

Financial Risk Management in Restructured Wholesale Power Markets: Concepts and Tools

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Abstract—The goal of this tutorial is three-fold: to facilitate cross-disciplinary communication among power engineers and economists by explaining and illustrating basic financial risk management concepts relevant for wholesale power markets (WPMs); to illustrate the complicated and risky strategic decision making required of power traders and risk managers operating in multiple interrelated submarkets comprising modern WPMs; and to briefly discuss the potential of agent-based modeling for the study of this decision making.

Index Terms—Financial Risk Management, Restructured Wholesale Power Markets, Agent-Based Test Bed

I. INTRODUCTION

THE importance of financial risk management is exemplified by the recent financial crisis. A key lesson learned is the need to consider carefully the intricate connections between financial and real markets. It has long been accepted that real-sector crises can lead to credit crunches and other forms of financial stress. No one can now doubt the ability of financial crises to trigger corresponding crises in real-sector markets leading to severe unemployment and recession.

A second key lesson learned is that company financial risk management practices must be continuously reexamined and retooled as financial instruments become increasingly complex. According to a recent survey [1], 53% of respondent Chief Financial Officers (CFO) at financial services companies view bank risk management practices as a reason for the financial turmoil. A majority of the surveyed CFOs stated that they plan to put their risk management practices under a microscope, and that this investigation should in many instances reach all levels of the organization, from the Board of Directors down, and from the shop floor up.

A third key lesson learned is that well-designed market regulations and proper market monitoring are also critical to the proper functioning of financial markets. In the United States, the Obama administration has proposed “Financial Regulatory Reform - A New Foundation” which aims at comprehensive restructuring of the regulatory landscape. In Europe, the Committee of European Banking Supervisors (CEBS) has also laid out guidelines and principles for addressing various loopholes in the existing regulations for banks [2].

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Similarly challenging financial risk management issues have recently arisen in *wholesale power markets (WPMs)* ([3], [4]). At the level of market participants, the transition from a monopoly paradigm characterized by a guaranteed rate of return to a more competitive market design has created various unfamiliar financial risks. Market participants have thus been struggling to set up a sound integrated risk management framework that can facilitate their decision making with regard to day-ahead energy market trading, Financial Transmission Rights (FTRs) auction participation, and bilateral contract negotiations. At the regional and national level, market operators and regulatory agencies are striving to revise WPM designs in an attempt to provide proper incentives for prudent short to medium-term management of financial risks.

Addressing these critical financial risk-management issues is particularly difficult for WPM participants due to the unique properties of electricity as a commodity. These properties include instantaneous delivery, limited storability, inelastic short-term demand, and compliance with Kirchhoff’s laws. These peculiar characteristics result in excessive volatility and spiking of electricity prices, unmatched by any other commodities and financial assets [5]. They also lead to the need for special market instruments and a WPM structure that involves integrated and interrelated market operations.

An additional layer of complexity arises due to game theoretic and behavioral aspects. A WPM in modern guise is an open-ended dynamic game among market participants, a market operator, and one or more regulatory agencies [6]. The market participants repeatedly interact with each other in interrelated submarkets. As researchers have shown (e.g., [7]), under these conditions pivotal generation companies empowered by even simple learning algorithms can easily learn to exercise market power either individually or through implicit collusion unless proper market monitoring and mitigation strategies are in place. This market power can be expressed through different types of strategic market behaviors (e.g. economic or physical capacity withholding).

Recently a variety of new tools have been proposed for managing financial risk management in WPMs. New modeling approaches have also been explored, such as *agent-based modeling (ABM)*, the computational modeling of real-world phenomena as systems of autonomous interacting units. This tutorial study provides a summary overview of these developments.

II. FINANCIAL RISK MANAGEMENT BASICS

A. Definition of Risk

The concept of *risk* does not have a universally accepted definition. Economists, statisticians, physicists, philosophers, psychologists, decision theorists, and insurance theorists all interpret risk in their own ways. The concept of risk not only varies by fields of application but also by situation.

Nevertheless, most risk definitions share two common elements. The first element is the possibility of an undesirable outcome that deviates from what is expected. The second element is a basic uncertainty regarding the occurrence of this undesirable outcome. If this uncertainty can be quantified in terms of probability assessments, then the situation is said to be one of *calculable risk*. If, furthermore, these probability assessments are interpreted as being objectively true assessments (i.e., independent of any person's beliefs or information state), the risk is said to be *objective*; otherwise it is said to be *subjective*.

Researchers focusing on risk management in wholesale power markets typically do not provide a clear definition of "risk." An exception is Liu and Wu [8], who define risk to be "the hazard to which a market participant is exposed because of uncertainty." This definition clearly reflects the two previously mentioned common elements. However, it does not include the idea of anticipation or expectation as a benchmark.

In the following section we consider the general characteristics of a typical financial risk-management process, where *financial risk* is defined to be "the possibility that financial outcomes for an investor deviate adversely from what he expects." In the remaining sections we focus in greater detail on the specific types of financial risk faced by a *generation company (GenCo)* operating within a WPM. In all cases we assume that financial risk is calculable in terms of probabilities, and that these probability assessments represent the subjective assessments of the risk manager.

B. Financial Risk Management as a Four-Stage Process

Consider a decision maker charged with managing financial risk for a portfolio of assets owned by an investor. Typically this risk-management process involves four stages.

In the first stage the *risk factors* representing the principal sources of financial risk are identified and modeled. In the second stage the financial risk arising from these multiple risk factors is mapped into a scalar *loss function*. In the third stage this loss function is used to derive one or more *financial risk measures* for gauging the financial riskiness of the portfolio as a whole. Finally, in the fourth stage these comprehensive financial risk measures, possibly in combination with appropriate supplemental tools (e.g., stress testing), are used to diversify the asset portfolio to appropriately protect against financial risk in accordance with the preferences and needs of the investor. These four stages are explained more carefully below.

Stage 1: Identification and Modeling of Financial Risk Factors

The first stage in a typical risk-management process is to identify the underlying risk factors and then build a sensible model for them. A simple example is given here to illustrate this stage.

Consider a risk manager attempting to manage a portfolio of assets for a profit-maximizing GenCo facing two sources of risk: a variable electric energy demand level D , and a variable fuel price level F . Suppose for simplicity that D and F can only take on two values, High (denoted by 1) or Low (denoted by 0). The sample space Ω consisting of all possible outcome pairs (D_i, F_j) for D and F then takes the form $\Omega = \{(1, 1), (1, 0), (0, 1), (0, 0)\}$. Define \mathcal{F} to be the collection of all subsets of Ω , including the empty set. The two risk factors D and F can then be modeled by defining an appropriate joint probability measure P on \mathcal{F} .

Additional discussion of this stage is provided in Section III-A.

Stage 2: Derivation of a Loss Function

The second risk-management stage typically involves the derivation of a real-valued loss function that measures the relative undesirability of different possible risk-factor configurations in accordance with the preferences of the portfolio investor. Continuing with the example presented in Stage 1, the risk manager would assign a real-valued *loss* $L(\omega)$ to each possible element ω of Ω . For example, if high fuel prices are the GenCo's main concern, the risk manager might assign losses as follows: $L(0, 1) > L(1, 1) > L(0, 0) > L(1, 0)$.

Stage 3: Risk Measure Selection

The third risk-management stage typically involves the choice of an appropriate risk measure for characterizing overall portfolio risk for the particular situation at hand. This risk-measure selection process could involve comparative consideration of several candidate risk measures, such as return-rate variance, Value-at-Risk and Conditional Value-at-Risk. The definitions and derivations of these commonly used risk measures are discussed in Section III-B.

Stage 4: Portfolio Optimization

The last stage in a typical financial risk-management process is portfolio optimization, i.e., the determination of an optimal portfolio augmentation and rebalancing to achieve the type of risk-return characteristics appropriate for the investor. This portfolio optimization problem will take on different forms and require different solution techniques depending on the particular risk measure(s) and supplemental risk-management tools selected by the risk manager.

III. RISK-MANAGEMENT TOOLS AND METHODS

This section provides additional details regarding the tools and methods used to implement the four-stage risk management process outlined in Section II-B. A more extensive discussion can be found in [9].

A. Tools for Modeling Risk Factors

In the financial industry, three methods are commonly used to model risk factors in any given time period. These methods are the "analytical variance-covariance method," "historical simulation," and "Monte Carlo analysis" [10].

The *analytical variance-covariance approach*, also called the *parametric approach*, assumes that changes in risk factors follow a multivariate normal distribution. In practice, the unconditional or conditional mean vector and covariance matrix

of the assumed multivariate normal distribution are estimated based on historical data for risk-factor changes. The main advantages of this method are the simplicity of the analytical solution and its speed of calculation. The main drawback is that the normality assumption can be problematic.

In the *historical simulation approach*, data are collected on the historical frequencies of risk-factor configurations, and the resulting histogram is then used to estimate the distribution of future risk-factor configurations. Compared to the variance-covariance approach, the historical simulation approach is very intuitive and easy to implement. However, if the historical frequencies vary over time, the resulting estimate for the distribution of future risk-factor configurations can be very misleading.

The *Monte Carlo approach* involves the construction and calibration of an explicit parametric model for a set of risk factors based on historical data, and the subsequent use of this model to predict future risk-factor configurations. Although this approach has the potential to provide a much greater range of outcomes than historical simulation, it is computationally intensive and hence time-consuming. Moreover, constructing a reasonable multivariate time series model for a specific group of risk factors can be a daunting task in practice.

B. Construction of Risk Measures

In theory, the probability density function of the loss function for a portfolio of assets provides complete information about its risk. However, portfolio managers have found these probability density functions too cumbersome and complex for practical applications. Instead, they have preferred to construct simpler measures of portfolio risk that can be reduced to the reporting of a single number. Although single-number measures clearly lose a great deal of information through aggregation, the issue is whether they adequately serve the risk-management purposes of portfolio managers [11]. Three such single-number measures are briefly reviewed below.

In traditional finance, following the work of Markowitz [12], the measurement of risk for a portfolio of assets was primarily associated with the variance of the portfolio's return rate. Although variance is a well-understood concept and is easy to use analytically, it has some major drawbacks [13]. The most important drawback is that variance does not distinguish between positive and negative deviations from the mean. Consequently it is not conceptually compatible with definitions of risk that focus solely on negative (unfavorable) deviations.

Beginning in the 1990s, alternative measures of portfolio risk have increasingly been adopted in financial practice. As discussed at length in [14]-[20], two of the best-known measures are "VaR" and "CVaR."

The *Value-at-Risk (VaR)* measure is used when a portfolio manager is interested in making the following type of statement: It is α percent certain that the portfolio loss will not be more than VaR dollars in the next N days. More precisely, for any given confidence level α , the VaR of a portfolio is given by the smallest number l such that the probability that the loss L exceeds l is no greater than $(1-\alpha)$.

To put this definition in more rigorous mathematical form, consider a *probability space* (Ω, \mathcal{F}, P) where Ω is a space of points called the *sample space*, \mathcal{F} is a sigma-field of subsets of Ω , and P is a probability measure on \mathcal{F} . Singleton subsets $\{\omega\}$ of Ω , assumed to be elements of \mathcal{F} , are called elementary events. Define $q = (x_1, x_2, \dots, x_n)$ to be a given portfolio, where x_n denotes the amount of money invested in the n th asset. Let L_q denote the *loss function* of portfolio q , where L_q maps Ω into the real line \mathfrak{R} . Define $A_{L_q}(l) \equiv \{\omega \in \Omega : L_q(\omega) > l\}$, and assume $A_{L_q}(l) \in \mathcal{F}$ for each l . The *Value at Risk (VaR)* for portfolio q at confidence level $\alpha \in [0, 1]$ is then defined to be

$$VaR_\alpha(L_q) = \inf\{l \in \mathfrak{R} : P(A_{L_q}(l)) \leq 1 - \alpha\}. \quad (1)$$

Since its inception, VaR has been widely used by corporate treasurers and fund managers as well as by financial institutions. It has also been incorporated into the Basel II capital-adequacy framework, an agreement among regulators on how to calculate the minimum regulatory capital requirements for banks. In spite of its popularity, however, VaR suffers from several theoretical deficiencies. First, as a simple quantile of the loss distribution, it does not provide any information about the severity of the losses when the loss exceeds the quantile level. This problem is illustrated in Fig. 1. Although the two depicted portfolios have the same risk level as measured by $VaR_\alpha(L_q)$, the portfolio on the right is clearly riskier due to its larger potential losses.

Another perceived problem with the VaR method is "non-subadditivity." Roughly, non-subadditivity contradicts the general principle that diversification should reduce overall portfolio risk. Furthermore, VaR is non-convex with respect to the portfolio positions. Hence, in practice, it is very difficult to solve portfolio optimization problems with VaR constraints because they tend to induce the existence of multiple local minima.

Having recognized the drawbacks of VaR, researchers have worked to develop an alternative risk measure, *Conditional Value-at-Risk (CVaR)*, with better properties than VaR. CVaR extends VaR by considering the expected loss for a portfolio q conditional on this loss being at least as great as $VaR_\alpha(L_q)$, for any given confidence level $\alpha \in [0, 1]$. More precisely, for any $\alpha \in [0, 1]$, the CVaR of a given portfolio q with loss function L_q is defined as:

$$CVaR_\alpha(L_q) \equiv E(L_q | \{\omega \in \Omega : L_q(\omega) \geq VaR_\alpha(L_q)\}) . \quad (2)$$

Equivalently, CVaR can be written as:

$$CVaR_\alpha(L_q) = \frac{1}{1 - \alpha} \int_{\bar{A}_{L_q}(VaR_\alpha(L_q))} L_q(\omega) dP(\omega) , \quad (3)$$

where

$$\bar{A}_{L_q}(l) \equiv \{\omega \in \Omega : L_q(\omega) \geq l\} . \quad (4)$$

To see the distinction between VaR and CVaR more clearly, refer again to Fig. 1. For the given confidence level α , the CVaR measure assigns heavier risk to the right-hand distribution because the expected loss over the loss range $l \geq VaR_\alpha(L_q)$ is greater for this distribution. In contrast,

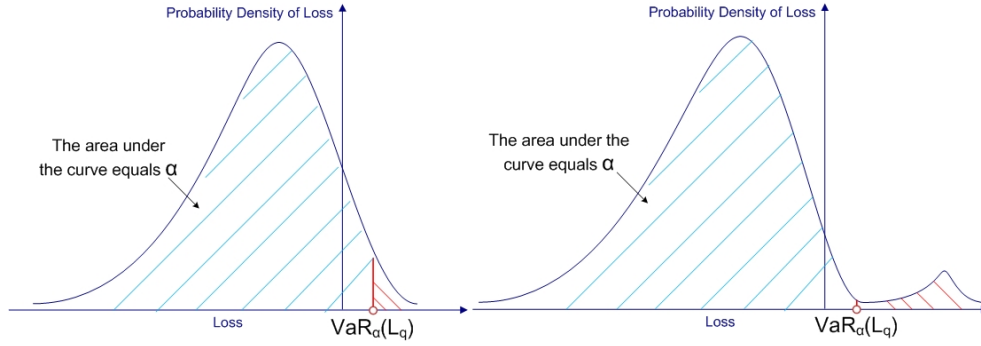


Fig. 1. Illustration of a major drawback of VaR as a Risk Measure: VaR assigns the same risk to each depicted probability density function for loss.

VaR assigns the same risk value $\text{VaR}_\alpha(L_q)$ to each depicted distribution.

As established in [17], CVaR has four properties required for a coherent risk measure: subadditivity, positive homogeneity, monotonicity and translation invariance. Moreover, in contrast to VaR, CVaR is convex with respect to portfolio positions, a major practical advantage of CVaR over VaR in applications.

C. Supplemental Tools: Stress Testing

To protect against the loss of information inherent in the use of single-number risk measures, portfolio optimization techniques are often supplemented with additional risk-management tools. One commonly-used supplementary tool is *stress testing*. Applied to portfolio analysis, stress testing examines how robust a portfolio's return rate is to the occurrence of extreme events falling outside normal market conditions.

As discussed at greater length in [18], the rationale for using stress testing is that risk measures derived from historical data might not adequately reflect possible future risks. For example, a portfolio manager might be concerned about the occurrence of a shock that he believes is more likely to occur in the future than the historical data suggest, or about shocks that he believes would substantially alter the historically observed correlation patterns among asset returns upon which his current risk-factor model is based.

Stress testing proceeds by examining responses to variously specified extreme-event scenarios; it does not address how likely it is that these scenarios will occur. If a portfolio manager is able to assign both probability and loss assessments to extreme-event scenarios, and derive the resulting loss distribution, he can then apply any of the previously discussed single-number risk measures. Given the meaning of "extreme events," however, it is unlikely that a portfolio manager could make probability and loss assessments with confidence. The separate scenario-conditioned results of stress testing can provide important cautionary information about portfolio vulnerabilities even when these assessments cannot be comfortably made.

IV. FINANCIAL RISK MANAGEMENT IN WHOLESALE POWER MARKETS

In this section we use a simple example to illustrate how the four-stage risk management process described in Section

II can be applied to wholesale power markets.¹ The scenario presented below considers the short-term risk-management problems faced by a GenCo operating in a wholesale power market with congestion managed by LMP.

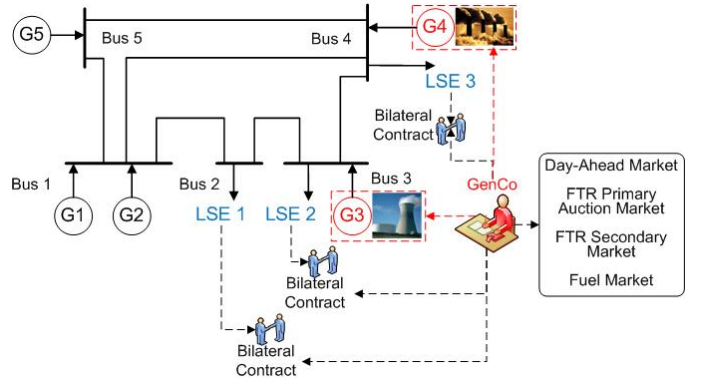


Fig. 2. Illustrative risk management problem for a GenCo operating in a 5-bus wholesale power market under LMP.

Consider the 5-bus scenario depicted in Fig. 2. In this scenario a particular GenCo owns a nuclear power plant, G3, located at bus 3, and a coal-fired power plant, G4, located at bus 4. Other generation plants G1, G2, and G5 are located at buses 1 and 5. There are also three LSEs 1, 2, and 3 located at buses 2, 3, and 4 whose demand for power in each hour is assumed to be fixed, i.e., not sensitive to price changes. Each transmission line has an associated thermal limit (not indicated in the figure).

Suppose that the GenCo is required each day to report a 24-hour supply offer to the day-ahead energy market for its coal-fired power plant, and it does this by reporting strategically in an attempt to secure for itself the highest possible net earnings. That is, for its coal-fired plant the GenCo can report higher-than-true marginal costs of production or less-than-true maximum operating capacity. On the other hand, suppose the GenCo's daily 24-hour supply of nuclear power is externally determined in accordance with safety regulations.

Given all supply offers for all generation plants and total LSE load for any given hour H of the day-ahead energy market, the ISO solves a standard *DC optimal power flow* (*DC*

¹A more detailed discussion and analysis of risk management for participants in wholesale power markets can be found [9] and [21].

OPF) optimization problem that involves the minimization of (reported) generation production costs subject to network constraints, (reported) generation operating capacity limits, and a balancing condition requiring that the total supply of power just equal total load. The solution of this problem determines for hour H the GenCo's dispatch levels for nuclear power at bus 3 and coal-fired power at bus 4, as well as dispatch levels for all other generation plants and a *Locational Marginal Price (LMP)* in \$/MWh at each bus. Given congestion anywhere on the 5-bus grid in a particular hour, the LMP solutions determined via DC OPF for this hour will "separate," meaning that the LMPs at two or more buses will deviate from each other. The price received by the GenCo for its dispatched supply of nuclear power at bus 3 is the LMP at bus 3, and the price received by the GenCo for its dispatched supply of coal-fired power at bus 4 is the LMP at bus 4.

Clearly drops in the LMP value at either bus 3 or bus 4 result in lower net earnings for the GenCo, all else equal. Moreover, lower LMP values over time result in lower net earnings for the GenCo, all else equal. Finally, increases in the GenCo's fuel input costs lower its net earnings, all else equal. Hereafter the possibility that the GenCo receives lower net earnings due to adverse price movements, either output or input, will be called the GenCo's *price risk*.

The GenCo can attempt to manage its price risk by engaging in physical or financial bilateral transactions² with other market participants. For example, the GenCo could write a contract C with an LSE j on day D specifying that the GenCo will inject q MWs of power at bus 3 and/or bus 4 during a specific hour H of day $D+1$ for a specific *strike price* p (\$/MWh), and the LSE j will in turn withdraw power q at its bus location during hour H of day $D+1$ and pay to the GenCo the strike price p .

However, as discussed at greater length in Section V, this bilateral contracting is complicated by the fact that injections and withdrawals of power on the transmission grid are in fact charged in accordance with LMP. To ensure the strike price p can be implemented in hour H of day $D+1$ under LMP, the bilateral contract C needs to incorporate an appropriate *contract-for-difference (CFD)* clause ensuring the effective price is p even if the LMP received by GenCo i or paid by LSE j differs from p . Further, given the possibility of LMP separation across buses, "making whole" the strike price p in hour H of day $D+1$ also requires additional contracts, such as *Financial Transmission Rights (FTRs)* associated with pairs of buses k and m . Roughly stated (ignoring network losses), a 1-MW FTR from a bus k to a bus m in hour H of day $D+1$ is a financial contract that entitles its holder to receive (or pay) compensation (\$/h) in amount 1-MW \times [LMP $_m$ - LMP $_k$] for hour H of day $D+1$.

As will be seen in Section V, an appropriate combination of an FTR contract and a CFD-extended version of the bilateral

contract C can ensure that the GenCo receives the strike price p for its injection of q MWs in hour H of day $D+1$, thus reducing its price risk. However, this reduction in price risk needs to be balanced against the cost of acquiring the supporting contracts.

In summary, for the scenario at hand, at any given time the GenCo's asset portfolio will include physical assets (power plants G3 and G4), a futures contract (cleared supply offer) for sales in the day-ahead energy market, and various forms of bilateral contracts and FTRs. We will next briefly consider how the four-stage risk management process set out in Section II-B might be applied to manage risk for this portfolio.

Stage 1 of this risk-management process is the identification and modeling of the principal underlying risk factors (sources of uncertainty) faced by the GenCo. For the scenario at hand, four key risk factors need to be considered: LSE loads at buses 2, 3, 4; fuel prices for the GenCo's power plants G3 and G4; plant or line forced outages; and the offer behaviors of the rival generation plants G1, G2, and G5 in the FTR and day-ahead energy markets. The modeling of these risk factors could take the form of a joint probability distribution describing the likelihood of any particular risk-factor configuration.

Stage 2 is the derivation of a loss function for the GenCo's portfolio. As discussed at some length in Yu [9], the appropriate formulation for this loss function will depend on the specific structures and rules governing the energy and financial markets in which the GenCo is participating. The GenCo's portfolio loss is affected by three different types of risk derived from the four previously identified risk factors: *price risk*, i.e., adverse movements in output or input prices; *volume risk*, which is the risk arising from uncertain future production levels at its coal-fired plant; and *credit risk*, which is the risk that one or more counter-parties for the GenCo's contracts could default, i.e., fail to meet their contractual obligations.

Stage 3 is the selection of an appropriate overall measure of portfolio risk. As discussed in Section III-B, no one risk measure is best for all circumstances and purposes; each has its particular strengths and weaknesses. The effectiveness of any particular candidate risk measure needs to be evaluated in context. Detailed experimental test results for the performance of variance, VaR and CVaR as portfolio risk measures for the particular scenario at hand are reported in Yu [9].

Stage 4 involves the choice of an optimal portfolio mix, conditional on a given choice of risk measure. The criterion of optimality will typically involve some form of trade-off between risk and return, e.g., maximization of expected return over a specified planning horizon subject to an upper bound on allowable risk. Depending on the particular specifications for the risk-factor model and the risk measure, the portfolio optimization problem can range from a simple linear programming problem to a complex multicriteria optimization problem. An in-depth analysis of various forms of portfolio optimization problems suitable for the scenario at hand can also be found in Yu [9].

²In U.S. ISO-managed energy regions such as MISO [22, p. 15], a bilateral transaction that involves the physical transfer of energy through a transmission provider's region is referred to as a *physical bilateral transaction*. Bilateral transactions that only transfer financial responsibility within and across a transmission provider's region are referred to as *financial bilateral transactions*.

V. INTEGRATED OPERATION OF FINANCIAL AND PHYSICAL ENERGY MARKETS

In this section we discuss in greater detail the risk management issues that arise for GenCos when they simultaneously participate in financial and physical energy markets.

We start with a preliminary discussion explaining how bilateral contracts, suitably extended with CFD clauses and accompanied by suitable FTR holdings, can be used to hedge price risk in day-ahead energy markets.³ We then use a relatively simple analytical example to illustrate the extremely complex multi-stage game problem faced by day-ahead energy market traders who attempt to optimally hedge their energy trades with bilateral and FTR contracts taking contract acquisition costs into consideration.

A. Risk-Hedging Through Bilateral and FTR Contracts

Consider a GenCo i and an LSE j that are participants in an ISO-managed day-ahead energy market with locational marginal pricing. GenCo i receives a price LMP_i for each MW of power it injects at its bus i , and LSE j pays a price LMP_j for each MW of power that its retail customers withdraw at bus location j , where these LMP values are determined by the ISO through an appropriate OPF calculation.

Suppose GenCo i wishes to use bilateral contracts to manage its (output) price risk. In particular, suppose GenCo i enters into a contract C with LSE j on day D specifying that GenCo i will inject q MWs of power at bus i during a specific hour H of day $D+1$ for a specific *strike price* p (\$/MWh). In turn, the contract C obliges LSE j to purchase q MWs of power at bus location j during hour H of day $D+1$ and to pay to GenCo i the strike price p for each MW of this withdrawn power.

As noted in Section IV, the implementation of this bilateral contract is complicated by the fact that power injected into or withdrawn from the transmission network is priced by means of LMPs. Consider, first, the case in which there is no network congestion during the designated hour H . In this case all bus LMPs for hour H collapse to a single value, say LMP^* . If LMP^* differs from the contract strike price p , GenCo i and LSE j will need to extend their original bilateral contract C to a contract C^* incorporating a CFD clause stipulating that either party will be compensated by the other for excessive or insufficient payment in relation to the intended strike price p .

For example, suppose $LMP^* > p$, implying that LSE j pays more than the strike price p for the power its retail customers withdraw at bus j and GenCo i receives more than the strike price p for the power it injects at bus i . The CFD clause should then require GenCo i to compensate LSE j with an extra payment $q \cdot [LMP^* - p]$, thus “making whole” LSE j by ensuring the effective price paid for the contracted power amount q is the strike price p . Similarly, in the reverse case $p > LMP^*$, the CFD clause should require LSE j to “make whole” GenCo i with an extra payment $q \cdot [p - LMP^*]$.

Hence, in the absence of congestion, the extended contract C^* provides a perfect hedge for GenCo i and LSE j against

price risk in the form of deviations of LMP^* from p . If network congestion arises in hour H , however, C^* will not be enough to ensure a complete hedging against this price risk. Congestion can lead to divergence between the LMP_i at bus i received by GenCo i and the LMP_j at bus j paid by LSE j . In particular, the LMP_i at bus i could drop below p while at the same time the LMP_j at bus j exceeds p , implying that both parties to the contract are in need of “make whole” payments.

This gap in hedge coverage can be filled by an appropriate parallel purchase of FTRs in the form of obligations, the only form of FTR to be considered below. An FTR in the form of an obligation entitles its holder to compensation (or obliges its holder to pay) based on the difference in LMP outcomes between two specified bus locations for some specified hour.⁴ For example, suppose a market participant holds an FTR position of q MWs for a source bus i and a sink bus j for a particular hour H . The holder is then entitled to receive a compensation of

$$\pi_{ij} = q \cdot [LMP_j - LMP_i] \quad (\$/h) \quad (5)$$

from the ISO if $\pi_{ij} \geq 0$; otherwise the holder must pay the ISO the amount $-\pi_{ij}$. Since bus LMPs collapse to a single value across the transmission network in the absence of congestion (ignoring typically small network losses), FTR compensations and payments only take place in congested conditions.

How might GenCo i and LSE j accomplish a complete hedge of their price risk through a combined holding of an appropriate CFD-extended bilateral contract and an FTR holding? Suppose GenCo i acquires an FTR position of q MWs from bus i to bus j on day D for hour H of the day-ahead energy market on day $D+1$. GenCo i 's net receipts on day $D+1$ from its energy injection and its FTR holding are then as follows:

$$q \cdot LMP_i + q \cdot [LMP_j - LMP_i] = q \cdot LMP_j \quad . \quad (6)$$

Consequently, under the FTR, GenCo i 's sale price in hour H of day $D+1$ has been effectively changed from LMP_i to LMP_j , the purchase price paid by LSE j at bus j in hour H of day $D+1$. Suppose, in addition, that GenCo i and LSE j extend their bilateral contract C with the following type of CFD clause applying only to bus j : GenCo i makes a payment to LSE j in amount $q \cdot [LMP_j - p]$ if $LMP_j > p$ or receives a payment from LSE j in amount $q \cdot [p - LMP_j]$ if $p > LMP_j$. This combination of contracts ensures that the price received by GenCo i and paid by LSE j for the contracted power level q in hour H of day $D+1$ is precisely p .

B. GenCo Participation in FTR and Day-Ahead Markets

As shown in Section V-A, the payoffs from FTR holdings depend on LMP settlements in the day-ahead market (DAM). The prices that energy traders are willing to pay to acquire FTR holdings in FTR auctions will thus presumably reflect

⁴More precisely, if network losses are considered, these compensations or payment obligations are based on the congestion components of LMPs rather than the LMP values per se. This complication is ignored in this introductory presentation.

³See [23] for an extensive discussion of the use of bilateral contracts and FTRs as an instrument to hedge against price risk.

their expectations with regard to payoffs in the DAM. On the other hand, after acquiring FTR holdings, market participants can report strategic supply offers to the ISO for the DAM in an attempt to influence the LMP outcomes upon which their FTR payments depend.

Previous work focusing on risk management in wholesale power markets has generally focused either on FTR auction bidding, conditional on expected outcomes in the DAM (e.g., [24]), or on DAM trading conditional on given FTR holdings.⁵ Thus the feedback mechanism linking strategy choices in the two markets has not been extensively studied.

In Somani [30] an analytical framework is developed to examine this complicated feedback mechanism. Successive choices in FTR and DAM markets are modeled as a game among rival GenCos. In particular, the bid strategies of the GenCos in the FTR auction are conditioned on their expectations of DAM payoffs as well as on their expectations of the bid and offer strategies of rival GenCos in the two markets. Conditions are explored for the existence (or not) of Nash equilibria for this dynamic multi-player game.

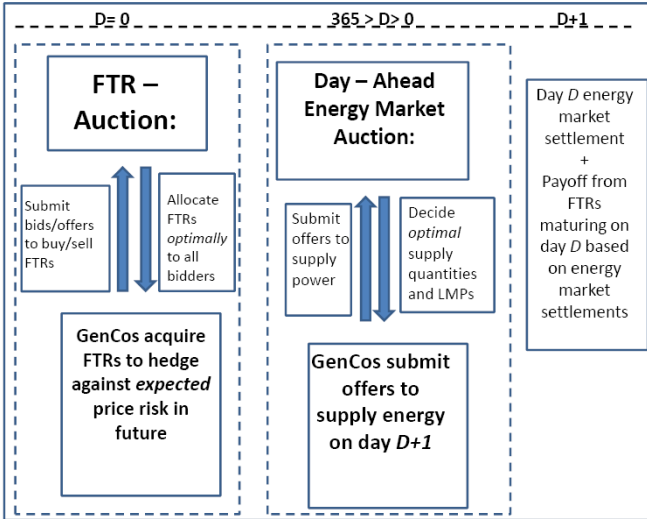


Fig. 3. Illustration of a the choice problem for a GenCo participating first in an FTR auction and then in a day-ahead energy market.

More precisely, as depicted in Fig. 3, the dynamic choice problem for the GenCos is modeled analytically as a three-stage process. In stage 1, day $D = 0$, the GenCos submit bids to acquire FTRs from the ISO's FTR auction. In stage 2, day $D > 0$, the GenCos report supply offers to the ISO for the DAM for dispatch for power production on day $D+1$. On day $D+1$, the GenCos receive (or are liable to pay) compensation for the FTRs acquired on day $D = 0$ based on the LMP outcomes for day $D+1$. The logical flow of information for this three-stage process is presented in Fig. 4. For a detailed explanation of the depicted sequential choice problems, see Somani [30].

Research to date shows the strong dependence of GenCo DAM supply-offer behaviors on their FTR holdings, and vice

⁵Important exceptions include [25]-[29], who study the effects of FTRs on the market power exercised by GenCos in day-ahead energy markets and on overall market efficiency.

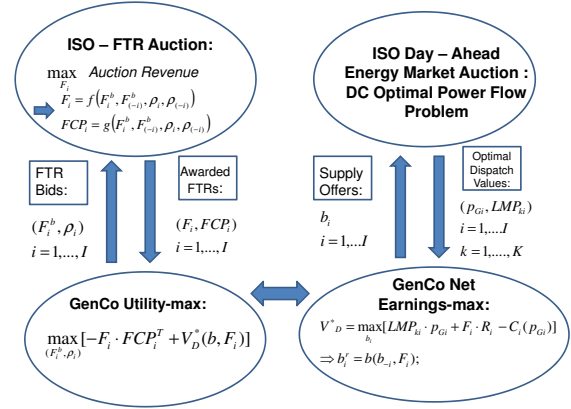


Fig. 4. Feedback mechanism between the FTR Auction and the Day-Ahead Energy Market

versa. A key finding is that existence of Nash equilibria is not guaranteed. Indeed, the best response functions for the GenCos are so complicated in form, even for simple 3-bus grid specifications, that it is doubtful whether market participants could practically make use of them as a decision-making tool even in cases where Nash equilibria exist.

This level of complexity suggests the potential desirability of undertaking the integrated study of FTR auction and DAM trading by means of a agent-based test bed with market participants modeled as adaptive learners. This would allow analysis to proceed even in cases in which Nash equilibria are difficult to calculate or fail to exist. The following section discusses this alternative approach.

VI. EXPLORING FINANCIAL RISK MANAGEMENT VIA AN AGENT-BASED TEST BED

As suggested by the discussion in previous sections, the study of risk management in wholesale power markets is complex, requiring the detailed modeling and analysis of strategic decision making by market participants, market operators, and oversight agencies. Fortunately, as demonstrated already in a number of studies (e.g., [7], [31], [32]), agent-based simulation tools are designed to handle this level of complexity.

In future work we plan to study financial risk management for wholesale power markets using an appropriately enhanced version of the AMES Wholesale Power Market Test Bed developed by a group of researchers at Iowa State University [33]. AMES is an open-source agent-based computational laboratory designed for the controlled experimental study of strategic trading in restructured wholesale power markets with congestion managed by LMP. AMES is fully implemented in Java, meaning that all structural, institutional, and decision making entities are rendered as "agents" encapsulating data and methods. This modular architecture permits great flexibility for the systematic exploration of various risk-management practices of market participants and overall market performance under alternative grid conditions, market designs, and learning capabilities.

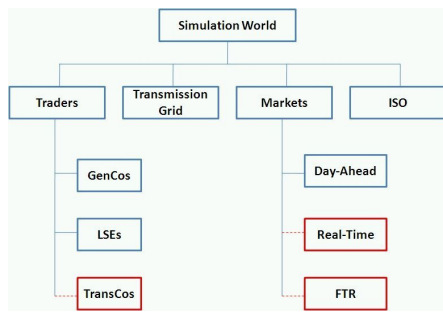


Fig. 5. Illustration of the AMES agent hierarchy. Blue (solid) lines denote current agent types, and red (dotted) lines denote planned agent types.

Fig. 5 depicts the currently implemented AMES agent hierarchy using blue (solid) lines. In addition, Fig. 5 depicts with red (dotted) lines the new agent types to be introduced under this project, described more carefully as follows. The Real-Time Market Module will permit us to examine more fully the effects of uncertainties in load, transmission, and generation operating conditions on the supply-offer and demand-bid strategies of GenCos and LSEs and on the overall performance of the market. The FTR Market Module will permit us to study the effectiveness of alternative FTR market designs as a means for financial hedging against congestion-induced price volatility in the day-ahead market, completion of bilateral contracts, and encouragement of new transmission investment.

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