



Valuing Generation Assets and Tolling Agreements using the Power Sector Model

By Carlos Blanco, Josh Gray, Marc Hazzard, and Craig Jimenez

Introduction

This article is the fifth and final article in a series on the FEA Power Sector Model. So far we have taken a tour through the both the specification, calibration and application of the hybrid modeling method. This method seeks to address the imperfections of exogenous stochastic models and non-market based fundamental models in simulating spot power prices. The first three articles covered the realistic simulation of the salient drivers of power prices (weather, load, and fuel price). In the penultimate article of this series, we used these drivers to address the valuation of full requirements contracts, whose embedded risks have recently drawn the ire of rating agencies and auditors.

In this article, we will illustrate using the Power Sector hybrid modeling method to tackle a problem that has bedeviled an entire industry, the valuation of merchant generation and tolling agreements. Many merchant generation assets are in default or on the auction block due to uncertainty of valuation in both the short and long terms.

A History of Innovations:

Valuation of Merchant Power Assets using Real Options

The influx of Wall Street quantitative talent during the rise of the merchant energy era resulted in a significant increase in the level of sophistication in pricing the embedded optionality in certain contracts that were previously considered traditional utility structures. Such esoteric contracts as swing, take or pay, peaking, and storage were analyzed as combinations of familiar instruments such as swaps and options. This is the heart of the real options approach, which attempts to map financial option pricing techniques onto physical assets and therefore offer more appropriate valuation and hedging methods. The valuation of these contracts using stochastic models has become industry standard (although approaches may vary).

The valuation of generation assets, tolling contracts, and cross-commodity options has seen a similar jump in sophistication. The relatively easy mapping that worked with other structures has not had the same degree of success with power plant valuation. Two main issues have hampered realistic modeling: plant constraints and the complexity of the power price process. We will subsequently describe how FEA's @Energy Power Generation module overcomes these obstacles.

Plant Constraints

In recognizing that power plant assets could be roughly decomposed into a portfolio of daily spread options (between fuel and power), the industry adopted the so-called “spark spread” (often referred to as a Margrabe or Kirk) approximation. Unfortunately, the spark-spread approach does not explicitly acknowledge plant constraints (start-up time, minimum up/down times), or start-up and shut-down costs. This obviously overvalued generation assets and understated the risks. Practitioners were therefore forced to make a-priori assumptions about the dispatch frequency of the plant so that they could “socialize” and “shoe horn” constraints and costs into the strike price (K). Lumping additional costs into the strike caused the analytic Margrabe and Kirk approximations (which require $K \ll$ asset prices) to break down, forcing practitioners to use numerical solutions for the valuation of spread options.

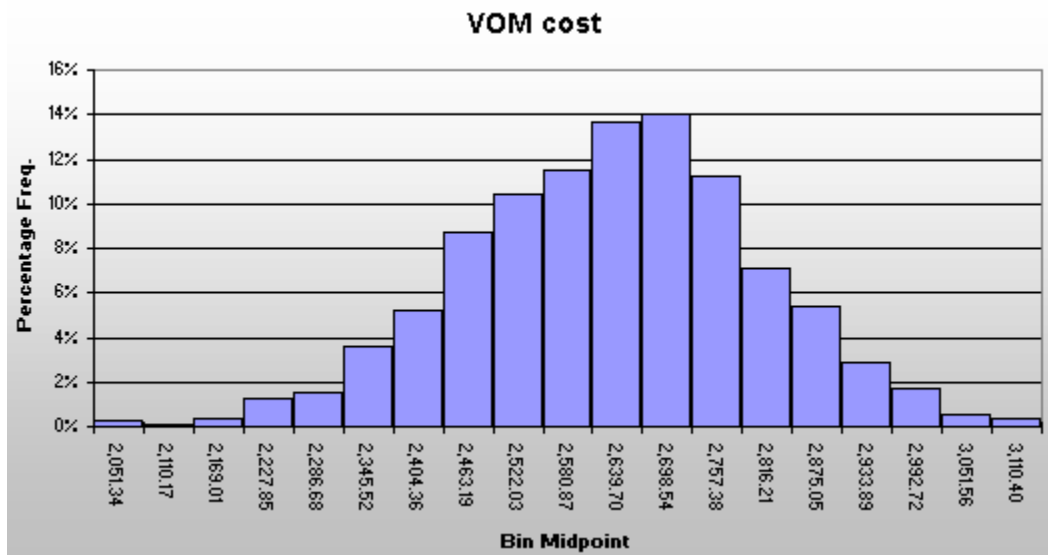


Figure 1: VOM cost histogram from Power Generation

Since representation of plant constraints required the use of numerical methods, analytical tractability was already slipping away. The next step in complexity was to simulate prices and dispatch strategies, which loses all analytical tractability. Dispatching could be considered a generalization of American exercise, which historically was not amenable to Monte Carlo simulation. The resulting forests of trees were complex and computationally slow.

Price Process

On another front, the assumption that power and fuel prices followed a joint lognormal distribution were put into question early on. The tendency of power prices to jump to extreme values and quickly revert back to the cost of production was noticed (in a painful manner by some participants). From the interest rate world, Hull-White models for yield curve evolution were modified for use in power price modeling. The Merton approach



for including jumps piled right on top of this method, sending computers wheezing through complex Monte-Carlo scenario calculations. Equally important, the co-movement between power and fuel prices implied in the spread option approach was entirely determined by the correlation coefficient between those two prices. Many quants soon learned that the use of an average correlation between fuel and prices was not enough to capture the complex dynamics of the joint evolution of these variables. A better model for the co-movement of the variables involved in the valuation of the generation assets was needed.

Through all of these innovations, the spark spread underpinnings of valuing generation assets remained. But the lack of liquid markets for the parameters specified by both exogenous power processes (mean-reversion, jump diffusion, regime switching and the like) and spread options models (correlation) forced quants to take a long look at their valuation models for generation assets.

Past the Spark Spread: Hybrid Models Appear

As the shortcomings of pure stochastic models and their analogues became apparent for the valuation of generations assets, an alternative class of models started to appear: the hybrid model.

Hybrid models attempt to blend the best of pure stochastic models and traditional utility valuation techniques. In response to the limited dataset used to estimate parameters, hybrid models attempt at every point to extend the dataset used by diving deeper into the underlying process, but not so deep as to enter into computational intractability or non-market based valuations. Therefore it must include every piece of accessible market information, but make no attempt to use parameters that cannot be calibrated from current market data.

If the process is correctly specified, the most salient drivers of generation asset cash flow would occur as a consequence of the process, and not have to specified on top of a stochastic process (for example, spikes or mean-reversion). All that remains is to choose the drivers of our hybrid process.

Weather

In our selection process, we quantitatively and qualitatively identify weather as the fundamental driver of load (demand), which subsequently accounts for a large amount of variance in the price of power. So the joint behavior of load and weather, whose calibration and simulation was covered in a previous article, is chosen to represent the demand component of power prices. The combination of plentiful historical weather data, the stationary nature of weather, and a re-emerging traded market allows us to use weather simulation tools with some degree of confidence.

Load

With the demand component of power prices represented by the load/weather pair, we must choose a simulation method for load. Unlike the future distribution of weather



phenomena, the specification of the future distribution of load is an altogether different exercise. In areas where the customer and industrial component of demand are relatively stable, we can assume the relationship between weather and demand will be stable, and that the past provides a reliable indication of the future. Since there is no traded market for load, we will have to use historical load data and shape it in an intelligent manner to form the future distribution.

Fuel

Now that we have chosen the demand component, let's turn to the raw material of power prices, fuel (assuming either natural gas or oil). With its liquid forward and options markets, stochastic simulation can be used to specify the future distribution of fuel prices. There is no need to draw on historical or fundamental "forecasting" approaches here, but the framework that we are presenting also allows for modeling the joint dependence between variables such as weather and fuel.

Power Price

So far we have chosen a hybrid specification for our model, included the load/weather pair to represent demand and fuel price to represent the raw material. From these choices the power spot price follows as a consequence. Spikes do not happen due to a "random" jump laid on top of a stochastic power process but because of response to an extreme temperature, supply, or transmission shock. Power and weather are not related by a correlation coefficient but are bonded together by a demand response and the cost of fuel. Thus, we have taken a step closer to the fundamentals of power pricing.

Dispatching algorithms

For any dispatching-algorithm that arrives at a generation plant's value, at each time-step we must consider the "cost-to-continue" in the current state (e.g. to remain "on"), versus the cost incurred to change states (e.g. "on" → "ramp-down"). The profits or losses associated with each state can be modeled via the input cost parameters (e.g. the "on" costs are determined by VOM, fuel, and emissions costs) and the value of the spark-spread payoff as a function of simulated prices, the heat-rate, and the generator output level. These terms, combined with a set of dispatching decision functions can be used to determine the value of the plant in a given state at time t to the value of the plant in a known state at time $t+1$ through a recursion relation.

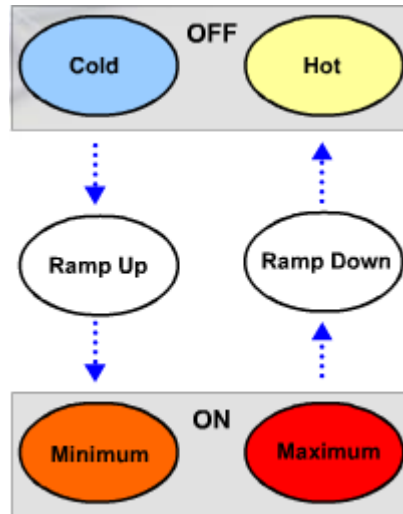


Figure 2: Flowchart of Generation States

For example, in the “on”-state, the value at time t is proportional to maximum of the sum of the optimal generation output used to maximize the spark-spread payoff at time t plus a determination of the minimum of the cost-to-continue or shutdown at time $t+1$. The manner in which this determination is made is the crux of the valuation.

While there are several ways of attacking the details of this dynamic programming algorithm, we will discuss here two variations: one which assumes “perfect foresight”, and therefore results in an upper bound value, a method generally applied in fundamental-type models, and another, as employed in FEA’s @ENERGY/Power Generation, which uses a relatively recently published algorithm for valuing American-style options, Least Squares Monte Carlo (LSMC). As such, the LSMC approach yields values in accordance with the standard valuation of options and achievable dispatch mechanics.

In both cases, we will have both the initial price values and contract parameters at the contract’s value date, (time = 0) and at the end of the contract (time = T), we can determine the plant’s residual value as a function of each state.

Perfect Foresight

- 1) Generate a time series of simulated prices for Power and Fuel from time 1 to time T ;
- 2) Working backward from time T , determine the generation plant’s value at time $t-1$, as the maximum of the dispatch commitment at time t and the optimally dispatched spark-spread payoff at time t ;
- 3) Continue working backward until time 0 is reached, and the optimal objective value is determined at time 0;
- 4) Repeat steps 1 thru 3 N -times (in practice, $N > 100$), and determine the average of all the optimal objective values

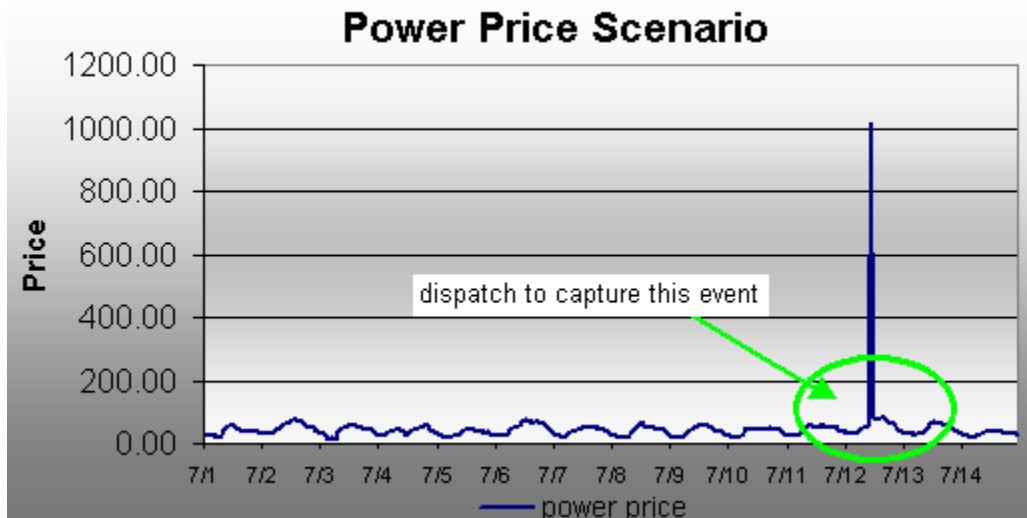


Figure 3: Dispatching commitment with perfect foresight – “on” for price spikes

This algorithm is straightforward to implement, but two fundamental flaws must be recognized:

- Both price series are fully revealed, and the plant is optimized for every simulated price series. Thus, we can only obtain an upper bound on the plant’s expected value.
- Each simulation yields an independent set of dispatching rules, and there is no cohesive application of the commitment decisions.

To eliminate these problems, we will incorporate the elements of price uncertainty to determine the dynamic dispatching decisions.

@ENERGY/Power Generation

As opposed to the “perfect foresight” algorithm, the goal of the LSMC approach is two-fold: for any number of simulations, arrive at a set of optimal dispatching rules (that is, the instruction set at any time, as a function of prices) and apply those rules to all the simulations to obtain the optimal expected value. We will continue to optimize the spark-spread payoff at all times, with knowledge of only the expected prices through their probability distributions.

To determine the optimal dispatching rules, we define a set of decision functions as the expected generator value for each time, t , conditional upon the generator being in a state and the spot prices being at a particular level at $t-1$. These decision functions are to be fitted using simulation data in simple powers of the spot power and fuel prices.



To produce the decision functions, we follow a tree-like, backward induction procedure. A least-squared fit (LSF) of the corresponding decision functions at any time t is performed by minimizing the distance between the decision functions and the generator value.

Armed with the decision functions, we move backwards in time and calculate the generator value as maximum of the sum of the hourly profit function at time t , and the decision function at time $t+1$. Finally, at time $t = 0$, we shall arrive at an optimal generator value.

Following any simulated price path pair, the optimal dispatching rules are applied as specified by the decision functions similarly to how the generator values are established. Thus sum of the generator hourly profit function and the decision functions for the simulated prices, optimized for all possible states, provides the optimal transition from time 0 to time T. The average of the generator values from all simulations is then obtained.

To forge the link between traditional spark-spread valuation and full-throttle plant valuation taking into account plant constraints and costs, the FEA Power Generation model allows for a specification of a traditional lognormal mean-reverting price process for both power and fuel. Once the user has identified the key weather and load drivers for a power region, the FEA Power Sector Model can be calibrated and Power Generation run with this more realistic power price process at hand.

After running any number of simulations, in addition to providing a single expected optimal dispatching value based on the LSMC algorithm, the full distribution of generator values and dispatching decisions can be displayed. By providing a confidence level, a drill-down analysis of the revenues, costs, profits, and operation can be performed.

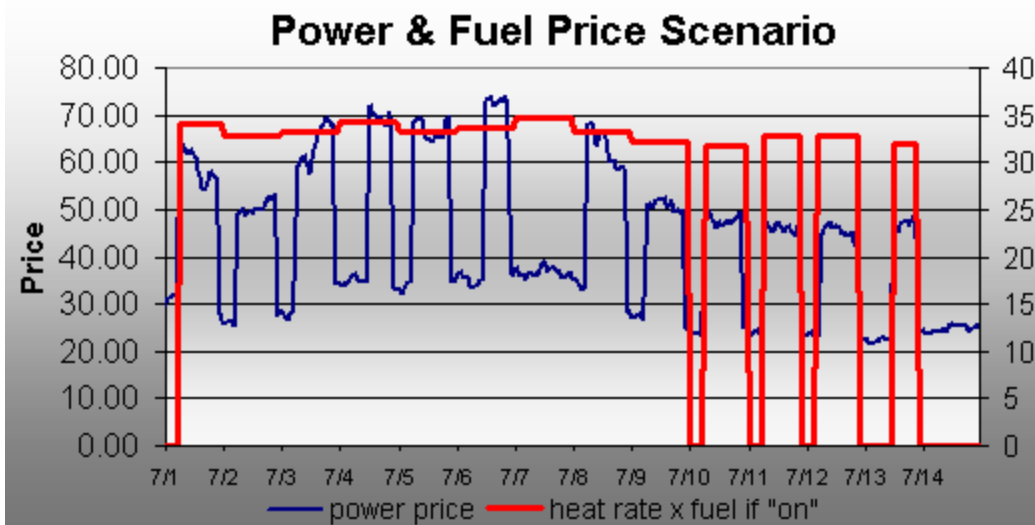


Figure 4: Power Generation dispatch with a lognormal price process model

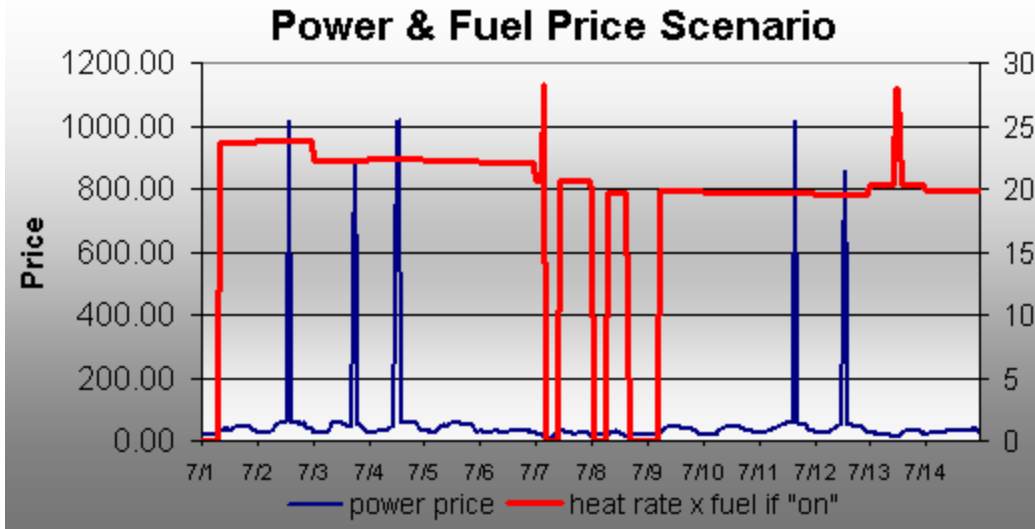


Figure 5: Power Generation dispatch with the Power Sector Model

Given the distribution of outcomes from applying the optimal dispatching rules, the operational statistics can easily be given. For example, a histogram of the number of starts from all the simulated dispatches is useful to determine the timing flexibility of the plant given its constraints. Furthermore, a forecasted distribution of NOX and SOX production is critical for determining required emissions credits, while a summary of fuel consumption provides a key fuel-procurement reference.

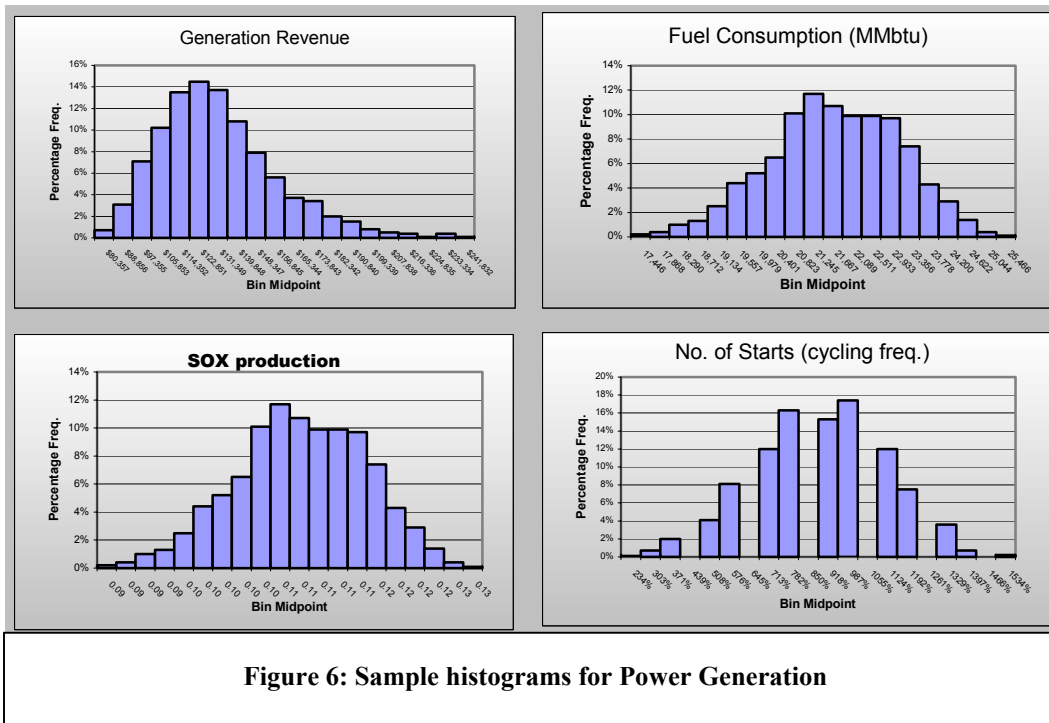


Figure 6: Sample histograms for Power Generation



Conclusion

Valuing generation assets is a complex task. We have argued that it is very important to bring the asset costs and constraints into the modeling framework. Early attempts to model generation assets as spread options are superior to discounted cash flow types of valuation methods and provide a quick answer to the problem, but fail to provide a realistic dispatch policy for the plant.

By using the Least Squares Monte Carlo simulation to capture the multi-stage decisions involved in operating a generation asset and the hybrid approach to simulate the co-movement of power and fuel prices, FEA's @Energy / Power Generation provides a powerful tool for the analyst to determine the expected value and risks of these assets.

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