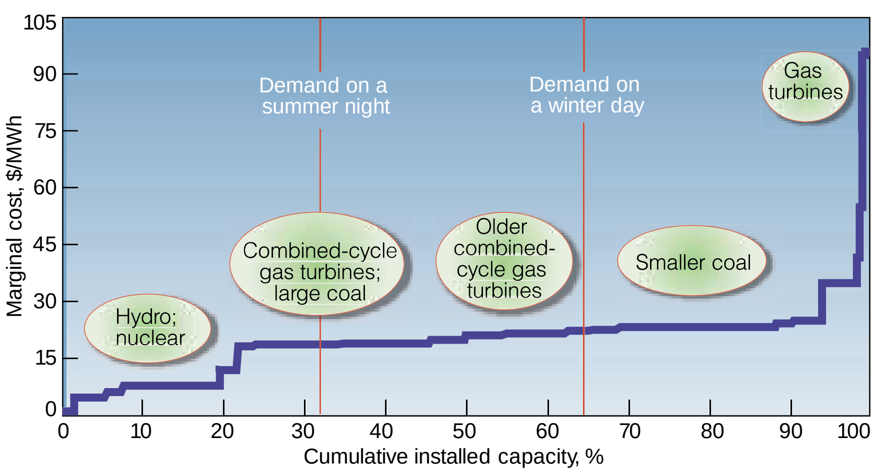
Generation modeling: *The next generation*

Stack modeling of power plant portfolios cannot account for the price uncertainty and volatility that competition brings to energy markets. Three new modeling approaches can, but each has upsides and downsides that planners must consider

By Adrian Palmer

Power plant owners have long looked to models to guide their operational and investment decisions. These decisions can involve everything from scheduling plant output over the next few hours or days to analyzing the potential value of a generation asset over its lifetime of 20 to 30 years.

To support the broadest range of decision making, the ideal model must have certain capabilities. It must be able to address market price uncertainty, recognize the optionality embedded in generation assets, incorporate a realistic approximation of physical plant constraints, and capitalize on available in-house and market data. This article provides an overview of three leading techniques for modeling generation assets in competitive electricity markets. It begins, though, by considering the drawbacks of traditional modeling methods.



1. Indicative supply and demand curves are shown for the British electricity market during 2001. Note that because winter and summer demand are assumed to be inelastic in the short term, they are represented as vertical lines

The stack approach

The conventional approach to modeling generation typically involves the creation of aggregate industry supply and demand curves for the region of interest. After the characteristics of all existing and planned generation facilities in the region are compiled, plants are "stacked up" in order of increasing expected production cost. The model then determines plant output levels and market clearing prices at which projected aggregate demand is met. This process is illustrated in Fig. 1.

A production stack model can be as simple as a spreadsheet, which provides a static snapshot of supply in the region. Most models, however, apply linear or dynamic programming techniques to determine equilibrium prices and output levels, enabling more complex factors—such as plant dynamic characteristics, transmission congestion, and emissions allowances to be accounted for.

Cost-based stack models can therefore provide a reasonably detailed representation of the physical properties of electric power systems. Nevertheless, their application to modeling generation assets in deregulated electricity markets has revealed several shortcomings.

First, cost-based stack models rarely reproduce all the features of observed market prices. Electricity spot prices are generally well behaved at low demand levels and often show a strong correlation to underlying cost drivers at such times, but this relationship tends to break down at higher load levels. Compared to the results of cost-based stack models, actual market prices typically exhibit much greater volatility and more frequent price spikes.

The strategic bidding behavior of market participants often contributes to this discrepancy because players exerting market power often elevate prices above cost-based levels, particularly as the margin of supply over demand tightens. By drawing upon game-theory approaches—such as Cournot pricing (see box, p. 37)—it is possible to extend the cost-based modeling framework to incorporate strategic bidding considerations. However, even these extended stack models still tend to be geared towards analyzing equilibrium market conditions. As such, they fail to replicate the dynamic nature of the price-setting process in deregulated electricity markets. Actual electricity prices behave stochastically, responding to changing weather conditions, demand fluctuations, and equipment outages. In short, electricity prices are hardly ever at equilibrium levels.

This brings us to the second significant drawback of traditional stack models—their inability to adequately address market price uncertainty. Stack models are generally deterministic in nature, with plant output choices made in full knowledge of the paths of key input variables—such as fuel cost and demand. In the real world, of course, operating decisions have to be made on the basis of uncertain views of the future. Even if multiple scenarios are run by sampling a range of possible values for key parameters, most models will not overcome their perfect foresight: They still know with certainty how the various parameters will evolve in each scenario.

The third disadvantage of stack modeling relates to changes in the level of information transparency resulting from retail electricity deregulation. Traditional, engineering-based output optimization models tend to require extensive knowledge of generation production costs and transmission system conditions for all facilities in a region, regardless of who owns them. Often, this information was historically available within vertically integrated utilities, but it is now increasingly "commercially confidential" in competitive markets. Conversely, conventional generation models often fail to capitalize on the rich pricing information now obtainable in spot and forward markets.

How financial options deal with price uncertainty

Financial options provide an obvious starting point for advancing generation modeling beyond traditional, engineering-based approaches to have them account for price uncertainty. This technique entails deconstructing the generation asset into a portfolio of simple options to which standard financial option pricing models can be applied.

As an example, financial options techniques treat power plants as strips of options on the margin between fuel and electricity prices—the spark spread. Several spark spread models are available, and they can be used to analyze the economic performance and value of a generation asset under conditions of market price uncertainty.

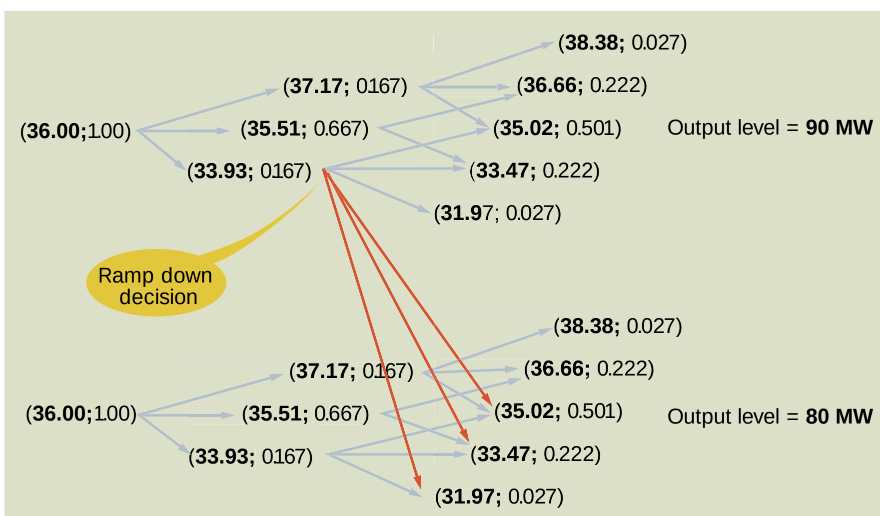
The inputs to these models typically include forward curves and volatilities of fuel and power prices, as well as the correlations among them. The models also need to know the efficiency of the power plant and its nonfuel variable operating costs, if any. In addition to being comparatively simple to implement, spark spread models can also provide a full range of sensitivity analysis to inform trading and hedging strategies. They may, for example, produce a set of "the Greeks" to quantify the impact of power and fuel prices and their volatility on a portfolio's performance.

The drawback of the financial option approach is often accuracy. Spark spread models do not always do a good job of predicting the payoff from operating a generating unit. In particular, inter-temporal constraints—a plant's startup costs, its dynamic operating characteristics, and its emissions performance—are difficult to account for because each time bucket is usually valued independently.

Spark spread models also require specification of the "granularity" of an option to determine whether it should optimally be exercised on a monthly, weekly, daily, or hourly basis. A finer granularity will lead to higher option values, but may also produce infeasible plant output schedules because inter-temporal physical constraints are usually ignored.

Simulation-based approaches

Thanks to inexpensive computing power, Monte Carlo modeling methods have become attractive and increasingly popular. The big advantage of simulation-based approaches is their extreme flexibility, both in terms of



2. A partial trinomial tree for a power plant is shown above. Each tree node represents an electricity price ($/MWh) in bold and its associated probability. There is a separate tree for each possible operational state of the generator. Transitions among the trees represent decisions to ramp output up or down or keep it steady

Glossary of generation modeling terms

Cournot model. From the field of game theory, a model in which each firm aims to maximize its profits by choosing an output level while assuming that its competitors are doing likewise.

Dynamic programming. The basis of optimization algorithms that solve sequential decision problems through backward recursion. That is, they start at the final time period and work their way backwards toward the present.

Monte Carlo simulation. A mathematical technique for numerically solving problems by randomly generating values for uncertain variables multiple times.

Stochastic dynamic programming. Used in algorithms designed to optimize under conditions of uncertainty.

The Greeks. A standard set of sensitivity results commonly used by traders to quantify the exposure of their portfolios to variations in factors such as price (delta and gamma), volatility (vega), and interest rates (rho).

Trinomial trees. A form of stochastic dynamic programming that uses branching trees to represent the probability of changing price states. A trinomial tree has three branches at each step.

modeling underlying pricing processes and incorporating physical plant constraints. It is straightforward to ensure that all simulated output paths represent feasible operational schedules, overcoming one of the chief shortcomings of the financial options approach.

While it is relatively simple to derive feasible decisions by using simulation techniques, determining the optimal decision can be more challenging. One promising approach for representing generation assets with complex inter-temporal constraints involves the creation of a decision or value surface. This surface represents the opportunity cost of exercising the option at each point in time as a function of relevant operational states, such as output level and run time. It can therefore provide a decision-maker or planner with an intuitive understanding of how the asset is operated by identifying pricing points at which the plant's output should be increased, held steady, or decreased for a given operational state.

As with financial options, one drawback of the simulation approach is the difficulty of assessing how accurate it is. This has led to the exploration of more rigorous modeling methodologies that still handle price uncertainty.

Stochastic dynamic programming

Dynamic programming (DP) in the context of traditional production cost models is discussed earlier. While DP algorithms have long been applied to derive feasible, cost-minimizing schedules for generation plants, such models are generally deterministic. Stochastic dynamic programming (SDP) extends this approach to handle uncertainties in market outcomes, jointly optimizing for both physical constraints and spot-price uncertainty.

A common misunderstanding is that feeding stochastically generated price paths into a regular DP model constitutes stochastic dynamic programming. As should be apparent from the previous discussion, this will result in overvaluing the asset, since it implicitly assumes perfect foresight in prices for each path. A true SDP algorithm takes into account the probability of each path and optimizes jointly over all of them.

Tree-based models are perhaps the most widely known SDP approach. Trees model price uncertainty by having each branch represent the probability of moving to the next price state. A sophisticated version of this model—such as the trinomial tree (Fig. 2)—can capture a wide variety of price process properties, including time-varying volatility and mean reversion characteristics.

Modeling generation assets requires the creation of a trinomial "forest"—a collection of price trees, each with an associated operational state. Each time an option to change output level is exercised, you move to a different tree. These transitions between trees are governed by the physical and economic constraints of the power plant.

Computation time is usually the biggest drawback associated with tree-based SDP models. Because the size of the tree grows both over time and as branches are added, it can become too unwieldy to work with if multiple correlated sources of uncertainties are modeled simultaneously.

Selecting the right approach

To summarize, the major shortcoming of traditional, stack-based modeling is its inability to address price uncertainty and volatility. Three alternative approaches for modeling generation assets in deregulated power markets reviewed are financial options, simulation-based methods, and SDP trees. Each has its strengths and weaknesses, and necessitates tradeoffs either in computation time, flexibility, or intuitive understanding of the model's inputs and outputs.

Accordingly, it is impossible to say which approach best suits the needs of any particular energy company. Different players have different requirements for decision support in operations, trading, and risk management. Some organizations may wish to use a combination of several modeling techniques. For example, an SDP approach could be used to benchmark a faster simulation or spark spread model under consideration. This would help ensure that trading and operational decisions are not significantly biased by the shortcuts used by real-time pricing models. ■

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