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Forecasting Long-Run Electricity Prices

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Introduction

With the structural changes in the power industry over the past 10 years, the market price of electricity has become the key determinant of resource value. In the past, resources were evaluated based on the cost to serve a specific load. Today, most resources can be viewed as competing against the (wholesale) market, and thus should be evaluated based on the market price.

Given this situation, long-run (twenty to thirty year) electricity price forecasting is not an academic exercise. These forecasts are absolutely central to many key decisions at power companies and to their success. Decisions must be made regarding assets that may be operated for 50 years; regulators require resource plans that extend 20 to 30 years; and many electricity and fuel contracts last 20 years or more.

Not only is price forecasting increasing in importance, but decision makers increasingly realize that common "single-path," most-likely estimates are inadequate. Single-path estimates, even when unbiased, provide no information on risk exposure. Furthermore, they provide no help evaluating resources that can be adapted, through operational changes and investments, to changes in prices, costs, and other factors. Risk and optionality can only be fully examined with a thorough, quantified picture of future uncertainty.

Current and recent industry experience is replete with examples illustrating the importance of long-run electricity price forecasting, and the problems created with simplistic and/or inaccurate forecasts. In 2001, the State of California signed over $40 billion in long-run electric contracts.[i] These contracts are now considered so expensive, there is considerable effort being devoted to cost allocation, renegotiation, and litigation. Throughout the country, plans to build new capacity have been shelved as prices have not risen as expected. In Texas, 32 power projects totaling 17,801 MW have been delayed or canceled since 2001[ii]. In Mississippi, the 822 MW Choctaw County combined-cycle plant was commissioned in July 2003 and mothballed in May 2004 because of low wholesale market prices[iii].

The bottom line is that a good long-run probabilistic forecast of electricity prices is required to understand the potential value and risks of many investments. What do we mean by a "good" long-run electric price forecast?

- Accuracy. This is a self-evident criterion, but it is more complex than generally recognized. Decision makers prefer that a point estimate or the expected value of a distribution be closer to what actually occurs rather than farther away. Decision makers prefer narrow bands of uncertainty to wider bands of uncertainty. However, accuracy has other important dimensions. It is important that forecasts be *unbiased*. The median or middle forecast should be over and under the true value in equal proportions. It is important that forecasts be well *calibrated*. By calibration, we mean that the probability distribution on future electric prices should accurately reflect the true level of uncertainty. Or, simply stated, the variance of the future price should be accurate. This is essential for valuing either financial options or "real" options in the management of a resource.
- Usefulness. Decision makers like forecasts that can be used for the widest possible range of decisions – both current and future decisions, and both investment and operations decisions. For options analyses, decision makers need forecasts that include an estimate of how uncertainty changes as time passes. Decision makers also need more than just a number; they need to identify and understand the price drivers.
- Efficiency. While good price forecasts are very valuable, they can also be costly. Of course, decision makers prefer forecasts that cost less, require fewer resources, and can be updated more quickly.

Common Forecasting Practice

There are four important sources of data that can be used to develop long-run forecasts.

- Historical electricity market prices;
- Forward[iv] electricity market prices;
- Results from supply/demand simulation models; and
- Expert judgments, particularly with respect to future technologies and regulations.

Not surprisingly, considerable effort has been devoted to price forecasting in recent years. However, most forecasts suffer because valuable data are not used appropriately or not used at all. There are two common fundamental problems that lead to inferior forecasts.

1) Forecasters rely almost entirely <u>either</u> on financial data (historical and forward prices) or engineering data (simulation model results and expert judgments); they do not use both as information sources.
2) Whatever data sources are used, forecasters focus too much on the past and present, basing forecasts on extending existing patterns; they do not fully and creatively think about the future.

These two problems are discussed in more detail below.

Reliance on Either Financial or Engineering Data

As noted above, many price forecasts can be characterized as either "finance driven" or "engineering driven."

The finance approach usually begins with the choice of a simple model of price dynamics. A number of models are popular, with the Geometric Brownian Motion model being the best known. After choosing a model, model parameters are determined by fitting the model to past price data, or to forwards, or to a combination.

The major advantage of forwards is that liquid markets reflect data and analyses from many sources, and it is generally believed to be rare that individual analyses can improve on these estimates. Further, forwards reflect both investor price predictions and their attitude toward risk. This helps with the difficult issue of risk adjusting future cash flows, but does complicate calculations when spot price estimates are desired.

The major problem with the financial approach is that the markets are not sufficiently extensive, mature, and stable to rely on the available data. Or said another way, there is just not enough applicable data to produce accurate long-run forecasts. Regional electricity markets may have only existed for a few years, and/or have been in a state of transition during most or all of their existence. For example, the California crisis of 2000-2001 dominates Western historical data but may be a unique disruptive event that will not be repeated. Forward markets are similarly limited as they only go out 5 to 7 years.[v] Accuracy when these data are projected forward 20 to 30 years is questionable at best.

The engineering approach usually begins with the choice of a detailed supply/demand simulation model. A number of models are popular, with FastForward by EPRI/Northbridge, MIDAS and ProSym by Global Energy Decisions, IPM by ICF Consulting, UPLAN by LCG, and MarketPower and ProMod by New Energy Associates all being well known. Typically, these models contain detailed data on generating plants, loads, and the transmission system. They match supplies to demands and can produce hourly, location-specific prices. The detailed description of the real world found in these models provides users with confidence that the results are realistic. Generally it is assumed that if credible 20 or 30 year fuel prices and demands can be provided to the models, the models can provide accurate 20 or 30 year price forecasts.

The major problem with the engineering approach is a strong tendency to understate the uncertainty in technology, system configuration, fuel prices, and demands. This results in a forecast that anchors on a very narrow range that can be inconsistent with market realities. In general, analyses that consider many uncertainties are discouraged by the time and expense of running these models.

The finance and the engineering approaches have contrasting strengths and weaknesses:

- Finance models reflect true market value, engineering models estimate market value;

- Finance models summarize thousands of diverse opinions and analyses, engineering models reflect limited expert opinions and scenarios;
- Engineering models provide a logic applicable to many time frames and locations, finance models are based on limited temporal and regional data.

Anchoring on the Past and Present

The second major problem identified above was a lack of focus on the future, an underlying assumption of little change. While often viewed as extremely stable, the power industry is actually a dynamic and changing industry. A few examples illustrate the risks of assuming that the future will resemble the immediate past.

- The history of electric markets is too short to illustrate major shifts; however, such shifts can be seen in related commodity markets. For example, the average natural gas price was $1.45/Mcf in the 1970's and $4.81/Mcf in the 1980's. While prices in the 1990's were similar to the 1980's, recent, experience suggests that another jump may be occurring.
- U.S. electric demand grew at a rate of 7.3% per year in the 1960's. Growth fell to 4.2% in the 1970's. Growth fell to 2.6% in the 1980's.[vi]
- Figure 1: Technology Changes Over Time illustrates the radical changes over time in the technologies chosen for power generation. In the 1970's coal, gas, nuclear, and petroleum technologies were all highly competitive. In the 1980's, the roles of petroleum and gas technologies were dramatically reduced while nuclear and coal technologies were close competitors. Most dramatically, the 1990's were completely dominated by gas powered plants.[vii]
- Average annual capacity additions in 1970's; 1980's; and 1990's were respectively, 29.4 GW/yr; 17.4 GW/yr; and 9.0 GW/yr. But more startling, capacity additions from 1995 to 1999 averaged 7.8 GW/yr; capacity additions from 2000 to 2004 averaged 44.5 GW/yr.[viii]

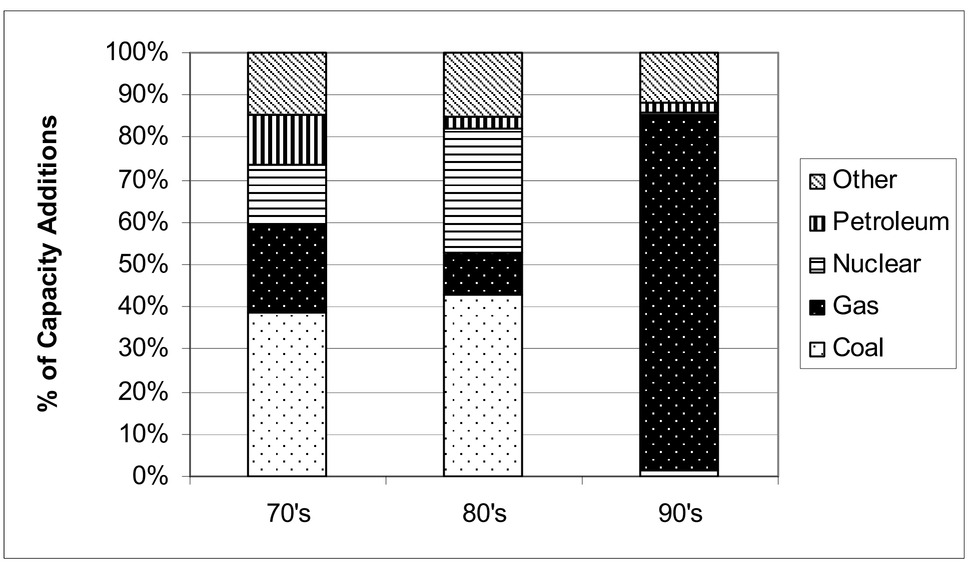

Figure 1: Technology Changes Over Time

In each case above, projecting one decade's trends into the next would have produced dramatically incorrect results. These examples show how blindly projecting current and historical data, whether financial or engineering, out 10 or more years is very likely to produce flawed estimates. Instead, attention to the future and a broad examination of uncertainty is required.

Suggested Changes

We suggest two changes in the common practices of price forecasting:

- Integrate the financial and engineering approaches, and
- Focus much more on the future, rather than the past and present.

Active markets provide the most relevant estimates of prices, but they simply do not provide enough data, particularly for long-run 20 or 30 year predictions. An engineering approach is certainly necessary for the long-run, and where markets are not robust may be needed in shorter time frames. The engineering approach needs to focus not on the details of the structure of the system today, but on the nature of the changes that will occur over the next 20 to 30 years.

A Compact, Balanced Approach to Long-Run Price Forecasting

We propose an approach with the following steps:

1) Structure the forecasting problem and select an appropriate model of electricity prices based on that structure;
2) Gather judgments about the future, especially factors relevant to the long-term cost of electricity generation;
3) Gather historical data, forward data, and simulation results; and
4) Fit the model to the gathered data.

Below we provide an example of this four-step approach. The example is based on recent projects, but has been modified to rely only on publicly-available data and to produce only illustrative results.

Step1: Structure the Problem

We begin by defining the long-term electricity price to be forecast. For most applications, we suggest the average annual price. Although price variations within a year are important for evaluating resources that will be shut down for a significant fraction of the year, we model these within-year variations separately. This modeling will not be discussed in this paper. We define "average annual price" as "spot" prices averaged over hours. For many markets, "spot" prices will be hour-ahead prices. The specification of prices to be forecast is flexible. It is important that the definition be clear and that historic data, forwards, and/or structural-model data must be temporally consistent with the forecast. We must recognize the different characteristics of weekly averages versus yearly averages, of day-ahead versus hour-ahead, and so on. Second, we must recognize that forwards are not direct estimates of expected spot prices.[ix]

Once price is clearly defined, we select a suitable model of price dynamics. There are a variety of models one can use. As noted above, Geometric Brownian Motion is popular, particularly for equities. However, it is a very specific model that has only limited applicability to electricity prices. Instead, a more complex model is required to capture three important aspects of electricity price dynamics:

- Medium-term (year-to-year) volatility,
- Reversion to a long-run price path, and
- Uncertainty with respect to the long-run path.

The short-term volatility of electric prices is illustrated in Figure 2: Historical Average Yearly Prices[x].

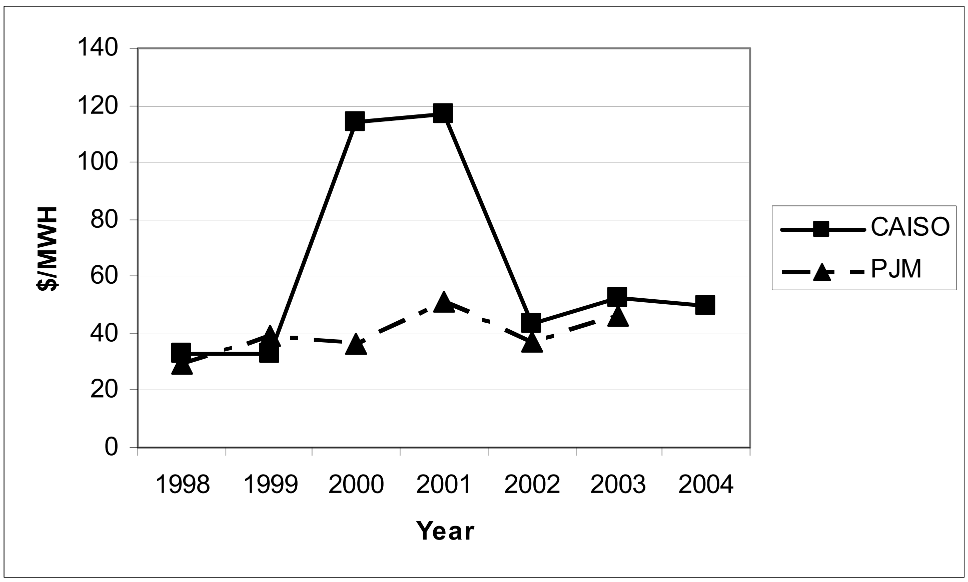

Figure 2: Historical Average Yearly Prices

As this Figure shows, electricity prices can exhibit considerable year-to-year variation, and that variation can differ widely among markets.

Strong statistical evidence is not available for reversion of electricity prices to a long-run path. However, most people find the logical argument for reversion very strong and related markets, such as coal and natural gas, are generally viewed as exhibiting mean-reverting behavior. The argument for reversion is that the underlying price for electricity is set by the cost of generation technology and fuels. Technologies serve as a large scale option for the power industry. In each decade or era, the industry chooses the expected lowest cost technology and market prices will tend to a level that will just support this technology. Significant variations from the underlying price will occur due to supply and demand imbalances. But when supply is "short," prices will rise and encourage new resources that will lower prices. The opposite will occur when supply is "long."

The statistical evidence for uncertainty in the long-run path is also limited. Pindyck, 1999[xi] examined up to 127 years of data for oil, coal, and gas prices. He states that "the behavior of real energy prices suggests reversion to trend lines with slopes and levels that are both shifting continuously and unpredictably over time, …" Smith and Schwartz, 1999[xii] also suggest a model for commodities, including oil, with uncertainty in the rate and level of mean reversion. This research and our own work suggest that the underlying path of electricity prices is uncertain.

The model we suggest is similar to that used by Smith and McCardle, 1999[xiii]. In this model, the logarithm of prices follows what is known as an "Ornstein-Uhlenbeck" process. The model is defined as follows:

- $\pi(t) + \alpha t = \ln(p(t))$, where $p(t)$ is the price at time t and α is an uncertain growth rate,
- $\pi(t)$ is normally distributed,
- the mean of $\pi(t)$ is $\pi' + (\pi(0) - \pi')e^{-\kappa t}$, and
- the variance of $\pi(t)$ is $\sigma^2(1 - e^{-2\kappa t})/2\kappa$. [xiv]

The model is not as formidable as it might first appear. $\pi' + \alpha t$ is simply the long-run path around which prices vary.[xv] As suggested above, we believe this is largely determined by the cost of building and generating electricity with the most economic new technology. The variance term, $\sigma^2(1 - e^{-2\kappa t})/2\kappa$ converges to $\sigma^2/2\kappa$ as we move into the future. This is more reasonable than the constantly-growing variance of the more common Geometric Brownian Motion model. The $(\pi(0) - \pi')e^{-\kappa t}$ term means that if the current price, represented by $\pi(0)$, is away from the long-run path, represented by π', there is a force driving future prices back to the long-run path. Finally, α, the growth in the long-run price path, is uncertain. We typically represent this by a discrete probability distribution.

The model requires three parameters and a probability distribution on growth, α. The three parameters are the current point on the price path, π'; the volatility parameter, σ; and the reversion parameter, κ. As noted above, we will estimate these parameters using all four sources of data.

Step 2: Gather Expert Judgments

Once the underlying model has been selected, we turn to gathering expert judgment regarding the underlying long-run price path. We need to think carefully and broadly about the future, and to recognize the high degree of uncertainty about technology and regulation. Areas of the future that need to be addressed include:

- Regulation, particularly CO_2 limits, credits, or taxes;
- Fuel prices, particularly for gas;
- Transmission development, both technology and investment, this will be a powerful determinant of regional price differentials;
- Generation technology, particularly the development of super critical coal, IGCC, renewables, and nuclear.

We use facilitated group brainstorming and assessment sessions to gather data. In these sessions, we have three types of activities: brainstorming with no comments, critical discussion, and voting or assessment exercises to quantify values and uncertainties. Assembling an organization's internal experts to exchange ideas about the future provides benefits beyond data gathering. The exchanges help people understand the major forces affecting the industry outside their own area of expertise and create a broader, more robust view of the future. Typically, the group will represent such functions as forecasting, strategic planning, regulatory affairs, environmental planning, marketing/trading, engineering, and management.

Outside the organization, there are a number of sources of technology information. Many organizations will have favored sources. One public source is the Energy Information Administration (EIA) "Annual Energy Outlook." This contains both technology and fuel data. Table 1: Advanced Generation Cost Data[xvi] provides some key data from this source. All costs are in 2003 dollars.

Table 1: Advanced Generation Cost Data

Technology	Overnight Cost (\$/kW)	Variable O&M (\$/MWh)	Fixed O&M (\$/kW)	Heat Rate (Btu/kWh)
Scrubbed Coal New	1213	4.06	24.36	8600
IGCC	1402	2.58	34.21	7200
IGCC w. Carbon Sequestration	2006	3.93	40.26	7920
Advanced CC	1114	2.6	17.60	7493
Advanced Nuclear	1957	0.44	60.06	10400

In a recent study, we considered fifteen uncertain variables influencing future electricity production cost. These could be roughly placed in three classifications: 1) economic variables such as discount and tax rates, 2) market prices for inputs and emissions, and 3) technical characteristics such as capital costs and heat rates. In this recent study, we used discrete distributions on these variables, but characterizing them as continuous distributions is also possible.

Table 2: Table 2: Uncertainties provides a few illustrative uncertainties. Gas Price is the price in 30 years in 2003 dollars. CO_2 Cost could literally be a \$/Ton emissions tax, but could also be the implied costs of traded credits or other controls. The transmission adder recognizes that coal and nuclear plants are more difficult to locate than gas plants and may incur significant costs moving power from production regions to load centers. The nuclear capital costs are construction costs not including financing.

Table 2: Uncertainties

Uncertain Variable	Low	Nominal	High
Gas Price (\$/MMBtu)	2.0	4.0	8.0
CO2 Cost (\$/Ton)	0.0	10.0	50.0
Transmission Adder for Coal and Nuclear (\$/MWh)	0.0	2.0	4.0
Nuclear Capital Cost (\$/kW)	1200	1957	2400

Step 3: Gather Historical Data, Forward Data, and Simulation Results

Once we have thought through the long-term scenarios, we turn to more traditional sources of near and mid-term data.

Figure 2: Historical Average Yearly Prices above shows typical historical price data from CAISO and PJM. For the calculations below, we use the CAISO data. There are often multiple sources for historic data. The best sources are those that represent a market (trading point or hub) and a time frame (hour-ahead or day-ahead) that would realistically be used as a resource. However, the data may often be from other markets or time frames, and statistical or subjective adjustments must be made.

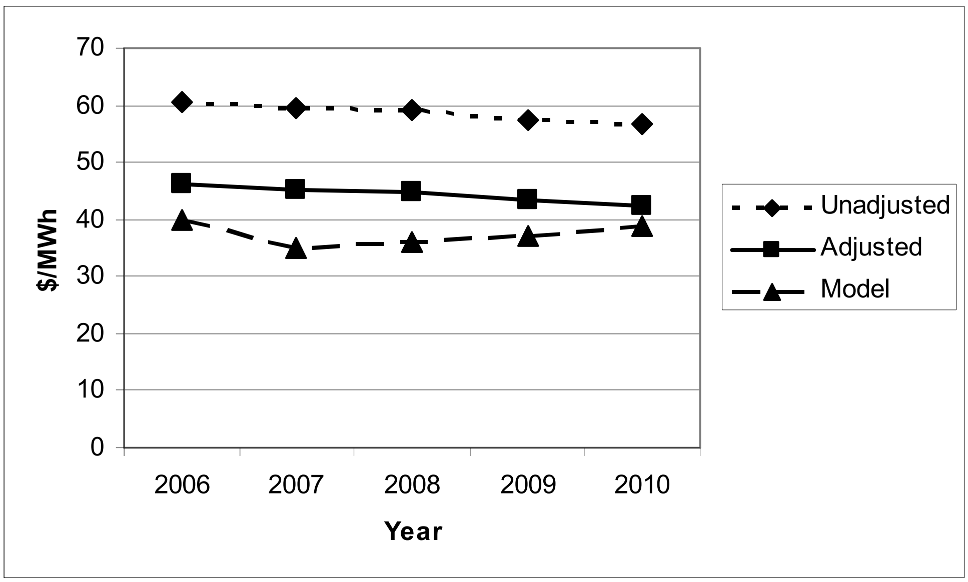

Figure 3: Forwards and Estimated Spot Prices

Figure 3: Forwards and Estimated Spot Prices shows three sets of "forward" data: The "Unadjusted" set is typical "raw" forwards data from the market; these are peak period forwards. The "Adjusted" set has been modified to represent future average annual spot prices rather than current forward prices. For comparison, we also show expected spot prices from a representative supply/demand simulation; this is the "Model" set. Like the historical spot price data, forwards data are selected from a representative market and time frame. Three adjustments are then made to make the forwards data and historic spot price data comparable: 1) risk adjustment between forwards and spot prices, 2) prices adjusted to 2003 dollars, and 3) prices adjusted from peak period prices to average annual prices.

The risk adjustment is the most complex. The key insight is that forwards incorporate market adjustments for risk. Forward prices should equal the *risk-adjusted* expected value of spot prices. The simplest form for this risk adjustment is to discount or inflate prices by a constant factor each year. We examined three ways to estimate this factor.

1) We compared one-year ahead electric forwards to actual spot prices. Very few points were available and the comparison did not show a significant relationship.

2) The capital asset pricing model suggests that the adjustment factor should be related to stock market value correlation. We found no significant correlation between electric spot prices and the stock market.
3) Parkinson, 1999[xvii] looks at the behavior of energy commodities with longer histories of forwards trading, specifically, the ratio of the spot price at delivery and the forward price of the same contract six months prior to delivery for seven oil and gas commodities. On an annualized basis, forwards provided an excess return of 5% to 20% versus a risk-free instrument. This suggests that forwards are lower than non-risk-adjusted spot prices.

Based on this research, we settled on a risk adjustment of 3% per annum from forwards to spot prices. Prices were adjusted to 2003 dollars using the Consumer Price Index, and average prices were assumed to be 80% of peak prices.

As noted above, the "Model" line represents expected spot prices from a supply/demand simulation model. Each point is the expected spot price at that time. We feel that good medium-run (5-10 year) projections can be efficiently derived from supply/demand simulation models. The uncertain factors driving prices in this time frame are not so diverse as to make use of the larger models inefficient and the power system structure in these models is relevant over this time frame. Uncertainties such as fuel prices, allowance prices, plant availability, and demand must be quantified. Enough scenarios and combinations of scenarios must be run to give a full picture of medium-run volatility and its drivers.

When both forwards data and supply/demand model data are available, subjective judgment guides their use – one, the other, or a blend. When the two sources differ widely, we favor using forwards data unless it is clear that forwards markets are too thinly traded to provide reliable data or the data represent markets that are geographically or temporally inappropriate.[xviii] For this example, we will assume that the forwards markets are robust enough to provide meaningful data.

Step 4: Fit the Model of Price Dynamics

Once we have gathered available data from all four sources, we fit the model using that data.

Table 3: Break-Even Electricity Prices (16% IRR)

Technology	**Scenario 1** Gas High CO2 High Transmission High Nuclear Nominal **($/MWh)**	**Scenario 2** Gas Nominal CO2 Nominal Transmission Low Nuclear Nominal **($/MWh)**	**Scenario 3** Gas Low CO2 Low Transmission Low Nuclear Nominal **($/MWh)**
Advanced CC	103	46	**30**
IGCC	72	40	31
IGCC with sequestration	41	39	37

Scrubbed Coal	83	45	34
Nuclear	**38**	**34**	34

We use a simple plant economics model to find break-even costs for various types of generators and scenarios at a target time in the future. Table 3: Break-Even Electricity Prices (16% IRR) shows the baseload electricity prices that provide a 16% IRR for investments in these technologies under three scenarios based on the uncertainties described earlier. The nuclear technology is lowest cost in Scenario 1 and 2 and Advanced CC is lowest cost in Scenario 3.

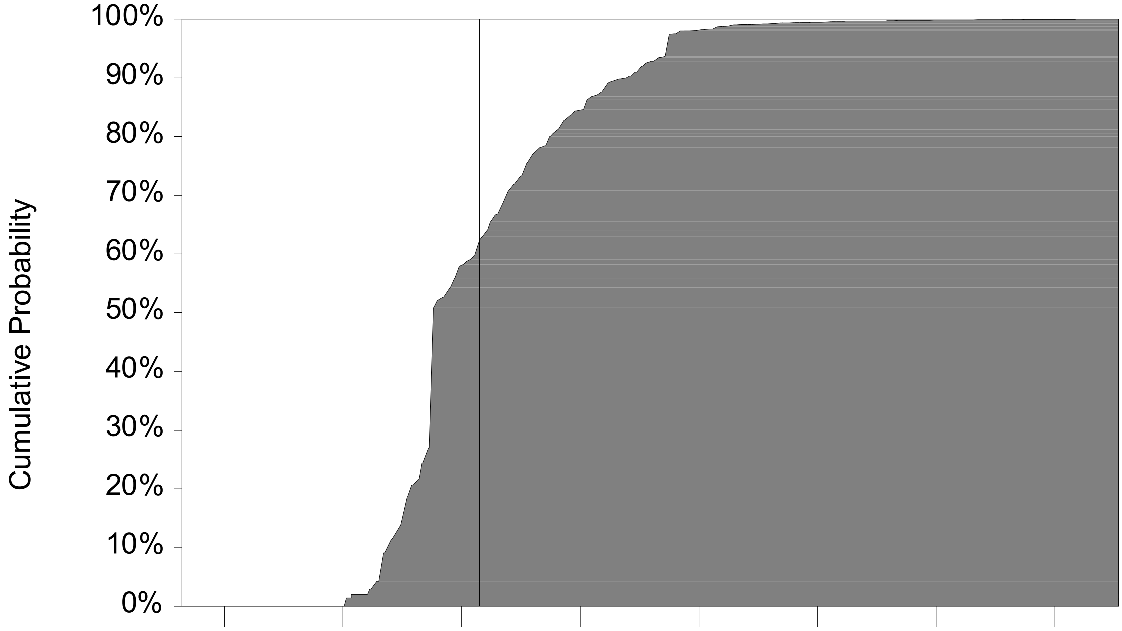

Figure 4: Distribution on Prices Supporting New Generation

Simulation of the interactions of many uncertain variables produces many such scenarios and a detailed distribution on the lowest price that will support new generation at some specified point in the future. Figure 4: Distribution on Prices Supporting New Generation shows such a probability distribution. While this curve represents millions of potential combinations of technology and business environments, usually we can identify informative patterns. For example, we might see the following pattern in dominant uncertainty outcomes and decisions:

- Low end of curve, low gas prices or a renewable breakthrough, gas turbines or renewables.
- Mid-portion of curve, moderate gas and coal prices, mix of gas and coal technologies
- High-portion of curve, high fuel and emissions costs, nuclear.

We discretize the future price distribution for calculation of the parameters of the dynamic price model and to simulate future price paths.

We settled on a three branch discretization of long-run (30 years out) prices: High, \$90; Nominal, \$48; and Low, \$30. We place probabilities of 30%, 40%, and 30% on these scenarios. Having established these future cases, it will be straightforward to solve for the distribution on growth, α, after the current point on the price path, π', is estimated.

The next step in our approach is to determine the long-run constant volatility, $\sigma^2/2\kappa$. We assume that the historic year-to-year price changes provide the best estimate of this term. We find the standard deviation of the natural logarithm (ln) of the year-to-year price change. For example, using the yearly price data from Figure 2: Historical Average Yearly Prices for CAISO (adjusted to 2003 dollars) and a current price estimate of \$49/MWh, we estimate a long-run constant volatility of 65%.[xix]

Given the stream of expected spot prices as shown in Figure 3: Forwards and Estimated Spot Prices, we have two remaining parameters to fit, the current point on long-run price path, π' and the reversion parameter, κ. Using our mean and variance expressions, we can write a likelihood for each expected price. We can then use maximum likelihood estimation to determine π' and κ.

The results of the model are shown below in Figure 5: Price Distribution for Long-Run Prices. These prices are shown in constant 2003 dollars.

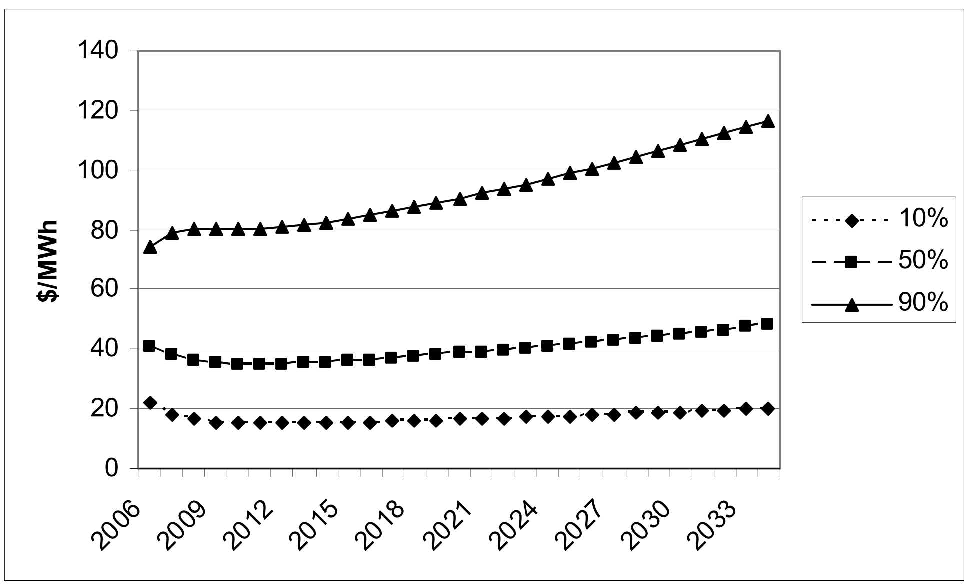

Figure 5: Price Distribution for Long-Run Price

In any given year, there is a 90% probability that the price will be below the 90% line and a 10% probability it will be below the 10% line. Correspondingly, it is equally likely to be above or below the 50% line.

What does this forecast tell us about electricity prices? First, the short run uncertainty is quite high. Even one year out, the 10-90% confidence bands cover a factor of three in prices. Consequently, it would not be a shock if prices doubled or were halved from year to year. This is a direct reflection of the considerable year-to-year volatility that has been observed historically in the chosen market, and ties the forecast to the available financial data. Second, the uncertainty grows only moderately over a longer time horizon, unlike the "expanding cones" that one typically sees with Geometric Brownian Motion and equity prices. This is a direct reflection of the strength of reversion to the long-run resource costs, and ties the forecast to the long-term engineering data.

Is this a good forecast per the criteria outlined above? We think so.

- The forecast is likely to show greater accuracy because we use all types of available data appropriately and a more sophisticated price dynamics model.
- The forecast is likely to be well-calibrated without false accuracy because we have recognized the high short-run volatility evident in recent price history, as well as the long-run changes in electric power technology and regulation.
- The model explicitly addresses the evolution of uncertainty over time, so that it is useful for both flexible and inflexible resources.
- The model development process is efficient. It requires time to meet and think creatively about the future, and time to gather and process available financial and engineering data. But it does not require hundreds or thousands of runs of complex supply/demand models.

Summary

Estimation of long-run, 20 to 30 year, electricity prices is extremely important and difficult. It is important because of the high cost and long lives of electric power resources. It is difficult because of the many uncertainties that will determine future prices, and because of the lack of sufficient historical and forwards data. The difficulty is further compounded when forecasters ignore part of the available information or unnecessarily limit their thinking about the future.

We have presented a practical approach that addresses these problems.[xx]

- Accuracy is improved by using all types of data and a flexible model of price dynamics. We use historical prices, forwards prices, supply/demand modeling, and expert judgment. The dynamic model of prices we use is logically sound and as simple as practical. The key characteristics of the model are dynamic volatility, reversion to a long-run path, and uncertainty with regard to the long-run path. In our experience if any of these are left out, illogical results that can be directly traced to the missing element occur.
- Our emphasis on intense, open, and clear thinking about the future improves the estimation of short- and long-run variance (calibration).
- The model is very useful in resource evaluation, producing both unconditional and conditional distributions on prices for option analysis, it is relatively easy to simulate, and it can be discretized to analyze options in a decision tree framework.
- Finally, the modeling process is very efficient.

The result is a better forecast.[xxi]

[i] California Legislative Analysts Office, Analysis of the 2002-03 Budget Bill, Department of Water Resources, California Energy Resource Scheduling (3860).
[ii] Texas PUC, July 18, 2005, www.puc.state.tx.us/electric/maps/gentable.pdf
[iii] Houston Business Journal, May 4, 2004.
[iv] We assume that at any point in time forwards contracts and futures contracts for the same date will be priced the same. While realizing that futures contracts dominate trading, the potential confusion of "electric futures prices" and "future electric prices" was judged to justify the use of the term forwards for both forwards and futures contracts.
[v] Some analysts assume that 5 years of data provide thousands of data points, and that no problem exists in fitting complex models. We believe that the data have strong serial correlations not accounted for in the models. Thus dividing years up into small pieces to create more data points is a not a feasible analysis strategy.
[vi] From http://www.eia.doe.gov/neic/a-z/electrica-z.htm, Table 8.9 Electricity End Use, 1949-2004.
[vii] From http://jec.senate.gov/_files/NaturalGas.pdf, The Pressures on Natural Gas Prices, Joint Economic Committee, October 6, 2004 for capacity additions 1970 through 2002. Electric Power Annual 2003, Table 2.6, EIA, 2004 for 2003 capacity additions. www.platts.com, Platts for 2004 capacity additions. Note that Platts data has minor differences with EIA data.
[viii] Ibid.
[ix] Note that these prices, unlike forwards, will not account for market attitudes toward risks. In evaluating resources, risk will need to be taken into consideration.
[x] CAISO prices from **CAISO, 2004 Annual Report**, Table 2.3 Wholesale Energy Market Cost Index for 2004 and Previous Years. PJM prices from **Electricity Prices in PJM**, June 3, 2004, Table 2.7. 1998 PJM price is estimated based on energy price in Table 2.7.
[xi] Pindyck, Robert S., "The Long-Run Evolution of Energy Prices," **The Energy Journal**, Vol. 20, No. 2.
[xii] Smith, James E. and Schwartz, Eduardo, "Short-Term Variations and Long-Term Dynamics in Commodity Prices," **Management Science**, Vol. 46, No. 7, July 2000.
[xiii] Smith, James E. and McCardle, Kevin F., "Options in the Real World: Some Lessons Learned in Evaluating Oil and Gas Investments," **Operations Research** 47 (1999), 1-15.
[xiv] In practice, we work with this model in discrete time. In discrete time, this is a first-order autoregressive model on the log of price with a random growth rate.
[xv] The long-run path is the long-run mean of the log of price. This is the median, not the mean of the price. With high volatility, the mean price can be much higher than this median. This can create serious confusion when interpreting prices.
[xvi] Energy Information Administration, Assumptions to the Annual Energy Outlook 2005, Table 38: Cost and Performance Characteristics of New Central Station Electricity Generating Technologies
[xvii] Parkinson, T.W., **Forward Price Forecasting for Power Valuation**, p. 2-2 to 2-5, EPRI TR-111860-R1, Final Report, March 1999.
[xviii] If forwards markets were established that actively traded 20 years into the future, we would recommend using the estimates from these markets for resource decisions and the forecasting problem would be very simple. At the same time, we understand that markets may be so thinly traded that they have no significant information more than 12 or 18 months out. In this circumstance, further reliance on historical data or on dispatch model simulations may be the best source of medium-run forecasts.
[xix] The seven price points in the figure are a very limited amount of data. The volatility might also be calculated from structural model runs or financial instruments such as options or futures.
[xx] We should note that this paper has not been a full presentation of our approach. We limited our long-run price paths to three. We would certainly suggest exploring and perhaps using more long-run price paths. We have not discussed fuel and electric price correlations. Similar analyses can be applied to long-run fuel price forecasting. Assuming that the probability distributions derived are the marginal distributions on electric and fuel prices, it is not difficult to add correlations to the analysis. We have not discussed the estimation of within year prices. We believe that this can be dealt with as a problem separate from long-run yearly average price estimation.
[xxi] Any errors in this paper are the sole responsibility of the authors. The authors would like to thank Tom Parkinson of The Northbridge Group for very kindly commenting on an earlier draft.