**Carnegie Mellon University**

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# Valuing Risk-Reduction: Three applications in the Electricity Industry

**A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Engineering and Public Policy**

**by**

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This dissertation is motivated by the belief that it is possible for regulators to attenuate some of the uncertainties that surround the operation of electricity markets, and therefore understanding the sources, implications and costs of these uncertainties can help shape policies in the field. At least in some cases, the quantification of the effects of uncertainty can serve as an incentive for industry participants and regulators to make a common front against unnecessary costs.

*Options theory* and the method of *risk-neutral valuation* provide a framework to quantify the value of hedging against uncertainty. By incorporating options theory – widely used in the financial world- this thesis contributes a framework to quantify the risks and value accordingly the instruments or strategies that provide hedging. Having an idea of what the fair cost of hedging is, we will have better tools to identify inefficiencies and opportunities for regulation improvement.

This dissertation looks at three cases of uncertainty in the electricity industry, related to generation, transmission and ancillary services, and proposes a method to quantify the cost of this uncertainty and use this value to inform policy making. In the three cases, there is a strategy or contract that can be seen as a hedging instrument and valued as such. In the ambit of electricity transmission, Financial Transmission Rights (FTRs) can be seen as hedging instruments that provide protection against highly volatile transmission congestion costs. An FTR is essentially a contract that allows (or obligates) the holder to get the monetary difference between the marginal price of electricity at the point where it is withdrawn to the marginal price electricity at its source. In the ambit of electricity generation, the investment in environmental-control-devices or cleaner generation technologies can be seen as protection against the risk of not being able to comply with potential stringent air-emission regulations. In the ambit of ancillary services, the provision of reliability-support resources can be seen as reduction of the risk of not being able to deal with contingencies that treat the instantaneous balance between supply and demand.

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A ti mi cielo, infinita gratitud por hacer que el sol salga todos los días para mi. Gracias por estos 12 años de viajes, aventuras y sueños. Laus Deo.

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# Introduction

Few would disagree that these are very interesting times for the electricity industry. The emerging complex situations in the restructured industry pose tremendous challenges to regulators and market participants. In the past (beginning in 1907), Investor owned utilities (IOUs), which provided the majority of electricity in the US, were subject to price-regulations by regulatory commissions(Dahl 2004). At the time, government intervention was justified by the agreement among economists that electric utilities were natural monopolies and regulation was needed to avoid social losses.

In 1944, “rate-of-return” regulation was established, allowing utilities to set their prices at a level equal to the costs plus an additional return to attract capital from investors. The electric companies (publicly or privately owned) were vertically integrated monopolies responsible for all the components of the power system, owning the power generating plants, and the transmission and distribution lines. This vertical integration and the cooperation among different utilities allowed the industry to keep operations under control and their customers satisfied.

For better or worse, industry participants during these periods did not harbor many concerns about financial risk. However, with the growing demand for electricity and the successes of deregulation in other industries (such as telecommunications and airlines) stakeholders began to think that the electricity industry could be restructured and function as a competitive market with minimal regulation. Since 1996, more than 24 states have enacted legislation or passed a regulatory order to start the process of restructuring(DOE/EIA 2003) and today six Independent System Operators coordinate wholesale electricity markets that account for more than half of the transmission lines and generation resources of the U.S. However in some states the plans for full restructuring have been indefinitely delayed or suspended and the success of deregulation is a highly debated topic, both in the industry and academia (Van Doren and Taylor 2004) (Lave, Apt et al. 2004). It seems that the promises of deregulation have not been realized; electricity prices are not lower (Apt 2005), and decision making in the industry has become harder.

## 1 Dissertation Motivation

In the competitive electricity markets, members of today's electricity industry face financial risks that either did not exist or were not so evident in the former days of vertically integrated utilities. Thus, industry participants are permanently confronted with the challenge of making decisions in a highly uncertain environment. These uncertainties affect all elements of the industry and make the already difficult investment and operating decisions even harder. Some of the sources of uncertainty are common to other industries such as uncertainty on future prices of raw materials (fuels) or uncertainty on the pace of technological advance, but the extent of the challenge they pose is exacerbated by physical attributes of power systems that make the industry unique. Because electricity cannot be stored, there is a need for real-time balancing of instantaneous demand and supply that makes the operation of the components of a power system; generation, transmission, and ancillary services, complex.

Electricity generators must constantly decide how to upgrade and expand their generating capacity, under the uncertainty of fuel prices, technological change, and regulatory framework that targets the negative externalities of their operation. Without rate-of-return regulation, generators face serious financial risks.

Uncertainty in generation costs is only part of the problem; in competitive markets, participants also face uncertainty on the ability and costs of transmitting electricity in a grid subject to losses and capacity constraints. Finally, in a system composed by different for-profit competitive agents, the task of ensuring the provision of ancillary services is more challenging than what it was when all parts cooperated towards the goal of reliability.

Keeping other variables constant, more uncertainty means higher costs of supplying electricity to the final consumers. More uncertainty increases the chances of inadequate decisions and makes industry participants pursue risk-reduction strategies that are never cost free. By identifying hedging strategies and quantifying their costs, we might learn something new about the industry and about how to shape policy to better pursue the goals of supplying affordable electricity, lowering as much as possible its negative externalities, and keeping the industry in good shape to face the challenges of years to come.

Different hedging strategies apply in different contexts, some come in the form of investments and others in the form of contracts, but they always come at a cost that will be, sooner or later, passed on to consumers. In this dissertation we study three cases of risk-reduction actions that arise in the context of major decisions that industry participants are forced to make 1) Handling of transmission congestion costs, 2) Complying with air-emissions regulations, 3) Provisioning real-time balance between electricity supply and demand. These three cases are important pieces of the whole puzzle of major concerns in this industry; 1) how to keep the size and capacity of the "arteries" of the power-system current with the growing electricity demand (transmission investment – congestion management), 2) how to do less harm to the environment (air-emissions reductions), and 3) how to keep the lights on (reliability).

## 2 Dissertation Method and Scope

This dissertation is motivated by the belief that it is possible for regulators to attenuate some of the uncertainties that surround the operation of electricity markets, and therefore understanding the sources, implications, and costs of these uncertainties can help shape policies in the field. At least in some cases, the quantification of the effects of uncertainty can serve as an incentive for industry participants and regulators to make a common front against unnecessary costs.

*Options theory* and the method of *risk-neutral valuation* provide a framework to quantify the value of hedging against uncertainty. By incorporating options theory this thesis contributes a framework to quantify the risks and value accordingly the instruments or strategies that provide hedging in the electricity industry. Having an idea of what the fair cost of hedging is, we will have better tools to identify inefficiencies and opportunities for regulation improvement.

## 3 Dissertation Outline

This dissertation looks at three cases of uncertainty in the electricity industry, related to generation, transmission, and ancillary services, and proposes a method to quantify the cost of this uncertainty and use this value to inform policy making. In the three cases, there is a strategy or contract that can be seen as a hedging instrument and valued as such. In the ambit of electricity transmission, Financial Transmission Rights

(FTRs) can be seen as hedging instruments that provide protection against highly volatile transmission congestion costs. An FTR is essentially a contract that allows (or obligates) the holder to get the monetary difference between the marginal price of electricity at the point where it is withdrawn to the marginal price electricity at its source. In the ambit of electricity generation, the investment in environmental-control-devices or cleaner generation technologies can be seen as protection against the risk of not being able to comply with potential stringent air-emission regulations. In the ambit of ancillary services, the provision of reliability-support resources can be seen as reduction of the risk of not being able to deal with contingencies that threaten the instantaneous balance between supply and demand.

This document is organized in three parts. Part I, constituted by Chapter 1 introduces options theory and extends its application to price contracts that allow risk reduction outside the financial setting. The theory of options in its present form cannot be applied meaningfully to certain instruments in the electricity industry, so we propose an extension that allows the valuation of derivatives even when the stochastic process of the underlying variable is not known. We state that a derivative can be priced if the probability density function of its value at the relevant time (the exercise time) is known, and present a method to do so.

Part II studies Financial Transmission Rights as hedging instruments and looks in detail at the PJM market. We present evidence that in the auction of annual FTRs in PJM for 2003-2004, clearing prices included a “risk-premium” that “hedgers” paid to reduce the risk of highly volatile congestion charges, and “insurers” charged for bearing this risk, confirming the idea that hedging comes always at a cost, and posing the questions of

1) how to find the value of the hedging instruments and 2) how efficient is the PJM market where these are traded. Using results of Chapter 1, in this part we present, and apply a method to find the “fair value” of the premium of the FTR based on the probability distribution function of the corresponding *Congestion Charges*. The comparison between the value predicted by the formula and the prices observed in the auction allows us to state that there are inefficiencies in this market.

Chapter 2 reviews the alternatives for managing transmission congestion in deregulated electricity markets and describes the characteristics of Financial Transmission Rights in the U.S., their motivation, their possible advantages and disadvantages. It summarizes the few studies that have attempted a diagnosis of the efficiency of markets of FTRs, and presents a simple comparison between FTR prices and payoffs in PJM as motivation for a more detailed analysis of this market.

Chapter 3 reviews the results of the auction of annual FTRs in the PJM market for the year 2003-2004, analyzing the effect that different variables had on the value of the premium paid/received for FTRs. It shows that several institutions that are not participants in the electricity market profited from trading FTRs, motivating the question of whether or not the quantity of money that “leaks” from the system is commensurate to the value of the hedging FTRs provide. This Chapter provides evidence that in PJM the lack of competition among insurers and the competition among hedgers increases the premium received by the former ones and paid by the others. It also shows that the higher the number of transactions for the same Point-to-point combination, the higher the premium paid by hedgers and received by insurers.

Chapter 4 applies the method presented in Chapter 1, to find the fair value of an FTR, and proposes a strategy to deal with the obstacle of having limited information about the uncertainty the FTR is supposed to hedge against.

Part III presents two other cases in which a quantification of the uncertainty according to the method proposed in Chapter 1 can inform related policy making. Chapter 5 looks at the problem that fossil-fuel fired electricity generators face, when making decisions on how to comply with air-emissions regulations. It argues that under certain regulatory contexts, installing an Air Emissions Control Device (ECD) can be seen as equivalent to buying and option to purchase emission's permits, and demonstrates that regulatory uncertainty lowers the value of this option and makes the installation of these ECD less likely. The examples presented are for ECDs that reduce the emissions of nitrogen oxides and sulfur dioxides.

Chapter 6 shows how methods of Chapter 1 can also be used to value those services that support real-time reliability in a power system. It presents a method to determine the value of having flexible generators to react to load fluctuations in the PJM region. This value is directly derived from the characterization of the uncertainty on the load due to the volatility of electricity demand, and can be used to redefine the arbitrary operating standards that have been used in the industry since the old days of vertically integrated utilities.

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# Chapter 1: The Fair Value of Risk-Reduction

## 1 Introduction

Options theory and the method of risk-neutral valuation provide a framework to quantify the value of hedging against uncertainty. Options and insurance contracts are closely related. A financial option can be seen as an insurance contract to hedge against uncertainty in a stock price. Similarly insurance contracts can be assimilated to option transactions. For example, insuring one's belongings is equivalent to buying a *put option*.[1] The insurance gives the holder the right to "sell" her belongings to the insurer at a specified price.

Several investment opportunities in today's electricity industry provide insurance against the possibility of high losses in the future. As we will see later, there are many contracts or investments that can be regarded as an option and priced as such. In this dissertation we present 3 cases: buying an FTR (Chapters 2-4), installing an environmental control device (Chapter 5), and scheduling operational resources for operational reliability (Chapter 6). We believe that the theory of risk-neutral valuation of options can be used to find the "fair" value of the premiums that should be paid for the reduction of risk that these "insurance" mechanisms provide.

In this chapter we propose a general method to find the fair value of instruments that reduce the uncertainty on a future cost. In Section 2, we introduce options theory and provide its historical context in the field of finance. Section 3 broadens the same concept

[1] A put option gives the right to sell one unit of the underlying asset at a fixed price.

to value a hedging instrument, or to find the fair value of the premium that should be paid in a contract that allows the holder to hedge against volatility in future costs.

## 2 Options Theory in Finance

How to value options has been a question asked for more than 40 years in the financial world. In the early sixties several authors[2] worked on the theory of warrants valuation. However, these early formulae were incomplete because each of them involved one or more arbitrary parameters. Samuelson (1965)(Samuelson 1965) first presented a formula to valuate warrants that depended upon arbitrary parameters –the expected return and the discount rate- related to the risk aversion of the traders, and did not allow buyers and sellers to agree on the price of the option.

In 1973(Black and Scholes 1973), Black and Scholes derived a theoretical valuation formula for options on a traded underlying stock. Their approach consisted of creating a hedged position with a portfolio of long and short positions in the option and the underlying stock, and applying the principle that the expected return of a hedged position must be equal to the return on a riskless asset. By applying the boundary conditions of the *European Call Option*[3], Black-Scholes solved the differential equation for the value of this option and obtained the famous Black and Scholes formula. A very important characteristic of this formula is that it does not depend on any assumption about the risk preferences of the investors.

[2] Black and Scholes cite Sprenkle (1961), Ayres (1963), Boness (1964), Samuelson (1965), Baumol, Malkiel, Quandt (1966) and Chen (1970)

[3] A *European Call Option* is a financial derivative that gives to the holder the option (but not the obligation) to buy one share of a trading asset, at a price X, at time T.

Cox and Ross (1976)(Cox and Ross 1976) showed that Samuelson's formula was equivalent to the Black-Scholes formula if both parameters; expected return and discount rate, reflected the same degree of risk aversion. The value of the derivative would be the same if both expected return and discount rate reflected a high level of risk aversion, or if both reflected a low level of risk aversion and it would be the same if both parameters reflected risk neutrality. This observation let them to propose the *risk neutral valuation* method, which treats financial assets as having an expected return equal to the risk-free rate and discounting them to the risk-free rate as if all investors were risk-neutral.

The method of *risk neutral valuation* is useful not only to price any derivative contingent on the price of an underlying traded asset, but it is also useful to price any derivative contingent on an underlying random variable that follows a continuous-time stochastic process. The most remarkable characteristic of this method is that this variable does not need to be the price of any traded security or related at all to financial markets (See Chapter 13: "General Approach to Pricing Derivatives" Hull 1997(Hull 1997)). Moreover, the general method of *risk neutral valuation*, as a sub product of the pricing of the derivative, gives the price of the risk associated with the underlying variable. This finding is independent of the nature of the derivative. Further, because of these properties of risk neutral valuation, it is possible to define artificial derivatives to set up a theoretical portfolio with certain desirable properties from which we can derive the *price of risk* of the underlying variable.

In this section, we present a general method to value the reduction of the risk associated to a random variable such as a future cost. This method does not make any assumption about the stochastic behavior of the variable. We first review the assumptions about stock prices, the Black-Scholes formula and the method of risk-neutral valuation to price derivatives of a non-dividend paying stock. We then review the approach of Bouchaud and Sornette (1994)(Bouchaud and Sornette 1994) to generalize and expand the Black and Scholes formula. Their results provide insight to valuing a contract that provides risk reduction without assuming any particular distribution for the underlying source of uncertainty.

### 2.1 Assumptions about stock prices for options valuation

An important assumption about stock prices is that they follow a stochastic process of geometric-Brownian motion or:

$$dS = \mu S dt + \sigma S dz \qquad \text{EQ.1.}$$

where $\mu$ is the drift (or variable trend) parameter, $\sigma$ is the volatility parameter, and $dz$ is a Wiener process, that is $dz = \varepsilon\sqrt{dt}$ with $\varepsilon$ being a draw from a standard normal distribution, so the expected value of $dz$ equals zero and its variance equals $dt$. (See Chapter 10 of Hull (1997), and Chapter 15 of Karlin and Taylor (1981)(Karlin and Taylor 1981)).

The assumption that stock prices follow a diffusion process implies that stock prices exhibit the strong Markov property, which means that in predicting future prices the information about prices in the past is irrelevant and all that counts is the present price. This assumption is consistent with the assumption that stock markets are efficient (so that the weak-form of markets efficiency holds- see for example(Brealey and Myers 1996)) so the present price of a stock contains all available information that can be extracted from observing and analyzing past prices.

A second implication of the assumption that stock prices follow geometric-Brownian motion is that the distribution of the prices at a time T in the future is lognormal, or that

$$\ln S_T \sim \phi\left[\ln S + \left(\mu - \frac{\sigma^2}{2}\right)(T-t), \sigma\sqrt{T-t}\right] \qquad \text{EQ.2}$$

where $\phi(\mu,\sigma)$ denotes a normal distribution with mean $\mu$ and standard deviation $\sigma$, and $S$ is the price at current time $t$. This means that the expected value of $S$ at time $T$ is $\langle S_T \rangle = Se^{\mu(T-t)}$, which is the future value of $S$, assuming that $\mu$ is the expected rate of return of the stock.

### 2.2 Black and Scholes formula to price a derivative

In order to derive a formula to value an option as a function of the stock price, the Black and Scholes approach creates a hedged position entailing a long position in the stock and a short position in the option. The value of such portfolio does not depend on the price of the stock, because any change in the position on the stock is offset by the changes in the position on the option. If the position in the option is adjusted continuously, the risk in the hedged position becomes zero and the return on the option is now known with certainty. If the return is certain, then it must be equal to the risk-free rate; otherwise the opportunity of making sure profits would exist.

If the position in the option is not adjusted continuously, then the risk in the "hedged position" is not zero, although it is small. Furthermore, this risk can be diversified away because there is no "market risk' in the hedged position. By equating the change in the "hedged position" to the value of setting up that position, multiplied by the risk-free rate, Black and Scholes derive a differential equation for the value of the option. The only formula that satisfies that equation, subject to the boundary condition of the European call-option, is:

$$call(S, X, T, r) \qquad \text{EQ.3.}$$

which is in fact the valuation formula for the European call-option.

### 2.3 The method of Risk Neutral Valuation

The method of risk neutral valuation states that the value of the derivative is equal to its risk-neutral expected payoff, discounted at the risk-free rate. The risk neutral expected payoff is the expected value of the payoff assuming the drift in the process followed by the price of S is equal to the risk-free rate. In other words,

$$DerivativePrice = e^{-r(T-t)} \langle DerivativePayoff \rangle_{RN}\ , \qquad \text{EQ.4.}$$

where $\langle\ \rangle_{RN}$ represents the risk-neutral expectation of the payoff of the derivative at time T.

In pricing a derivative like a European call-option with exercise price X and exercise time T, we know that its payoff is either 0 or the amount the price of the stock at time T exceeds the exercise price of the option. That is, the method of risk-neutral valuation states that

$$call(S, X, T, r) = e^{-r(T-t)} \langle Max[0, S_T - X] \rangle_{RN}\ , \qquad \text{EQ.5.}$$

where $call(S, X, T, r)$ represents the value of the call-option at current time t.

Ignoring the discounting factor, we can write the right hand side of EQ.5 as:

$$\langle Max[0, S_T - X]\rangle_{RN} = \int_X^{\infty} (S_T - X) f_{S_T}(S_T) dS_T \qquad \text{EQ.6.}$$

where $f_{S_T}(S_T)$ represents the probability density function (p.d.f) of the stock price at time T, assuming its drift is equal to the risk-free rate. The assumption that $S_t$ follows a geometric-Brownian motion with a drift equal to the risk neutral rate implies that $f_{S_T}(S_T)$ is equal to the p.d.f of a lognormal distribution with parameters

$$\left[\ln S + \left(r - \frac{\sigma^2}{2}\right)(T-t), \sigma\sqrt{T-t}\right].$$

## 2.4 The role of the risk-free rate

The risk-neutral valuation implies calculating a risk-neutral expectation $\langle \ \rangle_{RN}$ of the derivative payoff, by replacing the drift $\mu$ by r, in our assumption about the diffusion process followed by $S_t$ and in the parameters of the lognormal distribution assumed for $S_T$. However, we would obtain the same result if we allowed the drift of the diffusion process of $S_T$ take any value and then discounted the expected value of the payoff of the derivative at an equivalent rate, and adjusted the exercise price properly. In other words, we have that

$$call(S, X, T, r, \sigma) = call(S, Xe^{k-r(T-t)}, T, k, \sigma) \qquad \text{EQ.7}$$

for any value of $k$. (The change of the value of the interest rate from r to k not only affects the discounting in the formula but also the drift assumed to derive the pdf of $S_T$.)

The way the Black and Sholes formula prices risk reduction is made evident by observing the pricing of a call option. Suppose for example we are interested in pricing a call-option on a stock whose exercise price is the risk-neutral expected value of $S_T$, or $X = e^{r(T-t)}S$. Applying the Black and Sholes formula (EQ.3), we find that there is a relationship between the value of the option as a proportion of $S$ and the volatility –or risk—, which only depends on the exercise time $T$.

The next plot shows the relationship between the value of the call option, $c$ and the volatility of $S_t$, that holds for any value of $S$ and $r$ when the exercise price of the option is its expected risk neutral value.

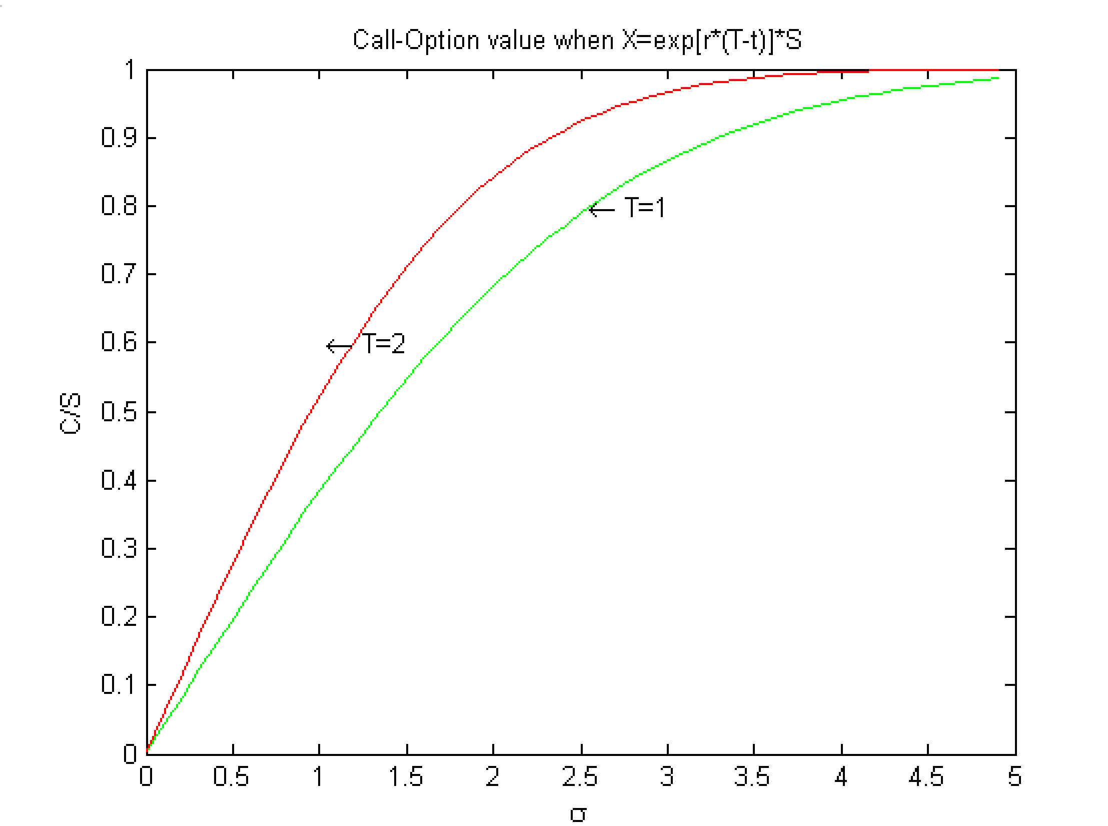


**Figure 1: Call-option value when X = $e^{[r(T-t)]}$S**

The value of $call/S$ depends on $T$ because the uncertainty on the value of $S_T$ is increased by $T$; in fact, the standard deviation of $\ln S_T$ is $\sigma\sqrt{T-t}$.

The following plot shows that there is a universal relationship between the price of the call-option (as a proportion of S), and the cumulative uncertainty ($\sigma\sqrt{T-t}$), that holds for any value of $S$, $r$ and $T$.

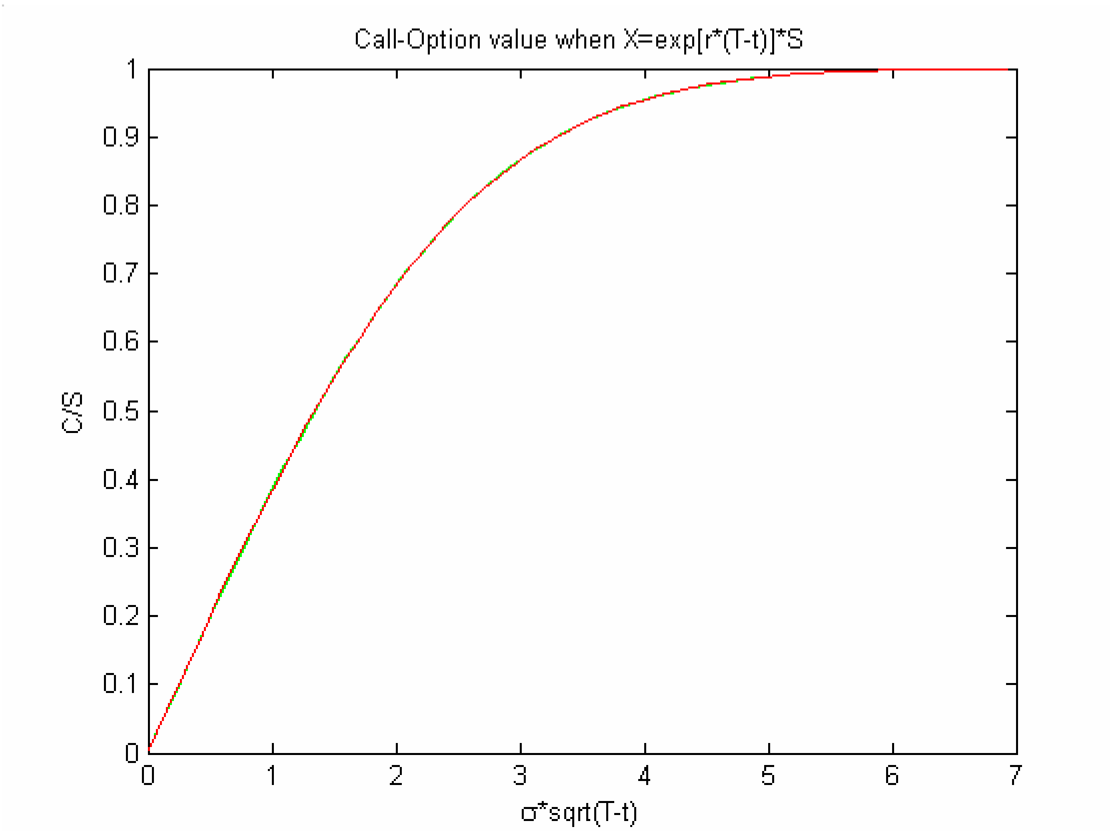


**Figure 2: Call-option value when X = $e^{[r(T-t)]}$S**

### 2.5 Options prices when the derivative does not follow a lognormal distribution:

What happens if the process followed by $S_t$ is not as the one shown in EQ.1, and therefore the pdf of $S_T$ is not lognormal? If we know (or can estimate) the parameters of the diffusion process followed by $S_t$, we can still follow the Black and Scholes approach, to find a differential equation for the value of a derivative on $S_T$, whose solution (if it can be found analytically) after applying the boundary conditions of the option, will be the value of the option itself. Alternatively, we can attempt an approach that does not require the use of Ito's calculus, and that always leads to a solution of the value of the option.

Bouchaud and Sornette (1994) generalize the analysis of Black and Scholes to price a financial call option $call(S, X, T, r = 0)$ when the stock price does not follow a geometric-Brownian stochastic process. Their approach analyzes the transaction of the option by applying two principles:1) the fair value of the option is such that the expected value of the change of the option seller's wealth $\Delta W$ in the time $(T - t)$ is zero and 2) the optimal investment strategy of the option's seller is such that the variance -or risk- of the change of wealth $\left\langle \Delta W^2 \right\rangle$ is minimized.[4] The first condition implies that there are no arbitrage opportunities and the second condition is stated after noticing that it is not possible to find the optimal investment strategy from an algorithm of profits maximization.

In this case, the total variation of the seller's wealth is the sum of three sources: 1) the quantity $call(S, X, T, r)$ paid by the options buyer, 2) the potential value of the loss that would incur if the buyer exercises the option, and 3) the net gain or loss from holding $\phi(S, \tau)$ shares of the stock at time $\tau \in (t, T)$, that is:

[4] Note: All references to the seller refer to the options seller, not the stock seller.

$$\Delta W = call(S,X,T) - \max[S_T - X, 0] + \int_t^T \phi(S,\tau)\frac{dS}{d\tau}d\tau \qquad \text{EQ.8}$$

If the local derivatives $\frac{dS}{d\tau}$ are independent for different times $\tau$, and if $\left\langle \frac{dS}{d\tau} \right\rangle = 0$, the expectation of the third term in the EQ.8 becomes $\phi(S,\tau)\left\langle \frac{dS}{d\tau} \right\rangle = 0$. By applying the "no arbitrage" condition $\Delta W = 0$, Bouchaud and Sornette arrive at the risk-neutral valuation equation for the value of the option $call(S,X,T,r)$ presented in EQ.5, with r = 0. Their derivation clearly shows that the risk-neutral valuation equation holds without any specific assumptions about the form of the pdf of $S_T$.

Because the risk-neutral valuation equation does not include any term on $\phi(S,\tau)$, it cannot be used to make any statement about the optimal investment strategy of the option's seller. Instead, the optimal strategy must be found as one that minimizes the variance of $\Delta W$. Bouchaud and Sornette show that this variance becomes zero whenever $S$ follows a geometric motion stochastic process, a Brownian stochastic process, and a "quasi-Gaussian" process ($\frac{dS}{d\tau} = g(S)\eta(\tau)$ where g is any function and $\eta(\tau)$ is a Gaussian noise). However, it does not become zero in general. They emphasize that nevertheless the strategy that minimizes the risk is optimal, and that in those cases where it is not possible to find a "risk-free" strategy for the option's seller, the price of the option must be adjusted.

Although the approach of Bouchaud and Sornette generalizes the Black and Scholes result for a wide set of stochastic processes, it still requires 1) the stochastic process of the underlying source of uncertainty to be known, and 2) a calculation of an optimal investment strategy to adjust the option price by the residual risk. We state that even when the stochastic process of the underlying variable is not known, a derivative can be priced if the pdf of its value at the relevant time (the exercise time) is known. In the next section, we propose a method to do so, which does not assume any specific pdf for the value of the variable at time T.

## 3 A Proposed Method to value instruments that provide risk-reduction

The result of Bouchaud and Sornette shows that even when the underlying source of uncertainty does not follow a Brownian or geometric-Brownian process, it is still possible to use the fundamental equation of risk neutral valuation to find (at least part of) the value of a derivative. They propose that when there is a risk-free investment strategy that involves the derivative, its value can be found just by applying the no-arbitrage condition (the condition that the expected value of losses or gains for both buyer and seller must be zero). Instead, when no such strategy exists, the seller of the derivative should add to her price the risk that still faces after using the optimal investment strategy.[5]

We propose a similar approach to value a contract (or an investment) that sets a limit on the losses of a party that faces an uncertain future payment that is highly volatile. Our approach relies on the method of risk-neutral valuation and Bouchaud's and Sornette's results, but it makes an "adjustment" for risk in a different way. Our "adjustment" comes up naturally in the application to the first case study of the dissertation, FTRs, and works well for the second and third case studies of operational

[5] Recall that the options buyer is hedged because the minimum payoff of the option is zero.

reliability and investment in emissions-control technologies, respectively. As will be explained in more detail later, we determine the value of the risk-reducer-instrument (e.g. an FTR) by assuming that the buyer is willing to pay at the present the expected price (mean) of the future cost plus a premium equal to the expected value of the gains. The value of the premium is regarded as the value paid for an insurance policy against the uncertainty in the future cost, and in particular against the possibility of the future cost exceeding its expected value.

For the premium to be zero, the expected value of the potential losses of the buyer of the contract (when the cost does not exceed its expected value), should be equal to the potential losses of the seller of the contract (when the cost does exceed its expected value). The premium cannot be zero, because one of the parties (the seller) is facing a risk that the other one (the buyer) does not face. The buyer's losses are limited by the price paid for the contract while the losses of the seller are not limited. This is why the buyer pays a premium over and above the expected value of the cost she wants to hedge against. The value of such premium is determined through the method of risk-neutral valuation as it is described in this section.

Before quantifying the value of the premium, however, the risk neutral valuation must be made more precise. As shown in earlier sections, the risk-neutral method states that the price of a derivative is given by $DerivativePrice = e^{-r(T-t)}\langle DerivativePayoff \rangle_{RN}$. This method implies calculating the risk-neutral expectation $\langle\ \rangle_{RN}$ of the payoff. But what does $\langle\ \rangle_{RN}$ mean outside the assumption of an underlying following geometric Brownian motion process?

In Bouchaud's and Sornette's example, both the interest rate *r* and "the bias" $\left\langle \frac{dS}{d\tau} \right\rangle$ are assumed to be zero. This is consistent with the condition of the risk-neutral valuation method, which states that the drift of *S* (implied by the pdf used for the risk-neutral valuation) and the discount rate *r* be the same. That means that just as it applies to the geometric-Brownian stochastic process, the risk neutral expectation requires choosing a "risk-neutral" stochastic process for $S$ such as the expected value of its instantaneous changes and the discount rate are the same.

We state that rather than referring to the stochastic process followed by $S_t$, we refer to the value of the variable at the time of interest $S_T$ as risk-neutral expectation. This means that the pdf of $S_T$ is adjusted in such a way that the same volatility is preserved, and its expected value is such that $\langle \ \rangle_{RN}$ is consistent with the current (today's) price $S$. In other words, the pdf of $S_T$ must be chosen so that the relationship $S = e^{-r(T-t)} \langle S_T \rangle_{RN}$ holds.

### 3.1 Estimating the value of a premium:

A financial instrument that reduces the risk associated with a future volatile cost *C* must be sold at a price $P$ that exceeds the expected value of $C$ by some premium. The "fair value" of this premium, *H*, is the risk neutral value of the option of paying the fixed price $P$ rather than the expected value of the volatile cost *C*. In other words, the premium is:

$$H(C,P) = P - \langle C \rangle \qquad \text{EQ.9}$$

If we can find another equation that relates the value of the premium *H*, the expected value of the cost $\langle C \rangle$ and the fair price of the financial instrument $P$, we can use it together with EQ.9 to find a solution for both *P* and *H*.

To find such equation we first state all we know about *H*:

First we know that $H(C,P)$ is a linearly homogeneous function

$$H(\lambda C, \lambda P) = \lambda H(C,P) \qquad \text{EQ.10}$$

For example, if we double both the value of $C$ and the price $P$, then, the value of the option is multiplied by two). Euler's theorem[6] implies that $H(C,P)$ has the general form:

$$H(C,P) = P\frac{\partial H(C,P)}{\partial P} + C\frac{\partial H(C,P)}{\partial C} \qquad \text{EQ.11}$$

For a given $P$, the larger $C$, the larger the value of $H(C,P)$, i.e. the value of paying the fixed price $P$ instead of being exposed to the volatility of $C$. Hence $\frac{\partial H}{\partial C}$ is positive. With a similar reasoning, $\frac{\partial H}{\partial P}$ should be negative, as for a given $C$, the larger the price $P$ paid, the smaller the value $H(C,P)$ of the transaction.

We assume that the buyers of the contract want to hedge against the possibilities of $C$ being much higher than its expected value $\langle C \rangle$, by paying $H$. The premium paid has to be such that these buyers end up in a risk-neutral position. This means the value of

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[6] If the function $f : R^n \to R$ is positively homogeneous of degree 1, then $f(x_1, x_2,..x_n) = \sum_{i=1}^{n} x_i \left[\frac{\partial f}{\partial x_i}\right]$

*H* has to be equal to the expected value of the money the buyer will save with the hedging instruments (in other words, the insurance policy). The hedge holder (the buyer) will be "saving money" whenever C exceeds the value paid for the hedge:

$$H(C,P) = e^{-r(T-t)}\langle Max[0, C-P]\rangle \qquad \text{EQ.12}$$

If we know the real pdf of $C$, $f_c(c)$, we can use EQ.9 and EQ.12 to solve for the value of P:

$$P = \langle C\rangle + H(C,P) \qquad \text{EQ.13a}$$

$$P = \langle C\rangle + e^{-r(T-t)}\langle Max[0, C-P]\rangle \qquad \text{EQ.13b}$$

$$P = \int_{-\infty}^{\infty} c f_c(c)dc + e^{-r(T-t)}\int_{P}^{\infty}(c-P) f_c(c)dc \qquad \text{EQ.13c}$$

The last expression can be solved numerically for P, for any pdf $f_c(c)$

### 3.2 The value of the premium when C is normally distributed

As an example and useful result of the formula presented above, this section derives the value of the premium when the cost is normally distributed. Let $P_{normal}\left(\langle C\rangle, \sigma\right)$ denote the price that should be paid for an instrument that gives to the holder the right to collect $C$ one year from now, with $C$ being normally distributed with mean $\langle C\rangle$ and standard deviation $\sigma$. Assuming r = 0 (t = 0, and T = 1), EQ.13c can be rewritten as:

$$\langle C \rangle + \frac{1}{\sqrt{2\pi}\sigma}\int_{P}^{\infty}(c-P)e^{-(c-\langle C \rangle)^2/2\sigma^2}\,dc - P = 0 \qquad \text{EQ.14}$$

It can also be shown that

$$P_{normal}(k\langle C \rangle, k\sigma) = kP_{normal}(\langle C \rangle, \sigma), \qquad \text{EQ.15}$$

That is, the price increases in the same proportion as the changes in $\langle C \rangle$ and $\sigma$. This allows us to express the price that should be paid for the contract as a proportion of the expected value of C, as a function of C's coefficient of variation. By replacing $k = 1/\langle C \rangle$ in previous equation we get:

$$\frac{P_{normal}(\langle C \rangle, \sigma)}{\langle C \rangle} = P_{normal}\left(1, \frac{\sigma}{\langle C \rangle}\right). \qquad \text{EQ.16}$$

Solving the previous equation numerically for P, we find that the relationship between the price that should be paid for the instrument as a proportion of the expected value of C, and the coefficient of variation of C is linear, as the following graph shows:

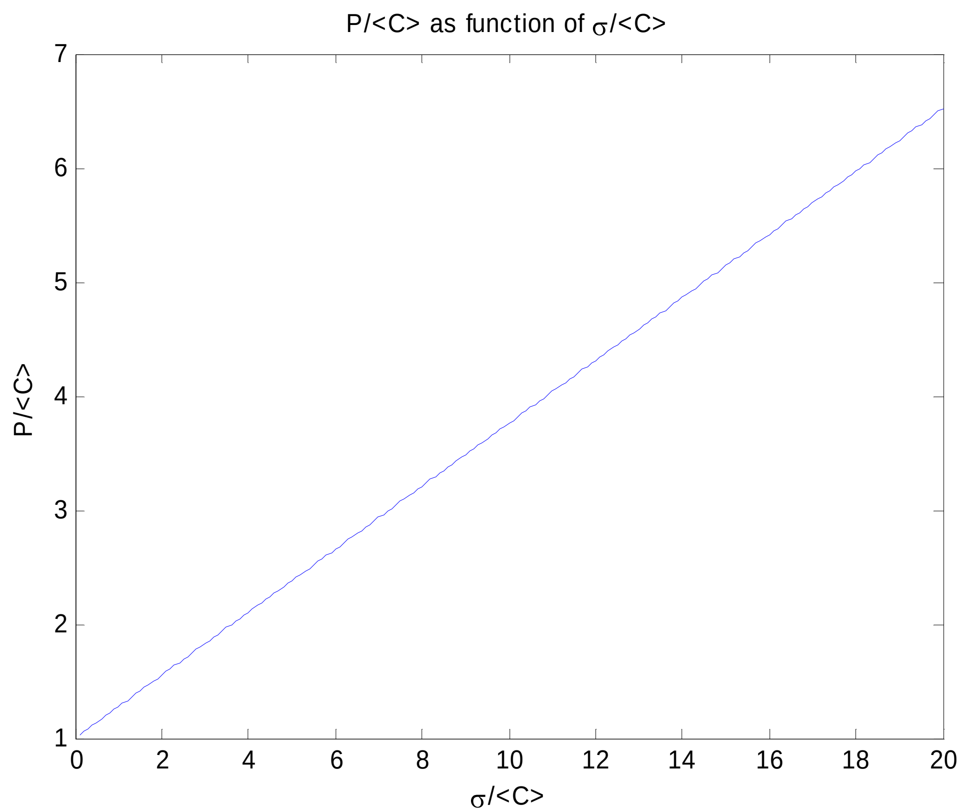


**Figure 3. P/<C> as a function of σ/<C>**

In this example we have,

$$\frac{P_{normal}\left(\langle C\rangle,\sigma\right)}{\langle C\rangle}\cong 1+\frac{0.2760\sigma}{\langle C\rangle} \qquad \text{EQ.17a}$$

or

$$P_{normal}\left(\langle C\rangle,\sigma\right)\cong\langle C\rangle+0.2760\sigma\,. \qquad \text{EQ.17b}$$

Replacing P in EQ.13a., we get that the fair value for the premium is

$H=0.2760\sigma$.

It is important to note that C represents a cost, and our method carries the assumption that $\langle C \rangle$ is positive. Describing C with a normal distribution implies that in theory C can take any value. If the expected value of C is positive, it makes sense for the agent facing this future cost to hedge against the possibility of C exceeding its expected value. The possibility of C taking a negative value should not worry this agent because it only means that C can represent an asset rather than a liability.

### 3.3 The value of the premium when C is log-normally distributed

Similarly, we can find the fair value of the premium when C follows a lognormal distribution with mean $\langle C \rangle$ and standard deviation $\sigma$. Assuming r = 0 (t = 0, and T = 1), EQ.13c can be rewritten as:

$$\langle C \rangle + \int_P^{\infty} (c-P) \frac{e^{-(\ln(c)-\alpha)^2/2\beta^2}}{\sqrt{2\pi}\beta c} dc - P = 0, \qquad \text{EQ.18}$$

where $\alpha = \ln\left[\frac{\langle C \rangle^2}{\sqrt{\langle C \rangle^2 + \sigma^2}}\right]$ and $\beta^2 = \ln\left[1 + \left(\frac{\sigma}{\langle C \rangle}\right)^2\right]$ are the parameters of the lognormal distribution followed by C.

Because the second term on the left hand of the equation represents the value of a call option on a stock C with exercise price P, we can replace it with the expression provided by Black and Scholes for a European call option $call(S, X, r, T)$ given by EQ.3 with $S = \langle C \rangle$, $X = P$, $r = 0$, $T = 1$ and the volatility parameter (or diffusion coefficient) $= \beta$.

As in the case of C following a normal distribution, when C follows a lognormal distribution, the price P that should be paid for the instrument meets the condition:

$$P_{\log normal}\left(k\langle C\rangle, k\sigma\right) = kP_{\log normal}\left(\langle C\rangle, \sigma\right) \qquad \text{EQ.19}$$

This allows us to find the value of $P_{\log normal}/\langle C\rangle$ as a function of the coefficient of variation $\sigma/\langle C\rangle$, as shown in the graph below:

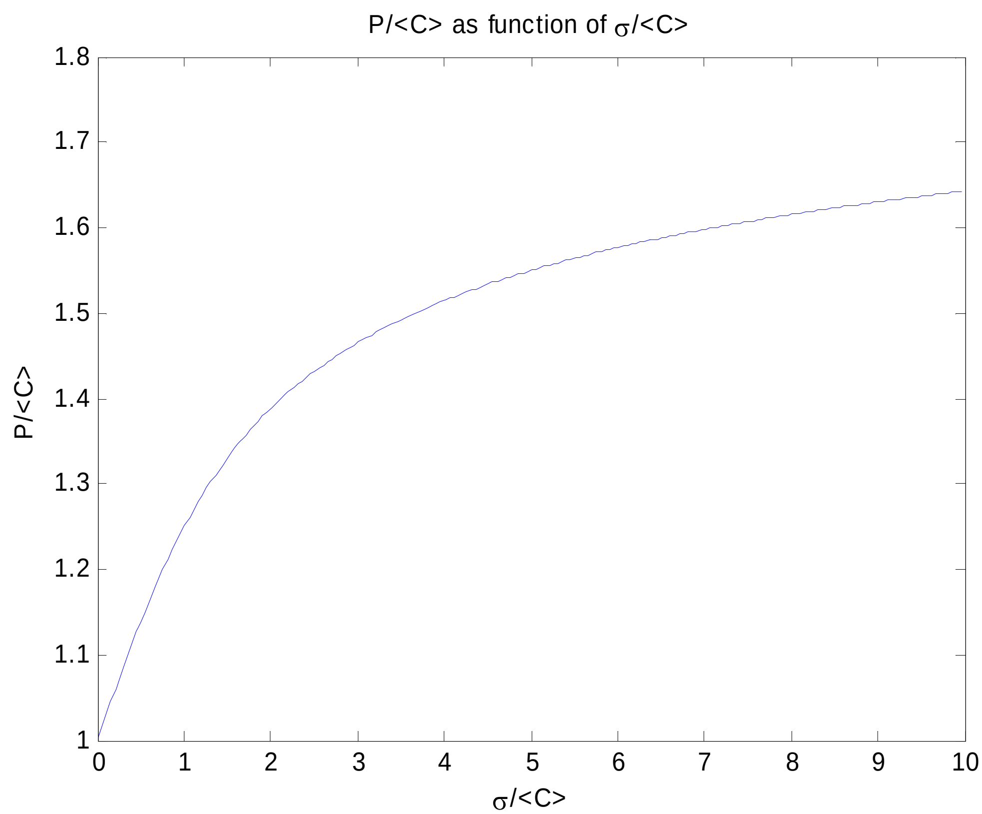


**Figure 4: P/<C> as a function of σ/<C>**

## 4 Conclusions

This chapter establishes the framework for extending the Black and Scholes and Bouchand and Sornette models beyond their original assumptions. The resulting formula we derive allows for detailed evaluations of the three cases that make up the remainder of this dissertation.

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# Part Two: Financial Transmission Rights

As described in the introduction to this dissertation, industry participants in competitive U.S. electricity markets, now face a variety of new financial risks that either did not exist before or were less evident in the former days of vertically integrated utilities. One example of these risks is the risk associated with highly volatile transmission congestion costs.

A financial instrument known as a *Financial Transmission Right* (FTR), has been introduced in several electricity markets in the U.S with the intention -among other things- of providing market participants with a mechanism to hedge against volatility in transmission congestion costs. The Federal Energy Regulatory Commission (FERC) in its *Standard Market Design* (SMD)[1] proposal suggested an FTR system should be implemented in all U.S. power markets.

Although a good number of papers on the theory of FTRs have been published in response to this FERC proposal, there have been no comprehensive analyses of the recent experience with FTR markets in the U.S.  The analyses in this section of the dissertation move in the direction of better understanding FTRs in practice.

The need to hedge against volatile transmission congestion is a consequence of the operating characteristics of restructured markets. The cost of hedging is an extra cost of deregulation that previously did not exist in regulated settings with vertically integrated utilities, with collective generation, transmission, and distribution assets. With the decoupling of generation and transmission ownership, uncertainty surrounding the

[1] Notice of Proposed Rulemaking of August 2002*:"Remedying Undue Discrimination Through Open Access Transmission Service and Standard Electricity Market Design" (67 Fed. Reg. 55,452)*

access to transmission capacity has increased, resulting in the need for hedging instruments such as FTRs.

The growing demand for FTRs in this new market structure raises the following questions: How well do FTR systems operate? How high are the costs of hedging with FTRs? and How useful could these markets be as incentives for investment in transmission? All three questions need to be asked and answered to take the electricity sector through a successful path in the years to come.

This work is a first-step toward answering these questions based on careful analysis of the PJM FTR market in 2003-2004. The goals of this second part of the dissertation are threefold: 1) to study the results of the FTR annual auction in PJM, 2) to draw some insights about the efficiency of these markets and 3) to identify actions that could be taken to improve the way transmission resources are currently managed.

In Chapter 2 we review some of the ideas that support the existence of FTRs and describe markets for FTRs in the U.S. In Chapter 3, we look at the results of the auction of annual FTRs in PJM for the year 2003-2004 paying special attention to obligation FTRs. In Chapter 4, we apply results of Chapter 1 to derive a fair value of the premium of the FTR and examine how this fair value compares to real prices.

Two recent empirical studies on the NY ISO reveal that the prices paid for FTRs are on average significantly larger than the average congestion costs they cover. The authors of these studies have raised the question of whether this finding is a result of market inefficiencies or perhaps strong risk aversion. The following chapters present a detailed examination of PJM auction results and show, in support of the NY ISO studies, that hedgers in this market also pay a premium for FTRs.

# Chapter 2: FTRs and Transmission Management in Competitive Electricity Markets

## 1 The transmission system

A *conditio sine qua non* for the success of a restructured electricity market is the operation of the transmission system in a way that guarantees open and non-discriminatory access for all market participants and at the same time provides the conditions for the improvement and expansion of the grid.

Long before the seminal FERC orders 888 and 889 of 1996, the question of how to make the transmission system an ally in the struggle to create truly competitive markets, has challenged the minds of industry members, academics, and regulators (Joskow and Schmalensee, 1983).

FERC Order 888 opened wholesale power sales to competition and required public utilities owning, controlling, or operating transmission lines to file non-discriminatory open access tariffs that offer others the same transmission service they provide themselves (FERC, 1996a). FERC Order 889 created the Open Access Same-time Information System (OASIS), to prevent transmission owners or their affiliates from taking advantage of their position over the other competitors in the market, by 1) making them separate their wholesale electricity operations from their transmission functions and 2) making them obtain information about their transmission system in the same way their competitors do, via OASIS on the internet (FERC, 1996b).

In the U.S. regions where utilities are organized around an Independent System Operator (ISO), the structure and operating rules of the markets for electricity, transmission and ancillary services are very similar. They all include a *Locational Marginal Pricing* (LMP) system at which electricity is priced at each node. In these markets, the (ISO) is in charge (among other tasks) of coordinating the spot market; collecting supply offers and demand bids from all generators and loads, and finding the optimal production schedule for each supplier. This optimal scheduling allows the calculation of the cost of providing the next MW at that particular node; this value is called the LMP and is used to price the sales that occur through the spot market.

Due to the limited power flow capability of transmission lines sometimes it is not possible to supply the electricity demanded with the cheapest generators and the ISO has to schedule more expensive generating units. The extra cost of scheduling an out-of-merit-order generator to supply electricity is the source of the transmission congestion cost (CC). If there were no transmission losses, nor transmission congestion, the LMP at every node of the electricity grid would be equal. With transmission congestion it is often the case that prices at the nodes of electricity withdrawal are higher -on average- than the prices at the nodes of electricity injection.

This difference in LMP is used to assign a monetary value to the cost of transmission congestion. The *Congestion Cost* between two nodes A and B ($CC_{A-B}$) is given by the difference between LMP at nodes A and B, or $CC_{A-B} = LMP_B - LMP_A$. These CCs are collected by the ISO that pays generators and charges Load Serving Entities (LSE) the LMP at their nodes. The money of CC is then allocated to the owners of the transmission lines, according to rules that are specific to the different market designs implemented by different regions in the U.S.

## 2 Types of Transmission Rights

In a system where all market participants have access to the grid to transport bulk electric power; a set of rules to govern transmission use becomes necessary. Electricity flow is governed by Kirchhoff's laws, and transmission from one point to another cannot be described in terms of a specific path on a network. As a result it is impossible to price the "transportation" of electricity as is done in other industries, and the task of designing rules suited to the complex operation of power systems that are also able to support competitive electricity trading poses a tremendous challenge.

Since before the deregulation process, there have been proposals of sets of rules to guide the allocation process of limited transmission capacity among market participants in need of that transmission for their power trade operations. A common element among proposals is the concept of "capacity reservation" or "capacity rights" that would affect the operation and financial position of capacity holders, depending on whether these "rights" were defined as 1) physical or financial, 2) point-to-point or "flow gate", and 3) obligation or option rights. Not all combinations of these three-tiers of rights exist in practice.

In the real system the definition of physical rights proved to be unworkable. Early recognition that for the sake of competition participation in the wholesale electricity market should not be tied to the holding of transmission rights, lead industry regulators to favor financial rights over physical rights.

The second-tier choice between flow-gate and point-to-point rights is not as easy as the choice between physical or financial rights, because both flow-gate and point-to-point have individual advantages and disadvantages. A flow-gate has the more straightforward definition of the two in theory. For any given set of power injection and power withdrawal operations it is possible to compute the total flows across each line of the transmission network. If the capacity of each transmission line is known, it is also possible to identify those lines that will become binding constraints in an optimal schedule to meet electricity demand at minimum cost. The rights to use the capacity on these key lines or “Flow gates” can be sold as “Flow-gate rights” to those that need to ship electricity on the network. ISOs can identify the flow gates and sell them in an auction. Then after energy transactions take place and participants pay and receive LMPs, they get the money they are entitled for each flow-gate right they own.

It has been hypothesized that flow-gate rights have several advantages over the point-to-point, or point-to-hub rights (Oren, 2000), because 1) there are only a few flow-gates or constraints, and therefore the trade of these rights could be more liquid, 2) the capacity limits at the flow-gates are known and fixed and therefore flow-gate rights can be defined independently of the pattern of power flows, and, 3) it is possible to decompose power transactions into flows over the flow-gates using known and fixed distribution factors (Chao et al., 2000).

But all the theoretical advantages of flow-gates are overwhelmed by the difficulties that have been observed in practice. In his paper “Flow gates rights and wrongs” Hogan (2000) exposes several difficulties that can arise while implementing a flow-based rights system. The first obstacle is that the identification of the binding transmission constraints is not easy; and also, even if constraints can be identified in advance, their number can be much higher than anticipated. In tests carried out in PJM in 2000 it was found that at a single point in time there could be more than 150 binding constraints; and therefore, a market participant would have to buy an equal number of flow-gate rights to secure a single point-to-point transaction. Also, the capacity limits of the flow-gates are not as "fixed" as it was suggested by proposals of the system. Capacity of the lines can change with the event of contingencies in the system, and the known and fixed thermal-limit can become meaningless.

In contrast, it has been argued that point-to-point rights are easier to use in practice, and they provide an exact hedge. A transmission user is only required to buy one point-to-point FTR for any given amount of capacity, and as long as the points of injection and extraction hold, this single FTR provides a precise hedge. More specifically, point-to-point FTRs are defined for a given pair of withdrawal and injection points (sink and source nodes), and for a specific period of time. The holder of the FTR has the "right" to collect (and the duty to pay) the difference in LMP between the sink and the source during the period the FTR is defined for. For example one FTR in PJM between points A and B, for the peak hours during the month of October 2004 gives the holder the right to collect the difference in the Day Ahead LMP of nodes A and B for each of the 375 peak hours of October.[2] This sum of the differences in LMPs is called "congestion rents" of the FTR. $Congestion\,\mathrm{Re}\,ntsFTR_{A,B}^{october} = \sum_{i=1}^{375} LMP_B^i - LMP_A^i$ .

Where $i$ represents the i-th on-peak hour in October 2004.

If a market participant schedules a transaction that consists for example of injecting 100 MW at point A and withdrawing 100 MW at point B during every on peak hour of October then $100\,FTR_{A,B}^{october}$ will provide her an exact hedge against congestion

[2]In PJM on peak hours are hours ending 8:00-23:00 during weekdays (excluding FERC holidays).

charges. The price this market participant pays for the 100 $FTR_{A,B}^{october}$ in the auction will be the entire amount she pays in congestion charges for the mentioned transaction.

As a result point-to-point rights bring two important benefits to the electricity market; 1) they provide a hedging mechanism for power traders and for load-serving entities against volatility in spot electricity prices and 2) they can serve to structure a mechanism to stimulate investments needed to maintain a reliable transmission system. These factors have led to the adoption of point-to-point rights over flow-gates. Thus, after ruling out physical rights and financial-flow based rights for the reasons outlined above, the only viable transmission-rights system remaining is a “point-to-point financial transmission rights” system, proposed by Hogan and implemented in the U.S. markets of PJM, ISO New England, NY ISO and Midwest ISO in recent years as described above.[3]

The third and final tier of transmission rights is the choice between obligations and options rights. In some markets (like PJM) FTRs are sold either as obligations or as options. However, options rights are more complex to implement, and as a result are less widely used. Given these complexities in the evolution of FTR markets, the sections to follow focus exclusively on financial, point-to-point, and obligations-rights FTRs which make up the large majority of FTR markets currently in use.

Taken as a whole, FTRs represent both a right and a liability. Holders of FTRs have the right to receive the difference in LMP from the ISO when it is positive, but have also the obligation to pay the ISO when this difference is negative. In the majority of the cases, an FTR that produces negative rents is also sold at a negative price. This can be

[3] These are called *Financial Transmission Rights(FTR)* in PJM, ISO NE and MISO, and called Transmission Congestion Contracts (TCC) in NY ISO.

interpreted as if market participants who schedule transactions that create counter flow on congested lines were paid in advance for this service a quantity equal to the price of the FTR. An FTR sold at a negative price can also indicate that a speculator is bearing the risk on future transmission congestions in the counter flow.

The following sections discuss the motivation for using FTRs for hedging and transmission investment, the implementation of FTRs within the institutional contexts of different regional ISOs, and finally the outcomes of FTRs auctions in NY ISO and PJM.

## 2.1 Hedging with FTRs

Transmission congestion costs represent an important percentage of the overall electricity cost. The large uncertainty implied in this costs creates a need for hedging(Hogan 1992), and is the primary motivation for implementing FTR markets. For those market participants whose FTR holdings match their electricity schedules, FTRs provide an exact hedge against the volatility in congestion costs, even when they pay a positive price for an FTR and collect negative rents. Even in this case, holders end up paying for congestion only up to the price of the FTR, since the negative rents are offset by the extra money they get from having a higher LMP at the injection point than at the withdrawal point. Therefore the fact that FTRs have the potential to provide a perfect hedge is undisputed, although the question of how high the price for hedging is remains open. Also, a market participant can fully hedge against the effect of transmission congestion on its power transactions only if FTRs are sold for the corresponding pair source-sink, in the same MW quantity as its planned transactions.

## 2.2 FTRs and market based transmission investment

A second, more subtle, reason for the use of FTRs is to motivate transmission investment, To support competition in electric markets it is not sufficient to have a fair system allowing all possible suppliers to use the available capacity of the transmission system in equal conditions. It is also necessary to have a grid with sufficient capacity, so transmission constraints do not give market power to any generator. And having enough transmission capacity is not important only to support competition, but also to add some flexibility to the operation of grid to be able to react at times of contingencies.

There is no disagreement about the fact that the transmission system needs to be upgraded. In the past decade transmission capacity in the U.S. has decreased relative to aggregate demand, and there is a long list of much needed projects that have not yet been constructed (Hirst, 2000).

The question of how to create the right conditions to upgrade the grid (to reduce transmission congestion, and increase reliability) inevitably leads to the confrontation between two different approaches. On one side there are those who argue that the externalities of a transmission network (and reliability) and the lumpiness of transmission investment, make it necessary for regulators to intervene, identify projects that are needed, and mandate their construction and funding structure. There are others opposed to this idea who argue that a well-structured market can respond to grid-level transmission needs and the government should only intervene in the case of proven market failure.

Advocates of relying on market-driven investment have proposed to compensate investors with the allocation of financial transmission rights that will allow them to collect transmission congestion charges. Joskow and Tirole (2004) have shown that when the attributes of wholesale power markets and transmission networks are considered, reliance in the merchant-investment model can lead to significant inefficiencies.

Because Financial Transmission Rights are only valuable in the case of transmission congestion, the idea of using FTRs as the “payment” to those who invest their money to reduce transmission congestion deserves further mention. In his paper *Market-based transmission investments and competitive electricity markets*, Hogan (1999) describes how a system in which an ISO coordinates an electricity spot market through a bid-based security-constrained economic dispatch provides the necessary structure to support efficient market-based transmission investments in which FTRs are the compensation for investors. As to the question of whether post-investment FTRs will really compensate the transmission-investment, Hogan argues that although investments might be lumpy, they do not necessarily have a large impact on nodal prices. In his words “if transmission investments can be made in small increments relative to the size of the market as a whole, they should have a minimal effect on market prices... Prices after the modular expansion would not be materially different than before, even though there would be and increase in capacity and throughput.” For those cases in which an upgrade of the transmission system would impact the nodal prices in such a way that the FTRs would be worthless, Hogan mentions the possibility of allowing investors to withhold some of the transmission capacity for a period of time so that collected nodal price differences become high enough to make the investment profitable. The problem with this approach is that it might increase the chances of having situations of pivotal[4] oligopoly in which electricity prices would reach the cap (Blumsack et al, 2002. Perekhodtsev, 2004)

To lessen the impact of market incentives for inefficient investments (that might reduce transfer capacity and increase congestion), Hogan explains that allocation of FTRs to investors should not render the FTRs allocated previously infeasible.[5]

## 2.3 The Stated purpose of FTRs and transmission investment

Currently, the stated purpose of FTR markets in different regions does not mention transmission investment, and refers to FTRs as a means to allow transmission customers to hedge against congestion charges. However in all markets, those who pay for the costs of the transmission network receive compensation directly linked to the market of FTRs. For the New England ISO, for example, Schedule 15 of the NEPOOL Tariff states: "An entity who pays for new transmission upgrades which increase transfer capability on the NEPOOL Transmission System, making it possible for the System Operator to award additional FTRs in the FTR Auction, shall be awarded ARRs."[6]

Nevertheless the debate about whether or not FTRs are useful as incentives for efficient market-based transmission investments is still open.

Hogan argues that when evaluating the tradeoff between an imperfect market system and imperfect regulation, the market seems more favorable, and states that

[4] A pivotal supplier is one who by withholding some capacity can create overall electricity supply to be less than demand. The concept can apply to a group of suppliers acting together.

[5] This is called the “Feasibility Rule.”

[6] http://www.iso-ne.com/support/faq/ftr/index.html

mandated investment could only come after a test of market failure is applied. His suggestion is that regulators should draw the line between the investments that should be market-driven and those that should be mandated valuing the corresponding FTRs.

### 2.4 FTRs and the role of the ISO

In new deregulated markets, ISOs exist to fill the immediate need for coordination of the use of the transmission network, and the embedded need of coordination of the wholesale electricity market. ISOs are non-for-profit and are expected to act neutrally and independently of the particular interests of the market participants, procuring reliability of the power system for the well-being of the customers in the regions they operate. In the markets where Financial Transmission Rights are in place, the ISO is in charge of allocating FTRs, honoring grandfathered rights (Midwest ISO) or through an auction (PJM, ISONE, NYISO).

The FTR allocation process is guided by the “revenue adequacy” principle, which states that the revenue obtained by the ISO from charging loads and paying generators at their nodal prices, is enough to pay the FTR holders the congestion charges they are entitled to. For this reason, FTRs are allocated in a quantity that is consistent with the network constraints after running a “Simultaneous Feasibility Test” (SFT) which guarantees that the ISO will collect enough congestion rents to pay FTR holders. The SFT is performed using the same algorithms used to obtain the security-constrained economic dispatch, and consists of verifying that all the power injections and power withdrawals implied by the FTRs are feasible.

### 2.5 When ISO revenue is not enough to pay Congestion Rents to FTR holders

In those ISOs in which FTRs are auctioned, all the money collected in the auction goes to the transmission owners and/or those who pay the costs of the transmission network. Since all the money collected in the auction is distributed, the money needed to pay the congestion rents to FTR holders, comes from the revenue the ISO obtains from paying generators a lower nodal price than what the loads pay.

It is always possible for the capacity traded at different nodes to be different from the capacity of the FTRs held by market participants. When the capacity traded in the wholesale electricity market is higher than the capacity of FTRs, the ISO will have a surplus that can be used to cover any past deficit of the FTRs system or redistributed among transmission users. When the revenue the ISO obtains for differences in nodal prices is lower than the congestion rents FTR holders are entitled to receive, the ISO has to distribute the revenue proportionally. At PJM for example the payout ratio in year 2002 was 95% and in the year 2003 was 96% (PJM, 2004).

In order to reduce a congestion-rents deficit an ISO might be motivated to be conservative in the estimation of the capacity of the grid and on the amount of MW that can be sold on FTRs. An ISO trying to minimize a congestion-rents shortage could try to allocate or sell fewer FTRs than those determined by the feasibility test, or equivalently, run the feasibility test imposing more stringent constraints on the lines' capacities. An action like this would 1) decrease the possibilities of hedging for transmission users and 2) increase the cost of the hedging.

## 3 FTR markets in the U.S.

Three regions, PJM, NE and NY, have implemented auctions of point-to-point FTRs in recent years. FTRs in these markets are defined for given pairs of nodes (designated as a source and sink or point of injection and point of withdrawal). In these regions FTRs are settled in the day-ahead market, and consistent with the definition of financial rights, they have no influence on the physical use of the network. In these markets FTRs can also be traded in a secondary market, but the ISO deals only with the primary holder. Bids for obligation FTRs can be positive or negative and so can be the corresponding congestion rents.

The periodicity of the auctions, the number of rounds, and the time the FTRs are valid for, varies across the different markets. Also, since the economic dispatch that determines the LMP includes thermal losses in some markets and not in others, the meaning of the FTRs differs across markets. For example, in PJM losses are not included, while in NY ISO they are.

### 3.1 Midwest ISO

The Midwest ISO provides an example of a different type of active FTR market. In Midwest ISO FTRs are allocated to Firm Transmission Service customers annually and monthly, proportionally to the transmission capacity they have reserved. FTRs can belong to one of eight different classes: off-peak and on-peak hours for each of the four seasons. Those who have been allocated FTRs might offer them for sale in the annual auction or in the monthly auction. The ISO also offers for sale in the auction any residual

FTR capability that might be left after the allocation. MISO expects to introduce FTR options in the market in 2006.[7]

### 3.2 Auction of Transmission Cost Contracts (TCCs) in NYISO

The FTR market in the NY ISO includes the auction of Transmission Cost Contracts (TCCs) –another name for FTRs-. The holders of historical entitlements to firm transmission capacity are allocated TCCs for the same paths, quantities and terms so their economic position is unaffected. TCCs corresponding to the remaining transmission capability of the network are allocated to transmission owners. All holders of TCCs can offer them for sale in the auctions organized by the ISO. Long term TCCs for six months, one year, two year and five years are auctioned in several rounds. Monthly TCCs are sold in monthly auctions.

The clearing price of TCCs in each auction is equal to the difference in the nodal prices between the sink and the source. Clearing prices of TCCs can be positive or negative depending upon the expected direction of transmission congestion. If the clearing price is negative, the buyer is paid by the ISO to accept the TCC. The number of TCCs in NYISO is approximately 120,000.

### 3.3 Auction of FTRs in ISONE

The New England ISO opened a market for FTRs in March 2003, which currently includes one-round, closed auctions for one-month, three-month, and six-month obligation-FTRs, and a secondary market. In this market FTRs are defined from any location to any location including node, external node, zone and hub.

[7] http://www.pjm.com/markets/downloads/20050630-item-4B-pjm-and-miso-ftrs.pdf

## 3.4 Auction of FTRs in PJM

The first FTR auction in PJM took place in May 1999. Since then, the volume of FTR purchases has continually risen (PJM, 2004). PJM has a four-round annual auction and a single-round monthly auction. The entire capacity of the system is offered in the annual auction, and only the leftover capacity is offered in the monthly auctions. Each auction offers FTRs in the forms of both obligations and options. PJM also facilitates bilateral trading of FTRs in a secondary market.[8]

Rather than assigning FTRs directly to transmission customers that pay for the embedded cost of the transmission grid, PJM assigns them the rights to the auction revenues collected for the sale of the specific FTRs. Auction Revenue Rights (ARR) are characterized in the same way that FTRs are, specifying a source, a sink and a capacity (number of MW). Market participants can present their requirements for ARRs that sink in the nodes where they serve load for an amount up to the quantity of the load served. ARRs are allocated before the annual FTR auction, but can be redistributed as LSE gain or lose load during the year.

The holder of each ARR is entitled to collect the price of the corresponding FTR that clears in the annual FTR auction. Like FTRs, ARRs can represent a liability.

An ARR/FTR system "removes all the biases that have existed in the original PJM FTR allocation system, and has all the advantages of a pure FTR system as "any party receiving an allocation to a specific point-to-point ARR that they deem desirable has the absolute ability to convert that ARR to an FTR with the same points of injection and withdrawal." (Shankar, 2003)

[8] http://www.pjm.com/markets/ftr/downloads/ftr-annual-allocation-course.pdf

There are four rounds for the annual auction. In each round:

- Participants present their bid for buying FTRs. Each bid specifies source, sink and MW. After the first round, participants who have bought FTRs in previous rounds can make offer bids for their FTRs.

- The ISO performs a feasibility test and clears prices for FTRs in a way that maximizes the value of the FTRs. The feasibility test is a DC power-flow analysis (with a single contingency criterion) that ensures that all the flows implied by the FTRs are feasible.

- The ARR holders receive the money collected in the transaction. ARR holders may have to pay or receive money depending on the target allocation. Each ARR is associated with an FTR. (It specifies a source, a sink and MW).

- ARR holders can convert their ARRs into 24-hour FTR obligations for the same path via a "self-scheduling" process in the annual auction. In this case, market participants act as price-takers. Capacity of FTRs is up to ARR capacity.

- During every day of the period the FTR is defined for, the *FTR target allocation* is calculated as the difference in the day-ahead LMP of the sink minus the day-ahead LMP of the source multiplied by the MW of the FTR.

- The congestion charges collected by the ISO are used to pay the FTR holders their target allocations. If funds are sufficient, then all target allocations are covered and the excess rents are used to cover previous deficits if any or distributed to the ARR holders. If funds are insufficient, then FTR holders receive rents prorated to their target allocation.

## 4 Efficiency of FTR markets in the U.S.

Since FTRs are currently the paradigm to manage transmission congestion, and proposals indicate that they may play a more important role in the future U.S. electricity markets, it is worth asking the question: How well do Point-to-Point FTR markets perform and what can we learn from the recent experience in the markets that have implemented this system? Also, since the proposal of treating "Incremental Financial Transmission Rights" as the right incentive to encourage market-driven transmission tacitly assumes that it is possible to value the future Congestion Rents associated with an FTR in an objective and accurate way, it might be important to learn more about the value of FTRs in those markets where these are auctioned, to have a better characterization of their efficiency. .

In the following section, we describe two studies that look at the results of the monthly auctions of FTRs (TCCs) in NY ISO, and a preliminary analysis of the PJM market. The three analyses imply that there is a significant discrepancy between the prices paid for the FTRs and the corresponding Congestion Rents that could imply market inefficiencies.

### 4.1 FTR markets in NYISO

There are only two empirical studies that examine the recent performance of FTR market. Using the data of all rounds of six-month TCC auctions in NY ISO for years 2000-2001, Siddiqui et al. (2003) conducted an empirical comparison between what the purchasers of FTRs paid for congestion per MW with what purchasers would have paid had they paid the congestion costs directly instead of purchasing FTRs. Although most participants guessed correctly the direction of transmission congestion, they paid too much for the FTRs. On average, the congestion costs are approximately half of the price paid for the FTRs. In other words, those who were hedging against the uncertainty of the congestions costs were paying a hefty premium. The value of the premium is higher for the most expensive FTRs. For less expensive TCCs intended to hedge against small congestion costs, the clearing price was close to the congestion rents collected. For expensive FTRs (higher than $1/MWh or $4380/MW) intended to collect high congestion costs, the clearing price was in general much higher than the congestion rents received. For twelve of the fourteen rounds analyzed, the authors found that the discrepancy between the clearing price of the TCC and the congestion rents is much higher for TCCs among nodes in geographically distant locations.

The authors state that in the absence of historical data, a rational expectation is that TCC clearing prices are unbiased estimators of resulting congestion rents. For each round studied they estimate the simple linear regression line and test the hypothesis that the parameters are significantly different than zero. Finally, the authors suggest that the TCC auctions are highly inefficient because market participants are unable to discover forward LMP. They argue that the illiquidity of this market, in which few market participants bid for TCC for the same path, makes it difficult to discover the price of these rights. They leave as an open question whether the results observed are due to the novelty of the market and the inexperience of the participants or are evidence of risk aversion.

In the second study, Adamson and Englander (2005) evaluated a database of one-month FTRs traded in 50 selected monthly auctions from November 1998 to April 2003, and concluded that "pricing in the NYISO TCC auction continues to be inefficient."

### 4.2 FTRs market in PJM

We made the same comparison of FTR prices vs Congestion Rents for the PJM market using data publicly available.[9] We analyzed the Annual FTR Auction for the period June 1st 2003 to May 31st 2004 in which there were approximately 15,000 FTR transactions.[10]

Figure 1 shows data for 12,123 "Buy" transactions.[11] Each point represents one transaction. The x-axis represents the Market Clearing Price of the FTR (FTR MCP is the price paid for the buyer of the FTR), and the y axis represents the rents received (Congestion Rents) which are equal to the differences in LMP in the Day Ahead Spot Electricity Market. The units of both x and y are given in MW and cover the hours specified in the contract; on-peak hours, off-peak hours, or 24 hours. The Ordinary Least Squared Error line is included as a way to summarize the relationship between the prices paid for buyers of FTRs and the Congestion Rents received.

[9] PJM web site www.pjm.com contains data of the FTR annual and monthly auctions, and data of the Day-Ahead hourly LMPs to compute congestion costs or "rents".
[10] There are 3030+ nodes in PJM for which the Day Ahead LMP is reported. 683 nodes served as sources and/or sinks for FTRs traded in the Annual Auction 2003-2004. For 16 out of 683 there was not data on the LMP, so we couldn't find the congestion rents for 337 FTRs out of the 14,966 traded.
[11] After the first round of the auction market participants can offer for sale the FTRs acquired in previous rounds. Such transactions would be reported as "Sale" transactions. We exclude "sale" transactions and focus only in those in which market participants are buying FTRs from the ISO.

The majority of the points fell in the top-right and bottom-left quadrants so most of the market participants correctly forecasted the direction of the congestion and obtained rents with the same sign as the price paid for the FTR.

For most of the FTRs with prices higher than $20,000, the price paid was higher than the congestion rents received. Had buyers received in congestion rents exactly the money they paid in the FTR auction, then all points would fall in the red line (45 degree line). If the deviation from the y=x line were in both directions, then the *Least-Squares* (LS) line[12], (that is the line that comes as close as it can to all data points) would be close to y=x. The graph shows the same phenomenon reported in the two studies previously mentioned: on average market participants pay more for FTRs than what they would have paid for congestion charges. The LS line for FTRs with positive market price has an intercept close to the origin and a slope of 0.74 which means that on average market participants paid a premium of about 26% of the FTR price.

On the other hand, those market participants who bought FTRs with a negative price were paid up front a monetary quantity that ended up being higher than the money they would have been paid for the counter flow if they did not buy any FTR. The slope of the LS line for FTRs with negative market price is 0.70, but the intercept is greater than 0, which means that on average participants buying FTRs at a negative price were paid a premium of less than 30% of the FTR price.

Of those market participants who are hedging against volatile transmission costs, we can expect willingness to pay a positive premium. They are paying to be certain of

[12] We use the least squares method here as a way to summarize the relationship between the price paid for FTRs and the Congestions Rents received (or paid) for such FTR for each transaction. At this stage we can not use the estimates of the intercept and slope of the LS line for statistical inference, because the assumptions of the Simple Linear Regression model are not met. Different observations are not independent because FTRs for the same combination of POI and POW will have equal congestions rents. For more on Regression analysis see for example Chapter 11: Simple Linear Regression and Correlation, in Milton and Arnold (1995).

their congestion costs, instead of waiting for the realization of actual congestion costs that can be very volatile.

For those market participants buying FTRs at a negative price it is exactly the opposite situation. They are being paid (in the FTR auction) a fixed amount and then reimbursing actual congestion costs later. In effect they are acting as insurers who receive a fixed amount for their exposure to an uncertain potential liability. If these buyers are pairing their FTRs with balanced schedules of electricity transactions, we can interpret the premium they are collecting as the compensation for selling in advance their right to collect a highly volatile compensation. When their energy transactions generate a counter flow on a congested line (therefore alleviating congestion) they receive revenue for this service. When they buy an FTR at a negative price it is as if they were agreeing to provide their service for a fixed quantity, instead of charging whatever the real price of the congestion cost determines.

The causes of the asymmetry between the value of the premiums that FTR buyers pay when they are hedging against congestion charges, and the premium they receive when they are providing the hedging become clear after the analyses of Chapter 3.

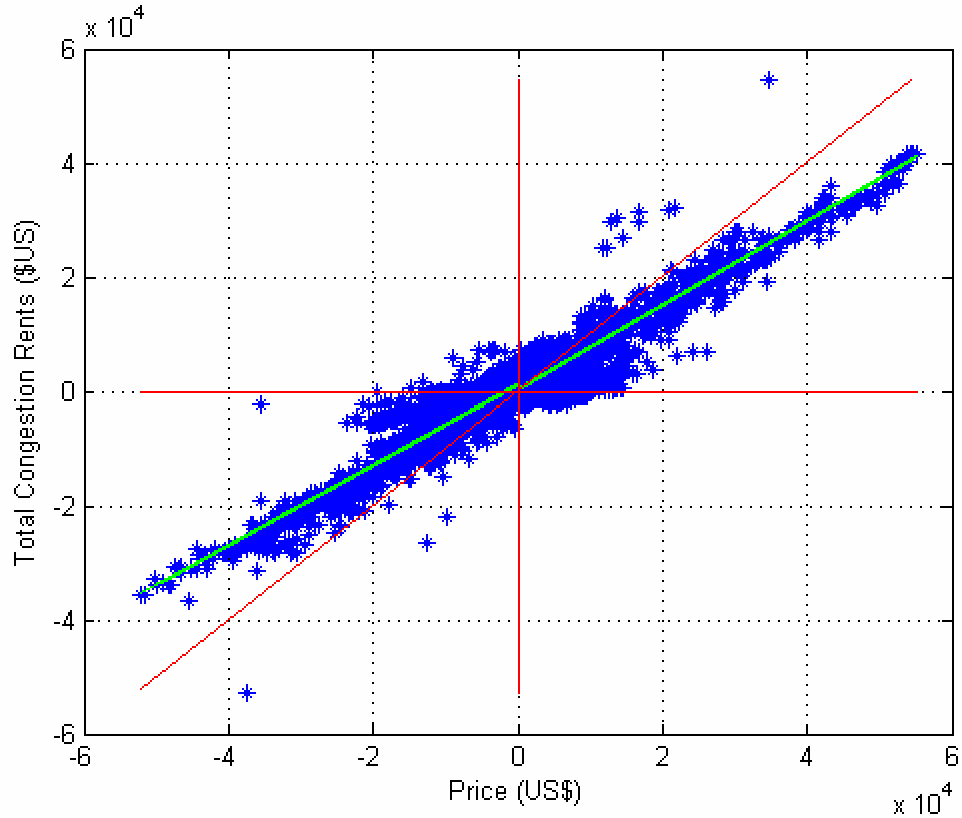


**Figure 1:** Plot showing the prices paid for FTRs against the corresponding value of the congestion costs they "covered" for 12,123 "Buy" transactions in the 2003-2004 Annual Auction in PJM. The slope of the LS line for FTRs with positive price is 0.74. The slope of the LS line for FTRs with negative price is 0.7.

Because those market participants who self-scheduled their ARRs were price-takers in the auction it is likely that they paid a premium higher than the average. PJM does not reveal the information about which FTRs were self-scheduled, but it is known that all self-scheduled FTRs are for 24 hours. If we plot again the price of the FTRs vs the corresponding congestion rents, excluding those for 24 hours, and fit again an LS line we observe that the slope indicates even a higher premium for the FTRs sold at a positive price, and almost the same premium observed in Fig.1 for those FTRs sold at a negative price.  This shows that even if we exclude the FTRs that were traded by price takers, on average, market participants paid/received a premium.

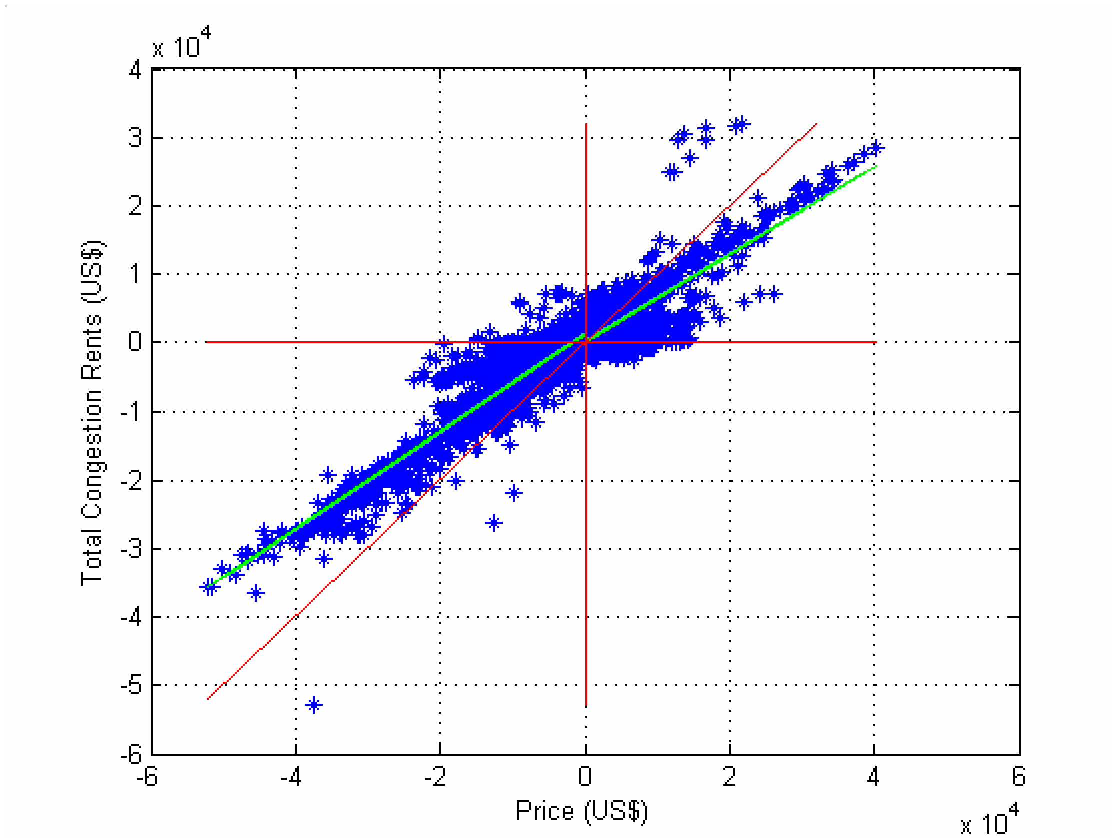


**Figure 2:** Plot showing the prices paid for FTRs against the corresponding value of the congestion costs they "covered" for 7,516 FTRs "buy" transactions in the 2003-2004 Annual Auction in PJM for "on-peak" and "off-peak" hours.  The slope of the LS line for FTRs with positive price is 0.64.  The slope of the LS line for FTRs with negative price is 0.71**.**

## 5 Conclusions

Taken as a whole, this chapter describes the role and importance of FTRs as hedging instruments in the electricity industry, and the necessity to characterize the efficiency of the markets in which these instruments are traded.  The example of PJM provides evidence that FTR hedgers currently pay a premium to reduce uncertainty about volatile congestion rents and motivates the use of the options theory methodology developed in Chapter 1, to assess how much of the value paid is just a fair compensation for the reduction of uncertainty and how much is due to inefficiencies of the market. This example is explored further in the next two chapters.

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# Chapter 3: Auction of Annual FTRs in PJM (2003-2004)

## 1 Introduction

This analysis explores the results of the auction of Annual FTRs conducted by PJM for the period 2003-2004. The data about the transactions that took place in the auction, and the data about historic Locational Marginal Prices (LMP) are analyzed to obtain information about different attributes of the FTR system. The analysis looks at the data from different perspectives, in order to understand the nature of the market and the processes of hedging and speculation that take place there, and to determine the impact of different attributes of the FTRs in the difference between selling price and corresponding congestion rents.

This chapter is organized in the following way. Section 2 looks at the data of the auction, by FTR traded. Section 3 looks at the Congestion Rents of the FTRs traded. Section 4 looks at the relationship between prices paid for the FTRs and congestion rents received. Section 5 analyzes the effect of the rounds in the prices of the FTRs traded, and Section 6 looks at the results of the auction for each of the 54 participants.

Section 7 analyzes the results for BuyObligation FTRs. The analysis is made grouping the FTRs by "paths"[1] covered. Each "path" is analyzed in detail to dig deeper into the characteristics of the hedging and speculation that occur in this market.

[1] Throughout, the term "path" refers to a pair of nodes, one of which is a Point of Injection (POI) or source of electricity and the other a Point of Withdrawal (POW) or sink of electricity.

## 2 Analysis of the Auction Data

In this section we analyze the data of the annual auction in PJM for 2003 -04.

### 2.1 Description of Auction Data

In the auction of annual FTRs in PJM for 2003-2004 a total of 14,966 transactions took place in four rounds:

- 3,928 transactions in Round 1
- 3,342 transactions in Round 2
- 3,822 transactions in Round 3
- 3,874 transactions in Round 4

A total of 683 nodes served as sources or sinks for the transacted FTRs. (In the annual auction, the only nodes that can serve as sources or sinks for the FTRs are the generation buses, hubs, zones or interfaces. In contrast, in the monthly auctions, where the residual capacity is offered, any node can serve as a source or sink).[2] 14,629 transactions we analyzed. The other 337 transactions were not included because they lacked the necessary LMP data to calculate their revenue. The records of the auction, kept by PJM and available to the public, contain the following information for each transaction:

1) The node source of the FTR.
2) The node sink of the FTR.
3) The period for the FTR will be valid for (on-peak, off-peak, or 24 hours).

[2] FTR Market Frequently Asked Questions. Updated February 1, 2005. www.pjm.com

4) The number of MWs.

5) The market participant involved in the transaction.

6) The type of hedge provided by the FTR, that is, if the FTR is an obligation or an option.

7) Whether the market participant is buying or selling the FTR.

8) The price of the obligation. Negative prices mean that the buying market participant gets money from the ISO. This price is specified for all the transactions, including those for FTR options.

9) The price of the option (It is specified for all the "paths" that were sold as options and for some of the "paths" that were sold as obligations).

## 2.2 Type of transaction and type of hedge:

The majority of the transactions in the annual auction (83%) were of the type "buy – obligation", while "buy-options" represented 9%. After the first round, some participants sold back the obligations and options they had acquired in the first round; these are labeled as "Sell" operations and account for 8% of the total of transactions. (7.5% are "sell-obligations" and 0.5% are "sell-options").

The average size of the FTRs traded as options was significantly higher than the average size of the FTRs traded as obligations. Consequently, although the number of "Buy-Obligations" is about 9 times higher than the number of "Buy-Options, the capacities covered by obligations is only a little more than 3 times bigger than the capacity covered by options. (Obligations for 24hours covered 30 times the capacity covered by options for 24hours, obligations for peak hours covered 2.5 times the capacity covered by options for on-peak hours and, obligations for off-peak hours covered twice the capacity covered by off-peak options). The FTRs sold for “on-peak”[3] hours account for most of the capacity covered by obligations and options.

| | Num FTRs | MW 24H FTRs | MW On Peak | MW Off Peak | Min Size (MW) | Max Size (MW) | Ave Size (MW) | Median Size | St.Dev Size |
|---|---|---|---|---|---|---|---|---|---|
| BuyObl | 12,123 | 21,547 | 28,446 | 20,618 | 0.1 | 400 | 5.825 | 2 | 14.005 |
| BuyOpt | 1,304 | 678 | 11,540 | 9,066 | 0.3 | 444 | 16.322 | 5 | 36.936 |
| SellObl | 1,133 | 304 | 2011 | 1740 | 0.1 | 26.4 | 3.579 | 2 | 3.428 |
| SellOpt | 69 | 0 | 532 | 407 | 1.3 | 37 | 13.601 | 10.2 | 8.701 |

**Table 1. Capacity covered by FTRs**

### 2.3 Prices

In this section we analyzed the FTRs according to their trading price.

#### 2.3.1 Comparison of Prices per Type of FTR

In order to compare the prices paid in the auction for different FTR types, it is necessary to calculate the number of MWh covered by each particular class of FTR. Between June 1st 2003 and May 31st 2004 there were 8,784 hours: 4,096 were peak hours and 4,688 were off-peak hours. Table 2 shows the price per MWh for each type of FTR.

We also disaggregated each type of FTR by the sign of the price paid. We can observe that the obligations sold at a positive price account for most of the capacity traded. For obligations for on-peak and off-peak hours, the absolute value of the price paid is higher for those sold at a negative price than for those sold at a positive price.

[3] In PJM “peak-hours” are all hours ending 8 to 23, for week days -excluding FERC holidays-. “Peak hours are from 7:00 AM to 11:00 PM (the hour ending 0800 to the hour ending 2300). Off-peak hours are from midnight to 7:00 AM (the hour ending 0100 to the hour ending 0700) and 11:00 PM to midnight (the hour ending 2400) Mondays through Fridays; also, all day Saturdays and Sundays (the hour ending 0100 to the hour ending 2400) and North American Electric Reliability Council holidays.” http://www.nymex.com/jsp/markets/JM_desc.jsp

Whether or not this is consistent with the characteristics of the congestion rents (CRs) received by the FTR holders is investigated in section 4.

The average price was calculated taking the price of each transaction as one observation. The average weighted price was calculated weighting each transaction price by the number of MWs covered. The differences between the two averages indicates the impact that single transactions for a large number of MW have on the price.

| | Num Hours Covered | NumFTRs | NumMW | MinPrice ($/MWh) | MaxPrice ($/MWh) | AvePrice ($/Mwh)* | AveWPrice ($/MWh) |
|---|---|---|---|---|---|---|---|
| BuyObl24PosPri | 8,784 | 4,190 | 19,996 | - | 6.29 | 1.96 | 1.48 |
| BuyObl24NegPri | 8,784 | 407 | 1,528 | (5.67) | - | (0.54) | (0.91) |
| BuyOblOnPosPri | 4,096 | 1,701 | 18,375 | 0.00 | 9.84 | 1.38 | 1.77 |
| BuyOblOnNegPri | 4,096 | 2,531 | 9,993 | (12.69) | (0.00) | (2.51) | (2.24) |
| BuyOblOffPosPri | 4,688 | 1,808 | 15,035 | 0.00 | 5.56 | 0.77 | 0.67 |
| BuyOblOffNegPri | 4,688 | 1,442 | 5,521 | (5.03) | (0.00) | (1.06) | (0.94) |
| SelObl24PosPri | 8,784 | 103 | 297 | 0.00 | 4.58 | 1.05 | 1.42 |
| SelObl24NegPri | 8,784 | 7 | 7 | (1.01) | (0.40) | (0.85) | (0.90) |
| SelOblOnPosPri | 4,096 | 250 | 1,273 | 0.00 | 7.53 | 0.83 | 0.64 |
| SelOblOnNegPri | 4,096 | 221 | 736 | (5.26) | (0.00) | (1.00) | (0.75) |
| SelOblOffPosPri | 4,688 | 367 | 1,241 | 0.00 | 5.59 | 0.93 | 0.58 |
| SelOblOffNegPri | 4,688 | 176 | 482 | (4.41) | (0.00) | (0.72) | (0.66) |
| BuyOpt24 | 8,784 | 43 | 678 | 0.67 | 4.29 | 2.84 | 2.58 |
| BuyOptOn | 4,096 | 457 | 11,540 | - | 8.13 | 0.80 | 0.70 |
| BuyOptOff | 4,688 | 804 | 9,066 | - | 3.06 | 0.57 | 0.20 |
| SelOpt24 | 8784 | - | - | - | - | - | - |
| SelOptOn | 4,096 | 36 | 532 | 0.04 | 1.38 | 0.39 | 0.34 |
| SelOptOff | 4,688 | 33 | 407 | 0.05 | 0.96 | 0.36 | 0.25 |

**Table 2. Prices of FTRs**

It can be observed that the highest average price reached in the auction occurred for the FTR options for 24 hours ($2.6/MWH), while the lowest occurred for the options for off-peak hours.

None of the participants who bought options for 24 hours resold them in the auction. The average price paid for FTR options for on-peak hours (0.70 \$/MWh) is lower than the average price paid for FTR obligations for the same period (1.77 \$/MWh). If both options and obligations were covering the same paths, we would expect the price of the options to be higher, however it is very likely that they are covering different paths, since the trade of options makes sense when there is uncertainty on the direction of transmission congestion, and the trade of obligations makes more sense when there is uncertainty on the cost of congestion. Later we will analyze in detail the characteristics of the congestion along the paths covered by FTR obligations.

As a point of reference we can compare the average price of the FTRs with the price of electricity generation, which for a coal-fired power plant is around 4.5cents/KWh. For example, the average price of an option for 24 hours (the type of transaction with a highest average price) is about 0.25cents/kwh, which is equivalent to 5.7% of the electricity generation price of a coal-fired power plant.

### 2.3.2 FTRs traded at price zero

There were also a few FTRs traded at a price zero, as the following table shows:

| | Num FTRs | NumMW | MinSize(MW) | MaxSize(MW) | AveSize(MW) | MedianSize | Stdev Size |
|---|---|---|---|---|---|---|---|
| BuyObl | 44 | 162.9 | 0.1 | 20 | 3.70 | 1.7 | 4.76 |
| BuyObl24 Price = 0 | 10 | 23.5 | 0.1 | 20 | 2.35 | 0.3 | 6.21 |
| BuyOblOnPrice=0 | 15 | 78.3 | 1.4 | 15 | 5.22 | 2 | 4.92 |
| BuyOblOffPrice=0 | 19 | 61.1 | 1 | 15 | 3.22 | 2 | 3.59 |
| SelObl | 9 | 19.7 | 0.8 | 10 | 2.19 | 1 | 2.96 |
| SelObl24Price=0 | 0 | - | - | - | - | - | - |
| SelOblOnPrice=0 | 1 | 1.9 | - | - | - | - | - |
| SelOblOffPrice=0 | 8 | 17.8 | 0.8 | 10 | 2.23 | 0.95 | 3.16 |
| BuyOpt | 6 | 1976 | 100 | 444 | 329.33 | 444 | 177.64 |
| BuyOpt24Price=0 | 0 | - | - | - | - | - | - |
| BuyOptOnPrice=0 | 3 | 988 | 100 | 444 | 329.33 | 444 | 198.61 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| BuyOptOffPrice=0 | 3 | 988 | 100 | 444 | 329.33 | 444 | 198.61 |
| SelOpt | 0 | - | - | - | - | - | - |
| SelOpt24Price=0 | 0 | - | - | - | - | - | - |
| SelOptOnPrice=0 | 0 | - | - | - | - | - | - |
| SelOptOffPrice=0 | 0 | - | - | - | - | - | - |

**Table 3. FTRs traded at price=0**

One case, that of options sold at a zero price, is particularly worth noting. Because we expect the rents received by the holder can never be negative, its price is expected to always be greater than zero unless the probability of having positive CRs were zero. Looking at the hourly CRs for the paths covered by these options sold at a zero price, we find that in fact they were zero for every single hour of the year.

# 3 Congestion rents:

## 3.1 Definition of Congestion Rents

The congestion rents received by the holders of annual FTR obligations are the differences in the day-ahead Locational Marginal Prices at the nodes, for example the CRs for an FTR for 24hrs for point A to point B is given by:

$CR_{A,B}^{24hour,Obligation} = \sum_{i=1}^{8784}\left(LMP_B^i - LMP_A^i\right)$, where $LMP_B^i$ is the locational marginal price at point B, at the $i$-th hour of the year that goes from June 1st 2003 to May 31st 2004.

The CRs for FTR options are settled on a monthly basis. For example the CRs for an FTR option for 24 hours from point A to point B are given by:

$CR_{A,B}^{24hour,Option} = \sum_{i=1}^{12}\max\left(0, \sum_j LMP_B^j - LMP_A^j\right)$ where $j$ is the number of hours in the $i$-th month. PJM makes public the day-ahead LMPs for each node of the network. Using these data it is possible to calculate the Congestion Rents of the FTRs traded in the auction.

### 3.2 Hourly congestion rents:

Although only annual CRs or the sum of monthly CRs have an effect in the return of FTR holders, the analysis of hourly congestion rents provides important information about the behavior of CRs. This section looks at hourly congestion rents for those paths covered by the FTRs traded in the auction.

#### 3.2.1 Sign of hourly congestion rents

The sign of hourly congestion rents for most of the paths covered by the different FTRs oscillated significantly. Even the most congested paths had hours in which CRs were non positive. For example, those paths for which market participants bought FTR obligations had positive CRs at most 87% of the time. On average, for "buy-obligation" FTRs, CRs were zero 24% of the time, and positive 42% of the time. For FTR options, the percentage of the time with zero CRs is 30%.

If we look at the FTRs classified by period of the day covered, we see that on-peak hours have the lowest proportion of time with zero CRs, and off-peak hours have the highest. Also, as expected, those FTRs sold at a positive price have a higher proportion of hours with positive CRs than the ones sold at a negative price.

| | NumFTRs | Min Prop Hrs CR>0 | Max Prop Hrs CR>0 | Ave Prop Hrs CR>0 | Min Prop Hrs CR=0 | Max Prop Hrs CR=0 | Ave Prop Hrs CR=0 |
|---|---|---|---|---|---|---|---|
| BuyObl* | 12123 | 0.00 | 0.87 | 0.42 | 0.06 | 1.00 | 0.24 |
| BuyObl24PosPri | 4190 | 0.04 | 0.76 | 0.52 | 0.17 | 0.86 | 0.24 |
| BuyObl24NegPri | 407 | 0.04 | 0.54 | 0.36 | 0.20 | 0.54 | 0.25 |
| BuyOblOnPosPri | 1701 | 0.02 | 0.87 | 0.51 | 0.07 | 0.98 | 0.18 |
| BuyOblOnNegPri | 2531 | 0.00 | 0.71 | 0.32 | 0.06 | 1.00 | 0.14 |
| BuyOblOffPosPri | 1808 | 0.04 | 0.67 | 0.39 | 0.25 | 0.87 | 0.37 |
| BuyOblOffNegPri | 1442 | 0.00 | 0.58 | 0.29 | 0.25 | 1.00 | 0.35 |
| SelObl* | 1133 | 0.00 | 0.81 | 0.40 | 0.07 | 1.00 | 0.28 |
| SelObl24PosPri | 103 | 0.26 | 0.73 | 0.52 | 0.18 | 0.38 | 0.24 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| SelObl24NegPri | 7 | 0.40 | 0.51 | 0.42 | 0.20 | 0.21 | 0.20 |
| SelOblOnPosPri | 250 | 0.05 | 0.81 | 0.47 | 0.07 | 0.93 | 0.21 |
| SelOblOnNegPri | 221 | 0.08 | 0.64 | 0.37 | 0.09 | 0.78 | 0.15 |
| SelOblOffPosPri | 367 | 0.04 | 0.67 | 0.39 | 0.26 | 0.86 | 0.36 |
| SelOblOffNegPri | 176 | 0.04 | 0.57 | 0.27 | 0.26 | 0.72 | 0.34 |
| BuyOpt* | 1304 | 0.00 | 0.85 | 0.31 | 0.09 | 1.00 | 0.30 |
| BuyOpt24 | 43 | 0.47 | 0.75 | 0.58 | 0.21 | 0.23 | 0.22 |
| BuyOptOn | 457 | 0.00 | 0.85 | 0.32 | 0.09 | 1.00 | 0.19 |
| BuyOptOff | 804 | 0.00 | 0.67 | 0.29 | 0.26 | 1.00 | 0.37 |
| SelOpt | 69 | 0.08 | 0.57 | 0.26 | 0.10 | 0.75 | 0.33 |
| SelOpt24 | 0 | NaN | NaN | NaN | NaN | NaN | NaN |
| SelOptOn | 36 | 0.11 | 0.52 | 0.29 | 0.10 | 0.68 | 0.23 |
| SelOptOff | 33 | 0.08 | 0.57 | 0.23 | 0.29 | 0.75 | 0.44 |

**Table 4. Sign of Hourly congestion rents. (Includes those FTRs traded at price zero)**

### 3.2.2 Variability of Hourly Congestion Rents:

The magnitude of the hourly CRs also varies significantly. Table 5 presents different measures of the variability of hourly CRs for each category of FTRs. For the FTR obligations, the range and standard deviation of hourly CRs is the highest for the FTRs for on-peak hours that were sold at a negative price. For the FTR options the standard deviation of hourly CRs is on average higher for those FTRs that cover on-peak hours, but the average range is higher for those FTRs for 24 hours.

In general, the distributions of congestion rents seem to be highly leptokurtic and skewed in the direction of the sign of the selling price of the FTR. The paths covered by obligations for off-peak hours that were sold at a positive price exhibit on average the highest kurtosis and the highest positive skewness. The paths covered by FTRs for off-peak hours sold at a negative price, have the second highest average kurtosis and the most negative skewness.

If for each path we analyze the series of positive congestion rents, separated from the series of negative congestion rents, we see that the resulting distributions have still very long tails.  The distribution of positive hourly congestion rents is positively skewed and the distribution of negative hourly congestion rents is negatively skewed.

| | Num FTRs | Min Range Hr CR | Max Range Hr CR | Ave Range HrCR | Min Stdev HrCR | Max Stdev HrCR | Ave Stdev HrCR | Stdev-Stded HrCR | Ave Kurtosis HrCR | Ave. Skewness HrCR |
|---|---|---|---|---|---|---|---|---|---|---|
| BuyObl* | 12123 | 0.00 | 536.78 | 75.13 | 0.00 | 19.63 | 4.33 | 2.52 | 71.66 | 1.65 |
| BuyObl24PosPri | 4190 | 3.65 | 287.64 | 70.16 | 0.10 | 16.71 | 4.06 | 1.93 | 41.94 | 2.92 |
| BuyObl24NegPri | 407 | 5.41 | 197.35 | 76.95 | 0.29 | 8.42 | 3.09 | 1.42 | 63.68 | -1.37 |
| BuyOblOnPosPri | 1701 | 0.16 | 536.78 | 78.08 | 0.01 | 19.63 | 4.47 | 2.58 | 69.04 | 3.58 |
| BuyOblOnNegPri | 2531 | 0.00 | 398.30 | 94.33 | 0.00 | 19.47 | 5.77 | 2.85 | 49.56 | -1.86 |
| BuyOblOffPosPri | 1808 | 0.57 | 223.93 | 60.83 | 0.04 | 16.82 | 3.57 | 2.53 | 144.84 | 5.80 |
| BuyOblOffNegPri | 1442 | 0.12 | 214.61 | 71.00 | 0.00 | 18.39 | 3.83 | 2.46 | 94.66 | -2.90 |
| SelObl* | 1133 | 0.00 | 360.99 | 79.44 | 0.00 | 17.32 | 4.38 | 2.76 | 77.96 | 1.55 |
| SelObl24PosPri | 103 | 23.00 | 193.61 | 59.47 | 1.05 | 6.93 | 2.71 | 1.29 | 61.16 | 3.08 |
| SelObl24NegPri | 7 | 76.16 | 149.20 | 86.67 | 3.54 | 3.81 | 3.58 | 0.10 | 39.11 | -1.72 |
| SelOblOnPosPri | 250 | 0.16 | 360.99 | 87.28 | 0.01 | 17.32 | 4.96 | 3.12 | 83.06 | 3.53 |
| SelOblOnNegPri | 221 | 6.88 | 314.70 | 102.54 | 0.26 | 13.36 | 5.53 | 2.49 | 62.19 | -1.52 |
| SelOblOffPosPri | 367 | 5.32 | 208.69 | 71.55 | 0.22 | 16.82 | 4.23 | 2.94 | 82.82 | 3.33 |
| SelOblOffNegPri | 176 | 2.71 | 193.48 | 71.06 | 0.09 | 9.74 | 3.68 | 1.82 | 65.36 | -2.48 |
| BuyOpt | 1304 | 0.00 | 482.58 | 59.08 | 0.00 | 20.99 | 3.28 | 2.43 | 57.49 | 0.22 |
| BuyOpt24 | 43 | 47.57 | 92.85 | 73.14 | 1.55 | 5.64 | 3.86 | 0.87 | 28.13 | 3.30 |
| BuyOptOn | 457 | 0.00 | 482.58 | 70.89 | 0.00 | 20.99 | 3.66 | 2.93 | 54.84 | -0.65 |
| BuyOptOff | 804 | 0.00 | 201.78 | 51.61 | 0.00 | 17.48 | 3.03 | 2.13 | 60.56 | 0.56 |
| SelOpt | 69 | 8.74 | 482.58 | 76.63 | 0.70 | 20.59 | 3.43 | 2.79 | 72.05 | -0.09 |
| SelOpt24 | 0 | - | - | - | - | - | - | - | - | - |
| SelOptOn | 36 | 10.17 | 482.58 | 86.91 | 0.70 | 20.59 | 3.92 | 3.52 | 67.66 | -0.88 |
| SelOptOff | 33 | 8.74 | 201.78 | 65.41 | 1.03 | 8.55 | 2.90 | 1.55 | 76.84 | 0.78 |

**Table 5. Hourly Rents (includes those FTRs traded at price zero)**

### 3.3 Total Congestion Rents Received By FTR holders

In total, the amount of money paid by market participants who bought obligation FTRs exceeded the amount they received in CRs by $4.8 million.   The money paid for options exceeded the money received in CRs by  $1.7 million.

| | Total Paid in Auction by Market Participant | Total Received in CRs by market participant (FTR holder) | Paid - Received | Paid-Received as % of Paid |
|---|---|---|---|---|
| BuyObl* | 5.32E+07 | 4.84E+07 | 4.77E+06 | |
| BuyObl24PosPri | 7.22E+07 | 5.67E+07 | 1.55E+07 | 21% |
| BuyObl24NegPri | -1.94E+06 | -8.76E+05 | -1.07E+06 | 55% |
| BuyOblOnPosPri | 9.62E+06 | 8.28E+06 | 1.34E+06 | 14% |
| BuyOblOnNegPri | -2.61E+07 | -1.76E+07 | -8.46E+06 | 32% |
| BuyOblOffPosPri | 6.50E+06 | 6.79E+06 | -2.98E+05 | -5% |
| BuyOblOffNegPri | -7.14E+06 | -4.87E+06 | -2.28E+06 | 32% |
| SelObl* | 1.84E+06 | 2.06E+06 | -2.19E+05 | -12% |
| SelObl24PosPri | 9.46E+05 | 7.72E+05 | 1.74E+05 | 18% |
| SelObl24NegPri | -5.21E+04 | -2.08E+04 | -3.13E+04 | 60% |
| SelOblOnPosPri | 8.46E+05 | 8.53E+05 | -7.03E+03 | -1% |
| SelOblOnNegPri | -9.02E+05 | -5.91E+05 | -3.12E+05 | 35% |
| SelOblOffPosPri | 1.60E+06 | 1.46E+06 | 1.34E+05 | 8% |
| SelOblOffNegPri | -5.95E+05 | -4.18E+05 | -1.77E+05 | 30% |
| BuyOpt* | 4.74E+06 | 3.00E+06 | 1.75E+06 | 37% |
| BuyOpt24 | 1.07E+06 | 6.01E+05 | 4.70E+05 | 44% |
| BuyOptOn | 1.51E+06 | 9.99E+05 | 5.07E+05 | 34% |
| BuyOptOff | 2.17E+06 | 1.40E+06 | 7.69E+05 | 36% |
| SelOpt | 1.12E+05 | 7.54E+04 | 3.70E+04 | 33% |
| SelOpt24 | - | - | - | - |
| SelOptOn | 5.70E+04 | 3.34E+04 | 2.36E+04 | 41% |
| SelOptOff | 5.54E+04 | 4.20E+04 | 1.34E+04 | 24% |

**Table 6. Total CRs received by FTR holders (includes those FTRs traded at price zero)**

# 4 Relationship between prices paid and CRs received

## 4.1 Correlation between prices and CRs

Although the CRs received by market participants differed from the prices they paid for FTRs, the average linear correlation between prices and CRs is higher than 0.8

for all subsets of FTR obligations traded, and for all the options bought by market participants, as the following table shows.

| | NumFTRs | NumMW | AveCorrCoef |
|---|---|---|---|
| BuyObl | 12123 | 70611 | 0.98218 |
| BuyObl24PosPri | 4190 | 19996 | 0.97992 |
| BuyObl24NegPri | 407 | 1527.8 | 0.82125 |
| BuyOblOnPosPri | 1701 | 18375 | 0.93818 |
| BuyOblOnNegPri | 2531 | 9992.8 | 0.95668 |
| BuyOblOffPosPri | 1808 | 15035 | 0.91153 |
| BuyOblOffNegPri | 1442 | 5521.2 | 0.88492 |
| SelObl | 1133 | 4055 | 0.9242 |
| SelObl24PosPri | 103 | 297.3 | 0.93002 |
| SelObl24NegPri | 7 | 6.6 | 0.95774 |
| SelOblOnPosPri | 250 | 1273.4 | 0.85782 |
| SelOblOnNegPri | 221 | 736 | 0.89635 |
| SelOblOffPosPri | 367 | 1240.5 | 0.8912 |
| SelOblOffNegPri | 176 | 481.5 | 0.90985 |
| BuyOpt | 1304 | 21284 | 0.96443 |
| BuyOpt24 | 43 | 678.3 | 0.96565 |
| BuyOptOn | 457 | 11540 | 0.97911 |
| BuyOptOff | 804 | 9065.8 | 0.9111 |
| SelOpt | 69 | 938.5 | 0.60341 |
| SelOpt24 | 0 | - | - |
| SelOptOn | 36 | 531.6 | 0.57271 |
| SelOptOff | 33 | 406.9 | 0.6443 |

**Table 7. Correlation between prices and CRs**

## 4.2 Premium paid by market participants

In this analysis, we define a *premium* as the difference between the price paid for the FTR and the rents received. A positive premium means that a market participant paid more for the FTR than what she received in rents. The following table shows descriptive statistics for the premium paid. The values for the obligations bought at a negative price have to be interpreted with care. A positive premium for an obligation bought at a negative price means that CRs were more negative that the price paid for the FTR. In this case, the holder of the FTR is paying a premium. Results show that in general holders of

FTRs that are sold at a negative price pay less than what they receive or in other words, are paid a premium. Under our conceptual framework, these buyers of obligations at a negative price, are the ones bearing the risk of volatile congestion charges, and therefore are not hedgers but insurers or speculators. In exchange for bearing the risk they receive a premium.

| | Num FTRs Prem>0 | Num FTRs Prem<0 | Num FTRs Prem=0 | Num MW Prem>0 | Num MW Prem<0 | MW for Prem=0 | Min Prem | Max Prem | Ave Pos Prem | Ave W Pos Prem | Ave Neg Prem | Ave W Neg Prem |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| BuyObl | 5772 | 6344 | 7 | 38769 | 31830 | 12 | -33056 | 16957 | 3568 | 2854 | -2495 | -2015 |
| BuyObl24PosPri | 3491 | 699 | 0 | 16043 | 3953 | 0 | -19767 | 16957 | 4772 | 3947 | -1636 | -1680 |
| BuyObl24NegPri | 79 | 328 | 0 | 222 | 1306 | 0 | -33056 | 4351 | 1327 | 1361 | -3573 | -4378 |
| BuyOblOnPosPri | 877 | 824 | 0 | 12037 | 6338 | 0 | -16938 | 11864 | 2783 | 3066 | -1332 | -1185 |
| BuyOblOnNegPri | 273 | 2258 | 0 | 1038 | 8955 | 0 | -17227 | 15474 | 1347 | 1211 | -3911 | -3528 |
| BuyOblOffPosPri | 797 | 1011 | 0 | 8603 | 6433 | 0 | -12159 | 6648 | 953 | 959 | -1046 | -761 |
| BuyOblOffNegPri | 243 | 1199 | 0 | 801 | 4720 | 0 | -15654 | 12841 | 956 | 746 | -2093 | -1623 |
| SelObl | 489 | 638 | 6 | 1818 | 2231 | 6 | -12865 | 12203 | 1684 | 1475 | -1634 | -1322 |
| SelObl24PosPri | 73 | 30 | 0 | 245 | 53 | 0 | -3098 | 12203 | 3117 | 3743 | -1771 | -1973 |
| SelObl24NegPri | 0 | 7 | 0 | 0 | 7 | 0 | -5738 | -3887 | - | - | -4469 | -4169 |
| SelOblOnPosPri | 127 | 123 | 0 | 703 | 570 | 0 | -12865 | 9724 | 1643 | 1436 | -1753 | -1030 |
| SelOblOnNegPri | 39 | 182 | 0 | 152 | 584 | 0 | -11747 | 2370 | 930 | 1063 | -1913 | -1851 |
| SelOblOffPosPri | 220 | 147 | 0 | 637 | 604 | 0 | -9550 | 7947 | 1443 | 802 | -1249 | -929 |
| SelOblOffNegPri | 30 | 146 | 0 | 82 | 400 | 0 | -9419 | 2495 | 1121 | 1022 | -1442 | -1465 |
| BuyOpt | 970 | 328 | 6 | 13966 | 5342 | 1976 | -3249 | 16431 | 1941 | 1639 | -417 | -402 |
| BuyOpt24 | 43 | 0 | 0 | 678 | 0 | 0 | 3329 | 16431 | 10936 | 10522 | - | - |
| BuyOptOn | 275 | 179 | 3 | 6754 | 3798 | 988 | -3249 | 11700 | 2101 | 1848 | -398 | -369 |
| BuyOptOff | 652 | 149 | 3 | 6535 | 1543 | 988 | -1768 | 5348 | 1280 | 501 | -440 | -483 |
| SelOpt | 47 | 22 | 0 | 546 | 393 | 0 | -1131 | 5268 | 1005 | 807 | -464 | -460 |
| SelOpt24 | - | - | - | - | - | - | - | - | - | - | - | - |
| SelOptOn | 24 | 12 | 0 | 314 | 218 | 0 | -761 | 5268 | 1161 | 969 | -351 | -401 |
| SelOptOff | 23 | 10 | 0 | 233 | 174 | 0 | -1131 | 4522 | 843 | 589 | -599 | -533 |

**Table 8. Premium paid by market participants**

In general the results of the table are consistent with the idea that buyers of obligations at a positive price, pay a premium, while buyers of obligations at a negative price, are paid a premium.

There are exemptions. For example, most of the transactions in which obligations for off-peak hours were sold, resulted in a negative premium for its holders. Nevertheless when we sum the MW of the FTRs that rendered a negative premium these are less than the ones of the FTRs that resulted in a positive premium.

## 4.3 Ordinary Least Squares Analysis: Price vs Congestion Rents

One way to observe the correlation between prices and CRs, and account for the magnitude of the premium paid is by plotting the prices paid, against the CRs received, as it was presented in Chapter 2. We can construct these plots by taking each transaction as one point, disregarding the number of MWs included in the transaction, or taking each MW sold as one point in the graph. We will call the first approach "per transaction" and the second one "per MW".

### 4.3.1 Analysis Per-transaction:

Table 9 shows the parameters of a regression analysis for CR as a linear function of the price paid for each transaction (CR=Bo+B1*Price). The coefficient of determination is higher than 0.67 for all the FTR obligations that participants bought. For the obligations that were sold by market participants, the coefficients of determination are also high, but the results need to be regarded with care, since in some cases there were just a few transactions, like the obligations for 24 hours sold at a negative price, for which there were only 7 transactions.

For the options sold by market participants a linear equation does not seem appropriate to express the relation between price and congestion rents.

| Type of FTR | Bo | B1 | R2 |
|---|---|---|---|
| BuyObl | 765 | 0.7360 | 0.9647 |
| BuyObl24PosPri | 1026 | 0.7255 | 0.9602 |
| BuyObl24NegPri | 668 | 0.5907 | 0.6745 |
| BuyOblOnPosPri | 931 | 0.6958 | 0.8802 |
| BuyOblOnNegPri | 535 | 0.7272 | 0.9152 |
| BuyOblOffPosPri | 455 | 0.9193 | 0.8309 |
| BuyOblOffNegPri | 237 | 0.7292 | 0.7831 |
| SelObl | 514 | 0.8028 | 0.8541 |
| SelObl24PosPri | 1181 | 0.6871 | 0.8649 |
| SelObl24NegPri* | 6066 | 1.2148 | 0.9173 |
| SelOblOnPosPri | -166 | 1.0573 | 0.7359 |
| SelOblOnNegPri | 358 | 0.7420 | 0.8034 |
| SelOblOffPosPri | 552 | 0.7896 | 0.7942 |
| SelOblOffNegPri | 267 | 0.7815 | 0.8278 |
| BuyOpt | 74 | 0.6115 | 0.9301 |
| BuyOpt24 | -3866 | 0.7162 | 0.9325 |
| BuyOptOn | 154 | 0.6169 | 0.9587 |
| BuyOptOff | -209 | 0.7223 | 0.8301 |
| SelOpt | 376 | 0.4398 | 0.3641 |
| SelOpt24 | - | - | |
| SelOptOn | 321 | 0.3825 | 0.3280 |
| SelOptOff | 434 | 0.4996 | 0.4151 |

**Table 9. OLS parameters (there were only 7 transactions in which participants sold obligations for 24hours at a positive price)**

The following graphs plot prices versus CRs, for each category of FTR transaction. (Each point represents one FTR transaction). The ordinary least squares regression equations are presented next to the title of each graph, and the regression lines are plotted. The equation on the right has been obtained forcing the intercept to go to zero. Details on the outliers are presented below each table.

Some market participants presented bids for the same path and class, in the same round. Because the clearing price is the same, it looks as if exactly the same transaction had taken place twice. See for example outliers of on-peak hour FTRs, price > 0 (participant 5), outlier for off-peak FTRs, price < 0 (participant 15 and participant 1).

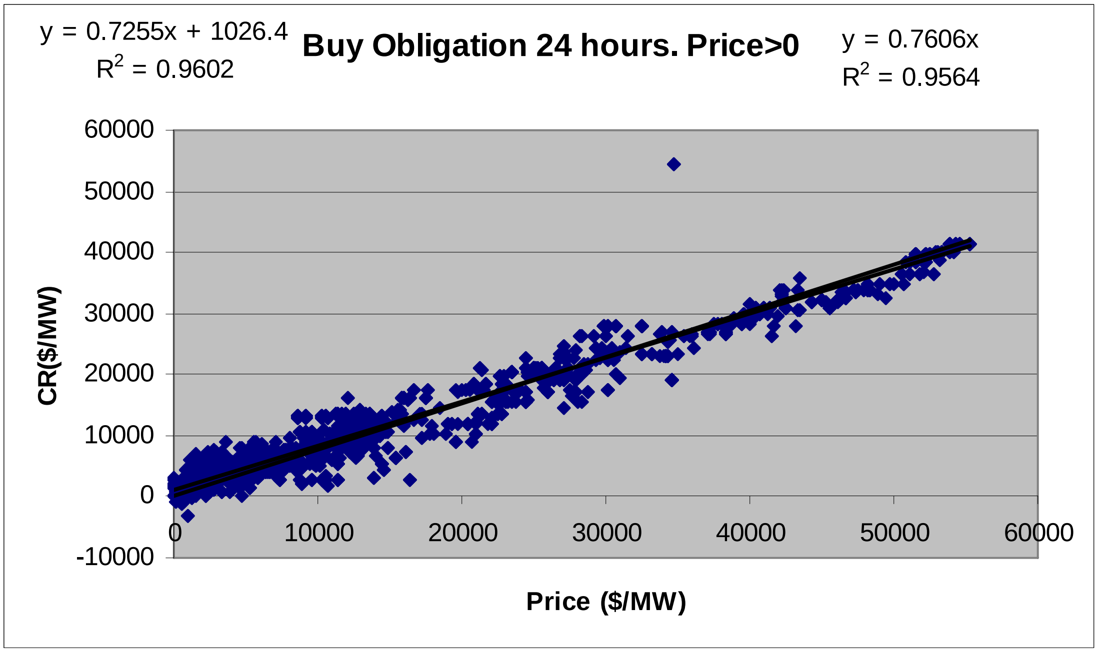


**Figure 1. Price Vs CR - Buy obligation 24 hours. Price >0**

| Participant | Price | CRs | Price-CRs | Source | Sink | MW | Round |
|---|---|---|---|---|---|---|---|
| 36 | $34,690 | $54,456 | -$19,766 | 84 | 555 | 5 | 4 |
| 36 | $34,690 | $54,456 | -$19,766 | 84 | 555 | 4.4 | 4 |

**Table 10. Outliers OLS line for Buy Obligation s 24 hours price >0**

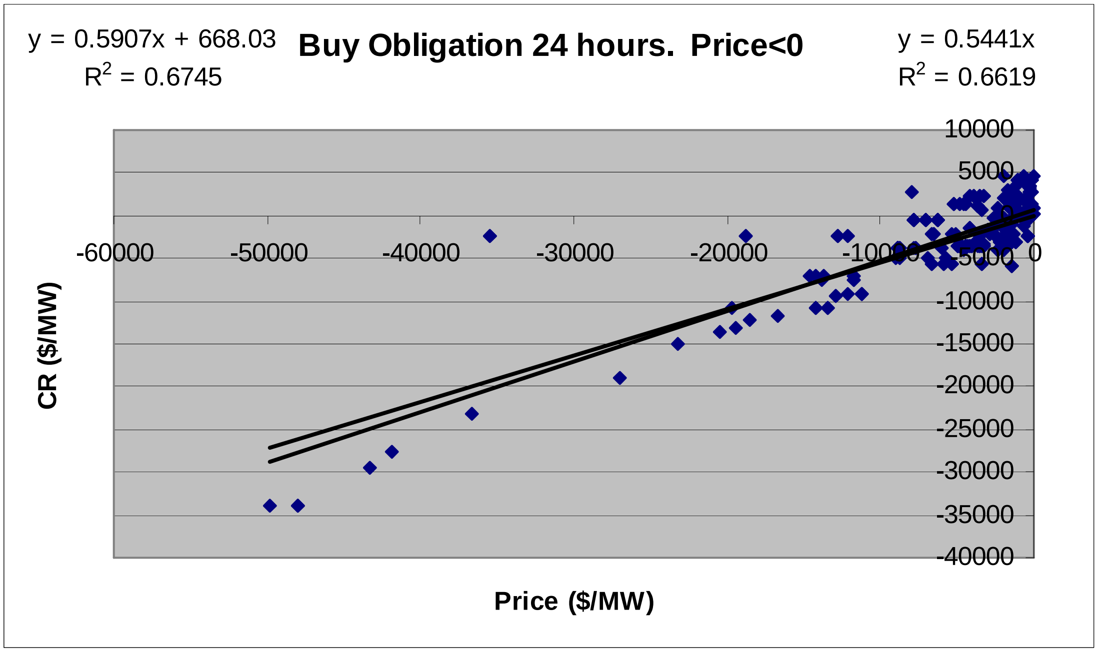


**Figure 2. Price Vs CR - Buy Obligation 24 hours. Price <0**

| Participant | Price | CRs | Price-CRs | Source | Sink | MW | Round |
|---|---|---|---|---|---|---|---|
| 17 | -$35,480 | -$2,424 | -$33,056 | 25 | 395 | 0.3 | 1 |
| 17 | -$35,480 | -$2,424 | -$33,056 | 26 | 395 | 0.3 | 1 |
| 17 | -$18,826 | -$2,424 | -$16,402 | 25 | 395 | 0.3 | 4 |
| 17 | -$18,826 | -$2,424 | -$16,402 | 26 | 395 | 0.3 | 4 |

**Table 11. Outliers OLS line for Buy Obligations 24 hours price <0**

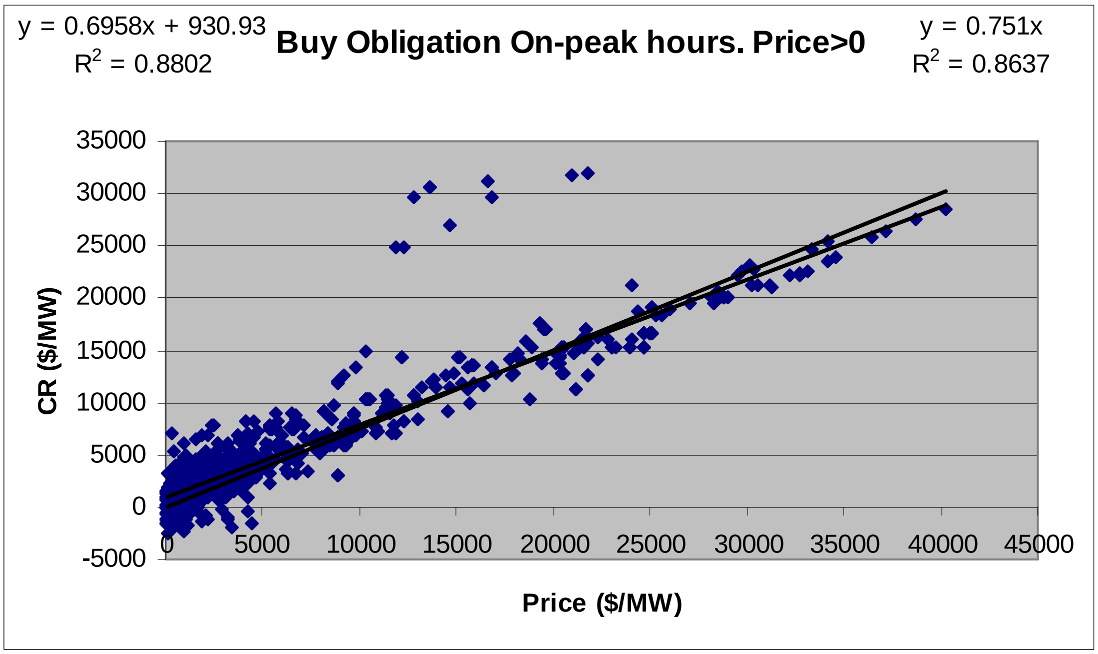


**Figure 3. Price Vs CR - Buy Obligation On-peak hours. Price>0**

Table 12 shows the outliers that are above the OLS line, from left to right:

| Participant | Price | CRs | Price-CRs | Source | Sink | MW | Round |
|---|---|---|---|---|---|---|---|
| 8 | $11,830 | $24,923 | -$13,093 | 395 | 73 | 10 | 3 |
| 8 | $12,264 | $24,923 | -$12,659 | 395 | 73 | 10 | 2 |
| 14 | $12,841 | $29,702 | -$16,861 | 146 | 555 | 1 | 1 |
| 5 | $13,577 | $30,515 | -$16,938 | 241 | 555 | 2.4 | 1 |
| 5 | $13,577 | $30,515 | -$16,938 | 241 | 555 | 3.1 | 1 |
| 5 | $13,577 | $30,515 | -$16,938 | 241 | 555 | 4.8 | 1 |
| 8 | $14,605 | $26,980 | -$12,375 | 341 | 73 | 7.2 | 3 |
| 14 | $16,609 | $31,256 | -$14,647 | 354 | 555 | 1 | 1 |
| 8 | $16,838 | $29,702 | -$12,864 | 146 | 73 | 4.9 | 2 |
| 8 | $20,920 | $31,788 | -$10,868 | 127 | 73 | 1.1 | 4 |
| 8 | $21,760 | $31,981 | -$10,221 | 129 | 73 | 7 | 4 |

**Table 12. Outliers OLS line for Buy Obligations on-peak hours price>0**

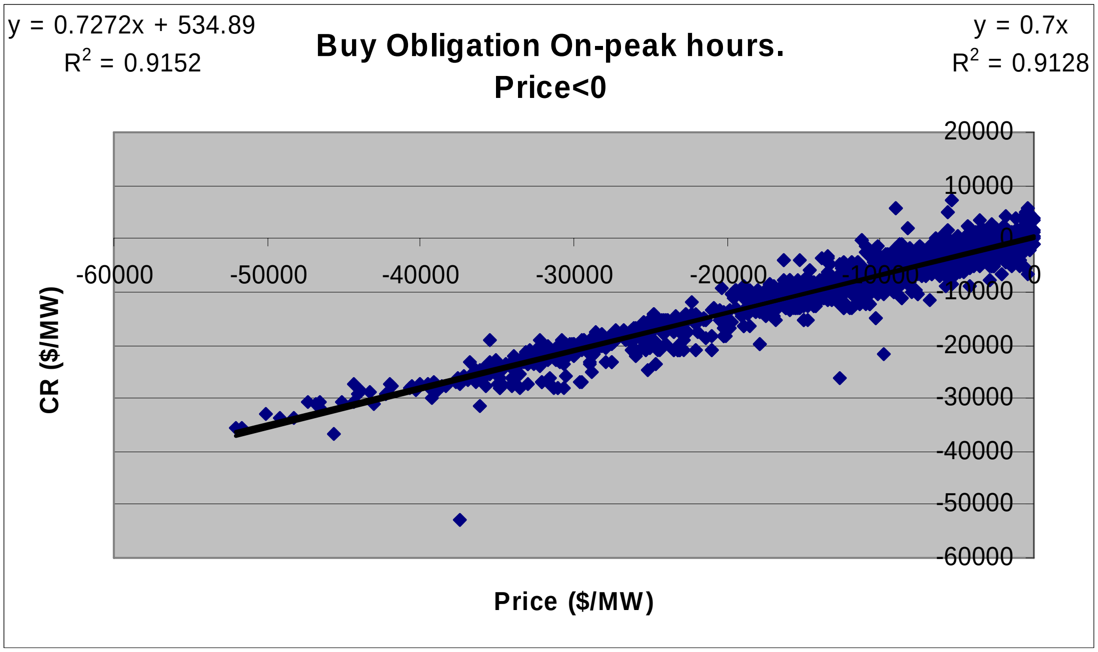


**Figure 4. Price Vs CR - Buy Obligation On-peak hours. Price <0**

Table 13 shows the outliers down the OLS line. These participants lost money as they had CRs more negative than the buying price of the FTR.

| Participant | Price | CRs | Price-CRs | Source | Sink | MW | Round |
|---|---|---|---|---|---|---|---|
| 1 | -$37,467 | -$52,940 | $15,473 | 73 | 207 | 1.5 | 1 |
| 13 | -$12,641 | -$26,331 | $13,690 | 555 | 449 | 5 | 3 |
| 13 | -$9,830 | -$21,867 | $12,037 | 555 | 44 | 5 | 3 |

**Table 13. Outliers line for Buy Obligations on-peak hours price<0**

There were also outliers above the OLS line. The profits/MW for these market participants were significantly above the average for this type of transaction.

| Participant | PriceOb | TotalCR | Price-CRs | Source | Sink | MW | Round |
|---|---|---|---|---|---|---|---|
| 1 | -$9,053 | $5,809 | -$14,862 | 24 | 158 | 1.4 | 1 |
| 1 | -$9,053 | $5,809 | -$14,862 | 24 | 158 | 1.4 | 1 |
| 18 | -$9,053 | $5,727 | -$14,780 | 26 | 157 | 5 | 1 |
| 1 | -$5,412 | $7,089 | -$12,502 | 24 | 194 | 1.4 | 1 |
| 1 | -$5,412 | $7,089 | -$12,502 | 24 | 194 | 1.4 | 1 |
| 6 | -$350 | $5,809 | -$6,159 | 24 | 158 | 2 | 2 |
| 6 | -$350 | $5,727 | -$6,077 | 26 | 157 | 2 | 2 |

**Table 14. Outliers OLS line for Buy Obligations on-peak hours price<0. Participants with profits above the average.**

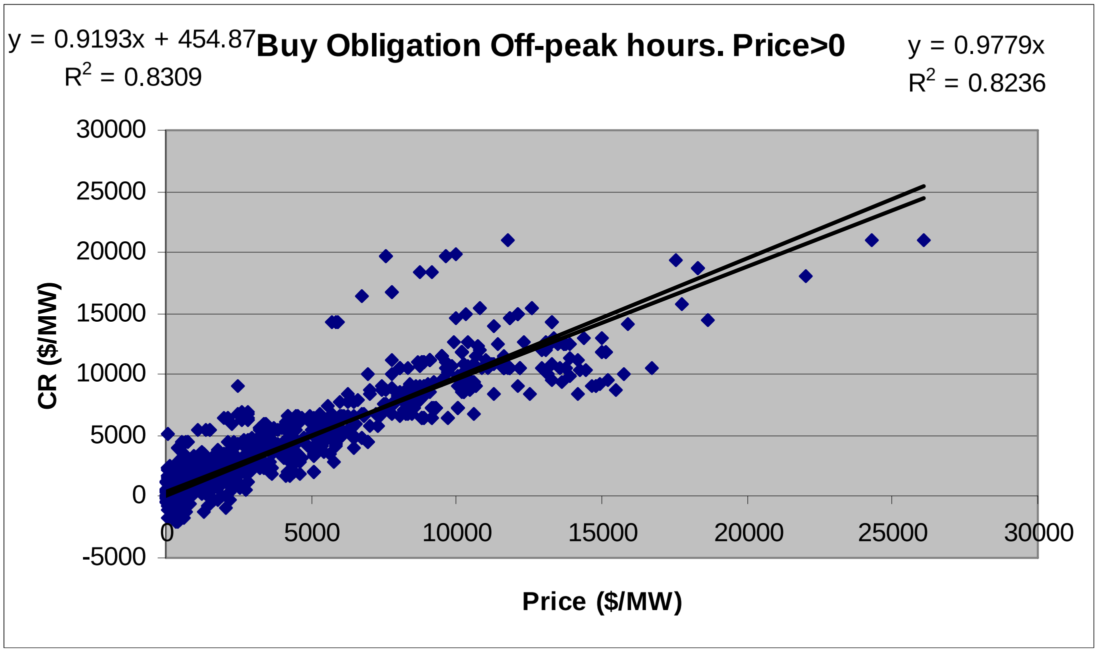


**Figure 5. Price Vs CR - Buy Obligation Off-peak hours. Price>0**

Table 15 presents the outliers above the OLS line.

| Participant | PriceOb | TotalCR | Price-CRs | Source | Sink | MW | Round |
|---|---|---|---|---|---|---|---|
| 5 | $7,583 | $19,742 | -$12,159 | 241 | 555 | 5.6 | 1 |
| 5 | $7,583 | $19,742 | -$12,159 | 241 | 555 | 2.8 | 1 |
| 5 | $7,583 | $19,742 | -$12,159 | 241 | 555 | 5.6 | 1 |
| 2 | $9,612 | $19,742 | -$10,130 | 241 | 555 | 0.9 | 3 |
| 5 | $9,612 | $19,742 | -$10,130 | 241 | 555 | 1 | 3 |
| 5 | $9,638 | $19,742 | -$10,104 | 241 | 555 | 5 | 2 |
| 4 | $9,991 | $19,872 | -$9,881 | 245 | 555 | 4 | 4 |
| 8 | $8,705 | $18,462 | -$9,757 | 1 | 73 | 5 | 3 |
| 14 | $6,729 | $16,389 | -$9,660 | 354 | 555 | 1 | 1 |
| 4 | $9,163 | $18,462 | -$9,299 | 1 | 555 | 4 | 4 |
| 8 | $11,800 | $21,017 | -$9,217 | 129 | 73 | 1.3 | 4 |
| 8 | $7,807 | $16,800 | -$8,993 | 341 | 73 | 3.3 | 2 |
| 8 | $7,807 | $16,800 | -$8,993 | 341 | 73 | 4.6 | 3 |
| 8 | $5,678 | $14,379 | -$8,701 | 395 | 73 | 5 | 3 |
| 8 | $5,857 | $14,379 | -$8,522 | 395 | 73 | 5 | 2 |
| 8 | $5,918 | $14,379 | -$8,461 | 395 | 73 | 7 | 4 |
| 13 | $2,504 | $9,022 | -$6,518 | 274 | 527 | 5 | 1 |

**Table 15. Outliers OLS line for Buy Obligations off-peak hours price>0.**

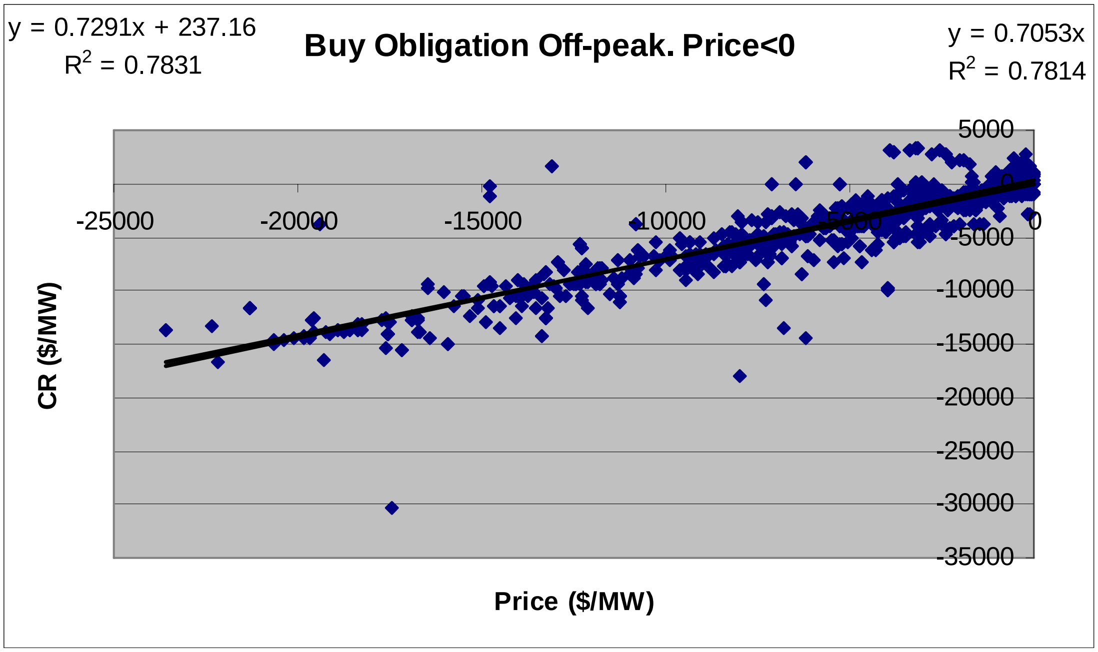


**Figure 6. Price Vs CR - Buy Obligation Off-peak. Price<0**

Table 16 presents the outliers below the OLS line.

| Participant | PriceOb | TotalCR | Price-CRs | Source | Sink | MW | Round |
|---|---|---|---|---|---|---|---|
| 1 | -$17,469 | -$30,311 | $12,842 | 73 | 207 | 1 | 1 |
| 13 | -$7,970 | -$17,987 | $10,017 | 555 | 449 | 5 | 3 |
| 13 | -$6,178 | -$14,361 | $8,183 | 555 | 44 | 5 | 3 |
| 1 | -$6,801 | -$13,483 | $6,682 | 4 | 436 | 1.7 | 1 |
| 15 | -$3,975 | -$9,861 | $5,886 | 132 | 436 | 0.2 | 1 |
| 15 | -$3,975 | -$9,860 | $5,885 | 326 | 436 | 1.2 | 1 |
| 15 | -$3,975 | -$9,860 | $5,885 | 327 | 436 | 1.2 | 1 |
| 15 | -$3,981 | -$9,840 | $5,859 | 131 | 436 | 1.2 | 1 |
| 15 | -$3,981 | -$9,840 | $5,859 | 133 | 436 | 1.2 | 1 |
| 15 | -$3,981 | -$9,840 | $5,859 | 134 | 436 | 1.2 | 1 |

**Table 16. Outliers OLS line for Buy Obligations off-peak hours price<0.**

There were also outliers above the OLS line. The profit per MW made by these market participants was significantly higher than the average for these trades.

| Participant | PriceOb | TotalCR | Prem | Source | Sink | MW | Round |
|---|---|---|---|---|---|---|---|
| 1 | -$19,391 | -$3,737 | -$15,654 | 24 | 31 | 1.7 | 1 |
| 1 | -$19,391 | -$3,737 | -$15,654 | 24 | 31 | 1.7 | 1 |
| 1 | -$13,119 | $1,544 | -$14,663 | 24 | 194 | 1.7 | 1 |
| 1 | -$13,119 | $1,544 | -$14,663 | 24 | 194 | 1.7 | 1 |
| 1 | -$14,790 | -$305 | -$14,485 | 24 | 158 | 1.7 | 1 |
| 1 | -$14,790 | -$305 | -$14,485 | 24 | 158 | 1.7 | 1 |
| 1 | -$14,773 | -$1,158 | -$13,615 | 24 | 18 | 1.7 | 1 |
| 1 | -$14,773 | -$1,158 | -$13,615 | 24 | 18 | 1.7 | 1 |

**Table 17. Outliers OLS line for Buy Obligations off-peak hours price<0.**

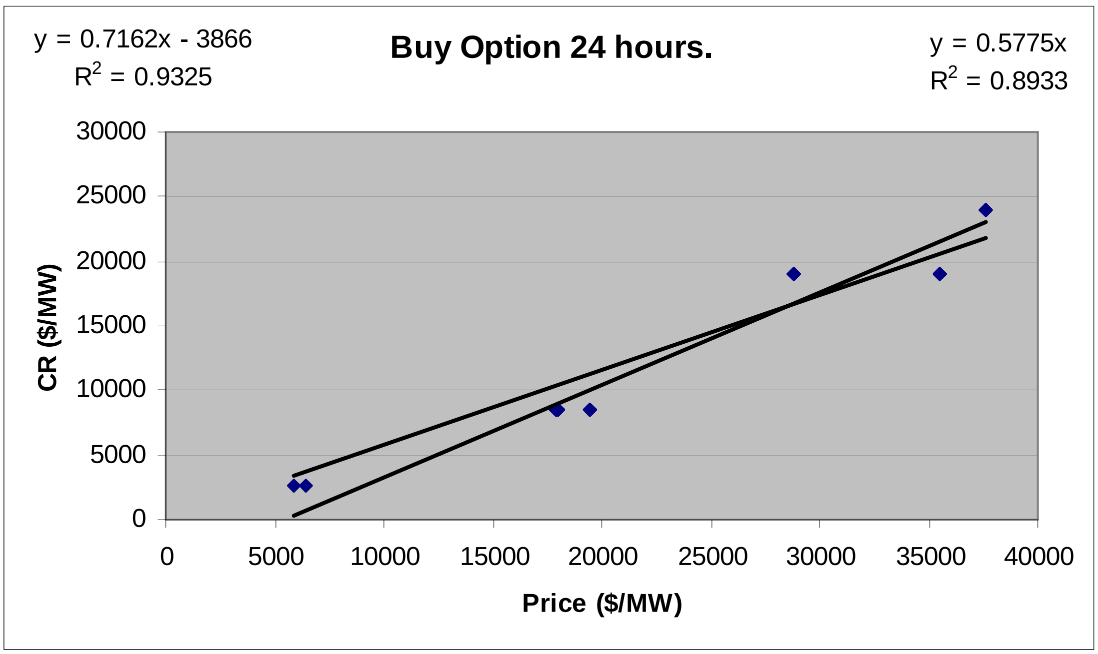


**Figure 7. Price Vs CR - Buy Option 24 hours**

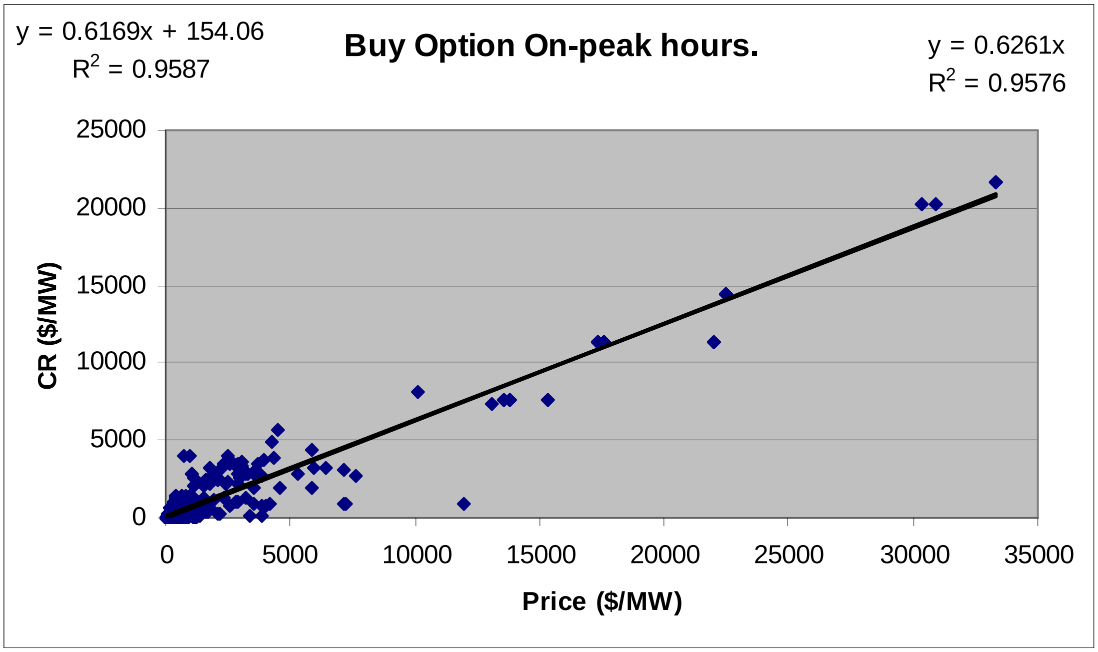


**Figure 8. Price Vs CR - Buy Option On-peak hours**

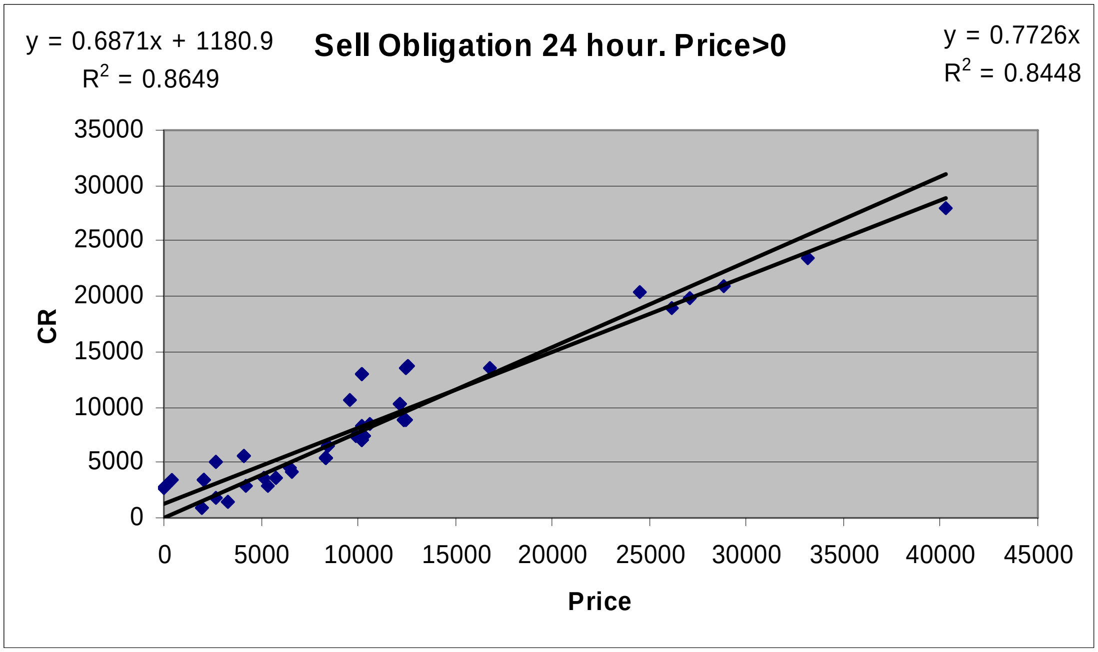


**Figure 9. Price Vs CR - Sell Obligation 24 hour. Price>0**

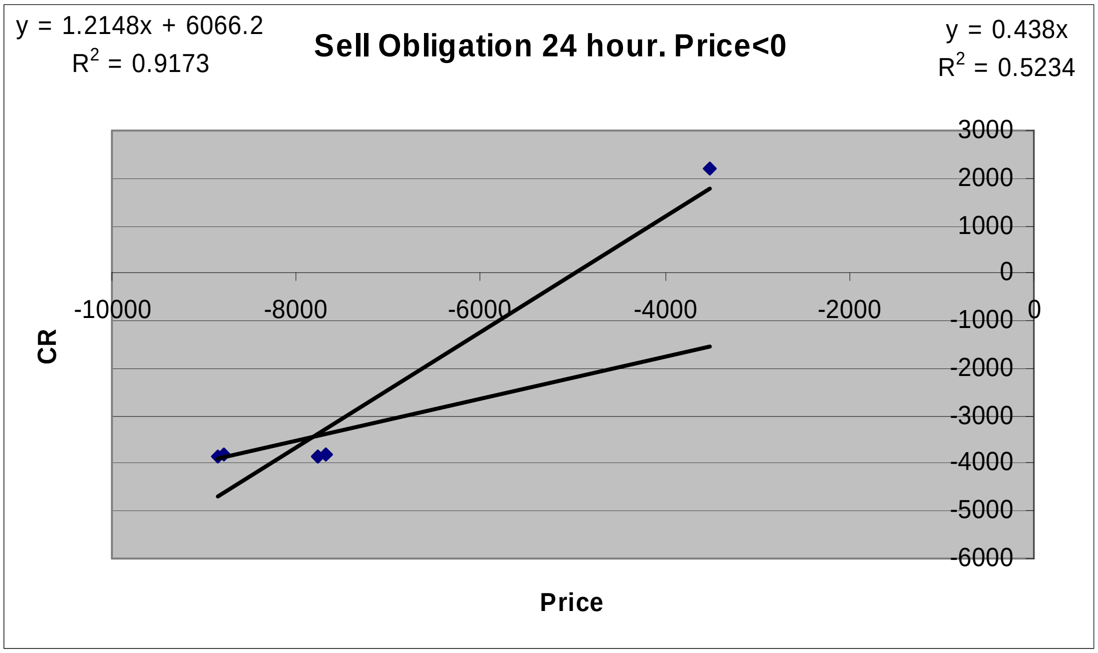


**Figure 10. Price Vs CR - Sell Obligation 24 hour. Price<0**

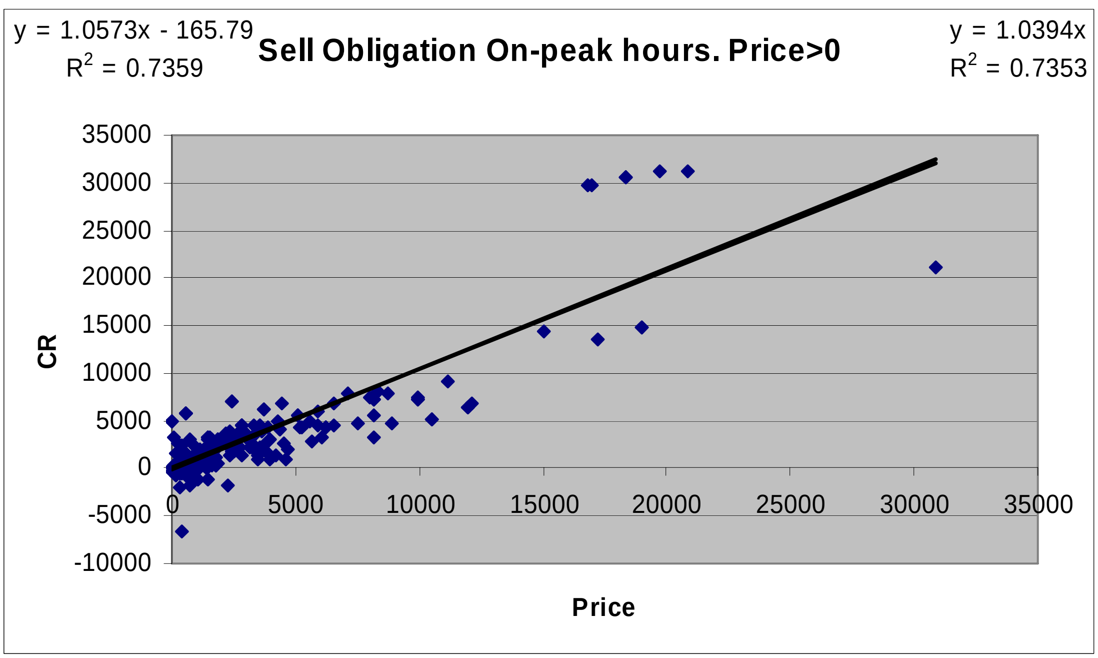


**Figure 11. Price Vs CR - Sell Obligation On-peak hours. Price>0**

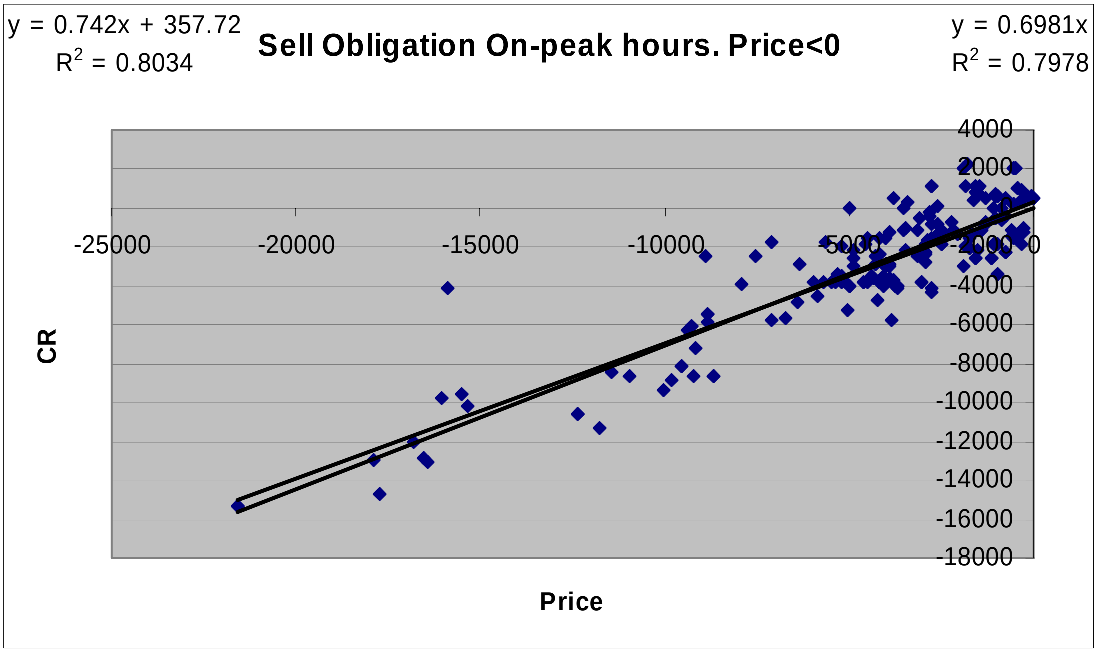


**Figure 12. Price Vs CR - Sell Obligation On-peak hours. Price<0**

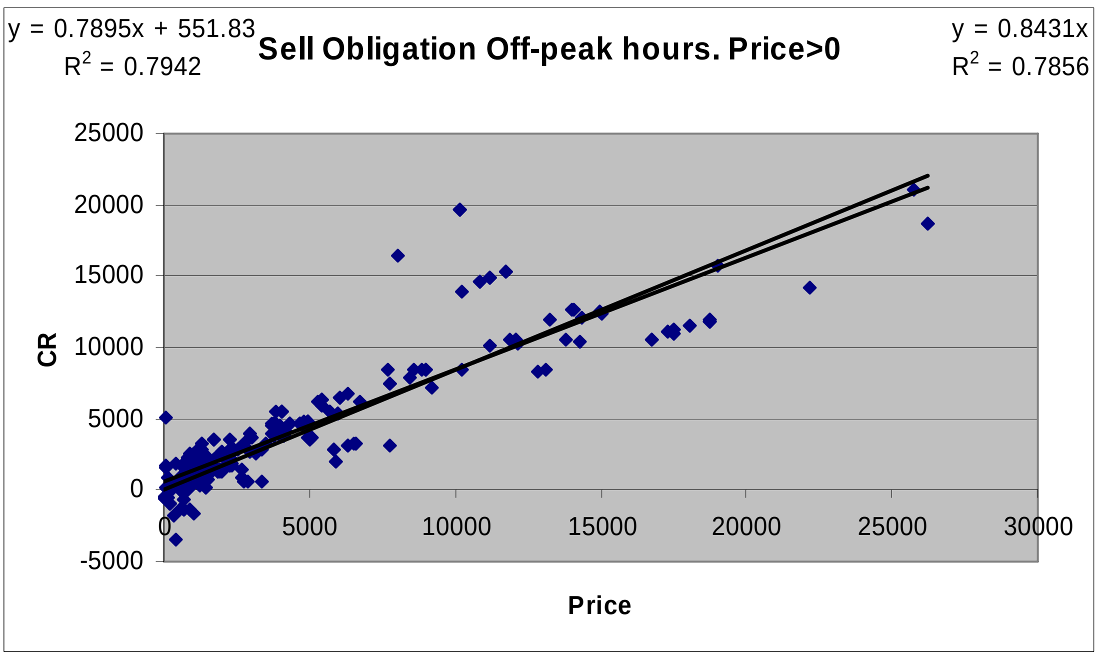


**Figure 13. Price Vs CR - Sell Obligation Off-peak hours. Price>0**

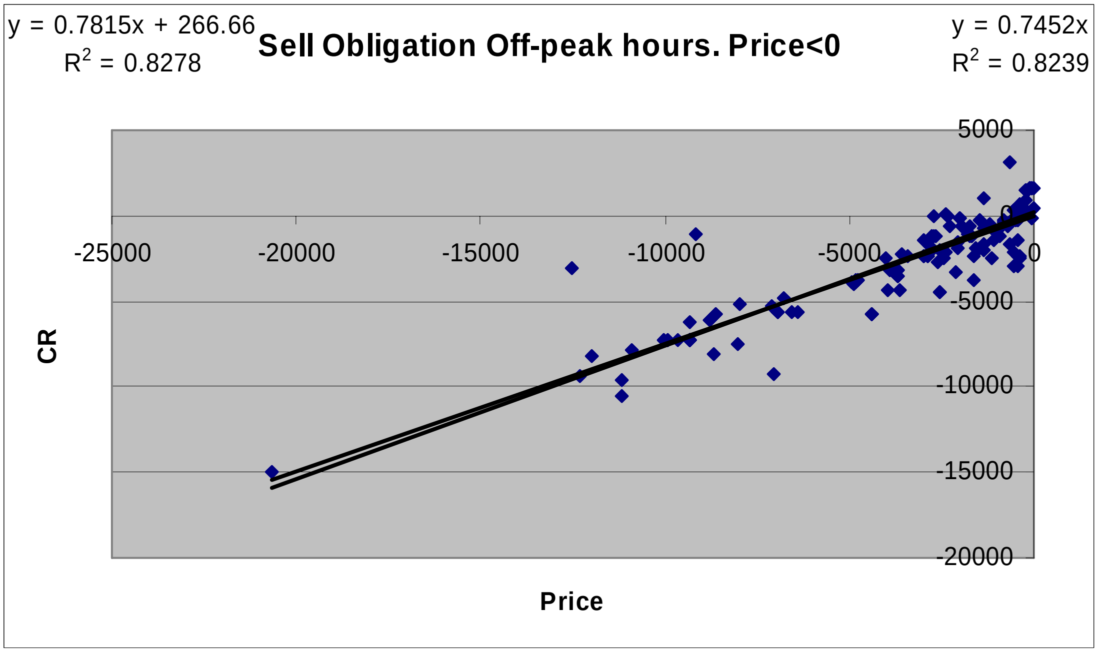


**Figure 14. Price Vs CR - Sell Obligation Off-peak hours. Price<0**

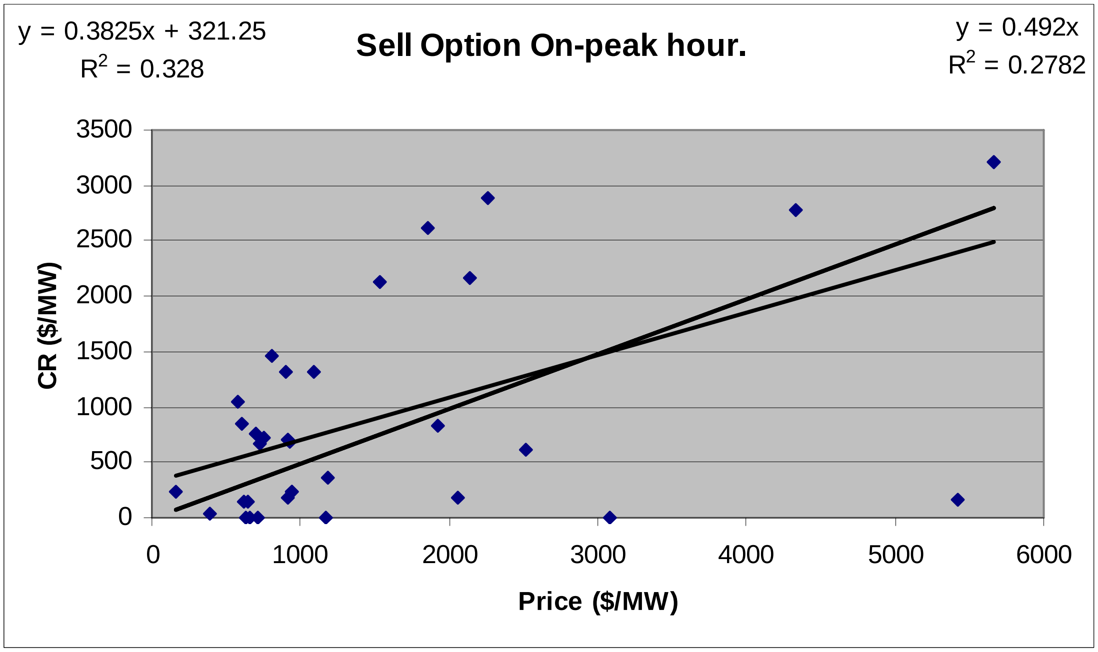


**Figure 15. Price Vs CR - Sell Option On-peak hour**

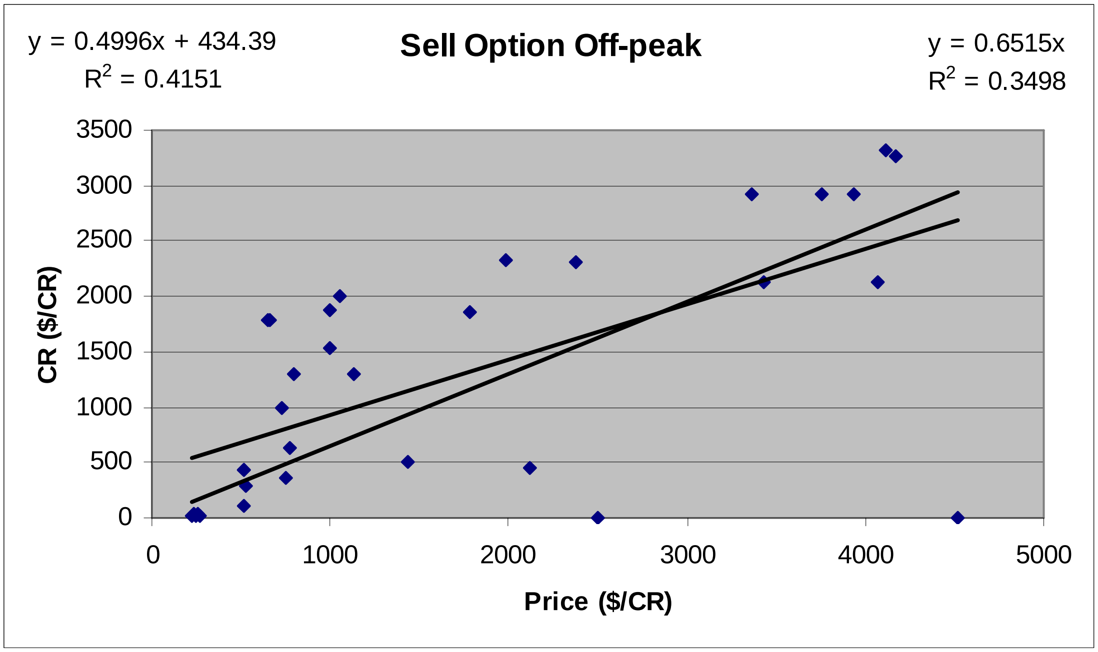


**Figure 16. Price Vs CR - Sell Option Off-peak**

### 4.4 Congestion Rents and the price paid do not always have the same sign

As seen in the previous graphs, it is generally the case that the FTR's price and its associated CRs have the same sign. (e.g. when a market participant buys an obligation at a positive price, gets paid later some money. Similarly, when a market participant buys an obligation at a negative price, later has to pay CRs). However, as the points in the northwest and southeast quadrants in the previous plots show, there are cases in which FTRs price and CRs have opposite signs. This mismatch in signs of price and CRs favors the participants acting as speculators, but makes the FTR a very bad business for those who act like hedgers. For participants who get paid to hold an FTR (speculators buying the FTR at a negative price), positive congestion rents mean that they are paid twice. For participants who pay to have an FTR (hedgers who pay to have an FTR), negative congestion rents mean that they pay twice for congestion.

The following table summarizes those cases in which CRs and prices had opposite signs. For 262 transactions, market participants who paid for FTR obligations had to pay also for the CR when congestion occurred in the counter-flow of the FTR. In total, such market participants paid $312,860 more than what they would have paid in CRs if they did not trade any FTRs. On the other side, those market participants who were paid to have an FTR obligation, had 612 transactions in which they also received CRs. In total these market participants obtained $1,863,500 for engaging in the FTR transactions.

| | Congestion did not occur in the expected direction. CRs and Price paid had opposite signs | | | | | |
|---|---|---|---|---|---|---|
| | FTRs for which market participants paid a premium. | | | FTRs for which market participants received a premium. (Paid a negative premium) | | |
| Type of FTR | Num FTRs | Num MW | Total Premium | Num FTRs | Num MW | Total Premium |
| BuyObl | 262 | 3002 | 312,860 | 612 | 2249 | (1,863,500) |
| BuyObl24PosPri | 16 | 141 | 30,186 | 0 | 0 | 0 |
| BuyObl24NegPri | 0 | 0 | 0 | 112 | 499 | (418,500) |
| BuyOblOnPosPri | 151 | 1260 | 203,740 | 0 | 0 | 0 |
| BuyOblOnNegPri | 0 | 0 | 0 | 293 | 1160 | (926,700) |
| BuyOblOffPosPri | 95 | 1601 | 78,936 | 0 | 0 | 0 |
| BuyOblOffNegPri | 0 | 0 | 0 | 207 | 590 | (518,290) |
| SelObl | 54 | 273 | 85,318 | 89 | 370 | (170,060) |
| SelObl24PosPri | 0 | 0 | 0 | 0 | 0 | 0 |
| SelObl24NegPri | 0 | 0 | 0 | 1 | 0 | (5,738) |
| SelOblOnPosPri | 19 | 159 | 41,634 | 0 | 0 | 0 |
| SelOblOnNegPri | 0 | 0 | 0 | 50 | 255 | (108,500) |
| SelOblOffPosPri | 35 | 114 | 43,684 | 0 | 0 | 0 |
| SelOblOffNegPri | 0 | 0 | 0 | 38 | 115 | (55,826) |

**Table 18. FTRs for which congestion did not occur in the expected direction**

## 5 Analysis of the effect of the Rounds in the Auction Results

The annual auction of FTRs is conducted in 4 different rounds. At each round 25% of the total capacity available is offered. To see if the number of rounds in the auction has an effect in the results, it is convenient to see how the different statistics vary at each stage of the auction. It is expected that keeping everything else equal, the more number of rounds in an auction, the higher the opportunities for price discovery (as bidders have chance to take feedback from the market and adjust their bids for subsequent rounds)(Ausubel, Crampton et al. 2004).

## 5.1 Prices per round:

The following graph shows the capacity traded (in MWh) per type of FTR in each round. During the first round all transactions between the market participants and the ISOs are "buy" transactions, because the market participants do not have yet any FTRs that can be sold. Once they acquire FTRs, these can be sold in subsequent rounds. Most of the capacity is traded in the form of obligations for 24 hours. A good portion of these transactions might represent "self scheduled" FTRs (as explained in section 3.4 of chapter 2). Since out of the cleared FTR buy bids, 25 percent were self-scheduled FTRs(PJM 2004), then about 73% of the buy-obligations for 24 hours might have been self-scheduled.

The volume of obligations is pretty much stable along the four rounds, but the trading of options increases in the last two. Participants sold back very little of the capacity acquired. Most of the capacity sold by market participants was traded in the last round.

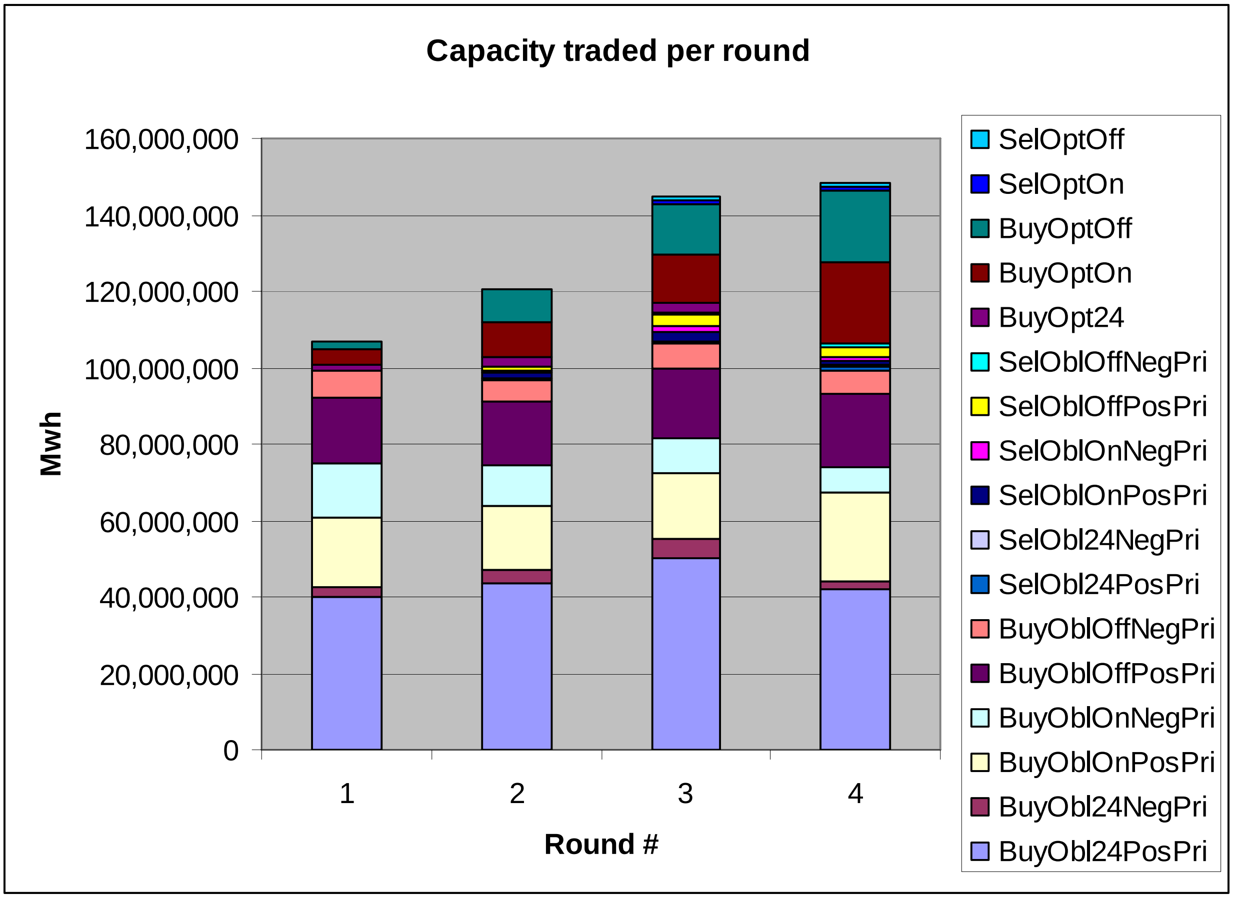


**Figure 17. Capacity Traded per round**

Fig. 18 shows the average weighted price for different types of obligations purchased by market participants at each round. The prices oscillate with no clear tendency, except for the obligations for on-peak hours sold at a positive price, for which the price decreased as the auction evolved. The obligations for on-peak hours sold at a negative price saw a decrease in the last two rounds.

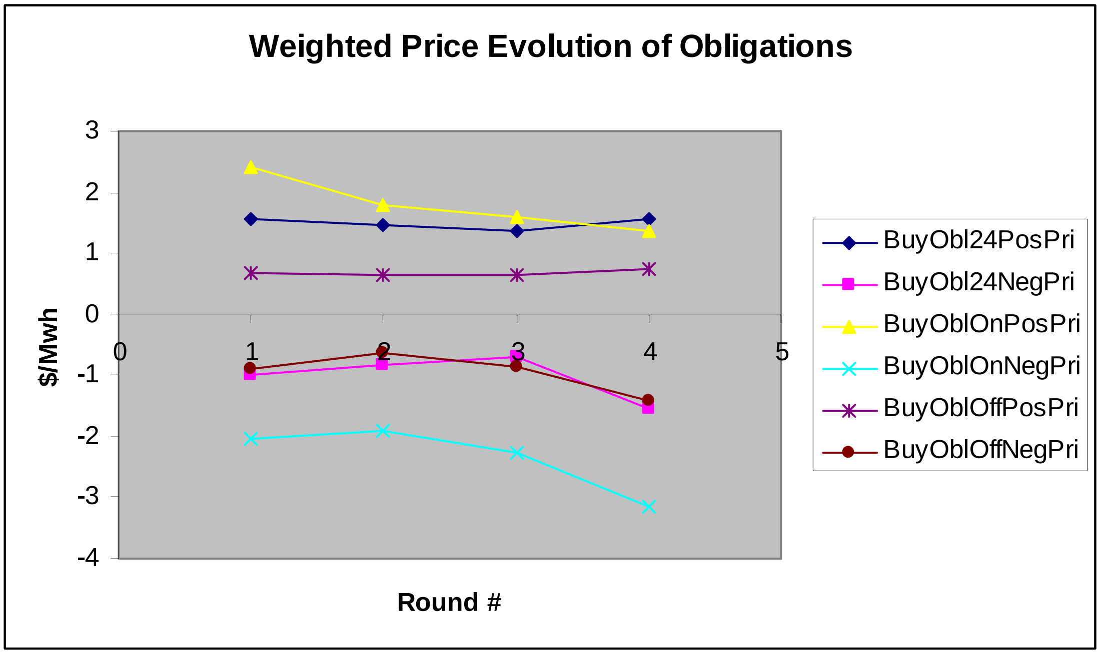


**Figure 18. Evolution of FTR prices**

The following graph shows this correlation for each type of FTR at each round.

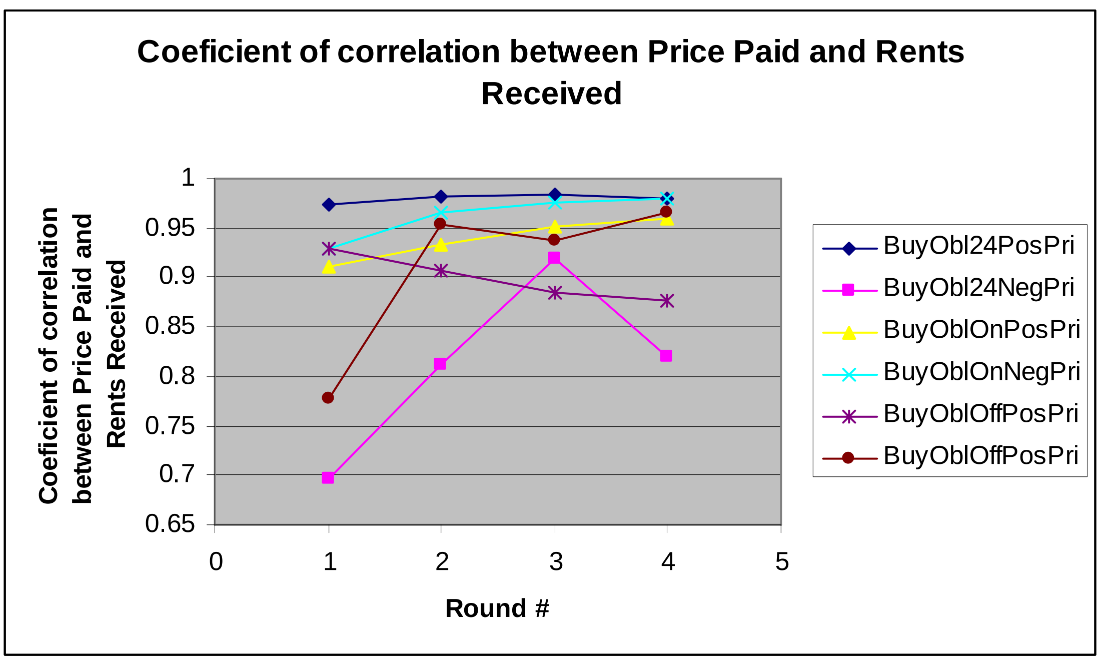


**Figure 19. Evolution of correlation between prices and CRs.**

For almost all the obligations it looks like the more advanced the auction, the higher the correlation coefficient between the prices paid for the FTRs and the rents received by the FTR holders. However at this stage we cannot say if the increase in the correlation is due to “price discovery” due to the interaction between the participants, or is perhaps due to the fact that those “paths” traded at the latest rounds were more predictable. In Section 7, we run an analysis per “path” and find that the number of transactions in fact has an effect in the difference between the price paid/received for the FTR and the corresponding CRs.

# 6 Market Participants

## 6.1 Goal of analysis by market participant

The goal of this section is to determine if results of the auction are consistent with the hypothesis that some market participants behave intentionally as speculators and charge a premium in the FTRs they trade, while others act as pure hedgers and pay to reduce their risk. If those who pay the premium are precisely the entities that serve load, and those who charge the premium are entities whose main business is not the production or distribution of electricity; then it would be safe to say that the FTR system allows entities outside the value chain of electricity in PJM to take money away from the system.

As it will be shown in the following sections, some market participants obtained substantial profits from their participation in the auction. The profits of these winners do not seem to be due to chance; the profits were made not only from buying FTRs at a negative price, but also from reselling FTRs previously acquired.

## 6.2 Summary of results by market participant

### 6.2.1 Information about the business of market participants

The 54 entities that participated in the FTR auction are listed in Table 19. Because it was not possible to find a unique source of information about the business core of each of the entities, or their economic activity in PJM market, a search of the institutional web pages was conducted, and the information summarized in the table is presented in the Appendix. For a list in alphabetical order and information about each participant, please refer to the Appendix.

| Num Participant | Participant | Participant Long Name |
|---|---|---|
| 1 | WPC | Williams Power Company, Inc. |
| 2 | CoralR | Coral Power, L.L.C. (Retail) |
| 3 | EMMT | Edison Mission Marketing and Trading, Inc. |
| 4 | CNCT | Conectiv Energy Supply, Inc. |
| 5 | DCELLC | DC Energy LLC |
| 6 | FPLEPM | FPL Energy Power Marketing, Inc. |
| 7 | PEPSRV | Pepco Energy Services, Inc. |
| 8 | CEPLLC | Citadel Energy Products, LLC |
| 9 | CPSI | Constellation Power Source, Inc. |
| 10 | BPBGS | BP Energy Company (BGS) |
| 11 | RESI | Reliant Energy Services, Inc. |
| 12 | RESR | Reliant Energy Services, Inc. (Retail) |
| 13 | PSERT | PSEG Energy Resources and Trade LLC |
| 14 | MPR | Mirant Americas Energy Mktg. (Potomac River) |
| 15 | WGCHZL | Williams Generation Company-Hazelton |
| 16 | AEVine | Atlantic City Electric Company (Vineland) |
| 17 | DTEBGS | DTE Energy Trading, Inc. (BGS) |
| 18 | SETC | Sempra Energy Trading Corporation |
| 19 | AETS | Allegheny Energy Supply Company, L.L.C. |
| 20 | EPLUS | PPL EnergyPlus, L.L.C. |
| 21 | DPL | Delmarva Power & Light Company |
| 22 | FESC | FirstEnergy Solutions Corp. |
| 23 | NRGNJ | NRG New Jersey Energy Sales LLC |
| 24 | SUSQEP | Susquehanna Energy Products, LLC |
| 25 | Morgan | Morgan Stanley Capital Group, Inc. |
| 26 | NEV | Constellation NewEnergy, Inc. |
| 27 | ODEC | Old Dominion Electric Cooperative |
| 28 | AECI | Allegheny Electric Cooperative, Inc. |
| 29 | BPGM | BP Energy Company (Green Mountain) |
| 30 | CITZNS | Reliant Energy Services, Inc. (Citizens Electric) |
| 31 | EXGNPT | Exelon Generation Co., LLC (Power Team) |
| 32 | MetEd | Metropolitan Edison Company |
| 33 | AHC | Amerada Hess Corporation |
| 34 | CPSDMB | Constellation Energy Commodities Group (DPL MD Base) |
| 35 | UGID | UGI Development Company |
| 36 | SELWM | Select Energy, Inc. (Wholesale Marketing) |
| 37 | RAMEP | Ritchie Energy Products, L.L.C. |
| 38 | PaElec | Pennsylvania Electric Company |
| 39 | CINSI | Cinergy Services, Inc. |
| 40 | JCPLFP | Jersey Central Power & Light (FP Load) |
| 41 | ConEdE | ConEdison Energy, Inc. |

| | | |
|---|---|---|
| 42 | ACNEgy | ACN Energy, Inc. |
| 43 | ECPDTE | Energy Cooperative Association of PA |
| 44 | EASTON | Easton Utilities Commission |
| 45 | CEDS | Consolidated Edison Solutions, Inc. |
| 46 | GALT | Galt Power Inc. |
| 47 | JARON | J. Aron & Company |
| 48 | TESI | Tractebel Energy Services, Inc. |
| 49 | AMPO | American Municipal Power-Ohio, Inc. |
| 50 | DTEET | DTE Energy Trading, Inc. |
| 51 | MLCS | Merrill Lynch Capital Services, Inc. |
| 52 | SES | Sempra Energy Solutions |
| 53 | QuarkP | Quark Power, L.L.C. |
| 54 | AEPAP | an umbrella agreement for firm point-to-point service with Appalachian Power Co. with AmericanElectric Power Service Corp. as Agent (“AEPAP”) |

**Table 19. Participants in the PJM’s FTR annual auction. “Num Participant” is the number that identifies market participants in this chapter, and is a number that only reflects the order in which each participant appeared in the reports of FTRs trades.**

PJM classifies market participants in 5 categories (Load Serving Entities (LSE), Marketers, Generators/Merchant Generators, Municipalities and End Users) but the information of the category to which each market participant belongs is not publicly available. This information would be useful to infer the interests of each entity (hedging or speculation) and to analyze the results of the auction for each participant. As an imperfect substitute for this information, we used the list of LSEs that signed the Reliability Assurance Agreement among LSEs in the PJM region to identify the entities that are LSEs (or entities whose parent company is an LSE). This information is displayed in the table of section 6.2.3.

### 6.2.2 Classification of participants by type of transactions

According to the transactions they were engaged in, we can classify participants in 5 different groups. These groups can be conceptually interpreted as degrees of hedging/speculation, if we accept the hypotheses that 1) those participants that bought obligations (on-peak and off-peak) at a negative price, are speculators, trying to make a profit in exchange for the risk they bear. 2) Those participants that traded obligations for

24 hours (at positive and negative prices), most likely were participants self scheduling their ARRs.

Table 20 summarizes the characteristics of the 5 categories of participants according to their transactions. Participants in category A are the hedgers. Those entities that not only bought obligations for 24h (perhaps self-scheduled), but also bought obligations for on-peak and off-peak hours and options. These participants did not buy any obligation for on-peak or off peak hours at a negative price. In contrast, participants in category E are speculators that bought obligations for on-peak and off-peak hours at a negative price. These participants bought also obligations at a positive price, but 8 of them made profits by selling later some obligations and options in the auction (see section 6.7). These participants made money not only by buying obligations at a positive price, or by reselling, but also from the obligations they bought at a positive price. For example participants 14, 5 and 8, who traded the FTRs outliers in the OLS line for on-peak and off-peak obligations sold at a positive price, belong to categories D and E. These participants perhaps did not have ARRs (and did not self-schedule any 24h obligation FTR).

| Category by type of transactions | Total # of Participants of this type | Bought Obligations 24H price>0 | Bought Obligations for 24H price<0 | Bought Obligations On-Off price > 0, or Bought Options | Bought Obligations On-Off price < 0 | Sold Obligations | Sold Options | Average profit per participant |
|---|---|---|---|---|---|---|---|---|
| A | 13 | Yes | 6 participants | Yes | No | 6 participants | No | (629,676) |
| B | 17 | Yes | 8 participants | No | No | 4 participants | No | (317,933) |
| C | 6 | No | No | Yes | No | 1 participant | No | (46,588) |
| D | 6 | Yes | 5 participants | Yes | Yes | 3 participants | 1 participant | (83,192) |
| E | 12 | No | No | Yes | Yes | 8 participants | 3 participants | 639,555 |

**Table 20. Description of categories of market participants**

### 6.2.3 Summary table of Results by Market Participant

The following table summarizes the information about each market participant and its results in the auction of annual FTRs. Participants are presented in descending order by profits with the first row corresponding to the participant that profited the most (see Section 6.5). The first 2 columns show the number by which the market participant is referenced in this document and the abridged name. Column 3 in the table indicates if the entity is included in the list of Load Serving Entities (LSEs) that signed the Reliability Assurance Agreement among LSEs in the PJM Region[4] (the entities marked with "*" are not in the list, but a parent, affiliate of sister company is in the list). Column 4 shows the participant's ranking by profits. The participants in positions 1st to 15th made profits, while the other 39 had losses. Column 5 shows the participants ranking by capacity traded. The 12 participants that traded most capacity are highlighted. See section 6.3. Column 7 shows the category of the participant according to the type of transactions made. See Section 6.4.

| # Participant | Acr | LSE? | Ranking By Profits | Ranking By MWh Traded | Category by Transactions |
|---|---|---|---|---|---|
| 8 | CEPLLC | | 1 | 1 | E |
| 5 | DCELLC | | 2 | 11 | E |
| 2 | CoralR | | 3 | 15 | E |
| 1 | WPC | x * | 4 | 13 | E |
| 15 | WGCHZL | x* | 5 | 23 | E |
| 14 | MPR | | 6 | 8 | D |
| 18 | SETC | x | 7 | 26 | D |
| 44 | EASTON | | 8 | 48 | B |
| 50 | DTEET | x | 9 | 33 | E |
| 17 | DTEBGS | x | 10 | 31 | A |
| 24 | SUSQEP | | 11 | 12 | E |
| 43 | ECPDTE | | 12 | 54 | B |
| 42 | ACNEgy | x | 13 | 51 | B |
| 25 | Morgan | | 14 | 4 | E |
| 37 | RAMEP | | 15 | 25 | C |
| 53 | QuarkP | | 16 | 45 | C |
| 49 | AMPO | x | 17 | 52 | B |

[4] Reliability Assurance Agreement Among Load-Serving Entities In the PJM Region. K:\pjm\RAARevs\New RAA.doc

| | | | | | |
|---|---|---|---|---|---|
| 52 | SES | x | 18 | 46 | A |
| 28 | AECI | x | 19 | 24 | B |
| 54 | AEPAP | | 20 | 39 | A |
| 35 | UGID | x* | 21 | 36 | B |
| 51 | MLCS | | 22 | 22 | C |
| 46 | GALT | | 23 | 53 | A |
| 41 | ConEdE | x | 24 | 34 | E |
| 45 | CEDS | x | 25 | 40 | C |
| 6 | FPLEPM | | 26 | 16 | D |
| 48 | TESI | | 27 | 42 | A |
| 47 | JARON | | 28 | 20 | C |
| 13 | PSERT | x | 29 | 9 | D |
| 32 | MetEd | x | 30 | 41 | B |
| 21 | DPL | x | 31 | 27 | C |
| 39 | CINSI | | 32 | 17 | E |
| 3 | EMMT | x | 33 | 6 | E |
| 30 | CITZNS | x* | 34 | 47 | B |
| 38 | PaElec | x | 35 | 29 | B |
| 4 | CNCT | x | 36 | 21 | E |
| 34 | CPSDMB | x* | 37 | 49 | B |
| 26 | NEV | x* | 38 | 44 | B |
| 16 | AEVine | x | 39 | 43 | A |
| 40 | JCPLFP | x | 40 | 37 | B |
| 31 | EXGNPT | x* | 41 | 5 | A |
| 29 | BPGM | x | 42 | 50 | B |
| 33 | AHC | X | 43 | 28 | D |
| 7 | PEPSRV | X | 44 | 18 | A |
| 27 | ODEC | X | 45 | 14 | A |
| 9 | CPSI | x* | 46 | 3 | D |
| 10 | BPBGS | | 47 | 32 | B |
| 19 | AETS | X | 48 | 38 | B |
| 23 | NRGNJ | X | 49 | 30 | B |
| 11 | RESI | X | 50 | 19 | A |
| 12 | RESR | X | 51 | 35 | B |
| 36 | SELWM | X | 52 | 10 | A |
| 20 | EPLUS | X | 53 | 2 | A |
| 22 | FESC | X | 54 | 7 | A |

**Table 21. Summary of market participants**

## 6.3 Capacity traded per participant

Five of the participants accounted for more than half the total MWh traded, and twelve participants accounted for more than 80%. The following graph shows the transmission capacity traded in the different forms of FTRs, for each of the 12 most important participants by amount of capacity traded:

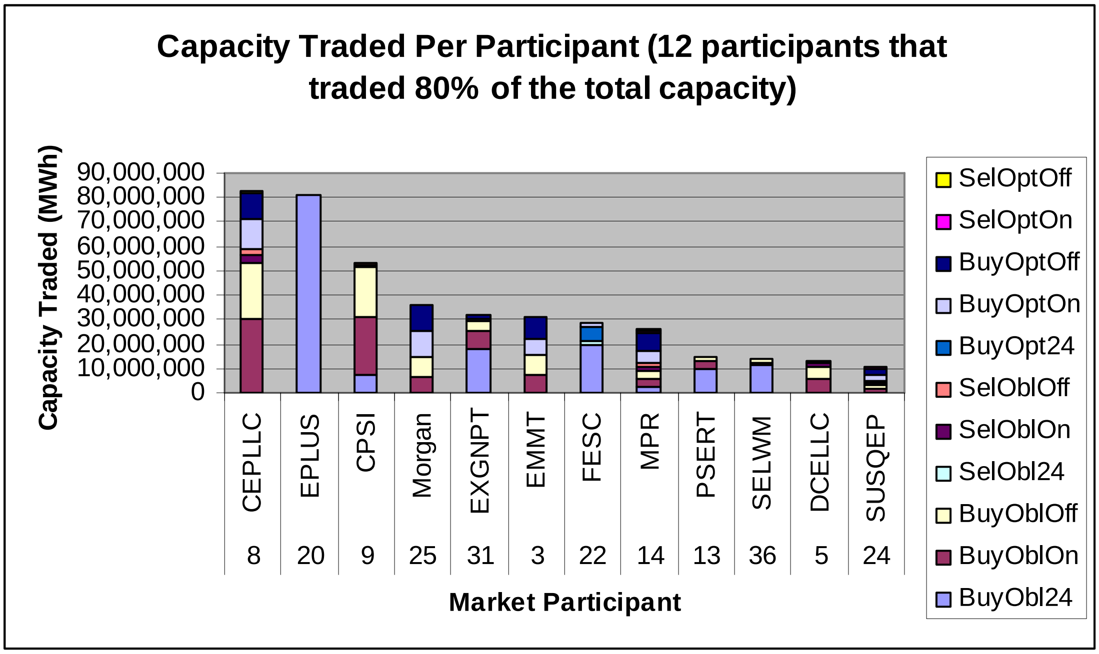


**Figure 20. Twelve participants traded 80% of the total capacity traded**

## 6.4 Transactions per participant

All but one participant traded obligations, only a quarter of the participants traded options. Table 22 presents a list of the participants involved in the trading of each type of FTR.

| Type of FTR | Num Participants trading these FTRs | Participants |
|---|---|---|
| BuyObl | 53 | |
| BuyObl24PosPri | 36 | 6,7,9,10,11,12,13,14,16,17,18,19,20,22,23,26,27,28,29,30,31,32,33,34,35,36,38,40,42,43,44,46,48,49,52,54 |
| BuyObl24NegPri | 19 | 6,9,10,11,13,14,17,18,19,20,23,26,27,28,36,42,43,44,52 |
| BuyOblOnPosPri | 34 | 1,2,3,4,5,6,7,8,9,11,13,14,15,16,17,18,20,21,22,24,25,31,33,36,39,41,45,47,48,50,51,52,53,54 |
| BuyOblOnNegPri | 18 | 1,2,3,4,5,6,8,9,13,14,15,18,24,25,33,39,41,50 |
| BuyOblOffPosPri | 25 | 1,2,3,4,5,6,8,9,13,14,15,18,21,24,25,31,33,36,39,41,45,46,47,51,52 |
| BuyOblOffNegPri | 14 | 1,2,3,5,6,8,9,13,14,15,18,24,33,50 |
| BuyOpt | 14 | |
| BuyOpt24 | 2 | 22,27 |
| BuyOptOn | 13 | 3,4,8,9,14,18,22,24,25,31,37,39,47 |
| BuyOptOff | 10 | 3,4,8,9,14,18,24,25,31,37 |

| | | |
|---|---|---|
| SelObl | 22 | |
| SelObl24PosPri | 11 | 6,7,9,11,17,22,26,38,43,46,52 |
| SelObl24NegPri | 2 | 6,28 |
| SelOblOnPosPri | 13 | 1,2,3,4,5,6,8,9,11,14,15,21,24 |
| SelOblOnNegPri | 8 | 1,2,5,6,8,9,14,15 |
| SelOblOffPosPri | 12 | 1,2,3,4,5,6,8,9,14,21,24,46 |
| SelOblOffNegPri | 9 | 1,2,3,5,6,8,9,14,15 |
| SelOpt | 4 | |
| SelOpt24 | 0 | |
| SelOptOn | 4 | 3,8,14,24 |
| SelOptOff | 3 | 8,14,24 |

**Table 22. Transactions made by each market**

## 6.5 Participant's Profits and Losses

A total of 53 out of the 54 participants traded FTR obligations, and 14 traded options. A total of 15 market participants made profits with the FTR trades. Participant 37 made profits trading only options. Among the 38 participants that did not profit from the transactions, 4 lost more than $1 million and 12 lost more than $500,000.

The next table shows the net economical position of all of those who bought FTR obligations, ordered by the amount of premium paid. The profits made from trading obligations by the 14 "winners" sum to $9,891,808, while the total losses of the 39 "loosers" sum to $14,877,655. Total profits (including profits or losses from options) by the 15 "winners" sum $9,118,223, while the total losses of the 39 "losers" sum $15,812,895. Summing all the profits and losses from the market participants, the net result is losses for $6,694,671. If all the winners of the auction were speculators that did not pay any fixed costs of the transmission network, we could say that the $9 million in profits they made is money that leaked from the system and constitutes an extra cost for transmission customers. However some of the winners cannot be labeled as "speculators", because they are either assumed to be LSE's (because are signatories of the reliability assurance agreement) or because they are engaged in some hedging activity (and are not classified as type D or E, according to the analysis of the previous section). The aggregated profit of those participants that are not LSE's and are either type E or D, is $7,315,051.

The participant that profited the most from the auctions collected a premium of more than $4 million in obligations but lost $0.8 million on the options traded. A total of 4 participants managed to make a profit when buying options.

| Market Participant | Profits From Trading Obligations* | Profits From Trading Options* | Total Profits* |
|---|---|---|---|
| CEPLLC 8 | 4,058,859 | -807,889 | 3,250,970 |
| DCELLC 5 | 2,207,030 | 0 | 2,207,030 |
| Coral 2 | 1,121,036 | 0 | 1,121,036 |
| WPC 1 | 815,930 | 0 | 815,930 |
| WGCHZL 15 | 697,888 | 0 | 697,888 |
| MPR 14 | 641,870 | 39,232 | 681,102 |
| SETC 18 | 95,968 | 1,249 | 97,217 |
| EASTON 44 | 55,853 | 0 | 55,853 |
| DTEET 50 | 48,720 | 0 | 48,720 |
| DTEBGS 17 | 44,102 | 0 | 44,102 |
| SUSQEP 24 | 46,750 | -3,835 | 42,915 |
| ECPDTE 43 | 21,561 | 0 | 21,561 |
| ACNEgy 42 | 18,341 | 0 | 18,341 |
| Morgan 25 | 17,900 | -5,902 | 11,998 |
| RAMEP 37 | 0 | 3,560 | 3,560 |
| QuarkP 53 | -6,642 | 0 | -6,642 |
| AMPO 49 | -7,406 | 0 | -7,406 |
| SES 52 | -9,046 | 0 | -9,046 |
| AECI 28 | -10,345 | 0 | -10,345 |
| AEPAP 54 | -13,159 | 0 | -13,159 |
| UGID 35 | -19,347 | 0 | -19,347 |
| MLCS 51 | -26,590 | 0 | -26,590 |
| GALT 46 | -31,449 | 0 | -31,449 |
| ConEdE 41 | -39,681 | 0 | -39,681 |
| CEDS 45 | -46,560 | 0 | -46,560 |
| FPLEPM 6 | -64,050 | 0 | -64,050 |
| TESI 48 | -66,720 | 0 | -66,720 |
| JARON 47 | -57,400 | -30,962 | -88,362 |
| PSERT 13 | -89,400 | 0 | -89,400 |

| | | | |
|---|---|---|---|
| MetEd 32 | -109,400 | 0 | -109,400 |
| DPL 21 | -114,936 | 0 | -114,936 |
| CINSI 39 | -100,110 | -21,064 | -121,174 |
| EMMT 3 | -155,969 | 5,415 | -150,554 |
| CITZNS 30 | -163,960 | 0 | -163,960 |
| PaElec 38 | -207,400 | 0 | -207,400 |
| CNCT 4 | -167,340 | -43,077 | -210,417 |
| CPSDMB 34 | -212,030 | 0 | -212,030 |
| NEV 26 | -258,434 | 0 | -258,434 |
| AEVine 16 | -340,000 | 0 | -340,000 |
| JCPLFP 40 | -402,600 | 0 | -402,600 |
| EXGNPT 31 | -421,200 | -6,057 | -427,257 |
| BPGM 29 | -440,000 | 0 | -440,000 |
| AHC 33 | -508,400 | 0 | -508,400 |
| PEPSRV 7 | -530,970 | 0 | -530,970 |
| ODEC 27 | -603,600 | -7,132 | -610,732 |
| CPSI 9 | -607,258 | -8,363 | -615,621 |
| BPBGS 10 | -801,200 | 0 | -801,200 |
| AETS 19 | -919,500 | 0 | -919,500 |
| NRGNJ 23 | -922,800 | 0 | -922,800 |
| RESI 11 | -961,993 | 0 | -961,993 |
| RESR 12 | -1,026,200 | 0 | -1,026,200 |
| SELWM 36 | -1,278,300 | 0 | -1,278,300 |
| EPLUS 20 | -1,606,200 | 0 | -1,606,200 |
| FESC 22 | -1,530,060 | -824,000 | -2,354,060 |

**Table 23. Participant's profit an losses (includes all obligations traded – at a positive price, negative price and zero)**

The next table shows the profits (or losses) obtained by participants for each type of FTR traded at a price different than zero. The six participants that profited the most from the auction made most of their profits by trading obligations for on-peak hours at a negative price. This means that they behaved mostly as speculators and charged a premium for bearing the risk of an obligation with expected negative congestion rents. None of the five participants who profited the most traded any obligation for 24 hours.

In contrast, most of the premium paid by those participants that lost money in the auction was paid for obligations for 24 hours. Perhaps most of their purchases of 24h FTRs were "self-scheduled", which means that they were the owners of the ARRs for those paths, and got back from the ISO the money they paid in the auction. Nevertheless, there was a significant amount of premium paid for the on-peak obligations and for options.

| | PROFITS FROM TRADING OBLIGATIONS | | | | | | PROFITS FROM TRADING OPTIONS | | | TOTAL PROFITS (Including Profits from FTRs traded at price 0) |
|---|---|---|---|---|---|---|---|---|---|---|
| Participant | 24H Price>0 | 24H Price<0 | On Price>0 | On Price<0 | Off Price>0 | Off Price<0 | 24 | On | Off | |
| CEPLLC 8 | 0 | 0 | 147,403 | 3,247,280 | 165,970 | 497,510 | 0 | -62,471 | -745,548 | 3,250,970 |
| DCELLC 5 | 0 | 0 | -148,060 | -1,442,269 | -42,360 | -574,392 | 0 | 0 | 0 | 2,207,030 |
| Coral 2 | 0 | 0 | -14,224 | -961,141 | -12,921 | -132,618 | 0 | 0 | 0 | 1,121,036 |
| WPC 1 | 0 | 0 | 62,552 | -682,550 | -38,056 | -149,386 | 0 | 0 | 0 | 815,930 |
| WGCHZL 15 | 0 | 0 | 60,498 | -700,680 | -22,173 | -34,850 | 0 | 0 | 0 | 697,888 |
| MPR 14 | -1,051 | -141,470 | -51,250 | -253,667 | -82,660 | -111,316 | 0 | -20,772 | -18,453 | 681,102 |
| SETC 18 | 3,391 | -28,633 | -6,841 | -49,265 | -5,146 | -4,113 | 0 | -1,347 | 98 | 97,217 |
| EASTON 44 | -24,536 | -31,318 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 55,853 |
| DTEET 50 | 0 | 0 | 5,266 | -48,010 | 0 | -5,965 | 0 | 0 | 0 | 48,720 |
| DTEBGS 17 | 285,498 | -337,828 | 5,171 | 0 | 0 | 0 | 0 | 0 | 0 | 44,102 |
| SUSQEP 24 | 0 | 0 | -28,538 | -5,992 | -9,260 | -2,944 | 0 | -2,477 | 6,311 | 42,915 |
| ECPDTE 43 | -664 | -20,897 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 21,561 |
| ACNEgy 42 | -3,403 | -14,938 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 18,341 |
| Morgan 25 | 0 | 0 | -11,079 | -2,575 | -4,247 | 0 | 0 | 1,772 | 4,130 | 11,998 |
| RAMEP 37 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | -4,036 | 477 | 3,560 |
| QuarkP 53 | 0 | 0 | 6,642 | 0 | 0 | 0 | 0 | 0 | 0 | -6,642 |
| AMPO 49 | 7,406 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | -7,406 |
| SES 52 | -2,476 | -12,513 | 22,364 | 0 | 1,672 | 0 | 0 | 0 | 0 | -9,046 |
| AECI 28 | 48,900 | -38,553 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | -10,345 |
| AEPAP 54 | 7,893 | 0 | 5,266 | 0 | 0 | 0 | 0 | 0 | 0 | -13,159 |
| UGID 35 | 19,347 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | -19,347 |
| MLCS 51 | 0 | 0 | 19,104 | 0 | 7,486 | 0 | 0 | 0 | 0 | -26,590 |
| GALT 46 | 26,559 | 0 | 0 | 0 | 4,885 | 0 | 0 | 0 | 0 | -31,449 |
| ConEdE 41 | 0 | 0 | 27,457 | -1,674 | 13,896 | 0 | 0 | 0 | 0 | -39,681 |
| CEDS 45 | 0 | 0 | 43,378 | 0 | 3,185 | 0 | 0 | 0 | 0 | -46,560 |
| FPLEPM 6 | 642,130 | -69,184 | 240,443 | -188,707 | -270,650 | -293,076 | 0 | 0 | 0 | -64,050 |
| TESI 48 | 36,920 | 0 | 29,785 | 0 | 0 | 0 | 0 | 0 | 0 | -66,720 |
| JARON 47 | 0 | 0 | 54,040 | 0 | 3,365 | 0 | 0 | 30,962 | 0 | -88,362 |
| PSERT 13 | 370,900 | -28,429 | -162,340 | -15,225 | -85,291 | 6,671 | 0 | 0 | 0 | -89,400 |
| MetEd 32 | 109,400 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | -109,400 |
| DPL 21 | 0 | 0 | 80,817 | 0 | 34,119 | 0 | 0 | 0 | 0 | -114,936 |
| CINSI 39 | 0 | 0 | 96,820 | -3,076 | 6,377 | 0 | 0 | 21,064 | 0 | -121,174 |
| EMMT 3 | 0 | 0 | 60,703 | 8,916 | 86,488 | -1,756 | 0 | -9,583 | 4,167 | -150,554 |
| CITZNS 30 | 163,960 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | -163,960 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| PaElec 38 | 207,400 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | -207,400 |
| CNCT 4 | 0 | 0 | 224,421 | -5,826 | -51,200 | 0 | 0 | 35,319 | 7,759 | -210,417 |
| CPSDMB 34 | 212,030 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | -212,030 |
| NEV 26 | 287,034 | -31,624 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | -258,434 |
| AEVine 16 | 331,100 | 0 | 8,901 | 0 | 0 | 0 | 0 | 0 | 0 | -340,000 |
| JCPLFP 40 | 402,600 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | -402,600 |
| EXGNPT 31 | 343,700 | 0 | 79,220 | 0 | -1,754 | 0 | 0 | 5,920 | 136 | -427,257 |
| BPGM 29 | 440,000 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | -440,000 |
| AHC 33 | 499,000 | 0 | 9,421 | -2,440 | 1,806 | 691 | 0 | 0 | 0 | -508,400 |
| PEPSRV 7 | 522,870 | 0 | 8,012 | 0 | 0 | 0 | 0 | 0 | 0 | -530,970 |
| ODEC 27 | 602,000 | 1,600 | 0 | 0 | 0 | 0 | 7,132 | 0 | 0 | -610,732 |
| CPSI 9 | 742,057 | -26,267 | 555,356 | -549,851 | 182,402 | -299,435 | 0 | 2,630 | 5,733 | -615,621 |
| BPBGS 10 | 816,600 | -18,430 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | -801,200 |
| AETS 19 | 933,900 | -17,453 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | -919,500 |
| NRGNJ 23 | 956,200 | -36,550 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | -922,800 |
| RESI 11 | 868,624 | -9,036 | 102,328 | 0 | 0 | 0 | 0 | 0 | 0 | -961,993 |
| RESR 12 | 1,026,200 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | -1,026,200 |
| SELWM 36 | 1,218,700 | -10,352 | 56,030 | 0 | 13,860 | 0 | 0 | 0 | 0 | -1,278,300 |
| EPLUS 20 | 1,769,800 | -163,953 | 1,420 | 0 | 0 | 0 | 0 | 0 | 0 | -1,606,200 |
| FESC 22 | 1,472,560 | 0 | 54,366 | 0 | 0 | 0 | 463,110 | 360,900 | 0 | -2,354,060 |

**Table 24. Profits and losses per transaction type**

## 6.6 Making money by reselling FTRs in the auction

The trading of FTRs can generate money for the market participants in two ways: 1) when the difference between the selling price of the FTR at the auction and the CRs is in the participant's favor, and 2) when the market participant is able to resell the FTRs (obligations or options) acquired previously at a price that leaves a net profit. Twenty participants made profits by selling obligations or options that they had acquired in previous rounds of the auction. Three participants had losses from these sales. Table 25 shows the 25 participants that had profits or losses for resselling options and/or obligations in the auction.

It is important to point out that among the 11 participants that made more than $10,000 in profits from selling in the auction, 8 participants are of type E and 3 participants are of type D (see type's description in Section 6.2.2). In contrast, the 3 participants that had losses from selling are either of type A or type B. This shows that the speculators made money not only but bearing the risk, but also by wisely buying and reselling in the auction. In contrast, 3 of the hedgers lost money by reselling in the auction what they had bought previously.

| Participant | Profits From Obligation Sales | Profits From Option Sales | Total Profits From Sales |
|---|---|---|---|
| 14 | 1,046,000 | 354,670 | 1,400,670 |
| 5 | 981,170 | 0 | 981,170 |
| 8 | 769,970 | 85,408 | 855,378 |
| 1 | 485,950 | 0 | 485,950 |
| 9 | 305,680 | 0 | 305,680 |
| 6 | 284,620 | 0 | 284,620 |
| 24 | 123,990 | 62,450 | 186,440 |
| 2 | 108,330 | 0 | 108,330 |
| 3 | 63,574 | 36,675 | 100,249 |
| 4 | 42,133 | 0 | 42,133 |
| 15 | 13,593 | 0 | 13,593 |
| 11 | 4,885 | 0 | 4,885 |
| 26 | 4,363 | 0 | 4,363 |
| 7 | 2,730 | 0 | 2,730 |
| 46 | 1,989 | 0 | 1,989 |
| 21 | 1,399 | 0 | 1,399 |
| 52 | 543 | 0 | 543 |
| 17 | 294 | 0 | 294 |
| 43 | 48 | 0 | 48 |
| 28 | -12,829 | 0 | -12,829 |
| 38 | -42,993 | 0 | -42,993 |
| 22 | - 163,770 | 0 | - 163,770 |

**Table 25. Participant's profits and losses from selling FTRs in the auction**

## 7 Buy Obligation FTRs - Analyses of Paths.

According to the auction rules any of the 667 nodes can serve as source or sink for an FTR, so there are (½)*667*666 = 222,111 pairs of nodes for which an FTR could be sold. In the auction analyzed there were only 3,767 pairs of nodes or “paths” for which there were FTR transactions.

For only 166 paths out of the 3,767 paths, there were trades of FTRs that implied conflicting expectations about the direction of transmission congestion. For the rest of the 3,601 paths, the prices of the FTRs traded show that different market participants had the same expectations about the direction of transmission congestion[5].

To visualize the paths and account for the direction of the expected congestion, this analysis treats the sinks of FTRs bought at a negative price as Points Of Injection (POI) and the sources of these FTRs are considered Points Of Withdrawal (POW), since in fact a trader of an FTRs at a negative price expects transmission congestion to occur in the direction sink to source.

The following graphs show the paths for which there were “Buy Obligations” FTR’s traded. Each point indicates that there was at least one FTR obligation bought by a market participant that implied expectations of transmission congestion in the direction POI to POW. Since there were paths for which there were transactions that implied expectations of transmission congestion in both directions (there was expected congestion

[5] A trade of an FTR at a positive price from A to B, implies that the buyer expects transmission in the direction A to B. Similarly, a trade of an FTR at a negative price from B to A, implies that the speculator expects transmission congestion in the direction A to B. However if for a given pair of nodes A and B, there are FTRs sold at a positive price for the path A to B, and there are also FTRs sold at a positive price for the path B to A, or FTRs sold at a negative price for the path A to B, then we state that there is disagreement about the direction of transmission congestion.

both from A to B and from B to A), the following graphs include 166 paths more, for a total of 3,933 paths.

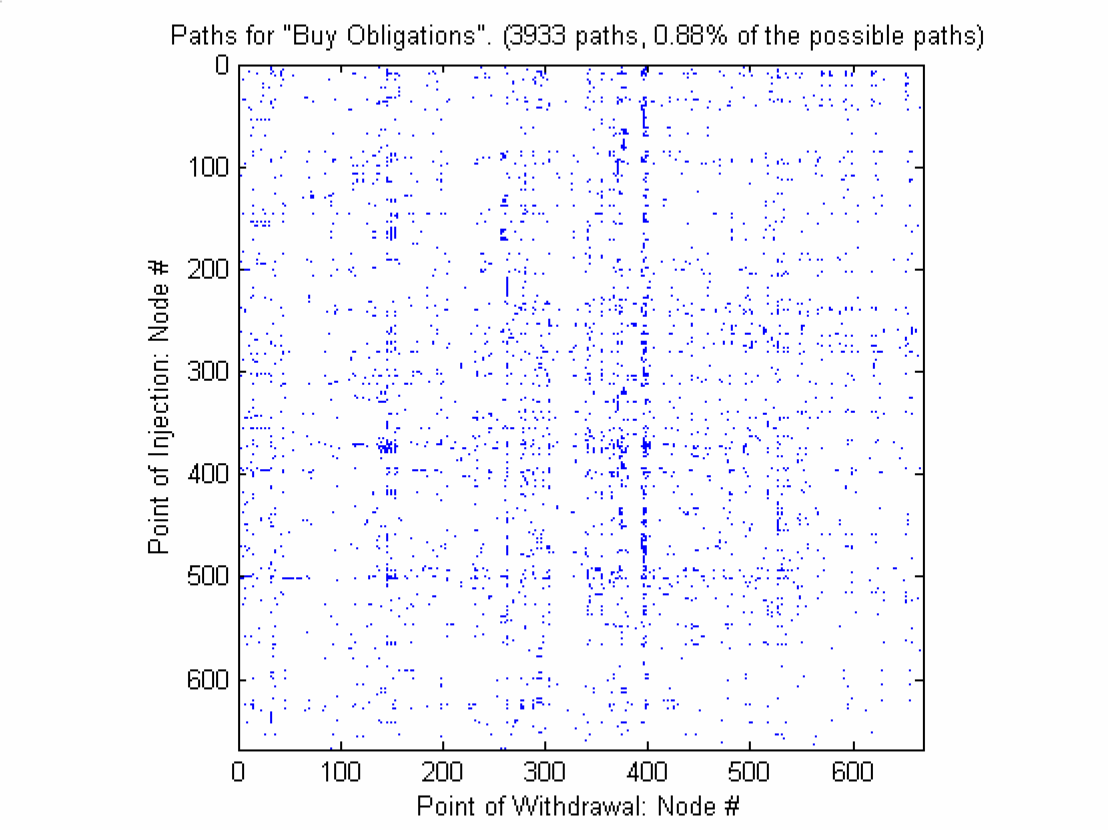


**Figure 21. Paths for buying obligations**

From observing these graphs, some important nodes can be identified. For example, it is evident that market participants forecasted congestion delivering power to node 400 from many other nodes of the grid, and therefore bought obligation FTRs with this node as Point of Withdrawal (that is as a sink of FTRs bought at a positive price or as a source for FTRs bought at a negative price).

The following plots present those paths for which different classes of obligation FTRs were bought by market participants.

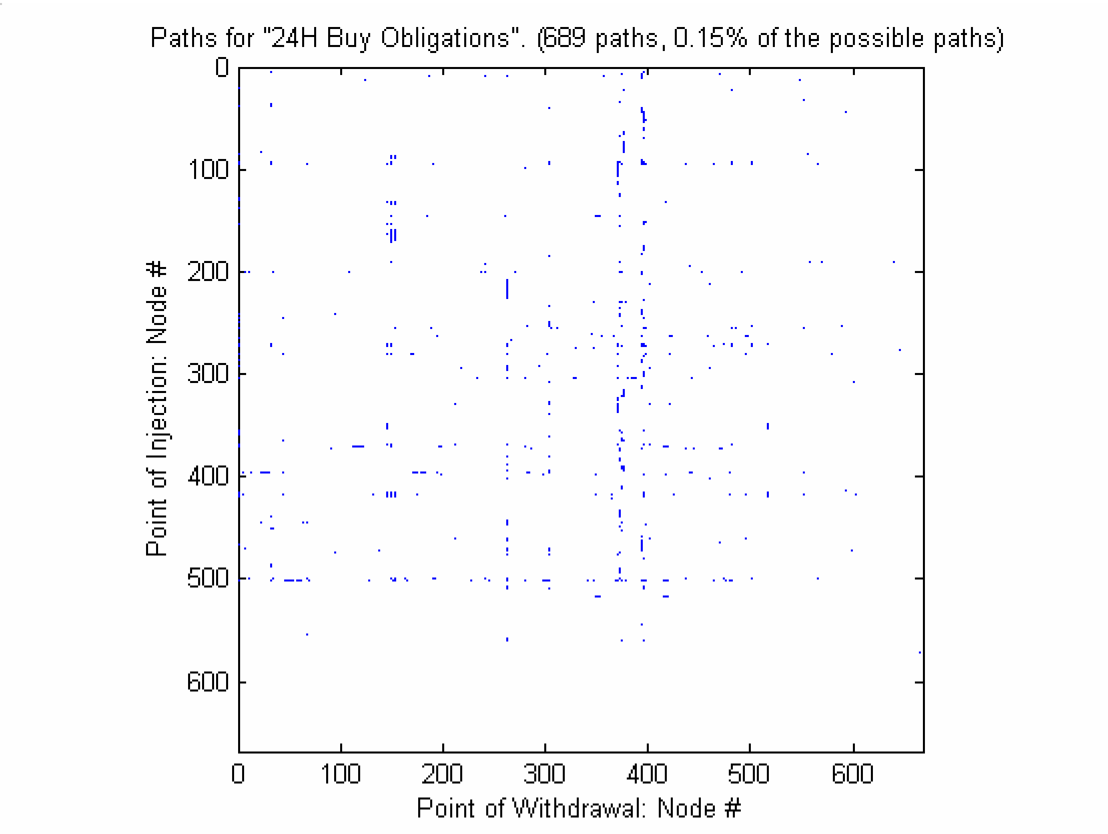


**Figure 22. Paths for "24H Buy Obligations"**

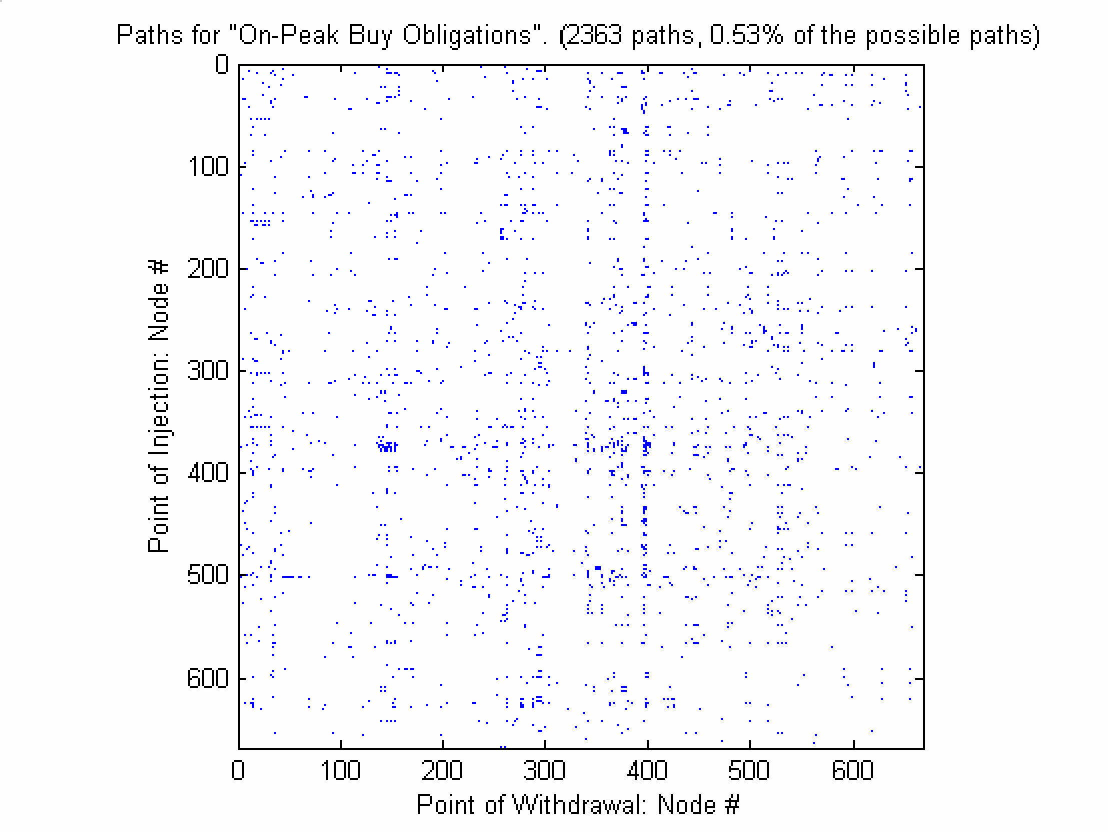


**Figure 23. Paths for On-peak Buy Obligations**

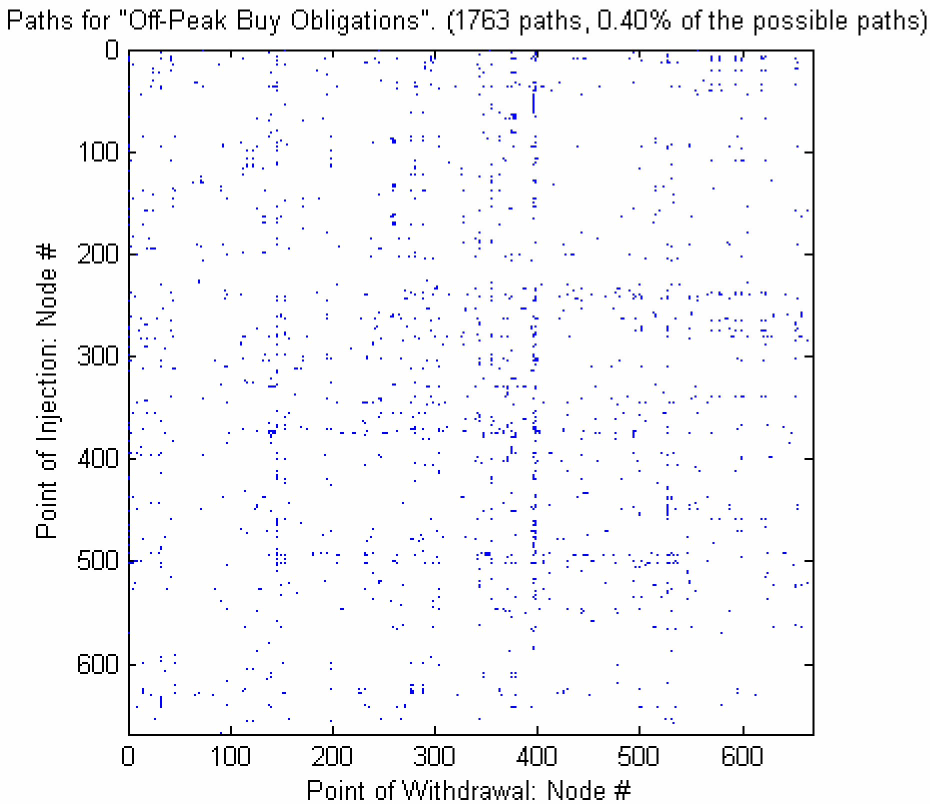


**Figure 24. Paths for Off-peak Buy Obligations**

### 7.1 Analysis of paths for which there was no disagreement about expected direction of transmission congestion

For 95.6% of the paths, there were no FTRs that implied disagreement in the expectation of the direction of transmission congestion. The capacity traded for these paths represents 95.6% of the total capacity traded in "buy obligation" FTRs, and 94.6% of the "buy obligation" FTRs traded. Most of the paths were traded either only by hedgers or only by speculators, and just 2% of the paths had transactions for both hedgers and speculators. The trades for those paths that had only hedgers participating, accounted for almost 63% of the total capacity traded (4.024E+8 MWh), while those paths that involved only speculators had trades for 17% of the total capacity traded for "buy obligation” FTRs . For those paths for which both hedgers and speculators purchased FTRs, the capacity traded by speculators was only 1.2%.

Given the physical laws that govern power flow, the offer of a speculator to bear the risk on one path, might affect the price that a hedger pays for an FTR on another path. In this sense, hedgers and speculators “interact” even if they do not trade FTRs for exactly the same paths.  Because the whole grid is connected and the congestion on one line has effects on many others, a bet on the congestion for a particular point-to-point implicitly implies a bet on the congestion everywhere else in the grid.

| | Num Paths | %Num Paths | Total MWh | % MWh | Total FTRs | % FTRs |
|---|---|---|---|---|---|---|
| Paths with FTRs only Traded By Hedgers | 1,634 | 43.4% | 2.52E+08 | 62.7% | 6,766 | 55.8% |
| Paths with FTRs only Traded By Speculators | 1,887 | 50.1% | 6.87E+07 | 17.1% | 3,821 | 31.5% |
| Paths with FTRs traded by Hedgers and Speculators | 80 | 2.1% | 5.90E+07 | 14.7% | 645 | 5.3% |
| | | | 4.83E+06 | 1.2% | 231 | 1.9% |
| Total | 3,601 | 95.6% | 3.85E+08 | 95.6% | 11,463 | 94.6% |

**Table 26. Analysis of paths for which prices of Buy-Obligation FTR did not imply disagreement about the direction of transmission congestion**

## 7.2 Paths traded exclusively by hedgers: classes of FTRs

Paths with 24 hour FTRs, represented only 12% of the total paths, but accounted for more than 30% of the total buy-obligation FTRs traded and more than 35% of the capacity. Most of the paths traded exclusively by hedgers had FTRs for off-peak hours.

| Class | Price | | | Num Paths | %Num Paths | Class | Total MWh | % MWh | Total FTRs | % FTRs |
|---|---|---|---|---|---|---|---|---|---|---|
| Only 24H | > 0 | | | 349 | 9.3% | 24 | 6.32E+07 | 15.7% | 2540 | 21.0% |
| Only On-peak | > 0 | | | 459 | 12.2% | On | 1.62E+07 | 4.0% | 631 | 5.2% |
| Only Off-peak | > 0 | | | 475 | 12.6% | Off | 1.73E+07 | 4.3% | 760 | 6.3% |
| | | | | | | | | | | |
| 24H and On | 24 > 0 | On>0 | | 53 | 1.4% | 24 | 2.15E+07 | 5.3% | 287 | 2.4% |
| | | | | | | On | 2.54E+06 | 0.6% | 68 | 0.6% |
| 24 and Off | 24 > 0 | Off>0 | | 35 | 0.9% | 24 | 2.47E+07 | 6.1% | 511 | 4.2% |
| | | | | | | Off | 1.07E+06 | 0.3% | 57 | 0.5% |
| On and Off | On > 0 | Off>0 | | 213 | 5.7% | On | 2.49E+07 | 6.2% | 527 | 4.3% |
| | | | | | | Off | 2.45E+07 | 6.1% | 526 | 4.3% |
| 24, On and Off | 24 > 0 | On > 0 | Off>0 | 50 | 1.3% | 24 | 3.38E+07 | 8.4% | 531 | 4.4% |
| | | | | | | On | 1.22E+07 | 3.0% | 177 | 1.5% |
| | | | | | | Off | 1.04E+07 | 2.6% | 151 | 1.2% |

**Table 27. Classes of FTRs for Paths traded exclusively by hedgers**

## 7.3 Paths traded exclusively by speculators: classes of FTRs

Most of the paths traded exclusively by speculators had FTRs for on-peak hours (35% of the paths) and accounted for more than 8% of the total MWh capacity traded.

| Class | Price | | | Num Paths | %Num Paths | Class | Total MWh | % MWh | Total FTRs | % FTRs |
|---|---|---|---|---|---|---|---|---|---|---|
| Only 24 | < 0 | | | 92 | 2.4% | 24 | 8.67E+06 | 2.2% | 232 | 1.9% |
| | 0 | | | 1 | 0.0% | 24 | 1.76E+05 | 0.0% | 1 | 0.0% |
| Only On | < 0 | | | 1,013 | 26.9% | On | 1.92E+07 | 4.8% | 1457 | 12.0% |
| | 0 | | | 3 | 0.1% | On | 2.09E+05 | 0.1% | 8 | 0.1% |
| Only Off | < 0 | | | 421 | 11.2% | Off | 9.03E+06 | 2.2% | 672 | 5.5% |
| | 0 | | | 3 | 0.1% | Off | 3.66E+04 | 0.0% | 5 | 0.0% |
| | | | | | | | | | | |
| 24H and On | 24<0 | On<0 | | 2 | 0.1% | 24 | 7.07E+05 | 0.2% | 10 | 0.1% |
| | | | | | | On | 3.22E+05 | 0.1% | 6 | 0.0% |
| 24 and Off | 24<0 | Off<0 | | 3 | 0.1% | 24 | 3.87E+04 | 0.0% | 12 | 0.1% |
| | | | | | | Off | 1.31E+05 | 0.0% | 5 | 0.0% |
| On and Off | On<0 | Off<0 | | 340 | 9.0% | On | 1.33E+07 | 3.3% | 725 | 6.0% |
| | | | | | | Off | 1.27E+07 | 3.2% | 592 | 4.9% |
| | On=0 | Off=0 | | 3 | 0.1% | On | 1.12E+05 | 0.0% | 7 | 0.1% |
| | | | | | | Off | 2.17E+05 | 0.1% | 13 | 0.1% |
| 24, On and Off | 24<0 | On<0 | Off<0 | 6 | 0.2% | 24 | 1.21E+06 | 0.3% | 34 | 0.3% |
| | | | | | | On | 1.45E+06 | 0.4% | 24 | 0.2% |
| | | | | | | Off | 1.21E+06 | 0.3% | 18 | 0.1% |

**Table 28. Paths traded by speculators**

## 7.4 Paths traded both by hedgers and speculators: classes of FTRs

Most of the paths that were traded both by hedgers and speculators had FTRs for on-peak hours, as the following tables show.

| Class | Price | Num Paths | %Num Paths | Class | Total MWh | % MWh | Total FTRs | % FTRs |
|---|---|---|---|---|---|---|---|---|
| Only 24H | 24 > 0 and 24 < 0 | 1 | 0.0% | 24 | 4.67E+05 | 0.1% | 8 | 0.1% |
| | | | | 24 | 4.67E+05 | 0.1% | 4 | 0.0% |
| Only On-peak | On > 0 and On < 0 | 4 | 0.1% | On | 2.17E+05 | 0.1% | 11 | 0.1% |
| | | | | On | 1.13E+05 | 0.0% | 5 | 0.0% |
| Only Off-peak | Off > 0 and Off < 0 | 1 | 0.0% | Off | 3.47E+04 | 0.0% | 2 | 0.0% |
| | | | | Off | 9.38E+03 | 0.0% | 1 | 0.0% |

**Table 29. MWH and FTRs for paths traded by hedgers and speculators - Paths with FTRs for only one class**

| Class | Price | | Num Paths | %Num Paths | Class | Total MWh | % MWh | Total FTRs | % FTRs |
|---|---|---|---|---|---|---|---|---|---|
| 24H and On | 24 > 0 | On<0 | 8 | 0.2% | 24 | 9.36E+06 | 2.3% | 35 | 0.3% |
| | | | | | On | 7.99E+04 | 0.0% | 12 | 0.1% |
| | | On>0 & On<0 | 2 | 0.1% | 24 | 7.91E+04 | 0.0% | 10 | 0.1% |
| | | | | | On | 1.64E+04 | 0.0% | 2 | 0.0% |
| | | | | | On | 2.05E+04 | 0.0% | 3 | 0.0% |
| | 24 < 0 | On>0 | 5 | 0.1% | 24 | 1.76E+05 | 0.0% | 11 | 0.1% |
| | | | | | On | 3.85E+05 | 0.1% | 9 | 0.1% |
| | 24 > 0 & 24 < 0 | On>0 | 1 | 0.0% | 24 | 3.92E+06 | 1.0% | 14 | 0.1% |
| | | | | | 24 | 8.78E+04 | 0.0% | 1 | 0.0% |
| | | | | | On | 2.05E+05 | 0.1% | 4 | 0.0% |
| | | On<0 | 1 | 0.0% | 24 | 1.11E+05 | 0.0% | 1 | 0.0% |
| | | | | | 24 | 2.20E+05 | 0.1% | 1 | 0.0% |
| | | | | | On | 6.14E+03 | 0.0% | 1 | 0.0% |
| 24 and Off | 24 > 0 | Off<0 | 1 | 0.0% | 24 | 6.32E+04 | 0.0% | 4 | 0.0% |
| | | | | | Off | 2.06E+04 | 0.0% | 3 | 0.0% |
| | 24 < 0 | Off>0 | 1 | 0.0% | 24 | 2.90E+04 | 0.0% | 4 | 0.0% |
| | | | | | Off | 3.28E+04 | 0.0% | 1 | 0.0% |
| On and Off | On > 0 | Off<0 | 7 | 0.2% | On | 1.46E+05 | 0.0% | 15 | 0.1% |
| | | | | | Off | 8.30E+04 | 0.0% | 15 | 0.1% |
| | | Off>0 & Off<0 | 2 | 0.1% | On | 6.51E+04 | 0.0% | 4 | 0.0% |
| | | | | | Off | 2.77E+05 | 0.1% | 7 | 0.1% |
| | | | | | Off | 7.03E+03 | 0.0% | 4 | 0.0% |
| | On < 0 | Off>0 | 12 | 0.3% | On | 2.95E+05 | 0.1% | 24 | 0.2% |
| | | | | | Off | 6.50E+05 | 0.2% | 24 | 0.2% |
| | | Off>0 & Off<0 | 2 | 0.1% | On | 1.02E+05 | 0.0% | 15 | 0.1% |
| | | | | | Off | 4.22E+04 | 0.0% | 3 | 0.0% |
| | | | | | Off | 9.38E+04 | 0.0% | 3 | 0.0% |
| | On > 0 & On < 0 | Off>0 | 4 | 0.1% | On | 1.77E+05 | 0.0% | 8 | 0.1% |
| | | | | | On | 1.00E+05 | 0.0% | 8 | 0.1% |
| | | | | | Off | 4.37E+05 | 0.1% | 11 | 0.1% |
| | | Off<0 | 9 | 0.2% | On | 1.84E+05 | 0.0% | 18 | 0.1% |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | On | 8.03E+05 | 0.2% | 23 | 0.2% |
| | | | | | | Off | 3.39E+05 | 0.1% | 15 | 0.1% |
| | | | Off>0 & Off<0 | 3 | 0.1% | On | 1.31E+06 | 0.3% | 23 | 0.2% |
| | | | | | | On | 3.73E+04 | 0.0% | 4 | 0.0% |
| | | | | | | Off | 1.10E+06 | 0.3% | 31 | 0.3% |
| | | | | | | Off | 1.31E+05 | 0.0% | 8 | 0.1% |
| 24, On and Off | 24 > 0 | On < 0 | Off<0 | 5 | 0.1% | 24 | 3.74E+06 | 0.9% | 51 | 0.4% |
| | | | | | | On | 3.73E+05 | 0.1% | 18 | 0.1% |
| | | | | | | Off | 2.36E+05 | 0.1% | 12 | 0.1% |
| | | On > 0 & < 0 | Off>0 | 3 | 0.1% | 24 | 3.77E+06 | 0.9% | 20 | 0.2% |
| | | | | | | On | 8.67E+06 | 2.2% | 79 | 0.7% |
| | | | | | | On | 1.25E+05 | 0.0% | 7 | 0.1% |
| | | | | | | Off | 4.54E+06 | 1.1% | 39 | 0.3% |
| | | | Off>0 & <0 | 3 | 0.1% | 24 | 2.74E+06 | 0.7% | 44 | 0.4% |
| | | | | | | On | 4.30E+06 | 1.1% | 31 | 0.3% |
| | | | | | | On | 2.68E+05 | 0.1% | 9 | 0.1% |
| | | | | | | Off | 4.70E+06 | 1.2% | 35 | 0.3% |
| | | | | | | Off | 3.47E+04 | 0.0% | 3 | 0.0% |
| | 24 < 0 | On > 0 | Off>0 | 1 | 0.0% | 24 | 1.24E+05 | 0.0% | 1 | 0.0% |
| | | | | | | On | 8.19E+04 | 0.0% | 3 | 0.0% |
| | | | | | | Off | 4.69E+04 | 0.0% | 2 | 0.0% |
| | 24 > 0 & 24 < 0 | On > 0 & On < 0 | Off<0 | 4 | 0.1% | 24 | 6.08E+06 | 1.5% | 75 | 0.6% |
| | | | | | | 24 | 2.27E+05 | 0.1% | 8 | 0.1% |
| | | | | | | On | 1.02E+06 | 0.3% | 21 | 0.2% |
| | | | | | | On | 1.03E+05 | 0.0% | 4 | 0.0% |
| | | | | | | Off | 1.18E+05 | 0.0% | 4 | 0.0% |

**Table 30. MWH and FTRs for paths traded by hedgers and speculators - Paths with FTRs for more than one class**

## 7.5 Competition for FTRs of the same path

There were more trades for those paths that attracted the interest of hedgers than for those paths that attracted the interest of speculators. Also, the number of FTRs traded by hedgers for the paths that were both traded by hedgers and speculators was more traded by hedgers than by speculators. The next table shows both the average number of FTRs per path (Total number of FTRs / Number of Paths) and the weighted average of the average number of FTRs per path (Sum over all classes of: Average Number of FTRs per path * Number of paths. Divided by total number of paths).

There were more market participants involved in trades for those paths traded only by hedgers, than for those paths traded only by speculators. Also, for those paths that were traded both by hedgers and speculators, there were more hedgers per path, than speculators.

| | Num Paths | Average Num FTRs per path | Weighted Average (Avg Num FTRs per path) | Weighted Average (Avg Num Part per path) |
|---|---|---|---|---|
| Paths with FTRs only Traded By Hedgers | 1,634 | 4.14 | 3.54 | 1.52 |
| Paths with FTRs only Traded By Speculators | 1,887 | 2.02 | 1.68 | 1.09 |
| Paths with FTRs traded by Hedgers and Speculators | 80 | 8.06 | 5.92 | 1.74 |
| | | 2.89 | 2.08 | 1.24 |
| Total | 3,601 | 3.18 | 2.61 | 1.30 |

**Table 31. Average number of buy Obligations FTRs and participants per path**

The following tables show in detail the average number of FTRs and market participants involved in FTR-trades for each path. For those paths traded exclusively by hedgers, the highest average of number of participants was for those paths that had FTRs for 24 hours and off-peak hours.

| Class | Price | | | Num Paths | Average NumFTRs | Avg Num Part per path |
|---|---|---|---|---|---|---|
| Only 24H | > 0 | | | 349 | 7.28 | 2.38 |
| Only On-peak | > 0 | | | 459 | 1.37 | 1.04 |
| Only Off-peak | > 0 | | | 475 | 1.60 | 1.08 |
| | | | | | | |
| 24H and On | 24 > 0 | On>0 | | 53 | 5.42 | 2.02 |
| | | | | | 1.28 | 1.00 |
| 24 and Off | 24 > 0 | Off>0 | | 35 | 14.60 | 4.40 |
| | | | | | 1.63 | 1.09 |
| On and Off | On > 0 | Off>0 | | 213 | 2.47 | 1.13 |
| | | | | | 2.47 | 1.13 |
| 24, On and Off | 24 > 0 | On > 0 | Off>0 | 50 | 10.62 | 3.12 |
| | | | | | 3.54 | 1.46 |
| | | | | | 3.02 | 1.38 |

**Table 32. Average number of participants per path for those paths traded only by hedgers**

For those paths traded exclusively by speculators, the highest average of number of participants was for those paths that had FTRs for on-peak and off-peak hours traded at zero price.[6] In general, there was more competition for FTRs for 24 hours.

| Class | Price | Num Paths | Average NumFTRs | Avg Num Part per path |
|---|---|---|---|---|
| Only 24 | < 0 | 92 | 2.52 | 1.16 |
| | 0 | 1 | 1.00 | 1.00 |
| Only On | < 0 | 1,013 | 1.44 | 1.07 |
| | 0 | 3 | 2.67 | 1.33 |
| Only Off | < 0 | 421 | 1.60 | 1.08 |
| | 0 | 3 | 1.67 | 1.00 |
| 24H and On | 24<0, On<0 | 2 | 5.00 | 1.50 |
| | | | 3.00 | 1.50 |
| 24 and Off | 24<0, Off<0 | 3 | 4.00 | 1.00 |
| | | | 1.67 | 1.00 |
| On and Off | On<0, Off<0 | 340 | 2.13 | 1.16 |
| | | | 1.74 | 1.11 |
| | On=0, Off=0 | 3 | 2.33 | 1.67 |
| | | | 4.33 | 1.67 |
| 24, On and Off | 24<0, On<0, Off<0 | 6 | 5.67 | 1.50 |
| | | | 4.00 | 1.33 |
| | | | 3.00 | 1.33 |

**Table 33. Average number of participants per path for those paths traded only by hedgers**

For those paths traded both by hedgers and speculators, the highest average of number of participants was for 24-hour FTRs at a positive price.

| Class | Price | Num Paths | Average NumFTRs | Avg Num Part per path |
|---|---|---|---|---|
| Only 24H | 24 > 0 and 24 < 0 | 1 | 8.00 | 1.00 |
| | | | 4.00 | 1.00 |
| Only On-peak | On > 0 and On < 0 | 4 | 2.75 | 1.25 |
| | | | 1.25 | 1.00 |
| Only Off-peak | Off > 0 and Off < 0 | 1 | 2.00 | 1.00 |
| | | | 1.00 | 1.00 |

**Table 34. Average number of participants for paths traded both by hedgers and speculators (Table continues below)**

[6] There were only 3 paths for which there were FTRs for on and off-peak hours traded at price = 0.

| Class | Price | | | Num Paths | Average NumFTRs | Avg Num Part per path |
|---|---|---|---|---|---|---|
| 24H and On | 24 > 0 | On<0 | | 8 | 4.38 | 1.38 |
| | | | | | 1.50 | 1.00 |
| | | On>0 & On<0 | | 2 | 5.00 | 2.00 |
| | | | | | 1.00 | 1.00 |
| | | | | | 1.50 | 1.00 |
| | 24 < 0 | On>0 | | 5 | 2.20 | 1.00 |
| | | | | | 1.80 | 1.40 |
| | 24 > 0 & 24 < 0 | On>0 | | 1 | 14.00 | 2.00 |
| | | | | | 1.00 | 1.00 |
| | | | | | 4.00 | 1.00 |
| | | On<0 | | 1 | 1.00 | 1.00 |
| | | | | | 1.00 | 1.00 |
| | | | | | 1.00 | 1.00 |
| 24 and Off | 24 > 0 | Off<0 | | 1 | 4.00 | 1.00 |
| | | | | | 3.00 | 2.00 |
| | 24 < 0 | Off>0 | | 1 | 4.00 | 1.00 |
| | | | | | 1.00 | 1.00 |
| On and Off | On > 0 | Off<0 | | 7 | 2.14 | 1.14 |
| | | | | | 2.14 | 1.14 |
| | | Off>0 & Off<0 | | 2 | 2.00 | 1.50 |
| | | | | | 3.50 | 1.00 |
| | | | | | 2.00 | 1.00 |
| | On < 0 | Off>0 | | 12 | 2.00 | 1.33 |
| | | | | | 2.00 | 1.00 |
| | | Off>0 & Off<0 | | 2 | 7.50 | 2.00 |
| | | | | | 1.50 | 1.00 |
| | | | | | 1.50 | 1.00 |
| | On > 0 & On < 0 | Off>0 | | 4 | 2.00 | 1.25 |
| | | | | | 2.00 | 1.00 |
| | | | | | 2.75 | 1.50 |
| | | Off<0 | | 9 | 2.00 | 1.00 |
| | | | | | 2.56 | 1.44 |
| | | | | | 1.67 | 1.00 |
| | | Off>0 & Off<0 | | 3 | 7.67 | 2.00 |
| | | | | | 1.33 | 1.00 |
| | | | | | 10.33 | 2.00 |
| | | | | | 2.67 | 1.00 |
| 24, On and Off | 24 > 0 | On < 0 | Off<0 | 5 | 10.20 | 2.20 |
| | | | | | 3.60 | 1.80 |
| | | | | | 2.40 | 1.40 |
| | | On > 0 & < 0 | Off>0 | 3 | 6.67 | 3.00 |
| | | | | | 26.33 | 6.00 |
| | | | | | 2.33 | 1.67 |
| | | | | | 13.00 | 3.00 |
| | | | Off>0 & <0 | 3 | 14.67 | 3.33 |
| | | | | | 10.33 | 4.33 |
| | | | | | 3.00 | 2.00 |
| | | | | | 11.67 | 3.33 |
| | | | | | 1.00 | 1.00 |
| | 24 < 0 | On > 0 | Off>0 | 1 | 1.00 | 1.00 |
| | | | | | 3.00 | 2.00 |
| | | | | | 2.00 | 1.00 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | 24 > 0 & 24 < 0 | On > 0 & On < 0 | Off<0 | 4 | 18.75 | 1.75 |
| | | | | | 2.00 | 2.00 |
| | | | | | 5.25 | 1.00 |
| | | | | | 1.00 | 1.00 |
| | | | | | 1.00 | 1.00 |

## 7.6 Prices and premiums

The following graphs show summary statistics of the price paid/received per MWh. Column 5 shows the Weighted Average Price (Weighted average price per path = Sum over all the FTRs of the path of (price*capacity)/sum off all capacity of the path. Weighted Average Price = Sum over all paths of weighted average price * capacity /sum(capacity))

For those paths traded only by hedgers, the highest price was for FTRs for On-peak hours, for those paths that had 24 hours and on-peak FTRs only.

| Class | Price | | | Num Paths | Class | WAvgPrice Min | WAvgPrice Perc100 | Wavg EAvgPrice | Wstd WAvgPrice |
|---|---|---|---|---|---|---|---|---|---|
| Only 24H | > 0 | | | 349 | 24 | 0.00 | 6.21 | 1.73 | 2.45 |
| Only On-peak | > 0 | | | 459 | On | 0.00 | 9.84 | 0.60 | 1.25 |
| Only Off-peak | > 0 | | | 475 | Off | 0.00 | 5.43 | 0.69 | 0.69 |
| | | | | | | | | | |
| 24H and On | 24 > 0 | | On>0 | 53 | 24 | 0.04 | 4.81 | 0.90 | 0.98 |
| | | | | | On | 0.00 | 7.37 | 2.94 | 3.04 |
| 24 and Off | 24 > 0 | | Off>0 | 35 | 24 | 0.05 | 5.96 | 1.36 | 1.26 |
| | | | | | Off | 0.03 | 3.39 | 0.68 | 0.24 |
| On and Off | On > 0 | | Off>0 | 213 | On | 0.03 | 7.62 | 0.91 | 0.98 |
| | | | | | Off | 0.01 | 2.90 | 0.46 | 0.21 |
| 24, On and Off | 24 > 0 | On > 0 | Off>0 | 50 | 24 | 0.04 | 5.47 | 1.21 | 1.19 |
| | | | | | On | 0.06 | 8.34 | 1.34 | 3.18 |
| | | | | | Off | 0.02 | 2.97 | 0.40 | 0.33 |

**Table 35. Price statistics for paths traded only by hedgers**

The following tables show price statistics for those paths traded exclusively by speculators. All the values shown here are in fact the quantity speculators received upfront for holding the FTR. For those paths traded exclusively by speculators the highest Weighted Average of Weighted Average price was for those paths that had trades for the three classes of FTRs, but the highest Average of Weighted Average Price was for those paths that had only on-peak FTRs.

| Class | Price | Num Paths | Class | WAvgPrice Min | WAvgPrice Max | Wavg EAvgPrice | Wstd WAvgPrice |
|---|---|---|---|---|---|---|---|
| Only 24 | < 0 | 92 | 24 | 0.03 | 4.93 | 0.56 | 0.57 |
| | 0 | 1 | 24 | NaN | NaN | 0.00 | 0.00 |
| Only On | < 0 | 1,013 | On | 0.00 | 12.69 | 2.76 | 7.24 |
| | 0 | 3 | On | NaN | NaN | 0.00 | 0.00 |
| Only Off | < 0 | 421 | Off | 0.00 | 4.54 | 1.06 | 1.29 |
| | 0 | 3 | Off | NaN | NaN | 0.00 | 0.00 |
| 24H and On | 24<0 On<0 | 2 | 24 | 0.07 | 0.42 | 0.42 | 0.00 |
| | | | On | 0.13 | 1.33 | 1.20 | 0.14 |
| 24 and Off | 24<0 Off<0 | 3 | 24 | 0.20 | 0.78 | 0.61 | 0.03 |
| | | | Off | 0.02 | 0.52 | 0.27 | 0.02 |
| On and Off | On<0 Off<0 | 340 | On | 0.03 | 11.55 | 1.58 | 3.85 |
| | | | Off | 0.00 | 4.77 | 0.77 | 0.84 |
| | On=0 Off=0 | 3 | On | NaN | NaN | 0.00 | 0.00 |
| | | | Off | NaN | NaN | 0.00 | 0.00 |
| 24, On and Off | 24<0 On<0 Off<0 | 6 | 24 | 0.41 | 5.51 | 4.76 | 2.79 |
| | | | On | 0.68 | 7.57 | 6.55 | 5.65 |
| | | | Off | 0.19 | 3.72 | 3.03 | 1.70 |

**Table 36. Price statistics for paths traded only by speculators**

For those paths that were traded by both hedgers and speculators it is interesting to contrast the price paid by the hedgers with the price received by the speculators. There were just a few paths (40) that had the same class of FTRs sold to both hedgers and speculators. For most of the paths (25) that had trades by hedger and speculators for the same class of FTR, the price paid by hedgers was lower than the (weighted average weighted) price received by speculators.

| Class | Price | Num Paths | Class | WAvgPrice Min | WAvgPrice Max | Wavg EAvgPrice | Wstd WAvgPrice |
|---|---|---|---|---|---|---|---|
| Only 24H | 24 > 0 and 24 < 0 | 1 | 24 | 0.91 | 0.91 | 0.91 | 0.00 |
| | | | 24 | 0.87 | 0.87 | 0.87 | 0.00 |
| Only On-peak | On > 0 and On < 0 | 4 | On | 0.07 | 1.00 | 0.60 | 0.11 |
| | | | On | 0.07 | 1.08 | 0.19 | 0.07 |
| Only Off-peak | Off > 0 and Off < 0 | 1 | Off | 0.37 | 0.37 | 0.37 | 0.00 |
| | | | Off | 0.37 | 0.37 | 0.37 | 0.00 |

**Table 37. Price statistics for paths traded both by hedgers and speculators. Paths traded for only one class.**

| Class | Price | | | Num Paths | Class | WAvgPrice Min | WAvgPrice Max | Wavg EAvgPrice | Wstd WAvgPrice |
|---|---|---|---|---|---|---|---|---|---|
| 24H and On | 24 > 0 | On<0 | | 8 | 24 | 0.23 | 4.05 | 1.09 | 0.72 |
| | | | | | On | 0.77 | 6.27 | 3.00 | 4.14 |
| | | On>0 & On<0 | | 2 | 24 | 0.28 | 2.19 | 0.47 | 0.33 |
| | | | | | On | 0.61 | 3.34 | 1.97 | 1.88 |
| | | | | | On | 0.61 | 3.12 | 2.11 | 1.52 |
| | 24 < 0 | On>0 | | 5 | 24 | 0.16 | 0.61 | 0.30 | 0.02 |
| | | | | | On | 0.14 | 0.86 | 0.43 | 0.05 |
| | 24 > 0 & 24 < 0 | On>0 | | 1 | 24 | 3.51 | 3.51 | 3.51 | 0.00 |
| | | | | | 24 | 3.08 | 3.08 | 3.08 | 0.00 |
| | | | | | On | 5.16 | 5.16 | 5.16 | 0.00 |
| | | On<0 | | 1 | 24 | 0.53 | 0.53 | 0.53 | 0.00 |
| | | | | | 24 | 0.58 | 0.58 | 0.58 | 0.00 |
| | | | | | On | 0.83 | 0.83 | 0.83 | 0.00 |
| 24 and Off | 24 > 0 | Off<0 | | 1 | 24 | 0.79 | 0.79 | 0.79 | 0.00 |
| | | | | | Off | 0.58 | 0.58 | 0.58 | 0.00 |
| | 24 < 0 | Off>0 | | 1 | 24 | 0.61 | 0.61 | 0.61 | 0.00 |
| | | | | | Off | 0.10 | 0.10 | 0.10 | 0.00 |
| On and Off | On > 0 | Off<0 | | 7 | On | 0.10 | 1.84 | 1.03 | 0.31 |
| | | | | | Off | 0.40 | 2.99 | 1.16 | 0.91 |
| | | Off>0 & Off<0 | | 2 | On | 0.21 | 0.93 | 0.75 | 0.09 |
| | | | | | Off | 0.22 | 0.68 | 0.61 | 0.03 |
| | | | | | Off | 0.53 | 1.05 | 0.74 | 0.06 |
| | On < 0 | Off>0 | | 12 | On | 0.08 | 4.92 | 2.08 | 1.88 |
| | | | | | Off | 0.29 | 2.60 | 1.22 | 0.42 |
| | | Off>0 & Off<0 | | 2 | On | 2.44 | 6.95 | 3.66 | 4.00 |
| | | | | | Off | 1.23 | 3.08 | 2.46 | 0.76 |
| | | | | | Off | 1.63 | 3.18 | 2.25 | 0.58 |
| | On > 0 & On < 0 | Off>0 | | 4 | On | 0.55 | 2.86 | 0.76 | 0.29 |
| | | | | | On | 0.68 | 3.02 | 2.55 | 0.76 |
| | | | | | Off | 0.25 | 1.22 | 0.69 | 0.18 |
| | | Off<0 | | 9 | On | 0.18 | 6.25 | 1.62 | 1.72 |
| | | | | | On | 0.60 | 4.92 | 1.11 | 1.71 |
| | | | | | Off | 0.02 | 2.39 | 0.60 | 0.26 |
| | | Off>0 & Off<0 | | 3 | On | 0.15 | 5.94 | 5.84 | 0.55 |
| | | | | | On | 0.69 | 5.75 | 3.61 | 4.89 |
| | | | | | Off | 0.32 | 1.95 | 1.80 | 0.21 |
| | | | | | Off | 0.68 | 1.98 | 0.86 | 0.17 |
| 24, On and | 24 > | On < | Off<0 | 5 | 24 | 0.56 | 4.17 | 0.93 | 0.12 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Off | 0 | 0 | | | On | 1.42 | 6.42 | 2.24 | 1.26 |
| | | | | | Off | 0.17 | 2.29 | 0.57 | 0.22 |
| | | | | | 24 | 0.05 | 4.66 | 3.25 | 2.85 |
| | | | | | On | 0.08 | 6.96 | 5.07 | 7.75 |
| | | | | | On | 0.13 | 6.92 | 6.36 | 3.02 |
| | | | Off>0 | 3 | Off | 0.04 | 2.68 | 1.88 | 1.00 |
| | | | | | 24 | 1.61 | 3.77 | 2.64 | 0.93 |
| | | | | | On | 2.39 | 5.72 | 4.94 | 0.75 |
| | | | | | On | 2.51 | 5.76 | 5.62 | 0.26 |
| | | | | | Off | 0.92 | 2.06 | 1.43 | 0.12 |
| | | On > 0 & < 0 | Off>0 & <0 | 3 | Off | 0.97 | 1.96 | 1.54 | 0.14 |
| | | | | | 24 | 0.17 | 0.17 | 0.17 | 0.00 |
| | | | | | On | 0.23 | 0.23 | 0.23 | 0.00 |
| | 24 < 0 | On > 0 | Off>0 | 1 | Off | 0.16 | 0.16 | 0.16 | 0.00 |
| | | | | | 24 | 1.33 | 1.59 | 1.48 | 0.02 |
| | | | | | 24 | 1.27 | 1.58 | 1.45 | 0.02 |
| | | | | | On | 1.54 | 2.31 | 2.01 | 0.05 |
| | | | | | On | 1.98 | 2.33 | 2.15 | 0.03 |
| | 24 > 0 & 24 < 0 | On > 0 & On < 0 | Off<0 | 4 | Off | 0.85 | 0.98 | 0.91 | 0.00 |

**Table 38. Price statistics for paths traded both by hedgers and speculators. Paths traded for more than one class.**

## 7.7 Premium Paid

The following tables show summary statistics of premiums paid per path, for different categories of paths organized by class of FTRs traded and type of market participants. There were many paths traded by hedgers for only one class, for which the premium paid was negative (so these hedgers on average paid less for the FTR than what they received), and the total premium paid by hedgers for those paths sold exclusively for on-peak and off-peak hours was negative. However these “profits” made by hedgers were more than offset for the high premium they paid for those paths traded only for 24 hours. For those paths traded for more than one class the total premium paid for FTRs was positive except for FTRs for off-peak hours.

| Class | Price | | | Num Paths | Class | Total Premium paid | Num Paths with Pos Prem | Average Pos Prem | Num Paths with Neg Prem | Average Neg Prem | Num Paths with zero Prem |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Only 24H | > 0 | | | 349 | 24 | 2.22E+07 | 246 | 5.52E+03 | 103 | -1.55E+03 | 0 |
| Only On-peak | > 0 | | | 459 | On | -5.93E+05 | 192 | 2.03E+03 | 267 | -1.49E+03 | 0 |
| Only Off-peak | > 0 | | | 475 | Off | -3.18E+05 | 192 | 9.90E+02 | 283 | -1.19E+03 | 0 |
| | | | | | | | | | | | |
| 24H and On | 24 > 0 | On>0 | | 53 | 24 | 6.00E+06 | 47 | 6.67E+03 | 6 | -1.68E+03 | 0 |
| | | | | | On | 1.58E+06 | 47 | 5.06E+03 | 6 | -9.42E+02 | 0 |
| 24 and Off | 24 > 0 | Off>0 | | 35 | 24 | 8.44E+06 | 30 | 3.98E+03 | 5 | -2.07E+03 | 0 |
| | | | | | Off | -2.98E+04 | 14 | 1.43E+03 | 21 | -4.38E+02 | 0 |
| On and Off | On > 0 | Off>0 | | 213 | On | 3.43E+06 | 87 | 2.15E+03 | 126 | -1.31E+03 | 0 |
| | | | | | Off | 8.82E+05 | 78 | 5.95E+02 | 135 | -9.51E+02 | 0 |
| 24, On and Off | 24 > 0 | On > 0 | Off>0 | 50 | 24 | 3.44E+06 | 31 | 3.99E+03 | 19 | -1.75E+03 | 0 |
| | | | | | On | 1.98E+06 | 31 | 3.16E+03 | 19 | -9.89E+02 | 0 |
| | | | | | Off | -3.32E+05 | 17 | 1.25E+03 | 33 | -5.88E+02 | 0 |

**Table 39. Premium statistics for paths traded by hedgers. Paths traded only one class.**
**Table 40. Premium statistics for paths traded by hedgers. Paths traded for more than one class.**

For paths traded exclusively by speculators, the total premium paid was always negative (so speculators profited from the trades), but there were still a number of paths for which the average premium had positive sign.

| Class | Price | | | Num Paths | Class | Total Premium paid | Num Paths with Pos Prem | Average Pos Prem | Num Paths with Neg Prem | Average Neg Prem | Num Paths with zero Prem |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Only 24 | < 0 | | | 92 | 24 | -2.76E+06 | 21 | 1.14E+03 | 71 | -3.83E+03 | 0 |
| | 0 | | | 1 | 24 | -2.00E+04 | 0 | 0.00E+00 | 1 | -9.98E+02 | 0 |
| Only On | < 0 | | | 1,013 | On | -1.68E+07 | 123 | 1.44E+03 | 890 | -4.23E+03 | 0 |
| | 0 | | | 3 | On | 2.56E+02 | 1 | 5.37E+02 | 1 | -4.63E+02 | 1 |
| Only Off | < 0 | | | 421 | Off | -2.86E+06 | 72 | 1.29E+03 | 349 | -1.94E+03 | 0 |
| | 0 | | | 3 | Off | 0.00E+00 | 0 | 0.00E+00 | 0 | 0.00E+00 | 3 |
| 24H and On | 24<0 | On<0 | | 2 | 24 | -3.90E+05 | 0 | 0.00E+00 | 2 | -2.80E+03 | 0 |
| | | | | | On | -3.18E+05 | 0 | 0.00E+00 | 2 | -2.58E+03 | 0 |
| 24 and Off | 24<0 | Off<0 | | 3 | 24 | -1.50E+04 | 0 | 0.00E+00 | 3 | -2.87E+03 | 0 |
| | | | | | Off | -1.30E+04 | 0 | 0.00E+00 | 3 | -6.35E+02 | 0 |
| On and Off | On<0 | Off<0 | | 340 | On | -7.46E+06 | 47 | 2.04E+03 | 293 | -3.74E+03 | 0 |
| | | | | | Off | -2.67E+06 | 90 | 1.02E+03 | 250 | -1.71E+03 | 0 |
| | On=0 | Off=0 | | 3 | On | -1.62E+04 | 0 | 0.00E+00 | 3 | -4.54E+02 | 0 |
| | | | | | Off | -6.78E+04 | 0 | 0.00E+00 | 3 | -1.26E+03 | 0 |
| 24, On and Off | 24<0 | On<0 | Off<0 | 6 | 24 | -1.77E+06 | 0 | 0.00E+00 | 6 | -5.85E+03 | 0 |
| | | | | | On | -3.14E+06 | 0 | 0.00E+00 | 6 | -4.31E+03 | 0 |
| | | | | | Off | -1.05E+06 | 0 | 0.00E+00 | 6 | -1.56E+03 | 0 |

**Table 41. Premium statistics for paths traded by speculators. Paths traded for only one class**
**Table 42. Premium statistics for paths traded by speculators. Paths traded for more than one class.**

For those paths traded only for one class by both hedgers and speculators, total premium paid had the expected sign; positive for hedgers and negative for speculators.

| Class | Price | Num Paths | Class | Total Premium paid | Num Paths with Pos Prem | Average Pos Prem | Num Paths with Neg Prem | Average Neg Prem | Num Paths with zero Prem |
|---|---|---|---|---|---|---|---|---|---|
| Only 24H | 24 > 0 and 24 < 0 | 1 | 24 | 1.60E+05 | 1 | 3.01E+03 | 0 | 0.00E+00 | 0 |
| | | | 24 | -1.38E+05 | 0 | 0.00E+00 | 1 | -2.59E+03 | 0 |
| Only On-peak | On > 0 and On < 0 | 4 | On | 2.43E+04 | 2 | 2.05E+03 | 2 | -3.70E+02 | 0 |
| | | | On | -2.04E+04 | 0 | 0.00E+00 | 4 | -6.11E+02 | 0 |
| Only Off-peak | Off > 0 and Off < 0 | 1 | Off | 3.23E+03 | 1 | 4.36E+02 | 0 | 0.00E+00 | 0 |
| | | | Off | -8.23E+02 | 0 | 0.00E+00 | 1 | -4.11E+02 | 0 |

**Table 43. Premium statistics for paths traded by both hedgers and speculators. Paths traded for only one class**

For most of those paths traded for more than one class by both hedgers and speculators, total premium paid had the expected sign; positive for hedgers and negative for speculators. The only exceptions are premiums for the 13 paths highlighted in red in the table below.

| Class | Price | | Num Paths | Class | Total Premium paid | Num Paths with Pos Prem | Average Pos Prem | Num Paths with Neg Prem | Average Neg Prem | Num Paths with zero Prem |
|---|---|---|---|---|---|---|---|---|---|---|
| 24H and On | 24 > 0 | On<0 | 8 | 24 | 2.77E+06 | 7 | 4.53E+03 | 1 | -8.77E+02 | 0 |
| | | | | On | -8.19E+04 | 0 | 0.00E+00 | 8 | -3.80E+03 | 0 |
| | | On>0 & On<0 | 2 | 24 | 1.43E+04 | 2 | 1.64E+03 | 0 | 0.00E+00 | 0 |
| | | | | On | 5.64E+03 | 2 | 1.41E+03 | 0 | 0.00E+00 | 0 |
| | | | | On | -4.49E+03 | 0 | 0.00E+00 | 2 | -9.46E+02 | 0 |
| | 24 < 0 | On>0 | 5 | 24 | 2.89E+04 | 5 | 1.16E+03 | 0 | 0.00E+00 | 0 |
| | | | | On | -1.43E+05 | 0 | 0.00E+00 | 5 | -1.53E+03 | 0 |
| | 24 > 0 & 24 < 0 | On>0 | 1 | 24 | 5.27E+06 | 1 | 1.18E+04 | 0 | 0.00E+00 | 0 |
| | | | | 24 | -8.00E+04 | 0 | 0.00E+00 | 1 | -8.00E+03 | 0 |
| | | | | On | 4.91E+05 | 1 | 9.82E+03 | 0 | 0.00E+00 | 0 |
| | | On<0 | 1 | 24 | 3.19E+04 | 1 | 2.53E+03 | 0 | 0.00E+00 | 0 |
| | | | | 24 | -7.54E+04 | 0 | 0.00E+00 | 1 | -3.02E+03 | 0 |
| | | | | On | -3.42E+03 | 0 | 0.00E+00 | 1 | -2.28E+03 | 0 |
| 24 and Off | 24 > 0 | Off<0 | 1 | 24 | 5.46E+03 | 1 | 7.58E+02 | 0 | 0.00E+00 | 0 |
| | | | | Off | -3.62E+03 | 0 | 0.00E+00 | 1 | -8.22E+02 | 0 |
| | 24 < 0 | Off>0 | 1 | 24 | 6.55E+02 | 1 | 1.98E+02 | 0 | 0.00E+00 | 0 |
| | | | | Off | -3.70E+03 | 0 | 0.00E+00 | 1 | -5.29E+02 | 0 |
| On and Off | On > 0 | Off<0 | 7 | On | 1.13E+04 | 2 | 6.70E+02 | 5 | -1.06E+03 | 0 |
| | | | | Off | -4.07E+04 | 1 | 2.98E+02 | 6 | -2.77E+03 | 0 |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Off>0 & Off<0 | 2 | On | -7.41E+03 | 0 | 0.00E+00 | 2 | -4.90E+02 | 0 |
| | | | | | Off | 4.29E+04 | 1 | 8.69E+02 | 1 | -5.50E+01 | 0 |
| | | | | | Off | -2.84E+03 | 0 | 0.00E+00 | 2 | -2.01E+03 | 0 |
| | | On < 0 | Off>0 | 12 | On | -1.67E+05 | 1 | 6.62E+00 | 11 | -2.93E+03 | 0 |
| | | | | | Off | 5.68E+04 | 5 | 1.32E+03 | 7 | -1.10E+03 | 0 |
| | | | Off>0 & Off<0 | 2 | On | -1.84E+05 | 0 | 0.00E+00 | 2 | -7.60E+03 | 0 |
| | | | | | Off | 9.68E+03 | 2 | 8.63E+02 | 0 | 0.00E+00 | 0 |
| | | | | | Off | -4.10E+04 | 0 | 0.00E+00 | 2 | -2.03E+03 | 0 |
| | | On > 0 & On < 0 | Off>0 | 4 | On | -3.53E+04 | 2 | 2.27E+03 | 2 | -1.11E+03 | 0 |
| | | | | | On | -8.46E+04 | 1 | 6.26E+02 | 3 | -1.80E+03 | 0 |
| | | | | | Off | -2.06E+04 | 1 | 1.94E+02 | 3 | -4.41E+02 | 0 |
| | | | Off<0 | 9 | On | 2.19E+04 | 5 | 4.11E+03 | 4 | -1.02E+03 | 0 |
| | | | | | On | -3.99E+05 | 1 | 1.28E+03 | 8 | -3.10E+03 | 0 |
| | | | | | Off | -2.50E+04 | 2 | 1.21E+02 | 7 | -1.86E+03 | 0 |
| | | | Off>0 & Off<0 | 3 | On | 2.81E+06 | 1 | 9.00E+03 | 2 | -2.56E+03 | 0 |
| | | | | | On | -3.16E+04 | 1 | 4.58E+03 | 2 | -4.96E+03 | 0 |
| | | | | | Off | 3.92E+05 | 2 | 1.35E+03 | 1 | -2.17E+03 | 0 |
| | | | | | Off | -6.34E+04 | 1 | 2.17E+03 | 2 | -2.29E+03 | 0 |
| 24, On and Off | 24 > 0 | On < 0 | Off<0 | 5 | 24 | 1.17E+06 | 5 | 4.05E+03 | 0 | 0.00E+00 | 0 |
| | | | | | On | -2.29E+05 | 0 | 0.00E+00 | 5 | -3.61E+03 | 0 |
| | | | | | Off | -4.22E+04 | 0 | 0.00E+00 | 5 | -1.48E+03 | 0 |
| | | On > 0 & < 0 | Off>0 | 3 | 24 | 3.21E+06 | 3 | 5.09E+03 | 0 | 0.00E+00 | 0 |
| | | | | | On | 1.34E+07 | 3 | 4.11E+03 | 0 | 0.00E+00 | 0 |
| | | | | | On | -2.34E+05 | 0 | 0.00E+00 | 3 | -4.29E+03 | 0 |
| | | | | | Off | 1.57E+06 | 3 | 1.10E+03 | 0 | 0.00E+00 | 0 |
| | | | Off>0 & <0 | 3 | 24 | 2.05E+06 | 3 | 6.91E+03 | 0 | 0.00E+00 | 0 |
| | | | | | On | 5.97E+06 | 3 | 5.33E+03 | 0 | 0.00E+00 | 0 |
| | | | | | On | -4.71E+05 | 0 | 0.00E+00 | 3 | -5.57E+03 | 0 |
| | | | | | Off | 1.49E+06 | 3 | 1.62E+03 | 0 | 0.00E+00 | 0 |
| | | | | | Off | -1.29E+04 | 0 | 0.00E+00 | 3 | -1.69E+03 | 0 |
| | 24 < 0 | On > 0 | Off>0 | 1 | 24 | 6.13E+04 | 1 | 4.35E+03 | 0 | 0.00E+00 | 0 |
| | | | | | On | -5.16E+04 | 0 | 0.00E+00 | 1 | -2.58E+03 | 0 |
| | | | | | Off | -1.50E+04 | 0 | 0.00E+00 | 1 | -1.50E+03 | 0 |
| | 24 > 0 & 24 < 0 | On > 0 & On < 0 | Off<0 | 4 | 24 | 1.98E+06 | 4 | 2.81E+03 | 0 | 0.00E+00 | 0 |
| | | | | | 24 | -6.99E+04 | 0 | 0.00E+00 | 4 | -2.69E+03 | 0 |
| | | | | | On | 5.41E+05 | 4 | 1.68E+03 | 0 | 0.00E+00 | 0 |
| | | | | | On | -6.56E+04 | 0 | 0.00E+00 | 4 | -2.61E+03 | 0 |
| | | | | | Off | -1.25E+04 | 0 | 0.00E+00 | 4 | -4.98E+02 | 0 |

**Table 44. Premium statistics for paths traded by both hedgers and speculators. Paths traded for more than one class.**

## 7.8 Effect of liquidity and competition on the FTRs premium

In order to asses the effect that liquidity and competition in the FTRs market can have on the magnitude of the premium paid, we conduct a series of linear-regression analyses to elicit the relative value of the premium for each path (premium per MW divided by CRs per MW) as a function of the number of MWh traded, number of FTRs traded and number of participants involved. The number of transactions can be an indicator of how liquid the market of FTRs for a particular path is. For those paths sold at a positive price, the amount of capacity sold and the number of participants involved is an indication of how much demand there is for a given path. It is important to acknowledge that a much better indication of how much demand there is for a path, would be the number of total bids. Cleared bids are only a portion of total bids (10% in PJM) and indicate not only how much demand there is for a path, but also how much capacity there is. Nevertheless, with this caveat, we continue to regard number of FTRs, number of MWh traded, and number of participants involved as good indicators of market liquidity and competition.

We hypothesize that the higher the competition among hedgers (higher number of participants and higher number of MWh sold), the higher the premium paid. We also hypothesize that with higher liquidity (higher number of FTRs traded) there are more opportunities for "price discovery" and the lower the premium. In fact, a market participant can present several bids for the same FTR (same path, and same class), in the same round or in different rounds. Keeping everything else constant, with a higher number of FTRs traded there are more opportunities for price discovery.

The following table shows results of the regression analyses that explain the premium paid by hedgers, for those paths in which only hedgers participated and the average premium paid was positive, as a function of the number of FTRs, the Number of MWh traded, and the number of participants involved. For those paths sold only for the class 24h, both the number of FTRs and the number of participants have coefficient estimates with the expected sign that are statistically significant ($p\text{-value} < 0.05$) and marginally significant (p-value <0.1) respectively[7]. For the paths sold only for peak hours, the estimated coefficients for the 3 explanatory variables have the expected sign and are at least marginally significant. For those paths sold only for off-peak hours only the coefficient for the number of MWh has statistical significance.

| Trade | Dependent variable | Num Paths | NumFTRs | | NumMWh | | NumPart | |
|---|---|---|---|---|---|---|---|---|
| | | | estimate | p-value | estimate | p-value | estimate | p-value |
| Only 24h | Prem 24P/CRs | 245 | -0.02645 | 0.0172 | -5.82E-08 | 0.6043 | 0.0803 | 0.0569 |
| Only On | PremOnP/CRs | 123 | -1.4591 | 0.0003 | 4.11E-05 | <.0001 | 2.2115 | 0.0951 |
| Only Off | PremOffP/CRs | 171 | -0.3791 | 0.2356 | 1.00E-05 | 0.0033 | 0.2407 | 0.8086 |

**Table 45. Coefficient estimates for explanatory variables of the premium. Paths traded only by hedgers, for only one class, and where the premium paid was positive. Estimate of constant term is positive**

For those paths sold for both 24 and peak hours, the three variables are statistically significant to explain the premium for 24 hours, and two of the variables are statistically significant to explain the premium for peak hours. In the other cases the coefficients are non significant.

| Trade | Dependent variable | Num Paths | NumFTRs | | NumMWh | | NumPart | |
|---|---|---|---|---|---|---|---|---|
| | | | estimate | p-value | estimate | p-value | estimate | p-value |
| 24 & On | Prem 24P/CRs | 47 | -0.0355 | 0.0052 | 2.42E-07 | <.0001 | 0.1169 | 0.0253 |
| | PremOnP/CRs | 47 | -0.0523 | 0.0015 | 6.95E-08 | 0.0877 | 0.2366 | 0.0007 |
| 24 & Off | Prem 24P/CRs | 30 | Not enough observations | | | | | |
| | PremOffP/CRs | 13 | Not enough observations | | | | | |
| On & Off | PremOnP/CRs | 76 | -0.0459 | 0.1272 | 3.21E-07 | 0.1693 | 0.1522 | 0.4222 |
| | PremOffP/CRs | 76 | 0.0283 | 0.3307 | -1.92E-07 | 0.4201 | 0.0059 | 0.9631 |
| 24,On&Off | Prem 24P/CRs | 31 | 0.0117 | 0.3645 | -3.70E-08 | 0.5723 | -0.1022 | 0.061 |
| | PremOnP/CRs | 31 | 0.0057 | 0.656 | -8.52E-08 | 0.1924 | -0.0072 | 0.8911 |
| | PremOffP/CRs | 14 | Not enough observations | | | | | |

**Table 46. Coefficient estimates for explanatory variables of the premium. Paths traded only by hedgers, for more than one class, and where the premium paid was positive. Independent variables are totals. Estimate term is positive**

[7] All coefficient estimates and p-values measure Type III effects, that is the effect of each independent variable after the effects of the other variables have been taken in to account. (Used Proc GLM SAS/STAT 8.2).
*Freund*, R. J., R. C. *Littell*, et al. (1991). <u>*SAS System for linear Models*</u>. *Cary, NC, SAS Institute Inc.*

For the paths sold only to hedgers, we hypothesize that more competition (higher number of market participants, and higher number of MWh sold) would decrease the premium. We also hypothesize that a higher number of transactions (keeping the number of participants constant) implies that speculators have more opportunity to increase the premium, by making several bids for the same path and discovering how high the price can be.

Table 47 shows the coefficient estimates and the p-values for the regression equations that explain the average premium paid by speculators (a negative quantity) for a given path, as a function of the number of FTRs, Number of MWh and Number of Participants. The estimate of the intercept of the regression equation is negative in all cases. We expect the estimate of Number of FTRs to be negative, so it makes the premium more negative (speculators are receiving more money), and the coefficients of Number of MWh and Number of participants to be positive, so the premium less negative (implying that speculators receive less money). For those paths sold only to speculators for 24 h and where the average premium was negative (speculators on average guessed well the direction of transmission congestion), both number of FTRs and Number of participants have coefficient estimates that have the expected sign and are statistically significant.

| Trade | Dependent variable | Num Paths | NumFTRs | | NumMWh | | NumPart | |
|---|---|---|---|---|---|---|---|---|
| | | | estimate | p-value | estimate | p-value | estimate | p-value |
| Only 24h | Prem 24N/CRs | 53 | -1.0976 | <.0001 | 5.45E-07 | 0.7598 | 3.6769 | 0.0016 |
| Only On | PremOnN/CRs | 788 | 0.4126 | 0.4616 | 8.61E-06 | 0.5906 | -0.6224 | 0.7463 |
| Only Off | PremOffN/CRs | 292 | -0.3312 | 0.9227 | 1.02E-04 | 0.4191 | -2.8549 | 0.7998 |

**Table 47. Coefficient estimates for explanatory variables of the premium. Paths traded only by speculators, for only one class, and where the premium paid was negative. Estimate of intercept is negative**

For the paths that were sold only to speculators for on and off-peak hours, the total number of FTRs sold per paths is significant and has the expected sign in the regression equation explaining the premium for FTRs for on-peak and off-peak hours. The coefficient estimate for Number of Participants has the expected sign and is statistically significant for the regression equation that explains the premium for on-peak hours. The coefficient estimate Number of MWh is significant and has the expected sign in the regression equation that explains the premium for FTRs sold for off-peak hours.

For other categories of paths that were sold only to speculators for more than one class there are less than 30 paths and the regression analysis was not performed.

| Trade | Dependent variable | Num Paths | NumFTRs | | NumMWh | | NumPart | |
|---|---|---|---|---|---|---|---|---|
| | | | estimate | p-value | estimate | p-value | estimate | p-value |
| On & Off | PremOnN/CRs | 340 | -0.2381 | 0.0085 | -6.34E-07 | 0.3416 | 0.8577 | 0.0643 |
| | PremOffN/CRs | 340 | -0.278 | 0.0068 | 1.31E-06 | 0.0834 | 0.5874 | 0.2637 |

**Table 48. Coefficient estimates for explanatory variables of the premium. Paths traded only by speculators, for On and Off-peak hours**

## 7.9 Relation between premium obtained and variability of the hourly CRs for each path.

The objective of this analysis is to assess the impact that variability of hourly CRs for a given path have in the value of the premium paid for corresponding FTRs. The following table presents mean, standard deviation and percentiles of the summary statistics of hourly congestion rents for each path. Despite the fact that the 3,767[8] paths analyzed have positive annual CRs, the table shows that at least 5% of the paths had hourly CRs averaging a negative value. The mean standard deviation of hourly CRs

[8] For the 166 paths for which there were FTRs that implied conflicting expectations about the sign of annual CRs, we define the path in the direction in which annual CRs are positive.

among paths is 4.59, and the kurtosis is always positive. The coefficient of variation is higher than 1 (in absolute value) for all paths.

| | Num Paths | Mean | Std Dev | Percentiles 99% | 95% | 90% | 75% | 50% | 25% | 10% | 5% | 1% |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Mean | 3,767 | 1.10 | 1.27 | 5.02 | 3.84 | 3.14 | 1.56 | 0.60 | 0.22 | 0.02 | (0.10) | (0.44) |
| Std Dev | 3,767 | 4.59 | 2.52 | 11.73 | 8.96 | 7.74 | 6.15 | 4.36 | 2.78 | 1.63 | 1.01 | 0.29 |
| Kurtosis | 3,767 | 96.64 | 332.72 | 814.63 | 348.55 | 189.03 | 90.69 | 31.98 | 18.28 | 10.96 | 8.92 | 6.28 |
| Average Deviation | 3,767 | 2.32 | 1.59 | 6.88 | 5.22 | 4.50 | 3.28 | 2.03 | 1.08 | 0.59 | 0.28 | 0.10 |
| Coefficient of Variation | 3,767 | 13.44 | 317.93 | 147.93 | 38.12 | 18.60 | 9.30 | 4.51 | 2.62 | 1.58 | (15.28) | (150.45) |

**Table 49. Summary of mean and variability statistics of hourly congestion rents for all paths for which there where Obligations FTRs traded. The number of hours analyzed for each path is 8784.**

### 7.9.1 Premium obtained and variability of the hourly CRs for each path.

Is there a relationship between the premium paid or obtained and the variability of hourly CRs? To investigate this question, we conducted a regression analysis that attempts to explain the value of the premium as a function of the variability of the hourly congestion rents, controlling for other factors that we already know might affect the value of the premium, such as liquidity (Number of FTRs) and competition (Number of MWh and Number of participants). To represent the variability of hourly CRs, we chose the Coefficient Of Variation.

The next box summarizes the results of the regression analysis for those paths sold only for Hedgers for 24 hours, for which the premium was positive (245 paths). As seen there, accounting for liquidity of the market and competition, the estimate of the coefficient for the Coefficient of Variation of hourly CRs is positive and statistically significant. This means that keeping liquidity and competition for a path constant, the ratio of the premium per MW to CRs paid by hedgers increases by 0.04 for each unit of increment in the Coefficient of Variation.

Dependent Variable: Prem24P_CRs Prem24P/CRs

| Source | DF | Sum of Squares | Mean Square | F Value | Pr > F |
|---|---|---|---|---|---|
| Model | 4 | 30.39337992 | 7.59834498 | 31.13 | <.0001 |
| Error | 240 | 58.58264529 | 0.24409436 | | |
| Corrected Total | 244 | 88.97602521 | | | |

| R-Square | Coeff Var | Root MSE | Prem24P_CRs Mean |
|---|---|---|---|
| 0.341591 | 102.8287 | 0.494059 | 0.480468 |

| Parameter | Estimate | Standard Error | t Value | Pr > \|t\| |
|---|---|---|---|---|
| Intercept | 0.3059198032 | 0.04960926 | 6.17 | <.0001 |
| NumFTRs | -.0218926501 | 0.00915033 | -2.39 | 0.0175 |
| NumMWh | -.0000000766 | 0.00000009 | -0.82 | 0.4106 |
| NumPart | 0.0742147329 | 0.03481247 | 2.13 | 0.0340 |
| CoeffVar_HouCRs | 0.0414107271 | 0.00393718 | 10.52 | <.0001 |

**Table 50. Results Multiple Regression Analysis for those paths sold only to hedgers, for 24 hours. Only paths with positive premium were included in the analysis.**

A similar analysis for those paths sold only to speculators for 24 hours show the same effect of the variability of hourly CRs on the value of the premium. The premium received by speculators increases with the coefficient of variation of hourly CRs[9]. It is important to note that for those paths traded only for 24h, the effect of the Coefficient of Variation on the premium received by speculators is more than 4 times the effect of the same variable on the premium paid by hedgers (abs(-0.1697) vs abs(0.0414)).

[9] As before, increasing the premium received by speculators means making it more negative. Therefore the coefficient estimate for the Coefficient Of Variation of hourly CRs is expected to be negative, as it is in fact.

Dependent Variable: Prem24N_CRs Prem24N/CRs

| Source | DF | Sum of Squares | Mean Square | F Value | Pr > F |
|---|---|---|---|---|---|
| Model | 4 | 329.2605851 | 82.3151463 | 23.55 | <.0001 |
| Error | 48 | 167.7621718 | 3.4950452 | | |
| Corrected Total | 52 | 497.0227570 | | | |

| R-Square | Coeff Var | Root MSE | Prem24N_CRs Mean |
|---|---|---|---|
| 0.662466 | -96.21732 | 1.869504 | -1.943002 |

| Parameter | Estimate | Standard Error | t Value | Pr > \|t\| |
|---|---|---|---|---|
| Intercept | -2.002430132 | 0.78170849 | -2.56 | 0.0136 |
| NumFTRs | -0.367128219 | 0.20057030 | -1.83 | 0.0734 |
| NumMWh | 0.000000528 | 0.00000123 | 0.43 | 0.6707 |
| NumPart | 2.610466395 | 0.77949521 | 3.35 | 0.0016 |
| CoeffVar_HouCRs | -0.169716635 | 0.02329810 | -7.28 | <.0001 |

**Table 51. Results Multiple Regression Analysis for those paths sold only to Speculators and only for 24h. Only Paths with negative premium**

The effect of the coefficient of variation on the premium paid by hedgers, for those paths sold for both 24 hours and on-peak hours is positive and significant, so the higher the coefficient of variation, the higher the premium paid.

Dependent Variable: Prem24P_CRs Prem24P/CRs

| Source | DF | Sum of Squares | Mean Square | F Value | Pr > F |
|---|---|---|---|---|---|
| Model | 4 | 5.59751879 | 1.39937970 | 59.11 | <.0001 |
| Error | 42 | 0.99439332 | 0.02367603 | | |
| Corrected Total | 46 | 6.59191211 | | | |

| R-Square | Coeff Var | Root MSE | Prem24P_CRs Mean |
|---|---|---|---|
| 0.849149 | 32.01655 | 0.153870 | 0.480596 |

| Parameter | Estimate | Standard Error | t Value | Pr > \|t\| |
|---|---|---|---|---|
| Intercept | 0.1593371313 | 0.04153330 | 3.84 | 0.0004 |
| NumFTRs | 0.0060253142 | 0.00914509 | 0.66 | 0.5136 |
| NumMWh | -.0000000742 | 0.00000004 | -1.71 | 0.0943 |
| NumPart | -.0566835130 | 0.03822750 | -1.48 | 0.1456 |
| CoeffVar_HouCRs | 0.1175171873 | 0.01441594 | 8.15 | <.0001 |

**Table 52. Results Multiple Regression Analysis for those paths sold only to hedgers, both for 24 and on-peak hours. Only Paths with positive premium were included in the analysis**

The effect of the coefficient of variation on the premium paid by hedgers, for those paths sold for both 24 hours and off-peak hours is negative and significant, so the higher the coefficient of variation the higher the premium received by speculators.

Dependent Variable: Prem24P_CRs Prem24P/CRs

| Source | DF | Sum of Squares | Mean Square | F Value | Pr > F |
|---|---|---|---|---|---|
| Model | 4 | 2.24901510 | 0.56225378 | 11.33 | <.0001 |
| Error | 25 | 1.24092571 | 0.04963703 | | |
| Corrected Total | 29 | 3.48994081 | | | |

| R-Square | Coeff Var | Root MSE | Prem24P_CRs Mean |
|---|---|---|---|
| 0.644428 | 61.81643 | 0.222794 | 0.360412 |

| Parameter | Estimate | Standard Error | t Value | Pr > \|t\| |
|---|---|---|---|---|
| Intercept | -.1469364850 | 0.17375652 | -0.85 | 0.4058 |
| NumFTRs | 0.0228357581 | 0.01550297 | 1.47 | 0.1532 |
| NumMWh | 0.0000000276 | 0.00000003 | 0.97 | 0.3419 |
| NumPart | -.0789762038 | 0.05626472 | -1.40 | 0.1727 |
| CoeffVar_HouCRs | 0.1706192738 | 0.02913114 | 5.86 | <.0001 |

**Table 53. Results Multiple Regression Analysis for those paths sold only to hedgers, for both 24 hours and Off-peak hours. Only paths with positive premium were included in the analysis.**

# 8 Conclusions

As explained in Chapter 2, the stated objective of FTRs in regions like PJM, is to provide transmission users with an instrument that allows them to hedge against volatile congestion costs. FTRs, by definition, provide a perfect hedge for LSE and generators, when their power transactions are for the same point-to-point and in the same MW quantity as the FTR, however, the level of hedging of a market participant depends on his ability to 1) anticipate which FTRs will be needed and 2) buy them in the market. Only 73% of the ARRs requested were allocated in 2003 and only 20% of the capacity bid for FTR buy obligations in the annual auction cleared (PJM 2004), which means that the ability to hedge against transmission congestion charges cannot be taken for granted.

If the ability to hedge cannot be taken for granted, a fair price for such hedge is not guaranteed either. The market participants that will offer the hedge are for profit institutions with the intention of benefiting as much as possible from their trades. Many of them have experience as speculators in financial markets and claim to have an advantage in the way they do quantitative analysis to profit from market opportunities. The two market participants that made the higher profits in the annual auction engaged in speculative activity and made money not only by bearing the risk of future transmission congestion buying obligations at a negative price, but also by reselling FTRs in different rounds of the option. Both market participants state in their mission that they act as market makers, "exploit market opportunities" and "strike the balance between risk and return". [10]

The presence of pure speculators and their relative success are both good and bad news. The market makers provide a service allowing others to fulfill their hedging needs and might help in the process of price discovery. The bad news is that without proper competition, the profits of these speculators could become excessive and add a significant extra cost to risk-averse transmission customers. Moreover, the money paid for transmission congestion that goes to the pockets of speculators is money that leaves the system and will not contribute towards the goal of a better transmission grid.

The approximately $7 millions that we attribute in this analysis as profits of the speculators (from the annual auctions) represent about 8% of the $88[11] million paid by those who bought obligation-FTRs at a positive price, and only 1.4% of the $499 reported congestion costs for PJM during 2003. However this quantity is a source of concern if we consider that there is a tendency for congestion costs to increase (Transmission congestion costs in PJM increased 16% from 2002 to 2003) and with higher congestion charges there will be more reasons for transmission customers to demand FTRs and more opportunities for speculators to demand high compensations.

[10] See information about market participants 8 and 5 in appendix.

[11] %88 million is the sum is the sum paid for Obligation-FTRs purchased at a positive price in table 6.

FTRs reduce uncertainty about future transmission costs and in some cases make power trades possible that otherwise would not take place. In this sense FTRs are a contributing factor of competition in the electricity market and their costs are justified if they are lower than the benefits they carry. Also, if the prices of FTRs truly reflect the risk on future transmission congestion, they provide valuable information that can be used by the ISO in the assessment of transmission capacity needs.

There is no easy way to assess the benefits of the FTRs because we do not have information about the trades that would not have happened if they did not exist, or about the outcomes of the decisions that would be taken in the absence of the information that FTRs provide. Consequently, to asses the goodness of FTRs, at this stage we can only try to assess if FTR markets are efficienty, by determining if the premium paid for FTRs corresponds to the implied risk they help to hedge against.

With the analysis of this chapter is has become clear that the variability of CRs is highly correlated to the relative premium of the corresponding FTRs, but it is also clear that demand and supply have also a significant impact, as well as the level of opportunities for price discovery. We have shown that the higher the demand for a hedge (e.g. competition among hedgers) the higher the price of an FTR, and similarly, the higher the supply of a hedge (e.g. competition among insurers), the lower the price of an FTR. We have also shown that the higher the number of trades by hedgers, the lower the price they pay, but the higher the number of trades by speculators, the higher the price they get.

Despite the high variability in hourly congestion rents, there is enough regularity during a year as to make the sign of the annual sum of congestion rents not that difficult to forecast. Market participants trying to hedge against congestion made a mistake about the sign of congestion in a just a few cases; representing 3.4% of the FTRs obligations purchased. The transactions in which speculators had an extra profit (by getting positive CRs) represented about 14% of the FTR obligations purchased by them,

The low chances of having an FTR obligation that renders CRs with an opposite sign of the purchasing price validate the concept of “obligations as hedging instruments”. When market participants are almost sure about the direction of congestion, but unsure about the size they will hedge with obligations. The trade of options makes more sense for those “paths” for which the direction of transmission congestion is uncertain and market participants want to protect against the chances of CRs being negative. We do not have yet a formula that relates the price of an FTR option with the variability of its potential CRs.

The fact that speculators profited also from reselling FTRs, may indicate that it is not impossible to forecast not only the direction but also the size of transmission congestion with enough accuracy as to make almost sure profits. The scarce number of trades per path, and in particular the low competition between speculators makes likely a deviation of the premium paid for FTRs from a fair value that reflects the uncertainty involved.

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# Chapter 4: The fair value of an FTR

## 1 Introduction

In Chapter 3 we showed that prices paid for FTRs are, on average, significantly larger than the average congestion costs they cover.

Our findings are similar to those found on empirical studies on NYISO market. Authors of such studies have raised the question of whether this finding is a result of market inefficiencies or perhaps strong risk aversion.

Although there are many reasons to believe that there are inefficiencies in FTR markets (Deng et al, 2004), we argue that the premium is not completely due to this cause. For market participants who need to back their electricity schedules, FTRs are a way to pay a fixed price for congestions instead of being exposed to volatile congestion costs, and in this way FTRs provide a risk reduction. Because hedging and risk reduction always come at a cost, the fact that FTRs are sold at a price that exceeds the expected congestion charges is not surprising.

We state that the theory of rational options, in particular the concept of "risk neutrality", can be used to find the fair price of the premium paid for FTRs. In this Chapter we present a method of calculating this price.

This application can be extended to other situations in which a fixed price is paid to avoid some uncertainty.

## 2 FTRs as hedging instruments:

As explained in Chapter 2, FTRs represent both a right and a liability. Holders of FTRs have the right to receive the difference in LMP from the ISO when it is positive, but they also have the obligation to pay the ISO when the difference is negative. In the majority of the cases, an FTR that produces negative rents is also sold at a negative price. This can be interpreted as if market participants who schedule transactions that create counter flow on congested lines were paid in advance for this service a quantity equal to the price of the FTR.

For those market participants whose FTR holdings match their energy schedules, FTRs provide an exact hedge against the volatility in congestion costs, even when they pay a positive price for an FTR and collect negative rents. Even in this case, holders end up paying only the price of the FTR for congestion, since the negative rents are offset by the extra money they get from having a higher LMP at the injection point than at the withdrawal point.

In our analysis of the results of the PJM Annual Auction of FTRs of Chapter 3, we showed that in general, buyers of FTRs at a positive price paid more for the FTR than what they received in CRs, and buyers of FTRs at a negative price were paid more in advance for the obligation than the CRs they had to pay. Furthermore, our analysis of Chapter 3, showed that if we combine some information about the identity of market participants and their observed behavior in the FTR auctions, we can clearly identify hedgers and speculators playing in the market.

The existence of hedgers and speculators using FTRs allows us to propose the idea that the prices of FTRs should naturally include a premium (that will be paid by hedgers and received by speculators).

We argue that because FTR transactions provide risk reduction for one party the price of FTRs should not be the expected value of congestion costs. If there were no risk reduction involved, one could view the FTR as a kind of future on congestion costs. The FTRs would converge toward the average value of the congestion costs between the two points. However, FTRs do provide risk reduction and therefore their price will deviate from the expected value of congestion costs by a quantity that will depend on the magnitude of the risk reduced. For those market participants who buy FTRs at a negative price, the premium will go to their pockets for agreeing to bear a volatile liability. For those market participants who buy FTRs at a positive price, then the premium will be the price they pay in exchange for reducing the risk they face in their energy transactions.

The question we pose here is whether we can compute a fair value for the premium, FTR hedgers should pay.

### 2.1 Options theory and the price of FTRs

It turns out that even though FTRs are not options (we are referring in this Chapter to FTR-obligations only), the theory of risk neutral valuation of options can be used to calculate the fair value of the risk reduction provided by FTRs compared to the congestion costs.

FTR obligations can be a liability if congestion rents turn out to be negative. However, most hedgers buy FTR obligations for those paths for which the direction of transmission is almost certain, and buy FTR-options for those “paths” for which the direction of transmission congestion is uncertain. Because of the reasons explained above, we can see FTR obligations as risk reduction instruments and price them as options in the way explained in Chapter 1. We can apply the formulae obtained in section 3.1 of Chapter 1, where *C* represents the uncertain congestion costs, *P* represents the fair value of the FTR-obligation, and *H* represents the premium that FTR buyers are willing to pay to reduced the risk associated with *C*.

## 3 The pdf of the Annual Sum of hourly Congestion Rents:

In Chapter 3 we presented evidence that FTRs hedgers pay a premium for the reduction of the risk this instrument provides; and in the previous section we explained how the arguments of Chapter 1 can be used in the framework of FTRs. A natural next step in our analysis is to investigate how the model fits with actual data.

Given the uncertainty on the total congestion cost over the period of time covered by the FTR, EQ. 13 “predict” what on average that premium should be. The observed values of the premium paid and received by FTR buyers should be distributed around this expected value.

Our EQ.13 imply that the value of the premium is completely defined by the size of the pdf of C, $f_c(c)$. A real test of the validity of our approach would require that the value of $f_c(c)$ is derived independently for each FTR and shown to correspond to the one suggested by the value of the premium paid.

There is one limitation that makes fully validating the theory from the data impossible: the data necessary to estimate $f_c(c)$ does not exist today and may never exist.

To estimate the expected value and volatility of the annual congestion costs $C$, it would be necessary to have many observations of these costs, or in other words, many years worth of data. FTR markets have been operating for only a few years. Even if we waited to have a good sample of observations of $C$, the fact that the pattern of congestion is affected by changes of the grid (addition of new transmission lines, introduction of new nodes, changes in the demand pattern, or appearance and disappearance of electricity generation plants, etc) would make questionable the validity of the data.

Nevertheless, we can use the observation of the hourly values of the congestion costs during a year, to estimate the pdf of annual congestion costs $C$.

### 3.1 A bootstrap approach to estimate the distribution of annual CRs

In the sections that follow, we describe how we implement our version of a bootstrap approach to find the distribution of annual CRs from the observation of hourly CRs for one year. A bootstrap is a computer-intensive method to do statistical inference based on the distributions of sample statistics (Simon 1997; Moore 2003; Hesterberg 2005). In the case described here, the bootstrap will consist of finding the distribution of a statistic (the sum of all observations) based on a large “sample” (that is obtained from our understanding of only one observation).

The whole idea consists of finding a way to express the hourly CRs as a function of deterministic variables and random variables with known distributions, so we can simulate many years of hourly CRs as if they were different observations of the same year. Once we have each year realization, we find the annual sum and obtain a sample of annual sums from which we are able to derive a distribution.

We generate 1,000 sequences of 8,784 values for hourly CRs corresponding to one year. Then for each year's simulation we sum all hourly CRs to obtain the annual CRs, so we obtain 1,000 "observations" for a year from which we can obtain an empirical version of the distribution of annual CRs.

The algorithm followed for determining the distribution of annual CRs for a path has five steps:

Step 1: Find a function that describes hourly CRs.

$$y_t = f(X, Y, R) \quad \forall \quad t \in (1,2..8784)$$

where *X* represents independent variables that help to explain the mean and the variability of hourly CRs, *Y* represents the information of all previous *t*, and *R* represents a random component.

Step 2: Simulate a sequence of the form $\hat{y}_1, \hat{y}_2, ..., \hat{y}_{8784}$

Step 3: For the simulated sequence, calculate the sum of annual CRs for 24 hours, on-peak hours, and off-peak hours. Let $\omega^j$ be the annual CRs for 24 hours, represented in sequence *j*. Then $\omega^j = \sum_{t=1}^{8784} y_t^j$. Similarly let $\omega_{On}^j$, and $\omega_{Off}^j$ be the annual CRs for on-peak and off-peak hours respectively. Let $\pi_t$ be an indicator variable of whether hour *t* is a peak hour or not, so $\pi_t = 1$ if hour *t* is a peak hour, and = 0 otherwise. Then we have that $\omega_{On}^j = \sum_{t=1}^{8784} y_t \pi_t$ and $\omega_{Off}^j = \sum_{t=1}^{8784} y_t (1 - \pi_t)$.

Step 4: Go back to step 2 until $j$=1,000.

Step 5: Analyze observations of $\omega$, $\omega_{On}$, and $\omega_{Off}$ to find an empirical version of their distribution.

### 3.2 Analysis of hourly CRs.

A wide body of literature on models of spot electricity prices (for markets around the world) seems to back the idea that mean-reverting and seasonal components (Barlow 2002) must be included to efficiently capture the part of the prices that can be predicted. To account for the high kurtosis of these prices (that makes unusually high, and unusually low values likely) several authors have proposed incorporating time-varying volatility and/or jumps in the models, with times of occurrence, sizes and durations determined by different stochastic processes (Weron, Simonsen et al. 2003) (Rambharat, Brockwell et al. 2005). For the variable we care about (hourly differences in the day-ahead (forward) electricity prices between two nodes) mean-reversion and seasonality may also play a role, but the effect of jumps might be canceled. Instead the time-varying volatility might do a better job, replicating the real price process.

In what follows we analyze congestion rents using time-series analysis methods(Brockwell and Davis 1996). We will denote with $y_t(k)$ the congestion rents for path $k$ at hour $t$ . As said before hourly CRs differ with path and type of hour, but in general exhibit a very high variability for all paths, as shown in Table 49 of Chapter 3. Hourly CRs exhibit daily, weekly and monthly seasonality but are stationary.

As an example of the characteristics of hourly congestion rents, the following graph shows hourly CRs for path 526. Path 526 refers to the combination of POI 94 and

POW 395, which is among the paths most heavily traded (with trades of buy-obligation FTRs made by 12 market participants) and with highest prices per MWh (in the 95% percentile).

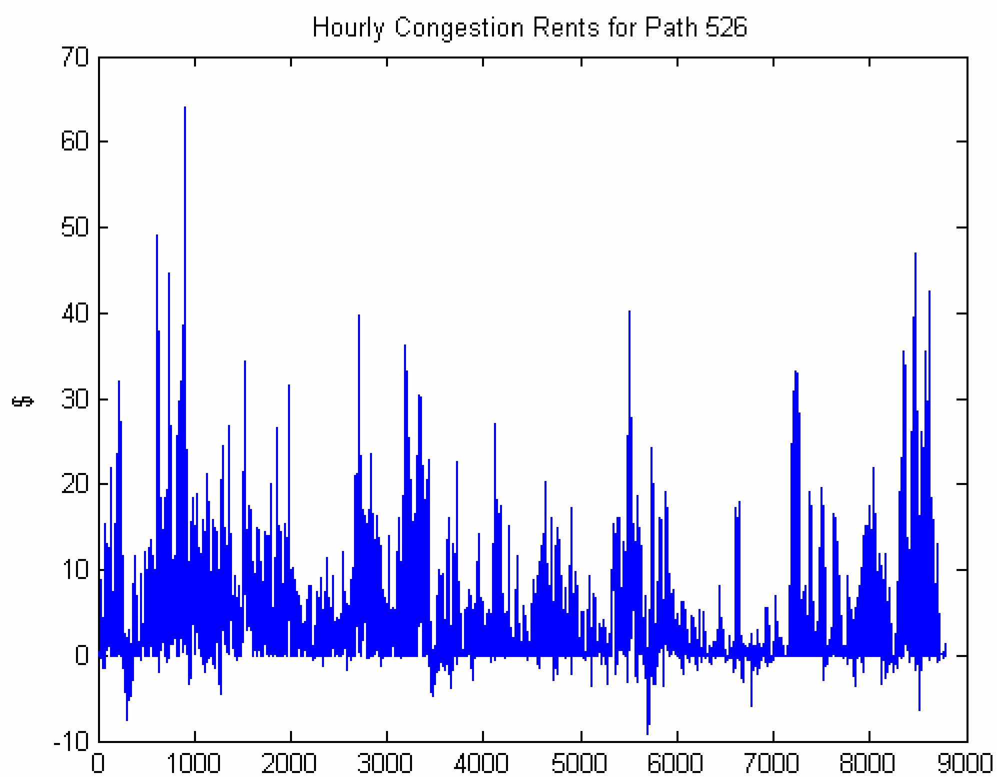


**Figure 1. Hourly Congestion Rents for Path 526**

The fact that the series of hourly CRs for this path is stationary and does not need any differentiation is confirmed by the Dickey-Fuller test, which allows us to reject the hypotheses that the time series has a unit root, and a seasonal root with p-values<0.0001 (Dickey (1976) 1994).

A typical histogram of $y_t$ for the paths for which there were FTRs traded looks very close to the one of path 526, shown in Fig 2. The observations are skewed to the right of the mean, and the tails (specially on the right side) are long.

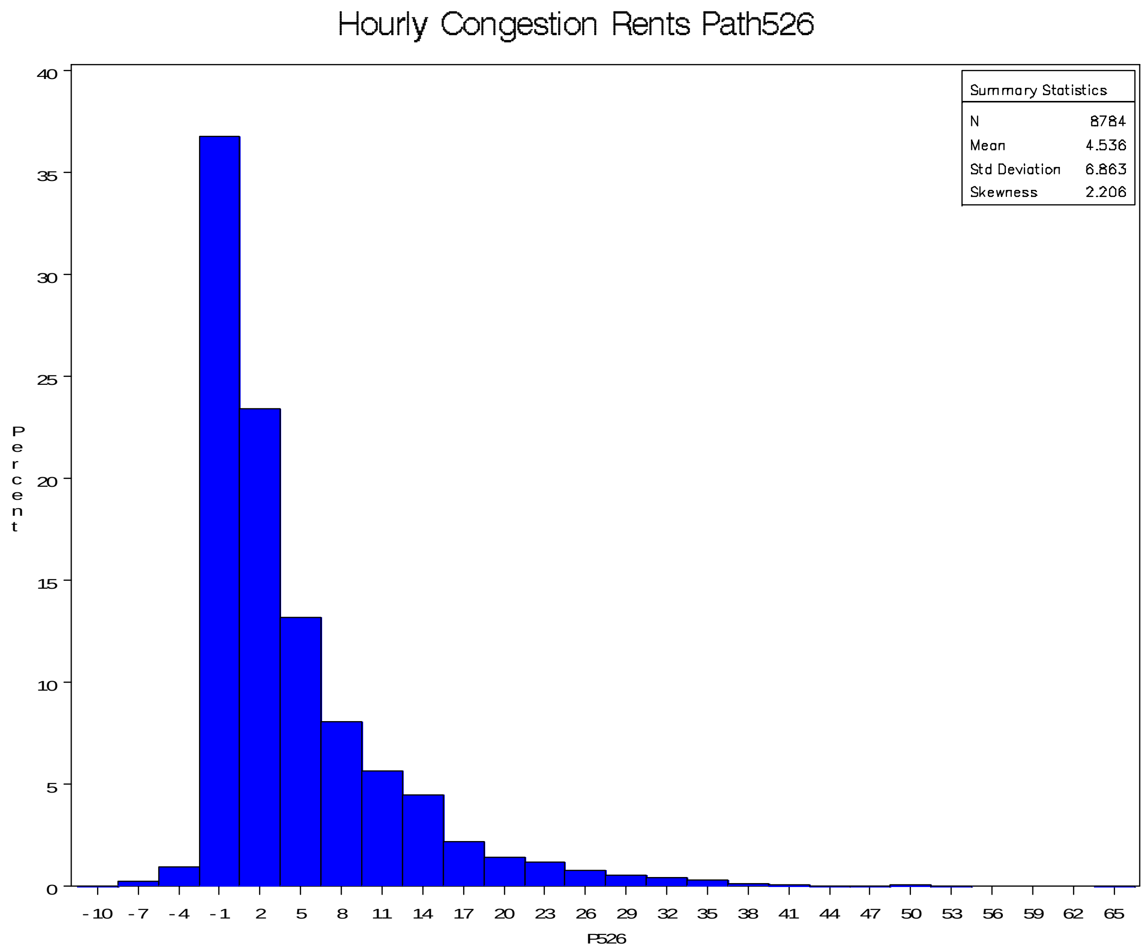


**Figure 2. Hourly Congestion Rents Path 526**

A scatter plot of the hourly CRs for a path, shows that there is seasonality and autocorrelation. A chi-square test allows us to soundly reject the hypothesis that the process of hourly CRs is white noise (p-value <0.0001).

Furthermore, as it could be expected, hourly CRs exhibit autocorrelation, that is linear correlation between the hourly CRs observed at a certain hour and the observations in previous hours. The following plot presents the average linear autocorrelation of hourly CRs for path 526, for the first 24 lags. The correlation is very high for lag 1 and reaches its lowest point at lag 12, where it starts increasing again.

```
                              The ARIMA Procedure

                           Name of Variable = P526

                      Mean of Working Series    4.536474
                      Standard Deviation        6.862824
                      Number of Observations        8784

                                Autocorrelations

 Lag    Covariance    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1      Std Error

   0     47.098355        1.00000    |                    |********************|             0
   1     42.950048        0.91192    |                    |******************  |      0.010670
   2     38.890611        0.82573    |                   .|*****************   |      0.017412
   3     34.634072        0.73536    |                   .|***************     |      0.021411
   4     30.179083        0.64077    |                   .|*************       |      0.024115
   5     25.838759        0.54861    |                   .|***********         |      0.025981
   6     21.556252        0.45769    |                   .|*********           |      0.027268
   7     17.307977        0.36749    |                   .|*******             |      0.028129
   8     13.427181        0.28509    |                   .|******              |      0.028671
   9     10.155965        0.21563    |                   .|****                |      0.028992
  10      7.566257        0.16065    |                   .|***                 |      0.029174
  11      5.686627        0.12074    |                   .|**                  |      0.029274
  12      4.600074        0.09767    |                   .|**                  |      0.029331
  13      4.445700        0.09439    |                   .|**                  |      0.029368
  14      5.031845        0.10684    |                   .|**                  |      0.029402
  15      6.411424        0.13613    |                   .|***                 |      0.029447
  16      8.467019        0.17977    |                   .|****                |      0.029518
  17     11.356560        0.24112    |                   .|*****               |      0.029642
  18     14.475074        0.30734    |                   .|******              |      0.029865
  19     17.552119        0.37267    |                   .|*******             |      0.030223
  20     20.663646        0.43873    |                   .|*********           |      0.030742
  21     23.613150        0.50136    |                   .|**********          |      0.031446
  22     26.125277        0.55470    |                   .|***********         |      0.032343
  23     28.089798        0.59641    |                   .|************        |      0.033409
  24     29.134898        0.61860    |                   .|************        |      0.034600

                            "." marks two standard errors
```

**Table 1**. Autocorrelation plot for hourly congestion rents for path 526.

If $y_t(k)$ for $t$=1,2,..8784 were independent and identically distributed (iid) random variables, following a known distribution, it would be possible to derive analytically the probability distribution function of the annual congestion rents for path *k*, *C(k)*. For example, if we had that $y_t(k)$ were iid~ $N(\mu_k, \sigma_k)$, then *C(k)*~ $N(8784\mu_k, 8784\sigma_k)$. However, as it has been shown, there is autocorrelation in the data, and therefore a good argument to try to express $Y_t$ with a time-series model.

### 3.3 Modeling hourly CRs as an ARMAX Time-series model with GARCH errors

Because data of CRs is constituted by observations that have been recorded every hour, the evolution of CRs can be analyzed using methods for the analysis of discrete time series.  The goal of this analysis is to find a way to express hourly CRs as a function of available information constituted by previous observations and independent variables. If we find a good model that allows us to generate hourly CRs, we can simulate a year worth of data many times and infer from there the distribution of the annual sum.

Out of several linear time-series models tried, the one with best-fit statistics is one that includes the hourly aggregated load of PJM and an Autoregressive Moving Average model with seasonal components or ARMA(1,1)(1,1)s.  The model is represented by the following equation:

$$
\begin{aligned}
Y_t &= \mu + \beta * LoadPJME_t + \phi_1(Y_{t-1} - (\mu + \beta * LoadPJME_{t-1})) + \phi_{24}(Y_{t-24} - (\mu + \beta * LoadPJME_{t-1})) \\
&- \phi_1\phi_{24}(Y_{t-25} - (\mu + \beta * LoadPJME_{t-1})) - \theta_1 E_{t-1} - \theta_{24} E_{t-24} + \theta_1\theta_{24}(E_{t-25}) + E_t
\end{aligned}
$$

Where $Y_t$ represents the CRs for hour *t*, $LoadPJME_t$ is the aggregated load at PJM east at hour *t*, in MW, and $\mu$, $\beta$, $\phi_1$, $\phi_{24}$, $\theta_1$, $\theta_{24}$ are the parameters for the seasonal ARMA model that includes $LoadPJME_t$ as a regressor.  The last term $E_t$ is a random variable that is normally distributed with mean zero and variance $\sigma^2$. Because of the presence of an independent variable X (in this case the aggregated load at PJM at time *t*, or $LoadPJME_t$), this model can be called an ARMAX model.  Different methods can be used to find the parameter estimates that minimize the error or maximize the likelihood of the observations $Y_t$.

The parameter estimates obtained for Path 526, using the Conditional Least Squares (CLS) method are shown in the following table[1]:

[1] The term *conditional* is used because the forecasts are computed by assuming that the unknown values of the response series before the start of the data are equal to the mean of the series. Thus, the forecasts are conditional on this assumption. . The CLS estimates are conditional on the assumption that the past unobserved errors are equal to 0. CLS

Conditional Least Squares Estimation

| Parameter | Estimate | Standard Error | t Value | Approx Pr > \|t\| | Lag | Variable | Shift |
|---|---|---|---|---|---|---|---|
| $\mu$ | -5.56619 | 1.21185 | -4.59 | <.0001 | 0 | P526 | 0 |
| $\theta_1$ | 0.04896 | 0.01208 | 4.05 | <.0001 | 1 | P526 | 0 |
| $\theta_{24}$ | 0.75566 | 0.01492 | 50.66 | <.0001 | 24 | P526 | 0 |
| $\phi_1$ | 0.89345 | 0.0054400 | 164.24 | <.0001 | 1 | P526 | 0 |
| $\phi_{24}$ | 0.90661 | 0.0096541 | 93.91 | <.0001 | 24 | P526 | 0 |
| $\beta$ | 0.0003113 | 0.00003325 | 9.36 | <.0001 | 0 | PJM_E | 0 |

| | |
|---|---|
| Constant Estimate | -0.05538 |
| Variance Estimate | 6.724398 |
| Std Error Estimate | 2.593145 |
| AIC | 41673.95 |
| SBC | 41716.44 |
| Number of Residuals | 8784 |

**Table 2. Conditional Least Squares Estimation**

The p-values for each parameter confirm the idea that all the independent variables are significant.

A linear regression of the values of $Y_t$ onto the values of the estimation obtained with the proposed model $\hat{Y}_t$ for path 526 has an R-squared of 0.96. The same model was tested for other 45 paths, and in all but one case R-Squared was 0.7 or more. Although the model seems to explain a good portion of the volatility of hourly congestion rents, the residuals still exhibit autocorrelation and therefore do not meet the condition of being white noise (WN).

A scatter plot of the residuals of the ARMAX model shows that there is *heteroskedasticity*, that is that the variance of the residuals is not constant. Furthermore, there seems to be “volatility clustering” in the sense that large residuals seem to be

estimates are found minimizing the sum of squared residuals that is the difference between the prediction and the real observation for each *t*.

together. The following graph presents the residuals obtained when we fit the proposed model to path 526.

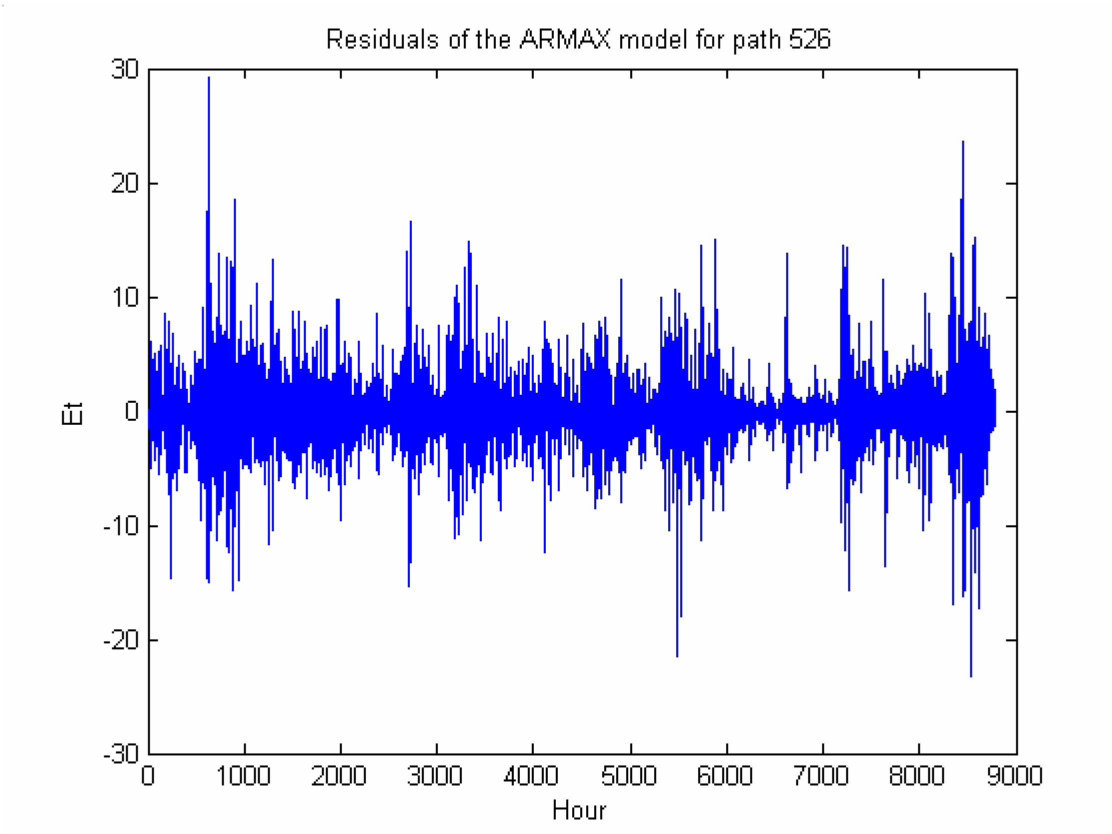


**Figure 3. Residuals of the ARMAX model for path 526**

For path 526, an autocorrelation check of the residuals makes clear that the residuals are correlated. Using a $\chi^2$ test, the hypothesis of no autocorrelation has to be rejected for lags higher than 12, as the next table shows.

Autocorrelation Check of Residuals

| To Lag | Chi-Square | DF | Pr > ChiSq | Autocorrelations | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 6 | 5.90 | 2 | 0.0524 | -0.000 | -0.000 | 0.023 | -0.008 | 0.003 | 0.008 |
| 12 | 25.77 | 8 | 0.0012 | -0.022 | 0.005 | -0.008 | 0.004 | -0.022 | -0.034 |
| 18 | 48.64 | 14 | <.0001 | -0.017 | -0.015 | -0.019 | -0.038 | -0.015 | 0.005 |
| 24 | 196.99 | 20 | <.0001 | -0.008 | 0.018 | 0.044 | 0.036 | 0.086 | 0.076 |
| 30 | 232.19 | 26 | <.0001 | 0.046 | 0.034 | 0.018 | 0.012 | 0.014 | 0.003 |
| 36 | 237.50 | 32 | <.0001 | 0.015 | 0.005 | -0.000 | 0.014 | -0.012 | 0.004 |
| 42 | 252.26 | 38 | <.0001 | -0.011 | -0.026 | -0.013 | -0.025 | -0.007 | -0.006 |
| 48 | 309.53 | 44 | <.0001 | 0.011 | 0.013 | 0.018 | 0.021 | -0.006 | -0.074 |

**Table 3. Autocorrelation Check of Residuals**

Equivalently, the Engle's test for the presence of ARCH effects allows us to reject the hypothesis that the residuals time series are a random sequence of Gaussian disturbances. (p-value <.0001 for lags 1,6,12,18,24,30,36,42 and 48).

Squared residuals also exhibit autocorrelation. The $\chi^2$ test for the null hypothesis that squared residuals are not autocorrelated is rejected with p-value <.0001 for lags 1,6,12,18,24,30,36,42 and 48).

The autocorrelation found in the residuals after the ARMAX model has been fit, may be due to the presence of extreme values in the hourly CRs data and also perhaps, the lack of some relevant information to predict hourly CRs. The fact that residuals are not WN might also mean that CRs follow a "long memory" process and that more parameters need to be included in the model.

The following graph shows the histogram of the residuals for the ARMAX model for path 526. As it can be seen, residuals are centered at zero, and there are long tails.

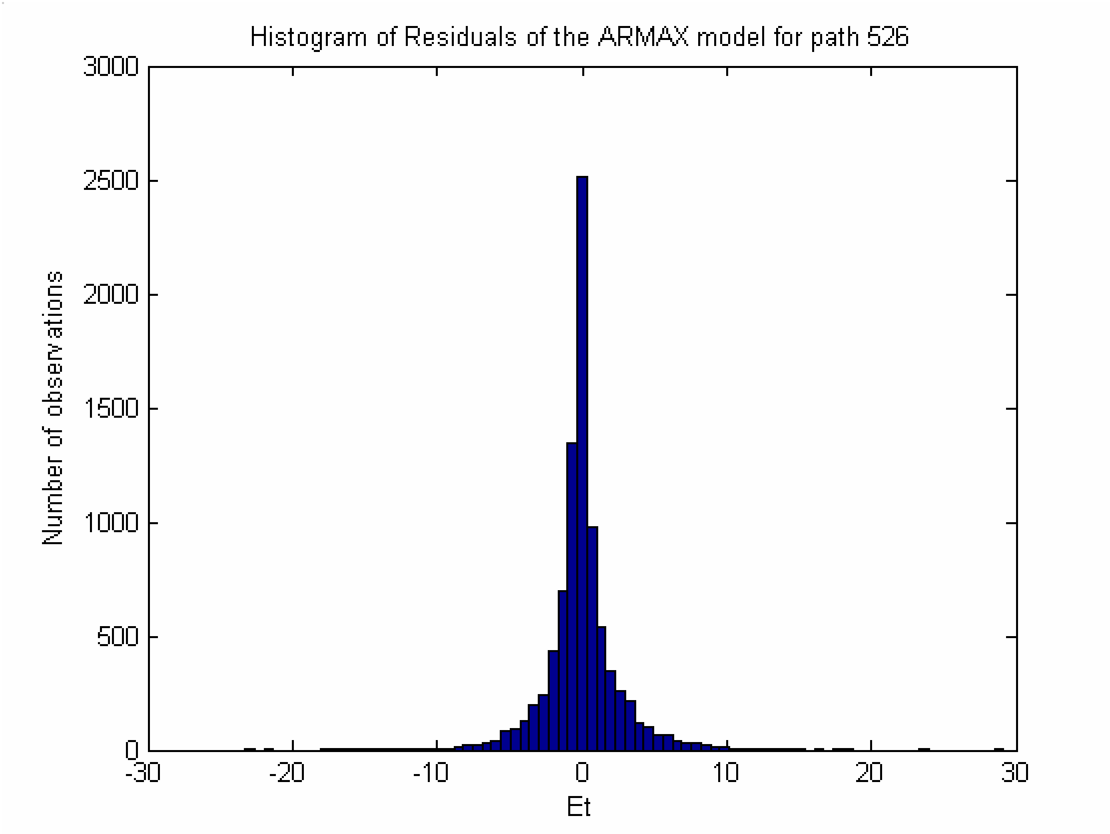


**Figure 4. Histogram of Residuals of the ARMAX model for path 526**

To account for the excess kurtosis observed in the histogram of residuals, and the volatility clustering observed in its scatter plot, we fit a General Autoregressive Conditional *Heteroskedasticity* (GARCH) model(Bollerslev 1986; Bollerslev 1987)to the residuals. After fitting the model, we will be able to generate the variance of the ARMAX prediction's error at a given point in time, as a function of the variance of previous errors.

The model chosen to describe the variance of the residuals has one ARCH term, two ARCH seasonal terms, and one GARCH term. Therefore the variance for the error at time *t* can be expressed as: $\sigma_t^2 = k + \alpha_1 \sigma_{t-1}^2 + \gamma_1 E_{t-1}^2 + \gamma_{24} E_{t-24}^2 + \gamma_{48} E_{t-48}^2$.

The estimates of the parameters $k$, $\alpha_1$, $\gamma_1$, and $\gamma_{24}$ are found assuming that $E_t$ is normally distributed with mean 0 and variance equal to $\sigma_t^2$. Although it would be possible to assume different distributions for $E_t$, we assume a normal distribution to ease the computation requirements.

The following graph shows 1) Congestion Rents for path 526, 2) the residuals of the ARMAX model $E_t$, 3) the corresponding standard deviation $\sigma_t$, and 4) the standardized residuals $E_t/\sigma_t$. From the graph, it can be concluded that the GARCH model helps in the description of the volatility of the residuals of the ARMAX model. As it can be observed from the graph, standardized residuals are stable and do not present cluster volatility. Furthermore, the $\chi^2$ test for the null hypothesis that standardized residuals are not auto correlated cannot be rejected for lags 1 to 12.

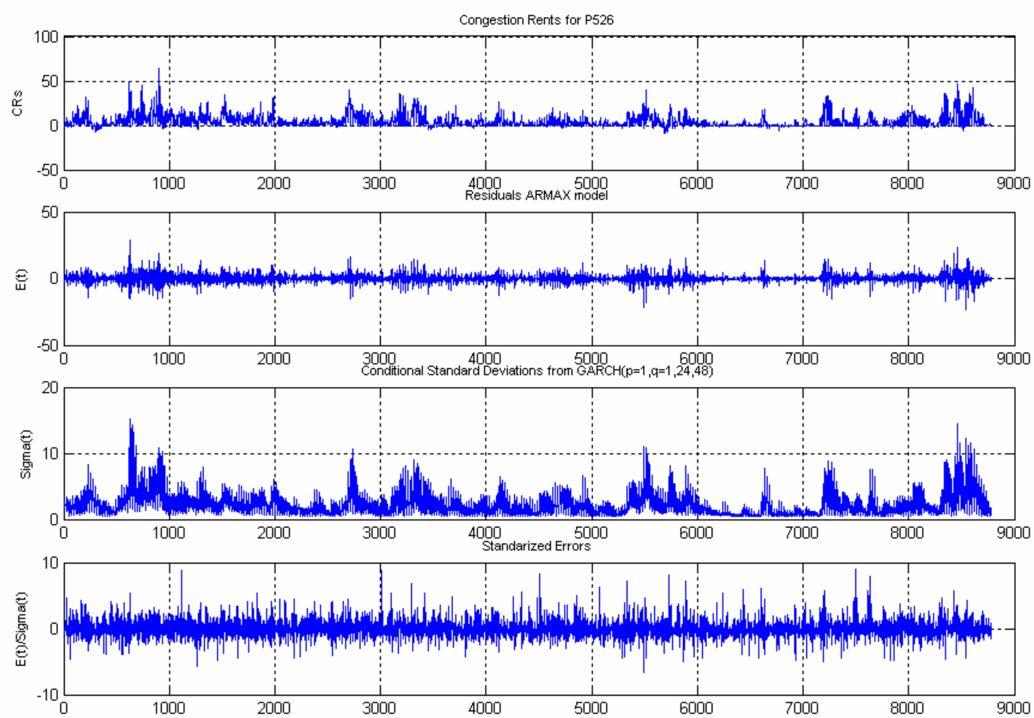


**Figure 5. Congestion Rents - Residual ARMAX model – Conditional Standard Deviation from GARCH (P=1, Q=1,24,48) – Standardized Errors**

### 3.3.1 Estimation of the distribution of Annual CRs

The histograms of 10,000 realizations of annual CRs for path 526 are shown below. For annual CRs for 24 hours, the minimum, maximum, mean and standard deviation are 37,803, 40,060, 38,966, and 316 respectively. The null hypothesis that the distribution of annual CRs for 24 hours is normally distributed cannot be rejected[2](Jarque-Bera Test: p-value = 0.8530 (Judge, Hill et al. 1985)).

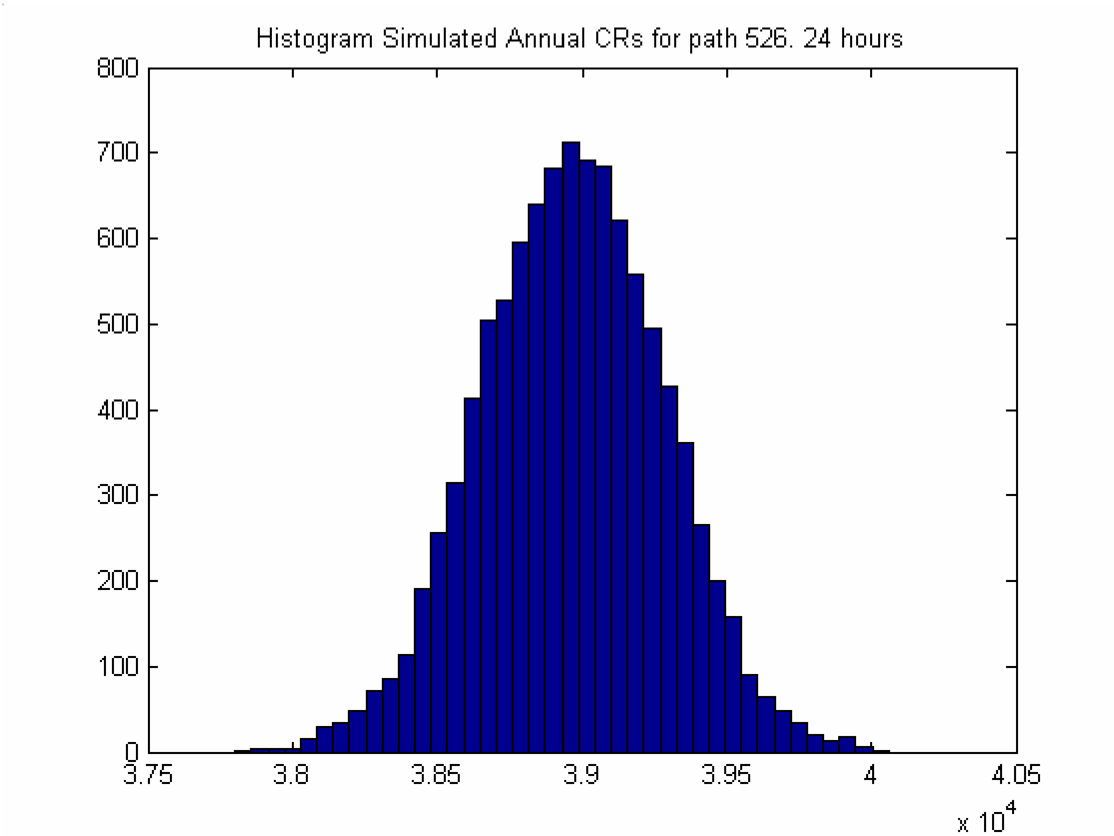


**Figure 6. Histogram Simulated Annual CRs for Path 526. 24 hours**

The histogram for annual CRs for on-peak hours for path 526 is shown in Fig.7. The minimum, the maximum, the average, and the standard deviation are 18,424, 27,554,

---

[2] The null hypothesis that the distribution of annual CRs for 24 hours is normally distributed cannot be rejected either, for 43 out of 45 paths tested. Same result is obtained for the distributions for on-peak and off-peak hours.

23,131, and 1,140 respectively. The hypothesis that annual CRs are normally distributed cannot be rejected (Jarque-Bera Test: p-value=0.8724).

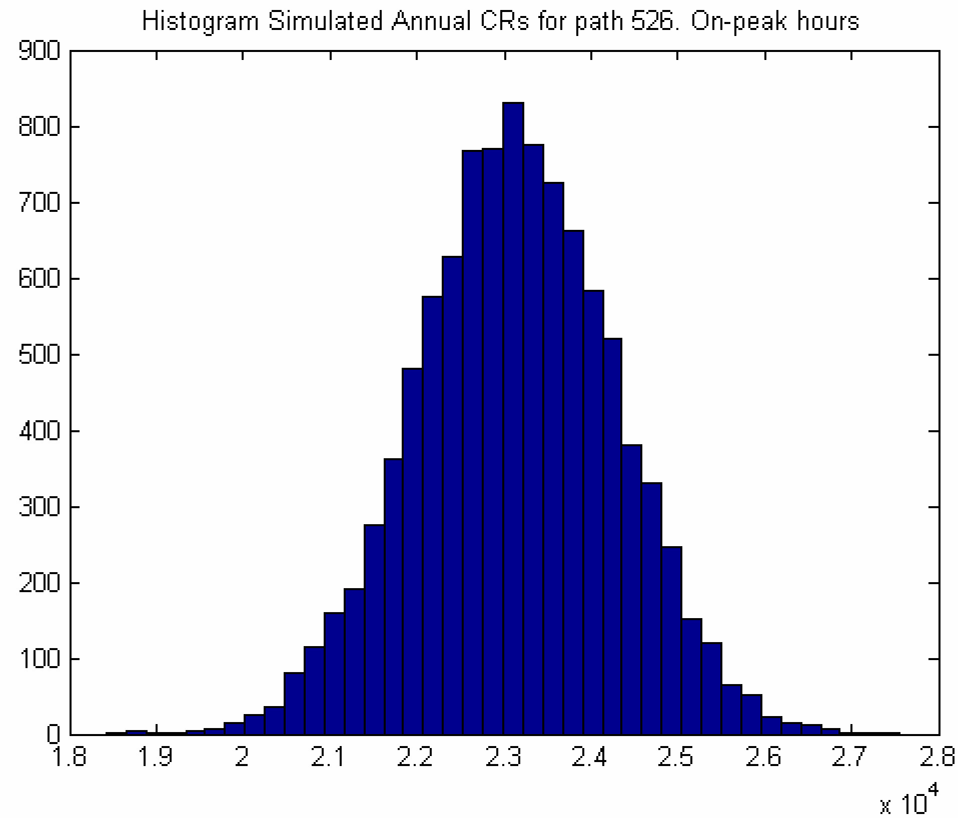


**Figure 7. Histogram Simulated Annual CRs for path 526. On-peak hours**

The histogram for annual CRs for off-peak hours is shown in Fig.8. Again, we cannot reject the hypothesis that the distribution is normal (Jarque-Bera Test: p-value = 0.3379). The minimum, maximum, average, and standard deviation of annual CRs for off-peak hours are 11,629, 20234, 15,836, and 1,122 respectively.

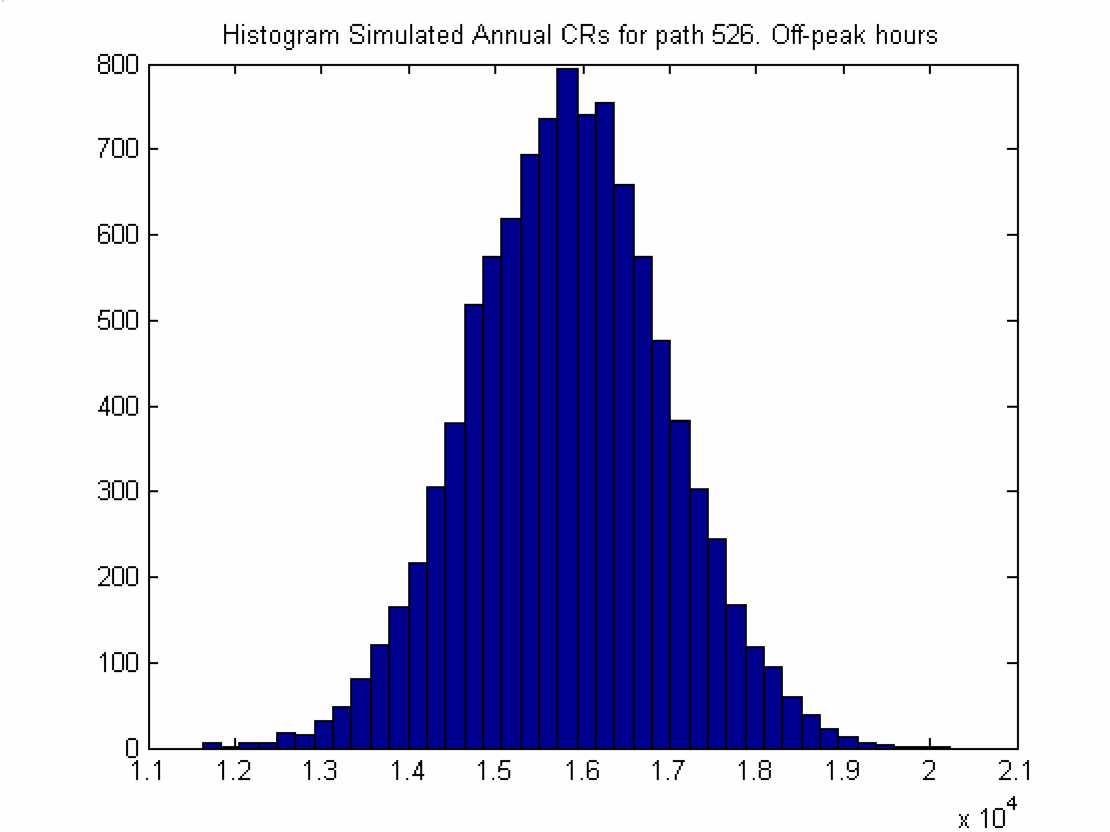


**Figure 8 Histogram Simulated Annual CRs for path 526. Off-peak hours**

## 3.4 Modeling hourly CRs as an ARMAX time-series model with residuals drawn from an empirical distribution

Although the use of a GARCH model seems appropriate to model the residuals of the ARMAX model, it would be convenient to have a simpler way of modeling such residuals that allowed the estimation of the function that determines them in a shorter time. Since our goal is to find a prediction of hourly CRs for many paths (about 4,000 for the 2003-2004 auction in PJM), avoiding the use of models that require long computation times becomes a priority.

In order to simulate a year of hourly CRs with a model simpler than GARCH, we let Et, be a random draw from an empirical version of the probability distribution function of the observed residuals.

To characterize the error in the ARMAX model we first find an empirical version of its probability density function.

The corresponding empirical Cumulative Distribution Function (cdf) derived from the observations of the ARMAX errors for path 526 is shown in the plot below.

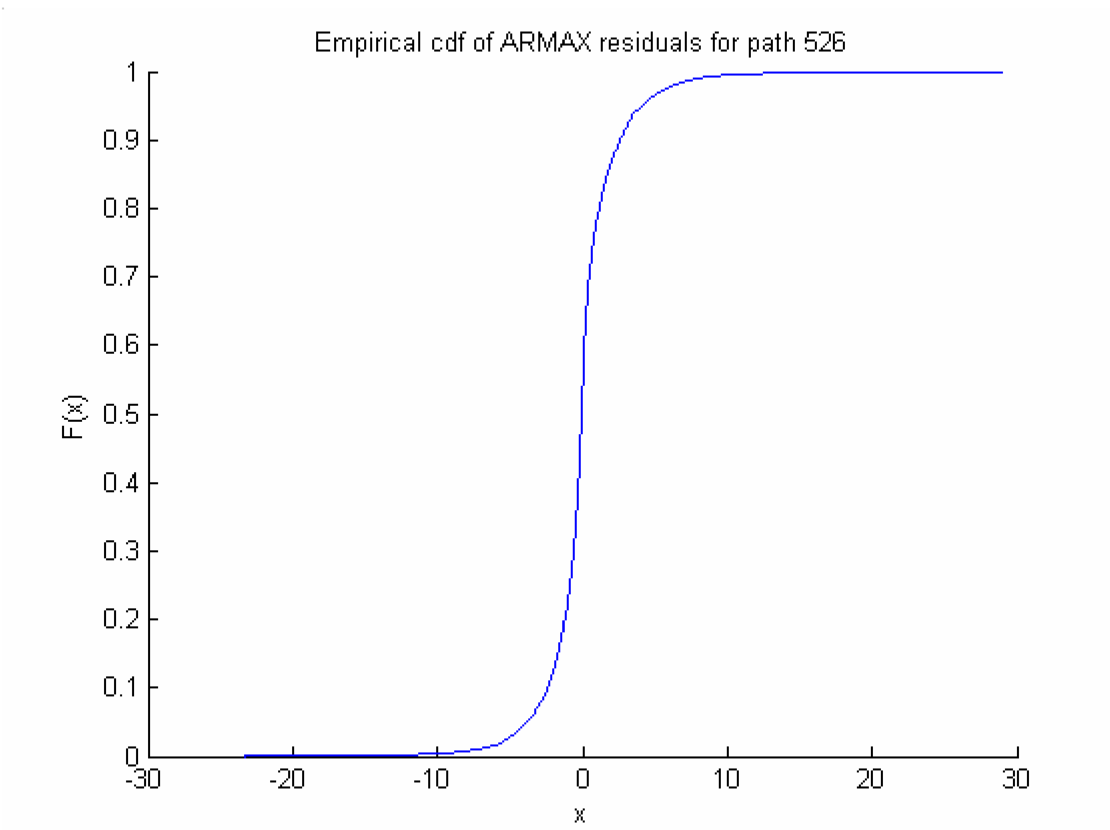


**Figure 9. Empirical cdf of ARMAX residuals for path 526**

To simulate one observation of Et, we use the method of the inverse cdf, which consists of generating an uniform random variable between 0 and 1, and then assigning to Et, the corresponding value in the inverse cdf.  In other words

$\hat{E}_t = F^{-1}(u_t)$ where $F^{-1}(u_t)$ is the inverse empirical cdf and $u_t \sim uniform(0,1)$ .

This method allows us to preserve the same distribution of errors observed in the model. However, the different realizations of Et generated in this way are one independent from the other, and this contradicts our observation of autocorrelation in the residuals. Although this can lead to errors in the estimations of hourly congestion rents, its impact might not be very important on the annual sum. If nothing more, results obtained with this method will be useful as a point of reference for a comparison with results from other methods to simulate annual CRs.

To find a distribution of the annual CRs we simulate 1,000 realizations of a year of hourly CRs, using the following equation:

$$\hat{Y}_t = \hat{\mu} + \hat{\beta} * LoadPJME_t + \hat{\phi}_1(\hat{Y}_{t-1} - (\hat{\mu} + \hat{\beta} * LoadPJME_{t-1})) + \hat{\phi}_{24}(Y_{t-24} - (\hat{\mu} + \hat{\beta} * LoadPJME_{t-1}))$$
$$- \hat{\phi}_1\hat{\phi}_{24}(Y_{t-25} - (\hat{\mu} + \hat{\beta} * LoadPJME_{t-1})) - \hat{\theta}_1\hat{E}_{t-1} - \hat{\theta}_{24}\hat{E}_{t-24} + \hat{\theta}_1\hat{\theta}_{24}(\hat{E}_{t-25}) + \hat{E}_t$$

For $t$<25, we assume that any unobserved Yt is equal to the overall mean miu.

An histogram of the simulated annual CRs is shown in the following graph.

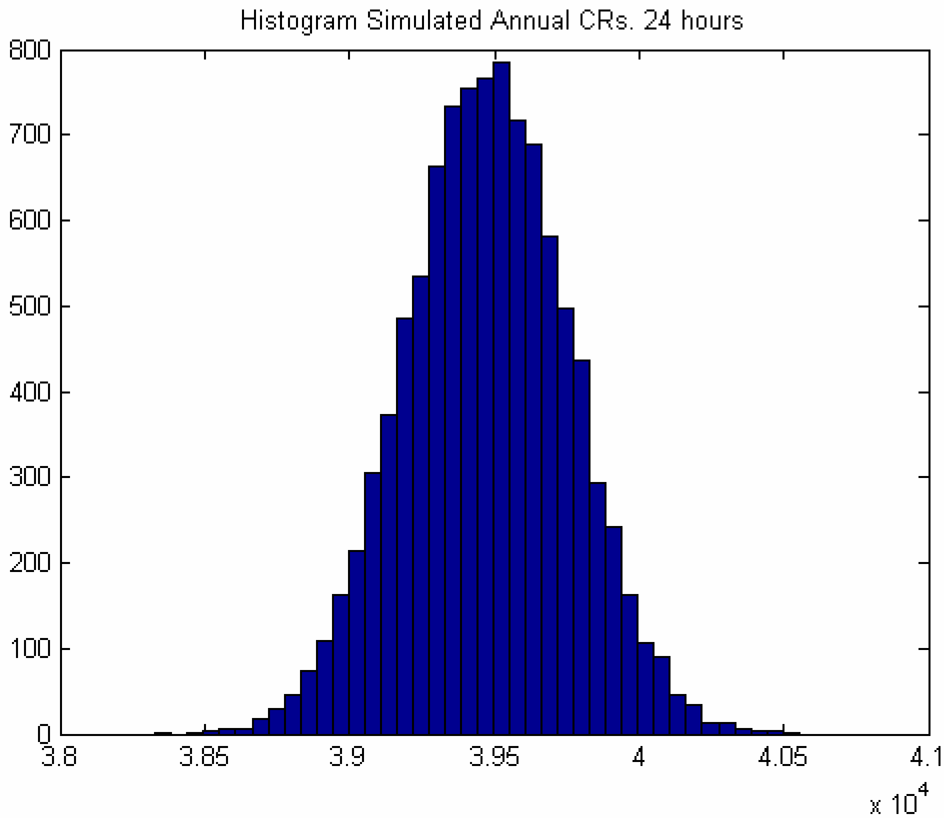


**Figure 10. Histogram Simulated Annuals CRs. 24 Hours**

The minimum, maximum, mean and standard deviation of annual CRs for this path are 38,330, 40,552, 39,475, and 282 respectively.  The null hypothesis that annual CRs follow a normal distribution cannot be rejected. (Jarque-Bera Test: p-value=0.9955)

The following graph shows the results of 10,000 simulated values of annual CRs for on-peak hours.

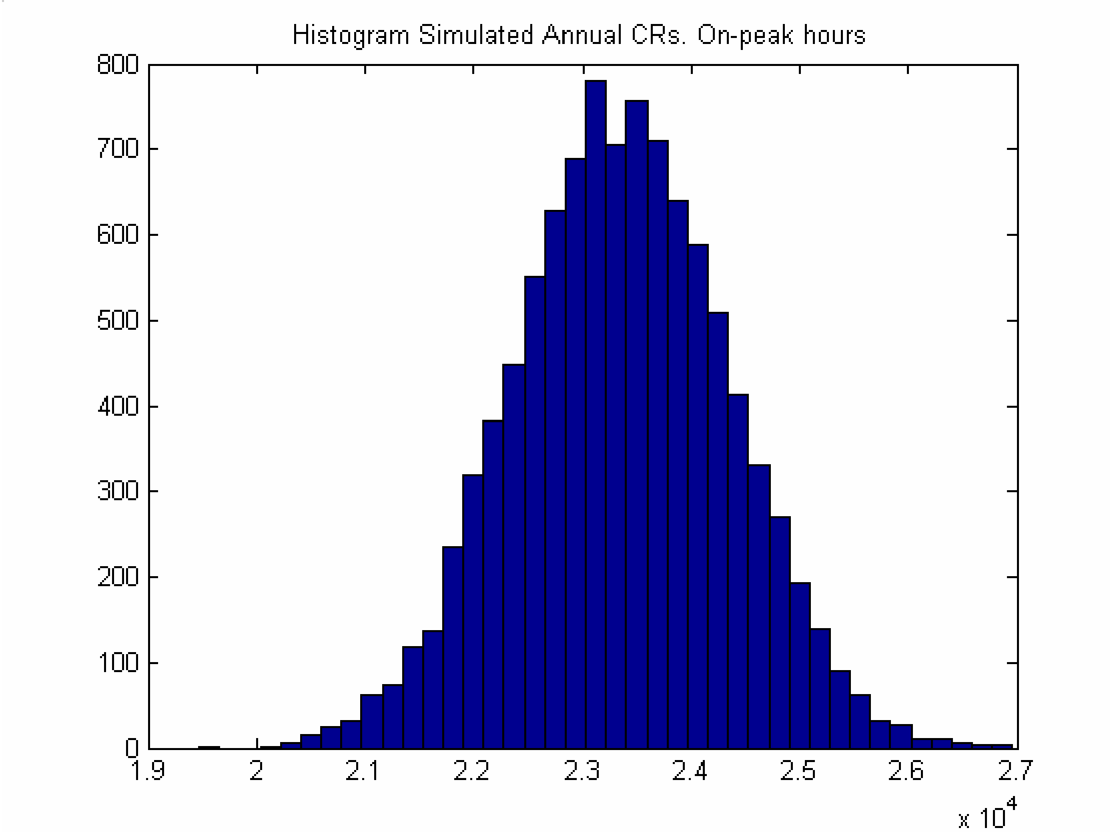

**Figure 11. Histogram Simulated Annual CRs. On-peak hours**

The minimum, maximum, mean and standard deviation of annual CRs for this path are 19,472, 26,932, 23,350, and 987 respectively. The null hypothesis that annual CRs follow a normal distribution cannot be rejected. (Jarque-Bera Test: p-value=0.8995)

The following graph shows the histogram of the 10,000 "observations" of annual CRs for off-peak hours.

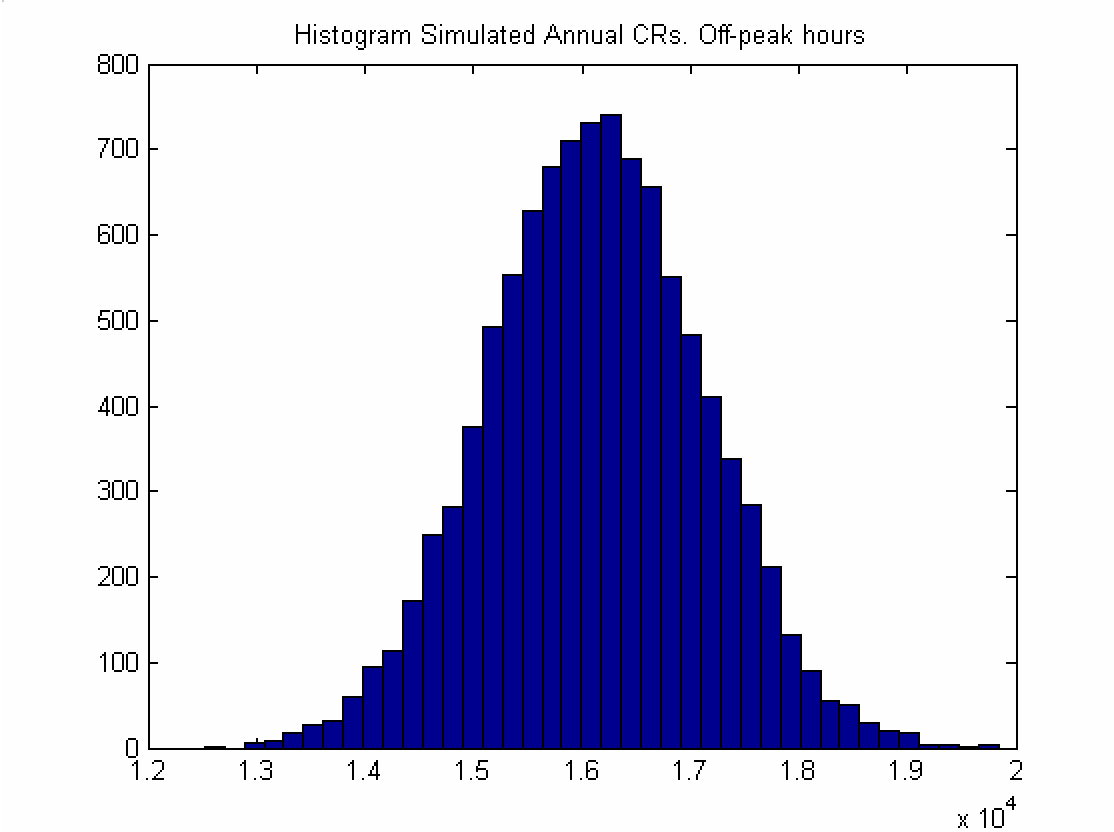


**Figure 12. Histogram Simulated Annual CRs. Off-peak hours**

The minimum, maximum, mean and standard deviation of annual CRs for this path are 12,521, 19,841, 16,125, and 990 respectively. The null hypothesis that annual CRs follow a normal distribution cannot be rejected (Jarque-Bera Test: p-value=0.7208).

### 3.5 Modeling Hourly CRs as random variables following empirical distributions based on type of hour and month.

In this section we try another version of the bootstrapping to get the distribution of annual CRs. We partition the sequence of 8,784 hours observed in 24 slots and treat each subgroup as a sample of iid variables, to infer a probability distribution. Then we generate a “year” of observations by randomly drawing an appropriate number of hours from the 24 empirical distributions.

The partition is based on month and type of hour. Since there are 12 months and two different types of hours (on-peak and off-peak) the hourly CRs are partitioned in 24 subsets that should be somewhat homogeneous.

To simulate a year of hourly CRs we generate each hour from the corresponding empirical distribution. For example to generate the month of June, we take 464 random draws from the empirical distribution of on-peak hours of June and 256 random draws from the empirical distribution of off-peak hours of June. We do the equivalent for each month until the 8,874 hours have been generated. Then we sum the 8,874 observations and take the result as one observation of annual CRs. We repeat the procedure many times as described above.

Even though we would expect CRs for the same month and type (on-peak or off-peak) be somewhat similar, the variability of each of the 24 distributions (but specially those corresponding to on-peak hours) is quite high. In many cases, the standard deviation exceeds the mean and the range is very large. The hypothesis that the distribution is normal is rejected for the 24 cases (Jarque-Bera test p-value<.00001). The following table shows summary statistics of the 24 subgroups of hourly CRs for path 526.

| | Num Hours | | Min | | Max | | Mean | | St dev | |
|---|---|---|---|---|---|---|---|---|---|---|
| Month | Off | On | Off | On | Off | On | Off | On | Off | On |
| Jun | 384 | 336 | -5.2 | -7.44 | 18.41 | 48.97 | 2.86 | 7.17 | 4.61 | 9.04 |
| Jul | 376 | 368 | -3.31 | -4.56 | 31.98 | 64.14 | 6.21 | 11.21 | 6.6 | 9.14 |
| Aug | 408 | 336 | -0.01 | -0.01 | 34.29 | 31.45 | 5.05 | 6.53 | 6.22 | 5.35 |
| Sep | 384 | 336 | -1.18 | -1.72 | 39.68 | 23.54 | 4.39 | 7.18 | 7.21 | 5.78 |
| Oct | 376 | 368 | -2.97 | -4.67 | 36.16 | 30.45 | 4.19 | 6.14 | 8.12 | 7.17 |
| Nov | 416 | 304 | -2.96 | -0.99 | 22.74 | 27 | 1.52 | 4.06 | 3.43 | 4.81 |
| Dec | 392 | 352 | -2.75 | -3.53 | 16.13 | 20.23 | 0.88 | 3.58 | 2.24 | 3.83 |
| Jan | 408 | 336 | -9.08 | -3.21 | 21.06 | 40.2 | 3.15 | 5.49 | 5.32 | 6.91 |
| Feb | 376 | 320 | -2.06 | -0.95 | 19.08 | 9.59 | 1.59 | 1.34 | 2.92 | 1.8 |
| Mar | 376 | 368 | -6.02 | -4.14 | 33.23 | 28.13 | 1.98 | 3.55 | 6.73 | 6.28 |
| Apr | 368 | 352 | -3.53 | -2.97 | 19.02 | 21.83 | 1.15 | 6.16 | 2.97 | 5.15 |
| May | 424 | 320 | -3.05 | -6.38 | 35.55 | 46.97 | 3.12 | 12.79 | 6.91 | 11.61 |

**Table 4. Summary Statistics of the 24 subgroups of hourly CRs for path 526**

A histogram of 1,000 “observations” of annual CRs for path 526, obtained with the method of the 24 empirical distributions is shown below. The minimum, maximum, mean and standard deviation of annual CRs for this path is 40,769, 46,272, 43,520, and 865 respectively. The null hypothesis that annual CRs follow a normal distribution cannot be rejected. (Jarque-Bera Test: p-value=0.7686).

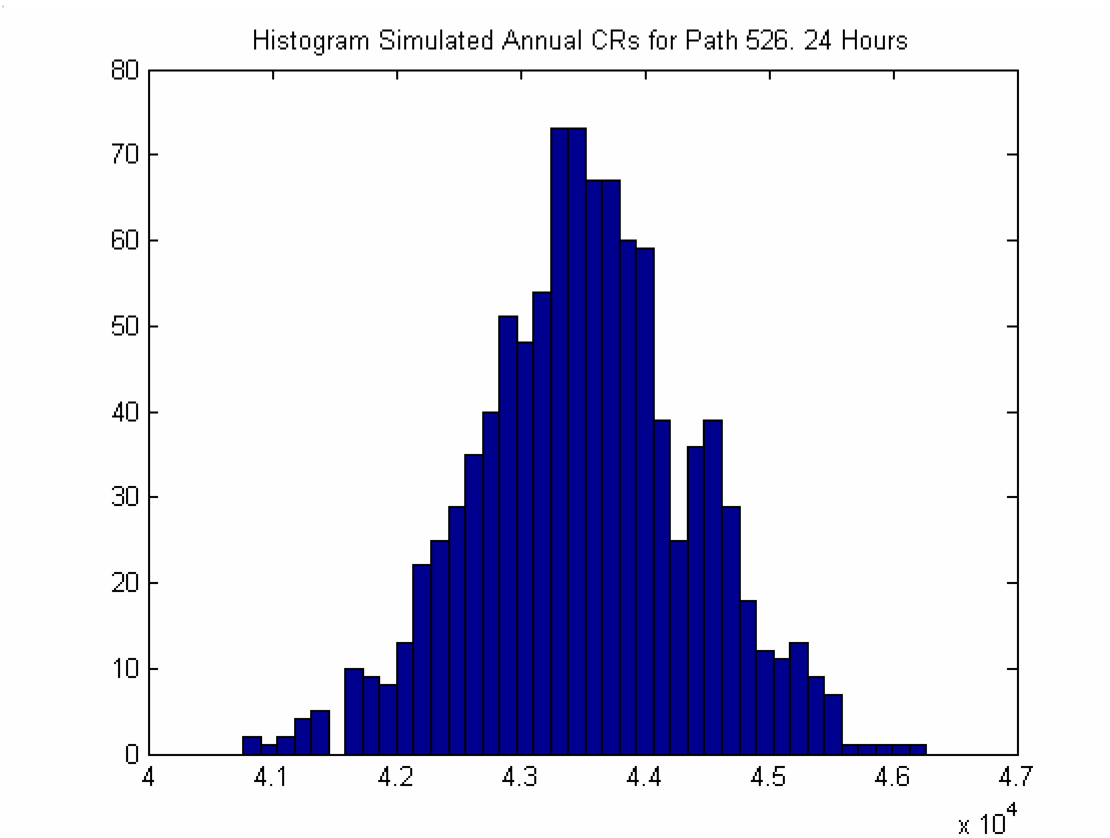


**Figure 13. Histogram Simulated Annual CRs for Path 526. 24 hours**

The histogram of annual CRs for off-peak hours is displayed below. The minimum, maximum, mean and standard deviation of annual CRs for this path are 13,650, 16651, 15,122 and 486 respectively. The null hypothesis that annual CRs follow a normal distribution cannot be rejected. (Jarque-Bera Test: p-value=0.2669).

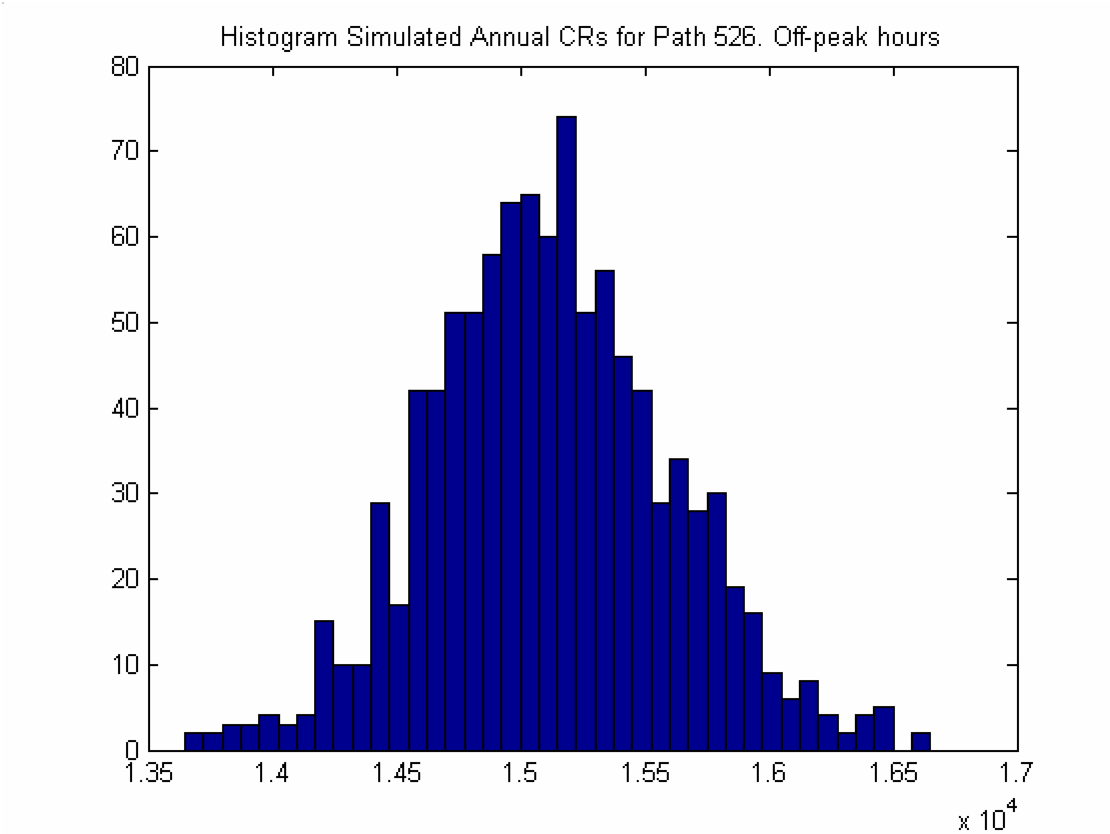


**Figure 14. Histogram Simulated Annual CRs for Path 526. Off-peaks hours**

The histogram of annual CRs for on-peak hours is displayed below. The minimum, maximum, mean, and standard deviation of annual CRs for this path are 26,517, 30,276, 28,397, and 543 respectively. The null hypothesis that annual CRs follow a normal distribution cannot be rejected. (Jarque-Bera Test: p-value=0.3724).

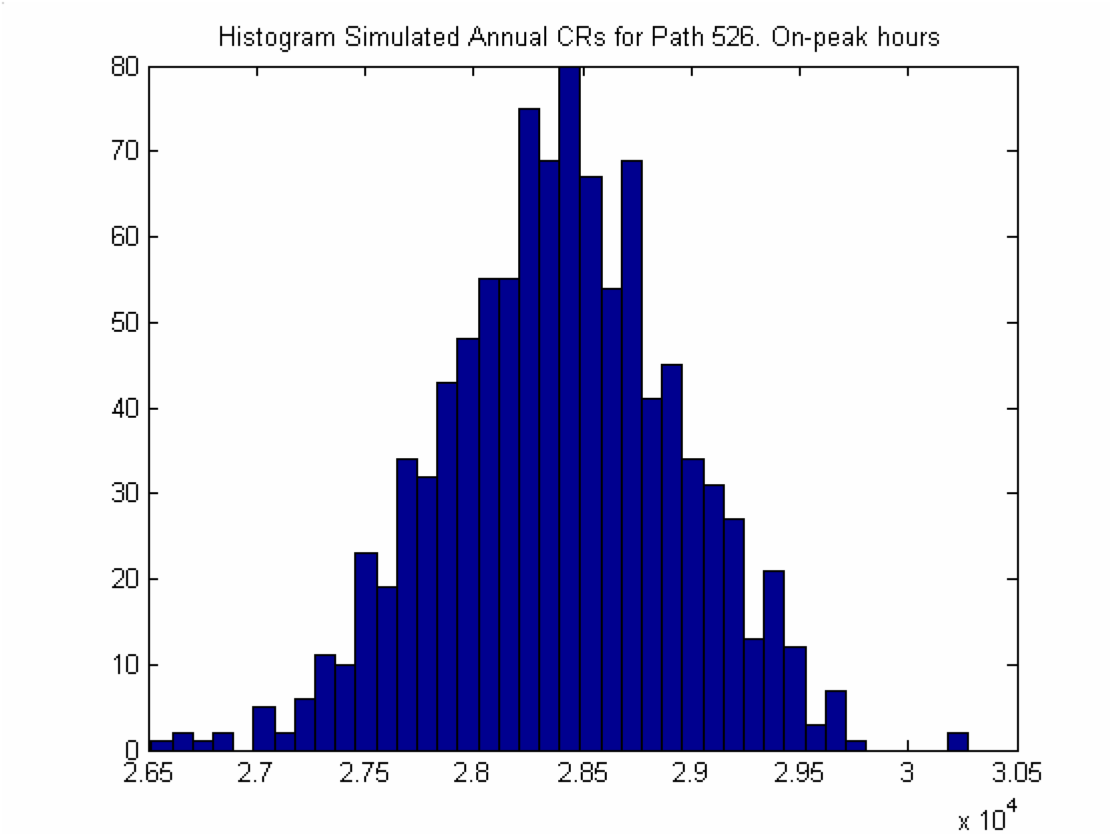


**Figure 15. Histogram Simulated Annual CRs for Path 526. On-peak hours**

The distribution of the annual CRs simulated with our method of the empirical distributions seems to be normal, for 24 hours, on-peak and off-peak hours. This result is not exclusive of path 526, but what we would expect from any path after applying the Central Limit Theorem -CLT (Feller 1945) and a property of the sum of normal distributions.

In its most simple form, the CLT states that the distribution of the sum of $n$ independent and identically distributed random variables with mean $\mu$ and finite variance $\sigma^2$, tends to be normal with mean $n\mu$ and variance $n\sigma^2$, as $n$ approaches infinite.

Therefore, if we generate the CRs corresponding to a given type of hour and month as independent draws from the same distribution its sum, will be normally distributed.

Also, if $X$ and $Y$ are normally distributed with means $\mu_X$ , $\mu_Y$, and variances $\sigma_X^2$ , $\sigma_Y^2$, then $X+Y$ is also normally distributed with mean $\mu_X + \mu_Y$ and variance $\sigma_X^2 + \sigma_Y^2$.

Hence the generation of annual congestion rents as the sum of monthly CRs (each being generated as a sum of iid rv, and therefore being normally distributed) can be described with a normal distribution.

This observation allows us to characterize the distribution of annual CRs for 24 hours, for all paths as normally distributed with mean $\mu = \sum_{m=1}^{12}\sum_{p=1}^{2} N_{m,p}\mu_{m,p}$ and variance $\sigma^2 = \sum_{m=1}^{12}\sum_{p=1}^{2} N_{m,p}\sigma_{m.p}^2$ where $N_{m,p}$, represents the number of hours of type $p$ in month $m$, and $\mu_{m,p}$ and $\sigma_{m,p}^2$ are the corresponding mean and variance.

## 4 Comparison of methods to find the distribution of annual CRs

All the methods presented to estimate the distribution of annual CRs are different and could lead to different estimations of the fair value of CRs. Because there is evidence that hourly congestion rents are not iid, the methods that express the value of congestion rents at one hour as a function of past values should be preferred. However, the time that the estimation of the necessary parameters takes, precludes at least for this dissertation its use for all the 3,601 paths. In this section we compare results for 45 paths, in order to understand better how the estimation methods differ, and how this affects the final estimation of the fair value of the FTR

### 4.1 Comparison of methods from sections 3.3, 3.4 and 3.5.

We applied the methods of section 3.3 and 3.4 to estimate the distribution of annual CRs for 45 selected paths, assuming 1) an ARMAX process with a GARCH error and 2) an ARMAX process with an error sampled from an empirical distribution.

Results show that for most of the cases, the distribution of annual CRs can be assumed to be normal, and the methods of Chapter 1 for a normal distribution can be applied (For the methods of section 3.3., out of the 45 paths analyzed, the hypothesis of normality was rejected for 2 paths for 24 hours, 2 paths for on-peak hours and 3 paths for off peak hours –no path had the hypothesis of normality rejected for the 3 distributions-. For the methods of section 3.4., out of the 45 paths analyzed, the hypothesis of normality was rejected for 7 paths for 24 hours, 3 paths for on-peak hours and 2 paths for off peak hours).

Because under the assumption of a normal distribution, the fair price of the FTR depends only on the coefficient of variation, we compare the coefficients of variation obtained with the methods of sections 3.3 and 3.4 to those obtained with methods of section 3.5. Under the assumption of CRs following a normal distribution, a higher coefficient of variation implies a higher fair price of the FTR.

The following graphs show a comparison of the coefficient of variation estimated with methods of section 3.3, 3.4 and 3.5, for each class of FTRs. We include a path in the comparison of Coefficients of Variation for a class, when the distribution of CRs can be assumed normal.  Paths are included in the three different graphs, when the distribution of the congestion rents for that class can assumed to be normal, even if there were no trades for that particular class of FTR

In general the coefficients of variation obtained with the three methods follow the same pattern. For CRs for 24 hours, the coefficients of variation obtained with the method of CLT are higher.

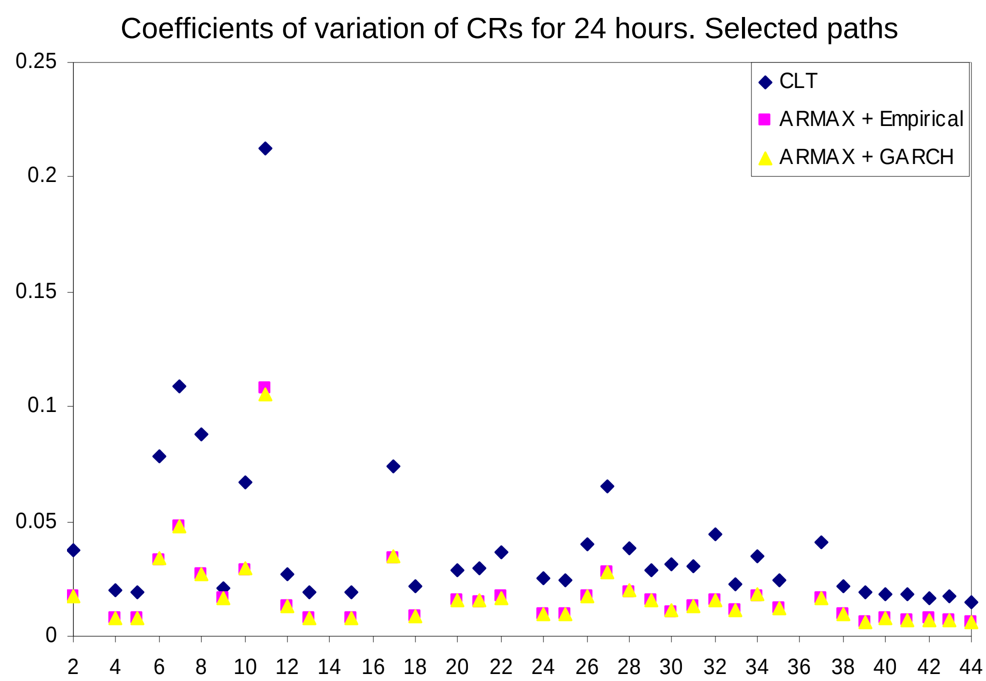


**Figure 16. Coefficient of Variation of Annual CRs for 24 hours.**

Coefficients of variation obtained for annual CRs for on-peak hours are in general lower when CLT is invocated.

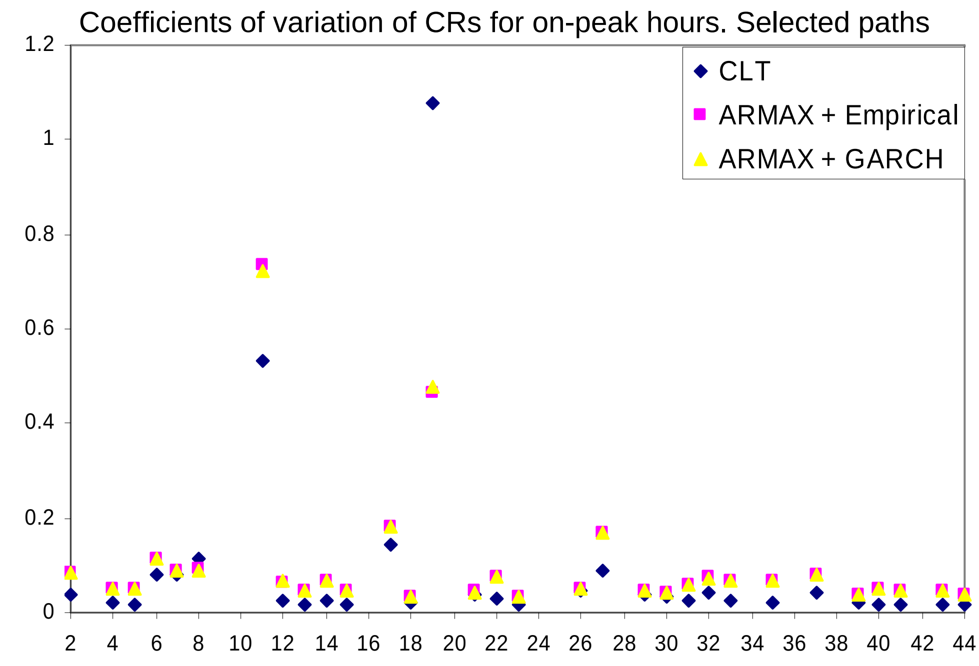


**Figure 17. Coefficient of Variation of Annual CRs for On-peak.**

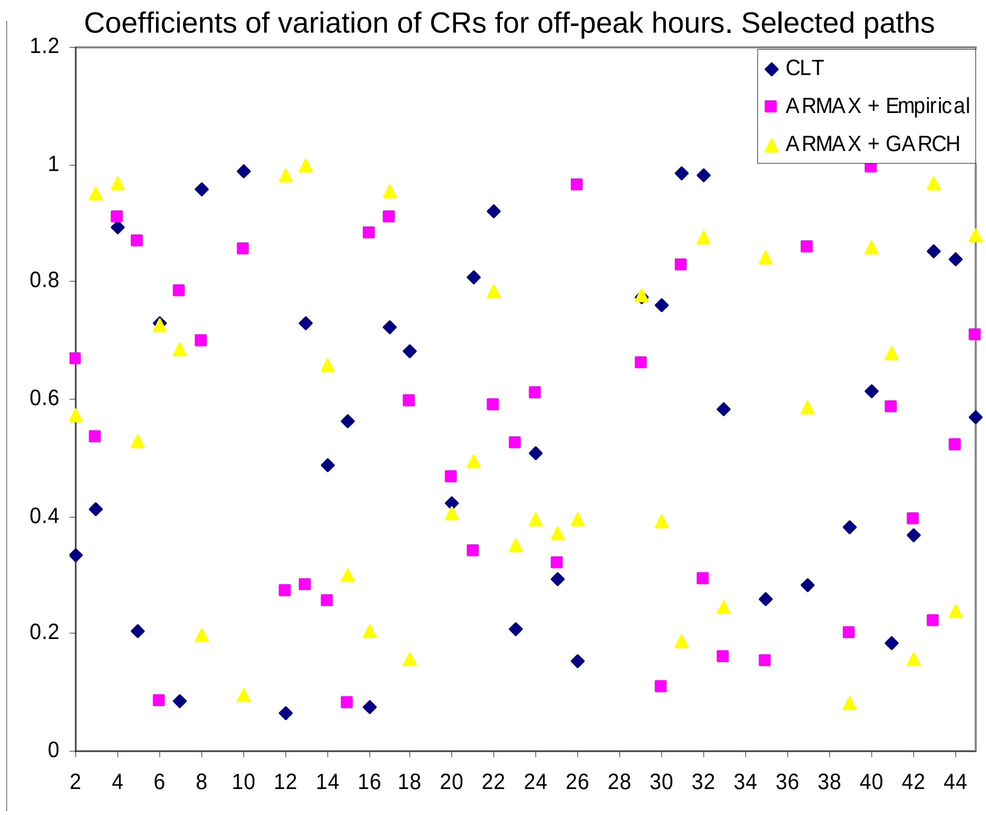


**Figure 18. Coefficient of Variation of Annual CRs for Off-peak.**

There is not a clear tendency for the coefficient of variation obtained for off-peak hours when CLT method is applied, relative to the other two methods.

For those paths for which corresponding CRs cannot be assumed to follow a normal distribution, the estimation of the fair value of the FTR has to be made by solving EQ. 13c from Chapter 1.

## 5 The fair value of FTRs for all paths assuming annual CRs are normally distributed (Standard deviation of CRs is found using methods of section 3.5)

In this section we present an estimation of the fair price of FTRs for all paths, based on the estimation of the distribution of annual CRs using methods from section 3.5[3], under which, the resulting distribution is normal and the fair price of a premium a linear function of the coefficient of variation according to the findings of Chapter 1.

The following table summarizes information about the estimated coefficient of variation (sigma/expected value of CRs) of annual CRs that would be generated for each path with the method of the 24 empirical distributions and the invocation of the CLT, explained in section 4. As explained in section 4, the generation of CRs for each hour as independent draws from an empirical distribution implies that the distributions of annual CRs are normal.

| | Estimated Coefficient of Variation Annual CRs | | |
|---|---|---|---|
| | 24 hours | On-peak | Off-peak |
| Minimum | 0.017 | 0.015 | 0.020 |
| 5% percentile | 0.026 | 0.022 | 0.032 |
| 25% percentile | 0.041 | 0.036 | 0.047 |
| Median | 0.074 | 0.068 | 0.075 |
| 75% percentile | 0.159 | 0.146 | 0.156 |
| 95% percentile | 0.686 | 0.506 | 0.785 |
| Maximum | 164.064 | 191.037 | 13,640.000 |

**Table 5. Estimated coefficient of variation of annual CRs**

From the previous table, the coefficient of variation for annual CRs for 24, on and off-peak hours, is less than 0.08 for half the paths, and 0.8 for 95% of the paths. From our results of Chapter 1 for a normal distribution a coefficient of variation of 0.08 implies

[3] In the appendix of this section we compare the fair value of the FTR versus the value observed in the auction, when the fair value is based on 1) an estimation of distribution of CRs assuming an ARMAX model with errors coming from an empirical distribution, and 2) an estimation of distribution of CRs assuming an ARMAX model with GARCH errors.

a fair price of the FTR of 1.022 times the expected value of annual CRs, and a coefficient of variation of 0.8 implies a fair price of 1.22 times the expected value of annual CRs. If our estimation of the probability distribution of annual CRs is correct, and if trades occurred at fair prices, then we should not observe prices more than 20% above the expected price of the corresponding CRs.

In what follows, we compare the real prices observed in the auction, to the fair price predicted by our formula $P_{normal}\left(\langle C\rangle,\sigma\right)\cong\langle C\rangle+0.2760\sigma$ presented in Chapter 1, assuming the expected value of annual CRs is equal to the real CRs observed. This assumption is strong, but is the only reasonable assumption we can make in the absence of more data.

The comparison is made by path for each class of FTR, and both for hedgers and speculators. As explained in Chapter 3, we call hedgers those market participants who paid for the FTR and later received the corresponding CRs, and speculators/insurers those who were paid to hold the FTR and later paid back the corresponding CRs. Those paths for which the holder did not guess correctly the direction of the congestion were excluded from the analysis.

For 24-hour FTRs, the price of FTRs was closely correlated to the fair price, but substantially higher. Hedgers paid on average 1.33 times the fair price as seen in the following graph.


**Figure 19. Fair Price Vs Price Paid by Hedgers**

There were very few cases of speculation with 24 hours FTRs, as explained in Chapter 3. (There were only 102 paths). For those cases, the average price received by speculators was more than 40% higher than the fair price.

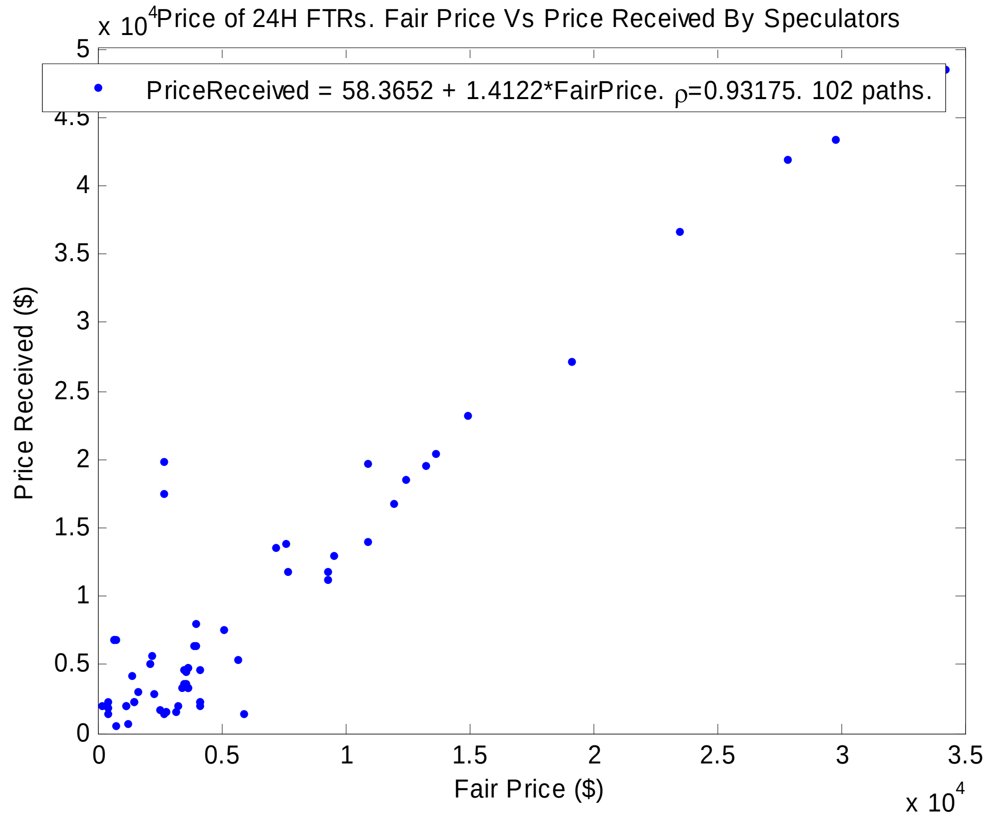


**Figure 20. Fair Price Vs Price Received by Speculators**

For on-peak FTRs, there is also high correlation between the fair price and the price received. As for 24h FTRs, the price observed in the auction is higher than the fair price predicted by our method.

Hedgers paid on average 20% more than the fair price for on-peak FTRs, as seen in the following graph.

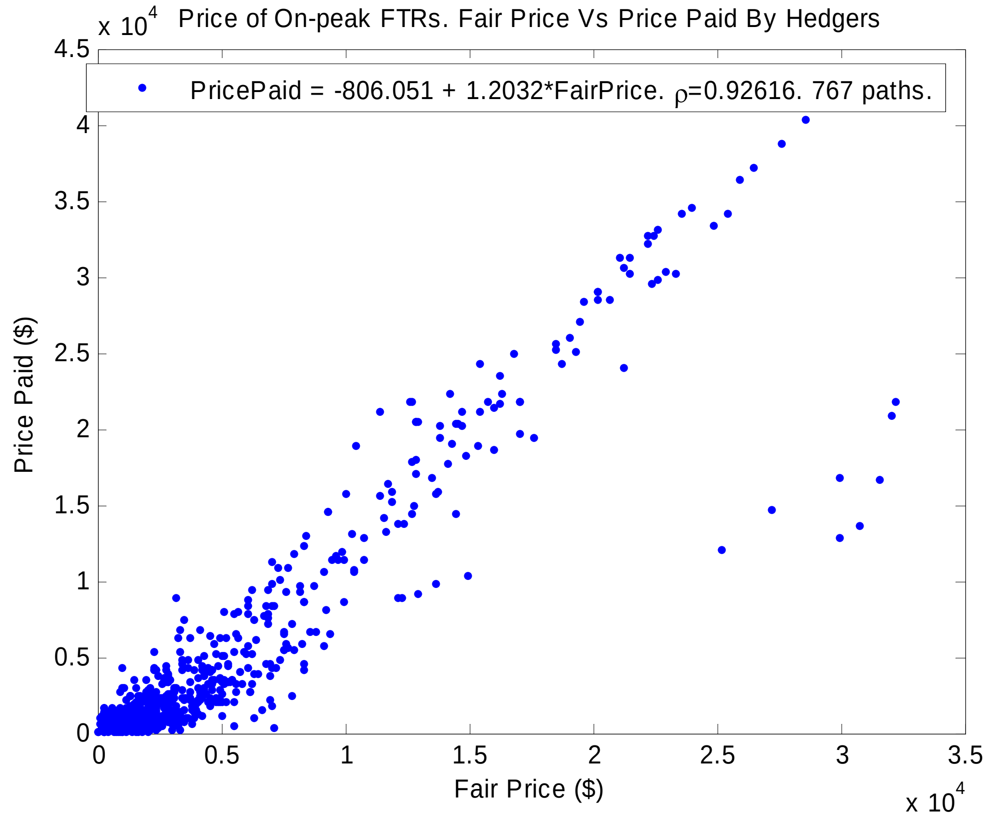


**Figure 21. Fair Price Vs Price Paid by Hedgers**

Speculators received on average a price more than 30% higher than the fair price, as seen in the following graph.

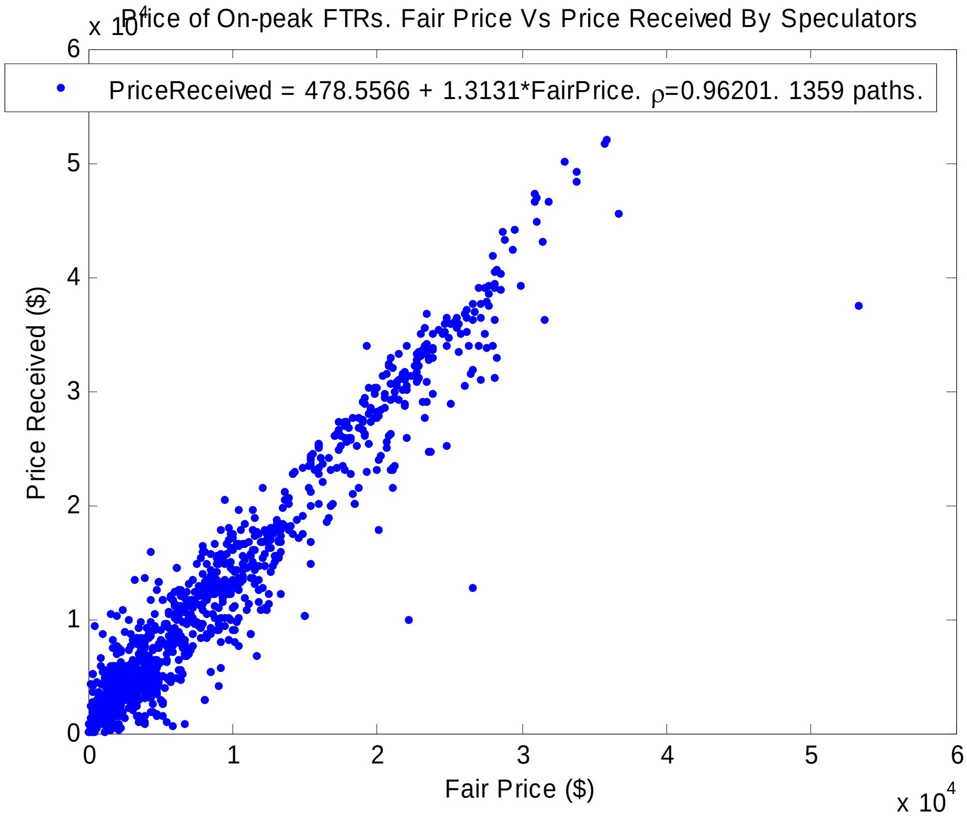


**Figure 22. Fair Price Vs Price Received by Speculators**

The only case in which the price observed in the auction is lower than our predicted fair price is the case of off-peak FTRs bought by hedgers. Hedgers paid only 90% of the fair price of off-peak FTRs.

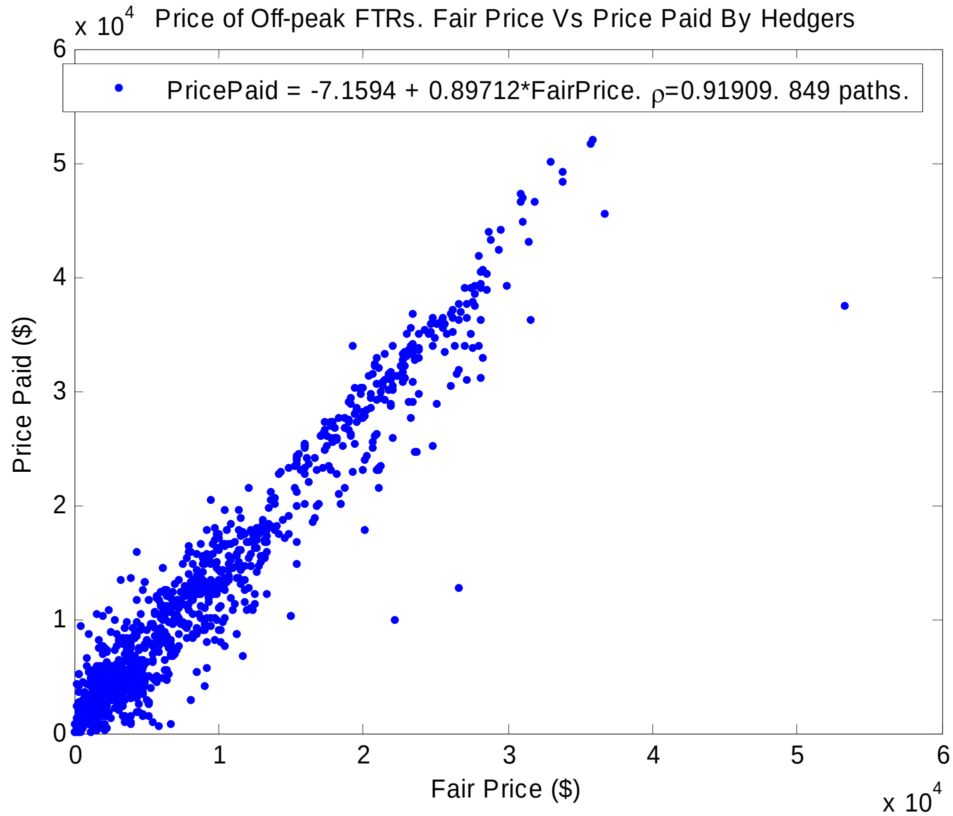


**Figure 23. Fair Price Vs Price Paid by Hedgers**

The price received for off-peak FTRs by speculators is only 11% higher than the fair price. The correlation between real and fair price is 0.9 which is the lowest for all the cases analyzed.

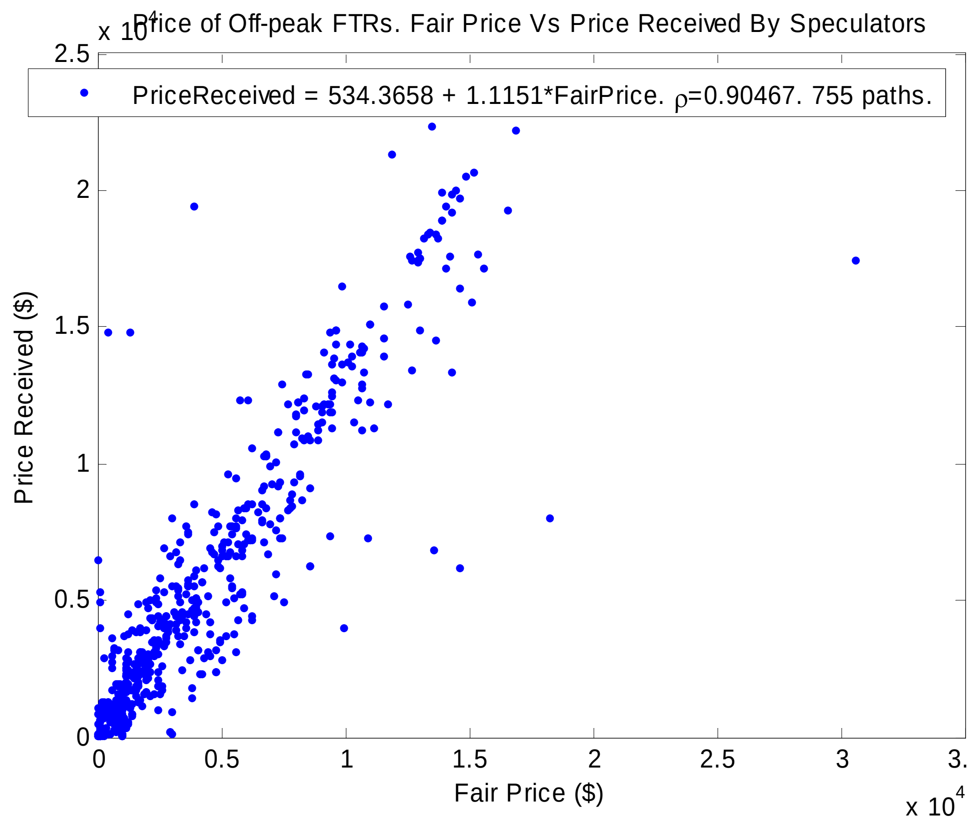


**Figure 24. Fair Price Vs Price Received by Speculators**

## 6 The Fair Value of FTRs when these are seen as protection against monthly CRs:

So far we have treated FTRs as instruments to hedge against annual CRs. This conceptualization seems reasonable because the payment for holding FTRs is in fact the annual sum of hourly congestion rents, but is not the only possible way to look at these contracts. It is very likely, that because transmission customers are billed monthly, they might see annual FTRs as a bundle of hedges against 12 monthly congestion costs.

Treating FTRs as insurance against annual costs vs as insurance against monthly costs for the whole year might have an important impact in the estimation of the fair value of the FTR. If we agree that it is reasonable to expect the sum of the variability of monthly CRs to be higher than the variability of annual FTRs, then we will agree that the fair price of FTRs when seen as protection against monthly CRs will be higher than when these are seen as protection against annual CRs.

Under the framework of FTRs as insurance against 12 uncertain future costs, the fair price of an FTR P is given by:

$$P\left(f_{c_1}(c_1), f_{c_2}(c_2),.., f_{c_{12}}(c_{12})\right) = \sum_{i=1}^{12} P\left(f_{c_i}(c_i)\right)$$

Where $f_{c_i}(c_i)$ represents the probability density function of CRs for month *i* and $P\left(f_{c_i}(c_i)\right)$ is the value of an FTR that covers CRs for month *i*, given by equation 13 in Chapter 1. Furthermore we could see FTRs as protection against 24 different uncertain costs, for each hour-class (on or off-peak) and month.

We could estimate the probability density function of monthly CRs, $f_{c_i}(c_i)$ using a bootstrap approach as we did to estimate the probability density function of annual CRs. We would need to find the empirical distribution of hourly CRs for each month (and class, e.g. peak or off-peak hour) and then use this distribution to obtain several "observations" of monthly CRs. The use of ARMAX models like the two presented in previous sections would most likely be useful to represent hourly CRs during a month, but the estimation of the parameters for the 12 different months for each of the 3,601 paths presented in previous sections would imply long computation times, inconvenient for the time frame of this dissertation. Therefore with the intention of illustrating only how the estimation of the FTR fair price would change with this approach, we choose to assume that the distribution of monthly CRs $f_{c_i}(c_i)$ are normal with mean and std deviations equal to those observed for the corresponding months and hour class during the period 2003-2004, and use EQ.13 to calculate the fair value of the FTR.

The following plots show a comparison for each path between the estimate of the fair value of an FTR when this is seen as protection against monthly CRs and the average observed price.

The two following plots compare the estimate of the fair price of the FTR as the sum of the fair price of 24 FTRs that provide protection against monthly CRs for peak and off-peak hours, and the average observed price for all the FTR transactions that occurred for that path.

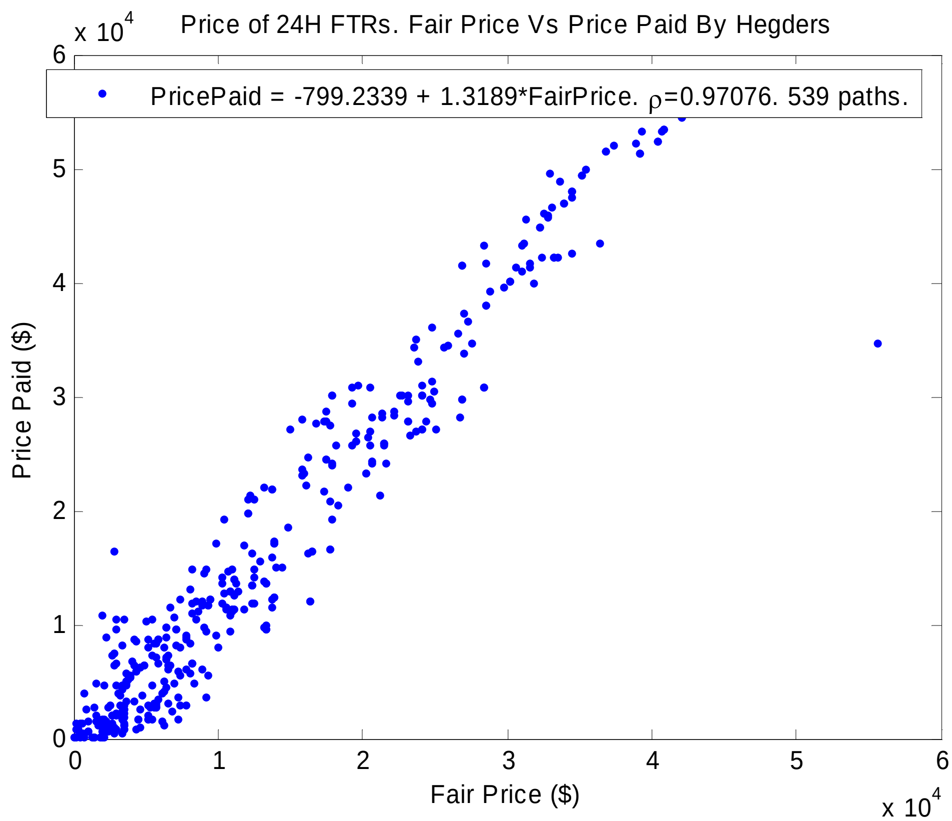


**Figure 25. Fair price vs average price paid for paths traded exclusively by hedgers for 24-hours. Assume FTRs are seen as protection against monthly CRs.**

The slopes of the lines that relate Fair Price and Price Paid, is less far from 1, than the slope calculated for the same paths when the fair price was estimated assuming with methods of section 5. For those paths traded by hedgers, the slope moves from 1.3317 (in figure 19) to 1.3189 (in figure 25), while for those paths traded by speculators, the slope moves from 1.4122 (in figure 20) to 1.3922 (in figure 26).

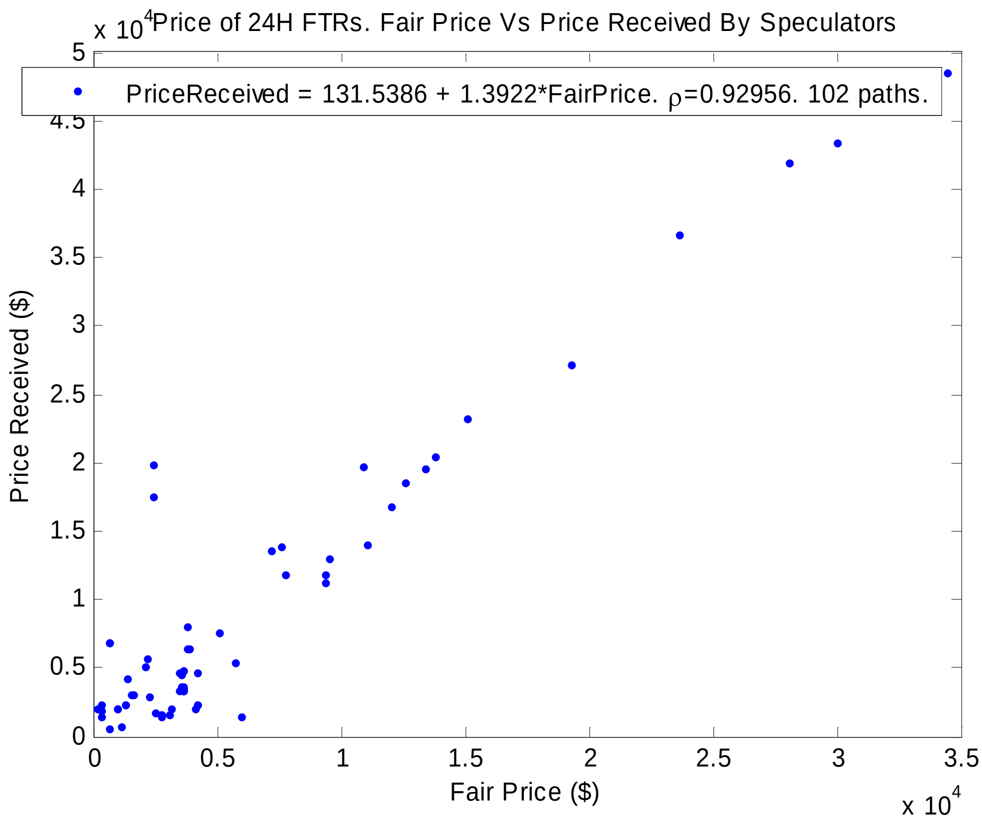


**Figure 26. Fair price vs average price paid for paths traded exclusively by speculators for 24 hours. hours. Assume FTRs are seen as protection against monthly CRs.**

The following two plots show a comparison between the average price of FTRs for those paths traded for on-peak hours, and the estimate of the fair price found by applying the methods of this section. Again the slopes of the lines that relate Fair Price and Price Paid, is closer to 1 than the slope calculated for the same paths when the fair price was estimated with methods of section 5. For those paths traded by hedgers, the slope moves from 1.2032 (in figure 21) to 1.1853 (in figure 27), while for those paths traded by speculators, the slope moves from 1.3131 (in figure 20) to 1.2931 (in figure 28).

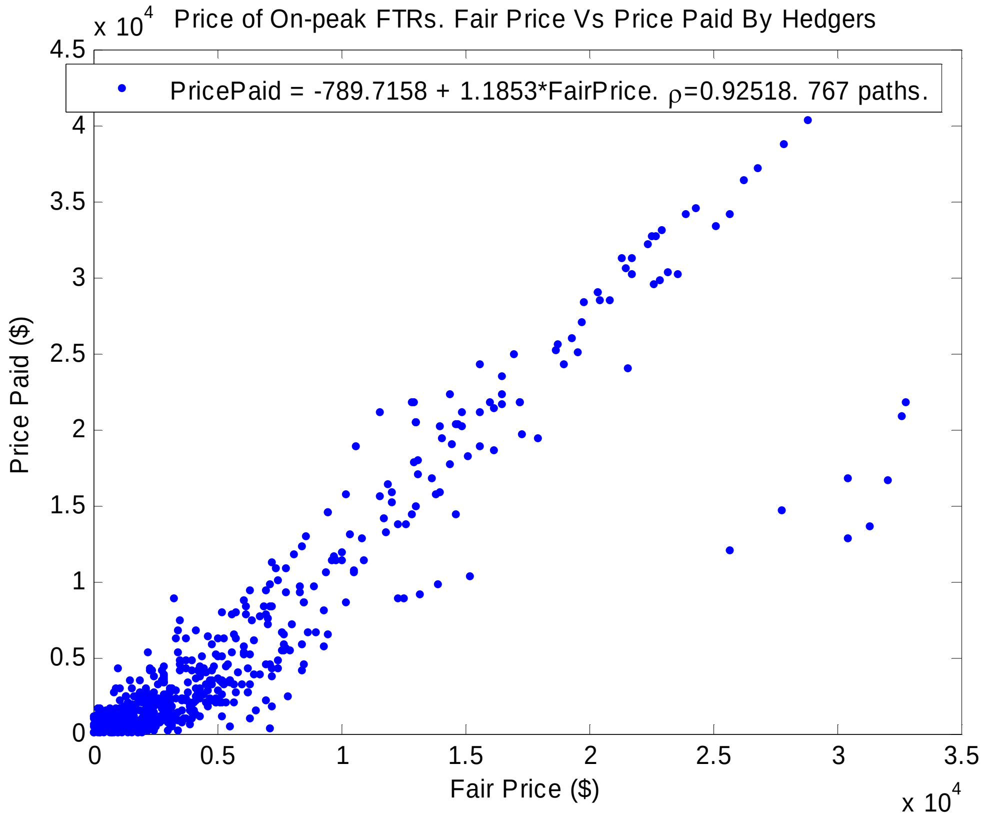


**Figure 27. Fair price vs average price paid for paths traded exclusively by hedgers for on-peak hours. Assume FTRs are seen as protection against monthly CRs.**

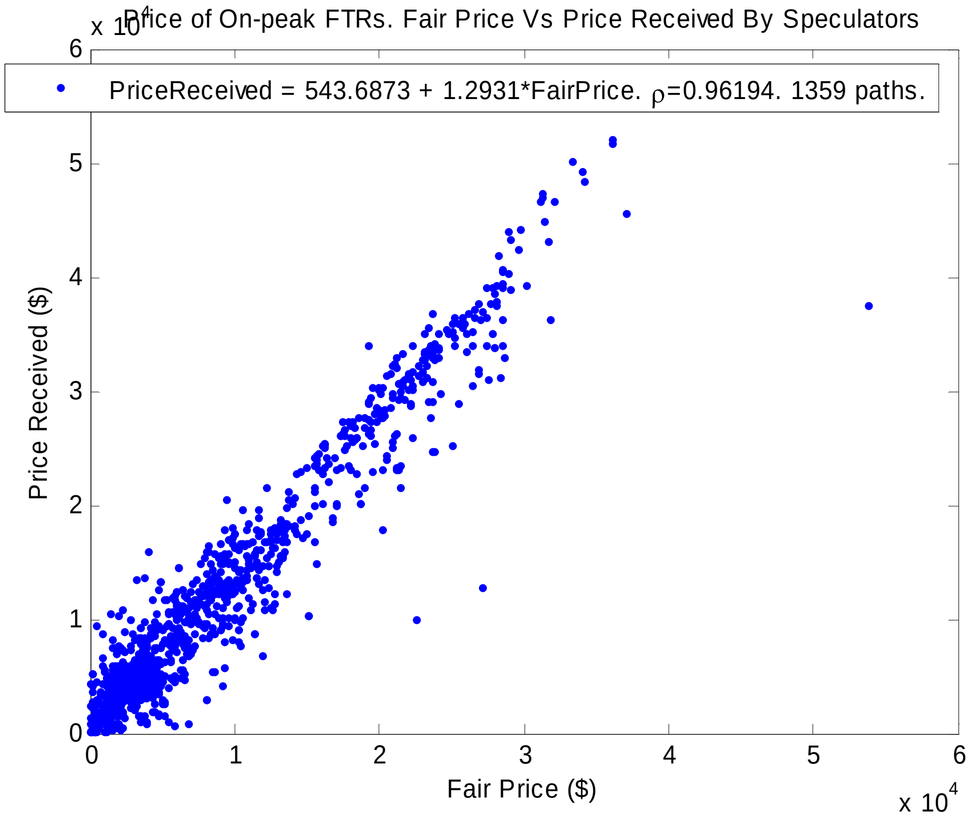


**Figure 28. Fair price vs average price paid for paths traded exclusively by speculators for on-peak hours. Assume FTRs are seen as protection against monthly CRs.**

For those paths traded for off-peak hours by hedgers, the slope of the LS line between the estimate of the fair price and the average of the observed price is farther than 1, than what it was when the estimate of the fair price was found with methods of section 5. The slope moves from 0.89712 (in figure 23) to 0.88207 (in figure 29). For those paths traded by speculators for off-peak hours, the tendency is the same as for the previous 4 cases analyzed; fair price and average of the observed price seem closer than when the estimates were given by those of section 5. The slope moves from 1.1151 (in figure 24) to 1.0942 (in figure 30).

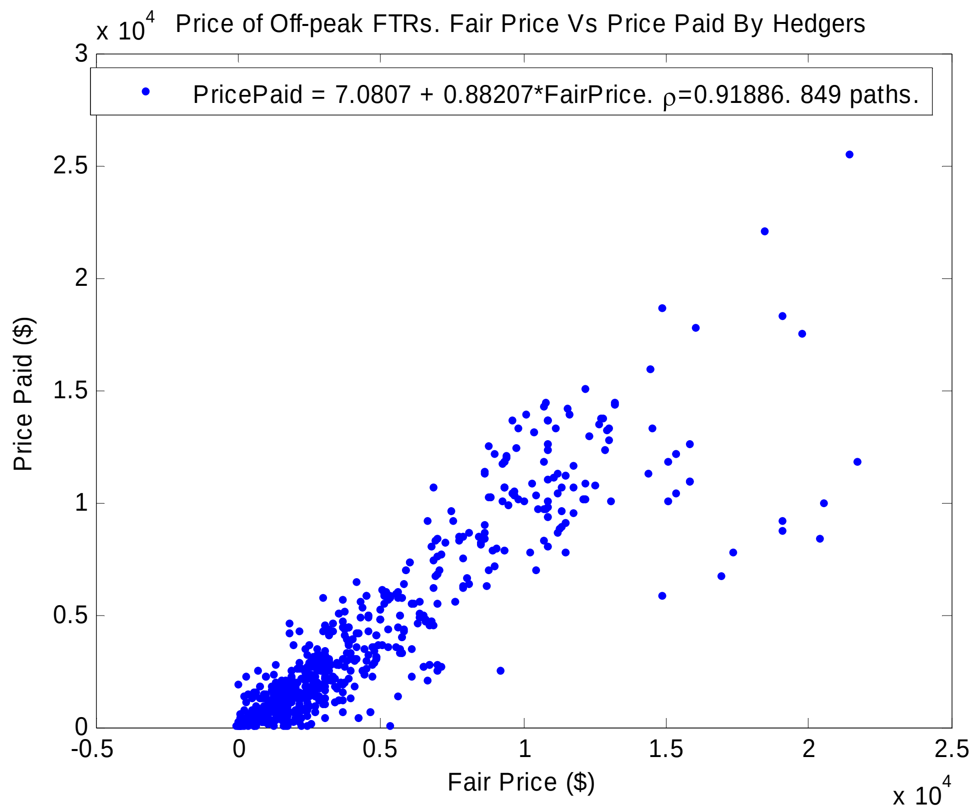


**Figure 29. Fair price vs average price paid for paths traded exclusively by hedgers for off-peak hours. Assume FTRs are seen as protection against monthly CRs.**

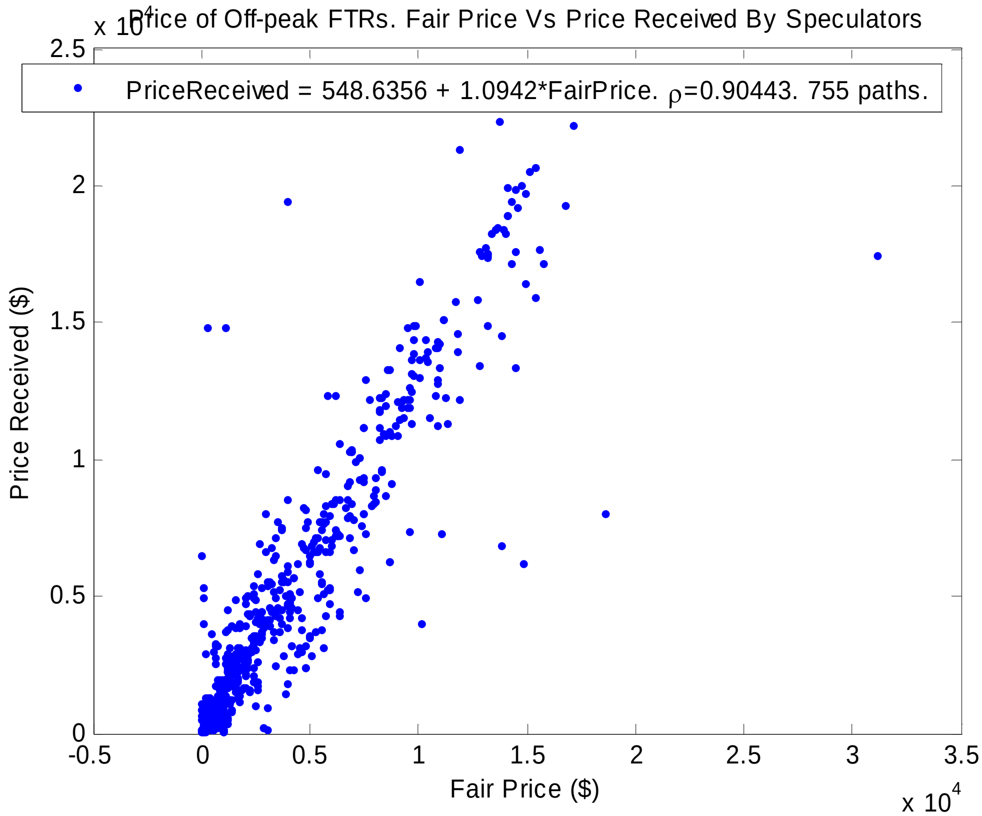


**Figure 30. Fair price vs average price paid for paths traded exclusively by speculators for off-peak hours. Assume FTRs are seen as protection against monthly CRs.**

## 7 Conclusions:

We proposed a framework to estimate the fair or risk neutral value of the FTRs. To find a precise estimate of that fair value poses a challenge, both because of lack of timely and consistent data and the changing conditions of the grid.

Attempting to overcome the absence of data about annual CRs, we used three different methods to estimate its distribution, based on the observation of hourly data on a year. Two of the methods require intensive computations and were only applied to 45 paths. The premiums predicted by these methods are in average much lower that the real prices observed.

A third method that assumes hourly CRs are independent random variables, makes use of the Central Limit Theorem to conclude that annual CRs are normally distributed and estimate the corresponding parameters. The estimates of the standard deviation for each path, using this method, were used to estimate the fair price of the FTRs. Altough fair and real prices are highly correlated, the real price is on average higher than the fair one, with the only exception of the FTRs traded by hedgers for off-peak hours.

Our predictions of a fair price need to be taken with care, not only because the method used to estimate the distribution of annual CRs is not infallible, but also, because the fair price depends heavily on the assumed expected value, which in our case is the observed value of CRs. This assumption is quite strong, but is our only alternative in the absence of better data.

In some years it will be possible to make an analysis that uses an estimation of the expected value and variance observed by the market participants before they participate in the auction, to predict a fair value. A comparison of such prediction with the real price, will be a better test of our method.

Given the size and nature of the uncertainty that the market participants currently face, and given the fact that auctions naturally select those whose willingness to pay is the highest, the observed price of FTRs may reflect their fair value. However we cannot rule out the possibility of higher risk aversion on the side of the hedgers, and the existence of strong market inefficiencies, as it has been discussed in Chapter 3.

This Chapter not only presents a way to estimate the value of reducing the exposure to risk in the context of FTR markets, but it also illustrates how the methods of option theory can be used for a much wider set of problems, even when the random variable of interest has an unknown probability distribution. Because the derivation of the mathematical formulae underlying this approach does not assume any specific properties for the source of the uncertainty, the framework can be used in very different settings.

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# Part Three: Other applications of options theory to value risk-reduction in the electricity industry

# Chapter 5: The Value of Installing an Emissions Control Device to Reduce Emissions from a coal-fired power plant

## 1 Introduction

Coal-fired power units account for more than 50%[1] of U.S. electricity generation and are the single biggest source of air pollution in the U.S. Changes in regulations controlling emissions of sulfur dioxide ($SO_2$), nitrogen oxide ($NO_x$), mercury (Hg), and carbon dioxide ($CO_2$) in the atmosphere will pose a serious challenge to the electricity generation sector and especially to coal-fired power plants.

Currently, $SO_2$ and $NO_x$ emissions from power plants are regulated by a combination of command-and-control (CAC) and cap-and-trade (CAT) instruments, depending on pollutant and plant location. Until recently there were no regulations controlling mercury emissions, but on March 15, 2005, the U.S. Environmental Protection Agency (EPA) issued the Clean Air Mercury Rule to permanently cap and reduce mercury emissions from coal-fired power plants across the U.S. by more than 70%. This rule assigns states a number of allowances, and requires each state to present a plan to keep emissions within their budget.[2] Further, while the current administration will not support $CO_2$ regulations in the near future, most experts believe that federal

[1] Electricity supply from coal accounted for 54% in 2001. EIA forecasts that under reference case assumptions, this tendency will remain in the next 20 years.
DOE/EIA. (2004). "Annual Energy Outlook 2004." 2005, from http://eia.doe.gov/oiaf/aeo/pdf/aeotab_16.pdf.
[2] http://www.epa.gov/mercury/control_emissions/

controls on greenhouse gas (GHG) emissions for U.S. power plants will eventually be required.[3]

The reduction of emissions from the electricity generation sector implies either retrofitting existing coal-fired power plants or replacing them with newer and cleaner technologies. Retrofitting existing coal plants to reduce emissions of sulfur-oxides, nitrogen-oxides, mercury, or carbon-dioxide requires equipment that is expensive to install and operate, and therefore the goal of reducing emissions inevitably conflicts with the goal of keeping electricity prices at their current level.

Policy makers might obtain important information from the analysis of how those trying to comply with regulations will evaluate their alternatives and make their choices. Because compliance decisions must be made under tremendous uncertainty, and imply significant financial risk, there is an opportunity in this problem to use the rational theory of options valuation exposed in Chapter 1.

The objective of this chapter is to illustrate with a simplified example how the "option" metaphor applies in the context of investment for air-emissions compliance, and how the methods of options-valuation can inform policy making in these field. Section 2 describes the difficulties that arise when the decision maker is deciding how to make its coal-fired power plant comply with air emissions regulations.

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[3] International treaties and recent laws appear to foretell Federal Controls: Consider for example: the State of New Hampshire House Bill 284-FN relative to additional emissions reductions from existing fossil fuel burning steam electric power plants http://www.gencourt.state.nh.us/legislation/2002/hb0284.html.
Oregon Carbon Dioxide Emission Standards for New Energy Facilities, House Bill 3283. http://www.leg.state.or.us/97reg/measures/hb3200.dir/hb3283.a.html.
State of Massachusetts DEP Regulation 310 that caps CO2 emissions from the six highest polluting power plants in 1,800lbs of carbon dioxide per megawatt-hour.
http://yosemite.epa.gov/globalwarming/ghg.nsf/actions/LegislativeInitiatives
California Automobiles/lemon law AB1058. http://www.dca.ca.gov/legis/2001 autolemon.htm

## 2 Investment decisions for compliance with air-emissions regulations for coal-fired power plants.

Under a CAT approach, the regulator sets a cap for the pollutant and issues an equivalent number of emission permits, or allowances, which can be traded in the market. Under the Acid Rain Program, the EPA allocates allowances to existing generating units for free, in a quantity determined by historical heat-rate input. Units are authorized to emit as many tons of pollutant as allowances have been allocated. Because, the number of allowances allocated covers only a portion of their emissions, individual plant operators must decide whether (a) install emissions control equipment, (b) buy "emissions allowances" in the market, or (c) reduce the electricity output (so less emissions are generated).

Often, units that install Environmental Control Devices (ECD) end up emitting less pollutant than what they have been allowed. Unused emissions allowances can be sold in the market, or if allowed they can be banked for use in future years. Generating units that end up with emissions over the number of allowances held must purchase allowances and pay a fine for each ton.[4] To make a choice about whether and when to install emissions-control equipment, decision makers have to consider the expected cost of compliance for each of the possible alternatives, which depends on the capital and operating cost of ECDs, number of allowances allocated, level of emissions, and price of allowances. Many uncertainties difficult the evaluation of the different compliance options:

[4] Fines were $2,000 per ton of $SO_2$ in 2004.

## 2.1 Uncertainty in future regulations.

The current number of allowances allocated for each pollutant is known by generator, but the number of allowances that will be allocated in future years is highly uncertain. As it has been mentioned, significant changes in the future air-emissions regulations are expected but neither the timing nor the stringency is known. This uncertainty essentially charges a toll, because waiting to decide until all legislative, regulatory, and judicial uncertainty is resolved can prove costly, but "locking in" an emission-control technology too soon could prove equally expensive. On one hand, plants might face stringent regulations without being prepared and could be forced to buy expensive emission allowances. On the other hand, the installment of a particular control technology can preclude or make more expensive the option to install newer technologies more efficient or better suited for updated regulations.

Regulatory uncertainty can be very costly. In previous work (Patiño Echeverri 2003), reproduced in Appendix 5, we proposed a method to compute the expected cost of regulatory uncertainty for coal-fired plants for a set of plausible regulatory scenarios with attached probabilities. Under this approach, each plausible regulatory scenario determines plants' emissions, price of allowances, and fuel prices, so when a regulatory scenario is realized there are no more uncertainties. We illustrated in a then current case study of a 500 MW coal-fired power plant that optimal ECD installment decisions in the face of such uncertainty could result in expensive investments that may never be used. The total cost of regulatory uncertainty over a 30 year period for this case study was $40 million or 20% of the cost of a new coal-fired plant of the same size. In the illustration included in this chapter we account for regulatory uncertainty by shortening the time the ECD is expected to operate.

### 2.2 Uncertainty in unit emissions

The emissions of an electricity-generating unit are proportional to the power output and therefore cannot be predicted with accuracy without knowing future utilization-capacity-factors. If the plant participates in the spot market, then its electricity output is also a random variable that depends upon electricity demand, market structure, and the generator's bid. If the bid is affected by the cost of compliance with environmental regulations, then the compliance strategy and unit emissions are related in a closed loop fashion. Coal-fired units are usually operated as base-load plants and therefore there is less uncertainty about the time of operation and the corresponding emissions.

### 2.3 Uncertainty in emissions-allowances prices

The price of allowances depends on the compliance decisions made by all the units participating in the market of allowances. For example, if all generating units decide to install ECDs and reduce emissions to a level below the legal requirements, then the price of allowances will drop to zero. On the other hand, if allowances are scarce, prices can approach the fine's price.

Forecasting allowances prices has proven to be a difficult task in the recent past. For instance, when the Clean Air Amendment was enacted, the cost of compliance with the Acid Rain Program standards for $SO_2$ was estimated to be \$400-\$1000/ton, but by 2000, allowances ranged in price from \$130 to \$155 and remained close to \$140 until

2003, when prices started rising. The $NO_x$ budget offers another example; although forecasts of marginal control costs ranged from \$500/ton to about \$2,500/ton and in very few cases close to \$5,000/ton, some trades in early 1999 occurred about \$7000/ton but prices later fell to less that \$1000/ton (Farrell 2000). In 2003, trades for $NO_x$ allowances for vintage 2004 and 2005 occurred at prices between \$3,000/ton and \$4,000/ton (Cantor-Fitzgerald 2005).

It is argued (Ellerman 1998) that in phase II of the CAAA90, a high supply of $SO_2$ allowances and prices much lower than expected occurred in part because owners of big power plants preferred to invest in expensive scrubbers rather than incur the risk of an allowances shortage. Later, the situation with $NO_x$ was the opposite. Many plants preferred to wait to see what would happen in the market of $NO_x$ allowances before installing any expensive control technology. This “wait and see” approach of many plants is at least one of the causes of the high prices of $NO_x$ allowances seen in recent years. Estimating allowance prices under multi-pollutant regulation poses additional difficulties, due mainly to synergies between the control of $SO_2$, $NO_x$ and $CO_2$.[5]

## 2.4 Modeling prices of allowances

In the example presented in this chapter, allowance prices are modeled with a geometric-Brownian stochastic process, with drift and volatility estimated from observed prices in the past 18 months. Allowance markets appear reasonably efficient. The trading of SO2 allowances between unrelated companies has been significant since the market opened in 1995. The volume of trading reached a peak of 15 million tons in year 2000 and in 2003 almost 8 million allowances were traded(Burtraw, Evans et al. 2005). The

5 For example, analysis conducted by EIA shows that while a scenario with stringent regulations only on SO2 leads to allowance prices of \$300, \$700 and \$1,000 in years 2008, 2010, and 2020 (in 1999 dollars), a scenario with the same stringent cap of SO2 and stringent caps for NOx and CO2, leads to prices of \$100, \$100 and \$50 for the same.

volume of trading appears important when compared to the annual cap of 8.5 million tons of SO2.

Trading programs for NOx seem to have been successful too. The OTC,[6] the RECLAIM[7], and the NOx SIP[8] call markets have shown increased trading as they mature. In the RECLAIM market, in year 2000 electricity generators were allocated 2,350 tons of credits and purchased about 2,250 tons in allowances(Ellerman 2003). The new NOx Budget Trading for Eastern States has had robust trading activity between separate economic entities, since its inception in 2003 (EPA 2005). Close observation of recent allowance prices might be the best source of information to characterize the uncertainty in these markets.

## 3 Incorporating financial risk management tools in the analysis of environmental regulations.

To illustrate the point of how to incorporate option theory in the decision making process regarding regulatory compliance, the next two sections consider the decision of whether to install an ECD to reduce emissions.

### 3.1 Traditional Approach: Real Options

Herbelot (Herbelot 1994), and Insley (Insley 2003) examine the problem of whether or not to install an ECD, using a "real options" approach (Dixit and Pindyck 1993). This approach looks at the ECD installation as an irreversible investment and the allowances as the alternative that allows delaying such investment. The option to install

6 The Ozone Transport Commision (OTC) was created by congress to facilitate ozone compliance in 11 States that include the northeastern and Mid-Atlantic States from Maryland to Maine, District of Columbia and northern counties of Virginia.

7 The Regional Clean Air Incentives Market (RECLAIM) is a program created by the South Coast Air Quality Management District to reduce emissions from 390 facilities by 8% each year from 1994 through 2003. It had low allowance prices and little trading in the early years, but demand for allowances increased in 2000.

8 The NOx State Implementation Plan (SIP) Call Program, began in 2003, after the petition of northeastern states to the EPA to require reductions from upwind states. It affects 19 eastern states.

an ECD is valuable only if it has not been yet exercised, and therefore it may be optimal to rely on allowances even if the present value of the expected cost of compliance with allowances is higher than the present value of the expected cost of compliance with the ECD. The solution requires finding a threshold value for allowances' prices for which the option of installing the ECD is equal to the present value of the compliance cost with ECD. When allowances' prices reach or exceed this value, the unit must install the ECD.

Herbelot showed that purchasing SO2 emissions allowances was the preferred alternative even if the present value of expected compliance cost with allowances was higher than the expected cost of compliance switching fuel or installing a scrubber. This study was completed before knowing what would be the industry response to the CAAA 1990. In fact, only very large plants installed scrubbers and many switched fuel, causing SO2 allowances' prices to drop to levels unexpected in the early 90s.

Insley (2003) also examined the choice of installing an environmental control, but this more sophisticated model accounted for the time that it takes to install a scrubber ("time to build") and the embedded options of halting the installation temporarily or permanently at different stages. It also accounts for the alternative of mothballing the scrubber if the benefits do not cover variable costs.

### 3.2 Alternative approach: Rational options

The underlying assumption of the traditional real options approach is that decision makers are more interested in minimizing regret associated with an irreversible investment, than minimizing the regret of a shortage of allowances. We look at the problem as if the order of concerns were just the opposite, and look at the installation of

ECDs not as irreversible investments that the unit should avoid but as insurance against high prices of allowances.

If the ECD can be installed and then used at will,[9] then the installation of the ECD can be seen as a transaction that gives the investor the right, but not the obligation, to "buy" a determined quantity of allowances at a specified price within a specific time period. The price "paid" per allowance is the ECD's O&M per ton pollutant removed. The time during which this right can be exercised is the remaining life-time of the generating unit, the life-time of the ECD or the time before a new regulation makes the unit and/or the ECD obsolete, whichever comes first. Therefore, the installation of the ECD is equivalent to the purchase of a bundle of call options. Whenever the capital cost of the ECD is exceeded by the value of these call options, the investment should be undertaken.

If the expected lifetime of the ECD is $T$, and the expected "generated allowances" on year *t* are $N_t$, then installing it is equivalent to getting $N_1$ call options at year 1, $N_2$ call options at year two etc.., and $N_T$ call options at year *T*. Since the number of allowances that can be generated each year is limited, the options generated by the ECD can only be exercised at the expiration date. In other words, they are European call options. Note here that "exercising the option" really means using the ECD. Since the decision of using an ECD could be made every day (or every few hours), we could divide the bundle of options obtained into periods shorter than one year. For simplicity, however, we assume that the decision of whether or not to operate the ECD (already installed) is made once per year, and therefore the expiration date of all this options is

[9] This is feasible for both an SO2 and an SCR because both generally have "bypass" units that allow the flue gas to completely bypass the vessels.

one year after they are obtained. (A change in this assumption would not change any of the derivations here. It changes only the numerical results of the example.)

The value of installing the ECD is then given by:

$$\sum_{t=0}^{T} e^{-\rho t} N_t call(t, t+1) \qquad \text{EQ.1}$$

Where $call(t, t+1)$ represents the value at time t of a European call option on one allowance, with exercise date at time t+1, and $\rho$ is the discount rate.

Note that EQ.1 sums the discounted value of options that will be received every year that we continue to have the ECD installed, instead of summing the value of options received today. Technically, the options are “received” at the same time, but they have different expiration dates, so EQ.1 could be written as:

$$\sum_{t=0}^{T} e^{-\rho t} N_t call(0, t) \qquad \text{EQ.1b}$$

where $call(0, t+1)$ represents the value at time 0 of a call option that expires at time t. When the call is valued assuming the process followed by allowance prices is geometric-Brownian motion, the value of $call(t, t+1)$, will be less than the value of $call(0, t+1)$. Therefore the value of the ECD will be lower if we use EQ.1. than if we use EQ.1b, assuming geometric Brownian motion for allowance prices. Because the period of evaluation of the options (T) is measured in years, the assumption that a characterization of the uncertainty based on observations of prices over a short period of (1 or 2 years) will hold, is very strong, and the value of $call(0, t+1)$ might be over estimated.  To account for the fact that by valuing options that will expire in several years, we are perhaps stretching the validity of our characterization of the underlying source of uncertainty, we choose to use EQ.1 instead of EQ.1b.  As we will see later, the use of EQ.1 will allow us to find a confidence interval for the value of the ECD.

### 3.2.1 The option to buy one allowance

As explained in Chapter 1, in order to value an option we need to characterize the stochastic process followed by the underlying source of uncertainty or equivalently, a probability distribution function for the value of the underlying at the time of expiration of the option.

For SO2 and NOx, the best source of information we can use to characterize the uncertainty of future allowance prices is today's market.  The market for SO2 has been operating for more than 10 years now, and in the absence of anything better it can be a good source of information about the trend and volatility of SO2 allowance prices.

Under the assumption of allowance prices following an Ito process (see chapter 1), we can use the Black and Scholes formula to calculate the value of the option to buy one allowance, and the value of the stream of call options on allowances that will be obtained at the installation of the ECD.  Applying the Black and Scholes formula to EQ.1 we conclude that the value of installing a scrubber is:

$$\sum_{t=0}^{T} e^{-\rho t} N_t \left[ S_t \Phi^s(d_1) - X e^{-r((t+1)-t)} \Phi^s(d_2) \right] \qquad \text{EQ.2}$$

where $d_1 = \dfrac{\ln\left(S/X\right) + \left(r + \sigma^2/2\right)(t+1-t)}{\sigma\sqrt{T-t}}$ and $d_2 = d_1 - \sigma\sqrt{t+1-t}$, and $\Phi^s(x)$ is the CDF of the standard-normal distribution. $S_t$ is the price of allowances at time t, $X$ is the ECD's per-ton O&M annual cost, (O&M /N), $\sigma$ is the per annum volatility of allowance prices, $t$ is the year when the allowances will be generated ($t <$ lifetime of the ECD), and T is the life time of the ECD.

If we were using EQ.1b, then we would have

$$\mathrm{I}\sum_{t=0}^{T} e^{-\rho t} N_t \left[S_t \Phi^s(d_1) - Xe^{-rt}\Phi^s(d_2)\right] \qquad \text{with:}$$

$$d_1 = \frac{\ln\left(S/X\right) + \left(r + \sigma^2/2\right)t}{\sigma\sqrt{T-t}} \text{ and } d_{21} = \frac{\ln\left(S/X\right) + \left(r - \sigma^2/2\right)t}{\sigma\sqrt{T-t}}.$$

### 3.2.2 Accounting for construction time

The time between the decision to install an ECD and the moment where it is ready to operate might be considerable for most technologies. Before the ECD is ready to operate, there will be no emission reductions and no "options" to "buy allowances" will be generated, therefore, EQ.2 must be modified to account for this reduction in the value to install an ECD. If $\tau$ is the time when the ECD will be ready, then the value of installing an ECD is given by:

$$\sum_{t=\tau}^{T} e^{-\rho t} N_t \left[S_t \Phi^s(d_1) - Xe^{-r((t+1)-t)}\Phi^s(d_2)\right] \qquad \text{EQ.2b}$$

$$\sum_{t=\tau}^{T} e^{-\rho t} N_t \left[S_t \Phi^s(d_1) - Xe^{-rt}\Phi^s(d_2)\right]$$

Where d1, d2, and $\Phi_s(x)$ are defined as in EQ 2.

If we wanted to be more precise, we should also account for the fact that to complete the final stages of installation of the ECD, it might be necessary to shutdown the generating unit. The cost of stopping the production of electricity for some weeks or months should be included in the capital cost.

### 3.2.3 Volatility of Allowance's prices for $SO_2$ and $NO_x$

The following graph shows transaction prices of $SO_2$ allowances in the past 19 months.[10]

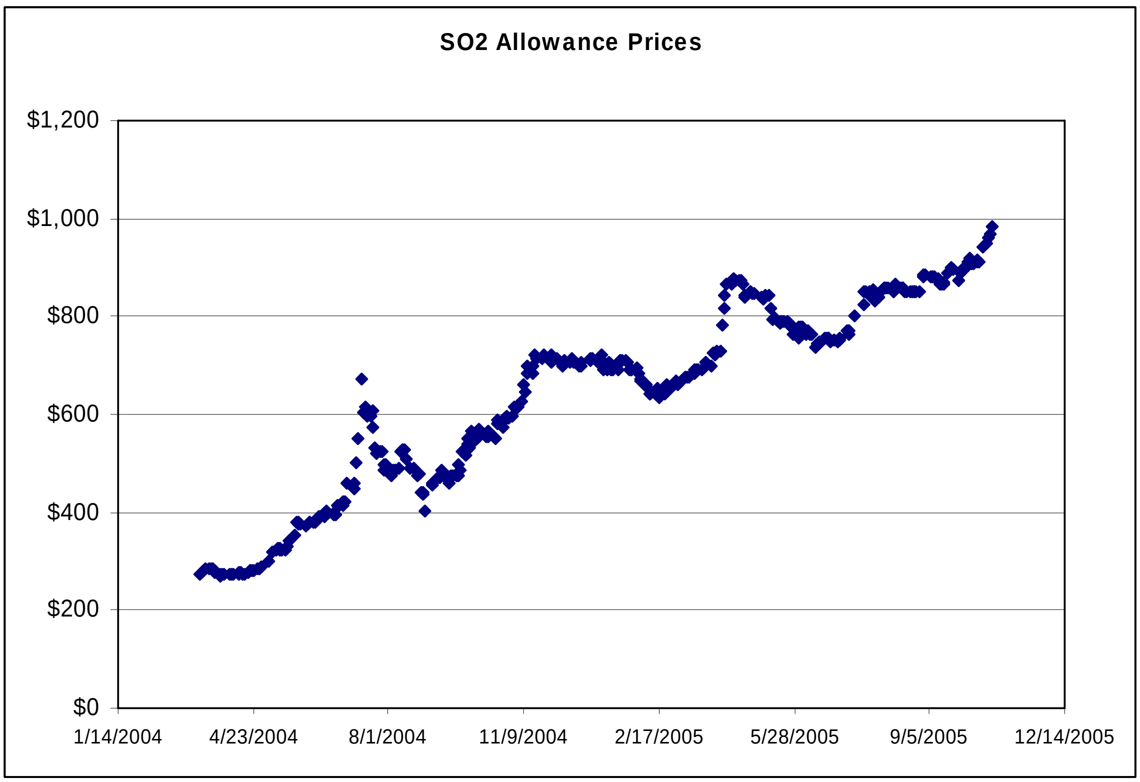


**Figure 1: $SO_2$ allowances prices**

[10] Prices of transactions reported daily by Cantor Environmental Brokerage between March 15 2004 and October 21 2005. Cantor Environmental is a broker active since 1992, with a very significant trading volume in the NOx and SO2 trading programs. See http://www.emissionstrading.com

The following graph shows transaction prices for $NO_x$ SIP Call allowances for different vintages.

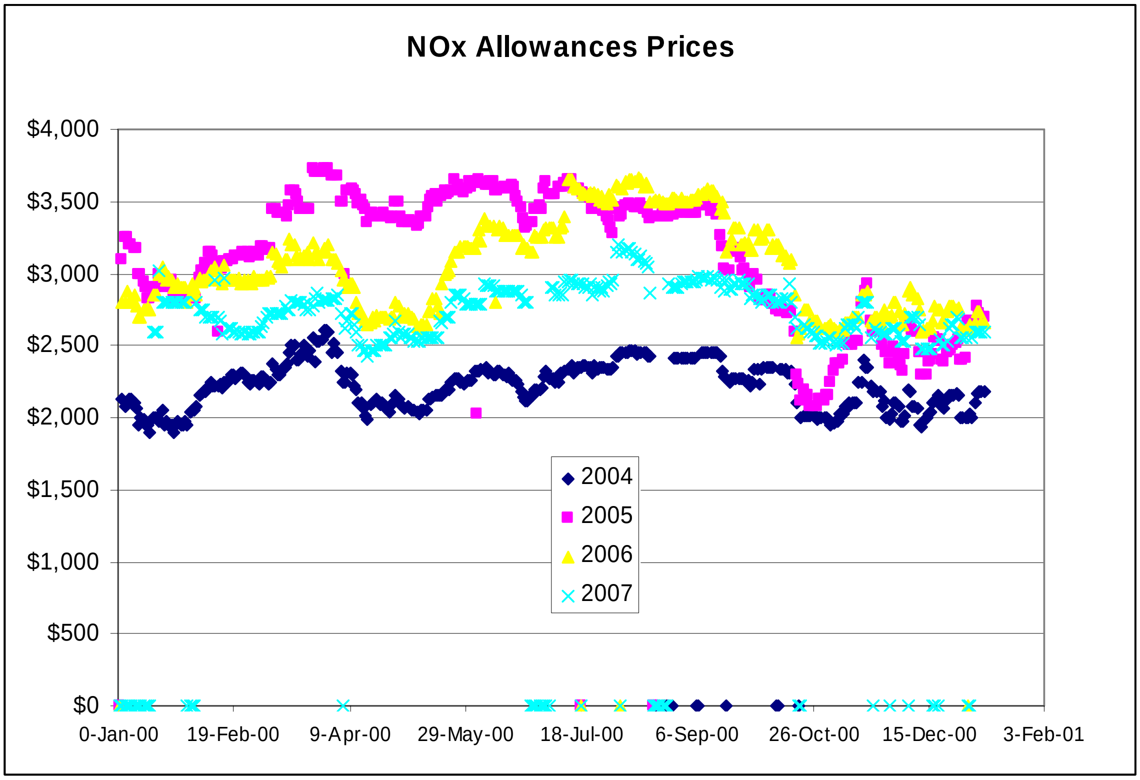


**Figure 2: $NO_x$ Allowance Prices**

As explained in Chapter 1, stock prices are usually modeled as following an Ito process or geometric-Brownian motion. Because allowances are traded in a market with robust liquidity, and because they can be banked, we can also model the stochastic process followed by its prices as following geometric-Brownian motion process. The practice of using this continuous-time stochastic model is widely accepted in finance, despite the fact that prices are discrete variables (records of trading are daily) and despite documented violations of the assumption of constant volatility.

Stating that allowance prices follow a geometric-Brownian stochastic process is equivalent to saying that their daily variation follows a normal distribution. Therefore, to test the goodness of fit of a geometric Brownian motion model to the observed prices we can test the hypothesis of normality for one-period "returns."

The following graph shows the time series of daily returns from SO2 allowance prices relative to current price $\ln\left(\frac{S_{t+1}}{S_t}\right)$.

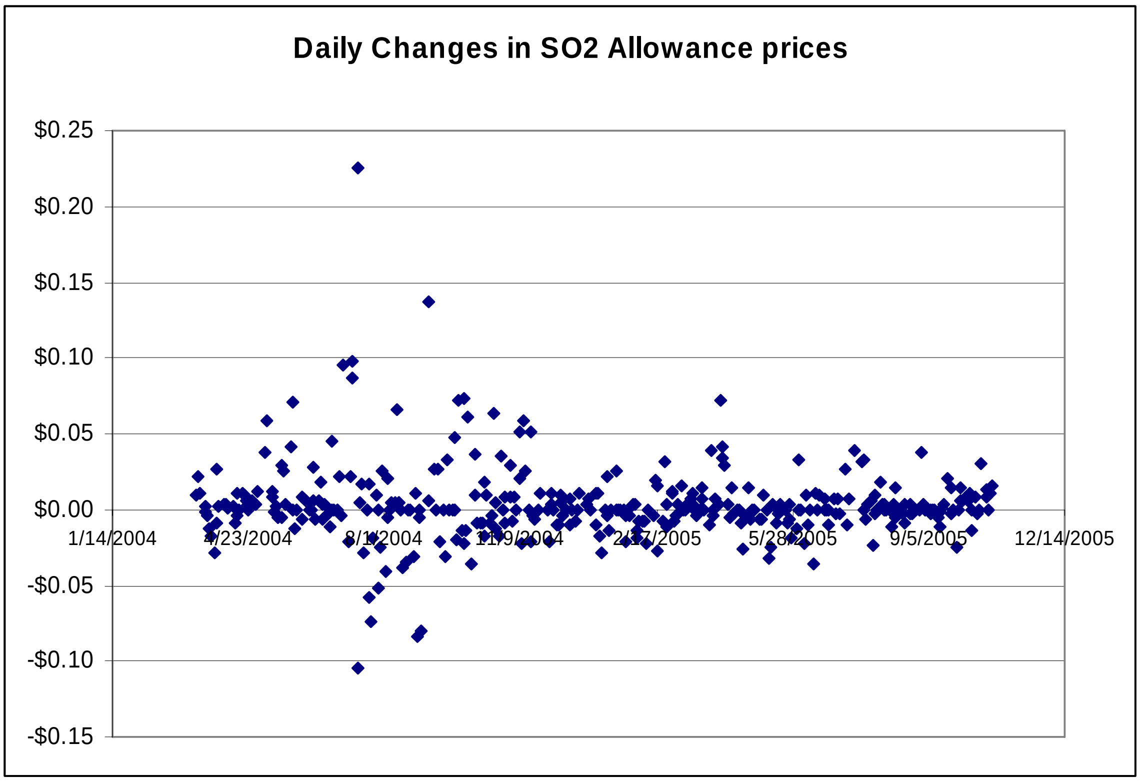


**Figure 3. Daily Changes in $SO_2$ allowance prices**

A histogram reveals that the distribution or daily changes in allowance prices is more "peaky" than a normal distribution, and in fact the hypothesis that daily returns follow a normal distribution is rejected (Jarque-Bera test, Kolmogorov-Smirnov test p-value<0.05), implying that the geometric-Brownian motion process does not accurately describe the uncertainty in allowance prices. In fact, the violation of the assumption of a Brownian-Motion process is relatively common in financial markets. Despite this violation, this model remains widely used because of its simplicity and also because it still provides good information about the price of derivatives. A more detailed analysis would use time-series theory (as in chapter 4) to determine a more accurate process for allowance-prices and the value of its derivative. However, since allowances are traded in markets that could be considered mature, the violation of the assumption of a geometric-Brownian process is not very serious here and the prices obtained for its derivative are typically close to those obtained with a process that better represents allowance's price dynamics. As a result, we maintain this assumption in the calculations that follow, but we acknowledge its limitations when more accurate analyses are needed.

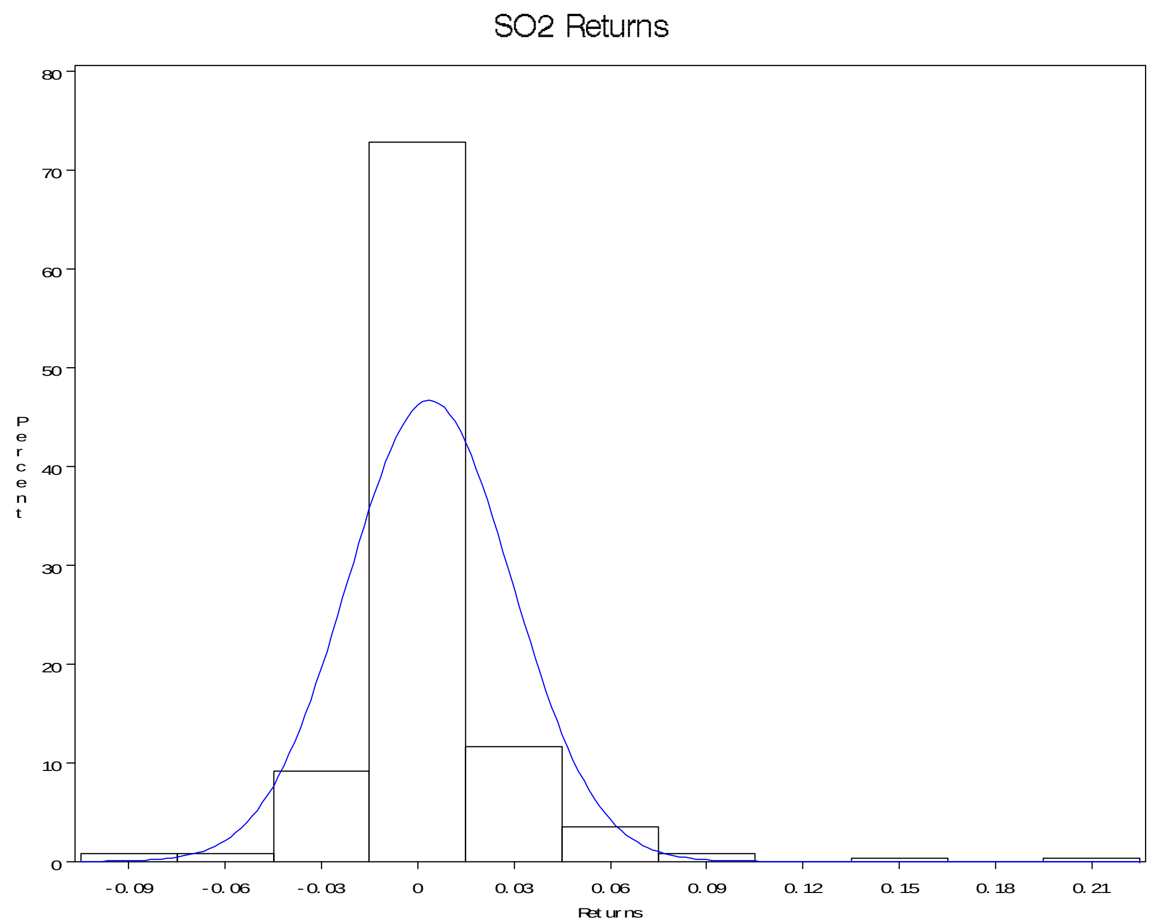


**Figure 4. Daily "returns" of $SO_2$ Allowance prices**

The estimate of the annual volatility of SO2 allowances, computed as the standard deviation of the natural logarithm of daily Price Relative Changes $\frac{S_{t+1}}{S_t}$ assuming years of 252 trading days is 39.63%. The standard error of this estimate is 2%.[11]

The following table shows volatility estimates and standard errors of the processes followed by NOx allowance prices for different vintages. The hypothesis that "returns" follow a normal distribution is rejected (p-value < 0.05 for Jarque-Bera Test and Kolmogorov-Smirnov, Anderson-Darling tests).

[11] We used a sample of 370 days.

### 3.2.4 The Investment Decision Rule

The decision of whether or not to install an ECD comes from the comparison between the value of the option (the value of the stream of call options received with the installation of the ECD) and the price of that option (the cost of installing the ECD). The installation decision rule is therefore given by a comparison between the ECD's capital cost per ton removed each year, and the value of the call options bundle. And the ECD should be installed if the Capital Cost ECD is smaller than the Value of the ECD as given in EQ.2 that is.

$$\textbf{Install ECD if capital cost ECD} < \sum_{t=\tau}^{T} e^{-\rho t} N_t \left[ S_t \Phi^s(d_1) - Xe^{-r} \Phi^s(d_2) \right] \qquad \textbf{EQ. 3.}$$

Note that EQ.3, depends on St, which for t-0 is a known value (today's price) but for t>0 is a random variable. From modeling the prices with an Ito process, the log of the price at time t is normally distributed: $\ln(S_t) \sim \phi\left[\ln S_o + \left(\mu - \sigma^2/2\right)t, \sigma\sqrt{t}\right]$.

Since for NOx we have information of allowance prices for the next 2 years, we can use those to calculate the value of the "option of using the ECD" for those years. For the rest of the periods, we need to get estimations of St.

The introduction of uncertainty in the equation of the value of installing an ECD changes the decision rule and demands from the investor an elicitation of his risk-attitudes. An investor could chose to install the ECD if the capital cost of installing it is lower than the Expected Value of the bundle of call options, or if it is lower than the lower bound of the 95% confidence interval. The more time into the future we expect the ECD to operate, the higher the uncertainty about the value of installing it.

## 3.3 Example:

In this section we illustrate how the methods described here can be applied to a real case. Consider a generating unit with the following characteristics:

-Name Plate Capacity: 570MW,

-Average Heat Rate: 10,690 Btu/kWh,

-Emission rates: 0.423lbsNOx/MMBtu, 5.786Lbs$SO_2$/MMBtu

Costs of installing a WFGD to remove $SO_2$:

-Capital Cost = $117.7M,

-Annual O&M = 18.28,

-Emissions rate after scrubber is in operation: 0.61lbs$SO_2$/MMBtu

-Number of allowances generated every year = 97,413

-Annual O&M per ton (allowance) = $187.6546

Installing an SCR:

-Capital cost = $63M,

-Annual O&M = $6.6M,

-Emissions rate after SCR is in operation: 0.15lbsNOx/MMBtu

-Number of allowances generated every year = 5,023

Assume that it is reasonable to expect both ECDs will be operating for 10 years (that is $T$=10 years), and construction time is 2 years ($\tau$ =2). Also the risk-free rate is 4%, and the discount rate is 10%. Assume that every year the scrubber could be operated to get N = 97,413 allowances, and the SCR could be operated to get 5,023 allowances.

### 3.3.1 Decision to install a scrubber to reduce emissions of SO2

The estimates of the drift and volatility parameters for the process followed by SO2 allowance prices are $\mu$ =0.0588 and $\sigma$ = 0.4126 respectively. Current price[12] is $985. The expected value of the price of one allowance at year 1, 2, .. 10, and the corresponding 5$^{th}$ and 95$^{th}$ percentiles are given below,

| SO2 allowance prices | | | |
|---|---|---|---|
| T | 5th percentile | 95th percentile | E(ST) |
| 0 | $985 | $985 | $985 |
| 1 | $427 | $2,154 | $959 |
| 2 | $298 | $2,933 | $935 |
| 3 | $224 | $3,694 | $910 |
| 4 | $176 | $4,468 | $887 |
| 5 | $142 | $5,268 | $864 |
| 6 | $116 | $6,097 | $841 |
| 7 | $96 | $6,960 | $819 |
| 8 | $81 | $7,859 | $798 |
| 9 | $69 | $8,794 | $777 |
| 10 | $59 | $9,767 | $757 |

**Table 1. Estimates of $SO_2$ allowance prices (So in EQ.3)**

Using EQ.3, and a discount rate ($\rho$ =10%) we get the expectation, and the 5$^{th}$ and 95$^{th}$ percentiles of the value of the stream of options that would be obtained after installing the scrubber.

[12] October 21 2005.

| Value of installing Scrubber | | |
|---|---|---|
| 5th percentile | E[ ] | 95th percentile |
| $ 14,527,958 | $ 297,789,268 | $ 2,407,894,124 |

**Table 2. Value of installing a WFGD**

Because the capital cost of the scrubber is $177 million, a decision rule that looked at the expected value would prescribe installation.

### 3.3.2 Decision to install an SCR to reduce emissions of NOx

The estimates of the drift and volatility parameters for the process followed by NOx allowance' prices for different vintage years are given below.

| Parameter estimates for NOx price's process | | |
|---|---|---|
| Vintage Year | Drift | Volatility |
| 2004 | 0.005 | 0.315 |
| 2005 | -0.002 | 0.442 |
| 2006 | 0.002 | 0.359 |
| 2007 | 0.004 | 0.356 |

**Table 3. Estimates of drift and volatility parameters for $NO_x$ allowance prices. (Assuming years of 252 trading days)**

Since under the assumption that construction time is 2 years, there will be no allowances before year 2007, then we will use the estimates of the process followed by prices for vintage year 2007 as inputs to find the estimates of the prices of allowances for years 2008 and on. The following table shows the estimates of allowance prices for each year (in that year US$).

| NOx Allowance Prices | | | |
|---|---|---|---|
| T | 5th percentile | 95th percentile | E(ST) |
| 2 | $2,600 | $2,600 | $2,600 |
| 3 | $1,219 | $4,924 | $2,450 |
| 4 | $860 | $6,195 | $2,308 |
| 5 | $649 | $7,288 | $2,175 |
| 6 | $507 | $8,279 | $2,049 |
| 7 | $405 | $9,198 | $1,931 |

| | | | |
|---|---|---|---|
| 8 | $329 | $10,059 | $1,819 |
| 9 | $270 | $10,870 | $1,714 |
| 10 | $224 | $11,635 | $1,615 |

**Table 4. Estimates of estimates of NOx allowance prices for years 2007 and on**

Applying EQ.3 and a discount rate of $\rho$ =10%, we get the expected value, the 5$^{th}$ and 95$^{th}$ percentile of the value of installing the SCR.

| Value of installing SCR | | |
|---|---|---|
| 5th percentile | E[ ] | 95th percentile |
| $5,882,748 | $21,062,733 | $107,592,862 |

**Table 5. Value of installing an SCR**

Because the capital cost of an SCR is $63 million, a decision rule that looked at the expected value, would suggest not installing it.

### 3.3.3 Accounting for the possibility of a change in regulation

In the presence of regulatory uncertainty the chances of having a new regulation that makes obsolete the ECD and/or the generating unit before their life-times had expired, might motivate decision makers to think of T as an uncertain value. In this case finding the minimum value of T for which the value of the option exceeds the per-ton capital cost, might be more important to inform the installment decision. The following graphs present the difference between the call option and the per-ton capital cost for both the WFGD and SCR for the generating unit considered in this example.

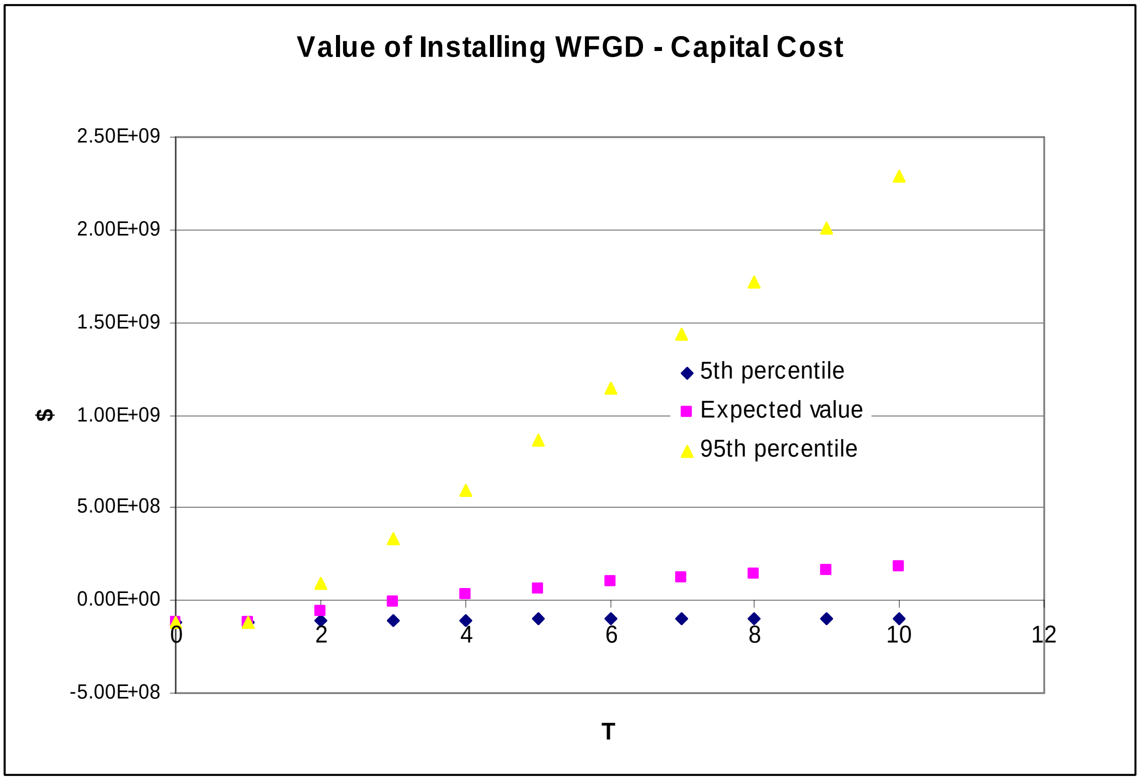


**Figure 5. Difference between the value of installing a WFGD and its capital cost**

If allowance prices reach the 5$^{th}$ percentile of the distribution or lower, then the WFGD will not be used and the investment will not be profitable. If allowance prices stay at their expected value, then the scrubber should be installed only if it is expected that the plant and the scrubber will operate for at least four more years.

The following graph shows the difference between the value to install a SCR and its capital cost, for different number of years of operation of the plant. Allowance prices should be much higher than their expected value, and the expected number of years before the plant or the SCR stop operating should be larger than 8, for the decision to install an SCR to be made.

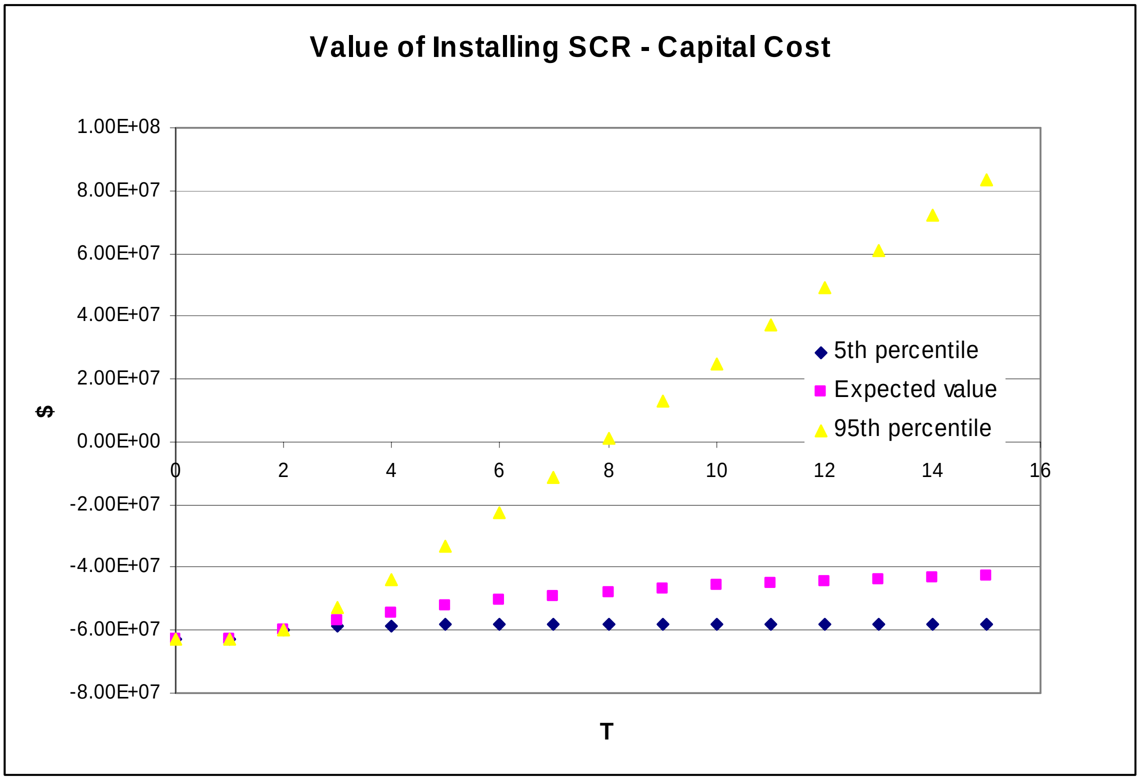


**Figure 6. Difference between the value of installing an SCR and its capital cost**

## 4. Policy implications

The analysis of how compliance choices are affected by regulation-related uncertainties can be enriched with our view of market participants' decisions.

When the time T is determined not by the life-time of the unit, but by the expected time when air-emissions regulations will change, then T is an uncertain value difficult to predict. Since T affects both the value of the project of installing the ECD and the threshold value to which it is compared, in the same direction, any decrease in T makes less likely the installation of an ECD and any increase makes it more likely.

The regulator has some control over the value of T decisions makers will use in their calculations. Market participants may estimate T from the deadlines of proposals for new regulations. By keeping deadlines of proposals for new regulations homogeneous, the perceived uncertainty in T can be reduced and installation of ECDs won't be unnecessarily delayed. Regulators could also offer special treatment for units that installed ECDs during a certain period guaranteeing a longer compliance time for new regulations that could render its operation obsolete. To inform policy making in this matter it may be useful to ask questions such as: By how much should the capital cost of the scrubber drop to offset a 1-year drop in T? The answer could be used for example to find the right value of subsidies or tax discounts that could be offered to speed the process of ECDs installation and the consequent reduction of emissions.

This approach also indicates that information about derivative prices in electricity and environmental markets (for example options on allowances) can be used as a source of valuable information for policy makers.

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# Chapter 6: The Fair Value of Operational Reliability

## 1 Introduction

Although current operation of bulk power systems in the U.S. makes use of important advances in information technology, operations research, and electric engineering, the reliability standards towards which that practice is directed have changed little since the old days of regulated industries. The processes are very modern, the inputs are not. For example, when running Optimal Power Flow (OPF) algorithms, the inputs of the objective function related to reliability, are very much like "rules of thumb" that have been traditionally used since the times of vertically integrated utilities.

These heuristics are used as standards to pursue when provisioning generation, transmission, and ancillary services resources. Examples of these rules are the (n-k) dispatching criteria and the Installed Reserve Margin as a fixed percentage of the peak-load. The (n-k) criteria states that the Systems Operator (SO) should dispatch and commit generation resources in a way that assures the reliable operation of the system even in the presence of any k outages among n total resources of generating or transmission equipment. To achieve this reliability requires, in many cases, scheduling generators out of merit-order and leaving enough transmission capacity available to sort out contingencies. An Installed Reserve Margin of for example 15%, states that the System Operator (SO) should commit generation to meet 115% of the expected peak load.

Why is it that an Independent Power Operator, who has the best technologies to monitor the current state of the system, access its past history, assess its current resources and forecast future needs, still designs the production schedule so as to have 10% of operating reserves? Where does this 10% come from? Why is it 10% and not 5 or 20%? Most of the operation standards for the bulk power system are arbitrary values that have worked in the past, but that have not direct relationship with the magnitude of the uncertainties that make difficult to meet electricity demand instantaneously.

We argue that information about the uncertainties that surround the operation of the power system can be used to enlighten the debate of how much reliability should be pursued and how resources should be allocated to pursue it. In this chapter we present a method to determine the value of having flexible generators in order to react to load fluctuations. Because having this flexibility is analogous to having a financial option, this value can be seen as the value of hedging against the uncertainty on the load due to the volatility of the demand and the possibility of congestion and we can use the methods of Chapter 1 to find its value. We will illustrate our point valuing the flexibility that leads to "operational reliability" in the PJM market.

This chapter is organized as follows. In Section 2 we review some concepts of reliability theory and introduce the concept of "operational reliability". In Section 3 we introduce the "options theory" relevant to this chapter. In Section 4, we explain how to use options theory to price "load following capability" which is fundamental for operational reliability. In Section 5, we present data for the PJM region and estimate the value of having load following capability in this market. In Section 6, we discuss how our results relate to the estimated costs of outages.

# 2 Reliability in a power system

## 2.1 Reliability requirements

Meeting the electricity demand in a particular power system requires a perfect balance in time and in space between power consumed and power generated. Since the demand side is often not under the control of the SO, the balance must be obtained by adjusting the supply side in a way that perfectly matches the demand at each point of the grid and at any particular time. The capacity of a power system to meet this demand depends on the availability and quality of three types of resources; the generation resources, the transmission grid, and the ancillary services' resources.

The installed capacity of the generating resources and the transmission capability of the grid are necessary for the reliable operation of the system, but are not sufficient to keep "the lights on". It is necessary to have resources suited to cope with soft and abrupt fluctuations of load and generation due to normal or emergency conditions. These resources, usually denominated as ancillary services resources, are generators[1] that have one or more of the following characteristics:

- *Flexible Dispatchable Output*: The ability to vary the output level within a range
- *Cycling Capability*: The ability to cycle between on and off, measured by the number of possible starts per day or week
- *Regulation Capability*: The ability of the generator to detect small differences between load and generation and tune its output to correct them

[1] Loads that can be disconnected as required by the system are also regarded as ancillary resources that provide the service of helping balance generated and consumed power. In essence, the MW amount available because of the load is disconnected can be seen as generation extra for the system.

- *Short Start Time* (Quick start capability): The ability to begin generating in a short period of time (usually 30 minutes or less)
- *Short Down Time*: The ability to be on after being shutdown in short period
- *Fast Ramp Rates*: The ability to increase or decrease the power output rapidly
- *Black Start Capability*: The ability to initiate without an outside energy supply or the ability to remain operating when automatically disconnected from the grid
- *Flexible Reactive Power Output*: The ability to increase the reactive power generated

The commitment of generation resources has to consider not only its location in relation to loads and transmission lines or its generation capacity, but also its potential to provide ancillary services. Because of this, the scheduling of generating units can be very different from the simple optimal scheduling that would be obtained if the system operator were trying only to minimize the cost of supplying power demand.

For simplicity, we have chosen to focus only on the extra cost of scheduling generators with flexibility or the potential to provide "load following capability", which we will call "the cost of operational reliability" and the subject matter of this chapter. Before speaking about the cost of operational reliability, it is useful to review the concept of reliability and the way it is conventionally measured.

## 2.2 Measuring reliability

The reliability of a power system is a measure of its ability to meet power demand at all times, despite contingencies. It is an emergent property of the system, difficult to assess without considering the characteristics and all the possible interactions of the components of the electric grid. Reliability is also a non-stable property that depends on external factors, such as power demand and weather conditions. (For example, the same system is less reliable when operating to meet peak load than when operating to meet only half of it. It is also less reliable if we account for the possibility of malicious intents.)

Reliability is usually measured with indices expressed as frequencies, durations, probabilities, or expectations of system problems (See for example:(DOE 2004)). A value-based approach is commonly taken to express reliability standards. Goals are stated in the form of indices values (averages or expected values) instead of distributions. Some authors advocate the use of index distributions as a complementary source of information that is very useful in some applications (e.g. (Billinton and Bagen 2004). Common indices for measuring system-wide reliability are:

- LOLP: *Loss of load probability*: The probability that the entire generation supply is lower than the system load.
- LOLE: *Loss of load expectation*: The number of time units that the load exceeds the generation supply.

– LOEE: *Loss of energy expectation* (EENS *Expected Value of Energy Not Served Or* EEU *Expected Energy Unserved*) Expected energy curtailed due to load loss. Looks at the magnitude and duration of load exceeding supply

– SAIFI: *Average Interruption Frequency Index*

– SAIDI: *System Average Interruption Duration Index*

– MAIFI: *Momentary Average Interruption Frequency Index*

– There are also common indices for distribution reliability that measure the frequency, duration and severity of system problems such as circuit overloads, bus load voltages, etc…)

### 2.3 Assessing and pursuing reliability

Measuring the reliability of a given power system is not an easy task. The failure probability distribution of each component must be determined and analyzed in conjunction with all other system components and external variables. The theoretical calculation of some reliability indexes requires the exhaustive enumeration of all possible contingencies and their associated likelihood. Several research efforts have lead to improved methods to assess system-wide and node-by-node reliability of a power system. The solutions are either methods to simplify the representation of the power system while keeping all the relevant information, or computer algorithms to speed up the tasks of diagnosing the state of the system.

Similarly, there are many documented efforts to incorporate reliability considerations in virtually every stage and aspect of the operation of a power system. Methods have been proposed for optimizing system maintenance, system expansion, and system operation considering both costs and reliability. The goals of such proposals are usually to minimize costs subject to reliability constraints expressed in the form of desired indices values.

There are two categories of strategies for improving reliability. The first category comprises those actions that seek to minimize the failure of a system component, such as trimming trees that could cause failure in transmission lines, installing grid equipment to manage voltage, and performing maintenance to generating units to minimize the probability of unscheduled outages. The second category includes those actions that seek to prepare the system for contingencies, such as scheduling extra generating capacity, allocating transmission margin, installing relays, and scheduling units with a black-start capability.

## 2.4 Operational reliability in a deregulated electric industry. PJM's example

In the time of vertically integrated utilities, it was not difficult to procure enough capacity, transmission or ancillary services to meet system's demand, as all industry participants cooperated towards the goal of reliable operation of the grid. But in today's restructured industry, any product or service that is not financially compensated inevitably will disappear. At PJM for example, the load following capacity of the generation fleet has decreased considerably in the last years ((PJM 2004). Generating units with the desirable characteristics listed in Section 2.1 have been retired, and have been replaced by units with inflexible operational characteristics. PJM plans to implement a new market-based system of incentives to pay for reliability related services, because it realized that if generators are not paid in proportion to the contribution of their flexibility to the reliability objective, very soon there will not be enough resources to satisfy the reliability-based constraints for dispatching. Most of the retirements of capacity have been of fossil-fueled steam resources with load-following capability, and the majority of the capacity additions have been gas-fired combined cycle units with inflexible operating characteristics and with combustion turbines and wind turbines that do not have load-following capability either.

At PJM it has also become evident that even if the generating resources have load-following capability, the service will not be offered unless there is a compensation system for it. Perhaps because they are trying to avoid increased maintenance due to cycling, bidders in the electricity market have started 1) offering less and less their ability to cycle, 2) reporting longer required down times and 3) reporting fewer number of possible starts per day or week.

If we accept the idea that including load following capability will likely increase the cost of electricity, then it makes sense to ask the question how much "load-following" capability should the SO allocate? Although it would be good to have as much as possible of all the services to maintain a reliable electricity supply, the inherent costs that ultimately are passed on to the consumers force us to ask how much is it fair to pay.

We do not claim to answer the questions of how safe is safe enough for a power system or how much should be paid to have a satisfactory level of safety. Instead, we show how a risk neutral SO would approach the problem of how much load following capability to provide to its system. We regard this approach as a small step to enrich the discussion of what level of reliability is needed and how much should be paid for it in the power system. The risk neutral result is to be used as a reference point and compared to the cost actually paid.

## 3 Options theory and the price of risk

As mentioned, having a flexible generator capable to follow the load is like having an option. Having flexible resources gives the SO the option of meeting changes in the load, instead of suffering the financial consequences of not meeting them.

As explained in chapter 1, the method of *risk neutral valuation* is useful not only to price any derivative contingent on the price of an underlying traded asset, but it is also useful to price any derivative contingent on an underlying random variable that follows a continuous-time stochastic process. The most remarkable characteristic of this method is that this variable does not need to be the price of any traded security or related at all to financial markets (See(Hull 1997) Chapter 13: "General Approach to Pricing Derivatives"). Moreover, the general method of *risk neutral valuation,* as a sub product of the pricing of the derivative, gives the price of the risk associated with the underlying variable. This finding is independent of the nature of the derivative.

Because of these properties of risk neutral valuation, we can define artificial derivatives to set up a theoretical portfolio with certain desirable properties from which we can derive the *price of risk* of the underlying variable. To illustrate how *risk neutral valuation* can be used, we will price the reduction in the risk of not having enough *load-following capability* at the daily time scale.

## 4 The fair value of "load-following capability"

Several events may create an imbalance between load and generation. For our analysis, we will assume that the system has reserve capacity to offset the effect of unscheduled outages of major generators and the only remaining task to provide reliability to the system is allocating load-following capability to adjust the electricity supply to the fluctuations of the load that cannot be forecasted. We will also assume that the analysis is conducted for a region without transmission congestion, so there will be no need to increase the electricity output due to the lack of transmission capacity.

After excluding the possibility of needing more generation because of transmission constraints or unscheduled outputs, there are two remaining reasons why there could be a supply-demand imbalance and therefore the necessity of suddenly increase the electricity output. One is the normal real-time fluctuation that is corrected by those units in the system equipped with Automatic Generation Controls or AGC to tune their output and correct instantaneously small imbalances between load and supply. The other source of imbalance is due to errors in the demand forecast that make the production plan inadequate to meet the real needs of the grid. In this case, it becomes necessary to increase or decrease the output of those units that are on, and perhaps to start or shutdown certain units, all in a short period. If the flexibility[2] of the units operating is not enough to correct these imbalances, it will not be possible to serve the load for the time that takes to restore balance. Note that the value of having load following capability and supplemental reserves is contingent on the magnitude of the deviations of the load from its forecasted value.

[2] Flexibility is used loosely and it refers to the characteristics listed in Section 2.1.

The cost of having load following capability depends on the characteristics of the generating fleet and the magnitude of the forecasted load. In cases where flexible units need to be scheduled to meet the forecasted demand, load following capability comes at no extra cost. In other cases, where forecasted demand can be met with low-cost generating units with no load-following capacity, the cost of providing load-following capabilities will be the cost of replacing low-cost inflexible generators with the more expensive units with load following capabilities.

If we let $C$ be the random variable representing the costs associated to the deviations from the load forecast, and *H* the premium that should be paid for having load following capability, then $H(C,P) = P - \langle C \rangle$ where $\langle C \rangle$ represents the expected value of $C$ (at time *T*), and *P* is the fair value that should be paid to have load following capability.

Applying the methods of Chapter 1, we obtain

$$P = \int_P^{\infty} (c - P)\varphi_C(c,T)\,dc + \langle C \rangle \qquad \text{EQ.11.}$$

where $\varphi_C(c,T)$ represents the pdf of *C* at time *T*. If *C(t)* does not follow a stationary process, then the value of *P* will change with time and should be defined as the "fair price that should be paid to have load following capability at time T.

## 5 The value of "load following capability" in PJM

In this section, we use data of the PJM region to illustrate how to use our formula to find the fair value of load-following capability. To characterize the stochasticity of fluctuations on the load, we formulate a time series model to forecast the PJM demand,

and then use the error in the forecast $E$ as the source of uncertainty that makes having load-following capability valuable. We will assume that the costs of having a load that exceeds the forecast are the same as having a load that is lower than the forecast if there is no load-following capability, because decreasing the electricity output might be as difficult as increasing it, when the generating units are inflexible. Therefore, the variable of interest will be the absolute value of the error in the forecast.

The cost $C$ of not having load following capability is an increasing function of the absolute value of error in the forecast. Because any choice of such function would be arbitrary, and would introduce unnecessary complexity to our example, we choose to let $C$ be the same as the absolute value of the error in the forecast and express it in MW units, so $C = |E|$. Since $C$ represents the number of MW that the load will fluctuate around the forecast, the units of its derivative $H$ are also MW.

### 5.1 The process followed by C

As previously mentioned, $C$ represents the absolute value of the error in the forecast of the load. In other words, $C$ is the irreducible uncertainty about future load—the uncertainty that remains after we account for all our knowledge about historical load and its relationship with some predictors as weather and date.

There are several models in the literature to forecast electric load for the short-, medium- and long-term (see (Feinberg and Genethliou 2005)). Most models use time-series analysis, artificial neural networks and fuzzy logic, and include weather related variables as the Temperature-Humidity Index and the Wind-Chill Index, as well as information on the hour of day, day of week, holidays, etc. For our example, we use a time-series model with predictors, and data of the aggregated PJM load (East PJM) for the period from March 1st 2001 to January 31st 2003.

Figure 1 shows the time series of the aggregated load for PJM East.

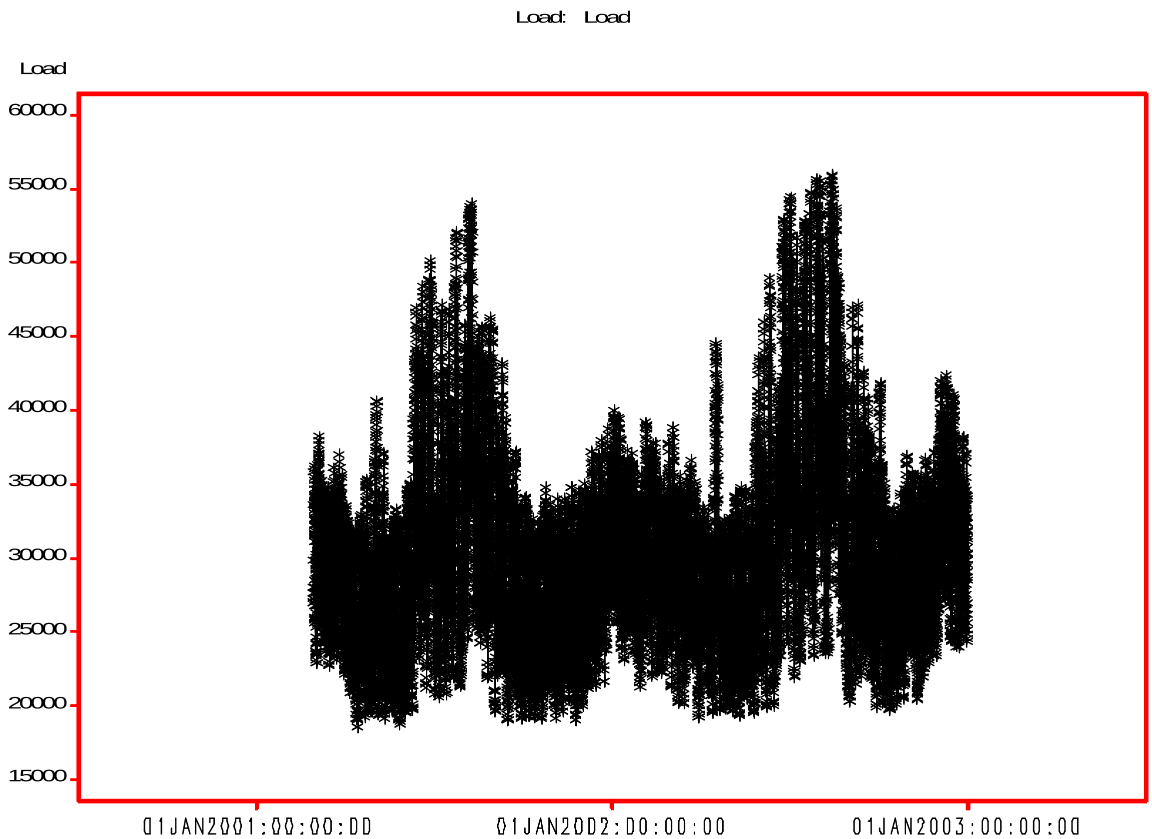


**Figure 1:** Aggregated Load for PJM East

The model chosen to forecast the aggregated load includes a) the time series of the Temperature-Humidity Index (THI) at Washington Reagan National Airport, b) a dummy variable that indicates whether or not the hour is a "peak hour"[3], and c) an Autoregressive model with 2 lags and a seasonal lag (AR(2)(24))(See for example: (Box,

[3] In PJM "peak hours" are hours ending 8:00-23:00, Monday trough Friday, excluding *Federal Energy Regulatory Commission* (FERC) holidays.

Jenkins et al. 1994)). Although simple, the model has an R-square of 0.9956, and a mean absolute error of 272 MW.

The absolute error in the forecast (that is, the difference between the load values predicted by the load and the actual values) is the variable we will take as $C$.

Figure 2 shows the error in the load forecast for each hour of the analyzed period. We can see that the time-series does not seem to have a trend or drift, and therefore its expected value does not change with time. It is also clear that the variance of the error is constant and therefore its probability distribution is the same at any time T and can be estimated from the values of the error along all the forecast period.

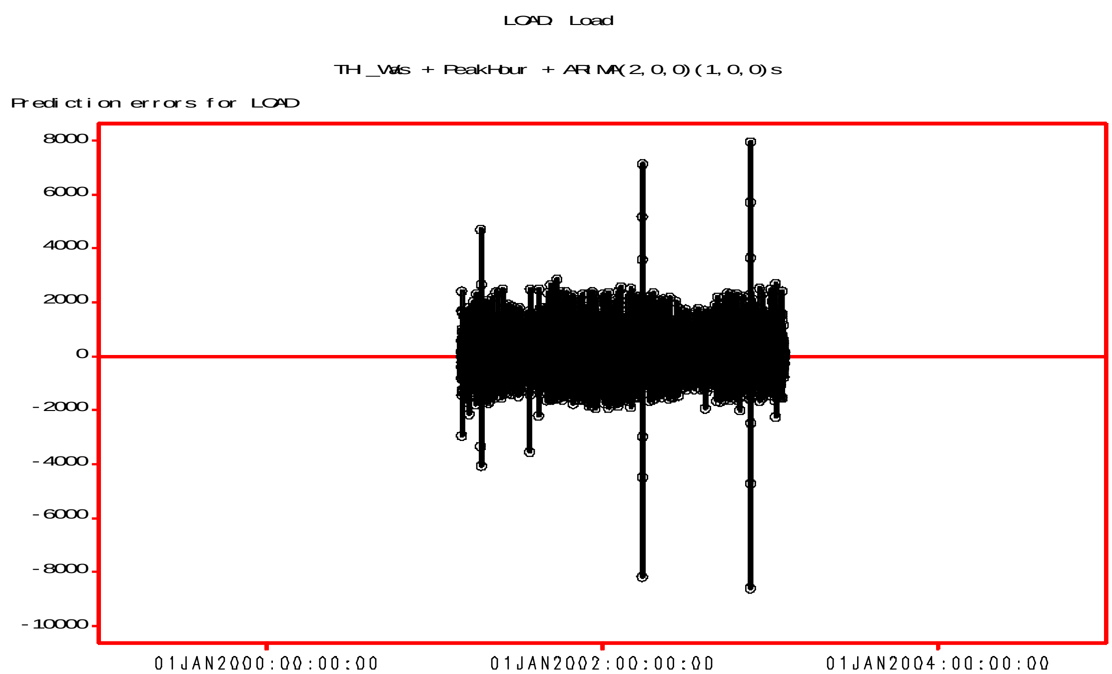


**Figure 2:** Error in load forecast for each hour analyzed

We choose to estimate the p.d.f of $C$, in a non parametric way, using a Kernel smoothing function and an associated bandwidth that is theoretically optimal (See for example (Silverman 1986)). Figure 3 shows the estimated p.d.f. for $C$.

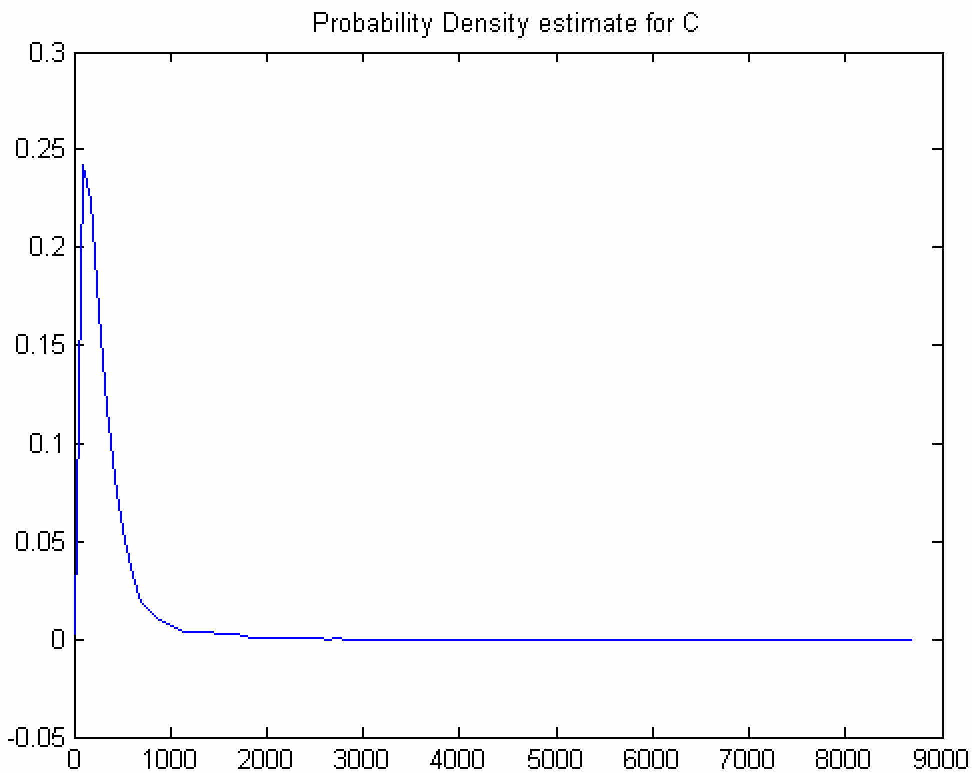


**Figure 3:** Probability density estimate for $C$

Using our estimation of $\varphi_C$ to solve EQ.11, we get a value of $P$ of 405MW and an associated value of $H$ equal to 80MW. The value of $P$ is 124% the mean value of $C$ and 222% the median value of $C$. This means that the amount the System Operator should be willing to pay for having load-following capability and reducing the risk associated to errors in the forecast is about 1.24 times the expected value of the losses incurred if that load-following capability was not present, or 2.22 times the theoretical median of those losses.

The results do not change by more than 0.5% if we estimate the p.d.f. with other kernel functions or bandwidths. The results are also not sensitive to small changes in the data. For example if we decided that the eight extreme values of the prediction error observed in Figure 1, are due to mistakes in the input data, and removed them from our sample to find the p.d.f., we would obtain a value of $P$ that is still 1.24 the mean value of $C$ and 2.18 its median. If we went further and removed the 10% most extreme observed values of $C$, then $P$ would be 1.23 times the mean of $C$ and 2.1 times its median.

Figure 4, shows the corresponding p.d.f. for the case when we remove from the observed error the 10% most extreme points of the load prediction error.

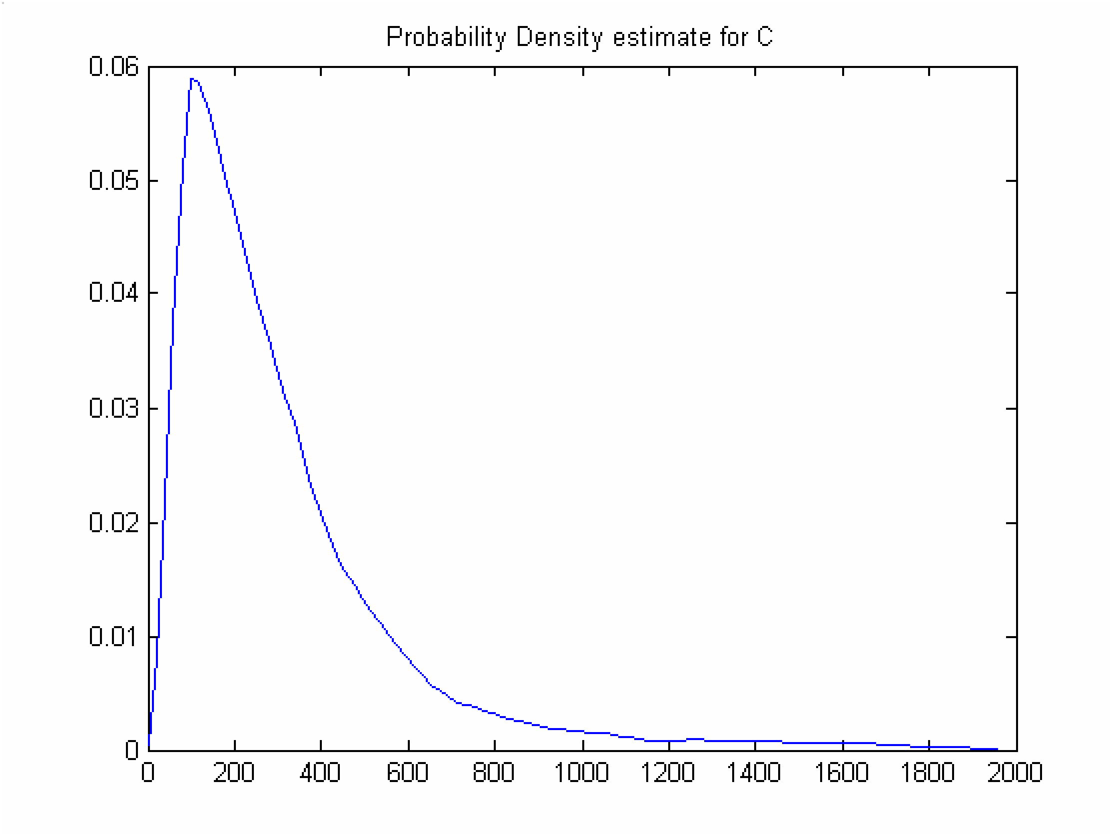


**Figure 4:** Probability density estimate for C, removing 10% most extreme values

## 6 The value of reliability

To allow a better interpretation of the results, it would be convenient to have a way to translate the units of $C$ from its MW units to a monetary unit. This would give us a way to price "load following capability". As mentioned before, this could be done with a function that assigns to each MW value of a change in the load the associated economic cost. The task of identifying such function is beyond the scope of this chapter; in the worst-case scenario, there could be an incapacity of the system to cope with such change and a black out would occur.

To get an idea of the translation of MWs lost into monetary values, the information about the cost of the latest blackouts can be useful. The costs of outages vary depending on the characteristics of the affected parties in conjunction with the characteristics of the outage. Industrial, commercial, and residential customers all have different needs and ways to value a reliable source of power and suffer different consequences depending on the frequency, duration, and time of occurrence. There are two ways of assessing the cost of an outage. One way is by assessing its direct and indirect costs accounting for all the activities disrupted and the associated consequences due to the loss of power. Another way to estimate the value of not having power outages for each costumer is assessing the consumers "willingness to pay" (WTP) for avoiding such disruptions.

For some customers, direct costs can be calculated based on the operation and maintenance of their back-up power equipment. However this only holds for short outages, as supplies to keep back-ups operating become scarce after prolonged times without power. For all other cases, direct costs relate to the value of forgone profits, equipment damaged, supplies spoiled, and even human lives lost or threatened. Factories must stop production lines, information based companies might lose important data and equipment, hours of labor might be wasted. For residential customers there maybe also damages of equipment and expenses for food and even lodging in extreme weather conditions.

Because of the difficulty of estimating direct costs and because of the possibility of leaving out many intangibles, the WTP approach is a useful alternative to value reliability. Usually the WTP is determined by surveying customers. The use of a WTP value to make system wide decision has to account for income effects that can bias survey respondents' values.

There have been some estimates of the direct costs of blackouts in the U.S. For example, the 1977 outage of New York City when more than 5,000 MW were not served for a period of 25 hours had direct costs estimated in $0.66/kWh. Indirect costs were estimated in $3.45/kWh, for a total of $4.11/kWh or $4,110/MWh, which is 120 times the national average retail electricity price of electricity in 1977 (ICF 2004)[4].

The blackout of August 14, 2003 affected 50 million people in the nine states of the Northeast and Midwest of the U.S and one Canadian province for almost 2 days, with more than 60,000 MW out of service, and generated a cost for the national economy estimated at $7-$10 billion (DOE 2003). The $4.67-$6.67 per KWh of losses for the economy are 63-90 times the national average retail price across all sectors of 7.42 cents per KWh in the year 2003 (DOE 2004).

In a survey conducted after the 2003 blackout (EPRI 2004), 53% of U.S. residential customers reported a willingness to pay up to 10% more on their electric bills for ten years to avoid a similar blackout. Similarly 54% of U.S. businesses would be willing to pay 1% or 2% more on their electric bills to enhance the power delivery system and improve power reliability. A third of the businesses would be willing to pay up to 5% more and 65% would be willing to pay 10% more.

In developing countries, the estimated costs of outages are also several times the cost of electricity. A study of the impact of power supply interruptions in the Sri Lankan

[4] ICF consulting presented this calculation in its article "The Economic Costs of the Blackout' based on data from the 1977 blackout from the U.S. Congress office of technology assessment "Physical vulnerability of power system due to natural disasters and sabotage." OTA-E-453 Washington, D.C. U.S. GPO. June 1990).

industrial sector shows that in a typical year of power shortages such as 2001 the losses for planned and unplanned outages are US$0.66 and US$1.08 per kWh of energy loss (Wijayatunga and Jayalath 2004). A survey on the Nigerian manufacturing sector shows that the costs of back-up equipment are on average 3 times the cost of publicly supplied electricity (Adenikinju 2003).

## 7 Conclusions

In this chapter we presented a method to determine the value of having flexible generators to react to load fluctuations. This value can be seen as the value of hedging against the uncertainty on the load due to the volatility of the demand and the possibility of congestion. Because having this flexibility can be related to a financial option, we propose to use the *risk-neutral valuation method,* to find a risk neutral quantification of its value. We illustrate our point valuing the flexibility that leads to “operational reliability” in the PJM market. Our formula for that value is what we call “the fair value” of operational reliability.

We would like to compare our theoretical value with what is actually paid for operational reliability in PJM, and we would like also to compare it to what people would be willing to pay for it. Because of the traditional different allocations of capacity to balance load and supply in a power system, like “Installed Reserves”, “Supplemental Reserves”, and “Load-Following Capability”, determining how much is actually paid for operational reliability posses a challenge. Establishing the characteristics of the function that translates the MW units of the error forecast, into monetary units, is equally challenging. Nevertheless, the framing of options theory has the potential to offer a contribution to use information about the uncertainties that surround the operation of the power system to enlighten the debate of how much reliability should be pursued and how resources should be allocated to pursue it.

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# Appendix – Chapter 3

## 1 List of market participants in alphabetical order

| Acr | # Participant | LSE? | Ranking By Profits | Ranking By MWh Traded | Category by Transactions |
|---|---|---|---|---|---|
| ACNEgy | 42 | x | 13 | 51 | B |
| AECI | 28 | x | 19 | 24 | B |
| AEPAP | 54 | | 20 | 39 | A |
| AETS | 19 | x | 48 | 38 | B |
| AEVine | 16 | x | 39 | 43 | A |
| AHC | 33 | x | 43 | 28 | D |
| AMPO | 49 | x | 17 | 52 | B |
| BPBGS | 10 | | 47 | 32 | B |
| BPGM | 29 | x | 42 | 50 | B |
| CEDS | 45 | x | 25 | 40 | C |
| CEPLLC | 8 | | 1 | 1 | E |
| CINSI | 39 | | 32 | 17 | E |
| CITZNS | 30 | x* | 34 | 47 | B |
| CNCT | 4 | x | 36 | 21 | E |
| ConEdE | 41 | x | 24 | 34 | E |
| CoralR | 2 | | 3 | 15 | E |
| CPSDMB | 34 | x* | 37 | 49 | B |
| CPSI | 9 | x* | 46 | 3 | D |
| DCELLC | 5 | | 2 | 11 | E |
| DPL | 21 | x | 31 | 27 | C |
| DTEBGS | 17 | x | 10 | 31 | A |
| DTEET | 50 | x | 9 | 33 | E |
| EASTON | 44 | | 8 | 48 | B |
| ECPDTE | 43 | | 12 | 54 | B |
| EMMT | 3 | x | 33 | 6 | E |
| EPLUS | 20 | x | 53 | 2 | A |
| EXGNPT | 31 | x* | 41 | 5 | A |
| FESC | 22 | x | 54 | 7 | A |
| FPLEPM | 6 | | 26 | 16 | D |
| GALT | 46 | | 23 | 53 | A |
| JARON | 47 | | 28 | 20 | C |
| JCPLFP | 40 | x | 40 | 37 | B |
| MetEd | 32 | x | 30 | 41 | B |
| MLCS | 51 | | 22 | 22 | C |
| Morgan | 25 | | 14 | 4 | E |
| MPR | 14 | | 6 | 8 | D |
| NEV | 26 | x* | 38 | 44 | B |
| NRGNJ | 23 | x | 49 | 30 | B |
| ODEC | 27 | x | 45 | 14 | A |
| PaElec | 38 | x | 35 | 29 | B |
| PEPSRV | 7 | x | 44 | 18 | A |
| PSERT | 13 | x | 29 | 9 | D |
| QuarkP | 53 | | 16 | 45 | C |
| RAMEP | 37 | | 15 | 25 | C |
| RESI | 11 | x | 50 | 19 | A |
| RESR | 12 | x | 51 | 35 | B |
| SELWM | 36 | x | 52 | 10 | A |
| SES | 52 | x | 18 | 46 | A |
| SETC | 18 | x | 7 | 26 | D |
| SUSQEP | 24 | | 11 | 12 | E |
| TESI | 48 | | 27 | 42 | A |
| UGID | 35 | x* | 21 | 36 | B |
| WGCHZL | 15 | x* | 5 | 23 | E |

| | | | | | |
|---|---|---|---|---|---|
| WPC | 1 | x * | 4 | 13 | E |

**Table 1. Market participants in alphabetical order. Category and Ranking by Capacity Traded and Profits.**

## 2 Information of market participants form their web pages:

The following is the description of the companies that participated in the FTR auction as it appears in their web pages or the web pages of the parent companies. This information might serve to fully identify the participants as hedgers or speculators.

### 2.1 WPC: Williams Power Company, Inc.

Formerly known as Williams Energy Marketing and Trading. Buys and sells energy commodities (including electricity, natural gas, and refined petroleum products) and provides risk management services, primarily to wholesale utility and industrial customers in North America.

Subsidiary of **Williams Companies**

### 2.2 CoralR: Coral Power, L.L.C. (Retail)

Coral acts as the marketer of Shell's North American natural gas production and benefits from access to a strategic portfolio of power generation and gas storage assets.

Affiliate of **Shell Coral** is aligned with the power generation activities of InterGen, which is a joint venture of Shell and Bechtel and a 30-percent equity owner of Coral.

### 2.3 EMMT: Edison Mission Marketing and Trading, Inc.

On behalf of EME affiliated generating facilities EMMT trades in U.S. domestic electricity, natural gas, crude oil, heating oil, unleaded gasoline and emission allowances, as well as associated financial instruments including futures, swaps and options. EMMT maintains a 24-hour scheduling desk for electricity that is responsible for monitoring all transactions that are flowing at any point in time.

Subsidiary of **Edison Mission Energy** ("EME"). EME is an IPP and a wholly owned subsidiary of Edison International

### 2.4 CNCT: Conectiv Energy Supply

Inc.Conective Power Delivery serves more than one million homes and businesses in the regulated electricity and natural gas markets of Delaware, New Jersey, Maryland and Virginia.

Subsidiary of **Pepco Holdings, Inc**. (PHI) is a holding company formed as a result of the merger between Pepco (POM) and Conectiv (CIV).

### 2.5 DCELLC: DC Energy LLC

DC Energy is an energy arbitrage firm that uses a rigorous quantitative analytical approach along with a robust framework for striking the balance between risk and return. Our focus is on the attractive investment opportunities in the complex deregulated energy markets emerging throughout the United States

A close partner of **Dean & Company**, a strategy consulting firm

## 2.6 FPLEPM: FPL Energy Power Marketing,

Inc.FPL Energy utilizes its enhanced energy marketing and trading organization - Power Marketing, Inc. - to realize the full value of its physical assets. The company employs a relatively low-risk, asset-based hedging strategy, rather than a speculative trading strategy, which enables it to moderate risk and enhance returns. Power Marketing, Inc. actively trades around FPL Energy's expanding portfolio and contracts for a substantial portion of its output, as market conditions warrant.

Part of **FPL Energy**, an industry leader in the production of clean energy with more than 80 percent of its generation coming from natural gas or renewable sources including wind, hydro and solar. FPL Energy is the unregulated electricity generation subsidiary of FPL Group with more than 5,000 net-megawatts in operation.

## 2.7 PEPSRV: Pepco Energy Services, Inc.

One of the Mid-Atlantic's leading providers of energy and energy-related products and services for the full range of energy users from residential customers and small business customers to large commercial, institutional, industrial and government users. Pepco Energy Services also provides both energy suppliers and large energy users such as utilities, municipalities, cooperatives and aggregators with an array of energy management services including risk management and acquisition and management of power generation assets. It has more than 100,000 customers (From Connecticut to Florida) and more than $1 billion in annual revenue from energy and energy-related products and services in 2003.

A wholly owned, separately managed subsidiary of **Pepco Holdings, Inc**. (PHI). See market participant # 4.

### 2.8 CEPLLC: Citadel Energy Products, LLC

*"Affiliate of **Citadel Investment Group**. Citadel Investment Group LLC. is a world leader in alternative investments. With professionals in Chicago, San Francisco, London, Tokyo and New York, explores, analyzes and invests in financial markets globally. We combine a unique intellectual foundation, superior technology and outstanding people to identify and exploit market opportunities. We find the edge between reward and risk and consistently transform our insights into high risk-adjusted returns for our investors. Because of this high volume, the company also acts as a market maker on smaller exchanges for some blue-chip stocks. Citadel currently manages approximately $10 billion for a wide range of investors. Characterized by its creator's rigorous application of quantitative trading methods and technology, the firm employs several different investment strategies."*

### 2.9 CPSI: Constellation Power Source Inc.

Constellation Energy Commodities Group (formerly Constellation Power Source) is a leading source of wholesale power in deregulated US markets. The company holds the energy marketing and trading operations of parent Constellation Energy Group. Subsidiary of **Constellation Energy**. See market participants # 26 and #35.

### 2.10 BPBGS: BP Energy Company (BGS)

Based in Stamford, Sempra Energy Trading Corporation (SET) is one of the largest commodity trading companies in North America. The company combines financial risk-management techniques with physical expertise to provide innovative solutions for customers

Part of **BP**. *"BP is one of the world's largest energy companies. Our main activities are the exploration and production of crude oil and natural gas; oil refining, marketing, supply and transportation; and the manufacture of petrochemicals. We have a growing presence in gas and power and in solar power generation. BP provides wholesale and large industrial electric power in select markets. Being a major consumer of electricity at our own facilities, we understand commodity fuels and their price relationship from both sides. This knowledge allows BP to offer energy solutions designed to create value for our power customers."* See market participant 29

### 2.11 RESI Reliant Energy Services

*"Inc.**Reliant Energy Inc** is one of the leading producers, suppliers, and marketers of electricity in the United States. We offer a complete suite of energy products and services to clients who range from residential and small commercial customers to large commercial, industrial, and institutional customers. The largest retail electric providers in Texas with more than 1,6 million residential customers, and within four months of entering the PJM market captured the number two position in the large commercial and industrial segment. Has approximately 20,000 megawatts of power generation capacity in operation, under construction or under contract."*

## 2.12 RESR Reliant Energy Services, Inc. (Retail See market participant # 11.)

## 2.13 PSERT: PSEG Energy Resources and Trade LLC

PSEG Energy Resources & Trade is the trading arm of PSEG Power. Markets the output of PSEG Power's generation assets, acquires and hedges fuel, economically dispatches plants and trades numerous energy-related products. PSEG Energy Resources & Trade trades a range of products, including electricity, generating capacity, natural gas, emission credits, transmission rights, coal and oil. PSEG Energy Resources & Trade mainly trades in PJM and the immediately adjacent electric pools. In order to limit risk and to extract maximum value from PSEG Power's generation assets, PSEG Energy Resources & Trade trades around the assets of PSEG Power. PSEG Energy Resources & Trade is one of the few trading operations with an integrated trading/generation model. The trading floor dispatches plants -- treating all of PSEG Power's plant assets as a whole from a trading and marketing perspective, rather than having each plant operate as a completely separate unit with its own separate P&L.

Subsidiary of **PSEG Services Corporation**. PSEG is a $28 billion energy and energy services company with three major subsidiaries: PSE&G, a regulated electric and gas distribution business, PSEG Power, a US power producer and PSEG Energy Holdings, the parent of PSEG's other unregulated businesses including: PSEG Global an international operator of power generation and distribution systems, and PSEG Resources, which invests in energy-related financial transactions.

### 2.14 MPR: Mirant Americas Energy Mktg. (Potomac River)

*"Mirant Americas Energy Marketing, L.P. is one of the leading electricity and gas marketers in the United States markets. MAEM engages in, among other activities, asset and risk management with respect to the operation of the core generation business. As asset and risk manager, MAEM is core generation business. As asset and risk manager, MAEM is responsible for, among other things, procuring and scheduling deliveries of fuel consumed by Mirant's domestic power generating assets, bidding and scheduling the generation facilities into local market areas, selling energy, energy capacity and related products produced by the plants, and hedging gross margin expectations to reduce the risks associated with market volatility. MAEM currently holds many of the regulatory approvals necessary for Mirant to continue operating within the gas and power market environments."*

*"Subsidiary of* ***Mirant Corporation****. Through its wholly owned subsidiary, Mirant Corporation. Mirant Americas Inc., and its indirect wholly owned subsidiaries, MAEM, Mirant Americas Generation, LLC and Mirant Mid-Atlantic, LLC, Mirant owns or controls generation facilities in the United States with an aggregate generation capacity of 18,000 megawatts."*

### 2.15 WGCHZL: Williams Generation Company-Hazelton

Williams Generation Company Hazelton is an affiliate of **Williams Power Company, Inc**

See market participant 1. "*Williams' businesses produce, gather, process and transport clean-burning natural gas to heat homes and power electric generation across* *the country. It has 7,900-megawatt power portfolio, in its 6 tolling agreements in Alabama, California, Louisiana, Michigan, New Jersey and Pennsylvania, and 2 owned generation facilities in New Mexico and Pennsylvania."*

**2.16 AEVine Atlantic City Electric Company (Vineland)**

*"The Group's principal activities are to generate, purchase, deliver and sell electricity throughout the United States. The utility, which operates as Conectiv Power Delivery generates, transmits, and distributes electricity to more than 520,000 homes and businesses in southern New Jersey. Atlantic City Electric operates more than 11,000 miles of transmission and distribution lines. The utility has sold most of its power generation assets, but it still has interests in selected fossil-fueled power plants. Parent company Conectiv was acquired by another utility holding company, Pepco Holdings, in 2002. Subsidiary of* ***Conectiv"***

**2.17 DTEBGS: DTE Energy Trading, Inc. (BGS)**

*"DTE Energy Trading is an active physical gas and power marketing company. Providing energy sourcing and management solutions for municipalities, electric cooperatives, independent power producers, investor owned utilities and retail energy suppliers, DTE Energy Trading's expert staff has the ability and know-how to manage large power generation, gas storage and transportation assets.*

*Subsidiary of* ***DTE Energy****. DTE Energy is an utility with $20 billion in assets and more than 150 years of energy expertise."*

### 2.18 SETC: Sempra Energy Trading Corporation

Based in Stanford, Sempra Energy Trading Corporation (SET) is one of the largest commodity trading companies in North America. *"The company combines financial risk-management techniques with physical expertise to provide innovative solutions for customers in natural gas, electricity, petroleum and base metals. With 650 employees in the United States, Canada, the United Kingdom, Switzerland, Spain and Singapore, SET serves more than 1200 customers worldwide. Our highly trained professionals, combined with a state-of-the-art trading facility, provide our customers with a unique combination of risk management products, trading experience, and physical capabilities to minimize their daily risks and strengthen their bottom line."*

Subsidiary of Sempra Energy. Sempra Energy is a Fortune 500, energy services holding company with nearly 13,000 employees worldwide. Headquartered in San Diego, Sempra Energy serves more than 10 million metered consumers, the largest customer base of any energy utility in the United States.

### 2.19 AETS: Allegheny Energy Supply Company, L.L.C.

PPL EnergyPlus is an asset-backed marketer and trader of wholesale electricity, capacity, options, risk management products, emission allowances, tolling and structured or customized products. *"Our firm sales are backed by more than 10,000 megawatts of PPL Generation's proven and reliable generating plants throughout the United States."*

Subsidiary of **PPL Generation**

### 2.20 EPLUS: PPL Energy Plus L.L.C.

### 2.21 DPL: Delmarva Power & Light Company

Formerly known as Conectiv. For many years the power companies in the Conectiv regions were known by traditional utility names; Delmarva Power and Atlantic City Electric. Those names were changed to Conectiv in the mid 1990s to reflect the many non-utility lines of business that were a part of the enterprise at that time. *"We merged with Pepco (the utility serving Washington DC and its Maryland suburbs) in 2002 and as part of the PHI family of companies we are refocused on our core utility business which accounts for 70% of our revenues. The return to the historic names we used for decades signifies a returning to our roots as local companies serving a local community, and more clearly indicates who we are and what we do"*

Sister company of **Atlantic City Electric**. Part of **Conectiv**.

### 2.22 FESC: FirstEnergy Solutions Corp.

FirstEnergy Solutions and its affiliates offer a wide range of energy and related products and services, including the generation and sale of electricity; exploration, production and sale of natural gas; mechanical and electrical contracting and construction; and energy management. *"You can see there's a lot of experience behind our national service, energy management and energy use strategies. In a competitive energy marketplace, we're providing our customers with a variety of innovative products and services, allowing them to remain focused on their core business. We're a licensed electric supplier in Ohio, Pennsylvania, New Jersey, Delaware, Maryland, Michigan and*

*Washington, D.C. We currently offer price quotes on natural gas to larger business and manufacturing customers located in Ohio, Pennsylvania, New Jersey, Kentucky and West Virginia.”*

Unregulated subsidiary of **FirstEnergy Corp**. FirstEnergy Corp. is a diversified energy company headquartered in Akron, Ohio. Its subsidiaries and affiliates are involved in the generation, transmission and distribution of electricity; marketing of natural gas; and energy management and other energy-related services. Its seven electric utility operating companies - Ohio Edison, The Cleveland Electric Illuminating Company, Toledo Edison, Metropolitan Edison, Pennsylvania Electric, Pennsylvania Power, and Jersey Central Power & Light - comprise the nation's fourth largest investor-owned electric utility system, based on serving 4.3 million customers in a 36,100-square-mile service area that stretches from the Ohio-Indiana border to the New Jersey shore. Its various subsidiaries have annual revenues of more than $12 billion and electric sales of approximately 124 billion kilowatt-hours. *"Our Corporate Vision is to become the leading retail energy and related services supplier in our region."*

### 2.23 NRGNJ: NRG New Jersey Energy Sales LLC

**NRG Energy** is a competitive energy provider founded in 1989. NRG owns and operates a variety of energy-related operations worldwide. “*We have one of the industry's most diverse generation portfolios, distinguished by its range in geography, fuel source and dispatch level.”*

### 2.24 SUSQEP: Susquehanna Energy Products, LLC

Affiliate of **Susquehanna Investment Group**. Susquehanna Investment Group (SIG) is one of the largest option market making organizations in the United States. As a specialist, designated primary market maker on the nation's option exchanges, SIG commits its capital to offer liquid markets to retail and institutional investors seeking to hedge investment risk. In addition to acting as specialist in approximately 600 equity options, 40 index options and dozens of currency options, SIG also fields market makers in nearly every other U.S.-listed option class.

### 2.25 Morgan: Morgan Stanley Capital Group, Inc.

*"Morgan Stanley bankers work hand in hand with corporations, institutions and governments to provide the best solutions for each of our clients' needs. In the Banking Group, Morgan Stanley bankers bring specific industry, regional and product expertise to each client, advancing Morgan Stanley's industry leadership in devising and executing the most innovative, customized answers to the most challenging issues in the global marketplace."*

### 2.26 NEV: Constellation NewEnergy, Inc.

*"Constellation NewEnergy is a leading competitive supplier of electricity and energy-related services to commercial and industrial customers throughout North America, providing products that enable customers to effectively manage and control energy costs. Constellation NewEnergy serves more than 8,000 commercial and industrial customers in nearly three dozen states and three Canadian provinces. These customers include more than half of the Fortune 200 and represent more than 10,000*

*megawatts of peak load. The company’s electric supply business operates in all competitive energy markets in the U.S. and Canada.”*

*“Subsidiary of* ***Constellation Energy****. Constellation Energy is the nation’s leading supplier of competitive electricity to large commercial and industrial customers. It is one of the nation’s largest wholesale power sellers, A major generator of electricity and a regulated distributor - Baltimore Gas and Electric utility - of electricity and natural gas in Central Maryland. Constellation Generation Group: owns more than 12,000 MW of electrical generating capacity. Constellation Energy Commodities Group sells power into the wholesale market. Constellation New Energy: provides and procures power and natural gas for large commercial and industrial customers. BGE: Transmission and Distribution of Electricity.”*

### 2.27 ODEC: Old Dominion Electric Cooperative

*"We exist to serve our Members. We shall provide reliable, safe and economical wholesale electric power sources, continually evaluate and meet the Members’ needs in order to facilitate their growth and strength, and to assure their continued success, take an active role in the development of opportunities advantageous to the Members. Old Dominion's systems and its 12 member electric distribution cooperatives have relationships of proven reliability and earned trust that go back 60 plus years. In fact, those served by these 12 local cooperatives are more than customers; they're also owners of the cooperative."*

### 2.28 AECI :Allegheny Electric Cooperative, Inc.

Allegheny Electric Cooperative is a generation and transmission cooperative formed by the electric distribution cooperatives in Pennsylvania and New Jersey. There are 14 distribution members/owners of Allegheny Electric Cooperative. The cooperative owns interests in 2 generation plants enough to provide about half of the cooperative's needs. The remainder is bought from other generation companies. The current supplier is Williams Energy Marketing and Trading.

### 2.29 BPGM: BP Energy Company (Green Mountain)

*"As the largest retail provider of less-polluting electricity to residential and commercial customers in the U.S., Green Mountain Energy Company offers electricity that is:Cleaner - All of our electricity comes from less-polluting sources like wind, water, solar, biomass, geothermal, and natural gas. Reliable - The source of the electricity you pay for changes, not how electricity is delivered."*

### 2.30 CITZNS Reliant Energy Services, Inc. (Citizens Electric)

*"The Reliant Energy Wholesale Group is a leading provider of electricity, natural gas and energy services with a focus on the competitive segments of the electric power industry in the United States and Western Europe. We acquire, develop and operate electric power generation facilities that are not subject to traditional cost-based regulation and therefore can sell power at market-determined prices. We also trade and market power, natural gas and other energy-related commodities and provide related risk management services. We refer to the combination of our power generation operations with our trading, marketing and risk management operations as our*

*"wholesale business." Our trading, marketing, and risk management skills complement our generation positions. The combination provides greater scale and skill associated with the management of our fuel and power positions, sophisticated commercial insights and understanding of the key regions in which we participate, and a wider range of ways in which we participate in the market and are able to meet customer needs."*

Citizens' Electric is a wholly owned subsidiary of **C&T Enterprises**, a subsidiary of **Claverack Rural Electric Cooperative** and **Tri-County Rural Electric Cooperative**.

### 2.31 EXGNPT: Exelon Generation Co., LLC

(Power Team)Exelon Generation manages a diverse portfolio of natural gas, coal, hydro, nuclear, solar and wind generated electricity.*" We are bold and aggressive. We seize opportunities, and then make the most of them - for our customers, shareholders, and communities. Exelon Generation is considered a world-class operator of nuclear power generation, a leader in wholesale power marketing, and an innovator in the fossil, hydro and wind and solar development areas. We are reaching, with all of Exelon Corporation, to become the most recognized and admired utility services company in the world."*

Subsidiary of **Exelon Corporation**. Exelon Corporation is one of the nation's largest electric utilities with more than $14 billion in annual revenues. It distributes electricity to approximately 5.2 million customers in Illinois and Pennsylvania, and gas to 460,000 customers in the Philadelphia area. Exelon Corporation is parent of PECO and ComEd

### 2.32 MetEd: Metropolitan Edison Company

The Group's principal activities are the distribution and sale of electric energy in an area of approximately 3,300 square miles in eastern Pennsylvania. The Group also sells, purchases and interchanges electric energy with other electric companies. The Group's retail customers are metered on a cycle basis. Revenue is recognized for unbilled electric service through the end of the year

Wholly owned subsidiary of **FirstEnergy Corp**. See market participant # 22.

### 2.33 AHC:Amerada Hess Corporation

Amerada Hess Corporation is a leading global independent energy company, engaged in the exploration and production of crude oil and natural gas, as well as in refining and in marketing refined petroleum products, natural gas, and electricity

### 2.34 CPSDMB: Constellation Energy Commodities Group

(DPL MD Base)Constellation Energy Commodities Group, formerly known as Constellation Power Source, sells  power into the wholesale market, providing utilities, electric co-operatives, municipalities, and power marketers reliable energy at predictable prices. Also manages fuel and power logistics and other energy services.

Subsidiary of Constellation Energy. See market participant # 26.

### 2.35 UGID: UGI Development Company

Wholly owned subsidiary of **Ugi Corp**. Ugi Corp is a distributor and marketer of power products and services.

### 2.36 SELWM: Select Energy, Inc. (Wholesale Marketing)

"Our Power Marketing and Trading divisions are active in all three Northeastern power pools (ISO New England, New York ISO and PJM Interconnection). Serving over 5,000 megawatts of peak load in New England, Select Energy is one of the largest wholesale energy suppliers in the region today. With decades of power sourcing and generation expertise, our risk-savvy team is well-regarded throughout the industry."

Subsidiary of Connecticut-based **Northeast Utilities** (NYSE: NU).
Select Energy manages and markets power output for approximately 1,300 megawatts of generation owned by the affiliate Northeast Generation Company.

### 2.37 RAMEP: Ritchie Energy Products, L.L.C.Formerly known as RAM Energy Products LLC.

### 2.38 PaElec: Pennsylvania Electric Company

The Company's principal activity is to distribute electricity on retail as well as wholesale basis. The Company distributes and sells electric energy in an area of approximately 17,600 square miles in western Pennsylvania to a population of approximately 1.6 million.  It also sells, purchases and interchanges electrical energy with other electric companies.

Wholly owned subsidiary of **FirstEnergy Corp**. (See market participant # 22.)
As a lessee of the property of its subsidiary, The Waverly Electric Light & Power, the Company also serves a population of about 13,400 in Waverly, New York and vicinity

### 2.39 CINSI: Cinergy Services, Inc.

Cinergy Service, Inc., a Delaware corporation ("Cinergy Services" or "Applicant"), Cincinnati, Ohio, a service company subsidiary of Cinergy Corporation ("Cinergy"), a registered holding company

Subsidiary of **Cinergy Corporation**. Cinergy's regulated operating companies are The Cincinnati Gas & Electric Company (Cinergy/CG&E)(Ohio), Union Light, Heat & Power (Cinergy/ULH&P) (Kentucky) and PSI Energy, Inc. (Cinergy/PSI) (Indiana).Cinergy’s regulated public utilities in Ohio, Indiana, and Kentucky serve 1.5 million electric customers and about 500,000 gas customers. In addition, its Indiana regulated company owns 7,000 megawatts of generation. Cinergy’s competitive commercial businesses have 6,300 megawatts of generating capacity. The interconnections of Cinergy's Midwestern transmission assets give it access to 40 percent of the total U.S. energy consumption. Cinergy's 2003 operating revenues were $4.4 billion.

### 2.40 JCPLFP: Jersey Central Power & Light (FP Load)

Jersey Central Power & Light Company serves more than 1 million customers in New Jersey

Subsidiary of **FirstEnergy Corp**. (See market participant # 22.)

### 2.41 ConEdE: ConEdison Energy, Inc.

*“Con Edison Energy is a wholesale energy company that designs innovative supply services to foster success, mitigate risk, and manage volatility in the wholesale energy marketplace. Customers in the generation, distribution, and power marketing*

*industries value our supply, logistics and risk management services because we tailor them to their individual needs. We're able to offer these services because of our unique capabilities. First, we know the region -- everything from weather patterns to regulatory requirements. Second, we've invested in sophisticated information systems that allow us to analyze market developments and track prices. Third, we have a broad range of experience in electricity and gas trading, fuel optimization, and generating asset and transmission system operations."*

### 2.42 ACNEgy: ACN Energy, Inc.

ACN Energy is another milestone in ACN's quest to provide consumers with choice in the services they use every single day. More than 85,000 ACN customers enjoy the convenience of a single provider for all essential services. ACN Energy, has been offering consumers an alternative choice for natural gas and electricity services in several deregulated markets throughout the U.S. since 1998. ACN Energy currently serves areas in California, Georgia, Maryland, New York, Ohio, Pennsylvania and Texas.

Wholly owned subsidiary of **ACN Inc**. "ACN is a leader in the rapid expansion of the global telecommunications industry and has become one of the world's leading direct sellers, having served millions of satisfied customers in 18 different countries."

### 2.43 ECPDTE: Energy Cooperative Association of PA

*"The Energy Cooperative is the only non-profit consumer cooperative in Pennsylvania licensed as a competitive electricity supplier. By combining the buying power of over 6,500 households and small businesses we are able to negotiate low prices and locked-in rates for electricity. We also provide renewable, Green-e certified*

*electricity to our members and promote energy efficiency services to permanently lower your electric bill. Although we are licensed to serve the entire Commonwealth of Pennsylvania, we have our hands full serving our members in the Philadelphia area."*

### 2.44 EASTON: Easton Utilities Commission Easton

Utilities operates, manages and maintains the electric, water, wastewater, natural gas, cable television and Internet utility services for the Town of Easton and portions of the surrounding area. In 1923, Easton became the first municipality in the state to own all of its utilities, an arrangement that is still unique today. The Electric Department now provides service to over 9,500 customers in a 53 square-mile service territory. *"We are connected to the PJM Interconnection, L.L.C. (PJM) power pool and use this venue to purchase our electricity on an hourly basis. Easton also owns 16 diesel generators and operates them to offset costs during times of high-priced PJM energy. Easton's installed electrical generation capacity is 60 megawatts, enough to meet the Town's service load during periods of normal demand. To meet the town's growing electricity needs, Easton will soon add another 10 megawatts."*

### 2.45 CEDS: Consolidated Edison Solutions, Inc.

Consolidated Edison Solutions (Con Edison Solutions) works to solve the energy supply needs of retail customers in the Northeast. The company markets electricity and natural gas as an alternative supplier for homes and businesses in deregulated utility markets. It also provides energy procurement and management services.

Subsidiary of **Consolidated Edison, Inc**. Consolidated Edison Inc is one of the nation's largest investor-owned energy companies, with $10 billion in annual revenues and approximately $23 billion in assets. Consolidated Edison Company of New York (Con Edison), a regulated utility, provides electric service in New York City (except for a small area of Queens), and most of Westchester County. *“We provide natural gas service in Manhattan, the Bronx, and parts of Queens and Westchester. Con Edison also owns and operates the world’s largest steam system, providing steam service in most of Manhattan.”*

### 2.46 GALT: Galt Power Inc.

Galt Power is engaged in the sale of electricity and related products through the wholesale electricity markets. This includes the day ahead and real time energy markets, capacity markets, ALM, Emergency and Economic Demand Side Response markets, and Financial Transmission Rights (FTR) markets. Galt Power became a PJM member in December 2003. Galt Power helps Load Serving Entities (LSEs) including Municipal and Cooperative Utilities in many of the regular transactional functions they must perform in the PJM and similar Independent System Operator (ISO) markets. In particular Galt Power helps LSEs cost effectively manage their participation in the ISO demand response programs. Galt Power is capable of trading demand response and distributed generation portfolios in the PJM market. Likewise Galt Power is able to help manage the congestion risk through a combination of Financial Transmission Rights and participation in the energy markets. Our research provides valuable analysis and understanding of the wholesale markets for clients involved in the bidding of demand response and distributed generation products.

## 2.47 JARON : J. Aron & Company

J. Aron is the commodities division of Goldman Sachs. They are members of COMEX and the LBMA in London. They specialize in over-the-counter options trading.

Part of **Goldman Sachs**. The Goldman Sachs' Commodities group provides full service commodity risk management to commercial, investor, and sovereign customers worldwide. *"We cover virtually all commodity related exposures including Oil, Natural Gas, Metals, Power, Weather and Forest Products. The group delivers a global approach to risk management with more than 150 professionals around the world, with offices in locations such as New York, London, Sydney, Singapore and Tokyo. We strive to combine our understanding of client objectives with superior derivative expertise, world-class block trading, and leading edge commodities research to create customized risk management solutions."*

## 2.48 TESI: Tractebel Energy Services, Inc.

Changed its name to SUEZ Energy Resources NA, Inc in April 2005. SUEZ Energy Resources NA provides electricity and risk management solutions to commercial and industrial customers looking to control their energy budgets. Licensed in 12 markets (Texas, New York, New Jersey, Massachusetts, Maryland, Maine, Pennsylvania, Ohio, Rhode Island, Delaware, Connecticut and Washington, DC),

Subsidiary of **SUEZ**, an international industrial and services group that designs sustainable and innovative solutions in the management of public utilities as a partner of public authorities, businesses and individuals. The Group aims to answer essential needs in electricity, gas, energy services, water and waste management. SUEZ is listed on the Brussels, Luxembourg, Paris, New York and Zurich stock exchanges and is represented in the main international indices: CAC 40, DJ STOXX 50, DJ EURO STOXX 50, Euronext 100, FTSE Eurotop 100, MSCI Europe and ASPI Eurozone. The Group employs 160,700 people worldwide and achieved revenues of EUR 40.7 billion in 2004, 89% of which were generated in Europe and in North America.

### 2.49 AMPO: American Municipal Power-Ohio,

Inc.American Municipal Power-Ohio supplies wholesale power to more than 80 community owned distribution utilities, primarily in Ohio. The power generation company, which is owned by its member municipalities, was formed in 1971. The municipally owned power systems are scattered throughout the state. Not all generate their own power; some buy all or part of their supply from AMP-Ohio at wholesale rates. At its dispatch center near Columbus, AMP-Ohio taps between two and three dozen suppliers, including the New York Power Authority, Louisville Gas & Electric and Cinergy.

### 2.50 DTEET DTE Energy Trading, Inc.

See Market participant 17

### 2.51 MLCS Merrill Lynch Capital Services, Inc.

Merrill Lynch is one of the world’s leading financial management and advisory companies, with offices in 36 countries and total client assets of approximately $1.6 trillion, at the end of 2004

## 2.52 SES: Sempra Energy Solutions

Sempra Energy Solutions offers comprehensive portfolio of electricity, natural gas and emissions risk management products.

Subsidiary of **Sempra Energy**. With more than 13,000 employees worldwide, the Sempra Energy companies develop energy infrastructure, operate utilities, and provide related products and services to more than 29 million consumers in the United States, Europe, Canada, Mexico, South America and Asia.

## 2.53 QuarkP: Quark Power, L.L.C.

Web page www.quarkpower.com not working yet.

## 2.54 AEPAP: Appalachian Power/American Electric Power

**American Electric Power** owns more than 36,000 megawatts of generating capacity in the United States and is the nation's largest electricity generator. AEP is also one of the largest investor-owned electric utilities in the United States, with more than 5 million customers linked to AEP’s 11-state electricity transmission and distribution grid. The company is based in Columbus, Ohio. Systemwide there are more than 38,000 circuit miles of transmission lines and more than 186,000 miles of distribution lines. Customer service is provided through seven regional utilities: AEP Ohio, AEP Texas , Appalachian Power , Indiana Michigan Power , Kentucky Power , Public Service Company of Oklahoma , Southwestern Electric Power Company . **Appalachian Power** (AP) provides service to AEP customers in West Virginia and Virginia. It has 929,000 customers, 2,370 employees, 6,972 transmission miles, 46,227 distribution lines, 5,871 megawatts of generation capacity and 5 billion in assets.

# Appendix – Chapter 5

# Clean air and affordable electricity?

Dalia Patiño-Echeverri, Zhiyong Wu and Marija Ilic

*Abstract*— **Performance criteria of the power industry such as environmental impact, electricity prices, and quality/reliability of the service are functions of fuel market, government regulations, the state of the art of technology, and the combined actions of different industry participants. We argue that to prescribe optimal government interventions, it is imperative to understand as much as possible about the dynamics of the interaction between industry participants, as well as the interactions with fuel and technology markets. In this paper we propose a model that relates air emissions and electricity prices with government policies regarding allocation of emissions allowances, fines, subsidies and investments in R&D. We present results of the simulation of a simplified model.**

*Index Terms*—**Pollution control, market models, governmental factors, game theory.**

## I. Introduction

Coal-fired power units account for more than 50%[1] of electricity generation and are the single biggest source of air pollution in the U.S. The reduction of emissions from the electricity generation sector implies either retrofitting existing coal-fired power plants or replacing them with newer and cleaner technologies. Retrofitting existing coal plants to reduce emissions of sulfur-oxides, nitrogen-oxides, mercury, or carbon-dioxide requires equipment that is expensive to install and operate. The retirement of existing power plants also implies intensive capital investments and therefore higher costs for electricity generation.

Since the availability of affordable electricity is a necessary condition for GDP growth, the goal of minimizing the level of toxic emissions in the atmosphere while keeping electricity prices low poses a very serious challenge to society.

A very relevant question arises: how should the government act over a finite period of time to achieve desired levels of atmospheric emissions and electricity prices?

In order to shed some light on this issue, we propose a model of the electricity generation system that (1) explicitly considers a number of control instruments that the government can use to balance atmospheric emissions and electricity prices, and (2) accounts for the fact that industry participants make strategic decisions to maximize their profits and face several sources of uncertainty. The model is constituted by four subsystems: the fuel market, the electricity market, the environmental or allowances market, and the market of equipment for control of emissions.

A computational implementation of a simplified model and a simulation over a number of years allow us to comment about how this problem needs to be studied.

## II. Background

There are at least three big efforts to understand the effects that environmental legislations for the electricity generation system may have on the U.S: 1) the National Energy Modeling System (NEMS)[2], 2) the Argonne National Laboratory's AMIGA model [3], and 3) the EPA's Integrated Planning Model (IPM)[4].

NEMS and AMIGA are general equilibrium models of the U.S. economy, while IPM is a bottom-up linear programming model of the electric power sector. All assume that decisions by industry participants are made with perfect foresight, and forecast electric power sector decisions for a given set of environmental regulations

The NEMS and AMIGA models forecast capacity additions, fuel dispatching, and electricity prices based on different endogenous and exogenous inputs of the electric sector and the U.S. economy. IPM forecasts decisions made from the national to the plant level in response to legislative requirements seeking to minimize the net present value of the cost of compliance over the planning horizon.

A recent analysis using NEMS was prepared in response to a request by the U.S. Congress to examine the costs of imposing caps on power sector emissions of $SO_2$, $NO_x$, Hg and $CO_2$. Some results of this analysis are contained in "Strategies for Reducing Multiple Emissions from Electric Power Plants"[5]. AMIGA and IPM models have also been recently used to assess the impacts of legislations to reduce emissions from the electricity sector[2].

We believe that it is necessary to analyze the problem with a model that differs from the existing ones in that the model (1) explicitly accounts for the fact that industry participants are making decisions under uncertainties about future regulations, fuel prices, and other participant's actions, (2) accounts for different instruments of government intervention

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[1] Electricity supply from coal accounted for 54% in 2001. EIA forecasts that under reference case assumptions, this tendency will remain in the next 20 years.[1]

[2] Also Johnson and Keith [6] developed a model that forecasts capacity additions, retirements, and retrofits for different prices of carbon emissions within the Mid Atlantic Area Council Region of the North American Electric Reliability Council.

such as subsidies and investments in R&D, and for details of the regulation such as how and when allowances are allocated to generating units, and (3) frames the question of what the government should do as an optimization problem in which both electricity price and air-emissions are considered.

## III. Model Description

We represent the electricity generation sector with a number of generating units that vary in fuel, size, and efficiency.

The generation cost for each unit is determined by some fixed costs, the cost of fuel, and the cost of complying with environmental regulations.

The cost of fuel for a particular unit depends on its heat rate and fuel price. Assuming that environmental regulations provide a Cap-and-Trade (CAT) System, the environmental cost for each plant will be a function of the number of allowances it has been allocated by the government, the price of allowances, and the price of add-on Emissions Control Devices (ECD).

We assume all generating units reserve all their capacity production for sale on the spot market. All generators submit their bids to the Independent System Operator (ISO), who runs an economic dispatch model to meet electricity demand.

The electricity price is the clearing price obtained in a uniform-price auction. Electricity demand is assumed to be inelastic and is treated as an exogenous input.

Figure 1 illustrates the interaction among different variables considered in the model.

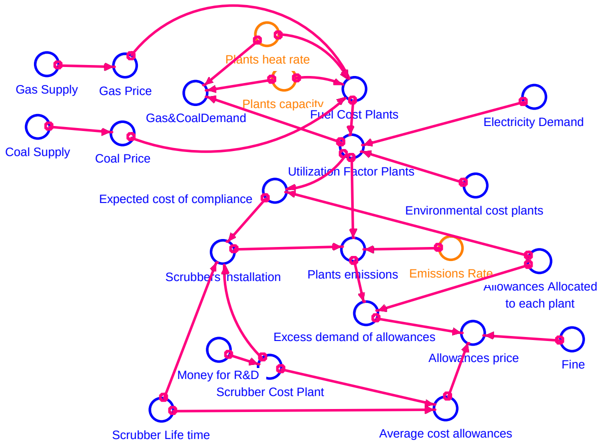


Fig. 1 Overview of the system

### *A. Electricity Market*

Let $pe_\tau^*$ represent the electricity price at time, and $\delta_\tau$ the demand of electricity. Let $s_\tau^i$ be the supply function bid by generator $i$ at time $\tau$ which specifies the quantity of power offered and the price demanded. If $pe_\tau^*$ is equal to the market-clearing price of an uniform-price auction, then $pe_\tau^* = pe_t^{(k)}$ where $pe_t^{(k)}$ is the electricity price bid by the last generator (most-expensive supplier) needed to meet demand. That is, $pe_t^{(k)}$ satisfies:

$$pe_t^{(1)} \le pe_t^{(2)}) \le ... \le + pe_t^{(k)} \qquad (1)$$

$$\delta_\tau = s_\tau^{(1)}(pe_t^{(k)}) + s_\tau^{(2)}(pe_t^{(k)}) + ... + s_\tau^{(k)}(pe_t^{(k)}) \qquad (2)$$

In our model we will assume that the market is truly competitive and generators are profit-oriented so they adjust their power output to the level for which their marginal cost of electricity generation is equal to the expected spot price [7]. Therefore, a generator's bid to the spot market corresponds to its marginal cost of electricity generation, which includes the cost of fuel and the cost of compliance with environmental regulations.

### *B. Market of Emissions Control Devices*

We assume that the capital cost of ECDs decreases as companies and the government put money in to Research and Development (R&D). We assume that the amount that firms devote to R&D is proportional to allowance prices.

The different technology-based alternatives that allow the reduction of emissions in electric generating units can be split into two categories: (1) installation of add-on emissions control equipment, (2) modification of the firing process. The first category includes devices such as wet and dry scrubbers to remove $SO_2$, selective catalytic reduction devices (SCR) to remove $NO_x$, Carbon Injection Devices (CI) to remove Mercury, and Carbon Capture and Sequestration technologies (CCS) to reduce $CO_2$ emissions. In the second category of alternatives to reduce emissions we can include methods such as switching fuel (for example to low-sulfur coal), modifying the unit to co-fire other fuels (for example, biomass or natural gas), and improving the heat rate of the unit. In this paper we use the term ECD to refer to all possible technologies of both categories.

For any ECD it is true that installation and operation costs, removal rates, and energy penalties are generator specific and cannot be forecasted with complete accuracy until they are operating. However, it is also true that the degree of uncertainty is somewhat higher for less tested technologies such as CCS.

Assuming that capital and OM (operation and maintenance) costs of ECDs evolve with time as new necessities to reduce emissions generate investments in R&D, we have chosen to model the capital cost of ECDs as a state variable related to government policies and private investments.

Let $\vec{r}_t$ represent the aggregated investment in R&D by all units in time $t$. Let $rg_t$ be the amount invested in R&D by the government and $m_{t,k}^i$ be the subsidy the government will give to unit $i$ for installing ECD $k$ at time $t$.

Therefore, $h_{t,k}^i$, the cost of installing ECD *k* to unit *I* at time *t* will be given by

$$h_{t,k}^i = h_{t-1,k}^i - m_{t,k}^i - \tilde{\alpha}_1(\vec{r}_{t-1}, \vec{r}_{t-2}) - \tilde{\alpha}_2(rg_{t-1}, rg_{t-2}) \qquad (3)$$

where $\tilde{\alpha}_1^i(.)$ and $\tilde{\alpha}_2^i(.)$ are random variables whose probability distributions have parameters that depend on the R&D investments of previous periods.

*C. Fuel market*

Prices of fuels are determined by the aggregated demand at a particular period of time. The quantities demanded of each fuel are a result of the amount of electricity generated by each generating unit. We assume here that the supply functions for each fuel are time invariant.

Let $p_\tau^k(Y^k)$ be the inverse supply function of fuel $k$ at time $\tau$, which measures the price at which sellers are willing to supply a given amount of fuel.

Let $y_{\tau,k}^i(s_\tau^i)$ be the amount of fuel $k$ consumed by generating unit $i$ at time $\tau$, when producing an electricity output of $s_\tau^i$. Let $Y_\tau^k$ be the aggregated demand of fuel $k$ at time $\tau$, e.g. $Y_\tau^k = \sum_i y_{\tau,k}^i(s_\tau^i)$, where $s_\tau^i$ is determined by the economic dispatch performed in the electricity market as in (2).

In this paper we will assume that supply functions for coal and gas are time invariant and exogenously determined. This means that conditions for the extraction and transportation of coal and gas for the time scope analyzed here are not affected by other variables of the model and remain constant.

*D. Environmental Market*

*1) Cap-and-Trade System*

In this model we will assume that there is a CAT system to control emissions of different pollutants. Under a CAT system, the government sets a cap and issues an equivalent number of emission permits or allowances which can be traded in the market. The government can allocate allowances in two different ways, grandfathering allowances or auctioning them. Under the grandfathering approach, government allocates to existing generating units a number of emission allowances for free. The number of allowances allocated to each plant might be determined by some historical data (as in the case of the EPA Acid Rain Program) and remain that way for a number of years, or can be periodically adjusted. The unit is authorized to emit as many tons of pollutant as allowances has been allocated. Since the number of allowances allocated covers only a portion of its emissions, to comply with regulations the unit has three alternatives: (a) to install emissions control equipment, (b) to buy "emissions allowances" in the market, (c) to reduce its electricity output.

Often, units that install Environmental Control Devices (ECD) end up emitting less than what they have been allowed . The emissions allowances not used can be sold in the market or if allowed, be banked for use in future years. Those generating units that have emissions over the number of allowances held must pay a fine to the government for each ton. In this sense, the government can be seen as a seller of an unlimited number of allowances at a price equal to the fine.

To make decisions regarding whether and when to install emissions-control equipment, decision makers have to consider the expected cost of compliance for each of the possible alternatives. The expected cost of compliance depends on the capital and operating cost of ECDs, number of allowances allocated, level of emissions, and price of allowances.

*2) The decision to install an ECD*

Modeling the decision that power plants' owners make in regard to ECDs poses several difficulties.

We can assume that at each period $t$, generators will design a strategy or a plan regarding which ECDs should they install and use every future period to minimize the expected cost of compliance over a planning horizon $T$, and will act accordingly. Such strategy will be reviewed next period as new information allows a more accurate calculation of the expected cost of compliance.

Let $L^i$ be an indicator matrix of the ECDs installed by generator $i$, at each period, so $l_{t,k}^i = 1$ if generator $i$ decides to install ECD $k$ in period $t$ and $l_{t,k}^i = 0$ otherwise. Similarly let $U^i$ be an indicator matrix of the ECD the generator uses in each period. Therefore $u_{t,k}^i = 1$ if generator $i$ uses ECD $k$ in period t and $u_{t,k}^i = 0$ otherwise.

Let $\vec{e}_t^i(.)$ represent the air emissions of generator $i$ at time $t$, and $\vec{a}_t^i$ represent the number of allowances (for each pollutant) allocated by the government, to generator $i$ for period $t$. If $\vec{w}_t^*$ represents the price of allowances at time $i$, $h_{t,k}^i$ represents the capital cost for generator $i$ to install ECD $k$ at time $t$, and $O_{t,k}^i$ represents the Operation and Maintenance Cost, then the expected value of the cost of compliance for unit $i$, over a planning horizon $T$, calculated at time $t$, $E\left[C_{t,T}^i\right]$, is given by:

$$E_t\left[C_T^i\right] = E\left[\sum_t^T \frac{\left[\left[\vec{e}_t^i - \vec{a}_t^i\right]^{\mathrm{T}} \vec{w}_t^* + \vec{h}_t^{i\mathrm{T}} \vec{l}_t^i + \vec{O}_t^{i\mathrm{T}} \vec{u}_t^i\right)\right]}{(1+\rho_i)^t}\right] \qquad (4)$$

We assume that in order to use a particular ECD, a unit has to install it $\eta$ periods in advance. Note that every installment decision that plant makes in previous periods is a constraint for future periods. In other words, at time *t*, columns 1, 2,..,*t*-1 of $L^i$ and $U^i$ are not decision variables, but initial conditions, because they represent decisions that were already executed in previous periods. These path dependencies in the solution make this problem one of Dynamic Programming. Also, since $\vec{e}_t^i$, $\vec{a}_t^i$ and $\vec{w}_t^*$ are random variables, the problem is a Stochastic Dynamic Program or a Multi-stage Stochastic Program [3][8].

[3] Given that variables $L^i$ and $U^i$ are binary, the problem is linear mixed-integer.

At each period the installation and use of ECDs is given by the first column of matrixes $L^i$ and $U^i$ that solve:

$$\underset{\substack{\vec{l}^{\,i}_{\cdot,j}:j\in[t,T] \\ \vec{u}^{\,i}_{\cdot,j}:j\in[t,T]}}{Min} \quad E_t\left[C_T^i\left(L^i,U^i\right)\right] \tag{5}$$

$$\text{S.t.} \qquad \vec{l}^{\,i}_{\cdot,j} : j\in[0,t-1] \tag{6}$$

$$u^i_{k,t} \le \sum_{j=0}^{t-\eta} l^i_{k,j} \tag{7}$$

Note that (4) implies that compliance is mandatory and that banking of allowances is not possible. This means that when emissions are higher than the number of allowances held, the unit has to buy the difference $\vec{e}^{\,i}_t - \vec{a}^{\,i}_t$ at a price $\vec{w}^{\,*}_t$. Similarly, when emissions are lower than the number of allocated allowances, the unit has to sell the difference at the same price $\vec{w}^{\,*}_t$. In practice, under the Acid Rain Program units are allowed to bank all the $SO_2$ allowances they have left and use them in future years. Units are also allowed to bank $NO_x$ allowances but these banked allowances are discounted.

*3) Calculating the expected cost of compliance*

If we accept that units make their compliance decisions by trying to minimize the expected cost, a natural question is how they calculate it. Given that the number of allowances allocated, price of allowances, and costs of ECDs in coming years are all random variables, how do units calculate the expected cost of compliance for a certain strategy?

In the following subsections we comment on the uncertainty inherent to key variables and the way they affect the decision making process of power plant makers in regard to a compliance strategy.

*3.1) Uncertainty in future regulations.*

The current number of allowances allocated for each pollutant is known by generators, but the number of allowances that will be allocated in future years is highly uncertain. It is expected that significant changes in the future air emissions regulations will heavily affect electricity generators that burn fossil fuels. However, neither the timing nor the stringency of these future regulations is known. This uncertainty in future regulations has a cost. Waiting to decide until all legislative, regulatory, and judicial uncertainty is resolved could prove costly; however, "locking in" an emission-control technology too soon could prove equally expensive. On one hand, plants might face stringent regulations without being prepared for that, and could be forced to buy expensive emission allowances. On the other hand, the installment of a particular control technology can preclude or make more expensive the option to install newer technologies more efficient or better suited for updated regulations. In [9] a method to compute the expected cost of regulatory uncertainty for coal-fired plants is proposed for a set of plausible regulatory scenarios with attached probabilities. Under this approach, each plausible regulatory scenario determines plants' emissions, price of allowances, and fuel prices, so when a regulatory scenario is realized there are no more uncertainties. In this paper, we take a different approach and assume that even in the absence of regulatory uncertainty, the plant has still to consider that other important variables such as emissions, allowances and fuel prices are unknown and partially determined by its own decisions and its interaction with other market participants.

*3.2) Uncertainty in unit emissions*

Unit emissions are proportional to the power output and therefore cannot be predicted with accuracy without knowing future utilization capacity factors for the unit. If the plant participates in the spot market, then its electricity output is also a random variable that depends upon electricity demand, market structure, and the generator's bid. If the bid is affected by the cost of compliance with environmental regulations, then the compliance strategy and unit emissions are related in a closed loop fashion.

*3.3) Uncertainty in emissions-allowances prices*

The price of allowances depends on the compliance decisions made by all the units participating in the market of allowances. For example, if all generating units decide to install ECDs and reduce emissions to a level below the legal requirements, then the price of allowances will drop to zero. On the other hand, if allowances are scarce, prices can approach the fine's price.

Forecasting allowances prices has proven to be a very difficult task in the recent past. For instance, when the Clean Air Amendment was enacted, the cost of compliance with the Acid Rain Program standards for $SO_2$ was estimated to be \$400-\$1000/ton, but by 2000, allowances ranged in price from \$130 to \$155 and have remained close to \$140. The $NO_x$ budget offers another example; although forecasts of marginal control costs ranged from \$500/ton to about \$2,500/ton and in very few cases close to \$5,000/ton, some trades in early 1999 occurred about \$7000/ton but prices later fell to less that \$1000/ton.[10] In 2003, trades for $NO_x$ allowances for vintage 2004 and 2005 occurred at prices between \$3,000/ton and \$4,000/ton.[11]

In [12] it is argued that in phase II of the CAAA90, a high supply of $SO_2$ allowances and prices much lower than expected occurred in part because owners of big power plants preferred to invest in expensive scrubbers rather than incur the risk of an allowances shortage. Later, the situation with $NO_x$ was the opposite. Many plants preferred to wait to see what would happen in the market of $NO_x$ allowances before installing any expensive control technology. This "wait and see" approach of many plants has been at least one of the causes of the high prices of $NO_x$ allowances seen in recent years. Estimation of allowance prices under multi-pollutant regulation poses additional difficulties, due mainly to synergies between the control of $SO_2$, $NO_x$ and $CO_2$[4]. In our

[4] For example, analysis conducted by EIA shows that while a scenario with stringent regulations only on $SO_2$ leads to allowance prices of \$300, \$700 and \$1,000 in years 2008, 2010, and 2020 (in 1999 dollars), a scenario with the same stringent cap of $SO_2$ and stringent caps for $NO_x$ and $CO_2$, leads to prices of \$100, \$100 and \$50 for the same.

model we will assume that the forecasts that power plant owners use to make their compliance decisions are based on the allowance prices they observe, which are clearing prices in a uniform price auction.

*4) Clearing allowances prices*

Allowances suppliers (for a certain pollutant) are the units that, as a result of having installed an ECD, have lower emissions than the number of allowances allocated by the government. In contrast, allowances buyers are the units whose emissions exceed the government allocated allowances.

Let $B_t^j$ represent the set of buyers of allowances for pollutant *j* in time *t*. Since ECDs reduce the emissions of different pollutants at different rate, a particular unit can be a supplier of allowances of one pollutant and a buyer of allowances of other pollutant. For example a unit that installs a dry scrubber can supply $SO_2$ allowances, but could need to buy $NO_x$ allowances. This situation might change over time as the unit changes its emissions because of a change in the electricity output or because of the use or non-use of certain ECD.

Let $\delta a_t^j$ represent the demand of allowances for pollutant *j* at time *t* and let $e_{t,j}^i$ and $a_{t,j}^i$ represent the *j*-th component of $\vec{e}_t^{\,i}$ and $\vec{a}_t^{\,i}$ respectively. Therefore,

$$\delta a_t^j = \sum_{i \in B_t^j} \left( e_{t,j}^i - a_{t,j}^i \right) \qquad (8)$$

As with electricity, we assume that the price of allowances for pollutant $j$ at time $t$, $w_{t,j}^*$ is the market clearing price of a uniform-price auction. If the demand of allowances is higher than the number of allowances supplied by units, then price will be equal to the fine, otherwise it will be equal to the bid of the last unit called to sell allowances to meet demand.

$$\vec{w}_{t,j}^* = \begin{cases} pa_{t,j}^{(i)} \text{ if } \delta a_t^j > \sum_{i \notin B_t^j} \left( a_{t,j}^i - e_{t,j}^i \right) \\ F_{t,j} \text{ otherwise} \end{cases} \qquad (9)$$

where $F_{t,j}$ is the fine for no compliance with regulations for pollutant *j*, and $pa_t^{(i)}$ is the bid of the last unit called to sell allowances to meet demand, when suppliers of allowances have been stacked in ascendant order according to their bids.

*5) Simulating compliance decisions by power plants*

If we accept that the outcome of every compliance decision made by a power plant is strongly dependent on the decisions made by other plants, then the interaction among different plants has to be modeled as a strategic game.

In our model, we assume that decisions made by unit are those that result in a Nash Equilibrium (NE).

To illustrate our thought, consider the example of a system with only three units making a decision regarding whether to install an $SO_2$-scrubber. To simplify the analysis assume:

a) The only pollutant capped is $SO_2$ and there is a CAT system in which the three units are partially grandfathered so they receive a fixed amount of $SO_2$ emissions allowances.

b) There is no uncertainty regarding future environmental regulations, so participant units know for certain how many allowances they will receive from the government for their entire planning horizon.

c) There is no uncertainty about future emissions. That is, participants can forecast with accuracy their future emissions because their future electricity output and fuel composition are known.

d) The allowances market clears as described in 3.

e) The choice to install a scrubber is a “now or never” option. That is, if the unit chooses not to install a scrubber, it can not install it later.

f) Once installed, the scrubber has to be used. For all plants, the scrubber reduces 90% of the unit $SO_2$-emissions.

g) Each seller of allowances (units that choose to control emissions) bids its variable cost for reducing emissions.

h) The payoffs of each plant under every circumstance are “common knowledge.”

i) All plants make their decision simultaneously.

Assumptions e) and f) are needed to justify the framework of a “one move” game. Otherwise, we would have to consider a repeated game in which units that have not installed a scrubber can decide to do it in future moves, and those that already installed it can decide not to use it.

Assume plant emissions, scrubber cost and allowances allocation as presented in Table 1. (Scrubber (Wet Flue Gas Desulfurization System WFGD costs retrieved from IECM model using default values. [13])

TABLE 1. WGFD COSTS AND ALLOWANCES ALLOCATION

| Unit | Capacity (MW) | Emissions (Tons) | WFGD costs | | Annual allocation of allowances (Tons) |
|---|---|---|---|---|---|
| | | | Capital Cost ($ million) | Variable Cost ($/Ton reduced | |
| 1 (Big) | 500 | 45,000 | 56 | 250 | 27,000 |
| 2 (Small) | 200 | 18,000 | 37 | 400 | 10,800 |
| 3 (Small) | 200 | 18,000 | 37 | 400 | 10,800 |

The payoff for each plant is its expected cost of compliance for the entire planning horizon. To represent all possible combinations of decisions of the three plants with their correspondent payoffs we can draw a “game-tree” [14] with three players as in Figure 2.

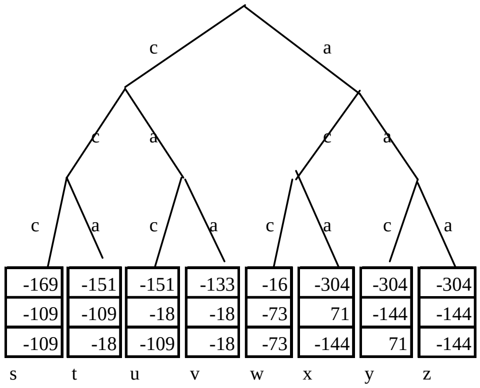


Fig. 2. Game tree

Each terminal of the three in Figure 2 corresponds to the vector of payoffs. The vector labeled as *v* corresponds to the payoff when the three plants chose to control their emissions, and the vector labeled as *z* corresponds to the payoff when all the plants choose to comply with regulation buying allowances. The first component of each vector of payoffs corresponds to the payoff of unit 1, the second component corresponds to the payoffs for unit 2, and so on.

If we assume a fine for no compliance of \$2,000, and an allowances market as the one described in section 3, then the price of $SO_2$ allowances will be \$0, for outcome *s*, \$250 for outcomes *t*, *u* and *v*, \$400 for outcome *w*, and \$2000 (fine price) for outcomes *x*, *y* and *z*.

Note that the best outcome for plant 1, *w*, occurs when this plant chooses to buy allowances and the other two plants choose to control their emissions. In this case, plants 2 and 3 supply all the allowances unit 1 needs to buy to comply, and the price of each allowance is \$400/ton. For plant 2 (or plant 3) the best outcome occurs when plant 2 (and/or plant 3) chooses to buy allowances and plant 1 chooses to control its emissions. In this case plant 1 can sell all the allowances that plant 2 and/or plant 3 needs to comply with regulations. The worst outcome for every unit occurs when it decides to buy allowances and these are sold at the fine price. There are two Nash equilibria in pure strategy, *v* and *w*. By finding the NE in mixed strategies we find that unit 1 chooses to control emission with probability P1=0.269, and units 2 and 3 choose to control emissions with probabilities P2=P3=0.661 (The units choose to control at "random" according to those probabilities).

If we remove assumption j) and force plant 1 to make the first move, then the only Nash equilibrium obtained is node *v*. In the simplified simulation that we describe before, a similar game is modeled, but in this case the decision of whether or not to install an ECD is not restricted to the previous period, but allowed to be made at any time in the planning horizon.

### *E. Control Instruments*

In this model we consider three different ways in which the government can intervene in the system:

1) Through allowances allocation: The government has a direct way to control the market of allowances by setting the acceptable emissions level at a certain point and allocating allowances to utilities accordingly.

2) Through the level of the fine for non-compliance: The government can also set the value of the fines for each ton of emissions that a unit has over its level of allowances.

3) Affecting the "installation threshold" for ECD: The government can make more attractive the option of installing ECD to power units in two ways:

a) Lowering the cost of ECD: The government could provide subsidies to buy ECD and have short-term impact in the level of installed ECD. The government can also support R&D activities to increase the likelihood of substantial improvements in the cost of ECD.

b) Even if the cost of ECD is the same, the government can make the option of installing ECDs seem more attractive by making utilities expect to use them for a longer time.

Let $A$ represent the allowances allocated by the government, $F$ represent the fines charged for non-compliance, $M$ represent the subsidies given to units that install ECDs and $RG$ be the money invested by the government in R&D for ECDs. To answer the question of which policy instruments are better to achieve low emissions and fair electricity prices, an optimization framework seems appropriate. The constraints of such an optimization problem are given by the characteristics of the units that constitute the sector, and the structure of the markets for fuel, electricity and allowances. At least three different ways to formulate this problem can be considered:

1.) A multi-objective optimization problem, where the goal is to minimize at the same time the amount of emissions over a planning horizon, the amount of money invested by the government in R&D and subsidies for ECD, and the electricity prices. All the goals are combined in a single objective function as a weighted sum of the money the government has to put into the system (subsidies and R&D investments, minus fines collected), emissions and electricity prices.

$$\begin{aligned} \min_{M,RG,F,A} z = \alpha \left( \sum_t \sum_i \sum_k m^i_{t,k} + \sum_t rg_t - \sum_t \sum_j F_{t,j} \right) + \\ \sum_j \beta_j \left( \sum_t \sum_i e^i_{t,j} \right) + \sum_\tau \gamma_\tau pe_\tau \end{aligned} \tag{10}$$

$$s.t. \qquad (1),(2),..(11)$$

In (10), $\alpha, \beta$, and $\gamma$ are weights which have to be chosen carefully so the tradeoffs between the three key variables (government expenditure, emissions and electricity prices) are well represented. In the last term in (10), $\gamma$ must be chosen related to the expected electricity demand $\delta_\tau$ because the demand level captures the relative importance of electricity prices at each period.

2.) An optimization problem where the goal is to minimize the amount of emissions while keeping electricity prices and money spent by the government under a certain level.

$$\min_{A,F,M,RG} z=\sum_j \beta_j\left(\sum_t\sum_i e^i_{t,j}\right)$$
$$s.t. \quad \sum_\tau \gamma_\tau pe_\tau \le \psi_1 \tag{11}$$
$$\sum_t\sum_i\sum_k m^i_{t,k}+\sum_t rg_t-\sum_t\sum_j F_{t,j}\le \psi_2$$
$$(1),(2),..(11)$$

$\psi_1$ and $\psi_2$ represent the maximum allowed levels for electricity prices and government expenditure in Environmental Policy.

3.) To minimize the electricity prices and amount of money spent by the government while keeping emissions under a certain level. So far this has been the approach adopted by the U.S. Acid Rain Program for controlling emissions of $SO_2$ which began in year 2000, setting a permanent annual cap of 8.95 million tons from all affected utilities [6].

$$\min_{A,F,M,RG} z=\sum_\tau \gamma_\tau pe_\tau$$
$$s.t. \quad \sum_j \beta_j\left(\sum_t\sum_i e^i_{t,j}\right)\le \psi_1 \tag{12}$$
$$\sum_t\sum_i\sum_k m^i_{t,k}+\sum_t rg_t-\sum_t\sum_j F_{t,j}\le \psi_2$$
$$(1),(2),..(11)$$

## IV. Simulation Of A Simplified Model

*A. Description of simplified model*

In order to illustrate the model described, we implemented a simplified model, in which we assume the only pollutant regulated is $SO_2$ and the only ECD available is a Wet Flue Gas Desulphurization System (WFGD). We also disregard here all the effects that money in R&D might have in the evolution of ECD technologies and assume there are no changes in the capital cost of the WFGD. We also disregard the effects that uncertainty in future regulations has in the optimality of decisions made by plants and assume they all have perfect foresight of government policies.

In order to keep running times short, we chose to represent the U.S. electricity market with a reduced number of plants. We looked at all the coal-fired units in the U.S. and divided them into four equally numerous groups according to its generation capacity. Then we calculated the average of key variables for each group, and defined four hypothetical plants as being the average plant of each group. These four hypothetical units correspond to what we could call the "very small," "small," "medium," and "large" prototypical units. Similarly we characterized the prototypical gas units and chose to include in the model only 6 units – the ones that represent the small, medium and large units of each type. To estimate the cost of installing WGFD we used the IECM[13][5]. These prototypical coal and gas units are included in the model with attributes as those in the table 2.

[5] For plants 2 and 3 (medium and large), heat rate and capacity were specified in the IECM. Other parameters were left as the default in the model. The cost of WFGD for plant 1 was extrapolated, accounting for economies of scale.

TABLE 2. UNITS INCLUDED IN MODEL

| Unit | Name Plate Capacity (MW) | type | Heat Rate (Btu/ kWh) | $SO_2$ Emissions Rate (ton/MWh) | Capital Cost ($) | WFGD | | |
|---|---|---|---|---|---|---|---|---|
| | | | | | | Annual O&M Cost ($) | Annual Variable O&M Cost ($/ MWh) | $SO_2$ Reduc-tion (%) |
| 1 | 59 | coal | 11,982 | 0.0347 | 3E+07 | 4.E+06 | 0 | 0.89 |
| 2 | 172 | coal | 11,000 | 0.0318 | 4.4E+07 | 7.E+06 | 0 | 0.89 |
| 3 | 571 | coal | 10,600 | 0.0306 | 7.9E+07 | 1.E+07 | 0 | 0.89 |
| 5 | 12 | gas | 12,773 | 0.0000 | 0 | 0.E+00 | 0 | 0 |
| 6 | 42 | gas | 11,973 | 0.0000 | 0 | 0.E+00 | 0 | 0 |
| 7 | 166 | gas | 11,067 | 0.0000 | 0 | 0.E+00 | 0 | 0 |

In order to explore the optimal values for the variables controlled by the government (number of allowances allocated and price of fine for no compliance), we simulate the electricity and allowance markets for 11 years, for different combinations of allowances allocated and fines. The algorithm followed can be summarized as follows:

-For all the plausible government policies, for each year of the planning horizon,

1. Simulate how units make their decision as to whether or not to install a WFGD.
2. For each day
    a. Simulate the electricity market. (Find schedules for each plant and clearing price.)
    b. Record $SO_2$ emissions and expenses in electricity.
3. Simulate market of allowances. Find clearing price for that year.
4. Calculate emissions and dollars spent in for each policy, as well as the value of the objective function as in (10).

The compliance decisions made by participant units are those that correspond to the NE of a strategic game in which each of the coal units has the option to install the WFGD at any time during the 11 years. Since we are modeling 3 coal-fired units there are 11^3=1,331 cases that each plant has to consider. If there is a non-unique NE we assume that units choose the one that optimizes the government objective function.

We also assume that all units estimate their payoffs in the game based in a forecast of the environmental costs of the future. Environmental costs are forecasted based on an estimation of emission levels and allowances prices. Estimations of future emission levels are made assuming the utilization factor of the plant will be similar to previous years.

The electricity market clears as described in IIIA. The electricity demand profile corresponds to the annual demand profile of ISO NE, scaled so it can be met with the capacity of the units modeled. Units bid their marginal cost which includes the cost of fuel and their environmental cost. The cost of coal is assumed to be \$1.2/mmBtu for 11 years, and the cost of gas is assumed to increase from \$4.18/mmBtu in year 1 to \$4.64/mmBtu in year 11.

The environmental cost for those units that do not have WFGD is the cost of the allowances they will have to buy to cover their emissions. For those units that are sellers of allowances the environmental cost is the annualized capital cost of the WFGD minus the revenue for allowances sold each year.

*B. Results*

If the government allocation required each plant to reduce its $SO_2$ emissions by 30% and fixed the fine for no compliance in \$2000/Ton, then the NE is obtained when the large plant installs an WFGD in year 1, and the other two plants do not install WFGD. In this case total $SO_2$ emissions during the 11 years considered are 228,000 tons and total expenditures in electricity are 1.11 billion. How good is this policy? Fig. 3 shows the minimum level of emissions that can be obtained for each level of electricity expenditure -"Pareto Frontier"- and the point of NE. The frontier is found by evaluating emissions levels and electricity expenditures for each of the 1,331 possible combinations of WFGD installation decisions (We omitted in the graph a very extreme point in which all the plants install WFGD). The point labeled as "optimal" corresponds to the ideal outcome if government assigned to emissions a value of \$1,000/ton, to make the objective of reducing emissions commensurable with the objective of reducing the cost of electricity. The NE would be far from this point and clearly, the policy of requiring reductions of 30% and fixing a fine of \$2,000 would not be good enough.

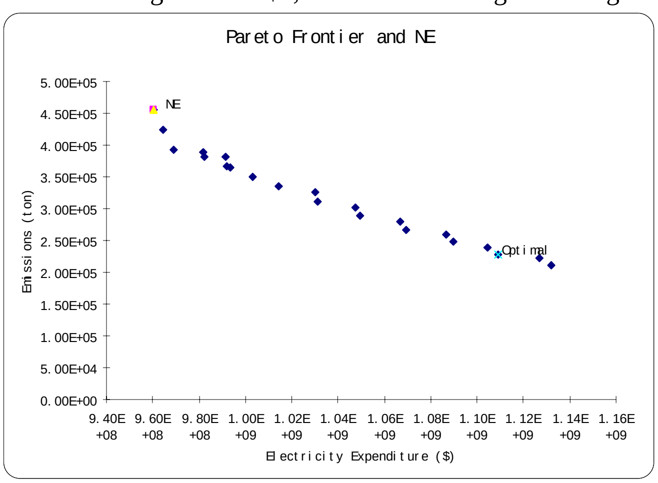


Fig. 3. Pareto Frontier and NE for a policy with 30% emissions reductions and \$2000/ton fines.

In order to find the best policy, we can compare Pareto frontiers. Figure 4 shows the Pareto frontiers for two policies in which the fine is still \$2,000/ton and the reductions required are 40% and 80%. The Pareto frontier when reductions required are 80% lies below the frontier when reductions required are 40%, so for the same electricity expenditures emissions can be much lower if the government allocates fewer allowances. A comparison of the Pareto frontiers of different levels of allowances allocation indicates that the best policy is to enforce reductions of more than 80%. However if the government wanted to cap the total expenditures in electricity at a level lower than \$1.05 billion, then the number of allowances allocated should be higher.

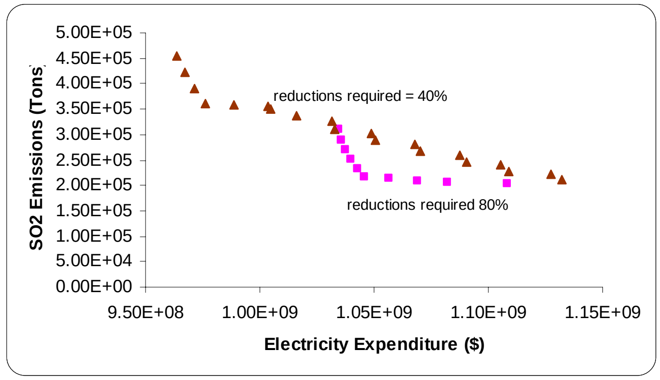


Fig. 4. Pareto frontiers of two policies with fine = \$2000.

A similar analysis of the effect of the fines shows that results do not change when fines are between \$1,000 and \$3,000/ton.

## V. Conclusions

We have described and illustrated a model that explicitly relates government policies with emissions and electricity prices. The accuracy of the analysis to design optimal policies depends upon the assumptions made regarding the behavior of industry participants. Such behavior is determined by the information the participants have available, the methods used to forecast future values of key variables, and participants' approach to the risk and uncertainty.

A detailed and accurate model of the behavior of industry participants when facing different policies can enlighten any analysis the government makes to choose policies that maximize social welfare.

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$$c = e^{-rT}\left[SN(d_1)e^{rT} - XN(d_2)\right]$$

[15] $$d_1 = \frac{\ln(S/X) + (r + \sigma^2/2)(T)}{\sigma\sqrt{T}}$$

$$d_2 = d_1 - \sigma\sqrt{T}$$

# Appendix – Chapter 5

## The Cost of Regulatory Uncertainty in Air Emissions for a Coal-fired Power Plant

**Dalia Patiño Echeverri, Paul Fischbeck, Benoit Morel, and Alex Farrel**

**Abstract:**

Uncertainty about the extent and timing of changes in air-emissions regulations for coal fired power plants makes the difficult problem of selecting a compliance strategy even harder. Capital investments made today under uncertainty can limit future compliance options or make them very expensive. In this paper, we present a method for computing the cost of operating a moderate-sized, coal-fired power plant under different conditions of future regulatory uncertainty. Using a Multi-Period Decision Model (MPDM) that captures the decisions (both capital investment and operating) that a power plant owner must make each year, the framework employs a Stochastic Optimization Model (SOM), nested in the MPDM to find the strategy that minimizes the expected net present value (ENPV) of plant operations over a fixed planning horizon. By comparing model runs under different uncertainty conditions, the cost of regulatory uncertainty can be calculated.

## 1. Introduction

Uncertainty imposes costs to society by preventing optimal decisions to be recognized and pursued. One source of uncertainty is the legislative/regulatory process. This paper quantifies these costs in one important example in the electricity industry, uncertainty of future air emission regulations.

Significant changes in the regulations controlling emissions of sulfur dioxide ($SO_2$), nitrogen oxides ($NO_x$), mercury (Hg), and carbon dioxide ($CO_2$) in the atmosphere will occur in the future, posing a serious challenge to the electricity generation sector and especially to coal-fired power plants. Uncertainty about the extent and timing of potential future regulations makes the difficult problem of selecting a compliance strategy even harder. These uncertainties may even be exacerbated by the industry if it follows the usual path of litigation.[1]

Significant emission reductions from coal-fired power plants could require installing expensive add-on controls, retrofitting the plant to burn alternative fuels, or even retiring the plant and replacing it with a new, cleaner one. The suitability of any compliance strategy is particularly dependent on which pollutants are regulated, when and how stringently they are regulated, and the details of the regulatory instruments. The same strategy that may look optimal under one regulatory scenario could prove to be very expensive under others.

Currently, $SO_2$ and $NO_x$ emissions from power plants are regulated by a combination of command-and-control (CAC) and cap-and-trade (CAT) instruments, depending on pollutant and plant location. New regulations are scheduled to come into force in the next several years. However, there is uncertainty about the future of both current and upcoming $SO_2$ and $NO_x$ regulations. At present, there are no Federal regulations on mercury emissions from power plants, but Congress has ordered the EPA to propose regulations on mercury emissions from coal- and oil-fired power plants by December 2003. Finally, while the current administration do not support $CO_2$ regulations in the near future, all credible observers believe that Federal controls on greenhouse gas (GHG) emissions for U.S. power plants will be required eventually.[2]

Several bills controlling some or all of these pollutants were introduced in the 107th Congress, and the issue is sure to arrive again in the upcoming session. Many of

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[1] Although there is a deadline of May 2004 for the implementation of more stringent $NO_x$ standards, recent suits by utilities could postpone the action. [Energy Argus Daily. Clean Air Regulations and Markets. Vol. 9 No 148 August 2002.]

[2] International treaties and recent laws appear to foretell Federal Controls: Consider for example: the State of New Hampshire House Bill 284-FN relative to additional emissions reductions from existing fossil fuel burning steam electric power plants http://www.gencourt.state.nh.us/legislation/2002/hb0284.html.
Oregon Carbon Dioxide Emission Standards for New Energy Facilities, House Bill 3283. http://www.leg.state.or.us/97reg/measures/hb3200.dir/hb3283.a.html.
State of Massachusetts DEP Regulation 310 that caps CO2 emissions from the six highest polluting power plants in 1,800lbs of carbon dioxide per megawatt-hour.
http://yosemite.epa.gov/globalwarming/ghg.nsf/actions/LegislativeInitiatives
California Automobiles/lemon law AB1058. http://www.dca.ca.gov/legis/2001 autolemon.htm

this bills feature CAT systems to control all these pollutants, while a few rely on CAC approaches.[3]

Future regulations may have broad economic impacts on the cost of fuel, type of generation, and control technologies that will be required. Despite these uncertainties, plant owners and operators must still make investment decisions to keep up with electricity demand. Waiting to decide until all legislative, regulatory, judicial uncertainty is resolved could prove costly; however, “locking in” an emission-control technology too soon could be equally expensive. Changes in the legislative/regulatory process that reduced or eliminated some of the underlying uncertainties could provide significant economic savings for the industry.

In this paper, we present a method for computing the cost of operating a moderate-sized, coal-fired power plant under different conditions of future regulatory uncertainty. Using a Multi-Period Decision Model (MPDM) that captures the decisions (both capital investment and operating) that a power plant owner must make each year, the framework employs a Stochastic Optimization Model (SOM), nested in the MPDM to find the strategy that minimizes the expected net present value (ENPV) of plant operations over a fixed planning horizon. By comparing model runs under different uncertainty conditions, the cost of regulatory uncertainty can be calculated.

This paper is organized as follows. In Section 2, we discuss previous models that have been developed to evaluate regulatory uncertainty and show how the proposed model is different. In Section 3, we describe the structure of the MPDM and SOM models and how they interact. In Section 4, we present assumptions used in a baseline analysis. In Section 5, we present the baseline analysis and its results. In Section 6, we present several sensitivity studies on the base case, and in Section 7, we outline opportunities for future work.

## 2. Models for Analyzing Impacts of Environmental Regulations

There are different models that forecast the effects that environmental legislations may have on the U.S. electric sector, four of them are: 1) the National Energy Modeling System (NEMS)(EIA, 2001a), 2) the Argonne National Laboratory’s AMIGA model (Hanson, 1999), 3) the EPA’s Integrated Planning Model (IPM), and 4) the Carbon Capture and Sequestration in an Electric Market Dispatch Model (Johnson & Keith, 2002).

NEMS and AMIGA are general equilibrium models of the U.S. economy, while IPM and the Johnson model are bottom-up linear programming models of the electric power sector. All assume perfect foresight and forecast electric power sector decisions for a given set of environmental regulations.

The NEMS and AMIGA models forecast capacity additions, fuel dispatching, and electricity prices based on different endogenous and exogenous inputs of the electric sector and the U.S. economy. IPM forecasts decisions made from the national to the

[3] Consider for example the Clean Power Act of 2001 Bill # S.556 (Jeffords) or the Clean Power Act and Modernization Act of 2001 Bill # S.1131 (Leahy), or the “Clear Skies Proposal”.

plant level in response to legislative requirements seeking to minimize the net present value of the cost of compliance over the full planning horizon.

A recent analysis using NEMS was prepared in response to a request by the U.S. Congress to examine the costs of imposing caps on power sector emissions of $SO_2$, NOx, Hg and $CO_2$. Some results of this analysis are contained in "Strategies for Reducing Multiple Emissions from Electric Power Plants" (EIA 2001d) and are used later in this paper as inputs for the baseline analysis.

AMIGA and IPM models have also been recently used (EPA 2001a) to assess the impacts of legislations to reduce emissions from the electricity sector.

The Johnson model forecasts capacity additions, retirements, retrofitting, and dispatching for different prices of carbon emissions within the Mid Atlantic Area Council Region (MAAC) of the North American Electric Reliability Council. Unlike the others, Johnson's considers Carbon Capture and Sequestration (CCS).

The model proposed here is different from the others in that it 1) is based on a unit-level analysis, 2) explicitly accounts for the uncertainty in future regulations, 3) allows future decisions to adjust to resolved uncertainties, and 4) can be used to determine the inherent costs of different types of regulatory uncertainty. It also varies from NEMS, AMIGA and IPM in that it considers CCS.

### 3. Modeling Decision Making of a Power Plant Operator

In this paper, we present a method to compute the cost of operating a power plant under different conditions of future regulatory uncertainty. To do so, the MPDM is used to model plant investment, operation, and allowance choices on a yearly basis. (Figure 1 shows model dynamics). Each year, the MPDM calls on the SOM to determine the optimal operating and investment strategy for that year that minimizes the cost of generating a fixed amount of electricity for the next 30 years, based on current and expected conditions.

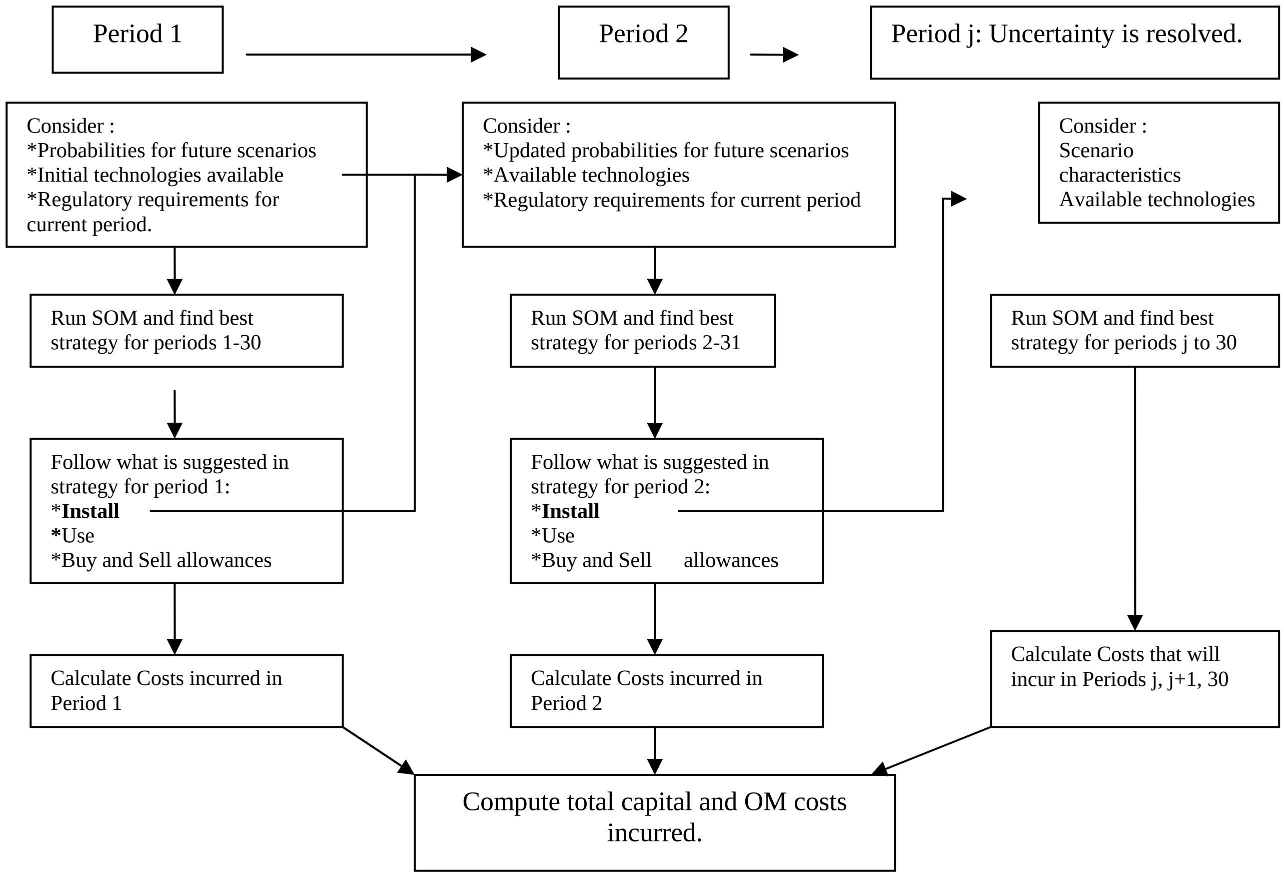


**Figure 1.** Multi-Period Decision Model

### 3.1 Representing the uncertainty: Probabilities on plausible scenarios

In this analysis, uncertainty is characterized by a probability that is assigned to each member of a set of mutual-exclusive, exhaustive plausible "scenarios." A scenario defines a sequence of future regulations, emissions caps, allowances prices and policy instruments. Every scenario is a "bundle" of assumptions on future regulations and allowances market behavior for every year of the planning horizon. Each scenario implies a deterministic trend for allowances prices, and therefore, when the uncertainty about regulations is resolved so are the uncertainties in allowances prices. Table 1 shows the five scenarios that will be considered for a baseline analysis.

| Scenario Name | | BAU | 2P+1 | | 3P | 3P+1 | | 4P |
|---|---|---|---|---|---|---|---|---|
| Number of phases | | 1 | 2 | | 1 | 2 | | 1 |
| Year of implementation | | 2003 | 2007 | 2009 | 2007 | 2007 | 2009 | 2011 |
| $SO_2$ | Reduction in allowances allocated | - | 63% | 63% | 63% | 63% | 63% | 63% |
| | Max Emissions Rate (lb/mbtu) | | | | | | | |
| | Policy Instrument | Trade | Trade | Trade | Trade | Trade | Trade | Trade |
| $NO_x$ | Reduction in allowances allocated | - | 60% | 60% | 60% | 60% | 60% | 60% |
| | Max Emissions Rate (lb/mbtu) | | | | | | | |
| | Policy Instrument | | Trade | Trade | Trade | Trade | Trade | Trade |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Hg | Reduction in allowances allocated | - | - | 60% | 60% | 60% | 60% | 60% |
| | Max Emissions Rate (lb/mbtu) | | | | | | | |
| | Policy Instrument | | Trade | Trade | Trade | Trade | Trade | Trade |
| $CO_2$ | Reduction in allowances allocated | - | - | - | - | - | 60% | 60% |
| | Max Emissions Rate (lb/kWh) | | | | | | | |
| | Policy Instrument | | Trade | Trade | Trade | Trade | Trade | Trade |

**Table 1.** Scenarios for Baseline Analysis.

Throughout this study, two types of cost calculations are computed using SOM at each time step: 1) The minimum cost of operating the plant when the future regulation scenario is known (a deterministic –perfect foresight optimization problem), and 2) The minimum expected cost of operating the plant when the decision maker does not know the future and assigns a probability to each possible scenario. This set of probabilities (which we will define to be α) is subjective, will vary from decision maker to decision maker, and will evolve over time as new information about which scenarios are still possible is acquired. The evolution of these probabilities is assumed deterministic given an actual scenario occurring. However, the decision maker will not know how the probabilities will change, until the uncertainty is revealed to her.

For our baseline analysis we assume the decision maker believes it is very likely that a new regulation will come in less than ten years and the future will take the form of one of the scenarios represented in Table 1. We also assume she believes that scenario BAU is the least likely while scenario *3P+1* is the most likely, assigning a probability of occurrence to each scenario as shown in Table 2.

| **Scenario** | BAU | 2P+1 | 3P | 3P+1 | 4P |
|---|---|---|---|---|---|
| **Initial Probabilities** | 0.05 | 0.15 | 0.20 | 0.50 | 0.10 |

**Table 2. Initial probabilities $\alpha$**

As time passes and scenarios are found not to occur, the decision maker will update her beliefs about the remaining scenarios. We assume the probabilities of the scenarios that are still plausible will preserve the original ratios.

### 3.2 Stochastic Optimization Model (SOM)

The optimization model finds the investment, operating, and allowance trading strategy that minimizes the expected cost to produce electricity subject to environmental constraints by selecting control or replacement technologies to install and use over a planning horizon.

A stochastic linear mixed integer programming model (see e.g., Birge & Louveaux, 1997) is used to find the plant's optimal compliance strategy for the remaining planning horizon. Tables 3 and 4 summarize the input parameters of the SOM.

| Dimension | Index | Range |
|---|---|---|
| **Scenario** | s | 1-5[4] |
| **Pollutant** | p | 1-4 |
| **Year** | t | 1-30 |
| **Control** | c | 1-49 |

**Table 3.** Dimensions in SOM

| | Description | Notation | Units |
|---|---|---|---|
| **Plant Initial Conditions:** | | | |
| Initial emissions | Plant's initial annual emissions of pollutant p. | $IE_p$ | -Tons/year for SO2, NOx and CO2.<br>-Lbs/year for Hg. |
| Initial emission rates | Plants Initial emission rates of pollutant p. | $IER_p$ | -Lbs/MBtu for SO2, NOx and Hg.<br>-Lbs/kWh for CO2 |
| Controls that are available from period 1 | | $AC1_c$ | =1 if control c is available,<br>=0 otherwise. |
| Controls that will be available from period 2 | Availability in next year | $AC2_c$ | =1 if control c will be available in next period, 0 otherwise. |
| Controls that will be available from period 3 | Availability in next two years | $AC3_c$ | =1 if control c will be available in two periods,<br>=0 otherwise. |
| **Scenarios** | | | |
| Number of allowances allocated | Number of allowances allocated under scenario *s*, for pollutant *p*, in year *t*. | $AA_{s,p,t}$ | -Tons/year for SO2, NOx and CO2.<br>-Lbs/year for Hg. |
| Maximum emissions rate allowed | Maximum emissions rate allowed under scenario *s*, for pollutant *p*, in year *t*. | $MER_{s,p,t}$ | -Lbs/MBtu for SO2, Nox and Hg.<br>-Lbs/kWh for CO2 |
| Allowances prices | Allowances prices under scenario s, for pollutant *p*, in year *t*. | $AP_{s,p,t}$ | In year 2000 dollars/allowance. |
| Policy instrument | Policy instrument: (Tradable allowances, taxes or emission standards) | | In the scenarios presented here it will be assumed a CAT approach |
| Probability of Scenario s being "reality" | Probability of scenario *s* | $\pi_s$ | |
| Capital cost for installing the new technology. | Capital cost for installing the control *c* in year *t*. | $CC_{c,t}$ | Year 2000 dollars |
| O&M costs | Total O&M costs of the plant with the new technology used (including fixed O&M, variable O&M and fuel costs) | $OM_{c,t}$ | Year 2000 dollars/year |
| Emissions reduction (as a percentage of initial emissions) | Emissions Percentage reduction of control c, for pollutant *p*, in time *t*. | $EPR_{c,p,t}$ | Percentage reduction from initial emissions. |
| **Other Parameters** | | | |
| Discount rate used by power plant operator to calculate NPV of the capital and operating expenses | Discount rate used by decision maker to calculate NPV of the capital and operating expenses | r | Percent |

**Table 4.** Input parameters for optimization program.

The decision variables in SOM represent three kinds of decisions; capital investment, operational choice, and allowances trading. Capital investment decisions are represented

[4] We consider 5 scenarios for the baseline analysis.

by binary variables that indicate whether a particular control or replacement technology is installed in a given period. Operating decisions are also represented by binary variables that indicate whether an available technology is used. Allowances trading decisions are represented by variables that indicate how many allowances to sell and buy. Table 5 describes the decision variables of the optimization program.[5].

| **Installation Variables** | **Description** | **Notation** | **Variable type** |
|---|---|---|---|
| Controls installed: | Whether the technology is installed or not. | $I_{c,t}$ | Binary<br>1 = Installed |
| **Operating variables** | | | |
| Technology used | Whether a particular available technology is used. | $U_{s,c,t}$ | Binary<br>1 = Used |
| Allowances Bought | Number of allowances bought | $AB_{s,p,t}$ | Continuous $\geq 0$ |
| Allowances Sold | Number of allowances sold | $AS_{s,p,t}$ | Continuous $\geq 0$ |

**Table 5.** **Outputs (Decision Variables) of the SOM.**

The objective function is given by:

*Minimize*

$$\sum_c \sum_t (1+r)^{-t} I_{c,t} CC_{c,t} + \sum_s \pi_s \sum_t (1+r)^{-t} \left[ \sum_c U_{s,c,t} OM_{c,t} + \sum_p AP_{s,p,t} (AB_{s,p,t} - AS_{s,p,t}) \right]$$

*Subject to the following engineering and emissions constraints:*

1. Allowances allocated for each pollutant plus net trading have to be greater than or equal to zero for each period, in each scenario. Banking of allowances is not allowed.

$$AA_{s,p,t} + AB_{s,p,t} - AS_{s,p,t} - \sum_c U_{s,c,t} (1 - EPR_{c,p,t}) IE_p \geq 0 \qquad \forall \quad s,p,t$$

2. Unit emission rates have to be lower than maximum emissions rates allowed by regulation.[6]

$$IER_p \sum_c U_{s,c,t} (1 - EPR_{c,t}) \leq MER_{s,p,t} \qquad \forall \quad s,p,t$$

3. Control technologies used in first period have to be initially available in Period 1.

$$U_{s,c,1} \leq AC_c \qquad \forall \quad s,c$$

4. Control technologies used in second Period have to be initially available in Period 1 or 2.

[5] The program is a "two-stage" stochastic program. Installation decisions are "first stage decisions" because need to be taken without full information about the scenarios, while the choice of which of the available technologies to use and number of allowances to trade are "second stage" or "corrective" decisions that are made to meet the constraints given for each particular scenario.

[6] The scenarios considered here do not consider specific emission rates requirements. See Appendix A for details on each scenario.

$$U_{s,c,2} \le AC1_c + AC2_c \qquad \forall \quad s,c\,)$$

5. Control technologies used from Period 3 on have to be initially available in Periods 1 or 2 or installed at least two Periods before being used.

$$U_{s,c,t} \le AC1_c + AC2_c + AC3_c + I_{c,t-2} \qquad \forall \quad s,c \quad \forall \quad t \ge 3$$

6. Only one control technology can be used in any period. (Different combinations of control technologies are defined as different technologies.)

$$\sum_c U_{s,c,t} = 1 \qquad \forall \quad s$$

7. If allowances cannot be traded, then number of allowances bought and sold has to be zero.

$$If \quad T_{s,p,t} = 0 \Rightarrow AB_{s,p,t} = 0 \qquad \forall \quad s,p,t$$

$$If \quad T_{s,p,t} = 0 \Rightarrow AS_{s,p,t} = 0 \qquad \forall \quad s,p,t$$

8. Non negativity constraints

$$AB_{s,p,t} \ge 0$$
$$AS_{s,p,t} \ge 0$$
$$U_{s,c,t} \in \{0,1\}$$
$$I_{c,t} \in \{0,1\}$$

The optimization program has been implemented as a mixed integer program (MIP) in the Optimization Programming Language OPL, with inputs preprocessed by Visual Basic in Excel.[7]

### 3.3 Multi-period decision model

The decision variables obtained from the optimization model define a plan of which technologies to install and use every period for a given scenario. In this analysis, it is assumed that for the first several periods, more than one regulatory scenario is possible, and that all uncertainty will eventually be resolved.

For each time period, the decision maker takes three actions: 1) updates the probability set for future scenarios, 2) uses SOM to design an optimal plan for future periods based on the plant's current conditions and the new probability set, and 3) executes the plan previously designed for the current period. Optimal plans designed in each period consider that period's regulation, expectation on future scenarios, and the capital investments made in previous years.

[7] Constraints that are specific to combination of control technologies are also included.

The multi-period decision process has been implemented as a Script in OPL. Table 6 describes inputs for the MPDM.

| **Inputs** | **Description** |
|---|---|
| Years of uncertainty | The number of years until the uncertainty is resolved. |
| Lead time | Time between the announcement of regulation and the implementation of the program when the emissions constraints must be met. |
| Probability set | A set with the probability of occurrence for each of the plausible scenarios, for every year of uncertainty. |
| Reality | The scenario that is occurring. |
| Available technologies | The initial availability of technologies |

**Table 6.** Inputs for the MPDM.

The result of the MPDM is a vector of yearly cash flows (recorded as costs) over the entire time horizon. It specifies for each year the capital and operating expenses incurred, and the number of allowances bought or sold. This cash flow is discounted back to current dollars using a constant discount factor.

### 3.4 Expected value of perfect information

The effects of the regulatory uncertainty are assessed by comparing the decisions made when there is one certain future scenario, to those made when several regulatory scenarios are plausible. The concept of "expected value of perfect information" EVPI (see, e.g., Clemen & Reilly, 2001) can be used to measure the effects of regulatory uncertainty.

Consider an analysis for the planning horizon *1, ...j, ...T*. Suppose that $d^*(\alpha, s)$ represents the optimal strategy when scenario *s* happens but the decision maker does not know this until the uncertainty is resolved in period *j* and has to make decisions in periods *1, ...j* based on a set of probabilities $\alpha$. Suppose $d^*(s)$ represents the strategy followed when scenario *s* is known to occur by decision maker in first period. If $\alpha_s$ represents the initial subjective probability of each scenario being the reality then the EVPI for decision maker $\alpha$ is given by:

$$EVPI(\alpha) = \sum_{s \quad in \quad scenarios} \alpha_s \Big(NPV\big(d^*(\alpha, s)\big) - NPV\big(d^*(s)\big)\Big)$$

To calculate the EVPI($\alpha$) the MPDM needs to be run 10 times. Table 7 describes the runs needed.

| | Model Run | *Scenario* | *1* BAU | *2* 2P+1 | *3* 3P | *4* 3P+1 | *5* 4P |
|---|---|---|---|---|---|---|---|
| No uncertainty | $d^*(1)$ | Initial Probabilities | 1 | | | | |
| | | Reality | 1 | | | | |
| | $d^*(2)$ | Initial Probabilities | | 1 | | | |
| | | Reality | | 1 | | | |

| | | | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|---|---|
| | $d^*(3)$ | Initial Probabilities | | | 1 | | |
| | | Reality | | | 1 | | |
| | $d^*(4)$ | Initial Probabilities | | | | 1 | |
| | | Reality | | | | 1 | |
| | $d^*(5)$ | Initial Probabilities | | | | | 1 |
| | | Reality | | | | | 1 |

| | | Scenario | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|---|---|
| | | | BAU | 2P+1 | 3P | 3P+1 | 4P |
| | | Initial Probabilities | 0.05 | 0.15 | 0.2 | 0.5 | 0.1 |
| Uncertainty: Alpha Runs | $d^*(\alpha,1)$ | Reality | 1 | - | - | - | - |
| | $d^*(\alpha,2)$ | Reality | - | 1 | - | - | - |
| | $d^*(\alpha,3)$ | Reality | - | - | 1 | - | - |
| | $d^*(\alpha,4)$ | Reality | - | - | - | 1 | - |
| | $d^*(\alpha,5)$ | Reality | - | - | - | - | 1 |

**Table 7.** MPDM runs to find EVPI($\alpha$)

## 4. Base Case Assumptions

### 4.1 Power plant studied:

We will illustrate how uncertainties on regulatory scenarios can impact power plant decisions and lead to uneconomical choices, studying one hypothetical coal-fired generating unit whose characteristics are typical to many in the current U.S. electric sector.

The unit chosen generates 3.5 billion of kW-hr every year and has the characteristics shown in Table 8. The plant currently complies with the $SO_2$ cap trading allowances in the clean air market. The allowances allocated annually cover 35% of plant's current emissions. Current $NO_x$ emissions rate for this plant is under the maximum limit allowed by law. Also, the plant is not placed in any of the 19 states that will be affected by new emissions standards in year 2004. (e.g. Kansas). The coal used is a mix of 55% low sulfur coal and 45% High sulfur Bituminous. Information on current emissions was retrieved using the Integrated Environmental Control Model (IECM, 2002[8]).

| | | |
|---|---|---|
| Nameplate Capacity (MW) | | 500 |
| Steam Cycle Heat Rate (Btu/kWh) | | 10,900 |
| Capacity Factor | | 85% |
| Firing Type | | Tangential |
| Environmental Controls | | ESP- Low $NO_x$ Burner |
| Years On line | | 30 |
| $SO_2$ | (lbs/MBtu) | 3.02 |
| | Tons per year | 70,059 |
| $NO_x$ | (lbs/MBtu) | 0.40 |
| | Tons per year | 9,166 |
| Hg | (lbs/MBtu) | 6.12E-06 |
| | Lbs per year | 284 |

[8] Other plant characteristics not specified here are equal to the default case in IECM, 2002.

| | | |
|---|---|---|
| $CO_2$ | (lbs/kWh) | 2.73 |
| | Tons per year | 4,785,544 |
| Coal | Heat Content (Btu/lb) | 10,819 |
| | Carbon Content (nearest 0.01%) | 60.92 |
| | Sulfur Content (nearest 0.01%) | 1.60 |
| | Nitrogen Content (nearest 0.01%) | 1.10 |
| | Ash Content (nearest 0.01%) | 9.58 |
| | Moist Content (nearest 0.01%) | 14.33 |
| | Mercury content (ppm) | 12.00 |
| | Price (Delivered) ($/ton) | 22.90 |

**Table 8**. Plant characteristics, current emissions, and coal properties.

### 4.2 Scenarios

For the preliminary analysis, we consider five hypothetical scenarios that differ in the number of pollutants addressed and timing. All scenarios assume a cap and trade system and no constraint on emission rates.[9]

For the business-as-usual (BAU) scenario, we assume that allowances or permits will be allocated to the power plant at no cost (grandfathered) and in a quantity that covers 35% of its current $SO_2$ emissions and all its current emissions of $NO_x$, Hg, and $CO_2$.

#### 4.2.1. Allowance prices

In a cap-and-trade system, expected allowance prices play a key role in compliance decisions. Forecasting allowance prices has proved to be a particularly difficult task in the past. For instance, when the Clean Air Amendment was enacted, the cost of compliance with the Acid Rain Program was estimated to be $400-$1000/ton, but by 2000 allowances ranged in price from $130 to $155(Acid Rain Program. Annual Progress Report, 2000) and have remained close to $140. The $NO_x$ Budget offers another example; although forecasts of marginal control costs ranged from $500/ton to about $2,500/ton and in very few cases close to $5,000/ton, some trades in early 1999 occurred about $7,000/ton but prices later fell to less that $1,000/ton. (Farrell, 2000).

Estimation of allowance prices under multi-pollutant regulation posses additional difficulties, due mostly to synergies between the control of the criteria pollutants and $CO_2$. For example while under an scenario with stringent regulations only on $SO_2$ leads to allowance prices of $300, $700 and $1,000 in years 2008, 2010 and 2020(in 1999 dollars) an scenario with the same stringent cap of $SO_2$ and stringent caps for $NO_x$ and $CO_2$, leads to prices of $100, $100 and $50 for the same years (EIA: Strategies for reducing Multiple Emissions From Power Plants, 2001). A complete analysis of how

[9] Note that any general regulation for coal-fired power plants may imply different reduction requirements for each unit. For example a regulation that imposes a cap 90% below current $NO_x$ emissions for the power sector would not necessarily imply a requirement of 90% reduction in emissions from the unit considered here. Because of this, the scenarios considered by the power plant are not generic legislations, but specific programs that will directly affect its operation.

stringent caps on some pollutants could lower the cost of control of other pollutants is out of the scope of this paper. For the baseline analysis, we will assume allowances prices for $SO_2$, $NO_x$, and Hg based on those forecasted by NEMS model[10]. For $CO_2$ we will assume that allowance prices start at $25 the first year of the cap and increase by $5 annually. See in appendix A allowance prices for each scenario.

### 4.3 Control Technologies

Alternatives considered are add-on emissions control devices and the replacement of the plant with new generation technologies. Table 8.1 summarizes the alternative technologies as well as the assumption and information sources for performance and costs. Table 8.2. presents detailed information about each technology.

| **Add-on Control Technologies** | |
|---|---|
| $SO_2$: Wet Flue Gas Desulphurization (WFGD) with no bypass and limestone as a reagent | Emissions, capital and O&M costs from IECM, using plant specifications as in Table 8. and retrofit factor of 1.2. O&M costs assumed to decrease by 0.09% annual because of declining coal prices. |
| $NO_x$: Hot Side Selective Catalytic Reduction (SCR) | |
| Hg: Carbon Injection. (Assumes plant has already a particulates control) | |
| $CO_2$: Carbon Capture and Sequestration (CCS) Amine System. MEA as a sorbent and Direct Contact Cooler DCC used | |
| **Replacement of existing plant with a new plant** | |
| New Coal Fired Power Plant with all the environmental controls. | Performance and O&M costs given by IECM model. |
| Integrated Coal Gasification Combined Cycle Plant (IGCC) with SCR | Performance and O&M costs of base plant with SCR from IECM results for an 800MW plant. CCS Capital and O&M costs from estimates for a 500MW. (Chen, 2002) |
| IGCC with SCR and CCS via Selexol Process | |
| Natural Gas Combined Cycle Power Plant (NGCC) + Dry SCR | Emissions and costs based on a 540 MW plant reported by The Northwest Power Planning Council (August 2002). |
| NGCC+SCR+CCS | CCS capital and O&M costs from Herzog 1999 |
| New Coal Plant with all environmental controls. | Performance and O&M costs given by IECM model. |

**Table 8.1** Control Technologies

| Technologies considered: | | Percentage Reductions from Base Plant | | | | Costs (In year 2000 $M) | | | |
|---|---|---|---|---|---|---|---|---|---|
| N | Control | $SO_2$ | $NO_x$ | Hg | $CO_2$ | Capital | O&M | CC Annual Increase % | O&M Annual Increase % |
| 1 | WFGD | 0.802 | 0.000 | 0.700 | -0.008 | 78.0 | 73.9 | 0.0000 | -0.0090 |
| 2 | SCR | 0.009 | 0.620 | 0.000 | 0.000 | 38.6 | 68.3 | 0.0000 | -0.0090 |
| 3 | CI | 0.000 | 0.000 | 0.855 | 0.000 | 13.9 | 102.9 | 0.0000 | -0.0090 |
| 4 | CCS | 0.995 | 0.011 | 0.000 | 0.900 | 378.6 | 504.7 | 0.0000 | -0.0090 |

[10] In forecasting allowance prices for different regulatory scenarios NEMS assumes that emission caps would be phased in beginning 2002. Also NEMS does not consider any 3P scenario, so the prices we assumed are based on NEMS's prices but do not exactly replicate them.

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 5 | FGD + SCR | 0.803 | 0.620 | 0.945 | -0.008 | 116.6 | 77.0 | 0.0000 | -0.0090 |
| 6 | FGD+CI | 0.802 | 0.000 | 0.855 | -0.008 | 81.9 | 80.8 | 0.0000 | -0.0090 |
| 7 | FGD+CCS | 1.000 | 0.012 | 0.700 | 0.899 | 349.0 | 137.7 | 0.0000 | -0.0090 |
| 8 | SCR+CI | 0.009 | 0.620 | 0.855 | 0.000 | 52.4 | 106.2 | 0.0000 | -0.0090 |
| 9 | SCR+CCS | 0.995 | 0.625 | 0.000 | 0.900 | 425.6 | 505.9 | 0.0000 | -0.0090 |
| 10 | CI+CCS | 0.995 | -0.820 | 0.855 | 0.900 | 392.6 | 543.0 | 0.0000 | -0.0090 |
| 11 | FGD+SCR+CI | 0.803 | 0.620 | 0.945 | -0.008 | 125.8 | 79.1 | 0.0000 | -0.0090 |
| 12 | FGD+SCR+CCS | 1.000 | 0.625 | 0.945 | 0.899 | 397.6 | 143.2 | 0.0000 | -0.0090 |
| 13 | FGD+CI +CCS | 1.000 | -0.820 | 0.855 | 0.899 | 353.7 | 145.2 | 0.0000 | -0.0090 |
| 14 | SCR+CI+ CCS | 0.995 | 0.625 | 0.855 | 0.900 | 439.5 | 544.1 | 0.0000 | -0.0090 |
| 15 | ALL: FGD+SCR+CI+CCS | 1.000 | 0.625 | 0.945 | 0.899 | 397.6 | 143.3 | 0.0000 | -0.0090 |
| 16 | Having FGD installing SCR | 0.803 | 0.620 | 0.945 | -0.008 | 38.6 | 77.0 | 0.0000 | -0.0090 |
| 17 | Having FGD installing CI | 0.802 | 0.000 | 0.855 | -0.008 | 3.9 | 80.8 | 0.0000 | -0.0090 |
| 18 | Having FGD installing CCS | 1.000 | 0.012 | 0.700 | 0.899 | 271.1 | 137.7 | 0.0000 | -0.0090 |
| 19 | Having SCR installing FGD | 0.803 | 0.620 | 0.945 | -0.008 | 78.1 | 77.0 | 0.0000 | -0.0090 |
| 20 | Having SCR installing CI | 0.009 | 0.620 | 0.855 | 0.000 | 13.9 | 106.2 | 0.0000 | -0.0090 |
| 21 | Having SCR installing CCS | 0.995 | 0.625 | 0.000 | 0.900 | 387.1 | 505.9 | 0.0000 | -0.0090 |
| 22 | Having CI installing FGD | 0.802 | 0.000 | 0.855 | -0.008 | 68.1 | 80.8 | 0.0000 | -0.0090 |
| 23 | Having CI installing SCR | 0.009 | 0.620 | 0.855 | 0.000 | 38.6 | 106.2 | 0.0000 | -0.0090 |
| 24 | Having CI installing CCS | 0.995 | -0.820 | 0.855 | 0.900 | 378.7 | 543.0 | 0.0000 | -0.0090 |
| 25 | Having CCS installing FDG | 1.000 | 0.012 | 0.700 | 0.899 | 0.5 | 137.7 | 0.0000 | -0.0090 |
| 26 | Having CCS installing SCR | 0.995 | 0.625 | 0.000 | 0.900 | 47.0 | 505.9 | 0.0000 | -0.0090 |
| 27 | Having CCS installing CI | 0.995 | -0.820 | 0.855 | 0.900 | 14.0 | 543.0 | 0.0000 | -0.0090 |
| 28 | Having FGD+SCR installing CI | 0.803 | 0.620 | 0.945 | -0.008 | 9.2 | 79.1 | 0.0000 | -0.0090 |
| 29 | Having FGD+SCR installing CCS | 1.000 | 0.625 | 0.945 | 0.899 | 281.0 | 143.2 | 0.0000 | -0.0090 |
| 30 | Having FGD+CI installing SCR | 0.803 | 0.620 | 0.945 | -0.008 | 43.9 | 79.1 | 0.0000 | -0.0090 |
| 31 | Having FGD+CI installing CCS | 1.000 | -0.820 | 0.855 | 0.899 | 271.8 | 145.2 | 0.0000 | -0.0090 |
| 32 | Having FGD+CCS installing SCR | 1.000 | 0.625 | 0.945 | 0.899 | 48.5 | 143.2 | 0.0000 | -0.0090 |
| 33 | Having FGD+CCS installing CI | 1.000 | -0.820 | 0.855 | 0.899 | 4.6 | 145.2 | 0.0000 | -0.0090 |
| 34 | Having SCR+CI installing FGD | 0.803 | 0.620 | 0.945 | -0.008 | 73.4 | 79.1 | 0.0000 | -0.0090 |
| 35 | Having SCR+CI installing CCS | 0.995 | 0.625 | 0.855 | 0.900 | 387.1 | 544.1 | 0.0000 | -0.0090 |
| 36 | Having SCR+CCS installing FGD | 1.000 | 0.625 | 0.945 | 0.899 | 0.5 | 143.2 | 0.0000 | -0.0090 |
| 37 | Having SCR+CCS installing CI | 0.995 | 0.625 | 0.855 | 0.900 | 13.9 | 544.1 | 0.0000 | -0.0090 |
| 38 | Having CI+CCS installing FGD | 1.000 | -0.820 | 0.855 | 0.899 | 0.5 | 145.2 | 0.0000 | -0.0090 |
| 39 | Having CI+CCS installing SCR | 0.995 | 0.625 | 0.855 | 0.900 | 46.9 | 544.1 | 0.0000 | -0.0090 |
| 40 | Having FGD+SCR+CI installing CCS | 1.000 | 0.625 | 0.945 | 0.899 | 271.8 | 143.3 | 0.0000 | -0.0090 |
| 41 | Having FGD+SCR+CCS installing CI | 1.000 | 0.625 | 0.945 | 0.899 | 0.5 | 143.3 | 0.0000 | -0.0090 |
| 42 | Having FGD+CCS+CI installing SCR | 1.000 | 0.625 | 0.945 | 0.899 | 43.9 | 143.3 | 0.0000 | -0.0090 |
| 43 | Having SCR+CI+CCS installing FGD | 1.000 | 0.625 | 0.945 | 0.899 | 0.5 | 143.3 | 0.0000 | -0.0090 |
| 44 | BasePlant | 0.000 | 0.000 | 0.000 | 0.000 | 0.0 | 65.2 | 0.0000 | -0.0090 |
| 45 | IGCC+SCR | 0.996 | 0.491 | 1.000 | 0.367 | 730.0 | 69.3 | 0.0000 | -0.0090 |
| 46 | Having IGCC+SCR installing CCS | 0.996 | 0.491 | 1.000 | 0.863 | 118.7 | 76.3 | 0.0000 | -0.0090 |
| 47 | NGCC+SCR | 1.000 | 0.974 | 1.000 | 0.659 | 282.5 | 79.1 | 0.0000 | 0.0200 |
| 48 | Having NGCC+SCR installing CCS | 1.000 | 0.974 | 1.000 | 0.900 | 282.5 | 104.4 | 0.0000 | 0.0200 |
| 49 | New Coal Plant All Controls | 0.99993 | 0.72705 | 0.950 | 0.927 | 799.0 | 105.8 | 0.0000 | -0.0090 |

**Table 8.2** Characteristics of Technologies Considered

It is assumed that different control technologies can be installed simultaneously or in different stages and can be turned off as desired, so there is always the option to run the base plant in its initial conditions. Costs and performance data for different combinations of control technologies was retrieved using the IECM model.

Similarly it is assumed that new capacity and environmental controls can be installed in stages at no additional cost.

Even after installing new capacity the option of running the original plant remains open, as if the plant were "moth-balled" at no cost.

Baseline model assumes no "learning-by-doing" so capital costs for all technologies remain constant in year 2000 dollars for the entire planning horizon. Based on fuel price predictions contained in Annual Energy Outlook AEO 2003, O&M costs for coal plants are assumed to decrease by 0.09% annually as a result of declining coal prices, while O&M for natural gas plants are assumed to increase by 2% annually[11]. The starting gas price is assumed to be $3.06/Gj (2000 dollars)(EIA 2001b) and the gas heat content is assumed to be 1,020 Btu per cubic foot. (EIA 2001c).

### 4.4. Lead time, discount rate, and other assumptions

For the base case we will assume that the calendar time between the announcement of the program and the compliance date (lead time) is shorter than the time required for constructing any of the control technologies considered (construction time)[12]. In the base case we will use a discount rate of 10% (real).

## 5. Baseline Analysis

### 5.1 Optimal strategy under no uncertainty

The first stage to calculate the expected value of perfect information is finding the capital and operating costs under no uncertainty. Table 9 summarizes the optimal operating and investment decisions $d^*(s)$ made when each scenario is known to occur from the beginning.

| Run | $d^*(1)$ | | $d^*(2)$ | | $d^*(3)$ | | $d^*(4)$ | | $d^*(5)$ | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **Scenario 1 (BAU)** | | **Scenario 2 (2P+1)** | | **Scenario 3 (3P)** | | **Scenario 4 (3P+1a)** | | **Scenario 5 (4P)** | |
| | **Install** | **Operate** | **Install** | **Operate** | **Install** | **Operate** | **Install** | **Operate** | **Install** | **Operate** |
| 2003 | - | Coal | - | Coal | - | Coal | - | Coal | - | Coal |
| 2004 | - | Coal | - | Coal | - | Coal | - | Coal | - | Coal |
| 2005 | - | Coal | SCR | Coal | SCR/CI | Coal | NGCC/SCR | Coal | - | Coal |
| 2006 | - | Coal | - | Coal | - | Coal | - | Coal | - | Coal |
| 2007 | - | Coal | CI | SCR | - | SCR/CI | - | NGCC/SCR | - | Coal |
| 2008 | - | Coal | - | SCR | - | SCR/CI | - | NGCC/SCR | - | Coal |

[11] Since AEO predictions extend only to the year 2025, for specifying expected prices for 2026 to 2032, it is assumed that price trends forecasted for the period 2015-2025 continue in a linear fashion to the end of the planning horizon.

[12] Even when new regulations set the compliance date so as to provide enough time to the industry to respond, the increased demand of new infrastructure enlarges dramatically both the times and installation times. Removing this assumption changes some of the results but does not change the fundamentals of the analysis and conclusions.

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| 2009 | - | Coal | - | SCR/CI | - | SCR/CI | - | NGCC/SCR | FGD/SCR/CCS | Coal |
| 2010 | - | Coal | - | SCR/CI | - | SCR/CI | - | NGCC/SCR | FGD/SCR/CCS | Coal |
| 2011 | - | Coal | - | SCR/CI | - | SCR/CI | - | NGCC/SCR | - | FGD/SCR/CCS |
| 2012 | - | Coal | - | SCR/CI | - | SCR/CI | - | NGCC/SCR | - | FGD/SCR/CCS |
| 2013 | - | Coal | - | SCR/CI | - | SCR/CI | - | NGCC/SCR | - | FGD/SCR/CCS |
| 2014 | - | Coal | - | SCR/CI | - | SCR/CI | - | NGCC/SCR | - | FGD/SCR/CCS |
| 2015 | - | Coal | - | SCR/CI | - | SCR/CI | Coal/FGD/CCS | NGCC/SCR | - | FGD/SCR/CCS |
| 2016 | - | Coal | - | SCR/CI | - | SCR/CI | - | NGCC/SCR | - | FGD/SCR/CCS |
| 2017 | - | Coal | - | SCR/CI | - | SCR/CI | - | Coal/FGD/CCS | - | FGD/SCR/CCS |
| 2018 | - | Coal | - | SCR/CI | - | SCR/CI | - | Coal/FGD/CCS | - | FGD/SCR/CCS |
| 2019 | - | Coal | - | SCR/CI | - | SCR/CI | - | Coal/FGD/CCS | - | FGD/SCR/CCS |
| 2020 | - | Coal | - | SCR/CI | - | SCR/CI | - | Coal/FGD/CCS | - | FGD/SCR/CCS |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | FGD/SCR/CCS |
| 2032 | - | Coal | - | SCR/CI | - | SCR/CI | - | Coal/FGD/CCS | - | FGD/SCR/CCS |

**Table 9.** Results for deterministic runs $d^*(s)$.

- Given that the BAU scenario is known to occur (there are no new environmental regulations over the next 30 years), the optimal strategy involves no new capital investments.
- Given that the 2P+1 scenario is known to occur (there are additional $SO_2$, $NO_x$ and mercury regulations), the optimal strategy involves investing in SCR in 2005 and later in 2007 in CI equipment.
- Given that the 3P scenario is known to occur (there are different $SO_2$, $NO_x$ and mercury regulations), the optimal strategy involves investing in SCR and CI simultaneously in 2005.
- Given that the 3P+1 scenario is known to occur (there are different $SO_2$, $NO_x$ and mercury regulations and a $CO_2$ cap), the optimal strategy involves investing in NGCC with SCR in 2005 and then in 2015 installing FGD and CCS on the original coal plant.
- Given that the 4P scenario is known to occur (there are still different $SO_2$, $NO_x$ and mercury regulations and a $CO_2$ cap), the optimal strategy involves investing in FGD, SCR, and CCS in 2009.

For the 3P+1 and 4P scenarios, the decision to install a CCS might not take place if we had to account for dispatching (i.e., held a utility perspective). The high energy-penalties associated with the FGD and CCS technologies might make these options infeasible if demand levels have to be met. Also it is important to note that the NGCC plant in the 3P+1 scenario would provide the necessary $CO_2$ emission reductions (66%). If the $CO_2$ cap were higher, then this “control” would not be sufficient. (e.g., it would to install a NGCC with SCR and CCS or to install a CCS on the original plant). Costs of these strategies are presented in Table 10.

| Model Run | $d^*(1)$ | $d^*(2)$ | $d^*(3)$ | $d^*(4)$ | $d^*(5)$ |
|---|---|---|---|---|---|
| NPV(Capital) | - | 36.78 | 39.44 | 313.35 | 204.01 |
| NPV(O&M) | 566.62 | 755.03 | 796.06 | 833.15 | 843.48 |
| NPV(SO2 Allowances) | 89.09 | 105.29 | 100.70 | 17.41 | 38.07 |

| | | | | | |
|---|---|---|---|---|---|
| NPV(NOx Allowances) | - | -2.98 | -2.97 | -22.77 | -0.91 |
| NPV(Hg Allowances) | - | -60.75 | -79.48 | -101.36 | -62.61 |
| NPV(CO2 Allowances) | - | - | - | -307.44 | -348.96 |
| Total NPV (2000 M$) | 656 | 833 | 854 | 732 | 673 |

**Table 10.** NPV of capital and operating costs for deterministic runs $d^*(s)$.(In year 2000 $M).

The NPV under 3P is higher than 2P+1 because the cap on mercury is set earlier. It is also higher than 3P+1 because there are no possibilities of selling $CO_2$ allowances. Case 4P has a lower NPV because all the caps are set in year 2011.

### 5.2 Sequential decisions under uncertainty

The baseline analysis corresponds to a decision maker with initial set of subjective probabilities α as in Table 2. Every year, probabilities will be updated as information about which regulations are still possible is revealed. In these scenarios, it is assumed that all of the uncertainty will be resolved at or before 2010, the time that the last program will be known. Every year before the uncertainty is fully resolved, the decision maker has to decide how to operate the plant (e.g., which of the available control technologies to use) and what capital investments to make if any. Since we have assumed that the future must be one of the five scenarios described, the probabilities will be updated accordingly the values in Tables 11-15.

| If BAU | Year | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 |
| Probabilities of scenario BAU | 0.05 | 0.05 | 0.05 | 0.33 | 0.33 | 0.33 | 0.33 | 1 |
| Probabilities of scenario 2P+1 | 0.15 | 0.15 | 0.15 | - | - | - | - | - |
| Probabilities of scenario 3P | 0.20 | 0.20 | 0.20 | - | - | - | - | - |
| Probabilities of scenario 3P+1 | 0.5 | 0.5 | 0.5 | - | - | - | - | - |
| Probabilities of scenario 4P | 0.1 | 0.1 | 0.1 | 0.66 | 0.66 | 0.66 | 0.66 | - |

**Table 11.** Probabilities set for run $d^*(\alpha,1)$

| If 4P | Year | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 |
| Probabilities of scenario BAU | 0.05 | 0.05 | 0.05 | 0.33 | 0.33 | 0.33 | 0.33 | - |
| Probabilities of scenario 2P+1 | 0.15 | 0.15 | 0.15 | - | - | - | - | - |
| Probabilities of scenario 3P | 0.20 | 0.20 | 0.20 | - | - | - | - | - |
| Probabilities of scenario 3P+1 | 0.5 | 0.5 | 0.5 | - | - | - | - | - |
| Probabilities of scenario 4P | 0.1 | 0.1 | 0.1 | 0.66 | 0.66 | 0.66 | 0.66 | 1 |

**Table 12.** Probabilities set for run $d^*(\alpha,5)$

| If 2P+1 | Year | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 |
| Probabilities of scenario BAU | 0.05 | 0.05 | 0.05 | - | - | - | - | - |
| Probabilities of scenario 2P+1 | 0.15 | 0.15 | 0.15 | 1 | 1 | 1 | 1 | 1 |
| Probabilities of scenario 3P | 0.20 | 0.20 | 0.20 | - | - | - | - | - |
| Probabilities of scenario 3P+1 | 0.5 | 0.5 | 0.5 | - | - | - | - | - |
| Probabilities of scenario 4P | 0.1 | 0.1 | 0.1 | - | - | - | - | - |

**Table 13.** Probabilities set for run $d^*(\alpha,2)$

| If 3P | Year | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 |
| Probabilities of scenario BAU | 0.05 | 0.05 | 0.05 | - | - | - | - | - |
| Probabilities of scenario 2P+1 | 0.15 | 0.15 | 0.15 | - | - | - | - | - |
| Probabilities of scenario 3P | 0.20 | 0.20 | 0.20 | 0.29 | 0.29 | 1 | 1 | 1 |
| Probabilities of scenario 3P+1 | 0.5 | 0.5 | 0.5 | 0.71 | 0.71 | - | - | - |
| Probabilities of scenario 4P | 0.1 | 0.1 | 0.1 | - | - | - | - | - |

**Table 14.** Probabilities set for run $d^{*}(\alpha,3)$

| If 3P+1 | Year | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 |
| Probabilities of scenario BAU | 0.05 | 0.05 | 0.05 | - | - | - | - | - |
| Probabilities of scenario 2P+1 | 0.15 | 0.15 | 0.15 | - | - | - | - | - |
| Probabilities of scenario 3P | 0.20 | 0.20 | 0.20 | 0.29 | 0.29 | - | - | - |
| Probabilities of scenario 3P+1 | 0.5 | 0.5 | 0.5 | 0.71 | 0.71 | 1 | 1 | 1 |
| Probabilities of scenario 4P | 0.1 | 0.1 | 0.1 | - | - | - | - | - |

**Table 15**. Probabilities set for run $d^{*}(\alpha,4)$

For example, if BAU occurs, then, no new environmental programs will ever be announced and probabilities in scenarios will have to be redistributed each year. If by 2006 no new regulations have been announced, then scenarios 2P+1, 3P and 3P+1 are not longer possible (because these involve reductions in year 2007 that would have to be announced in 2006) and therefore the probabilities for scenarios BAU and 4P have to be updated. We assume that new probabilities are updated preserving the initial ratios, so scenario 4P is twice as likely as scenario BAU. Finally if in year 2010 there is no legislation announced then that implies that scenario 4P will not happen and therefore the probability of scenario BAU becomes 1.0. Note that scenario's probabilities do not change during the first three years in any model run.

Running the MPDM with these probability sets identifies the optimal strategies shown in Table 16. In all cases, the strategy that minimizes the ENPV is to install a NGCC with SCR before any of the uncertainty is resolved (i.e., in year 2005).

- If the BAU scenario occurs, though constructed, the NGCC plant is never used.
- If the 2P+1 scenario occurs, then the NGCC plant is started in 2007 and replaced by the coal plant with SCR and CI in 2026.
- If the 3P scenario occurs, then the NGCC plant is started in 2007 and replaced by the coal plant with SCR and CI (identical to the 2P+1 scenario).
- If the 3P+1 scenario occurs, then the NGCC plant is started in 2007 and replaced in 2017 by the coal plant with FGD and CCS.
- If the 4P scenario occurs, the NGCC plant sits idle for four years before being used. And the coal plant with FGD and CCS controls is used from 2018 to the end of the planning period.

| Run | $d^{*}(\alpha,1)$ | | $d^{*}(\alpha,2)$ | | $d^{*}(\alpha,3)$ | | $d^{*}(\alpha,4)$ | | $d^{*}(\alpha,5)$ | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **Scenario 1 (BAU)** | | **Scenario 2 (2P+1)** | | **Scenario 3 (3P)** | | **Scenario 4 (3P+1a)** | | **Scenario (4P)** | |
| | **Installation** | **Operation** | **Installation** | **Operation** | **Installation** | **Operation** | **Installation** | **Operation** | **Installation** | **Operation** |
| 2003 | - | Coal | - | Coal | - | Coal | - | Coal | - | Coal |
| 2004 | - | Coal | - | Coal | - | Coal | - | Coal | - | Coal |
| 2005 | NGCC/SCR | Coal | NGCC/SCR | Coal | NGCC/SCR | Coal | NGCC/SCR | Coal | NGCC/SCR | Coal |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| 2006 | - | Coal | - | Coal | - | Coal | - | Coal | - | Coal |
| 2007 | - | Coal | - | NGCC/SCR | - | NGCC/SCR | - | NGCC/SCR | - | Coal |
| 2008 | - | Coal | - | NGCC/SCR | - | NGCC/SCR | - | NGCC/SCR | - | Coal |
| 2009 | - | Coal | - | NGCC/SCR | - | NGCC/SCR | - | NGCC/SCR | - | Coal |
| 2010 | - | Coal | - | NGCC/SCR | - | NGCC/SCR | - | NGCC/SCR | - | Coal |
| 2011 | - | Coal | - | NGCC/SCR | - | NGCC/SCR | - | NGCC/SCR | - | NGCC/SCR |
| 2012 | - | Coal | - | NGCC/SCR | - | NGCC/SCR | - | NGCC/SCR | - | NGCC/SCR |
| 2013 | - | Coal | - | NGCC/SCR | - | NGCC/SCR | - | NGCC/SCR | - | NGCC/SCR |
| 2014 | - | Coal | - | NGCC/SCR | - | NGCC/SCR | - | NGCC/SCR | - | NGCC/SCR |
| 2015 | - | Coal | - | NGCC/SCR | - | NGCC/SCR | FGD/CCS-Coal | NGCC/SCR | - | NGCC/SCR |
| 2016 | - | Coal | - | NGCC/SCR | - | NGCC/SCR | - | NGCC/SCR | FGD/CCS-Coal | NGCC/SCR |
| 2017 | - | Coal | - | NGCC/SCR | - | NGCC/SCR | - | Coal/FGD/CCS | - | NGCC/SCR |
| 2018 | - | Coal | - | NGCC/SCR | - | NGCC/SCR | - | Coal/FGD/CCS | - | Coal/FGD/CCS |
| 2019 | - | Coal | - | NGCC/SCR | - | NGCC/SCR | - | Coal/FGD/CCS | - | Coal/FGD/CCS |
| 2020 | - | Coal | - | NGCC/SCR | - | NGCC/SCR | - | Coal/FGD/CCS | - | Coal/FGD/CCS |
| 2021 | - | Coal | - | NGCC/SCR | - | NGCC/SCR | - | Coal/FGD/CCS | - | Coal/FGD/CCS |
| 2022 | - | Coal | - | NGCC/SCR | - | NGCC/SCR | - | Coal/FGD/CCS | - | Coal/FGD/CCS |
| 2023 | - | Coal | - | NGCC/SCR | - | NGCC/SCR | - | Coal/FGD/CCS | - | Coal/FGD/CCS |
| 2024 | - | Coal | SCR/CI-Coal | NGCC/SCR | SCR/CI-Coal | NGCC/SCR | - | Coal/FGD/CCS | - | Coal/FGD/CCS |
| 2025 | - | Coal | - | NGCC/SCR | - | NGCC/SCR | - | Coal/FGD/CCS | - | Coal/FGD/CCS |
| 2026 | - | Coal | - | Coal/SCR/CI | - | Coal/SCR/CI | - | Coal/FGD/CCS | - | Coal/FGD/CCS |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| 2032 | - | Coal | - | Coal/SCR/CI | - | Coal/SCR/CI | - | Coal/FGD/CCS | - | Coal/FGD/SCR/CCS |

**Table 16.** Optimal Investment and operating decisions under uncertainty given each scenario. “$d^*(\alpha,s)$”.

This cycling between the NGCC plant and the modified coal plant occurs because of the increasing O&M costs associated with gas prices, the low coal costs, and in the 3P+1 and 4P scenarios, the profitability of selling $CO_2$ allowances at a high price. Table 17 shows costs associated with optimal strategies under the five scenarios.

| Model Run | $d^*(\alpha,1)$ | $d^*(\alpha,2)$ | $d^*(\alpha,3)$ | $d^*(\alpha,4)$ | $d^*(\alpha,5)$ |
|---|---|---|---|---|---|
| NPV(Capital) | 212.25 | 218.68 | 218.68 | 313.35 | 304.16 |
| NPV(O&M) | 566.62 | 815.58 | 815.58 | 833.15 | 768.68 |
| NPV(SO2 Allowances) | 89.09 | 21.08 | 21.08 | 17.41 | 38.7 |
| NPV(NOx Allowances) | - | -49.72 | -49.57 | -22.77 | -6.65 |
| NPV(Hg Allowances) | - | -92.88 | -122.24 | -101.36 | -52.53 |
| NPV(CO2 Allowances) | - | - | - | -307.44 | -249.52 |
| Total NPV (2000 M$) | 868 | 913 | 884 | 732 | 803 |

**Table 17.** NPV of capital and operating costs for $d^*(\alpha,s)$. (In year 2000 $M)

### *5.3 Calculating the expected value of perfect information*

Given the cost data shown in Tables 10 and 17 it is possible to calculate the expected value of perfect information using the equation presented in Section 3.4. Inputs to this equation can be found in Table 18. The calculation is the weighted difference between the no uncertainty case and the case with uncertainty summed over all scenarios.

| Scenario *S* | 1<br>BAU | 2<br>2P+1 | 3<br>3P | 4<br>3P+1 | 5<br>4P |
|---|---|---|---|---|---|
| $NPV[d^*(\alpha,s)]-NPV[d^*(s)]$ | 212 | 79 | 30 | 0 | 130 |
| Initial probabilities | 0.05 | 0.15 | 0.20 | 0.5 | 0.10 |
| EVPI (in year 2000 $M) | 41 | | | | |

**Table 18**. EVPI($\alpha$)

The decision maker should be willing to pay $41 million (2000$) to know in 2003 which of the 5 scenarios will occur. The relative contribution to this value for each of the scenarios is closely related to initial probabilities that the decision maker had. Because the decision maker felt that the BAU scenario was unlikely, if it turns out to occur, she will have to pay a hefty penalty ($212 million (2000$). The decision maker's most likely scenario, 3P+1 occurs, then no penalty is incurred. A different set of initial probabilities could result in different set of optimal strategies and a larger or smaller expected value of perfect information.

## 6. Sensitivity Analyses

To understand the intricacies of the problem space many inputs to the decision problem can be changed. In this section, we explore how changes to 1) the initial probabilities, 2) CO2 cap and 3) the relative costs of coal and gas fuel affect the strategies selected and the expected value of perfect information.

### 6.1 Changing the initial probabilities

As was noted in the previous section, different initial probabilities of scenarios can affect the decisions made and in turn the expected value of perfect information. To explore this, we changed the probabilities from the baseline analysis so that BAU and 4P had zero probability (could not occur) and 2P+1, 3P, and 3P+1 are equally likely (all with probability 0.333). See Table 19.

| **Scenario** | (2) 2P+1 | (3) 3P | (4) 3P+1 |
|---|---|---|---|
| **Initial Probabilities** | 1/3 | 1/3 | 1/3 |

**Table 19.** Initial $\beta$ probabilities.

Results for this combination of probabilities are very similar to the baseline case. In fact the optimal decisions under uncertainty given that each scenario occurs are exactly the same and an NGCC is installed in 2005.

- If the 2P+1 scenario occurs, then the NGCC plant is started in 2007 and replaced by the coal plant with SCR and CI in 2026.
- If the 3P scenario occurs, then the NGCC plant is started in 2007 and replaced by the coal plant with SCR and CI (identical to the 2P+1 scenario).

- If the 3P+1 scenario occurs, then the NGCC plant is started in 2007 and replaced in 2017 by the coal plant with FGD and CCS

Since the same decisions are being made given the scenario that occurs, the differences between the no uncertainty case and the uncertain case are the same. See Table 20. The EVPI for this probability set is $36 million.

| Scenario *S* | 2<br>2P+1 | 3<br>3P | 4<br>3P+1 |
|---|---|---|---|
| $NPV[d^*(\beta,s)]-NPV[d^*(s)]$ | 79 | 30 | 0 |
| Initial probabilities | 1/3 | 1/3 | 1/3 |
| EVPI (in year 2000 $M) | 36 | | |

**Table 20.** EVPI(β)

### 6.2. A more stringent $CO_2$ cap

To explore how a change in the CO2 cap will affect the decisions and value of information, the 2P+1 and 3P scenarios were used with a modified 3P+1 scenario. The new 3P+1 scenario increased the $CO_2$ emissions reduction from 60% to 70%. All three scenarios were assumed to be equally likely (see Table 21).

| **Scenario** | (2) 2P+1 | (3) 3P | (6) 3P+1b |
|---|---|---|---|
| **Initial Probabilities** | 1/3 | 1/3 | 1/3 |

**Table 21**. Initial $\lambda$ probabilities.

Because of the changes to 3P+1 scenario, the no uncertainty case for this scenario had to be calculated (the other two remain unchanged):

- Given that the 2P+1 scenario is known to occur, the optimal strategy involves investing in SCR in 2005 and later in 2007 in CI equipment.
- Given that the 3P scenario is known to occur, the optimal strategy involves investing in SCR and CI simultaneously in 2005.
- Given that the 3P+1 modified scenario is known to occur, the optimal strategy involves investing in CI in 2005 and then in 2007 installing a new coal plant with FGD, SCR and CCS controls.

Because of this change in the 3P+1 scenario, the optimal strategies given uncertainty are now totally different than before. In year 2005 SCR and CI controls are installed. (See Table 22)

| Run | $d^*(\lambda,2)$ | | $d^*(\lambda,3)$ | | $d^*(\lambda,6)$ | |
|---|---|---|---|---|---|---|
| | **Scenario 2 (2P+1)** | | **Scenario 3 (3P)** | | **Scenario 6 (3P+1b)** | |
| | **Installation** | **Operation** | **Installation** | **Operation** | **Installation** | **Operation** |
| 2003 | - | Coal | - | Coal | - | Coal |
| 2004 | - | Coal | - | Coal | - | Coal |

| | | | | | | |
|---|---|---|---|---|---|---|
| 2005 | SCR/CI | Coal | SCR/CI | Coal | SCR/CI | Coal |
| 2006 | - | Coal | - | Coal | - | Coal |
| 2007 | - | Coal/SCR | - | Coal/SCR/CI | FGD/CCS | SCR/CI |
| 2008 | - | Coal/SCR | - | Coal/SCR/CI | - | SCR/CI |
| 2009 | - | Coal/SCR/CI | - | Coal/SCR/CI | - | FGD/CCS |
| ... | - | ... | - | ... | ... | ... |
| 2032 | - | Coal/SCR/CI | - | Coal/SCR/CI | - | FGD/CCS |

**Table 22.** Optimal strategies under uncertainty. "$d^*(\lambda,s)$"

- If the 2P+1 scenario occurs, then the SCR is used from 2007 and the CI from 2009.
- If the 3P scenario occurs, then SCR and CI are used from 2007 (same as the no uncertainty case above).
- If the 3P+1 modified scenario occurs, then SCR and CI are used in 2007-08 and then FGD and CCS are used.

EVPI is $3 million. See Tables 23 and 24.

| Model Run | $d^*(\lambda,2)$ | $d^*(\lambda,3)$ | $d^*(\lambda,6)$ |
|---|---|---|---|
| NPV(Capital) | 39 | 39 | 254 |
| NPV(O&M) | 755 | 796 | 962 |
| NPV(SO2 Allowances) | 105 | 101 | 30 |
| NPV(NOx Allowances) | -3 | -3 | -2 |
| NPV(Hg Allowances) | -61 | -79 | -101 |
| NPV(CO2 Allowances) | - | - | -31 |
| Total NPV (2000 M$) | 836 | 854 | 1,111 |

**Table 23.** NPV capital and operating costs for $d^*(\lambda,s)$

| Scenario *S* | 2<br>2P+1 | 3<br>3P | 6<br>3P+1b |
|---|---|---|---|
| $NPV[d^*(\lambda,s)]-NPV[d^*(s)]$ | 2..52 | 0 | 3..58 |
| Initial probabilities | 0..33 | 0..33 | 0..33 |
| EVPI (in year 2000 $M) | 3 | | |

**Table 24**. EVPI($\lambda$ )

### 6.3 Changes in fuel price

For the last example we consider 2P+1, 3P and 3P +1 with equal probabilities assuming smaller differences in O&M costs for coal and gas[13]. All the deterministic cases involve installing an NGCC plant with SCR. See Table 25

| $d^*(7)$ | $d^*(8)$ | $d^*(9)$ |
|---|---|---|

[13] This time we assume that O&M costs for a coal plant remain flat while for a gas plant increase by 0.05% per year.

| | Scenario 7 (2P+1c) | | Scenario 8 (3Pc) | | Scenario 9 (3P+1c) | |
|---|---|---|---|---|---|---|
| | **Installation** | **Operation** | **Installation** | **Operation** | **Installation** | **Operation** |
| 2003 | - | Coal | - | Coal | - | Coal |
| 2004 | - | Coal | - | Coal | - | Coal |
| 2005 | - | Coal | NGCC/SCR | Coal | NGCC/SCR | Coal |
| 2006 | - | Coal | - | Coal | - | Coal |
| 2007 | NGCC/SCR | Coal | - | NGCC/SCR | - | NGCC/SCR |
| 2008 | - | Coal | - | NGCC/SCR | - | NGCC/SCR |
| 2009 | - | NGCC/SCR | - | NGCC/SCR | - | NGCC/SCR |
| 2010 | - | NGCC/SCR | - | NGCC/SCR | - | NGCC/SCR |
| 2011 | - | NGCC/SCR | - | NGCC/SCR | - | NGCC/SCR |
| 2012 | - | NGCC/SCR | - | NGCC/SCR | - | NGCC/SCR |
| 2013 | - | NGCC/SCR | - | NGCC/SCR | CCS | NGCC/SCR |
| 2014 | - | NGCC/SCR | - | NGCC/SCR | - | NGCC/SCR |
| 2015 | - | NGCC/SCR | - | NGCC/SCR | - | NGCC/SCR/CCS |
| 2016 | - | NGCC/SCR | - | NGCC/SCR | - | NGCC/SCR/CCS |
| ... | ... | ... | ... | ... | ... | ... |
| 2032 | - | NGCC/SCR | - | NGCC/SCR | - | NGCC/SCR/CCS |

**Table 25.** Optimal strategies for deterministic runs on "Low gas"

Given that the 2P+1 scenario is known to occur, the optimal strategy involves investing in SCR in 2005 and later in 2007 in CI equipment.

- Given that the 2P+1 modified scenario is known to occur, an NGCC/SCR is used in year 2009, when the cap on mercury is set.
- Given that the 3P modified scenario is known to occur, the optimal strategy involves installing and using the NGCC with SCR from year 2007.
- Given that the 3P+1 modified scenario is known to occur, the optimal strategy involves installing an NGCC/SCR in year 2005 and then installing a CCS so that can be used from period 2015 when CO2 allowance prices are at $55.

See the NPV for these scenarios in Table 26.

| Model Run | $d^*(7)$ | $d^*(8)$ | $d^*(9)$ |
|---|---|---|---|
| Scenario | 2P+1c | 3Pc | 3P+1c |
| NPV(Capital) | 175.41 | 212.25 | 311.26 |
| NPV(O&M) | 782.2 | 806.68 | 894.65 |
| NPV(SO2 Allowances) | 27.13 | 10.23 | 17.42 |
| NPV(NOx Allowances) | -27.72 | -54.19 | -31.47 |
| NPV(Hg Allowances) | -95.28 | -124.64 | -124.64 |
| NPV(CO2 Allowances) | - | - | -344.94 |
| Total NPV (2000 M$) | 862 | 850 | 722 |

**Table 26.** NPV of capital and operating costs for Scenarios 7, 8 and 9.

Optimal strategies under uncertainty are presented in Table 27.

| Model Run | $d^*(\omega,7)$ | $d^*(\omega,8)$ | $d^*(\omega,9)$ |
|---|---|---|---|

| | Scenario 7 (2P+1c) | | Scenario 8 (3Pc) | | Scenario 9 (3P+1c) | |
|---|---|---|---|---|---|---|
| | Installation | Operation | Installation | Operation | Installation | Operation |
| 2003 | - | Coal | - | Coal | - | Coal |
| 2004 | - | Coal | - | Coal | - | Coal |
| 2005 | NGCC/SCR | Coal | NGCC/SCR | Coal | NGCC/SCR | Coal |
| 2006 | - | Coal | - | Coal | - | Coal |
| 2007 | - | NGCC/SCR | - | NGCC/SCR | - | NGCC/SCR |
| 2008 | - | NGCC/SCR | - | NGCC/SCR | - | NGCC/SCR |
| 2009 | - | NGCC/SCR | - | NGCC/SCR | - | NGCC/SCR |
| 2010 | - | NGCC/SCR | - | NGCC/SCR | - | NGCC/SCR |
| 2011 | - | NGCC/SCR | - | NGCC/SCR | - | NGCC/SCR |
| 2012 | - | NGCC/SCR | - | NGCC/SCR | - | NGCC/SCR |
| 2013 | - | NGCC/SCR | - | NGCC/SCR | CCS | NGCC/SCR |
| 2014 | - | NGCC/SCR | - | NGCC/SCR | - | NGCC/SCR |
| 2015 | - | NGCC/SCR | - | NGCC/SCR | - | NGCC/SCR/CCS |
| 2025 | - | NGCC/SCR | - | NGCC/SCR | - | NGCC/SCR/CCS |
| ... | - | ... | ... | ... | ... | ... |
| 2032 | - | NGCC/SCR | - | NGCC/SCR | - | NGCC/SCR/CCS |

**Table 27.** Optimal strategies for probabilities $\omega$.

For scenarios 3P and 3P+1 the strategies are equal to the strategies in the deterministic case. For scenario 2P+1 the NGCC is installed 2 years before than in the deterministic case. EVPI is $6M. See Tables 28-29.

| Model Run | $d^*(\omega,7)$ | $d^*(\omega,8)$ | $d^*(\omega,9)$ |
|---|---|---|---|
| Scenario | 2P+1c | 3Pc | 3P+1c |
| NPV(Capital) | 212.25 | 212.25 | 311.26 |
| NPV(O&M) | 806.68 | 806.68 | 894.65 |
| NPV(SO2 Allowances) | 9.54 | 10.23 | 17.42 |
| NPV(NOx Allowances) | -54.34 | -54.19 | -31.47 |
| NPV(Hg Allowances) | -95.28 | -124.64 | -124.64 |
| NPV(CO2 Allowances) | - | - | -344.94 |
| Total NPV (2000 M$) | 879 | 850 | 722 |

**Table 28**. NPV of capital and operating costs under scenarios with “low gas prices”.

| Scenario *S* | 7<br>2P+1c | 8<br>3Pc | 9<br>3P+1c |
|---|---|---|---|
| $NPV[d^*(\omega,s)]-NPV[d^*(s)]$ | 17.11 | 0 | 0 |
| Initial probabilities | 0.33 | 0.33 | 0.33 |
| EVPI (in year 2000 $M) | 6 | | |

**Table 29.** EVPI($\omega$)

## 7. Limitations, Conclusions, and Future Work

### 7.1 Limitations

Because of the complexity of the problem space, this study had to make a large set of simplifying assumptions. These assumptions fall into four general categories.

- Assumptions about the plant: location, life span, efficiency, costs/feasibility of new technologies
- Assumptions about regulations and fuel prices: CAT system, no banking allowed, only five scenarios studied at one time
- Assumptions about the market: based on EIA projections, deterministic trend for prices
- Assumptions about how the decision process: discount rate, expected value decision rule, "systematic" updating of probabilities

We were only able to explore the sensitivity of the results to a few of these assumptions. Future work should expand the exploration of the decision space and conduct a series of controlled experiments in order to understand the importance of the various factors. In order to analyze the importance of plant characteristics, a number of "representative plants"[14] should be studied.

Unfortunately, limitations with optimization software may severely limit the size of studies that can be run. In order to complete necessary number of optimizations, it might be necessary to reduce several of the problems dimensions (e.g., planning time horizon, number of technologies) while increasing the number of scenarios considered.

### 7.2 Conclusions

*Cost of uncertainty can be significant.* In our baseline study we found that the expected cost of uncertainty was $40 million in 2000$. This is approximately 80% of the plant's yearly O&M and 5% of the cost of a new plant. If we consider that there are 400[15] plants with similar characteristics, the cost of regulatory uncertainty for all of them increases to $16 billion.

*Uncertainty costs can be small if the solution set is small.* Several factors can limit the number of technologies that are likely to make sense. If there is a narrow set of possible regulations (i.e., they all require tight controls on $CO_2$ emissions) then the choice of plant controls is obvious and though it may be expensive, there is little cost in not knowing which regulation will finally occur. Likewise, if there is a dominant technology because of other economic factors, (extremely low relative fuel prices or cheap control technologies), then the solution set is narrow, and the cost of uncertainty is small.

[14] Such plants could be identified via cluster analysis (see e.g., Hair et al. 1992). All U.S. coal-fired power plants could be placed in groups or clusters suggested by the emissions data, not defined a priori, such that those plants in a given cluster tend to be similar to each other in some sense, and plants in different clusters tend to be dissimilar. By analyzing the "average" plant in each cluster one could have an idea of how the analysis would look for all the country.

Minor changes in regulations can have major impacts on the optimal strategies because there are some emissions thresholds for which the optimal technology changes substantially. For example, we demonstrated that adjusting the CO2 cap between 60% and 70% could lead to very different new generating technologies (NGCC or new coal plant with CCS). Even in the case when only one of the scenarios includes a standard of 70% the strategies change completely. However, adding this scenario greatly reduced the cost of uncertainty (see previous conclusions).

### 7.3 Future Work

Also, releasing the assumption of “zero allowances banking” can make a difference in the EVPI as decision makers could use this mechanism to hedge against uncertainty and delay capital investments.

To achieve better understanding of how uncertainties can cause uneconomical options, several scenarios need to be considered including those that do not provide cap-and-trade systems and the ones that call for old plants retirements.

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## Appendix A: Scenarios considered

**Scenario 1.** BAU.

| Parameter | Pollutant | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 -2032 |
|---|---|---|---|---|---|---|---|
| Allowances Allocated | $SO_2$ | 35% of current emissions | | | | | |
| | $NO_x$ | 100% of current emissions | | | | | |
| | Hg | 100% of current emissions | | | | | |
| | $CO_2$ | 100% of current emissions | | | | | |
| Maximum Emissions Rate Allowed | $SO_2$ | Maximum emissions rate allowed > Current plant emissions rate | | | | | |
| | $NO_x$ | Maximum emissions rate allowed > Current plant emissions rate | | | | | |
| | Hg | Maximum emissions rate allowed > Current plant emission rate | | | | | |
| | $CO_2$ | Maximum emissions rate allowed > Current plant emissions rate | | | | | |
| Allowance Prices | $SO_2$ | $142 | $149 | $157 | $166 | $175 | $184 - $383 |
| | $NO_x$ | - | - | - | - | - | - |
| | Hg | - | - | - | - | - | - |
| | $CO_2$ | - | - | - | - | - | - |
| Policy Instrument | $SO_2$ | Cap and Trade (Can buy and sell allowances) | | | | | |
| | $NO_x$ | - | - | - | - | - | - |
| | Hg | - | - | - | - | - | - |
| | $CO_2$ | - | - | - | - | - | - |

**Scenario 2.** 2P+1.

| Parameter | Pollutant | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012-2032 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Allowances Allocated | $SO_2$ | 35% of current emissions | | | | 13% of current emissions | | | | | |
| | $NO_x$ | 100% of current emissions | | | | 40% of current emissions | | | | | |
| | Hg | 100% of current emissions | | | | | | 40% of current emissions | | | |
| | $CO_2$ | 100% of current emissions | | | | | | | | | |
| Maximum Emissions Rate Allowed | $SO_2$ | Maximum emissions rate allowed > Current plant emissions rate | | | | | | | | | |
| | $NO_x$ | Maximum emissions rate allowed > Current plant emissions rate | | | | | | | | | |
| | Hg | Maximum emissions rate allowed > Current plant emissions rate | | | | | | | | | |
| | $CO_2$ | Maximum emissions rate allowed > Current plant emissions rate | | | | | | | | | |
| Allowance Prices | $SO_2$ | $142 | $149 | $157 | $166 | $182 | $245 | $162 | $173 | $184 | $196 - $331 |
| | $NO_x$ | - | - | - | - | $2,477 | $2,558 | $2,490 | $2,497 | $2,404 | $2,510 - $2,648 |
| | Hg | - | - | - | - | - | - | $207,198 | $200,340 | $193,710 | $187,299 - $95,546 |
| | $CO_2$ | - | - | - | - | - | - | - | - | - | - |
| Policy Instrument | $SO_2$ | Cap and Trade (Can buy and sell allowances) | | | | | | | | | |
| | $NO_x$ | | | | | Cap and Trade (Can buy and sell allowances) | | | | | |
| | Hg | | | | | | | Cap and Trade (Can buy and sell allowances) | | | |
| | $CO_2$ | Cap and Trade (Can buy and sell allowances) | | | | | | | | | |

**Scenario 3.** 3P.

| Parameter | Pollutant | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012-2032 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Allowances Allocated | $SO_2$ | 35% of current emissions | | | | 13% of current emissions | | | | | |
| | $NO_x$ | 100% of current emissions | | | | 40% of current emissions | | | | | |
| | Hg | 100% of current emissions | | | | 40% of current emissions | | | | | |
| | $CO_2$ | 100% of current emissions | | | | | | | | | |
| Maximum Emissions Rate Allowed | $SO_2$ | Maximum emissions rate allowed > Current plant emissions rate | | | | | | | | | |
| | $NO_x$ | Maximum emissions rate allowed > Current plant emissions rate | | | | | | | | | |
| | Hg | Maximum emissions rate allowed > Current plant emissions rate | | | | | | | | | |
| | $CO_2$ | Maximum emissions rate allowed > Current plant emissions rate | | | | | | | | | |
| Allowance Prices | $SO_2$ | \$142 | \$49 | \$157 | \$166 | \$143 | \$152 | \$162 | \$173 | \$184 | \$196- \$331 |
| | $NO_x$ | - | - | - | - | \$2,477 | \$2,484 | \$2,490 | \$2,497 | \$2,504 | \$2,510 - \$2,648 |
| | Hg | - | - | - | \$221,624 | \$214,289 | \$207,198 | \$200,340 | \$193,710 | \$187,299 | \$181,101 \$95,546 |
| | $CO_2$ | - | - | - | - | - | - | - | - | - | - |
| Policy Instrument | $SO_2$ | Cap and Trade (Can buy and sell allowances) | | | | | | | | | |
| | $NO_x$ | | | | | Cap and Trade (Can buy and sell allowances) | | | | | |
| | Hg | | | | | Cap and Trade (Can buy and sell allowances) | | | | | |
| | $CO_2$ | 100% of current emissions | | | | | | | | | |

**Scenario 4.** 3P+1.

| Parameter | Pollutant | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012-2032 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Allowances Allocated | $SO_2$ | 35% of current emissions | | | | 13% of current emissions | | | | | |
| | $NO_x$ | 100% of current emissions | | | | 40% of current emissions | | | | | |
| | Hg | 100% of current emissions | | | | 40% of current emissions | | | | | |
| | $CO_2$ | 100% of current emissions | | | | | | 40% of current emissions | | | |
| Maximum Emissions Rate Allowed | $SO_2$ | Maximum emissions rate allowed > Current plant emissions rate | | | | | | | | | |
| | $NO_x$ | Maximum emissions rate allowed > Current plant emissions rate | | | | | | | | | |
| | Hg | Maximum emissions rate allowed > Current plant emissions rate | | | | | | | | | |
| | $CO_2$ | Maximum emissions rate allowed > Current plant emissions rate | | | | | | | | | |
| Allowance Prices | $SO_2$ | $142 | $49 | $157 | $166 | $143 | $152 | $134 | $117 | $102 | $90 - $6 |
| | $NO_x$ | - | - | - | - | $2,477 | $2,484 | $2,490 | $2,181 | $1,911 | $1,674 - $118 |
| | Hg | - | - | - | - | $221,624 | $214,289 | $207,198 | $200,340 | $193,710 | $187,299 - $95,546 |
| | $CO_2$ | - | - | - | - | - | - | $25 | $30 | $35 | $40 - $140 |
| Policy Instrument | $SO_2$ | Cap and Trade (Can buy and sell allowances) | | | | | | | | | |
| | $NO_x$ | | | | | Cap and Trade (Can buy and sell allowances) | | | | | |
| | Hg | | | | | Cap and Trade (Can buy and sell allowances) | | | | | |
| | $CO_2$ | | | | | | | Cap and Trade (Can buy and sell allowances | | | |

**Scenario 5.** 4P.

| Parameter | Pollutant | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011-2032 |
|---|---|---|---|---|---|---|---|---|---|---|
| Allowances Allocated | $SO_2$ | 35% of current emissions | | | | | | | | 13% of current emissions |
| | $NO_x$ | 100% of current emissions | | | | | | | | 40% of current emissions |
| | Hg | 100% of current emissions | | | | | | | | 40% of current emissions |
| | $CO_2$ | 100% of current emissions | | | | | | | | 40% of current emissions |
| Maximum Emissions Rate Allowed | $SO_2$ | Maximum emissions rate allowed > Current plant emissions rate | | | | | | | | |
| | $NO_x$ | Maximum emissions rate allowed > Current plant emissions rate | | | | | | | | |
| | Hg | Maximum emissions rate allowed > Current plant emissions rate | | | | | | | | |
| | $CO_2$ | Maximum emissions rate allowed > Current plant emissions rate | | | | | | | | |
| Allowance Prices | $SO_2$ | $142 | $49 | $157 | $166 | $175 | $184 | $194 | $205 | $102 - $6 |
| | $NO_x$ | - | - | - | - | - | - | - | - | $1,911 - $118 |
| | Hg | - | - | | - | - | - | - | $193,710 | $187,299 - $95,546 |
| | $CO_2$ | - | - | - | | | - | - | - | $25 - $130 |
| Policy Instrument | $SO_2$ | | | | | | | | | Cap and Trade (Can buy and sell allowances |
| | $NO_x$ | | | | | | | | | Cap and Trade (Can buy and sell allowances |
| | Hg | | | | | | | | | Cap and Trade (Can buy and sell allowances |
| | $CO_2$ | Cap and Trade (Can buy and sell allowances | | | | | | | | |

**Scenario 6.** 3P+1b. (Stringent $CO_2$ cap)

| Parameter | Pollutant | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012-2032 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Allowances Allocated | $SO_2$ | 35% of current emissions | | | | 13% of current emissions | | | | | |
| | $NO_x$ | 100% of current emissions | | | | 40% of current emissions | | | | | |
| | Hg | 100% of current emissions | | | | 40% of current emissions | | | | | |
| | $CO_2$ | 100% of current emissions | | | | | | **30% of current emissions** | | | |
| Maximum Emissions Rate Allowed | $SO_2$ | Maximum emissions rate allowed > Current plant emissions rate | | | | | | | | | |
| | $NO_x$ | Maximum emissions rate allowed > Current plant emissions rate | | | | | | | | | |
| | Hg | Maximum emissions rate allowed > Current plant emissions rate | | | | | | | | | |
| | $CO_2$ | Maximum emissions rate allowed > Current plant emissions rate | | | | | | | | | |
| Allowance Prices | $SO_2$ | $142 | $49 | $157 | $166 | $143 | $152 | $134 | $117 | $102 | $90 - $6 |
| | $NO_x$ | - | - | - | - | $2,477 | $2,484 | $2,490 | $2,181 | $1,911 | $1,674 - $118 |
| | Hg | - | - | - | - | $221,624 | $214,289 | $207,198 | $200,340 | $193,710 | $187,299 - $95,546 |
| | $CO_2$ | - | - | - | - | - | - | $25 | $30 | $35 | $40 - $140 |
| Policy Instrument | $SO_2$ | Cap and Trade (Can buy and sell allowances) | | | | | | | | | |
| | $NO_x$ | | | | | Cap and Trade (Can buy and sell allowances) | | | | | |
| | Hg | | | | | Cap and Trade (Can buy and sell allowances) | | | | | |
| | $CO_2$ | | | | | | | Cap and Trade (Can buy and sell allowances | | | |