CVAR-CONSTRAINED MULTI-PERIOD POWER PORTFOLIO OPTIMIZATION WITH TRANSMISSION CONSIDERATIONS

by

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ABSTRACT

The deregulation of electricity markets is introducing risk and uncertainty into a sector of the economy that was traditionally state-regulated. In order to manage risk from market prices, consumers and producers use financial methods to support decentralized decision making under uncertainty. Due to the non-storable nature of electricity and the unpredictable nature of demand and daily weather, risk is a real-time dilemma in the electric industry. Companies in the power sector not only have to be concerned with the sale and purchase of electricity, but also the risks involved with an unknown real-time price and transmission constraints on power flow. The simplistic view of the power supplier is how to best transmit its purchased electricity from the power source to its customers. In addition to finding the best route, the company chooses to maximize profit while taking an acceptable calculated risk.

Many power portfolio optimization problems have been developed to combat the issue of risk tolerance, but very few (if any) have included transmission constraints. In this research, portfolios of real and contractual assets, including derivative instruments, are optimized in a multi-period setting. The problem is approached from a load-serving entity perspective where transmission constraints exist in addition to procurement decision risk. Fixed transmission rights are used as a measure of transmission congestion utilizing data from the PJM market, which is located in the eastern United States. PJM was formed in the early 1900s by utilities in the Pennsylvania-New Jersey-Maryland area

to coordinate transmission in order to take advantage of cost savings by pooling their resources. When the eastern states deregulated the electricity sector, PJM expanded into some of the surrounding states and took over the role of market operator, overseeing prices and transmission in order to stave off market manipulation. It is the most mature independent system operator and was used for model implementation because it uses a nodal pricing system (rather than a zonal average) and data are readily available from PJM's website.

The model developed in this paper is a multi-period stochastic nonlinear model solved using Monte Carlo Simulation and the Microsoft Excel Solver tool in order to reach an optimal solution. Once the scenarios are determined, value-at-risk (VaR) and conditional value-at-risk (CVaR) values were calculated at a 95 percent confidence interval, also through Monte Carlo simulation. CVaR was determined to be the appropriate measure of risk because it was significantly lower than the VaR measurement, signifying extreme losses in the tail of the distribution. Load-serving entities care about extreme losses because they must provide power for their customers and create dividends for their shareholders.

The model's results show that transmission considerations in a power portfolio optimization problem do have an impact on the profit function. By omitting transmission congestion from their models, previous studies may have over-stated expected profit. The numerical results from the model presented in this paper show that when transmission risk is considered, profits are half of what they are when transmission is absent from the model. Transmission constraints are a type of unknown risk in the power sector; by mitigating the risk, power companies will have to accept lower profits.

However, the probability of sustaining extreme losses is much lower than if constraints are not considered. While the model presented in this paper does not find that companies will change their specific procurement decisions when a transmission constraint is introduced, further research with company-specific data could provide more conclusive results.

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CHAPTER 1

INTRODUCTION

The pre-deregulation electricity markets were characterized by predictable power prices and utility-owned power projects. In the 1990s, regulators in certain states began to explore deregulating the markets. They theorized that the increase in competition would result in lower power prices for consumers. By the late-90s, some states had deregulated their markets and others followed in the early 2000s. The result for utilities was the introduction of competition for customers and more price volatility in power procurement. Companies that were interested in entering the power market could now apply to solicit customers and sell electricity on the wholesale market. All players in the electric market were faced with the risk of uncertain fuel prices, weather conditions and, therefore, unpredictable power prices due to electricity's non-storable nature. In order to combat the uncertainty, companies have developed hedging strategies.

This paper builds on previously-developed models for the electric industry dealing with a multi-period portfolio optimization while incorporating the conditional value at risk (CVaR). Further, existing models have not considered hedging transmission congestion as another strategy in avoiding risk. Especially in the PJM market, congestion can lead to power prices that are three times the regional average. In order to combat price uncertainty, it is very important for load-serving entities to consider transmission when making power procurement decisions. The model presented in this paper incorporates fixed transmission rights in a three-node unidirectional network in order to evaluate the significance of transmission considerations in power portfolio optimization.

There has been a vast amount of research done in recent years dealing with power portfolio optimization. The non-storable nature of electricity and the increasing complexity of financial instruments as a tool for hedging against risk make the area of research very useful in the real world. Work done previously in this area provides models to help energy companies optimize profits, but very few incorporate transmission constraints into their models. The contribution of this research is to help companies not only hedge the risk of unknown power prices but also unknown transmission congestion.

Literature on power portfolio optimization has used different measurements of risk: value at risk (VaR), CVaR, and variation of spot price. The standard definition of a VaR portfolio is the maximum loss that the portfolio is allowed to sustain over a specified period of time and at a specified level of probability. The difference between VaR and CVaR is the way they are calculated. Whereas VaR takes the value that exists at a certain point in the distribution, CVaR takes into account each value that exists until that point in the distribution and the probability that the outcome will occure. While VaR had historically been used as a risk measure for electricity markets, the advantages of CVaR include more robust mathematical properties for a more accurate measure of extreme risk situations contained in the tail of the distribution. Likewise, different articles have incorporated financial portfolios of varying scope. Some focus primarily on day ahead, forward, and spot prices. Other papers also include power purchase agreements and/or options. Some authors use generation location or performance (such as ramp rates, heat rates, etc.) as constraints while others focus on different execution and reservation prices for options. Varying timeframes are used in the models, too.

Kwon et al (2006) focus more on the agent that sells power either through long-term purchase agreements or through other financial arrangements. The model developed then aides the selling agent in developing the optimal mix of custom contracts. The authors use a two-stage stochastic programming model where the first stage's result is the quantity of forward contracts to buy, and the second stage gives the electric capacity to make or buy in future time periods.

Kleindorfer and Li (2005) develop a model that decreases the allowable time period for using the VaR measure from one year to one month, which allows for a more realistic decision timeframe. A Monte Carlo simulation is run to arrive at different portfolio combinations. The end result is an efficient frontier of financial instrument combinations that maximize profits.

Xu et al (2006) focus on the issue facing a utility of how to best procure power for its customers. They use semi-variances of spot market transactions to measure risk and offer a model that can analyze the procurement situation with different types of power generation and financial tools.

The model presented by Conejo et al (2008) only deals with forward contracts that can be signed up to one year in advance. These contracts are then compared with the spot price to determine volatility and risk between the two prices; risk is measured using CVaR. Without considering risk, more power is bought on the spot market.

While it does not appear that transmission constraints have been incorporated into a power portfolio optimization problem that includes risk, many authors have incorporated transmission constraints into their models, especially when dealing with market power. A particularly interesting article was written by Olmos and Neuhoff (2006) and deals with finding a balancing point in a transmission network where companies cannot utilize market power by owning transmission rights. Although an actual logical point was not found in the European Union's network, the model is a good start to researching equitable fixed transmission rights (FTR).

The rest of this paper is organized as follows. Chapter 2 provides the relevant literature in power portfolio optimization and transmission constraints pertinent to the focus of this study. Additionally, a broad overview on how the PJM market operates and FTR auctions work is provided. A stochastic model (with linear mixed integer terms) is presented in chapter 3, whereas chapter 4 shows its possible application in the PJM market; the pertinent data for this purpose are also displayed. Chapter 5 discusses results of the empirical study completed using the application of the model developed in chapter 3. Finally, chapter 6 discusses limitations and proposes ideas for extensions of the work presented in this paper.

CHAPTER 2

LITERATURE REVIEW

Since the inception of deregulated markets for electricity, we see a vast amount of research elaborating on models to maximize profit under uncertainty. Existing models offer solutions for a diverse range of energy-related issues. Some deal with on-peak pricing for only one period; others offer multi-period modeling. Many models incorporate operating conditions such as ramp rate, heat rate, and ambient conditions. All models add knowledge to the industry as a whole. Following is a brief overview of different models that have been developed to aid in electric power portfolio optimization, in particular.

2.1 Power Portfolio Optimization

The literature review begins by mentioning a seminal article that appeared in Management Science (2003) by Kleindorfer and Wu. The main idea presented incorporates how companies will integrate contracting and market structure with operational decisions, given their respective risk management preferences. The authors explain in detail why a company would choose the forward/options market over the spot market and vice versa, using a graph with corresponding costs. Basically, the more "make to order" businesses would favor the contracts market due to variability in product. This article gives an excellent review of financial instruments and how they can be used in power markets.

Kleindorfer and Li (2005) provide an important work in which a multi-period setting is considered with a VaR constraint as the risk measure. The main focus of the article is to translate annual VaR constraints into a smaller timeframe. One of the usual assumptions when computing VaR is that of normality. Due to the variability (big spikes) in electricity markets, this assumption is not feasible. Through mathematical modeling, the authors develop a Regularity Assumption (RA) whereby the VaR is not necessarily distributed normally but with a fatter-tailed distribution. The RA also relaxes the assumptions that the cash flows are identically and independently distributed variables. The assumption that remains with the RA is that the VaR of a portfolio should be increasing in standard deviation and decreasing (or non-increasing) in mean. With the RA, the distribution could still be normal, but it also accounts for other distributions such as the student-t or Weibull.

The authors develop a model based on an efficient frontier of possible profit and VaR expectations. The basic idea is that the VaR will decrease as expected profits increase. The main objective of the model is to find an efficient frontier, which maximizes profit and minimizes risk, for an optimal portfolio of financial instruments. They define Q as a vector of instruments including owned generation, bi-lateral contracts (power purchase agreements), forward contracts, call options, put options and the spot market. The instruments are measured in megawatts and can be called or sold in a specific period. There are two types of costs associated with the contracts: reservation price and execution price. For bilateral contracts and owned generation, the reservation price is zero and the execution price is fixed (the marginal cost of running own generation or the cost set in the contract). The authors also set upper and lower bounds on the generation so that the solution does not lead to unrealistic contracts (such as an infinite amount of generation). The authors define retail price as given since they are looking at a regulated utility with retail customers where rates are set. (In other words, the utility is a price taker.)

After the authors deal with the distribution and build their model (proving that you can optimize a portfolio constrained by a VaR by maximizing profits), they move on to an example of how it could work using a hub in West PJM, which was chosen due to its relative liquidity. They pick a company with retail load that represents 5% of the PJM market load. The retail price is set at $50/MWh, although the authors do not state why they picked that number. The data are from the West PJM hub and include spot and forward prices. (Options prices are not included, most likely due to their sensitive nature. One must be a market participant in order to obtain that information.)

A Monte-Carlo simulation is run in order to obtain statistical measures including mean, standard deviation, and covariance. The time period evaluated is the three summer-peaking months – June, July and August – in 2003 during peak hours. In addition to optimizing the given portfolio, they add a scenario with one more generation supplier. They show that the additional generation improves the efficiency frontier and conclude that their model could help industries where portfolio management is conducted more frequently than on an annual basis. They comment that possible extensions could be considering technological and price uncertainty for generation acquisition and developing transmission or credit constraints. This paper, in effect, aims to extend the approach in Kleindorfer and Li (2005) to take into account the related transmission congestion and also substitute the CVaR risk calculation for the VaR measurement. To be able to develop this extension, the following summarizes some other relevant literature.

The Xu et al (2006) paper addresses a midterm optimization problem including risk analysis, where a load serving entity chooses a mix of different financial instruments to maximize profit while adequately serving its load; strips and call/put options are the typical financial instruments used. Different timeframes are analyzed, from a month to a year. However, in this study transmission congestion is not considered at all. The authors develop a nonlinear mixed-integer stochastic model. The risk term incorporates semi-variances of spot market transactions.

$$\sum_{j\in\Omega(k)} a(k,j)\{P_{spot}(k,j)[S(k,j)-E(S(k))]\}^2 * \Pr[S(k)=S(k,j)]$$

Where $S(k,j)$ is the price level j at time k, $\Omega(k)$ is the set of possible price levels at time k, $E(S(k))$ is the mean spot price at time k, and $P_{spot}(k,j)$ is the spot price at level j and time k. The integer variable $a(k,j)$ is positive if $P_{spot}(k,j) > 0$ and $S(k,j) > E(S(k))$ or if $P_{spot}(k,j) < 0$ and $S(k,j) < E(S(k))$; otherwise it is equal to zero.

The original problem is set up as a group of sub-problems that are solved subsequently and then integrated with each other following a heuristic strategy. The authors use data from the New England Independent System Operator – Connecticut Zone. When compared to a simplistic model, the model presented in this paper shows near-optimal results with the ability to analyze the situation with different types of generation and financial instruments.

In a recent study, Conejo et al (2008) show how a power producer can optimize its profits by utilizing forward contracts when they can be signed up to one year in advance. Only two tools are considered for power purchases in their model development: forward contracts and the "pool market" – day ahead, rather than real time. The decision of when to participate in the forward market is a complex one, involving lots of uncertainty over an extensive period of time. Given the volatility of day ahead prices (and therefore profits), modeling possible risk is a worthwhile endeavor. In the model presented, CVaR as a measure of risk is used. The model considers the optimal selection of forward contracts in a one-year timeframe where the company must make decisions before knowing the outcome of the stochastic variables (mainly, the day ahead prices). Real options are not considered, even though they are considered another helpful tool for hedging against price uncertainty.

The authors argue that a producer either can buy power in the futures market and attempt to sell it in the day ahead market for a profit (at a greater risk) or sell power in the futures market, decreasing the risk that is inevitable in the volatile day ahead market. The authors develop a stochastic mixed-integer linear programming problem. Rather than including the risk as a constraint, it is incorporated into the objective function as a risk measure of the profit. The modeling includes the development of price scenarios. Since spot prices are very unpredictable, they are modeled using historical information which is aggregated to only reflect 72 time periods within the year. Therefore, each scenario is comprised of 72 prices. The model is deployed on the electricity market of mainland Spain. Not surprisingly, the authors conclude that the deterministic results are inferior to the stochastic ones. In addition, the inclusion of risk results in a decrease in power bought in the forwards market and an increase in the power sold.

In a similar framework, Kwon et al (2006) develop a stochastic program that can be used by a company supplying a specialized contract with the purpose of developing a methodology for power procurement that minimizes costs of supplying power for other contracts. Forward contracts are defined as "contracts for differences" because they are the difference between the contract price and the spot price. The difference between this price and a benchmark or target is defined as the risk the buying and selling agents assume by entering into the contract. Transmission congestion is omitted from the model. The main contribution of the paper is a model for a selling agent who can sell incremental amounts of power through long-term contracts combined with contracts from other producers. It allows for "swing options", which means that the buying agent has the option of obtaining whatever quantity of power that he desires up to a maximum quantity. It is assumed that volume requirements for the contract only represent a small percentage of the total output of an electric generating unit. The model delivers an optimal price that the selling agent can charge for a custom contract. The actual model is set up as an asset/liability problem: the asset side is the available generation and market forwards; the liability side is the capacity specification in the negotiated contract. The authors use a two-stage stochastic programming model where the first stage's result is the quantity of forward contracts to buy, and the second stage gives the electric capacity to make or buy in future time periods. The model integrates the financial management of forwards with the operational issue of generating.

The model is solved using AMPL/CPLEX 7.0 software. It is run first with fixed generation and then with variable generation, since demand isn't known until just before a time period. There are also two types of forward contracts: the first considers a buying agent drawing fixed volumes for each time period and the second considers the buying agent drawing variable volume of power but within known lower and upper limits. Four cases are considered. In case 1, the selling agent uses fixed volume market forwards only as part of the replication of a custom contract F that requires a fixed volume of power for each time period. In case 2, the selling agent uses fixed volume market forwards only as part of a replication of a custom contract with variable volume requirements. In case 3, the selling agent uses variable volume market forwards as part of a replication of a variable volume custom contract. In case 4, the selling agent uses a mixture of fixed and variable volume market forwards as part of a replication of a variable volume custom contract. Cases 2, 3, and 4 are options from the point of view of the buying agent. The article focuses on three-month custom electricity contracts to illustrate the usefulness of the model. This model is different from the Kleindorfer/Li model in that it only considers the replication of a single custom contract, the time period can be long-term, and no unit commitment decisions are made.

The next few articles give more detailed examples of how utilities can use different financial schemes to optimize their situation.

The Kamat et al (2002) article examines interruptible supply with the current (at that time) financial environment. It reviews how utilities treated interruptible contracts historically and states that the treatment no longer works in deregulated markets. Utilities should view interruptible contracts as comparable to forward contracts, with the stipulation that there are many different ways to enact the contract. The article examines three: geometric Brownian motion model, affine diffusion with a logarithmic mean-reverting price and pricing of forward contracts with exotic options embedded in the contract. The scope of the model is very limited and only examines a small portion of the power demand picture and how it affects utilities financially.

In contrast, the Sen, et al (2006) article attempts to help utilities manage their power supply portfolio using the majority of available factors. They explore the effects of deregulating electricity markets, i.e. the focus shift of generators from minimizing costs to developing a power trading strategy. The authors analyze the DASH model for power portfolio optimization in order to determine its worth as a tool to electric utilities. The DASH model is a multi-stage stochastic integer program which recommends future power buying decisions. In order to determine the helpfulness of the model, the authors use a "fixed-mix" policy that was (at the time) used by traders as a "base-case" scenario by which to compare the DASH results. This policy makes a prediction of expected demand and capacity for the following month. If expected demand is greater than available capacity, then it recommends assuming a long position for forwards. If the reverse is determined to be true, a short position should be assumed. One of the benefits of the DASH model is that it allows for on- (16 hours) and off-peak (8 hours) modeling. It also can be modified to include several markets for utilities that trade in regions outside of their service territories; the model incorporates heat rates, start-up costs, minimum downtimes, etc.

The main objective of the DASH model is to help financial analysts and traders for the producer who wish to rebalance and/or reevaluate their power portfolio at the beginning of each month (or cycle). Possible extensions of the DASH model include introducing hydroelectric facilities in the model, modeling market power (game theory), and accommodating gas inventory.

Oum et al (2006) also attempt to aid utilities in finding the optimal financial portfolios given a set amount of available resources for additional capacity taking into account fluctuating demand. Due to the fact that load-serving entities cannot keep inventories of power in order to supply extra electricity when demand increases, there is not only pricing uncertainty but also volumetric uncertainty in the power industry. Loads are volatile, with spikes due to weather variability and other unforeseen events. In addition, electricity users have no incentive to curtail their demand, since their rates are fixed by regulation. The paper analyzes current available tools for volumetric hedging and proposes a different type of hedging solution. It addresses the problem of developing an optimal hedging portfolio consisting of forward and options contracts for a risk-averse load-serving entity when price and volumetric risks are present and correlated. The paper reviews instruments that can be traded to mitigate volumetric risks: fixed-price fixed-volume contracts, vanilla options, swing options, interruptible service contracts and weather derivatives. Ideas for further research include imposing credit limits on the hedging strategy and accounting for possible errors in choosing the risk-neutral probability measure.

While the focus of the DASH model and Oum article is optimizing available resources, the Murphy and Smeers (2005) article explores capacity expansion. Utilities seek to optimize their generation portfolios in order to have a sufficient amount of baseload, peaking and cycling capacity while minimizing costs. Here fuel costs can still be passed along to the customers and an oligopolistic market (where each player can influence prices) is assumed. The paper is presented based on a two-stage model: in the first stage investment decisions are made and in the second stage operational decisions are made. The model in this paper deals with an oligopolistic market with players using different technologies and having different cost characteristics. There are only two types of capacity: baseload and peaking. Three scenarios are explored: perfect competition, open-loop Cournot and closed-loop Cournot[1]. The open-loop model assumes that plants can be simultaneously built and the output is sold under long-term contracts (industry is organized under power purchase agreements). The closed-loop model assumes that capacity decisions are made in the first period and operating decisions in the second period (industry is organized around spot market). Forward contracting is not explored and is left for future research. A separate theory (Allaz (1992) and Allaz and Vila (1993)) evaluates the forward commodity markets with market power through an equilibrium model. Constraints include equilibrium conditions and incentives for producers to trade in the forward market before the spot market.

The focus of the present study is to expand upon existing "power portfolio optimization with risk" literature by introducing a transmission constraint into the model. Historically, transmission congestion has been modeled in different ways including flowgates, transmission rents and fixed transmission rights. Following is a brief literature review in the area of electric transmission.

2.2 Transmission Constraints

Historically, transmission constraints were viewed mainly as the physical limitation of the transmission line or its maximum thermal load. When markets were

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[1] Cabral (2000) explains that the Cournot model assumes that competitors in an oligopoly to choose their output, conditional on the output of other firms. Given firm A's belief of what firm B will produce, firm A chooses an optimal quantity to produce. For each possible level that firm B would choose, firm A has an optimal quantity. The combination of all of these optimal quantities makes up firm B's reaction curve. Firm A also makes a reaction curve to possible firm B choices. The intersection of the two curves gives the equilibrium level of output for each firm. The result is a market price that is between the price of perfect competition and that of a monopoly.

regulated, transmission lines were owned and operated by local utilities, and all power sent over the lines was either owned by the operating utility or wheeled for another utility based on existing agreements. With the advent of deregulation, utilities were forced to wheel other companies' power, which introduced more risk in terms of transmission constraints. In the case of PJM, existing utilities were given Fixed Transmission Rights (FTR) proportional to their load, which would help them to hedge against congestion charges. Utilities could also trade these rights to other entities in PJM's FTR auctions. Much research has been done on different ways to represent transmission constraints.

Olmos and Neuhoff (2006) focus on the problem of whether transmission contracts influence market power. The main theory is that transmission contracts should only be offered from predetermined balancing points, not from all distinct nodes (or hubs) in a system. They employ a Cournot model representation of profit maximization including transmission contracts.

$$\pi_{max} = q_i p_i(q_i) - c_i(q_i) + t(p_r(q_i) - p_i(q_i))$$

Where π is profits, q_i is generator output in MW, p_i is local price, t is transmission contracts owned by the generator between his location and the balancing node and p_r is the price at the balancing node. The authors also assert that if $\frac{\partial p_r}{\partial q_i} > \frac{\partial p_i}{\partial q_i}$, then transmission contracts will increase the output (q_i) of the generator and reduce its market power; if $\frac{\partial p_r}{\partial q_i} = \frac{\partial p_i}{\partial q_i}$, there will be no effect of transmission contract on the market; if $\frac{\partial p_r}{\partial q_i} < \frac{\partial p_i}{\partial q_i}$, the price at the balancing point is more responsive to output changes of a generator located at *i* than the price at *i* and the node would not be a suitable balancing node.

The increase in price at the balancing node should be small when the power output at any node in the system is decreased. This idea brings up another important characteristic of a balancing point: it would have to be well-connected to ensure low volatility in prices. Also, the point is representative of the whole system and not just showing regional differences. Given that the number of transmission contracts is fixed and assuming that they cannot be reconfigured, the authors delve into their model.

In order to apply the theory developed in the introduction, the authors elaborate on the balancing point idea and how to determine whether a participant enjoys a significant amount of market power. The cross price sensitivities are computed using data from the Union for the Coordination of Transmission of Electricity (UCTE). The cross price sensitivity is defined as the change in price at the balancing point when the generation node output decreases by one unit.

Three assumptions are made in the model. First, the group of constraints is constant. This assertion should not affect the outcome of the model for the following reasons. Marginal changes are not likely to change whether the constraints are binding. The UCTE network is very large so many constraints are simultaneously binding; therefore, a change in one of the binding constraints is unlikely to have a significant impact. Generators do not have access to complete information on the status of the network so will not know which constraints are binding.

Second, the net demand (proportional to power generation) at any node is reactionary to the price of energy in a linear manner. The authors concede that the actual demand and output curves of generators are far from being linear; since they are only concerned with marginal changes, the mathematical approach does not limit the results from being applicable to nonlinear forms. In addition, a Cournot approach does not provide for a price response from competing generators. This imperfection could be overcome by using a measure of market power (like the Herfindahl Hirschman Index (HHI)) to adjust the demand slope.[2]

Finally, they assumed a congested line to be defined by a flow capacity ratio above 0.7 (ratio of flow over the line to its capacity) because the available data did not indicate which lines were congested. After incorporating these assumptions and removing constraints that were highly collinear so the matrices could be inverted, they develop a tool to compute relative cross price sensitivities involving a set of transmission constraints, the linear net demand equation, impact of a change in output, and flow gate prices. Once cross-price sensitivities are computed, it can be ascertained which players could use contracts as an incentive to increase their market power by the methodology developed in the introduction (in other words, if the sensitivity is greater than one).

Analyses were performed to arrive at a plausible balancing point. The authors concede that only one scenario was available, which is definitely not reason enough to conclude that there exists even one appropriate balancing point. They show an example of a decrease in generation at a node in Germany and how it affects the surrounding nodes price and their respective price sensitivities. Some of the sensitivities were determined to be negative, which is justified due to their loss in competitive advantage in access to the node where the generation had decreased.

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[2] HHI is a standard index of market concentration. See Cabral (2000) for more details.

The remaining qualifier is how well-connected the balancing point is to the rest of the network. This characteristic is determined from the change in price due to a change in generation at the node. The lower its own price sensitivity, the larger the node and the more well-connected it should be. This attribute would ensure that if a generator decreases output, the value of its transmission contract would also be decreased; the ownership of transmission contracts reduces the exercise of market power at the node. The balancing node must have low cross-price sensitivities relative to all generation nodes in the network, not just one dominant generating node. Using the common price sensitivity in the absence of constraints, only those nodes with own price sensitivities of less than ten times below the unconstrained system's price elasticity were considered.

The results show 20 nodes that are well-connected with maximum relative cross price sensitivities below 1.1 and are in the lowest 95th percentile of cross-price sensitivities. Of these 20 nodes, the most appropriate one to choose as a balancing point is located in the Netherlands, which is surprising since this region is known for transmission constraints. The authors conclude that some of their bounds or constraints may have to be reconsidered. The criteria by which well-connected nodes are determined might not have been rigorous enough. If the model uses only those nodes with own price sensitivities of less than five times below the unconstrained system's price elasticity, the 20 possible balancing nodes would be located in France. In addition, the criteria by which congestion is located by the model may not capture some of the constraints that transmission operators take into account when operating the grid due to operating inefficiencies and security issues. Also, changing regulation of the European system and the possibility of new trade among countries could change existing constraints and flows considerably.

Niu et al (2005) argues that the supply function equilibrium (SFE) model is more realistic in dealing with the electricity markets due to its more flexible approach to elasticity of demand and parameters (not just price and quantity). The contribution to the literature is combining forward contracts, transmission constraints and multi-period strategy into the linear asymmetric SFE framework. Transmission congestion rights are explored as a linear combination of forward contracts. The article also explores flow gate constraints.

Kaymaz et al (2007) identify transmission constraints as a flowgate, or “a group of lines in the network that has limited flow capability in its lines.” They are mainly imposed by the transmission system operator (TSO) for thermal reasons, voltage considerations or to control the interregional flow of electricity. A portion is assigned to each generator in the area. The paper assumes that the TSO decides what amount of power needs to be transmitted to each node of the network, considering constraints. Bertrand pricing behavior is used to model the TSO’s behavior because of the assumption that it cannot control power prices.[3]

Stoft (1999) provides a very good overview of game theory and congestion rent and then explores transmission rights. Stoft ascertains that using Cournot modeling at the nodes may result in ambiguous results because of zero elasticity of demand. The

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[3] With Bertrand pricing, it is assumed that firms set prices conditional on the pricing of other firms. In the same way as the Cournot model, each firm creates a reaction curve to the other firm’s potential actions. The difference between the models is that the firms react to potential output in the Cournot model and potential prices in the Bertrand model. In general, it is better to use the Bertrand model when the relevant industry participants can easily adjust capacity and output. Conversely, the Cournot model should be utilized when output and capacity cannot be easily adjusted. See Cabral (2000) for more details.

assumption that market power decreases when the number of firms increases could not be correct. He gives the example of a kinked demand curve where firms would act cooperatively instead of "cut-throat". There is a great explanation of how Nash equilibriums could be reached in the market, depending on the generators' marginal cost and available capacity.

Oum et al (2003) states that if a generalized Nash equilibrium is used, it will resolve the Cournot ambiguity. Stoft (1999) explains the behaviors of market participant in a 3-bus system using a Cournot model with mixed-strategy Nash equilibrium. The latter part of the article focuses on transmission congestion contracts and how they function in the market; they basically give the owner increased market power due to their hedging abilities.

The Hobbs and Pang (2007) paper discusses the issue of using a smooth demand function when dealing with electricity markets. It proposes a piecewise linear demand function, which deals with price caps more effectively. The model assumes only one way of purchasing power – through bilateral contracts. The spot market could be considered through an easy extension. Zero cross-price elasticity is assumed. The authors explain that transmission fees are used in conjunction with congestion: the more constraints on the line, the higher the transmission fee. Each generating company (GENCO) tries to maximize its profit according to other participants' bidding behaviors and power systems operating conditions. Therefore, it is critical for a GENCO to devise a good bidding strategy.

The Li and Shahidehpour (2005) paper explores a non-cooperative incomplete game using a bi-level program in which the upper-level sub-problem maximizes

GENCOs' payoffs and the lower-level sub-problem (linear programming) solves the Independent System Operator's (ISO) market clearing problem. The paper agrees with Niu et al (2005) in that the SFE model is the appropriate method to use, as a good compromise between Cournot and Bertrand. The GENCOs submit bids to the ISO using a piecewise supply curve (which is like the demand curve in Hobbs and Pang (2007)). The ISO then takes all of the bids and limits consumer payments (maximizes social welfare), given the bids and transmission constraints. By this method, the ISO calculates locational marginal prices (LMP). Then the ISO lets each GENCO know its allowed capacity and the associated LMP. The GENCO takes this information and reevaluates how it will bid the next time.

Yuan et al (2005) first explores a two bus system with transmission constraints using a Cournot game (competitions' output is constant). Each node (or generator) has an optimal capacity. As long as the transmission line capacity is less than the generator's optimal capacity, there will be a transmission constraint. The model shows how the generators react to each others' decisions. The optimal solution for one generator is not equal to the optimal solution for the other generator. Given different conditions, the equilibrium solution will vary. In general, profits for both will be higher when transmission constraints exist; conversely, social welfare will decrease.

Liu and Wu (2007) develop another paper that uses bi-level programming to model generators' bidding strategy, taking into account transmission constraints. The problem starts when the ISO dispatches generation and determines prices. In the second stage, the generator optimizes its supply function with the Nash-SFE strategy. A three-node network is studied, with one demand node and two supply nodes. Capacity limits are ignored and the transmission constraint that is proposed ($\beta_1 q_1 + \beta_2 q_2 \leq q^{max}$) seems to be a flowgate constraint. The results show that the equilibrium exists when generators bid at the constraint line, which implies that there are no congestion charges. The authors contend that this will pose an issue for ISOs that want to expand transmission lines through congestion charges.

2.3 Review of the PJM Market

Since data from the PJM market will be employed, it is helpful to first review the origin of PJM and the methodology behind its pricing and Fixed Transmission Rights (FTR) markets. PJM Interconnection was formed in 1927 in order for three utilities in the Pennsylvania/New Jersey area to realize cost savings by giving up coordination of their lines to a central authority and pooling their resources. The main purpose of PJM is to maintain reliability and efficiently manage load to achieve the highest value for its customers. It evolved into a fully functioning ISO with the combination of the introduction of markets in 1996 and Locational Marginal Pricing (LMP) in 1997. PJM has worked to improve and refine its LMP pricing over the years.

LMP reflects the price of energy purchases and sales in the PJM market and also the price of transmission congestion charges. It is based on how energy actually flows and system conditions, not on some optimal power flow between nodes. LMP equals the marginal cost of generation plus the transmission congestion cost plus the cost of marginal losses. The marginal cost is defined as the cost to serve the next megawatt (MW) of load; it depends on the marginal cost to operate the power generators, total demand on the system and the cost of delivering energy on transmission system. The marginal loss is the change in MW capacity due to current flowing through resistance.

Losses can be increased by lower voltage, longer lines or higher current. PJM started using actual marginal losses (rather than estimated losses) in its calculation of LMP on June 1, 2006. The congestion price represents the price of congestion for binding constraints. It is calculated using the cost of marginal units controlling constraints and sensitivity factors on each bus.

The economic dispatch model used by PJM works in the following manner. First, PJM receives all generation offers for the next day. PJM then stacks the offers by price and looks at load forecast for the next day. The question is asked, "How much generation do we need?" PJM starts with the cheapest generator bids and systematically moves upward in price until the projected load is met. Therefore, the generation is marginal cost the next day is the lowest bid per MW that satisfies load; it is also the price if there is no congestion.

The main cause for transmission congestion is when there are thermal limits being violated on a line. The dispatcher can choose from three actions when this occurs. His first choice is system reconfiguration, such as opening normally closed breakers. This choice is the best option because it can be done without dispatching generation out of merit order. Second, the dispatcher can initiate transaction curtailment. The procedure is to look at transactions where the owner is not willing to pay congestion and any of these that has 5% effect or greater on easing the constraint will be curtailed. The final option is to re-dispatch generation. The dispatcher can take some generator and run it out of merit order because it is more advantageously located on the power system. The goal is to choose the most cost-effective unit to control the constraint. This strategy is also known as "security constrained dispatch" where delivery limitations prevent the use of "next least-cost generator" so the higher-cost generator located closer to load must be used.

There are five main factors that affect LMP: energy demand, economic dispatch, available flexible generating units (units that agree to follow PJM dispatch), network topology (what lines are in/out of service), and binding transmission limits. Here are a few simplifying assumptions that can be used to better understand the LMP system as it exists in PJM. First, the PJM real-time economic dispatch solution is the basis for calculating the real-time energy prices. Second, the price of energy is based on actual PJM operating conditions as described by the PJM state estimator, a computer model that estimates conditions between meter readings. Third, the price of energy is calculated at five-minute intervals and is based on the concept of LMP. The main idea is that the calculation starts with the state estimator and then goes to the locational pricing algorithm (compares actual output and the bidding curve for each generator) and is then published for the public. The day-ahead and balancing settlements are performed based on hourly integrated LMP.

LMP has a few important characteristics. There is a single market-clearing price when the system is unconstrained. Under constrained conditions, the marginal cost of energy varies by location as low-cost supply cannot reach all demand. LMPs reflect increased cost to deliver energy when insufficient transmission exists. Under constrained conditions, LMPs can be quite different from the economic dispatch rates due to costs to deliver energy from marginal generating units to load buses.

There are a few steps that occur in the process of executing the LMP model. First, the current conditions are determined, including energy demand, generator MW values and system topology. The generator bids and dispatch rates are then processed to determine flexible generators. The current system constraint data are collected and the locational price algorithm is executed. PJM uses the model to pay generators at generation bus LMP. Conversely, loads pay PJM at load bus LMP. Transactions pay congestion charges equal to the differential in source and sink LMPs. Zones are set up by historical utility territories, an aggregation of all nodes in that area.

2.4 Fixed Transmission Rights

Fixed transmission rights (FTR) are a financial contract that entitles the holder to a stream of revenues (or charges) based on the hourly energy price differences across the path. Unfortunately, LMP exposes PJM market participants to price uncertainty for congestion cost charges. Also during constrained conditions, the PJM market collects more from loads than it pays generators. (Load is at the receiving end of the constraint.) The solution is to buy FTRs, which provide the ability to have price certainty. FTRs provide a hedging mechanism that can be traded separately from transmission service.

Companies use FTRs for a variety of reasons. One possibility is that they create a financial hedge that provides price certainty to market participants when delivering energy across the PJM system. They can also provide firm transmission service without congestion cost. Another option is to provide a methodology to allocate congestion charges to those who pay the fixed cost of the PJM transmission system.

There are four different methods by which companies can obtain FTRs. Network service is an obligation FTR that is annually allocated for entities with load. Utilities are allowed up to annual peak load but can also opt out of the obligation. The FTRs are designated as the path from resources to aggregate loads. Firm point-to-point service, which is an option FTR, may be requested with transmission reservation. It is designated as the transmission line from source to sink. The secondary market is where bilateral trading takes place. FTRs that exist are bought or sold on this market. Finally, the FTR auction is a centralized market where entities can purchase "left over" capability. Entities that wish to sell FTRs can also put them into the auction rather than do it on the secondary market.

The economic value of FTRs is determined by hourly day-ahead LMPs. A benefit (credit) is applied when the FTR is in the same direction as congested flow. In contrast, a liability (charge) occurs when the FTR is in the opposite direction as congested flow.

The Congestion Charge is MW times the difference between day-ahead sink LMP and day-ahead source LMP. Therefore, the point-to-point FTR credit is MW times the difference between day-ahead sink LMP and day-ahead source LMP. Network service is calculated a bit differently. Its FTR credit is MW times the difference between day-ahead aggregate load LMP and day-ahead generation bus LMPs.

FTRs are defined from source to sink. The MW level is based on the transmission reservation amount. They are financially binding and are a financial entitlement, not a physical right. They are independent of energy delivery. PJM does all settlements if FTRs are traded on the PJM website.

PJM's responsibilities for FTR approval are as follows. PJM timestamps and acknowledges the receipt of transmission service requests (TSR). PJM then analyzes the FTR and determines both the reliability impact of the TSR and the feasibility of the FTR within the required time period, as defined in the tariff. Next, PJM notifies customers of disposition of requests within the required time period. Finally, PJM incorporates FTRs into the eFTR and settlements databases.

Network service companies specify designated network generating resources (sources) and aggregate loads (sink) up to value of peak load. The annual FTR auction covers planning period from June 1 through May 31. Companies submit desired FTRs during the April enrollment window. All requests received during the enrollment window are deemed to have arrived simultaneously. FTR modifications can be made at any time for any length of time (either because the company no longer wants the FTR or because it is taken away due to load decreases). Point-to-point transmission service customers specify the MW amount, transaction receipt (source) and delivery (sink) points. FTRs are for the same duration as associated firm point-to-point transmission service – either daily, weekly, monthly, or annually. The FTR is optional in that the company is not required to have it, but requests MW capacity up to its transmission service MW level.

The FTR Auction provides a method of auctioning the residual FTR capability that remains on the PJM transmission system at the time of the close of the auction quoting period. It allows rights to be purchased without firm service, and it allows market participants to bid for FTRs and offer to sell existing entitlements. The auction is needed for a variety of reasons. First, it facilitates a more robust and liquid market for transmission entitlements. Second, it allows PJM market participants to submit bids to purchase residual entitlements and to submit offers to sell existing entitlements. Third, it maximizes efficiency of FTR trading by providing automatic reconfiguration of FTRs.

Any holder can offer the FTR for sale, and any transmission customer or PJM member can bid for and acquire any number of FTRs. A single-round monthly auction is held for both on-peak (hours ending 08:00 to 23:00) and off-peak (hours ending 24:00 to 07:00). An internet application called eFTR allows PJM market participants to participate in PJM's FTR auction and secondary market. Bidding starts 15 days before the start of the month and ends 10 days before the start of the month. The participant must select the market, FTR source node, FTR sink node, whether they are buying or selling, MW, price ($/mw month), and class (on peak or off peak).

PJM awards bids by choosing them from highest to lowest cost effectiveness, until all of the selected line's capability is utilized. PJM compares sell offer cost effectiveness ratios (sorted highest to lowest) to cost of last marginal bid If cost effectiveness of sell offer is favorable to marginal bid cost effectiveness, sell offer is awarded. Additional bids are awarded to consume the FTR capability made available during Step 2 (where bids are compared). Steps 1, 2, and 3 are repeated until all capability is utilized.

A lot of trading takes place at hubs, which are cross section of representative buses. The reason is that the price is less volatile than single point. Also, it is a common point for commercial trading. There are three hubs: Western (111 Buses), Eastern (237 Buses) and Interface (3 Buses). The LMP at these points is the weighted-average price, based on fixed, equal weights at each bus.

CHAPTER 3

MODEL DEVELOPMENT

The purpose of the model developed in this paper is to determine the profit-maximizing combination of different power purchasing portfolios given transmission constraints and risk tolerance. Rather than using a flowgate constraint as a representation of transmission congestion, FTRs have been utilized. In addition, CVaR was chosen over VaR as a risk measurement for two different reasons. First, it is important to have a good representation of the tradeoff between the best expected profit and the volatility experienced when obtaining that profit. Second, it provides protection against very undesirable scenarios that may occur with low probability. Here it is expressed in terms of the minimum acceptable profit. The difference between the two measures is discussed in more detail below. In order to simplify the FTR contracts, a three-node network is used with unidirectional flow.

The model incorporates the following prices in power procurement optimization: power purchase agreements, forwards, options, and day-ahead prices. Hull (2006) provides a comprehensive review of derivative instruments. Power purchase agreements are considered the least risky way to procure power. Selling and buying agents agree on a \$/MWh price for power purchased over a period of time. Some contracts last as long as twenty years and have provisions that increase the price of the contract to combat inflation. The forward market offers a contract for power whereby the seller and buyer agree on a price for an assessment period in the future. A call option is a contract whereby the buyer has the option, but not the obligation, to buy the power at a certain price (strike price) in the future. A put option is a contract whereby the seller has the option, but not the obligation, to sell the power at a certain price in the future. We chose not to incorporate the put option into our model because our focus is power procurement; therefore, the utility would not be selling power through an options contract. A fee is paid for the option, which is called the premium. The day-ahead prices are set by generator bids the day before the power will be purchased.

3.1 Symbolic Elements

Sets

I is a set of all of the financial instruments that could be used to purchase power.

$i \in I$; I = {spot, forward (for), power purchase agreement (ppa), call, FTR contract}

T is the time period over which the model is optimized. Here it represents the number of peak hours during the assessment period (summer 2007).

$t \in T; T = \{1,\ldots,65\}$

D is the set of months ahead of power delivery that a forward contract can be purchased.

$d \in D; D = \{1,\ldots,5\}$

K and X are the nodes in the model where K is the set of source nodes and X is the set of sink nodes.

$k \in K; K = \{1, 2, 3\}$

$x \in X; X = \{2, 3, 1\}$

J is a scenario comprised of different financial instrument mixes.

$j \in J; J = \{1,\ldots,8\}$

Input parameters

p_t = customer rate in time t (t = 1,…,T)

ce_{tk} = execution price/MWh for call asset for time t (t = 1,…,T) at node k (k = 1, 2, 3)

f_{tkd} = forward price for time t (t = 1,…,T) at node k (k = 1, 2, 3) purchased d months ahead of delivery (d = 1,…, 5)

a_t = price of power purchase agreement contract in time t (t = 1,…,T)

r_{tkx} = FTR price for time t (t = 1,…,T) from source node k (k = 1, 2, 3) to sink node x (x = 2, 3, 1)

l_{kx} = maximum flow allowed from source node k (k = 1, 2, 3) to sink node x (x = 2, 3, 1)

b_j = probability of instrument mix j (j = 1,…, J)

Deterministic input

ζ = minimum value at risk (VaR) at a confidence level of α.

Stochastic inputs

D_{tk} = retail demand (MW) in time t (t = 1,…,T) at node k (k = 1, 2, 3)

S_{tk} = spot price in time t (t = 1,…,T) at node k (k = 1, 2, 3)

E_{tkx} = Difference between the spot price from source node k (k = 1, 2, 3) to sink node x (x = 2, 3, 1) during time t (t = 1,…,T)

Choice variables

Q_{itkx} = amount (MW) of instrument i purchased or sold (i = 1,…,I) from source node k (k = 1, 2, 3) to sink node x (x = 2, 3, 1) during time t (t = 1,…,T)

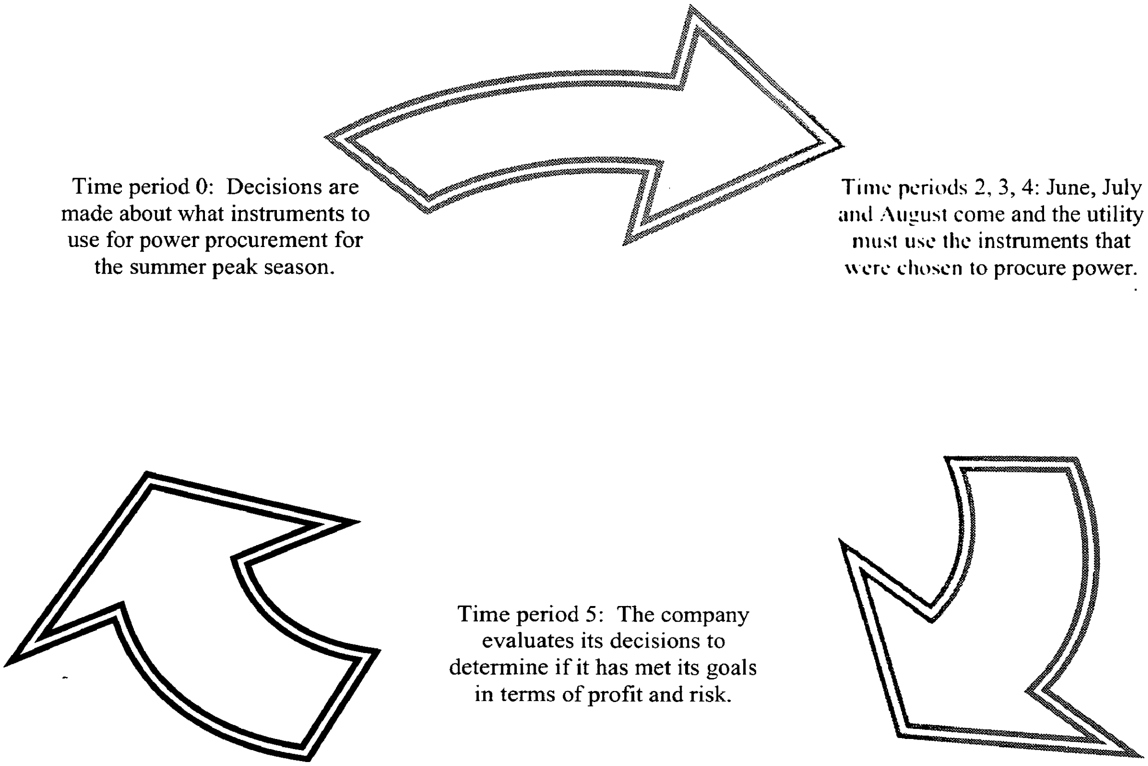
G_{tk} = amount (MW) of power to buy on spot market at node k (k = 1, 2, 3) in order to satisfy demand

Value of the objective

B_j = Profit in scenario j (j = 1,...,J)

3.2 Objective Function

In general, a company will want to maximize its profits by determining the optimal way to purchase power at the beginning of the cycle. Figure 3.1 shows the annual decision process.



Time period 0: Decisions are made about what instruments to use for power procurement for the summer peak season.

Time periods 2, 3, 4: June, July and August come and the utility must use the instruments that were chosen to procure power.

Time period 5: The company evaluates its decisions to determine if it has met its goals in terms of profit and risk.

Figure 3.1: Decision Timeframe

Maximize expected profit

$$B_j = \sum_{t=1}^{T}\sum_{k=1}^{K} p_t D_{tk} - \left[\sum_{t=1}^{T} \sum_{k=1}^{K} \sum_{x=1}^{X} \begin{pmatrix} S_{tk}(Q_{'spot'tkx} + G_{tk}) + f_{tkd} Q_{'for'tkx} + a_t Q_{'ppa'tkx} + ce_{tk} Q_{'call'tkx} \\ + (r_{tkx} - E_{tkx}) Q_{'ftr'tkx} \end{pmatrix} \right]$$

This problem seeks to maximize the expected profit. The revenue consists of the retail price of power times the demand. The quantity purchased for each power procurement instrument is multiplied by its respective price to arrive at the costs. The FTR auction price is then compared against the difference between the two nodes to arrive at whether the company won or lost by purchasing the FTR.

3.3 Constraints

Demand constraint:

The utility is responsible for meeting its customers' demand at all times.

$$\sum_{i=1}^{I}\sum_{t=1}^{T}\sum_{k=1}^{K} Q_{itk} = D_{tk} \forall t,k$$

Transmission constraints:

This constraint says that you cannot have more capacity on a line than is physically possible.

$Q_{itkx} \leq l_{kx}, \forall$ i,t,k,x

The following constraints represent flow in one direction in the network where the capacity that flows into the node must be able to satisfy the capacity demanded at that node. In other words, these are flow-conservation constraints.

$$\sum_{i=1}^{I}\sum_{x=1}^{X} Q_{itxk} + G_{tk} \geq D_{tk}, \forall t,k$$

$Q_{it21} = 0$, $Q_{it32} = 0$, $Q_{it13} = 0$

The left hand side gives the capacity purchased through instrument i traveling to node k plus the amount of additional power that must be purchased on the spot market to satisfy demand at node k in time period t. The right hand side represents the demand at node k. Figure 3.2 gives a representation of the network.

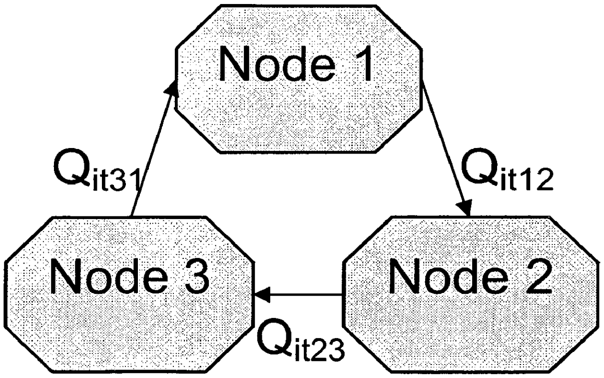


Figure 3.2: 3-Node Unidirectional System

In addition to the constraints, we need to define B_j as a function of the solution for the calculation of CVaR.

$B_j \geq 0$, $B_j^- - \zeta + B_j \geq 0$, $B_j^-(B_j^- - \zeta + B_j) = 0$ (Variational Inequality)

CVaR is then defined as

$$\zeta - \frac{\sum_{j \in J} b_j * B_j^-}{1-\alpha} \geq \mathrm{CVaR}_{\min}$$

If $B_j > \zeta$, then $B_j^- = 0$, and this constraint just says that the VaR must be greater than or equal to $\mathrm{CVaR}_{\min}$. If $B_j < \zeta$, then the constraint contains the difference between VaR and profit and displays how much risk is acceptable.

<u>Auxiliary report variable</u>

B_j^- = auxiliary variable that is equal to zero when $B_j > \zeta$ and equal to ζ - B_j when $B_j < \zeta$.

<u>Logical bounds:</u>

The confidence level and the probability of each scenario must be between zero and one. The sum of all probabilities must equal one.

$0 \leq \alpha \leq 1$

$\sum_{j \in J} \mathrm{bj} = 1$

Q_{itkx}, ζ, D_{tk}, S_{tk}, $B_j \geq 0$, $\forall i, t, a, j$ (non-negativity)

3.3.1 Using VaR vs. CVaR

Risk management is a procedure for shaping a loss distribution. CVaR is generally (and sometimes exactly) the average for some percentage of the worst-scenario loss cases. The VaR risk measure is a percentile of a loss distribution. The VaR risk constraint is the same as the chance constraints on probabilities of losses. VaR and CVaR are similar, but with the same confidence level VaR is a lower bound for CVaR. The need to estimate VaR and CVaR arises typically when the analyst is interested in estimating tails of distributions. Whether VaR or CVaR is the measure of choice is decided upon because of their differing mathematical properties, stability of statistical manipulation, simplicity of optimization procedures, acceptability by regulating authorities, etc.

One might choose CVaR because it has mathematical properties superior to those of VaR. The CVaR of a portfolio is a continuous and convex function with respect to positions in instruments, whereas the VaR could be a discontinuous function. It is possible to optimize and constrain CVaR with convex and linear programming techniques, whereas VaR is relatively difficult to optimize. The VaR risk measure does not have control over scenarios that exceed VaR. On the other hand, the indifference of the VaR risk measure to extreme tails could be beneficial if poor models are used for building distribution. VaR estimates are statistically more stable than CVaR estimates. Conversely, the inability of the VaR estimate to consider extreme tails could be an undesirable property because it allows high uncontrollable risks. CVaR accounts for losses exceeding VaR, which could be good or bad depending upon the objectives of the model.

For normally distributed random variables, VaR is proportional to the standard deviation. It can be difficult to optimize VaR numerically when there is no normal distribution of losses. As a tool in optimization modeling, CVaR has superior properties in many respects. CVaR optimization is consistent with VaR optimization for normal or elliptical distributions and produces the same results. The main issue in comparisons of the two is that some confidence level is chosen and estimations of VAR and CVaR are analyzed against the common value of a confidence level (usually 90%, 95% and 99%). The problem with these comparisons is the two estimates with the same confidence level measure different sections of the distribution.

There are several advantages to using the VaR estimation tool. It is a relatively simple idea; insight behind a percentage of a distribution is easy to understand. VaR has a straightforward analysis: how much could be lost with 100% confidence. One important aspect of VaR is its constancy of estimation processes. Because VaR ignores the tail of the distribution, it is unaffected by excessive tail losses. There are also disadvantages to using VaR, such as it does not incorporate properties of the distribution past the given confidence level. This attribute implies that VaR may grow significantly with a small increase in the set percentage. Using VaR as a risk control measure could result in unfavorable results for skewed distributions. VaR is a nonconvex and discontinuous function for discrete distributions.

CVaR also has its advantages. It provides a understandable engineering analysis and measures results that are the least desirable. CVaR is also continuous with respect to the given percentage. A disadvantage of CVaR is that it is more sensitive than VaR to approximation errors. If there is not an accurate model for the tail of the distribution, the CVaR value could be deceptive.

The question then arises about which tool should be used in different situations. VaR and CVaR estimate different portions of the distribution. Depending on what estimation is desired, one could be favored over the other. A trader could choose VaR over CVaR because he may be partial to high uncontrolled risks; VaR is not as limiting as CVaR with an equivalent confidence level. A business owner would most likely choose CVaR; he has to pay for big losses if they happen; so he should control events that occur in the tail. VaR could be superior for optimizing portfolios when accurate models are unavailable for tails. If an accurate model is available, then CVaR can be precisely obtained and it should be employed.

CHAPTER 4

APPLICATION

The data that are analyzed with the model presented in chapter three were obtained from Platts' proprietary database.[4] All data, with the exception of the Platts Megawatt Daily forward prices, are publicly available on the PJM or New York Mercantile Exchange (Nymex) websites. PJM is used for the analysis because it is a mature independent system operator with fixed transmission rights auctions and nodal pricing data. The data include PJM hourly day-ahead prices for summer 2007, PJM Financial Transmission Rights (FTR) auction prices for the assessment period of June, July and August of 2007, PJM daily forward prices for the summer months of 2007, New York Mercantile Exchange (Nymex) future prices for summer 2007, and PJM hourly load data from the summer of 2007. In order to determine which PJM nodes could be used in the model, first an analysis is performed on possible nodes with FTR data for the three summer months of 2007 that could be used as a simplistic three-node unidirectional network, which enables transmission constraint analysis. The summer of 2007 is used for the empirical implementation of the model because it was the most recent set of summer peaking season data available when this study was begun.

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[4] Platts is an energy information company with headquarters in New York; its proprietary database is maintained by a group of energy analysts based in Denver. The information included in the database ranges from commodities pricing data to tracking of proposed infrastructure projects. For more information on Platts and its market coverage, visit www.platts.com.

4.1 Fixed Transmission Rights Data

Valid sources and sinks for the PJM FTR auction are limited to: hubs, zones, aggregates, interface buses, load buses and generator buses. PJM hubs are reference nodes at which standard energy goods are traded. Hubs serve as a common point, or reference price, for commercial trading. The hubs are fixed weighted averages of the LMP at a set of typical buses for the chosen area. Hub prices are demonstrative of the PJM market, are fairly steady under many system conditions and are not interfered with by local transmission confines or system topology variations. Zones are a collection of load-weighted LMPs and correspond to transmission zones. Each participating electric distribution company has its own transmission zone through which it supplies its customers. An aggregate node represents a portion of the nodes that exist in the zones. The node is created at the request of the distribution utility and can be either generation- or load-weighted. Interface buses are those which connect two adjacent transmission areas. Generator buses are located adjacent to the major generating units within PJM.

The PJM FTR data are analyzed in order to find a three-node network with pricing information for the 2007 summer assessment period. Three sets of networks are found in the data. An analysis of their attributes follows. The first network is composed of the following three nodes: 12 Dresd18 KV DR-3, ComEd, and 21 Kinca20 KV KN-1. These nodes are located in the Commonwealth Edison (ComEd) zone around the Chicago, Illinois, area. ComEd's transmission system was integrated into the PJM grid on June 1, 2003. The Comed node is a zonal LMP, which means that it is a load-weighted LMP including all 1,104 of the nodes in the zone. 12 Dresd18 KV DR-3 is a generation node as is 21 Kinca20 KV KN-1.

The second set of 3 nodes is: Pepco DC, Pepco MD and Pepco. These nodes are located in the Potomac Electric Power (Pepco) zone around the Maryland/District of Columbia area. The Pepco node is a zonal LMP, which means that it is a load-weighted LMP including all 113 of the nodes in the zone. Pepco DC (60 nodes) and Pepco MD (49 nodes) are aggregate nodes that were probably requested by the load-serving entity, in this case – Pepco. An aggregate node can be either generation- or load-weighted, but both Pepco MD and Pepco DC are load-weighted.

The third network is comprised of the nodes: Greenbri138 KV T1, Hinton 138 KV T1, and Roncever138 KV T1T3T5. These nodes are located in the American Electric Power (AEP) zone in West Virginia and belong to one of its subsidiary utilities, Appalachian Power. Greenbri138 KV T1, Hinton 138 KV T1 and Roncever138 KV T1T3T5 all represent load nodes.

Out of these three choices, it is decided that the AEP nodes will be the least problematic data with which to work, since it is important that each node is an independent source of data. None of the nodes in the three-node network are aggregate or zonal nodes; they are all buses. In the ComEd set, there exists a zonal node, which would include the other two nodes' prices in its average. In the Pepco set, there are two aggregate nodes and a zonal node. All three nodes contain some of the same prices in their averages. If the Pepco or ComEd set are chosen, there might exist collinearity issues since the zones and aggregates include prices used in one of the other aggregates/zones/buses in the network.

Each FTR is classified as an obligation FTR, which means that the selling entity is allocated the FTR based on its load. Since the focus of the problem is from a utility's perspective, the sign on the peak prices is changed to represent what the FTR is worth to the selling agent. Table 4.1 shows the original data.

Table 4.1: FTR Obligation Prices – 2007

Source Node	Sink Node	Month	Peak Prices
GREENBRI,138-KV T1	HINTON,138-KV T1	June	-512.85
		July	-290
		August	-211.41
HINTON,138-KV T1	RONCEVER,138-KV T1T3T5	June	501.85
		July	282
		August	200
RONCEVER,138-KV T1T3T5	HINTON,138-KV T1	June	11
		July	8
		August	11.41

4.2 Power Procurement Prices

The next determination is whether to use day ahead or real time prices. As mentioned above, the value of the FTR is determined using the day ahead price at the source and sink nodes. The Greenbri138 KV T1 data are analyzed for the year 2007. Figure 4.1 shows the general day-ahead price trend.

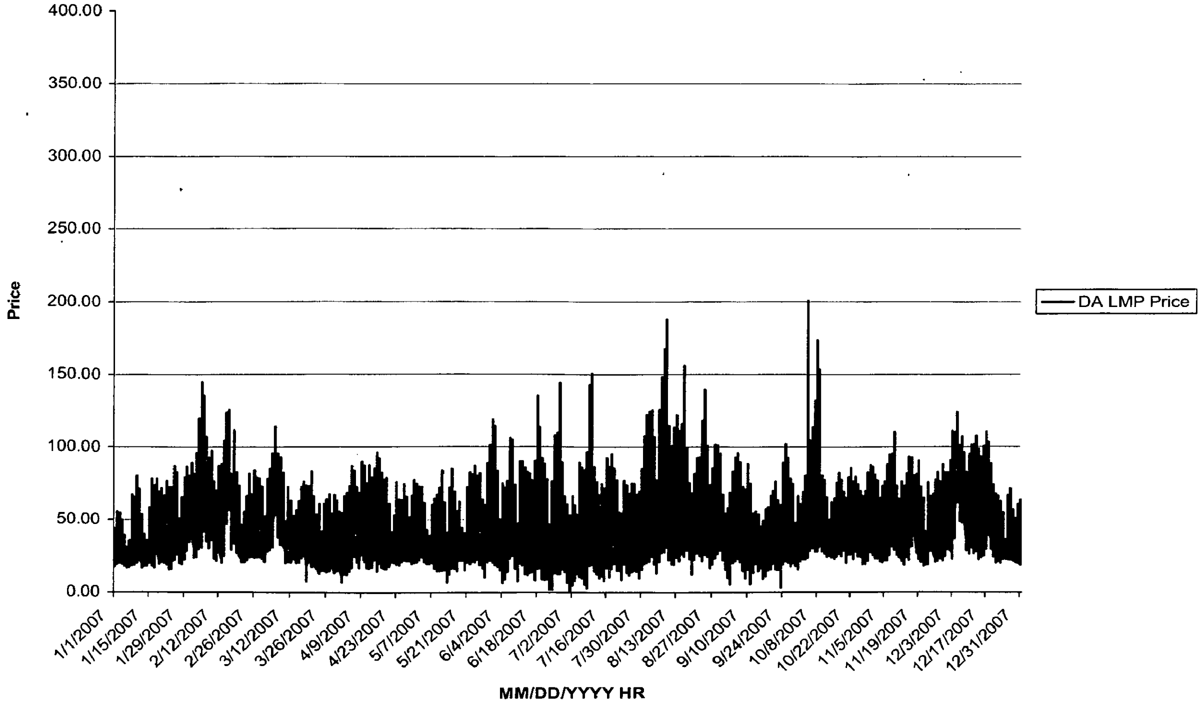


Figure 4.1: Day-Ahead LMP Price - 2007

Figure 4.2 shows the trend for the real time price.

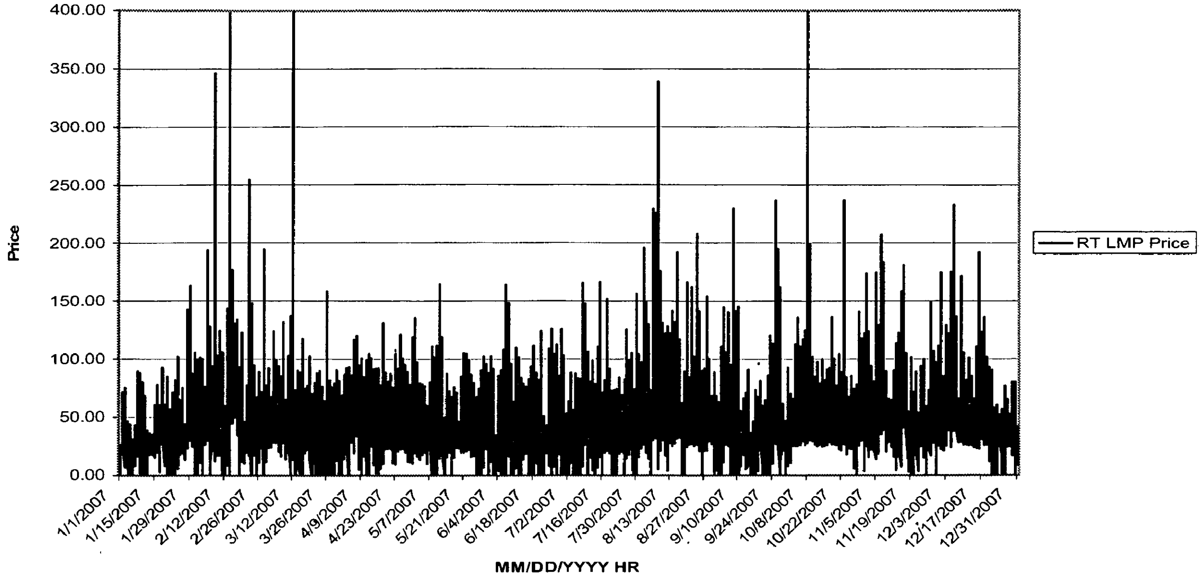


Figure 4.2: Real-Time LMP Price - 2007

Both graphs are on the same scale (from \$0 to \$400) so that it is easily seen how much more volatile the real time price is than the day ahead price. Figure 4.3 shows the trend for the percent difference between the two, using the formula (DA-RT)/RT.

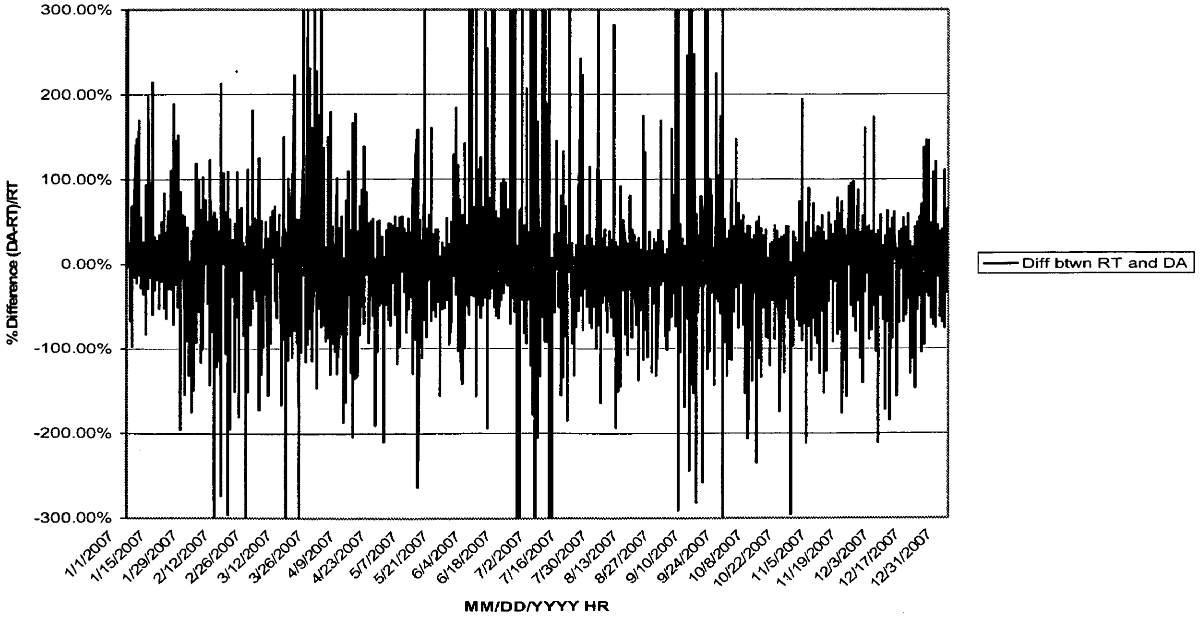


Figure 4.3: Real-Time vs. Day-Ahead

The difference between the two price measures can be either positive or negative on a regular basis, but there is no real trend on either side of the x-axis. Table 4.2 shows the basic metrics for the day-ahead prices in the selected time period.

Table 4.2: Average On-Peak Prices

	Greenbri138 KV T1			Hinton 138 KV T1			Roncever138 KV T1T3T5		
	Low	High	Average	Low	High	Average	Low	High	Average
6/2005	28.99	110.95	63.99	26.35	104.95	61.37	28.06	108.93	63.10
7/2005	30.82	147.60	82.82	27.34	146.49	78.25	29.60	147.58	81.35
8/2005	37.27	180.78	91.33	34.94	157.77	85.04	30.02	176.15	89.26
6/2006	24.78	104.50	56.45	24.78	91.34	54.96	24.78	91.34	54.96
7/2006	26.41	141.86	67.55	26.41	141.86	67.55	26.41	141.86	67.55
8/2006	25.72	260.10	75.35	25.72	260.10	75.35	25.72	260.10	75.35
6/2007	22.21	144.01	68.44	21.50	139.46	66.28	22.20	143.93	68.40
7/2007	23.42	150.64	62.34	22.48	144.06	60.26	23.42	150.57	62.32
8/2007	27.55	187.96	83.66	26.67	181.22	80.80	27.59	187.89	83.64

The Platts Megawatt Daily forward prices are collected from a random anonymous selection of market participants. They indicate the trade date, the assessment period, whether the agreement is for peak/off peak power and the price in dollars per megawatt-hour. Table 4.3 shows the metrics for the 2007 summer peak trades for the AEP Dayton Hub, which is chosen due to its relative proximity to the nodes. Plus, the nodes are managed by Appalachian Power, which is a subsidiary of AEP (American Electric Power).

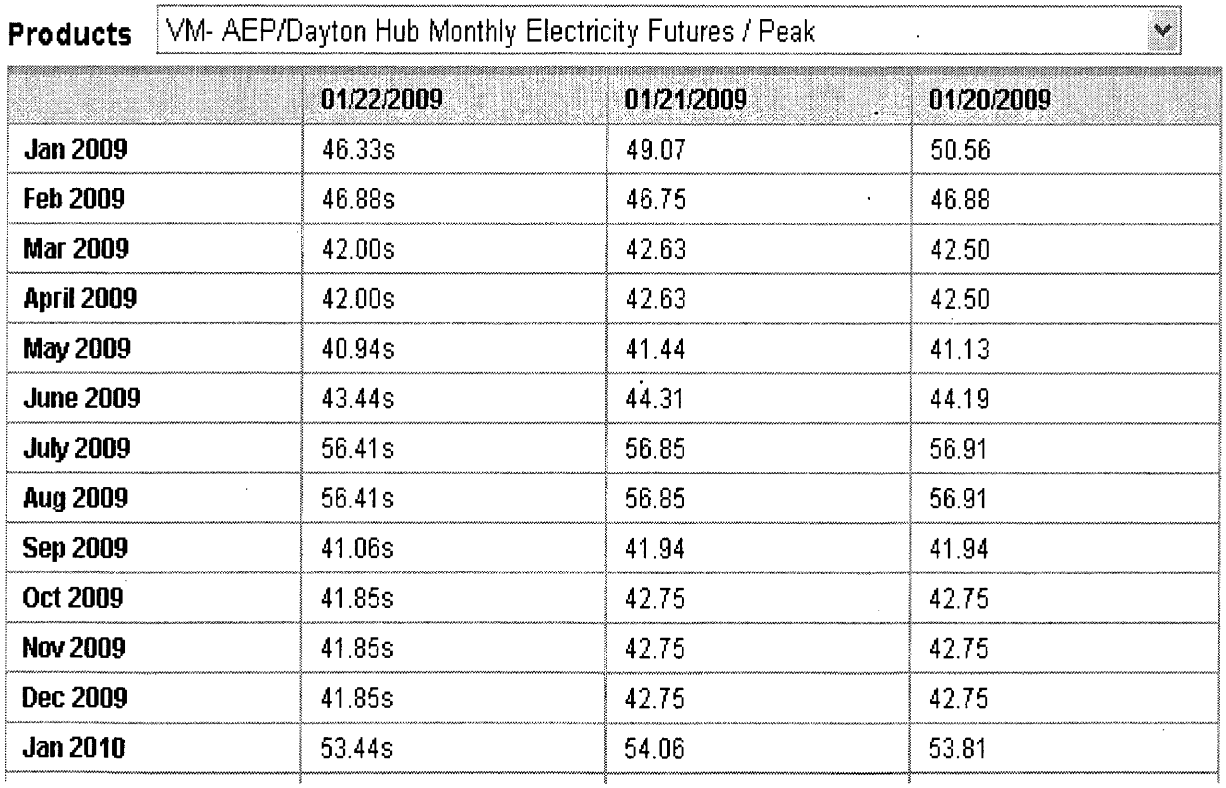
Table 4.3: Platts Megawatt Daily Forward Prices (AEP Dayton Hub)

Assessment Period	Minimum	Maximum	Average
June 2007	49.90	69.25	59.49
July 2007	64.75	84.00	77.56
July/August 2007	65.00	85.35	76.80
August 2007	57.50	86.00	71.30

In order to obtain nodal level data for the forward prices, a spread between the day-ahead price for the AEP Hub and the price for each node is calculated. That spread is then multiplied with the AEP forward price in order to obtain a unique forward price for each node.

Finally, the New York Mercantile Exchange (Nymex) provides monthly futures contracts to customers based on the daily floating price for each peak day of the month at the AEP-Dayton Hub. Additional hedging opportunities are offered through options on the contracts. The following snapshot is a sample of the data available via Nymex.

Table 4.4: NYMEX Future Prices



Products VM- AEP/Dayton Hub Monthly Electricity Futures / Peak

	01/22/2009	01/21/2009	01/20/2009
Jan 2009	46.33s	49.07	50.56
Feb 2009	46.88s	46.75	46.88
Mar 2009	42.00s	42.63	42.50
April 2009	42.00s	42.63	42.50
May 2009	40.94s	41.44	41.13
June 2009	43.44s	44.31	44.19
July 2009	56.41s	56.85	56.91
Aug 2009	56.41s	56.85	56.91
Sep 2009	41.06s	41.94	41.94
Oct 2009	41.85s	42.75	42.75
Nov 2009	41.85s	42.75	42.75
Dec 2009	41.85s	42.75	42.75
Jan 2010	53.44s	54.06	53.81

4.3 Capacity Data

In general, the unit of measurement for transmission lines is considered to be kilovolts (kV). This study's chosen unit of measurement (megawatts - MW) cannot be directly converted from kilovolts, as one must know the amperes involved and power factor of the generation. In a 2006 filing with the Utah Public Service Commission, PacifiCorp (a local electric utility) makes a generalization that a 138 kV transmission line can carry around 200 MW of new capacity. The same generalization is used in this paper.

Unfortunately, load data at the nodal level is not available for the PJM market. PJM only releases data at the load zone level, which only encompasses 18 entities. For this study's purpose, the hourly load data for the AEP zone are chosen, since the given nodes all reside in that zone. Per PJM data, each of these three nodes represents around 0.08 percent of the zonal data. The fact that each node represents the same fraction does not lend itself to having unique demand data for each node. Using nodal pricing data to estimate demand at each node was considered, but that the estimation would not be correct because nodal price is set not only by demand but also by other factors such as system topology, weather, demand at other surrounding nodes, etc. Therefore, the assumption is made that demand at each node could vary by ten percent in either the positive or negative direction and a random number generator was applied so that demand at each node would have the possibility of being unique. The data represent the daily peak load for days when the market was open.

4.4 Financial Instrument Scenario Generation

In order to estimate different portfolio combinations, the load duration curve for AEP for the summer of 2007 is utilized. A load duration curve demonstrates a company's load in megawatts from largest to smallest load for a given time.

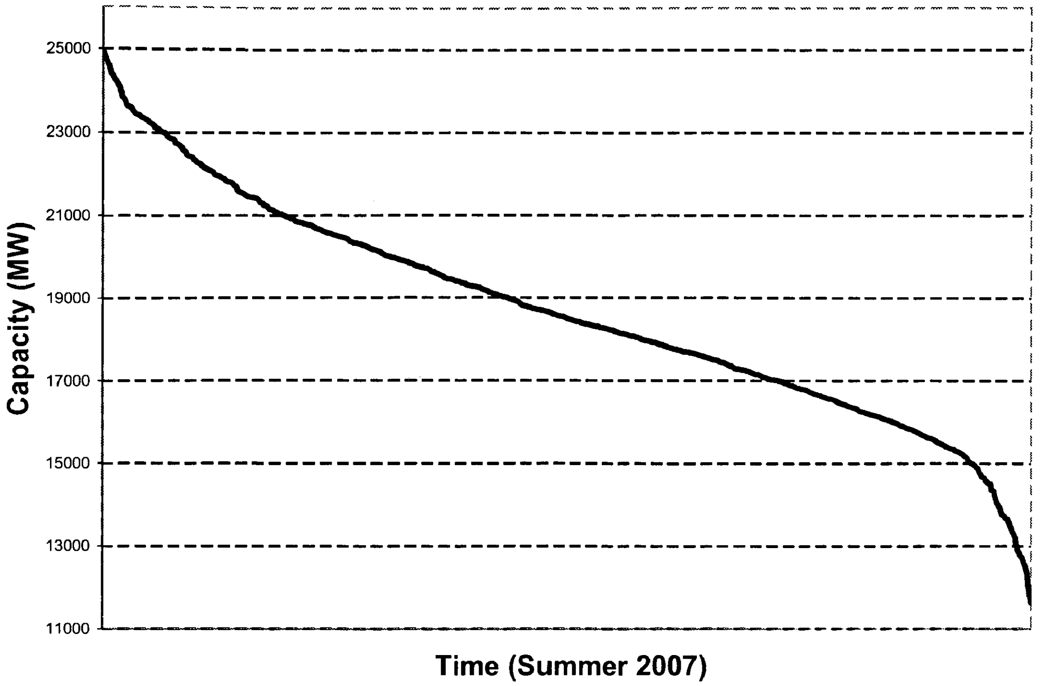


Figure 4.4: Load Duration Curve - AEP, Peak Hours, Summer 2007

As a general rule, a utility may serve around 85 percent of its peak by more secure contracts like power purchase agreements; the remaining 15 percent would be obtained through forwards, options and the spot market (based on conversation with industry experts). When the company makes procurement decisions, it does not know what the actual load will be. Therefore, it may not need to use the spot market because the load may not be high enough to warrant additional power purchases. It follows that two of the scenarios do not contain any spot purchases. Forward data are available for power bought up to 12 months before power delivery, but only the forwards that are purchased up to five months were used; it is assumed that a utility begins to think about summer peak season in January of the same year. In total eight scenarios are considered, which are represented in table 4.5.

Table 4.5: Instrument Mix Scenarios

SCENARIO	PPA	FOR1	FOR2	FOR3	FOR4	FOR5	OPTION	SPOT
Lowest base	64%	5%	3%	2%	3%	3%	10%	10%
Low base (plan late)	68%	6%	5%	4%	2%	0%	4%	11%
Low base (plan early)	72%	2%	2%	3%	4%	5%	8%	4%
Middle (plan early)	76%	3%	2%	0%	5%	5%	9%	0%
Middle (plan late)	80%	5%	3%	1%	0%	1%	3%	7%
Conservative (plan late)	84%	4%	3%	3%	0%	0%	2%	4%
Conservative (plan early)	88%	2%	0%	0%	1%	4%	5%	0%
Highest Base	92%	2%	0%	0%	0%	2%	2%	2%

The probability of each scenario being chosen is generated by Monte Carlo simulation (using an add-in tool called YASAI Simulation Version 2.0[5] in Microsoft Excel) for each of the three nodes, which gives the average profit for each scenario. The profit differential is then used to estimate the probability that each scenario will be used by the utility to purchase power.

4.5 VaR and CVaR Calculations

In order to calculate VaR and CVaR values, the Monte Carlo simulation method is used again. Combinations of the eight scenarios for each node are evaluated for a total of 512 scenarios. The same random number seed is used for each scenario and each run has a sample size of 1,000. The simulation with an output of 512 scenarios is run a total of ten times because there is very little variation in output in each of the ten runs; each individual run took around 15 minutes to complete. The slight numerical difference among the ten simulation runs is probably due to the fact that historical data are used for the analysis. The variation in pricing and demand data that is normally observed is eliminated by using actual data from 2007. The estimated nodal demand and actual nodal prices are used to determine the profit for each of the scenarios. The probability for the

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[5] Yasai was developed in order to run elementary Monte Carlo simulation in Microsoft Excel by Jonathan Eckstein and Steven Riedmueller, professors at Rutgers, the State University of New Jersey. More information can be found at www.yasai.rutgers.edu.

combination of scenarios is calculated from the combined probabilities of each of the component scenarios. Figure 4.5 displays the expected profit distribution.

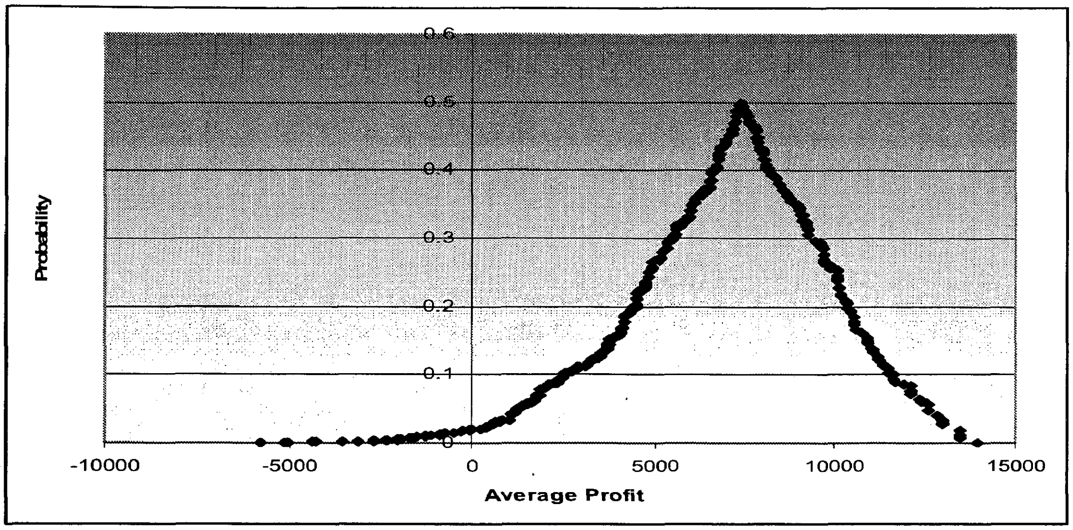

Figure 4.5: Average Profit Distribution

The confidence level for the problem is set at 95 percent based on the level most-used by previous studies in the area of power portfolio optimization. The scenarios are then sorted in ascending order based on expected profit. In order to find the VaR, the probabilities of the scenarios (starting with the most negative profit) are added up until the five percent VaR is reached. The value is found to lie between the 88th and 89th records and is equal to a profit of around \$1,216. The CVaR is then calculated basically as the weighted average of the tail from the most negative profit to the VaR profit value. This method is used in order to take into account possible extreme behavior in the tail as shown in Sarykalin et al (2008). The value for the CVaR is calculated at a loss of \$82. The fact that the CVaR is negative signifies that the VaR does not take into account extreme losses in the tail, which is demonstrated in Figure 7. Given a negative CVaR, the utility may want to decrease the confidence level to 90 percent. Table 4.6 is a snapshot of the Monte Carlo Simulation analysis.

Table 4.6: Monte Carlo Simulation for VaR/CVaR Calculation

Record	Scenario	Probability	Observations	Mean Profit
1	512	0.0156%	1000	$ (5,800.47)
2	448	0.0156%	1000	$ (5,111.05)
3	511	0.0313%	1000	$ (5,025.84)
4	504	0.0156%	1000	$ (5,025.11)
5	447	0.0313%	1000	$ (4,336.41)
⋮	⋮	⋮	⋮	⋮
84	310	0.0469%	1000	$ 1,187.08
85	380	0.1250%	1000	$ 1,188.34
86	303	0.0313%	1000	$ 1,199.12
87	407	0.0313%	1000	$ 1,199.75
88	352	0.0156%	1000	**$ 1,214.14**
89	442	0.3125%	1000	**$ 1,260.75**

CHAPTER 5

RESULTS

Although the Monte Carlo Simulation is calculating scenarios based on nonlinear, stochastic data, the actual model run for the optimization is deterministic and linear. The model is run using the Solver[6] tool in Microsoft Excel. The majority of the rigorous calculation takes place in deciding the scenarios and CVaR/VaR values, Solver took less than one minute to solve the problem. Table 5.1 shows the vital statistics from the results.

Table 5.1: Results from Optimization

GREENBRI138 node (Scenario = Conservative (plan early))							
%PPA	**%FOR1**	**%FOR2**	**%FOR3**	**%FOR4**	**%FOR5**	**%OPTION**	**%SPOT**
88%	2%	0%	0%	1%	4%	5%	0%
Qppa	**Qfor1**	**Qfor2**	**Qfor3**	**Qfor4**	**Qfor5**	**Qcall**	**Qspot**
1,019.87	23.18	0.00	0.00	11.59	46.36	57.95	0.00
Profit				**Added Qspot for transmission constraint**			
$ 8,983.75				0			
RONCEVER138 node (Scenario = Conservative (plan early))							
%PPA	**%FOR1**	**%FOR2**	**%FOR3**	**%FOR4**	**%FOR5**	**%OPTION**	**%SPOT**
88%	2%	0%	0%	1%	4%	5%	0%
Qppa	**Qfor1**	**Qfor2**	**Qfor3**	**Qfor4**	**Qfor5**	**Qcall**	**Qspot**
1,021.24	23.21	0.00	0.00	11.61	46.42	58.03	0.00
Profit				**Added Qspot for transmission constraint**			
$ 10,407.71				0			
HINTON node (Scenario = Conservative (plan early))							
%PPA	**%FOR1**	**%FOR2**	**%FOR3**	**%FOR4**	**%FOR5**	**%OPTION**	**%SPOT**
88%	2%	0%	0%	1%	4%	5%	0%
Qppa	**Qfor1**	**Qfor2**	**Qfor3**	**Qfor4**	**Qfor5**	**Qcall**	**Qspot**
1,016.19	23.10	0.00	0.00	11.55	46.19	57.74	0.00
Profit				**Added Qspot for transmission constraint**			
$ (5,465.44)				5.75			
TOTAL PROFIT							
$ 13,926.02							

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[6] The Microsoft Excel Solver tool is one of the most widely-distributed and used general-purpose optimization modeling system. It comes standard with the Excel application as an add-in. For linear models, it uses the simplex algorithm.

Since the model is linear, the local optimum is ensured to be a global optimum. Multiple runs of the model arrived at the same solution for the decision variables. The results show that all three nodes arrive at an optimal solution with the same strategy – the one in which the utility has a fairly high percentage of its power coming from fixed-price power contracts and purchases the majority of the rest of its needed power in the five-month forward market and in options. Rather than using the spot market, the utility estimates the max peak for the following month and purchases one-month forward contracts for that amount. The only spot purchased is for the extra demand at the Hinton node in order to satisfy the transmission constraint. The Hinton node generally has a negative profit because of the unfavorable conditions of the financial transmission rights contract from the Greenbri138 node to the Hinton node and because of the additional demand at Hinton that must be satisfied through the spot market. One assumes the utility will reevaluate its positions at this node for the following summer season so that the profit will have the opportunity to turn positive. A total profit of $13,926 is reasonable because it represents only the earnings from three nodes in a total network of hundreds of nodes.

5.1 Sensitivity of Model to Pricing Changes

Since each of the scenarios has a fairly high percentage of its supply coming from long term power purchase agreements (the lowest percentage being 64), the price chosen for the fixed contract will have a large effect on the outcome. The power purchase price for the optimization is set at $64 per MW based on a sampling of released prices to various regulatory agencies by utilities. By increasing this price by only two dollars, the profits are cut in half. Once the contract price is increased to $69, all profits are negative.

In addition, some of the scenarios with a lower percentage of power purchased through long term contracts begin to appear in the top ten scenario combinations' profits. For the $66 trial, the "middle (plan early)" scenario (number four) is chosen for the Hinton node for the fifth highest profit, whereas in the initial optimization, this scenario did not appear until the eighth highest profit. For the $69 trial, it rises to the scenario combination with the second-highest profit. The results displayed in Table 5.2 emphasize just how important the power purchase agreement price is for the analysis.

Table 5.2: Power Purchase Agreement Analysis

Base Case (a = $64/MW)				Middle Case (a = $66/MW)				High Case (a = $69/MW)			
Highest Profits				**Highest Profits**				**Highest Profits**			
Profit	No.G	No.R	No.H	Profit	No.G	No.R	No.H	Profit	No.G	No.R	No.H
$13,926.02	7	7	7	$7,811.41	7	7	7	($1,360.50)	7	7	7
$13,471.86	8	7	7	$7,264.54	8	7	7	($1,740.41)	7	7	4
$13,464.63	7	8	7	$7,257.18	7	8	7	($1,992.82)	7	4	7
$13,462.29	7	7	8	$7,255.31	7	7	8	($1,995.31)	4	7	7
$13,010.47	8	8	7	$7,015.79	7	7	4	($2,046.44)	8	7	7
$13,008.14	8	7	8	$6,761.30	7	4	7	($2,053.99)	7	8	7
$13,000.90	7	8	8	$6,759.38	4	7	7	($2,055.17)	7	7	8
$12,853.26	7	7	4	$6,710.31	8	8	7	($2,372.73)	7	4	4
$12,597.39	7	4	7	$6,708.43	8	7	8	($2,375.22)	4	7	4
$12,595.84	4	7	7	$6,701.07	7	8	8	($2,426.35)	8	7	4
Lowest Profits				**Lowest Profits**				**Lowest Profits**			
Profit	No.G	No.R	No.H	Profit	No.G	No.R	No.H	Profit	No.G	No.R	No.H
($5,800.47)	2	2	2	($10,525.39)	2	2	2	($17,612.78)	2	2	2
($5,111.05)	2	2	1	($9,743.59)	2	2	1	($16,692.40)	2	2	1
($5,025.84)	1	2	2	($9,658.04)	1	2	2	($16,606.36)	1	2	2
($5,025.11)	2	1	2	($9,657.20)	2	1	2	($16,605.32)	2	1	2
($4,336.41)	1	2	1	($8,876.24)	1	2	1	($15,685.98)	1	2	1
($4,335.69)	2	1	1	($8,875.39)	2	1	1	($15,684.95)	2	1	1
($4,250.48)	1	1	2	($8,789.85)	1	1	2	($15,612.84)	2	2	5
($3,561.06)	1	1	1	($8,109.74)	2	2	5	($15,598.90)	1	1	2
($3,107.67)	2	2	5	($8,008.04)	1	1	1	($15,216.95)	5	2	2
($2,709.27)	5	2	2	($7,712.34)	5	2	2	($15,205.12)	2	5	2

Another possible pitfall of the model could deal with the options pricing. Unfortunately, the prices were not available at the nodal level from Nymex. For the forward prices, the lack of nodal-level pricing was solved by taking the spread between the nodal and zonal spot prices and applying the percent difference to the zonal forward prices in order to arrive at a nodal pricing scheme. If the same methodology had been applied to the options, there would have been a direct correlation between the options and forward prices for each node. Since the prices are then not evaluated at a nodal level, the question arises whether or not they should be included in the model. Table 5.3 demonstrates the comparison between the results with and without options.

Table 5.3: Results with and without Options

With Options				Without Options			
Highest Profits				**Highest Profits**			
Profit	No.G	No.R	No.H	Profit	No.G	No.R	No.H
$13,926.02	7	7	7	$11,950.82	7	7	7
$13,471.86	8	7	7	$11,941.13	8	7	7
$13,464.63	7	8	7	$11,931.30	7	8	7
$13,462.29	7	7	8	$11,921.61	8	8	7
$13,010.47	8	8	7	$11,833.72	7	7	8
$13,008.14	8	7	8	$11,824.03	8	7	8
$13,000.90	7	8	8	$11,814.20	7	8	8
$12,853.26	7	7	4	$11,804.51	8	8	8
$12,597.39	7	4	7	$10,324.30	7	7	4
$12,595.84	4	7	7	$10,314.61	8	7	4
Lowest Profits				**Lowest Profits**			
Profit	No.G	No.R	No.H	Profit	No.G	No.R	No.H
($5,800.47)	2	2	2	($9,645.26)	1	1	1
($5,111.05)	2	2	1	($9,523.01)	1	1	2
($5,025.84)	1	2	2	($9,413.95)	1	2	1
($5,025.11)	2	1	2	($9,407.58)	2	1	1
($4,336.41)	1	2	1	($9,291.69)	1	2	2
($4,335.69)	2	1	1	($9,285.33)	2	1	2
($4,250.48)	1	1	2	($9,176.26)	2	2	1
($3,561.06)	1	1	1	($9,054.01)	2	2	2
($3,107.67)	2	2	5	($6,484.63)	1	1	5
($2,709.27)	5	2	2	($6,363.08)	1	1	3

The profits when the model does not include options are generally around ten to 20 percent lower than when options are included. The optimal scenario combination (7, 7, 7) does not change, but the lowest profit scenario combination changes from each node choosing the "low base (plan late)" scenario to choosing the "lowest base" scenario. This result shows that the utility is putting even more emphasis on the power purchase agreement price since the "lowest base" scenario has the lowest percent of power being obtained through long-term contracts. In addition, the VaR plummets into the negatives to -\$1,122. This value is around a 200 percent drop from the original positive \$1,216. The lower profits can be justified by looking at the Nymex prices. In general, they are fairly comparable to the forward prices. When they are dropped from the model, the old percentage of options purchased is spread out among other instruments, whose prices are generally higher than the options prices. The profit suffers from subtracting one of the choices. One could also hypothesize that by subtracting a decision variable from the model, the robustness of the objective function suffers.

5.2. Sensitivity of Model to Transmission Considerations

The main role of this study is the addition of transmission-related constraints to the power portfolio optimization problem. This contribution is satisfied in two main ways: a transmission constraint to make a unidirectional three-node system and fixed transmission rights that are included in the objective function. The question remains if the constraint and FTRs affect the overall solution and whether they are worthwhile. The model is run three additional times: once with no transmission constraint, once with no FTRs and once with neither. Table 5.4 contains the varying ten highest and ten lowest profits for each run along with the VaR and CVar values.

Table 5.4: Results of Model with Varying Transmission Considerations

With FTR & Constraint	Without FTR, With Constraint	With FTR, Without Constraint	Without FTR & Constraint
Highest Profits			
$13,926.02	$25,033.92	$14,967.60	$26,075.49
$13,471.86	$24,579.76	$14,513.44	$25,621.34
$13,464.63	$24,572.53	$14,506.20	$25,614.10
$13,462.29	$24,570.19	$14,503.87	$25,611.77
$13,010.47	$24,118.37	$14,052.05	$25,159.94
$13,008.14	$24,116.03	$14,049.71	$25,157.61
$13,000.90	$24,108.80	$14,042.48	$25,150.37
$12,853.26	$23,961.15	$13,894.83	$25,002.73
$12,597.39	$23,705.29	$13,638.97	$24,746.86
$12,595.84	$23,703.73	$13,637.41	$24,745.31
Lowest Profits			
($5,800.47)	$5,307.43	($4,758.89)	$6,349.00
($5,111.05)	$5,996.85	($4,069.47)	$7,038.42
($5,025.84)	$6,082.06	($3,984.26)	$7,123.64
($5,025.11)	$6,082.78	($3,983.54)	$7,124.36
($4,336.41)	$6,771.48	($3,294.84)	$7,813.06
($4,335.69)	$6,772.21	($3,294.11)	$7,813.78
($4,250.48)	$6,857.42	($3,208.90)	$7,898.99
($3,561.06)	$7,546.84	($2,519.48)	$8,588.42
($3,107.67)	$8,000.22	($2,066.10)	$9,041.80
($2,709.27)	$8,398.63	($1,667.70)	$9,440.20
VaR			
$1,215.72	$12,337.50	$2,258.59	$13,380.38
CVaR			
($82.05)	$10,174.84	$959.52	$12,067.42

The FTRs have a larger impact on the objective function than the transmission constraint. The model without FTRs has a profit function that is about 80 percent higher than the model with FTRs included. Omitting the transmission constraint only contributes to around an eight percent increase in profits. When both FTRs and the transmission constraint are dropped from the model, profits just about double. The gap between VaR and CVar lessens as the FTRs are dropped from the model. This result signifies that the FTRs contribute greatly to the extreme losses in the tail of the profit distribution.

The results given in table 10 suggest that the transmission considerations in the model do make a difference in the overall optimization. It makes sense that the inclusion of transmission in a power portfolio optimization would be important. A utility not only has to take into consideration what its customers' needs will be in the future but also how to optimally deliver the power to its customers. There is not only risk involved with the financial instruments chosen but also with the uncertainty of transmission conditions. The effect of the FTR on the Hinton node suggests that the utility would need to reconsider its strategy to hedge congestion on that particular line.

It is not surprising that the FTR effect is more potent than the transmission constraint's effect. Unfortunately, the model does not contain nodal demand data and each node seems to represent the same percent of the AEP zone. Since the nodal demand data are estimated from the percent each node represents of the zone times a random number generator, the transmission constraint does not represent the actual system. The real constraint could vary greatly from the one presented in this paper. Overall, though, the presence of the constraint goes to prove the importance of its existence even if it is not quantified correctly.

CHAPTER 6

LIMITATIONS, EXTENSIONS AND CONCLUSIONS

Although an attempt was made to mimic the key features of a likely situation for a utility in the PJM area, it is possible that reality does not agree with the chosen possibilities. Looking at the load duration curve for Appalachian Power, it is estimated that the bulk of the load would be provided through long term contracts (power purchase agreements). The remainder of the instruments (forwards, options and spot) is then estimated based on if the utility would try to estimate its peak summer needs early in the year or closer to the time the power would be used. Unfortunately, utilities don't generally publish their power procurement strategies in their entirety so the scenarios presented in this paper are best guesses based on industry knowledge. The model could definitely be improved by having insider information.

The lack of public nodal demand and options data is categorically a limitation in the study. Since the main focus of the model is to focus on transmission, it is very important to have pertinent data at the nodal level in order to accurately estimate congestion and system demands. Without the availability of this data, the relevance of the results is called into question. Again, it would be beneficial to attain company-level data.

This model focuses only on a unidirectional three-node network. In the future, it would be interesting to expand the model to a larger network and also consider a bidirectional system. It is not very realistic to assume that power in the system will only travel in one direction, but the assumption is made here in order to prove viability. In addition, FTR data in both directions between two distinct nodes may not be available. It is possible that these data could be estimated, but then the same issue of validity would arise that is brought to light with the estimated nodal demand data in this study.

The analysis presented in this paper has been from the utility (customer-serving) perspective. It would be entirely possible to consider the problem from the side of a power marketer or generator. In that case, bidding of generation could be included. The possibility of incorporating a game theoretic model with either Cournot or Bertrand competition also poses an interesting extension.

Finally, it could be beneficial to refine the power purchase agreement price. Multiple variables could be used to assign prices for each type of generation under long-term contracts. For example, the price per megawatt for coal-fired baseload generation could be very different from natural gas-fired peaking generation (where price of fuel tends to be fairly volatile and the technology tends to be less efficient). In the future, renewable generation contract pricing could also become more important as utilities are forced to meet state-mandated renewable portfolio standards.

The model outlined in this paper was developed in order to show the effect of transmission considerations on how a utility chooses to procure power. Historically, models have accounted for differing time horizons, types of generation and risk. Many have commented that transmission constraints should be considered, but none has attempted to incorporate them into the model. The model presented shows that transmission constraints and fixed transmission rights can have a significant effect on the choices a utility will make when dealing with power procurement. It is demonstrated that the inclusion of transmission constraints drastically decreases the value of the objective function. Whereas a utility was comfortable with a 95 percent confidence level for risk measurement without the constraints, the company may have to reconsider its actual risk tolerance with transmission incorporated into the model. Although the optimal scenario combination does not change with the introduction of transmission constraints, it could be due to the scenario and probability estimation. Using actual utility data could shed light on whether transmission should cause a shift in the percentage of power a company procures though each financial instrument.

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