Pricing Multiple Triggers—An Electrifying Example

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PRICING MULTIPLE TRIGGERS - AN ELECTRIFYING EXAMPLE

For insurance products, multiple loss triggers have emerged as a tool for both risk managers and insurance companies to customize coverage. This paper will focus on an example drawn from a utility industry coverage that has triggers based separately on spot prices for electricity and lost power generation capacity. This paper provides a background to the current electric industry to help understand the interaction of the triggers. A regional supply and demand model for electric power is described that will simulate spot prices for electricity. A separate model is developed to simulate generation plants and their failure. Losses are calculated as a Monte Carlo simulation using the combined interaction of the supply/demand model and the plant generation model. Expanding the model to include various other triggers and the shortcomings of available hedges is also discussed. Finally, some practical observations on pricing multiple triggers will be drawn from the example.

INTRODUCTION

For insurance products in the next century, multiple loss triggers are emerging as a tool for both risk managers and insurance companies to customize coverage. Multiple trigger coverage requires more than one event to occur before a loss occurs, or is triggered. Modeling losses under this type of coverage requires not only knowledge about the size and frequency of loss, but also requires insight into the physical process you are insuring.

We will look at an actual example of modeling a dual trigger: the forced outage product for utilities. Coverage is triggered by the simultaneous occurrence of two events: sudden increases in a spot price (a spike) for a commodity, namely electricity AND the fortuitous loss of generating capacity.

The forced outage example will be placed in a generalized framework of a multiple trigger model diagrammed in figure 1:

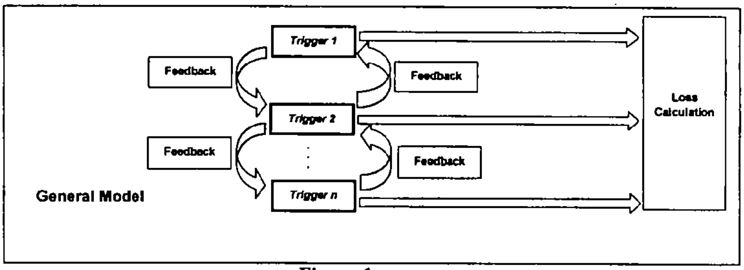


Figure 1.

Unlike most insurance contracts where one event causes a loss, multiple triggers require more than one event before a loss occurs. Triggering events are frequently related, and quantifying the interaction or correlation – feedback in the diagram – between these various events is the challenge for loss modeling. It is the rare pair of triggers that are completely unrelated, operate independently and can be modeled as independent events. A useful technique to build in the desired interactions or correlations that you choose to model and not ignore, yet are difficult to explicitly quantify, is to sample from past data. Sampling from past data incorporates previously observed interactions through the empirical distribution. This non-parametric process is known as bootstrapping. How much past information is enough before you can rely on the empirical distribution is an issue, but any information is almost always superior to an assumption of independence. Independence assumptions certainly meet the often cited "simpler is better" criterion, but bootstrapping – leveraging results from actual empirical data – is a pragmatic middle ground between naively ignoring any correlation and hopelessly trying to resolve every correlation.

In examining the forced outage example we will look at:

1. Spot prices and focus on spot price drivers we can model.

2. How the electric power grid is separated and how demand, supply and shortfall on a grid interact in the electric marketplace: we will describe how to place this example in a simple and readily accessible supply demand framework.
3. How utilities coordinate their available supply, the supply "stack", and how utilities address a shortfall.
4. Spot price vs. supply-demand relationships: spot price jumps coincide with shortfalls.
5. The model itself: how supply and demand can be modeled to create daily spot prices, and how a utility's capability can be modeled.
6. How the events simulated in (5) can be related within a loss calculation
7. How additional triggers can be added as coverage evolves, and hedging challenges presented by customizing coverages.

FORCED OUTAGE COVER EXAMPLE

Most of us depend on utilities to provide reliable and cheap electric power. What happens when power is neither reliable nor cheap? We are going to look at an example of pricing a cover for a newly emerging insurance risk for electric utilities, the forced outage cover. A forced outage cover provides utilities with the replacement cost of power if they unexpectedly lose generating units during periods of high spot market prices for electricity. For pricing this risk the new power trading market unfortunately does not provide a long history of deregulated pricing. To overcome this issue we will leverage a simple and accessible supply-demand concept as well as a relationship from the electric industry of temperature and demand to simulate many years of possible spot prices based on historical temperatures. We will use these simulated spot prices as triggers to generate expected losses for pricing this coverage.

Electricity has been traded for decades in a regulated marketplace. However starting in 1998, the electric power market was deregulated. Prices were allowed to vary with demand, and vary they did. In the summers of 1998 and 1999, Midwest prices per megawatt hour of electricity soared briefly from a typical average of $40 to spike between $7,000 and $9,000. It became apparent that utilities will buy power, even expensive power, to guarantee delivery to their customers. A megawatt hour of electricity (Mwh), or 1,000 kilowatts for one hour is roughly the electricity needed to power 1,000 homes for one hour. Regulated prices from 1997 and prior were stable, and gave no indication of what would happen in 1998-99. Historical prices under regulation are an unreliable base for projecting spot prices into 2000 and beyond. We need a method of generating spot prices– our first trigger – from past data that will act like deregulated prices of the future

1. SPOT PRICES

Spot prices for electric power are the prices to deliver or receive power at a central location, or *hub*, in the United States. There are several such hubs throughout the U.S., representing the intersection of transmission flows of electricity and does not necessarily represent power generated at the hub – power deliverable at "Palo Verde" need not be generated at the Palo Verde plants. The spot prices to be modeled are for same day delivery of electric power. Same day prices have the shortest horizon and are the most volatile. The volatility arises out of two factors:

1. A mismatch between how much electricity is being demanded vs. the available supply of electricity being produced.
2. The impracticality of storing electric power: the resulting lack of inventory distorts hedging strategies and without reliable hedging, volatility increases.

The second factor is addressed in section 7. The model developed to address the forced outage example will focus on the first factor, the mismatch between demand and supply:

Demand: A variety of factors influence the amount of electricity demanded. The amount of industrial, commercial and retail demand is obviously going to vary from region to region all across the country However when you are in a given region the biggest variant in demand is seasonal temperature

Peak demand for electricity on a given day is strongly related to the high temperature for that day (see figure 2) In summer demand increases as temperature increases to power cooling and in winter demand increases as temperature decreases to power heating Demand is at a minimum when the temperature is mildest roughly between 60 and 70 degrees Also demand varies for workdays vs weekends weekend demand is lower than workday demand It is easy to see in figure 2 the demand vs temperature relationship and a clear but parallel separation between workday and weekend demand

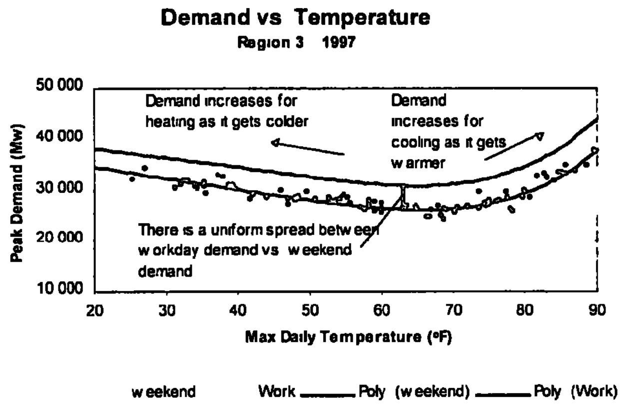


Figure 2

Supply The available supply of power is the combined capacity to produce electricity from all generators that are on line or available Unavailability of generators is measured by their outage rates Outages can be *scheduled* for regular maintenance or *forced* due to unexpected failure Regular maintenance is not typically scheduled for periods of high demand in the hot summertime If a generator experiences an outage either forced or scheduled its capacity is removed from the available pool of power

Capacity margins measure the amount of capacity or capability (supply) in excess of demand. It is a good indication of how much electricity will be available after peak demand has been met. A *shortfall* occurs when the amount of electricity demanded exceeds the available supply or capacity. The model chosen for the spot price trigger (which we have yet to justify) is to show that if there is a shortfall, then spot market prices jump or spike. Prices for electricity spiked severely in the summers of 1998 and 1999. The U.S. Senate investigated the origin of the 1998 price spikes (SD366 9/24/98), and three major factors were cited:

1. unusual temperatures
2. large number of plants outages
3. capacity of transmission lines

The model deals directly with these three factors.

2. REGIONAL SUPPLY, DEMAND AND SHORTFALL

The lower 48 states are physically segmented into three large interconnections: the Eastern, the Western and the Texas Interconnections. Utilities in these interconnections are continuously synchronized so that their systems operate at the same frequency. The interconnections are further broken up into a total of ten regions or *control groups* (figure 3).

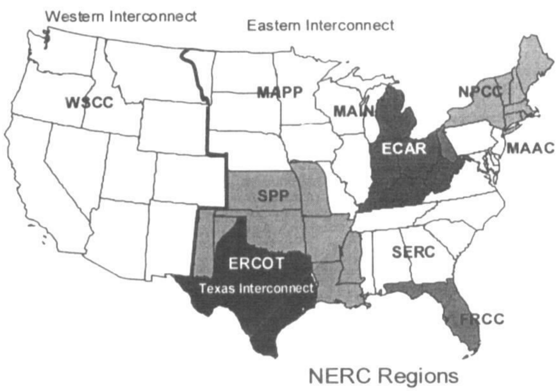


Figure 3.

The model separately looks at supply and demand on the ten North American Electric Reliability Council (NERC) regions. NERC was established in 1968 to coordinate and promote the reliability of the generation and transmission system.

The ten regions are geographically distinct. There are variations between the regions for both supply and demand:

Supply: The capacity to produce power within a grid and transmit power across a grid is limited by the physical plants and transmission capability within the region. Excess power from one region or grid can be transferred to another region through transmission ties, which connect or tie one grid to another. This transfer is not at will - power transfers across utility systems have to be carefully monitored and coordinated. A major bottleneck is the fixed capacity of the transmission ties to transfer power from one region to another. There can be excess power on one grid, a shortfall on another grid, but the transmission ties between the regions are not large enough to match the shortfall and maintain a balance. There is no easy resolution to the bottleneck: transmission ties are as large as they can be without destabilizing the power grids on either end of the tie.

Demand: Demand also varies by region. In particular, temperature/demand relationships are different by region. Looking at Figure 4 we see the same shape as in Figure 2, but the temperatures at which each region transitions is markedly different. This is not surprising when you consider that after allowing for differences in industrial usage, peak temperature in one area does not hold in another area - although 65 degrees is balmy in Wisconsin, it is frigid in Florida. Since the main driver of electric consumption (demand) is temperature, these relationships have to be built up independently for each region.

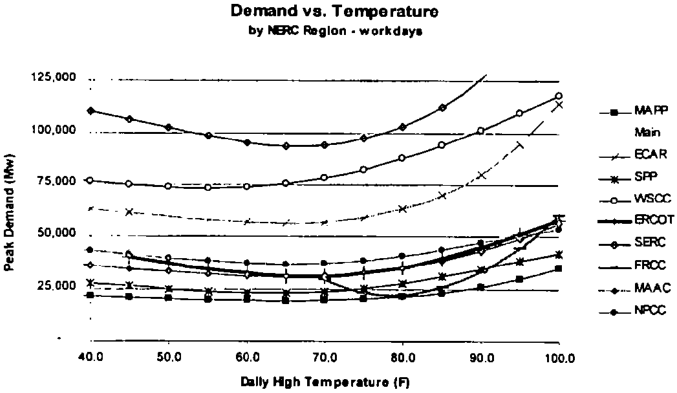


Figure 4.

As demand climbs with temperature, available generators are *dispatched*, or turned on, to meet the increase in demand. When dispatched capacity is inadequate to meet rising demand (plus any additional reserve requirements) a shortfall can arise. An anticipated shortfall can be met by:

1. Increasing supply, by dispatching idle generators if the system is not at peak capacity
2. Purchasing excess power from another area, which can be expensive.
3. Reducing demand by both requesting the public to reduce usage and exercising contractually interruptible service.

How does the utility decide?

3. HOW UTILITIES OPERATE IN A REGION: THE SUPPLY STACK AND λ

How a utility operates will affect its control area, the other utilities around it, and possibly even the surrounding regions. A utility tries to balance customer demand with the most economical operation of its own system. The utility dispatches the lowest cost generating capacity available to meet changing demand requirements by adjusting the mix of generating units in use or complements its capacity by purchasing power to maximize availability while minimizing the cost of production (EIA, 1995).

Utilities think of their generators which are available for dispatch as a *supply stack*. A typical stack will have large, high capacity plants on the bottom providing the baseload needs. These plants are dispatched first, operate virtually all the time, and are inefficient at low capacity. As demand increases over the course of the day, additional units are dispatched to meet demand. In general a utility will not gladly produce excess electricity for resale (that is, production beyond its current demand level) unless it can recover at least the cost of producing that last megawatt of electricity in the resale market, or spot price. Thus, as the utility's demand level increases, the marginal cost to meet the increase, or λ, increases and the clearing price that the utility is willing to provide excess electricity also increases. As displayed in Figure 5, climbing a supply stack equates to climbing a cost curve for power production.

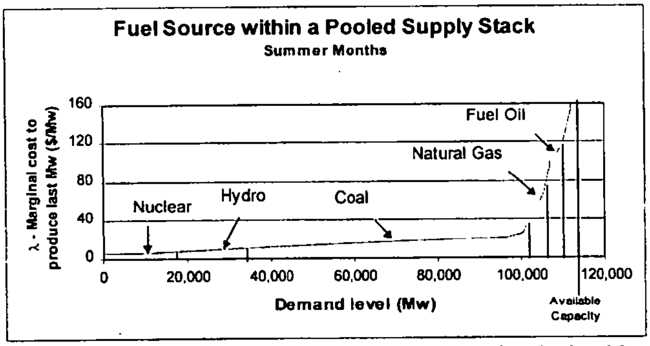


Figure 5: as more power is demanded, the cost of producing the last Mw of power increases. As peak demand approaches available capacity, the marginal cost of producing the last Mw increases dramatically.

4. SUPPLY, DEMAND AND SPOT PRICES

Lambda (λ) is a recorded measure of the marginal cost of generating electricity. Like spot prices, it is expressed in $/Mwh. A high lambda indicates you are in the tail of the supply stack with few idle resources, and a low lambda means you are in the front of the stack with a number of generators left to dispatch. Figure 6 displays actual peak lambda and same day spot price for a particular hub in 1998. Note the close following of spot price and lambda, the first indication that the cost to produce electricity and its resale or spot price are closely related. Spot price is a broken line because trading is sometimes thin. Lambda is as continuous as the power supply:

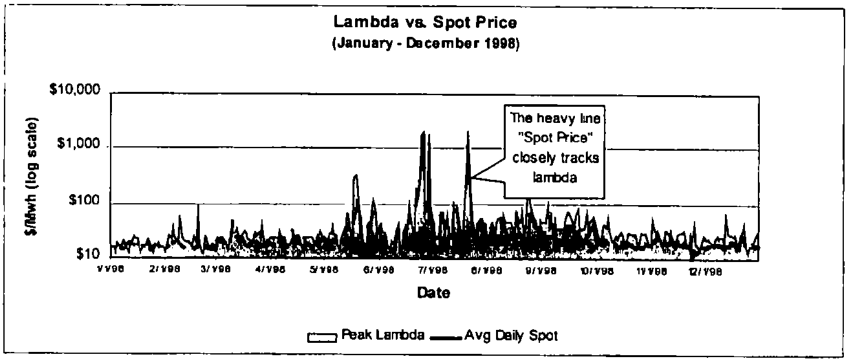


Figure 6.

Another way to think of lambda is how much the current demand level burdens the available supply. A high lambda implies most capacity has been dispatched. Similarly a low lambda implies substantial unused resources. We can then view a lambda-supply relationship. Figure 7 relates lambda and available supply, or capacity:

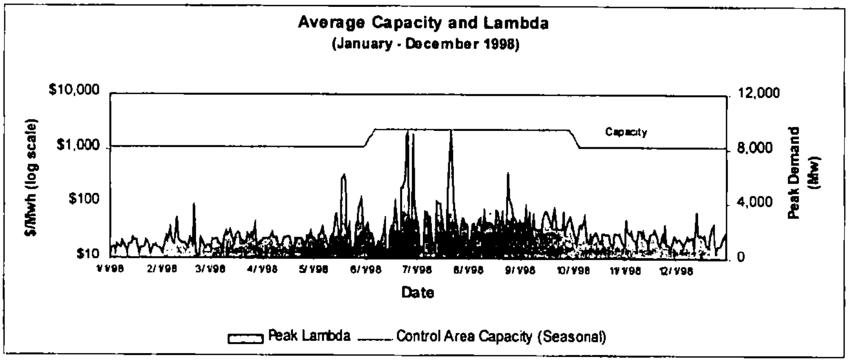


Figure 7.

The available supply (capacity) is an obvious constraint when considering how much power can be demanded. A shortfall occurs when the available supply is unable to meet the amount demanded. If we overlay demand on top of supply we can see (figure 8) several discrete instances where shortfalls occur:

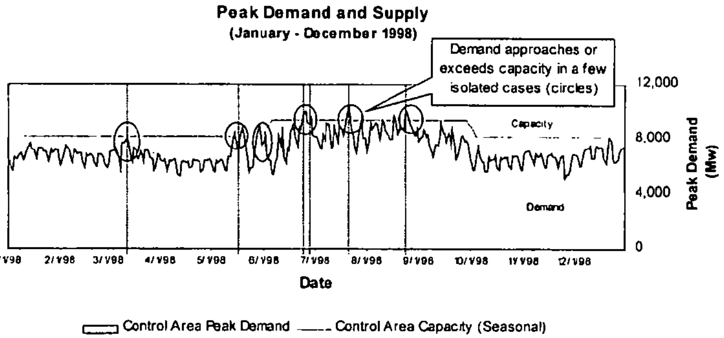


Figure 8.

The last remaining link is to overlay spot prices, demand and available supply or capacity:

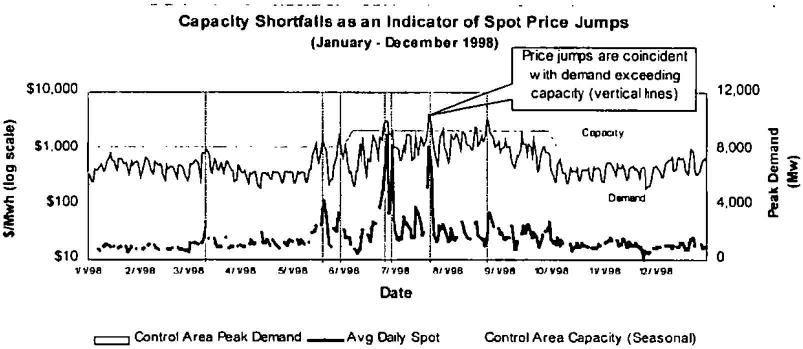


Figure 9.

As seen in Figure 9, shortfalls are a very good indicator of price spikes. All the severe and intermediate jumps coincide with shortfalls.

As a final observation, although temperature is a prime mover for demand, not all shortfalls/price-spikes are purely temperature driven. Shortfalls are also supply driven, more appropriately lack-of-supply driven, and the available supply is far from static. If we overlay temperature as well (figure 10), we see temperature extremes where spikes did not occur.

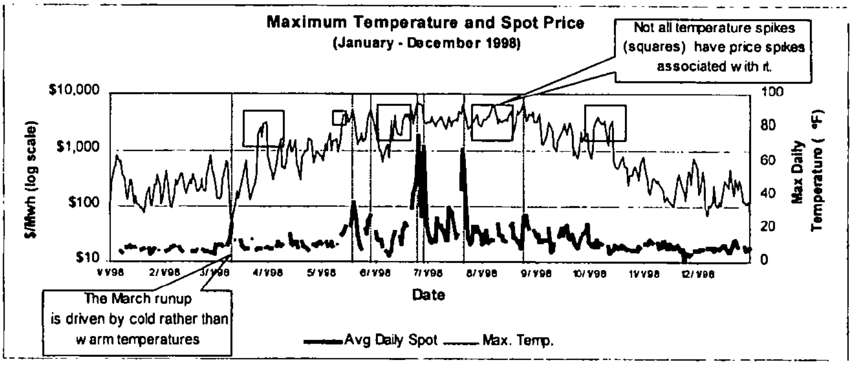


Figure 10.

5. THE MODEL

Tailoring our forced outage example to the generalized model presented earlier, the forced outage model can be diagrammed as in figure 11. Modeling was performed via Monte Carlo simulation. The actual calculations were performed in EXCEL using @RISK, an add-in to EXCEL. Each iteration recreates a string of days from June 1 to September 30, or longer. Events that are simulated include:

5a. Demand, as a function of temperature

5b. Non-nuclear availability (supply)

5c. Nuclear availability (supply)

5d. Shortfall

5e. Spot Prices

5f. Individual utility outages

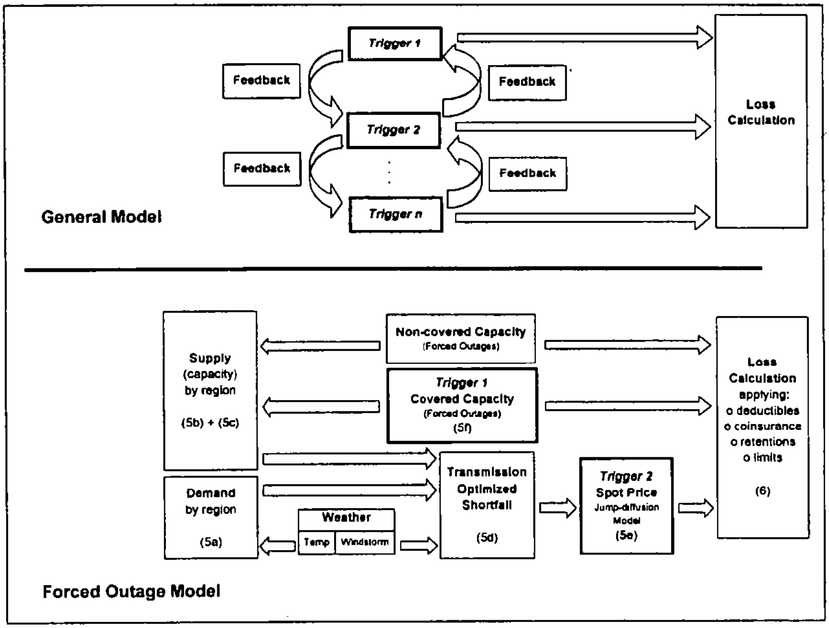


Figure 11

The engine to determine price spikes has been described above and is laid out in (5a) to (5e). A second trigger to be modeled covers forced outages on a utility (5f) and is necessary before the loss event (6) can be calculated.

5a. Temperature and Regional Demand: The dynamics that create the temperatures across the country – basically our weather – is a complicated string of relationships from Washington to Florida, California to Maine. Instead of trying to reproduce these relationships, we used a bootstrapping technique that relies on the geographical dependencies embedded in the actual temperature readings for a given year across the country. An outline of the method is detailed in Exhibit 1. We used a database of high temperatures from cities in each region for each day in the period 1948 to 1998. To represent warming temperatures historical highs can be adjusted upward. For one iteration, a random year was generated between 1948 to 1998 and the actual daily string of high temperature readings for that year was used to generate high temperatures by day by region all across the country.

Temperature is then used to determine demand for a given day, separately by region for workdays vs. weekends, using a fit of temperature and demand. We fit the peak load required to meet the amount of electricity demanded to the average high temperature across the cities in the region by day for the most recent years (1997-1998). Peak load incorporates the additional reserve required when a certain amount of electricity is demanded. Demand, or peak load, rises at both extremes of temperature: power is used to heat and to cool. However, demand flattens out faster for heating (declining temperatures), than for cooling (increasing temperatures). In other words, the curve has two maximums and a minimum. If as a general rule when fitting a polynomial to a curve you try to fit a polynomial with order equal to the curve's maximums + minimums + 1, then a fourth-degree polynomial is suggested as a fit in this case. Using this polynomial the model then calculates demand from the historical high temperature generated above.

5b. Non-nuclear Outages on the Grid: a day's capacity for a region is total capacity reduced for generators forced out on the region. The number of generators on a grid can be anywhere from 400-2,000 generators. Each individual plant is simulated for availability on each day – for the cooling season it is a 122-day string from June 1st to September 30th. The incidence of a forced outage is a daily check of a uniform random number against the industry daily forced outage rate.

If the random number is less than the industry outage rate, a duration is generated from a distribution of durations based on non-nuclear plants. The capacity for that plant is 0 for each day in the simulated outage duration, otherwise the plant's capacity is considered as available. This calculation is performed for each generator in each region for each day. Non-nuclear regional capacity for a given day is calculated as the sum of all the non-nuclear generators available in the region for that day.

5c. Nuclear Forced Outages: An unusually large number of nuclear plants were out when prices spiked in 1998, and this makes them of special interest in modeling price spikes. To recreate the devastating reduction to capacity that the loss of an individual nuclear plant can represent, each of the reactors is separately simulated and tied back to their related region. The incidence of a forced outage is from nuclear industry data and is a daily check of a uniform random number against the industry daily forced outage rate. If the random number is less than the industry rate, then a duration is randomly generated from actual forced outage durations. Since these events can be quite extended, nuclear plants need to be simulated as early as March 1, allowing forced outages to spill over into the cooling period commencing June 1. A nuclear forced outage, for whatever reason, is a reduction in grid supply. Exhibit 2 displays temperature, demand and simulated capacity based on (5a) to (5c).

5d. Shortfall – Regional capacity and demand: The supply demand relationship is not a straightforward comparison. Peak demand has to include the reserves required in excess of the load to meet needed demand. Supply should include the first transfer capability of transmission lines into or out of a region. The first transfer or base capability is the switching that normally can be handled without extraordinary intervention. Second or higher capabilities can be much greater than the first transfers which are modeled, but extraordinary intervention is required to achieve second or higher capabilities. When we are looking for an indicator of price spikes, we are looking for those scenarios where shortfalls are imminent (or a reality) for a region without extraordinary intervention. Prices would climb in advance of any news that extraordinary balancing transfers were being coordinated, so that any additional balancing due to higher capabilities is not considered.

Balancing transfers for transmission lines were optimized subject to the first transfer constraints outlined in Exhibit 3. Random outages of the transmission lines, which would carry the balancing transfers, were also generated based on windstorm occurrences. Windstorms were generated based on a daily frequency that varied by month, as described in figure 12:

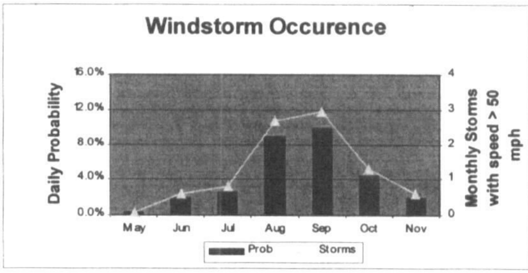


Figure 12

The reduction in transmission capacity from a generated windstorm was based on damage curves by region. As windstorms hit the Carolina-Florida coast, the affect was staggered up the coastline and inland after the storms made landfall. After a windstorm is generated, its intensity is also randomly generated based on the Florida-Carolina arrival windspeed. The windstorms cause additional damage in other regions, but not as severe as in Florida and SERC, the southeastern region. Four separate tables are used to measure both the percent of degradation and recovery time for the transmission system. The recovery time for transmission outages is mitigated by the nature of the transmission system, which was designed for survivability. Figure 13 displays which damage tables are used:

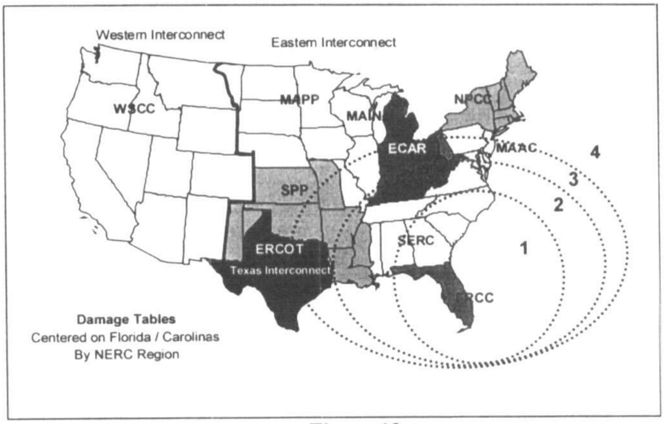


Figure 13

The most widespread windstorm is unlikely to degrade a region's capability by more than 50%, and capacity returns rather quickly to 90% or so. The last jump to 100% is slow, as every last line needs to be repaired. Damage curves at various windspeeds are displayed in figure 14:

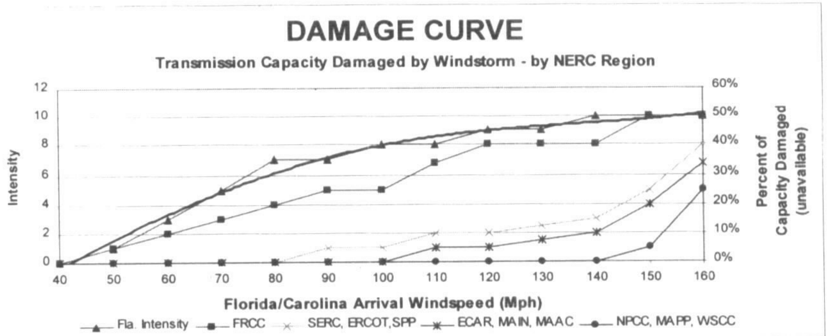


Figure 14

Localized windstorms were generated with a 10% probability in the summertime for those days unaffected by widespread windstorm. Localized windstorms have a one-day 9% partial outage.

A transmission outage reduces the transmission capability for the cell that is affected for as long as the outage is simulated. A transmission outage erodes the balancing capability between regions, and increases the likelihood of a supply-driven shortfall. For example, looking at Exhibit 3, region 3 can send up to 2,350 MW to Region 9 or receive almost 4,000 Mw to balance anticipated shortfalls. If region 3-9 transmission capabilities are reduced, then region 3 can only partially send to or receive from region 9 for the duration. Any excess capacity above the transmission capability in region 9 can not benefit region 3 and vice-versa.

Total grid supply and the resulting shortfall is calculated by region as:

Capacity Resources = (non-nuclear availability) + (nuclear availability) + transmissions

Pricing Shortfall = (Demand induced load) – .95 x (capacity resources).

The pricing shortfall implies a 5% capacity margin, which is slightly less stringent than the typical 5-8% actually experienced. If the shortfall is positive, then there is insufficient available capacity to meet demand, and a spike scenario will ensue.

5e. Spot Prices: Spot prices were generated as a form of the jump diffusion model. The traditional jump diffusion model, attributable to Robert C. Merton and outlined in a survey of pricing models by John Putney in Energy Modelling (1999), has a Poisson number of random jumps (dq) arriving at rate γ with lognormal (μ,σ) pricing and average proportional jump size k:

$$dS/S= (\mu-\gamma k)dt + \sigma dz +dq$$

This should be familiar to all of us as the frequency (jump)-severity (diffusion) model.

In the example we are modeling, supply/demand shortfalls define the spacing and number of jump events rather than a Poisson random variable and γ, and the proportional jump size k is modeled as the amount of shortfall. The motivation behind the modification was that, unlike a

Poisson process which assumes constant jump (claim) intensity, the changing weekend vs. weekday and demand vs. temperature levels implies a changing jump (claim) intensity.

Spot market prices for same day delivery exhibit a tendency that, once prices are high, they tend to go higher – as the current price increases, the average price that the market will go to, excess of the current price, increases. This is indicative of an increasing mean residual life **e(x)** for prices, which in turn suggests a lognormal, Pareto or Weibull distribution for pricing (Hogg & Klugman 1983). Lognormal pricing assumptions are used in the traditional jump-diffusion model; i.e. as x increases, e(x) increases but at a decreasing rate. When we model same day prices, we use Pareto pricing instead of lognormal prices. Pareto prices assume e(x) increases at a constant rate. Bootstrapping is not ideally suited for generating prices because of the limited number of price observations (1998-99).

Jump events were defined as shortfall days, and two scenarios were modeled for spot prices:

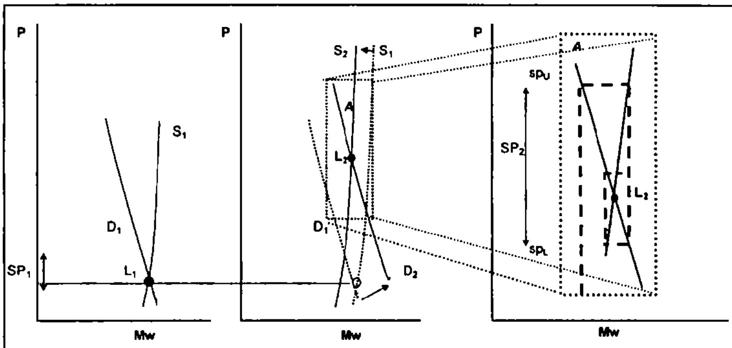
1. baseline scenario: days with no shortfall
2. spike or jump scenario: days with shortfall

The equilibrium price is set to an average baseline value for weekdays and a separate value for weekends. Spot prices f(x) are simulated based on a "single" parameter Pareto distribution:

$$f(x) = \frac{\theta a^{\theta}}{x^{\theta+1}}$$

with parameters for θ (shape) and **a** (post) that generate the baseline price on average, and the **a** value as a minimum. Baseline parameters vary by hub and region, for weekdays separate from weekends. The baseline scenario is appropriate when there are no shortfalls. When there are shortfalls, and the market is strained, the post parameter **a** is modified for the amount of system shortfall.

Simulated spot prices (SPn) are a random variable around the point (Ln) where transmission enhanced supply (Sn) meets temperature defined demand (Dn). The average resulting spot price



(a) baseline Scenario with spot prices centered around L_1

(b) Demand Shock D_1 to D_2 and supply outages S_1 to S_2 applied to (a).

(c) post-shock spot prices SP_2 are then oscillating between sp_U and sp_L, as the corresponding short-term equilibrium price spirals within *A* to L_2. The $P(SP_2>s)$ between sp_U and sp_L is modeled as a Pareto dis-distribution with mean L_2.

Figure 15. Prices SP_1 fluctuate around an equilibrium price L_1, until a shock drives equilibrium price level to L_2. The resulting spot price SP_2, or market-clearing price, will oscillate around L_2.

for all simulations is the equilibrium price, but variations around the equilibrium price reflect the oscillat' g effect of spot prices as they spiral or cobweb to a stable equilibrium price. The random variability around the intersection of supply and demand is replicating the additional price strains that the market imposes on prices: in a bid-asked market, imperfect information and uncertainty of needs will introduce more variability or a wider cobweb effect than a market that easily clears.

The a and θ parameters need to be calibrated to achieve the same variability, mean and number of price spikes as observed in 1998 and 1999 when using actual data in the simulation. This establishes a sort of "on-leveling" effect that makes 1998 deregulated prices appropriate on average for 1998 temperatures and outages. Temperatures are then set to the 1998 readings by day and nuclear outages are set to match actual outages. Calibration is established as matching the number of spikes by hub, the mean and standard deviation of actual same-day prices separately for weekend and weekday. The average number of spikes is matched to the actual observed by solving for the shortfall-coefficient value. The "shape" parameter is kept the same, and only the "post" parameter is modified for the shortfall-coefficient. After calibration, temperatures are allowed to vary uniformly between 1947 and 1998. Allowing temperatures to vary according to historical values achieves the variability in demand not present in one isolated year's weather pattern. Similarly, outage scenarios are allowed to vary the full spectrum of potential failures.

Some results of actual and modeled prices for 6/1-9/30 – 122-day summer peak period - are displayed by average price range in Exhibit 4. The accompanying percentile that matches the actual observation is displayed in the exhibit for three regions. Not all days have observed data. Any day without a trade (i.e. observation) is assumed to be stable and placed in the 0-50 range.

5f. Utility outages: Outages on the covered utility or on covered generators are modeled much the same as generators by region. Actual forced outage rates for covered plants can be substituted for industry averages. Care has to be taken that the subject plants are pulled out of the available supply in the regional calculation, modeled separately, and added back in as a feedback process. That is, your subject plant outages, if severe, can actually contribute to lack of supply and even price spikes.

If it is a nuclear utility, each reactor is modeled independently. The actual forced outage rate and duration is important when modeling a reactor for the individual utility. Unlike when we consider availability for a grid, Nuclear Regulatory Commission action is typically excluded from coverage, and should not be included in the forced outage rate for utility generator data.

Multiple generators found at a single site often share equipment. Failure of the shared equipment can force-out more than one generator, and has to be modeled separately.

From NERC – *Predicting Unit Availability*, forced outages can be modeled based on top-down or bottom-up approaches. A top down approach focuses, whereas a bottom-up approach focuses on component performance. Bottom-up approaches focus on component performance and tend to be more of an engineering approach, whereas top-down approaches focus on key factors that influence availability. We focused on a top down approach, and the most important factor we considered was the forced outage rate. A plant's lifetime is going to be separated into service hours, forced outage hours and planned outage hours. Some additional factors that have been isolated as influencing next year's outage rate include:

Previous years' forced outage rate (FOR or EFOR – EFOR includes deratings)

Previous years' forced outage hours

Current year's planned outages

Current year's operation and maintenance spending

Previous years' operation and maintenance expenditures

Fuel Type

Turbine/Generator manufacture

Boiler Manufacture

Past forced outage rates were considered predictive of future plant outage rates as long as maintenance expenditures and the operator remained the same. As an indicator, individual plants were compared to plants of comparable size and fuel source for higher/lower FOR. Higher than average FORs are indications of a higher price and/or a need for higher retentions.

6. THE COVERAGE AND LOSS CALCULATION

Coverage is triggered when two events coincide on the same day:

1. forced outages exceed a specified threshold
2. Daily spot prices exceed a certain strike price.

Since the model is simulating by day, forced outages for the day are checked versus the threshold. The daily model can be converted to an hourly model by sampling from hourly relativities to the average from a hub that publishes hourly (e.g. PJM). If a utility's total forced outage (FO) exceeds the threshold, the daily generated spot price is checked against the strike price. If the average daily spot price exceeds the threshold, then a loss can be calculated. The FO threshold and spot strike price are typically retentions for the utility. Losses are calculated as:

$$\text{Event Loss} = (\text{Util F.O.} - \text{threshold}) \times (\text{Spot} - \text{strike}) \times (n) \text{ hours}$$

Coverage is for power purchased to replace a forced outage. Coverage can be modified to be in effect every day for 24 hours (7x24) or for the 16 peak workday hours from 6:00am to 10:00pm (5x16). Typically only peak capacity needs to be replaced. Lost capacity due to a forced outage at off-peak times may not have to be replaced at all. Available capacity, even after the outage, is likely to exceed off-peak demand.

Any retained deductible is subtracted from the event loss. Consecutive days can have capacity forced out in excess of the threshold, and thus an event can last longer than one day. This is more likely for a nuclear utility than for a non-nuclear utility. Deductibles can be applied per event or per day.

What events are covered in the trigger (forced outages in our example) is mirrored in the data collected. Reported events for forced outages encompass a variety of causes, including:

a) Mechanical failure

b) Lack of fuel: delays in coal delivery are dependent on railroads, an external variable.

c) Weather: lightening strikes and windstorm, which can be excluded.

Mechanical failure includes anything at the generator or plant up to the transmission system. Specifically not covered is the transmission system and distribution system. If the plant is capable of generating power, but power is not distributed to customers due to a distribution system failure, or not transmitted due to a transmission system failure, then there is no covered loss. Spot prices will be affected by transmission failures (less balancing capacity), but the transmission system itself is specifically not covered.

Premium can be calculated on a sigma-based approach. @Risk captures a variety of statistics, not the least of which are the mean and standard deviation of the sample. Sample sizes appear to need about 20,000 iterations for stability. Premium can then be based on the observed mean and standard deviation:

Premium = observed mean + % of sample standard deviation

The additional charge based on the standard deviation represents risk load. Any additional expenses (commission, acquisition costs) also need to be included.

What does the future hold for this coverage? The electric industry is evolving. A significant increase in electricity use and new demands on system operators, especially during times of peak demand, are stressing the electric system (DOE - *Findings of the Summer of 1999*). Stresses mean more price volatility. Historically high capacity margins during the 1980's and 1990's were the legacy of overestimated needs and the underestimation of future realized energy savings built into the construction plans of the 1970's. As the final inefficiencies are wrung out of the system, capacity margins will decline and price volatility will rise. The integration of non-utility capacity into the bulk power supply is an added strain.

7. ADDITIONAL TRIGGERS AND HEDGING THE EXPOSURE

The model framework should be broad enough to encompass additional triggers. In the forced outage example, a natural additional trigger is precipitation. As much as one-fifth of North American summertime electric capacity is hydro or water generated. High water flow increases:

1. Hydro plant capacity, because there is more water to spin the turbines
2. Nuclear plant capacity, because the likelihood of environmental reductions in capacity (derating) is reduced with increased water coolant flow.

A precipitation trigger would also produce the complex feedback diagrammed in Figure 16:

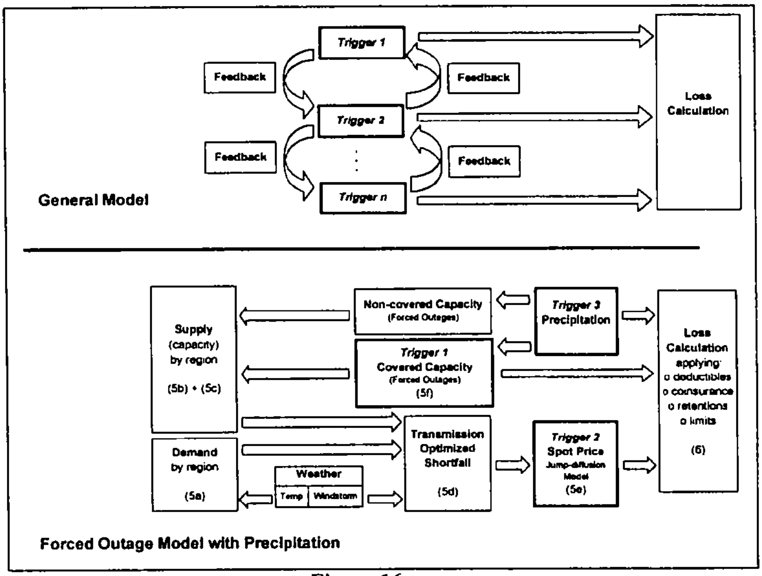


Figure 16

This is a natural addition but the capacity/rainfall relationship is a complex one. It is staggered to at least one or two years prior rainfall and snow cover rather than to the most immediate year or prior year's rainfall. Loss payout would be triggered by the simultaneous event oflow rainfall or water level, high spot prices and forced outages.

Another choice for a trigger might be high temperature for the day. However demand-driven shortfalls are already highly correlated to maximum temperature, so it is unclear whether temperature as an additional trigger makes the loss event much more remote. If requested, it can readily be added as an additional trigger.

Multiple triggers are used to customize coverage. Customization serves to make the coverage inherently unique. It is this uniqueness which makes multiple triggers difficult to hedge. Options to buy power can be purchased as a hedge for the exposure. However, as alluded to in the front section, hedging in the power markets is imperfect. Power markets are thin – not all spot prices and futures are available – and the bulk of transactions require actual physical delivery. Greater liquidity, which might result from more financially resolved contracts, would add to the capability to freely synthesize positions to offset this exposure. Even if we assume that power options can be synthesized to corral the limit and deductible, there is an additional basis risk associated with the payout. As defined by the American Academy of Actuaries (AAA), basis risk is the risk that there may be a difference between the performance of a hedge and the losses sustained from the hedged exposure. Just such a difference exists since losses are indemnified based on actual power purchases, and recoveries under the hedge or option are for average prices paid at the hub. A further observation by the AAA is that reinsurance offers a perfect hedge (zero basis risk) for the direct writer, but then the same question is just moved back one degree to the reinsurer. How does the reinsurer offset this risk?

Currently the ultimate perfect hedge for the forced outage exposure is a real option: to own actual generating capacity. Cooling degree day (CDD) covers – weather products that payoff when not enough warm days are registered in a summer - are negatively correlated to the forced outage product. Digital event covers – number of days exceeding say 90 degrees – are positively correlated. An electric utility would have a natural interest in hedging against the lost revenue caused by a cool summer. The forced outage product tends to have loss payments when the weather is warm, and to be loss free when the weather is cool. CDD covers tend to be "in the money" (require a payment) when the weather is cool, and be out of the money (loss free) when the weather is warm. There is still substantial basis risk if the CDD cover does not match the hub's weather characteristics, or the notional amount of the CDD is unrelated to the magnitude of price spikes.

8. CLOSING OBSERVATIONS

Some practical observations on modeling multiple triggers to be drawn from this example include:

1. Simpler models are better: Multiple triggers will naturally have more variables than standard loss models, but parsimony remains a guiding principle - use as few variables as possible to accurately represent the process.
2. The assumption that events are independent takes on added significance when the events are triggering events. This leads to a natural reliance on bootstrapping techniques to build-in correlations from past data that are difficult to quantify externally.
3. To be a flexible pricing tool, the modeling framework should encompass all the triggering events, and possibly allow for expansion as the coverage evolves. As we develop a model, we are representing the loss process within a modeling framework. For multiple trigger coverage the modeling framework should be broad enough to include as many of the

triggering events within the framework as possible and allow for additional triggers as the coverage evolves.

4. Actuaries should expand their knowledge into areas not touched on in the traditional syllabus in order to model processes for new insurance products where no experience exists.

Exhibit 1

Generating temperature by Region

Randomly generated year

Date	Day	1992 MAPP	1992 Main	1992 ECAR	1992 SPP	1992 WSCC	1992 ERCOT	1992 SERC	1992 FRCC	1992 MAAC	1992 NPCC
1-Jun	Tuesday	71.5	83.0	74.0	76.5	78.5	87.5	73.0	90.0	72.5	59.5
2-Jun	Wednesday	77.5	85.0	76.0	74.0	81.0	83.0	79.0	89.0	75.5	73.5
3-Jun	Thursday	79.0	88.0	78.0	79.5	82.5	89.5	69.5	85.0	80.0	82.5
4-Jun	Friday	76.5	79.5	70.0	83.5	85.0	88.5	76.0	90.0	77.5	80.5
5-Jun	Saturday	79.0	79.5	78.0	85.0	83.8	90.0	82.0	89.0	69.0	65.0
6-Jun	Sunday	72.5	76.0	82.0	83.0	81.3	89.5	87.0	86.0	83.5	76.5
7-Jun	Monday	74.5	77.0	76.0	85.0	79.5	84.0	86.5	86.0	88.0	83.0
8-Jun	Tuesday	67.5	74.5	76.0	83.0	79.0	88.5	81.0	86.0	87.5	87.0
9-Jun	Wednesday	76.5	84.0	77.0	82.5	80.3	89.5	81.5	88.0	81.0	79.5
10-Jun	Thursday	76.5	83.5	76.0	79.0	80.5	90.0	87.0	89.0	81.0	76.0
11-Jun	Friday	83.0	86.5	78.0	78.5	80.3	94.0	81.5	91.0	82.0	73.5
12-Jun	Saturday	85.0	91.0	81.0	84.5	79.3	91.5	66.5	91.0	84.0	84.5
13-Jun	Sunday	86.0	90.0	78.0	85.0	77.8	90.5	69.5	91.0	82.5	86.5
14-Jun	Monday	81.5	90.0	77.0	82.5	80.0	91.0	80.5	93.0	82.5	86.5
15-Jun	Tuesday	80.0	85.0	81.0	89.5	78.5	91.5	86.0	86.0	87.5	75.5
16-Jun	Wednesday	83.0	80.0	86.0	92.0	77.3	91.5	88.5	85.0	78.0	77.5
17-Jun	Thursday	76.0	77.5	87.0	89.5	81.5	91.5	83.5	87.0	80.0	79.5
18-Jun	Friday	83.0	83.0	81.0	92.5	85.3	91.5	82.0	91.0	80.0	79.0
19-Jun	Saturday	71.5	76.0	76.0	89.0	87.8	92.5	88.0	89.0	78.0	76.0
20-Jun	Sunday	68.0	79.0	65.0	82.5	88.3	93.0	87.5	92.0	78.0	80.0
21-Jun	Monday	70.0	77.5	67.0	84.5	91.8	93.5	79.0	94.0	70.5	77.5
22-Jun	Tuesday	71.5	68.0	70.0	84.5	92.5	91.5	79.0	94.0	69.0	67.0
23-Jun	Wednesday	81.5	77.5	74.0	90.5	91.5	93.0	83.5	87.0	76.0	75.5
24-Jun	Thursday	80.0	78.5	79.0	87.5	92.0	94.0	87.5	81.0	80.5	72.0
25-Jun	Friday	77.0	79.0	83.0	90.0	89.8	93.0	90.5	80.0	81.0	76.5
26-Jun	Saturday	74.0	79.0	83.0	86.0	83.8	91.5	85.5	90.0	83.0	81.0
27-Jun	Sunday	74.5	81.0	77.0	86.5	86.0	93.0	84.0	90.0	82.5	79.0
28-Jun	Monday	84.5	86.0	82.0	86.0	86.8	91.0	83.0	84.0	83.0	82.5
~~29-Jun~~	Tuesday	79.5	81.0	84.0	~~88.5~~	83.3	93.0	87.0	90.0	85.0	86.5
30-Jun	Wednesday	79.5	82.5	86.0	82.0	84.8	92.0	81.0	92.0	89.5	84.5

⋮

Actual average high temperature for cities in region on June 30, 1992

Capacity of all generators available in region

Exhibit 2

(1) Weekday	(2) Temp.	(3) Capacity	(4) Demand	(5)=(4)-(3) First Shortfall	(6) Trans-mission	(7)=(5)+(6) Enhanced Supply	(8)=.95 x (7) 95% of Enhanced	(9)=(4)-(8) Pricing Shortfall
Sunday	89.0	32,741	23,460	(9,280)		32,741	31,104	0
Monday	81.0	31,930	22,199	(9,731)		31,930	30,334	0
Tuesday	80.0	32,062	21,881	(10,181)	-500	31,562	29,984	0
Wednesday	78.5	31,469	21,457	(10,013)		31,469	29,896	0
Thursday	80.0	31,969	21,881	(10,089)		31,969	30,371	0
Friday	81.0	32,646	22,199	(10,447)		32,646	31,014	0
Saturday	85.0	33,593	20,674	(12,918)		33,593	31,914	0
Sunday	93.0	33,170	27,274	(5,896)		33,170	31,512	0
Monday	96.5	31,113	31,797	684	+500	31,613	30,032	1,765
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Demand determined by temperature and weekday

If first shortfall is positive, then extra capacity is transmitted from neighboring regions

If 95% of enhanced supply is greater than demand, then there is no pricing shortfall, and the baseline scenario ensues; otherwise a pricing shortfall feeds the Spot price

Exhibit 3

Transmission Capabilities (Mw)

To:		Region1	Region2	Region3	Region4	Region5	Region6	Region7	Region8	Region9	Region10
From:	Region1	xx	1,250	-	-	510	-	1,700	-	-	-
	Region2	1,850	xx	5,000	-	-	-	4,300	-	-	-
	Region3	-	1,200	xx	-	-	-	3,900	-	**2,350**	
	Region4	850	900	-	xx	420	856	2,500	-	-	
	Region5	460	-	-	420	xx	-	-	-	-	
	Region6	-	-	-	784	-	xx	-	-	-	
	Region7	400	3,250	5,300	-	-	-	xx	3,600	4,000	
	Region8	-	-	-	-	-	-	2,500	xx	-	-
	Region9	-	-	**4,000**	-	-	-	3,100	-	xx	2,600
	Region10	-	-	-	-	-	-	-	-	3,150	xx

Region 9 can receive up to 2,350 Mw from Region 3

Region 3 can receive up to 4,000 Mw from region 9

Exhibit 4

Simulated Percentile of Observed Same Day Spot Prices						
		Observed days			Simulated Percentile Of Observed	
Hub	Average Daily $/Mwh	1998	1999	Sim. Avg. # of days	1998	1999
MAAP	0-50	111	112	104.4	90%	95%
	50-100	7	5	10.5	15%	5%
	100-250	3	4	4.6	25%	40%
	250-500	1	0	1.5	35%	30%
	500-1000	0	0	0.8	55%	55%
	1000+	0	1	0.8	60%	65%
ComEd Border	0-50	104	106	101.3	65%	75%
(MAIN)	50-100	11	7	10.5	60%	15%
	100-250	2	6	5.6	10%	55%
	250-500	3	1	2.3	75%	40%
	500-1000	0	1	1.3	40%	45%
	1000+	2	1	1.0	75%	60%
Cinergy	0-50	95	102	88.7	80%	95%
(ECAR)	50-100	16	7	17.0	40%	5%
	100-250	4	7	8.6	5%	30%
	250-500	2	4	3.8	25%	55%
	500-1000	2	1	2.7	50%	30%
	1000+	3	1	1.2	85%	55%

A simulated 40th percentile (40%) was interpreted to mean 60% of the observations are greater than the observed value.

References:

American Academy of Actuaries Index Securitization Task Force, *Evaluating the Effectiveness of Index-based Insurance Derivatives in Hedging Property/Casualty Insurance Transactions* , AAA; 1999

Committee on Ratemaking Principles, *Statement of Principles regarding Property and Casualty Insurance Ratemaking,* Casualty Actuarial Society

Energy Information Administration – *Performance Issues for a Changing Power Industry*; 1995

Hogg, Robert V. and Klugman, Stuart A. – Loss Distributions, New York, John Wiley & Sons; 1984.

Klugman, Stuart A.; Panjer, Harry H. and Willmot, Gordon E. –Loss Models from Data to Decisions; New York, John Wiley & Sons; 1998

Jameson, R (ed.) – Energy Modelling and the Management of Uncertainty; London, Risk Books, 1999

MAAC/ECAR/NPCC Study Committee - *Summer Peak Load Study*; 1998

North American Reliability Council - *1999 Summer Assessment*; 1999

North American Reliability Council – *Predicting Unit Availability, Top-down Analyses for Predicting Electric Generating Availability*; 1991

North American Reliability Council - *Reliability Assessment 1998-2007*; 1998

Pilopovic, D. - Energy Risk: Valuing and Managing Energy Derivatives; New York, McGraw Hill, 1998

Task Force on Complex Models of the Casualty Committee of the Actuarial Standards Board – *Using Models Outside the Actuary's Area of Expertise* (Exposure Draft); 1999

U.S. Department of Energy – *Interim Report of the U.S. Department of Energy's Power Outage Study Team – Findings from the Summer of 1999*, 2000

U.S. Senate Committee on Energy and Natural Resources – *Oversight Hearing on the Recent Midwest Electricity Price Spikes;* September 24, 1998; http://energy.senate.gov/spikes/spikes.htm