation of the tolling agreement's five-year average per MWh cost expectation, and (c) the 0.80 correlation coefficient reported in Table 1.

The average net spot-price expectation in Table 3 is μ_1 = \$37.52/MWh and the associated variance is σ_1^2 = \$0.724/MWh. The seemingly small variance is reasonable, because it is the variance of an average of daily net spot prices over a five-year period in which low-price days offset high-price days.

The \$37.52/MWh price expectation translates into a large cost expectation of buying 1-MW spot electricity (enough to serve about 1,000 households), 24 hours a day, 7 days a week, during the five-year procurement horizon. This cost expectation is (1 MW x 24 hours/day x 365 days/year x 5 years x \$37.52/MWh =) \$1.643 million. Its associated cost variance is (1 MW x 24 hours/day x 365 days/year x 5 years)^2 x \$0.724/MWh =) \$1,389 million. Hence, the cost exposure under normally expected circumstances is (\$1.643 million + 1.65 x (1389 million)$^{1/2}$ =) \$1.705 million.

The average per MWh variable-cost expectation of the tolling agreement is \$33.96/MWh, which is \$3.56/MWh less than μ_1. If the tolling agreement's per MWh capacity payment is \$5/MWh, the cost of the tolling agreement per MWh is μ_2 = \$5/MWh + \$33.96/MWh = \$38.96/MWh. The variance of the tolling agreement per MWh is σ_2^2 = \$0.303/MWh, which is \$0.421/MWh less than σ_1^2.

Finally, \$0.391/MWh is the estimate of the covariance between the average net spot price and the tolling agreement's per MWh cost.

5.3 The efficient frontiers

Since we do not have actual bid data collected from an LDC's RFP process, we derive three efficient frontiers based on the hypothetical values in Table 4. The forward-contract price in Table 4 has three possible values. The first value is the base-case price of $\mu_3 = (\mu_1 + 1.65\sigma_1)$ = 37.52/MWh + 1.65 x \$0.851/MWh = \$38.92/MWh. The base-case price contains a (1.40/37.52) = 3.7% risk premium. This risk premium is consistent with a 0.95 probability that the seller of the forward contract will earn a profit on that contract [18 - 19]. To demonstrate how the shape of the frontier varies with the forward-contract price, the next two values are set at 110% and 120% of the \$38.92/MWh price, respectively.

The tolling agreement's capacity payment in Table 4 has three hypothetical values. The first value is a base-case charge based on π = \$3.56/MWh, the expected difference between the expected net spot price and the tolling agreement's expected per MWh variable cost. Hence, π is the expected per MWh profit of the tolling agreement's output sold into the Mid-C spot electricity market. The variance of π is $\sigma_\pi^2 = (\sigma_1^2 - 2\ \rho\sigma_1\sigma_2 + \sigma_1^2)$ = \$0.724/MWh – 2 x \$0.374/MWh + \$0.303/MWh = \$0.279/MWh. Hence, a capacity payment of $(\pi + 1.65\sigma_\pi)$ = \$3.56/MWh + 1.65 x \$0.528/MWh = \$4.43/MWh would allow the seller a profit with a probability of 0.95 when compared to the alternative of a spot-market sale. The resulting per MWh cost is μ_2 = \$33.96/MWh + \$4.43/MWh = \$38.39/MWh, which is slightly less than the first forward-contract price of \$38.92/MWh. in Table 4. To demonstrate how the frontier's shape may vary with the capacity charge, the next two values are set at 110% and 120% of the \$4.43/MWh charge, respectively.

Figure 1 portrays the three efficient frontiers drawn under the three different assumed forward prices and capacity charges of Table 4. The three frontiers share a common point at which all electricity is procured through the spot market and regardless of the forward price and capacity payment management places an upper limit of M = \$37.52 on the per MWh expected procurement cost that it is willing to incur. Total reliance on the spot market implies a maximum risk, as reflected through the cost variance, of $\sigma^{*2} = \sigma_1^2 = 0.724$, and a minimum expected cost of $\mu^* = \mu_1 = 37.52$. By increasing the upper limit on the expected procurement cost management can take advantage of electricity forwards and the tolling agreement to reduce the variance. Indeed, the variance can be virtually eliminated through forward contracts. Regardless of the forward price and the capacity payment, however, even when varying optimal mix among the purchase alternatives in optimal fashion additional reductions in the variance become increasingly costly. That is, the efficient frontiers are downward sloping and strictly convex. In each case, however, the particular frontier shows both the minimum variance with which LDC management must live at any given upper bound in the expected procurement cost, and alternatively the minimum expected procurement cost that management must be prepared to accept for a portfolio of options that entails a given level or risk, or variance.

The frontier closest to the vertical axis corresponds to the base-case values for the forward price and the capacity payment. This first frontier is relatively steep because the relatively low forward price of $38.92 and capacity payment of $4.43 permits a large reduction in the portfolio's cost variance through forward contracting and a tolling agreement, without substantially raising the cost expectation, or the binding cap.

Immediately to the right of the base-case frontier is the one that is constructed with a forward price and a capacity charge equal to 110% of the base-case values. This frontier is flatter than the base-case frontier because the higher forward price and capacity charge implies that to achieve the same variance reductions as those achieved with the base-case price and charge requires larger expected procurement costs than in the base case. This is so, since variance reductions can only be brought about by reduced reliance on the spot market.

The third and last frontier is constructed with a forward price and a capacity charge equal to 120% of the base-case values. Although still convex, this frontier is the flattest among the three frontiers. The flatness reflects the fact that reducing the portfolio's cost variance by a given amount has become more expensive than in the previous case.

Taken as a whole, the frontiers of Figure 1 affirm the intuition that at relatively low forward prices and capacity charges, it is not very costly to reduce the risk of a procurement portfolio. This affirmation would support management's selection of a portfolio containing relatively less spot purchase. But as forward prices and capacity charges rise, a binding budget constraint will cause management to choose a portfolio with relatively more spot purchases.

6. Conclusions

Efficient frontiers have had steady employment as visually appealing and analytically useful decision-making aids in a variety of multi-objective settings in which management has to evaluate and choose among alternatives for which there are tradeoffs among those objectives. Those settings extend well beyond mean-variance financial portfolio analysis [22] to hospitals [43-44], mutual fund performance appraisal [45], managerial performance assessment [46], regional development [47], marketing [48], and production [49].

Management of an LDC that must procure electricity to meet customer demand in real time must also evaluate and choose among alternatives for which there are tradeoffs, in this case between expected procurement cost and risk. In this novel setting, too, the efficient frontier is a visually appealing and analytically useful decision-making aid. Developing the frontier, however, is a rather complex proposition that involves determining the optimal blend of three sources of electricity: the spot market, electricity forward contracts, and tolling agreements with generators. Optimality in this context implies the blend that provides the minimum variance for a given expected procurement cost. The frontier then traces out the tradeoffs that are available to management between cost and risk. Those tradeoffs depend upon the price of electricity forwards and the capacity payment in the tolling agreement.

Estimating the parameters that are required for assessing the expected costs and variances is also a rather complex proposition. The complexities notwithstanding, this paper has shown how to both estimate the parameters and develop the frontier, and how management can determine its most preferred alternative on that frontier, given the tradeoffs that it is willing to accept between cost and risk. Moreover, the paper has also shown that all of this is eminently doable and immediately applicable. Thus, while one can hope that neither California nor any other region will ever again confront an energy crisis of the sort that plagued the state and punished end-users and LDCs alike from May 2000 to June 2001, it is our further hope that by implementing the efficient-frontier approach management will not only be dealing with short-term and unavoidable spot-price volatility in a prudent fashion, but will also be mitigating the impact of any future crisis on both the company and its customers.

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Table 1. Summary statistics, augmented Dickey-Fuller (ADF) statistics and pair-wise correlation coefficients for daily Mid-C spot electricity prices, daily per MWh variable cost of a tolling agreement with an 8,000 Btu/kWh heat rate, and daily Henry Hub spot natural-gas prices for the period of 07/02/01 – 09/02/03.

Statistic	Mid-C spot electricity price ($/MWh)	Per MWh variable cost ($/MWh)	Henry Hub spot gas price ($/MMBtu)	Sumas spot gas price ($/MMBtu)
Mean	29.45	24.01	3.94	3.25
Standard deviation	13.60	10.63	1.52	1.33
ADF statistic	-4.87*	-3.13*	-4.15*	-2.47
Correlation coefficient:				
Mid-C price	1.0	0.80	0.59	0.67
Per MWh variable cost	0.80	1.0	0.84	0.93
Henry Hub gas price	0.59	0.84	1.0	0.94
Sumas gas price	0.67	0.93	0.94	1.0

Note: "*" = "Significant at the 5% level"

Table 2. Maximum likelihood estimation of equation (5a): daily price and per MWh variable cost regressions with lagged dependent variable and first-order auto-regressive (AR(1)) errors for the sample period of 07/02/01-09/02/03. Values in ( ) are t-statistics.

Explanatory variables and regression statistics	Dependent variable	
	Mid-C electricity price ($/MWh)	Tolling agreement's per MWh variable cost at 8,000 Btu/kWh heat rate
Intercept	0.021 (0.05)	-0.047 (-0.177)
Henry Hub price ($/MMBtu)	1.280 (9.68)*	1.250 (9.68)*
= 1, if April; 0, otherwise	-1.373 (-2.53)*	-0.631 (-1.74)
= 1, if May; 0, otherwise	-2.194 (-3.92)*	-1.549 (-4.16)*
= 1, if June; 0, otherwise	-2.424 (-4.20)*	-1.965 (-4.87)*
Lagged dependent variable	0.836 (52.2)*	0.810 (42.2)*
AR(1) parameter	0.008 (0.04)	0.184 (4.72)*
Total R-squared	0.92	0.96
Mean squared error	14.50	4.58
ADF statistic for testing H_0: Regression residuals follow a random walk	-19.0*	-19.1*

Note: "*" = "Significant at the 5% level"

Table 3: Expectation and variance of five-year (Nov/03 – Oct/08) averages of daily spot electricity prices and daily per MWh variable costs paid under a tolling agreement with an assumed heat rate of 8000 Btu/kWh. The computation is based on equations (12) – (13b), Table 3, and NYMEX natural-gas futures prices settled on October 15, 2003.

Statistic	Spot electricity price ($/MWh)	Per MWh variable cost ($/MWh)
Expectation	37.52	33.96
Variance	0.724	0.303
Standard deviation	0.851	0.550
Correlation coefficient	0.8 (from Table 2)	
Covariance	0.374	

Table 4: Assumed values for a 5-year forward contract's price and a tolling agreement's capacity payment.

Assumption	Forward price ($/MWh)	Capacity payment ($/MWh)
Base-case prices to effect profitability with 95% probability	38.92	4.43
110% of the base-case prices	42.81	4.87
120% of the base-case prices	46.70	5.32

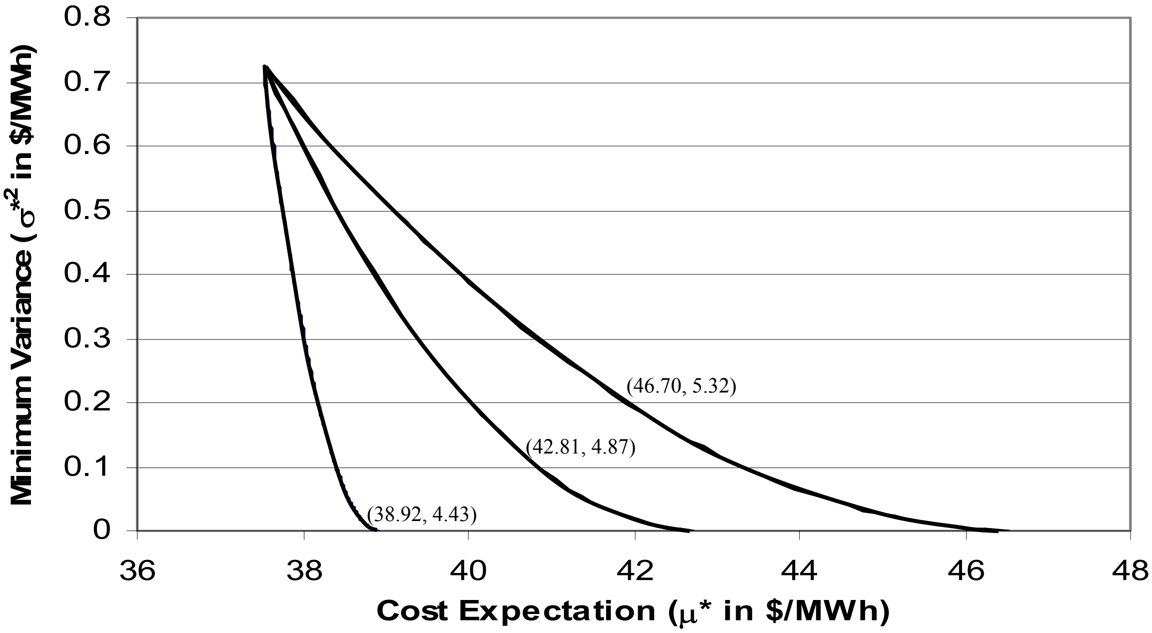

Figure 1: Efficient frontiers by forward price and capacity charge in parenthesis.