Information requirements for strategic decision-making: energy market

by

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DEDICATION

To my family Gilberto Gutierrez, Josefina Alcaraz, Martin, Norma Patricia and Jose Gilberto

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LIST OF ACRONYMS AND DEFINITIONS

Ancillary Services (AS). AS are those functions performed by electrical generating, transmission, system-control, and distribution system equipment and people to support the basic services of generating capacity, energy supply, and power delivery.

Generation Company (GENCO). A generation company produces electricity for sale in a competitive market. The goal for a GENCO, which has to fill contracts for the cash and futures markets, is to package production at an attractive price and time schedule.

Distribution Company (DISTCO). The goal for distribution companies, which have to provide services by contracts, is to package the availability and the cost of the radial transportation network to facilitate transportation from suppliers to buyers.

Energy Management Company (EMCO). Energy management companies are non-profit, consumer-owned cooperatives or large industrial customers, whose objective is to provide customers with the lowest possible rates on electricity with no compromise in service.

Small, Medium, and Large Consumers (SCO, MCO, LCO). Some power consumers may choose to participate directly in the marketplace. Classification could be based on the level of peak demand or trading capacity.

Independent System Operator (ISO). An organization created to control the operation of the power system, monitor reliability and coordinate the supply of electricity in a region

Market Clearing Price (MCP). The price that sellers will receive and buyers will pay at any time in the spot market.

ABSTRACT

Over the last two decades, the electricity sector has been involved in a challenging restructuring process in which the vertical integrated structure (monopoly) is being replaced by a horizontal set of companies. The growing supply of electricity, flowing in response to free market pricing at the wellhead, led to increased competition. In the new framework of deregulation, what characterizes the electric industry is a commodity wholesale electricity marketplace. This new environment has drastically changed the objective of electricity producing companies. In the vertical integrated industry, utilities were forced to meet all the demand from customers living in a certain region at fixed rates. Then, the operation of the Generation Companies (GENCOs) was centralized and a single decision maker allocated the energy services by minimizing total production costs.

Nowadays, GENCOs are involved not only in the electricity market but also in additional markets such as fuel markets or environmental markets. A gas or coal producer may have fuel contracts that define the production limit over a time horizon. Therefore, producers must observe this price levels in these other markets. This is a lesson we learned from the Electricity Crisis in California. The Californian market's collapse was not the result of market decentralization but it was triggered by other decisions, such as high natural gas prices, with a direct impact in the supply-demand chain.

This dissertation supports generation asset business decisions –from fuel supply concerns to wholesale trading in energy and ancillary services. The forces influencing the value chain are changing rapidly, and can become highly controversial. Through this report, the author brings an integrated and objective perspective, providing a forum to identify and address common planning and operational needs.

The purpose of this dissertation is to present theories and ideas that can be applied directly in algorithms to make GENCOs decisions more efficient. This will decompose the problem into independent subproblems for each time interval. This is preferred because building a complete model in one time is practically impossible. The diverse scope of this report is unified by the importance of each topic to understanding or enhancing the

profitability of generation assets. Studies of top strategic issues will assess directly the promise and limits to profitability of energy trading. Studies of ancillary services will permit companies to realistically gauge the profitability of different services, and develop bidding strategies tuned to competitive markets.

CHAPTER 1 INTRODUCTION

1.1 Chapter overview

Over the last two decades, the electricity sector has been involved in a challenging restructuring process in which the vertical integrated structure is being replaced by a horizontal set of companies. This new parading has not changed the philosophy of power system operation but evolving the way of making financial arrangements. This chapter describes the background and structures of the present research work.

1.2 Introduction

The vertical integrated supply-chain generally is solved as an optimization problem where the objective function is to minimize total costs and satisfy the demand with a satisfactory level of reliability. After the liberalization of the energy sectors, its operation has changed from a centralized process to a market ruled by the law of offer and demand.

The different activities of the energy supply chain nowadays are organized through markets: fuel markets, electricity market and environmental market among others, as indicated in Figure 1.1.

The left side in Figure 1.1 represents the supply side of the electricity sector, making up by electricity generating companies, owning power plants. Based upon the prices that they offer, the processes that occur in the market decide upon the quantity of electricity that each generation company is allowed to sell at each moment in time. The generating companies themselves however decide autonomously in their biddings, which plants they run and how they run them.

The electricity generation portfolio is not only the distribution of the types of plants that GENCOs own but also the different services in they can participate. Among these services, ancillary services (AS) play an important role in a player’s decision in decentralized markets.

By way of example, the lack of reactive power will reduce the amount of energy transferred through the power system. If such information is mined by a player, that player may make additional revenues, by probably exercising market power based on the locational characteristic of reactive power.

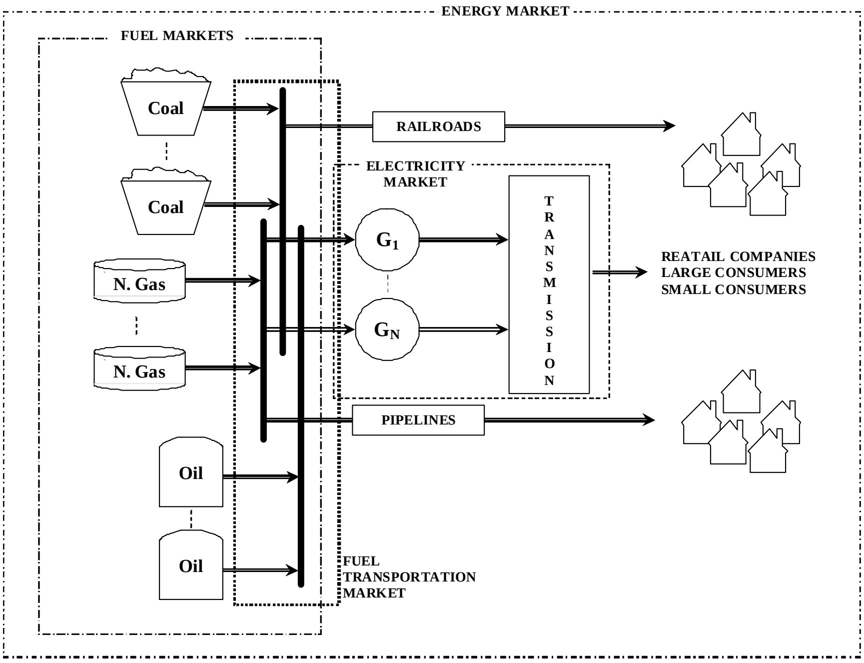

Figure 1.1 Energy market

In order to improve the GENCOs decision-making, it is necessary to have detailed and reliable optimization models and methods available. However, finding the optimal plan for production power and ancillary services, possibly also taking into account the optimal use of storage, is a difficult optimization problem. This difficulty can be relaxed decomposing the problem in time and activity, where each time-step is solved independently. The time dimension is divided into discrete, one-hour time-steps.

Producers and consumers of electricity could trade through multiple related markets. For instance, trade of large blocks of electricity mainly takes place in the bilateral market. This means that the producers directly trade electricity to large consumers, traders or retail companies. Bilateral contracts are confidential, as a result of which there are no good data available regarding their price and duration. Small end consumers acquire their electricity via the retailers. Additionally, electricity can be trade on the spot market. Every day, each plant owner can bid a price and an amount he wants to produce for the next day, specified per hour of that next day. Hourly prices result from those bids together with the bids of the consumer side of the market. Prices are higher when demand relative to supply is larger. Bids are anonymous, but the market prices are public. Prices on the spot market can be highly volatile. Finally, the balancing market facilitates additional electricity generation to balance actual supply and demand in the moment due to the actual use of electricity is unpredictable; supply and demand of electricity must be equal at any moment. The extra electricity has to be obligatory sold on the balancing market to the parties that predicted and bought less than their actual electricity withdrawals.

Due to the complexity of GENCOs decision making process we have decided to decompose the problem into independent subproblems, see Figure 1.2. This is preferred because building a complete model in one time is practically impossible.

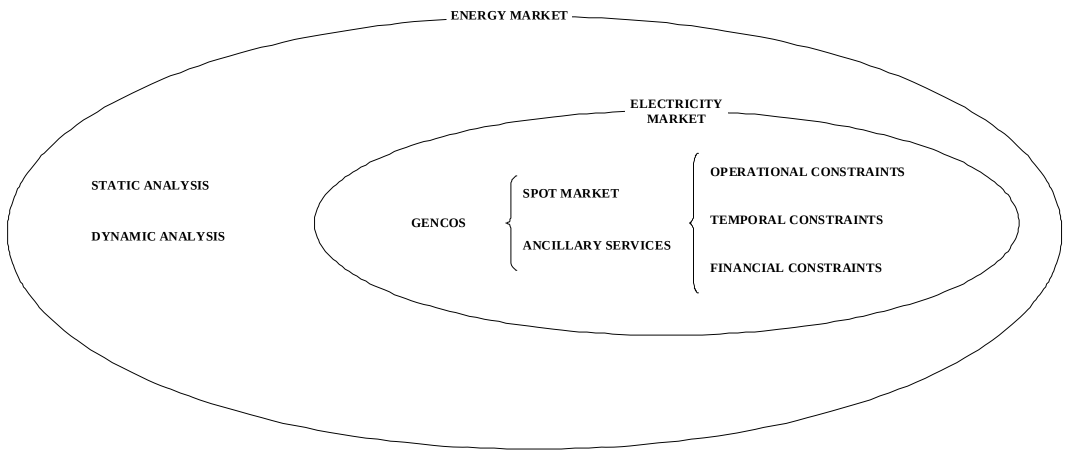

Figure 1.2 Energy market decomposition

The Electricity Market

With the deregulation of power industry, real power, which had been centrally dispatched and sold to customers in the traditional power systems, become the first product to be auctioned and sold in electricity markets. The purpose of an auction is to expose information about buyers' and sellers' respective willingness to pay or sell. Commodities like electricity often have no explicit fixed worth; instead, their worth is a function of current market conditions, and an auction attempts to define this worth [12]. Essentially, an auction allows discovery of the equilibrium price, defined as the intersection of the demand and supply curves of the buyers and sellers respectively. Electricity auctions are designed for simplicity and transparency. However, the physical constraints placed on the power system by the laws of physics are unique to electricity, and care must be taken to establish the most appropriate production, transportation, and consumption mechanisms for this commodity.

Spot electricity markets[1] operate repeatedly on the hourly basis, generation companies might learn from available historical market data to forecast or estimate the strategic behavior of competitors'. Expectations of market participants have to be assumed to get these dynamic learning.

In the market information block in Figure 1.3, the market operator conducts a market-clearing mechanism. Once market equilibrium and price-quantity are discovered, this information is made public. A GENCO observes this new market information and chooses from a finite set of actions. The market then enters into a new state and again the GENCO must make a decision. Its objective, therefore, is to select the sequence of actions that return the highest cumulative payoff. Any GENCO whose bid is accepted is obligated to provide the quantity of electricity accepted. This situation occurs for every period. Hence, each GENCO can study the past choices of its rivals. In addition, each GENCO may assess other information it gathers over time, and especially the data which will most likely influence its present choice. In other words, when the same bidder plays the same opponents multiple times, it can be expected that the bidding agents will adjust their own behaviors to maximize

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[1] The day-ahead hourly electricity market is referred to as the spot electricity market, but in reality, a true spot market for power exists with time horizons as short as 10 minutes and is named *real-time market*

their profits [5]. To accomplish with this learning process, we do consider that both GENCOs adopt Forward expectations. Forward expectation is valid when GENCOs anticipate a possible future equilibrium for competitors.

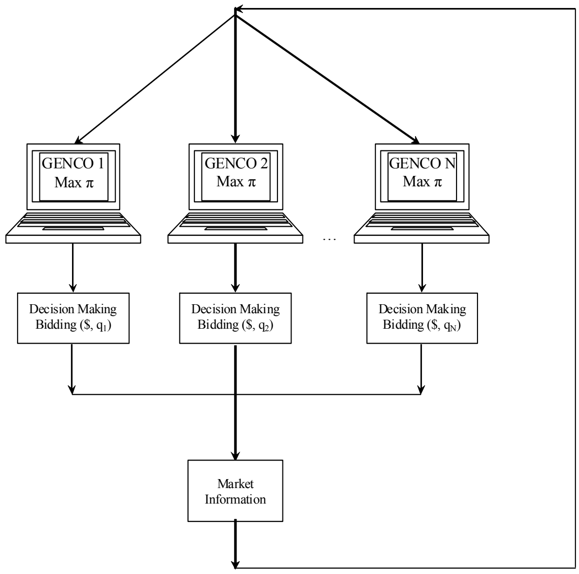

Figure 1.3 GENCOs feedback information

The transmission services provided by the system operators for system stability and reliability are still provided centrally and not yet being traded in the markets. With the further development of electric energy market and electricity financial market, more and more services are, or will be traded in the ancillary service market.

Contingent markets have been introduced to reduce uncertainty by trading commodities/services at date *t* to be delivered sometime in the future [1]. The objective of contingent delivery contracts is to make the markets complete, one contract for every good in every state of the market. The introduction of complete markets, therefore, apparently permits the accounting of uncertainty with a large economy of means. Forwards and Futures markets are two of the additional markets in which contracts of contingent delivery can be traded. A Forward market reflects short term future system conditions. In the forward market, prices are determined at the time of the contract, but transactions occur at some specific date in the future. The settlement of forward contracts can be either physical or financial. Physical contracts consider it an obligation of the generation company to fulfill the specified amount of energy at the hours and network node arranged at the fixed price agreed. On the other hand, Financial Contracts do not imply a physical energy transaction but they pertain to a cash flow. Unlike forward contracts, where credit risk exists, in Futures contracts there are no credit risk. In a Futures contract, the counterpart is always the exchange-clearing house. The exchange guarantees that the term of the contract will be honored at maturity. Future contracts are financially derived contracts used to spread risk and they are a means of risk management.

Options markets for electric energy are expected to be common and will be an important means of mitigating risk. An options contract is a form of insurance that gives the purchaser the right, but not the obligation, to buy (sell) a contract at a given price. This is the main difference between option contracts and forward/futures contracts, in which the holder is compelled to buy or sell the underlying commodity.

In the swap market, the contract position can be closed with an exchange of physical or financial substitutes. The trader may find another trader who will accept delivery and end the trader's delivery obligation.

Figure 1.4 represents schematically the electricity-derivative markets.

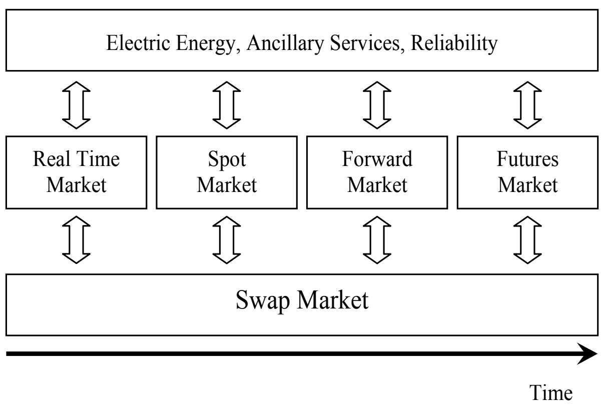

Figure 1.4 Electricity Market mechanism

Three interesting tangential derivatives for managing risk in the industry are also being used: emissions trading, weather derivatives, and insurance contracts.

1.3 Literature review

Energy models have been developed to support local energy planning and recently to observe the effects of interdependencies in the case of terrorist attacks [1][2][3]. However, analyses to date have focused mainly on the interrelation between the energy sector and the larger economy in the long-term. A useful example is the computer-based National Energy Modeling System (NEMS) in the United States that models energy markets driven by the fundamental economic interactions of supply and demand [4]. Additional examples of large-scale energy models include Electricity Markets Complex Adaptive Systems (EMCAS) and Energy and Power Evaluation Program (ENPEP) [5, 6]. EMCAS is an agent-based modeling system used to simulate various market operating rules [5] while ENPEP is a set of integrated energy, environmental, and economic analysis and planning tools [6].

A supply chain network perspective for electric power production, supply, transmission, and consumption is presented in [6]. Various decision-makers operating in a decentralized manner such as generation companies, transmission companies and market consumers are taken into account. A generalized network flow model of a national, integrated energy system that incorporates production, storage, and transportation of coal, natural gas, and electricity in a single mathematical framework for a medium-term analysis has been reported in [7, 8]. The model focuses on the economic interdependencies of the integrated system along with a detailed characterization of their functionalities (supply, demand, storage, and transportation), within a single analytical framework that allows for their simultaneous study. A novel electric power supply chain network model with fuel supply markets that captures both the economic network transactions in energy supply chains and the physical network transmission constraints in the electric power network is reported in [9]. The theoretical derivation and analyses are done using the theory of variational inequalities.

We propose the Leontief model, also known as Input-Output model, to study market integration and agent participation in a multiple-market framework. The Input-Output model is an equilibrium model that assumes no surplus production or consumption, having the advantage of providing an organizational framework. An input-output model is a convenient tool for description of action of market forces even when the model is a snapshot of the economy at one point in time. Specific limitations to the input-output model's accuracy include:

Constant coefficients
Linearity
Sector homogeneity
No capacity constraints

To overcome with some of these drawbacks we have developed two market models of integrated electricity and fuel markets. The first formulation is a closed form solution of the Cournot model represented by a set of linear equations. The second formulation is an equivalent of the first in a Discrete Event System Simulation (DESS) framework. The main advantage when formulating the energy market by using DESS is the possibility to expand the analysis to study market dynamics, and allow companies to tailor their strategic planning and forecasting.

Electricity market design trends toward a decentralized self-scheduling model. A centralized auctioneer, Power Exchange (PX), is seen as the fictitious Walrasian Auctioneer in the Walrasian General Equilibrium model [10]. PXs normally provide bidding trading in contracts for power delivery during a particular hour of the next day, called day-ahead or spot market. The usual trading method varies from a daily single-side auction to double-side auction for every hour to match transactions at a uniform price [11]. In decentralized markets, price is adjusted dynamically based on the response of market supply-demand. GENCOs offer energy into the market at prices offered based on estimated future conditions. As market participants, GENCOs in single-side or double-side decentralized models, are not price takers but price setters. The aggregate quantity of electricity offered is a nondecreasing function of price. Depending on market rules, GENCOs may offer power in block contracts. This implies that the market supply curve has the form of a step functions. Similarly, buyers may make bids into the market at prices that they are willing to pay. The aggregate demand curve is a decreasing step function of price. The market clearing price is commonly determined by the intersection of these demand-supply curves. In addition, the market clearing price must incorporate consideration of any transmission constraints. When the bulk system does not have transmission constraints, the spot market price of electricity can be computed by successively dispatching generation with the lowest price until the demand is met.

Price dynamics can be analyzed from the bidding strategy that each player develops to maximize profits. A bidding decision is formulated as a Markov Process as reported in [12]. Those authors used bidding decisions to determine the price and amount of electricity for a supplier assumed to be risk-neutral. The same authors in [13] developed a systematic method to calculate transition probabilities and rewards for the Markov Decision Process model. All other suppliers are modeled by their bidding parameters with corresponding probabilities. The optimal strategy is calculated to maximize the expected reward over a planning horizon. The authors considered a simplified market in where the suppliers' bids are chosen from the cheapest until the load that period is met. For all units that are called into operation, the last selected bid price defines the spot price in that load period. Security constraints and other market characteristics are neglected. The no-arbitrage-pricing principle is applied to the pricing of flexible electricity contracts in [14]. Pricing of flexible contracts involves a scheduling policy. By representing the spot price with an appropriate stochastic process, the scheduling policy can be found using stochastic dynamic programming. The mathematics of finding optimal bidding strategies in multi-period electricity market auctions of energy and reserve markets is presented in [15] and [16]. Generator costs, operating constraints, and exogenous price uncertainties are fully taken into consideration within the approach. These authors studied strategies for generators making offers into wholesale electricity markets when both demand and competing generators behavior is unknown but represented by a probability distribution in [17]. Their analysis is restricted to markets in which the supply of power in a given time interval is defined by generators of power in the form of offers of energy blocks. We propose to study market dynamics with interaction among participants by using a discrete linear system model. The model is a closed-loop dynamic system in which current and previous information are use as a feedback signal into decision support systems. Price market dynamics is emphasized as the bidding iterative process associated to each trading period in game theory framework by using difference equations [18].

Also important is the change in the flow of information between various entities that now compose the revamped electric power industry [19]. Market pricing, capacity reservations, energy schedules and financial settlements data now dominate the data exchange for wholesale operation. Nearly gone are the days of operational information exchange, limited to engineering and system scheduling data, primarily between the utility control centers [20]. We discusses what additional informational is required such as firms' strategic decision-making is improved in the quest for profits.

In a decentralized market design, price summarizes this information. Transmission system capacity information is embedded in the Locational Marginal Price (LMP). Market participants should have access to transmission system information. This information is needed to forecast the market state. Perfect information is not available as the contractual (trading) information is not revealed. LMP provides more than locational information based on transmission system losses and congestions. LMP provides insights to production fuel type dominance [21]. Observing fuel prices in their respective markets and the price of electricity, enable a player to identify price at a given point of time. Such a dependency is shown by spark contracts. Such contracts are beyond the scope of this thesis [22].

Most of the work applied to the electricity market analysis reported in the literature covered a single period. At the beginning most of these models were constructed as single-node generation-only models [23]. A procedure to identify multi-period equilibria in an electricity market is important for market regulators who may use it for market monitoring [24]. A multi-period equilibrium in a pool-based electricity market that may include minimum profit constraints for on-line generating units is analyzed in [25]. An oligopoly with spatially dispersed generators and consumers as well as with multiperiod demand is modeled in [23]. We have studied GENCOs production decisions in the spot electricity market. The model developed is based upon static model equilibrium solved sequentially.

Later, basic representations and linear DC transmission network were introduced for modelling geographical distribution, also called spatiality [26][27][28][29]. Recently, AC network representation has been incorporated in a non-linear programming problem in order to systematically study for the impacts of network constraints on the market equilibrium [30].

Since GENCOs operate in a sequential-period market where, in each period, simultaneous output decisions are made, in most market scenarios, it may not be enough to maximize gain in the current and next period. Therefore, the GENCOs will seek to maximize total gain over the next several periods. However, not knowing (or being unaware of) their competitors' future output decisions will make it difficult for any one GENCO to predict its rivals' behavior [31][32]. Faced with this difficulty, a GENCO may adjust its own output expectation of the current period according to both the output of the last period and the expected output in the next subsequent period. In addition, each GENCO will probably rely upon other information it gathers over time, especially the data which will most likely influence its present choice. In other words, when the same bidder plays the same opponents multiple times, we would expect that the bidding agents will adjust their own behaviors to maximize their profits [32]. The earliest model of oligopolistic market behavior states that every firm in the market deducts some "expectations" about the reactions of all other firms in the play. Such expectations are best known as *conjectural variations (CV)*, a term derived from game theory [33]. The concept of dynamic CV and its relationship to equilibrium behavior in a two-period Cournot model with imperfect information about the market demand is introduced by Riordan in [34]. Thus, changes in one firm's output in the current period cause the market price to change, and therefore influence the rivals' estimates about future demand. In this setting, a firm perceives that an increase in its output decreases the current market price, causing rival firms to estimate that demand has gone down and in reaction they reduce their output in the following period [35].

Recently, there has been considerable interest in oligopoly models with "consistent" conjectural variations. A conjectural variation is considered consistent if it is equivalent to the optimal response of the other firms at the equilibrium defined by that conjecture [36]. A general treatment of consistent conjectural variations in an oligopoly model with a homogeneous product is reported in [37]. The existence and uniqueness of consistent CV equilibrium in electricity markets is investigated in [38]. By identifying the market's optimum characteristics and applying an infinite horizon optimization model, it is shown that the consistent conjecture variation will satisfy a set of coupled nonlinear equations and that there will be only a single equilibrium. A CV-based learning method for a generation firm intending to improve its strategic bidding performance is proposed in [39]. Using this method, each firm learns and dynamically regulates its conjectures upon the reactions of its rivals to its own bidding in agreement with the available information, and only then makes its optimal generation decision based on the updated CV of its rivals. A parameter inference procedure based on two stages is proposed in [40]. The first stage infers historical values of the parameter by fitting the models' results to historical market data. The second stage is based on a statistical time-series model whose objective is to forecast parameter values in future scenarios.

A method for estimating the CVs of GENCOs is presented in [32]. Based on an actual electricity market, an empirical methodology is also proposed to analyze the dynamic oligopoly behaviors underlying market power. A new, unified framework of electricity market analysis based on co-evolutionary computation for both the one-shot and the repeated games of oligopolistic electricity market is reported in [41].

The need to make adjustable market decisions in a rapidly changing environment has encouraged the development of new procedures [42]. Among them is the Forward Expectations (FE) model [43]. We have introduced Forward expectations to accomplish with this learning process. This integration is crucial for two reasons: forward expectations teach a GENCO how its current stock valuation is affected (since stocks are the physical link between successive periods, and the valuation will transform expectations about future trading into desires to exchange current goods), and they are based on available information, i.e., the stream of past and present price-quantity signals [44]. In today's competitive, volatile markets, accurate modeling of both the operational and temporal constraints of all of its generating units may give a GENCO the "edge" over its competition.

Even what appears to be an insignificant constraint can quickly alter a GENCO's market strategies [45]. For example, the strategic use of ramp rates beyond elastic limits in generation dispatch has been investigated in [46], because they incur ramping costs and also widen the possible range of energy delivery. A detailed formulation to model the power trajectories followed by a thermal unit during start-up and shut-down processes, as well as the ramping limitations when increasing or decreasing power is reported in [47]. In [48] intertemporal decisions related with maintenance decisions are reported. In an electricity market with only a few major competing GENCOs, maintenance plays a critical role that goes beyond traditional least-cost analysis. We have implemented a rigorous formulation of the ramping constraints to analyze the effect of intertemporal constraints on a GENCO's decision-making process.

1.4 Objective

This dissertation supports generation asset business decisions, from fuel supply concerns to wholesale trading in energy and ancillary services. The forces influencing the value chain are changing rapidly, and can become highly controversial. Through this dissertation, the author proposes an integrated and objective perspective, providing a forum to identify and address common planning and operational needs.

The objective of this dissertation is to propose and develop theories and ideas that can be applied directly in algorithms to make GENCOs decisions more efficient. This will decompose the decision-making problem into independent subproblems for each time interval. This is preferred because building a complete model in one time is practically impossible. The diverse scope of this dissertation is unified by the importance of each topic to understanding or enhancing the profitability of generation assets. Studies of top strategic issues will assess directly the promise and limits to profitability of energy trading, the business risks represented by overbuilding and the logic of determining how much to spend on power plants. Studies of ancillary services will permit companies to realistically gauge the profitability of different services, and develop bidding strategies tuned to competitive markets.

1.5 Contributions

The algorithms and models developed and the conceptual ideas reported in this dissertation were useful in the preparation of the following conferences and journals articles

Published papers

Journal papers

1. G. Gutiérrez-Alcaraz, and G. B. Sheblé "Electricity Market Dynamics: Oligopolistic Competition," *Electric Power Systems Research,* Vol. 76, No. 9-10, pp. 695-700, June 2006.
2. G. Gutierrez-Alcaraz, "Sequential Time-Step Generation Companies Decisions in Oligopolistic Electricity Market," *Electric Power Systems Research,* Vol. 78, pp. 824-834, May 2008.

Conference papers

1. Guillermo Gutierrez, Gerald B. Sheblé, "Spot Fuel Markets' Influence on the Spot Electricity Market Using Leontief Model," *2003 IEEE Bologna Power Tech*, Bologna, Italia, June 2003
2. Guillermo Gutiérrez-Alcaraz, Gerald B. Sheblé, "I-O Model in the Energy Market: A GENCOs Perspective," *35th North American Power Symposium*, Rolla, Missouri, USA, October 2003.
3. Guillermo Gutiérrez-Alcaraz, Gerald B. Sheblé, "Real Option Data Requirements of Power System Data for Competitive Bidding," *37th International Conference on System and Sciences, HICSS-37*, Hawaii, USA, January 2004.
4. Guillermo Gutiérrez-Alcaraz, Gerald B. Sheblé, "Decentralized Electricity Market Price Dynamics," 2004 *General Meeting del IEEE Power Engineering Society*, Denver, Colorado, USA, June 2004.
5. Guillermo Gutiérrez-Alcaraz, Gerald B. Sheblé, "GenCo's Self-Scheduling: Real Option Approach," *36th North American Power Symposium*, Moscow Idaho, USA, August 2004.
6. Guillermo Gutiérrez-Alcaraz, Gerald B. Sheblé, "Electricity Market Price Dynamics: Markov Process Analysis," *8th International Conference on Probability Methods Applied to Power Systems (PMAPS)*, Ames, Iowa, USA, September 2004.
7. Guillermo Gutiérrez-Alcaraz, Gerald B. Sheblé, "GenCos' Participation in the Unbundled Energy Market," *2004 Power Systems Conference and Exposition (PSCE'04)*, New York, USA, October 2004.

8. Guillermo Gutiérrez-Alcaraz, Gerald B. Sheblé, "Operational Planning Constrained by Financial Requirements," *Electricity Transmission in Deregulated Markets: Challenges, Opportunities, and Necessary R&D Agenda*, Pittsburgh, USA, December 2004.
9. Gutierrez-Alcaraz and Gerald B. Sheblé, The Value of Technical Information in the Unbundled Electric Market, 10th International Conference on Probabilistic Methods Applied to Power Systems (PMAPS 2008), Puerto Rico, May 2008.

Accepted Journal Papers

10. Gutierrez-Alcaraz and Gerald B. Sheblé, "Modeling Energy Market Dynamics using Discrete Events System Simulation," accepted to be published at *Energy Journal*

CHAPTER 2 SPOT FUEL MARKET'S INFLUENCE ON THE SPOT ELECTRICITY MARKET USING LEONTIEF MODEL

A paper published in the 2003 IEEE Bologna PowerTech

Guillermo Gutiérrez, *Member, IEEE*, and Gerald B. Sheblé, *Fellow, IEEE*

Abstract

Nowadays, the new electric industry has segmented the vertically integrated utility into a horizontally integrated set of companies. This segmentation promotes competition in the different sectors (Generation, Transmission, and Distribution). However, generation presents the highest level of competitiveness. Generation is not only involved in selling power but also ancillary services. Prices of energy are directly related with prices in fuel such that any variation in fuel prices will be reflected in energy prices to consumers. Therefore, the operation of the electricity market is related with other markets, such as fuel markets, transportation markets, and environmental markets. This document presents an overview of fuel markets impact in the electricity spot market. Leontief energy model is used to model the interaction among the different markets in a more global viewpoint. The interaction of markets is analyzed by simulating an energy market with small number of participants.

Index Terms—Energy markets, electricity competition, electricity generation.

I. NOMENCLATURE

The main mathematical symbols used throughout this paper are classified below

x = vector of total output
M, A = nxn matrix of input/output coefficients
d = vector of final demand

I = identity matrix
y_t = vector of final deliveries
B = *nxn* matrix of nonnegative capital coefficients
h, k = 1, . . . , m regions
s = 1, . . . , r fossil fuel types
d_h = market demand for electricity in region h
f_{hs} = supply of fuel s in region h
t_{hks} = amount of fuel s sent from region h to region k.
c_{hks} = per unit shipping costs of sending fuel s from region h to region k.
w_{hk} = KWh of electricity sent from region h to region k
x_{hs} = amount of electricity for region h produced by burning fuel s
a_{hs} = amount of fuel s needed to produce one unit of electricity in region h.
b_{hs} = unit operating cost for producing electricity at region k from fuel s
g_{hk} = unit cost of power loss when sending energy (KWH) from region h to region k
X_{hs} = upper bound of x_{hs}

II. INTRODUCTION

Electric industry has segmented the vertically integrated utility into a horizontally integrated set of companies. Therefore, the production decisions are decentralized as well as consumption decisions, and are made in fact by each one of the independent utilities [1].

The operation of the electricity market is strongly related with other markets, such as fuel markets, transportation or environmental markets. Any decision of those markets will impact the electric energy market. Thus, for the analysis of the market interactions is necessary to understand energy market behavior. Partial equilibrium analysis is considered to understanding the market behavior itself, but it isolates markets, assuming that the changes in the equilibrium conditions in each market do not affect any of the other markets in the economy and that changes in other markets do not affect the market under consideration [2, 3].

With deregulation, the traditional plant merit-order base load generation is no longer guaranteed as such, because, now it is possible to have different fuel generation plants supplying base load demand according with fuel price variations and Generation Companies (GENCOs) marketing strategies. GENCOs must compete in a market environment where their decisions focus on activities over a month-to-month basis. The effort in such decisions is to manage effectively and efficiently the product flow in the strategically planned supply chain with uncertainties in both sides of the chain (inputs and outputs).

Nowadays, each GENCO has to contract fuel in a most optimal way that permits them to participate in the electricity market without incurring any negative profits. Thus GENCOs must build a portfolio of contracts for fuel purchases [4]. Controlling fuel cost, then, becomes the essential input variable for GENCOs strategies. It must be controlled in order not to swamp the revenues of the project over the time. Fuel costs must be flexible not only with regard to fuel input markets, but also with respect to power sale output markets. Operating a portfolio of fuel types GENCOs add more flexibility in generation. But, to build such portfolio requires taking into account all potential fuel contracts characteristics, transportation contracts, storage/consumption commodity and other services (uncertainty in inputs).

This paper presents an overview of the fuel markets externalities, embodied in fuel price variations, impacting the electricity spot market from GENCOs' perspective. The Leontief energy model is used to model the interaction among the different markets in a more global viewpoint. Porter's five forces bridge markets relationships in the Leontief model.

The rest of the paper is organized as follows: Section III describes briefly the Porter's five forces to evaluate the potential profit of an industry in the competitive environment and the role of Fuel substitutes on the electricity production and hence in the electricity market. Section IV presents the storage model. Static and Dynamic Leontief Model are presented in Section V. In section VI the Static Input-Output (I-O) Model applied to the energy market is described. Section VII presents examples of the interaction of Fuel markets with the power exchange electricity market. Conclusions are given in section VIII.

III. PORTER FIVE FORCES MODEL

In the new paradigm aggressiveness will depend on different factors such as number of competitors, competitor’s strategies, market substitutes, among others. Those factors are represented in the Porter’s five forces model [5, 6].

The Porter’s model brings the big picture to evaluate the potential profit of an industry in the competitive environment.

The five forces are:

1) Barriers to entry;
2) Rivalry among existing competitors;
3) Substitutes;
4) Power of Buyers;
5) Power of Suppliers.

Each of those five forces collectively impacts the potential profit and jointly determines the intensity of the industry competition and profitability. In order to analyze the specific activities through which firms can create a competitive advantage, it is useful to model the firm as a chain of value-creating strategies taking in consideration the five forces. The goal of these strategies is to create value that exceeds the cost of providing the product or service, thus generating a profit margin.

Clearly, there is a need for a mechanism through which these five forces can be integrated together. Supply chain management is a strategy through which such integration can be accomplished. The value chain describes the full range of required activities to bring a product or service from conception, through the intermediary phases of production, delivery to final consumers [7].

Figure 2.1 represents seller’s bids as a function of Porter’s forces in the electricity supply chain. Note that substitutes are present and they influence customer behavior. Buyer’s bids are also function of the five forces.

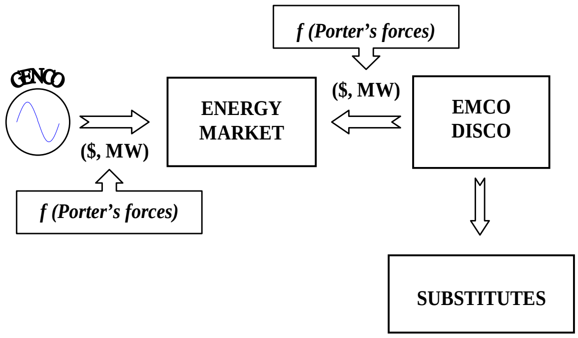

Figure 2.1 Seller and consumer bids as a function of Porter's forces in electricity supply chain

Market prices will drive GENCOs' decisions based on GENCOs' expectations. In a perfect competition dynamic market, supply-demand will stabilize prices helped on substitutes. Fuel price variations -substitutes- would modify expected GENCOs' strategies such as electricity price must be below the substitute prices, unless GENCO is involved in selling fuel. Under this condition, higher substitute prices, GENCOs face two different scenarios:

1. Market clearing price below GENCOs' price. When market clearing price is below GENCOs' own price, implies that GENCOs' are not delivering power since exits cheapest generators which impose the market clearing price. However, GENCOs will probably decide to continue generating (banking) given their expectations of demand behavior in the next hours as well as operational constraints such as minimum and maximum times up/down

2. Market Clearing Price above GENCOs' price. GENCOs are selling energy at a profit.

Fuel Spot prices change in time and new possible scenarios are likely to turn up. When prices of substitutes are below of the market price, substitutes will be used by consumers, such as natural gas for heating. Changes in electricity spot prices and other services, give real time value to each one of the services or product. We define this as real time option pricing.

In the energy market, auctions are used for finding the equilibrium price-quantity each trading period for the different products or services. Since each trading period is carried out in advance -24 hrs in the case of electricity- auctions have a component for the future value of each product.

During GENCOs participation and according with market behavior it is possible GENCOs make negative profits in several trading periods, however the whole expected profit should be positive. Figure 2.2 shows graphically the expected GENCOs' Cash Flow Diagram, CFD. Negative profits can occur when GENCOs were not committed for a trading period and it keep generating according with its expectative behavior of the market demand, input prices variation, and its best response strategy.

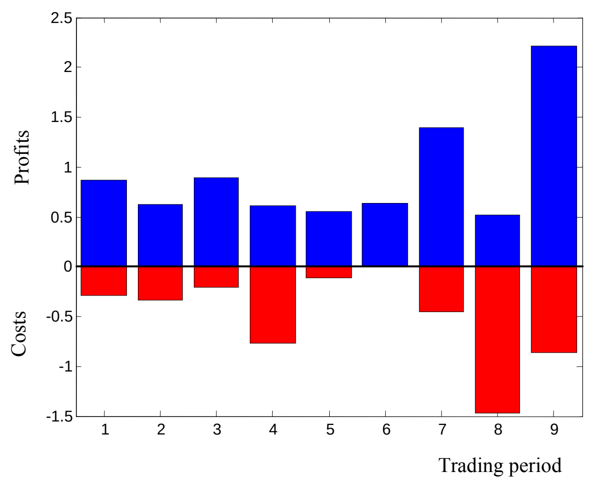

Figure 2.2 An example of GENCOs' Cash Flow Diagram

GENCOs will need to find a value for each of the products and services contributing to the economic profit every trading period. The estimation of economic benefits is difficult given the future uncertainty, but it is only necessary to estimate it with enough accuracy to justify future investments.

Strategic decisions, then, must integrate above mentioned aspects of the supply chain. Operational decisions address the day-to-day, month-to-month, operation of the supply chain where each product would contribute to total revenue. Strategic decision can be assisted by the use of financial markets. The ability to effectively manage price volatility through the financial market is important in determining the financial condition of market participants in the short term [8]. Price volatility is a key element of risk and therefore financial risk management.

IV. STORAGE MODEL

In a competitive commodity market subject to stochastic fluctuations in production and/or consumption, producers will hold inventories. Producers hold inventories in order to diminish costs of adjusting production over time. Industrial consumers of a commodity also hold inventories, to facilitate their own production processes. However, in the case of electricity, given that it cannot be stored, GENCOs will storage fuel (Oil, Coal, etc) for generating electricity [9].

With deregulation, electricity becomes more of a commodity-driven business. The Plant becomes a merchant plant -it must compete in a market environment month to month to sell its output. Therefore the GENCO will compare wholesale electric prices to wholesale fuel prices to determine whether to operate a gas fired electric power plant or sell its gas fuel in the wholesale market. Some of the time, fuel and electric prices move in a similar direction, but in some markets, nearly half of the time they move opposite directions. This allows for arbitrage of fuel and electric commodities in volatile markets. Therefore, GENCOs must decide whether to produce [10]. In this document we restricted our study to the electricity market.

The motives for storing fuel are similar to those for holding inventories. Those motives are: Transaction, Speculation and Precautionary Motives [11].

A Transaction motive bridges the gap between supply and demand since the time path of the commodity's demand may not be synchronized with time path of the commodity's supply.

The possibility to sell or use the commodity later than now, if prices are expected to increase over time is represented by speculative motive. Precautionary motive becomes more intense because the uncertainty on the demand, sales prices and supplies prices.

The use of storage plays an important role according with expected strategies of participants in each commodity market. The objective of the firm is to obtain the required amount of the commodity in such a way to minimize the difference between profits from speculation and the cost of obtaining the commodity for productive purposes. For instance, Natural Gas suppliers can speculate in the respective market, which may modify prices in other markets and consequently prices in electricity. The model in [11] is considered in our model.

In any other commodity market the firm can buy, sell, deliver or store the commodity. This applies for the case of fuel but not for electricity. Storage is considered in this document as part of GENCOs' decision variables and its effect is internalized in each period bids.

V. THE LEONTIEF MODEL

Wassily Leontief developed one of the most interesting theories in economics, the theory of input-output, I-O. This theory allows to represents the interdependencies among various productive sectors of an economy in which goods are produced in those industries by main of primary factor. A sector is an industry or group of industries. The desired result is the gross output needed to cover final and intermediate demands arising from other sectors given the final demand for the outputs of all sectors [11].

The interdependence among the sectors of the given economy can be described by a set of linear equations expressing the balances between the total input and the aggregate output of each commodity and service produced and used in the course of one or several periods of time [11, 12].

In our framework, the Leontief model is a spatial model of the flow of fuels to the generation utilities, and transmission and distribution of electricity. Unit fuel costs consist of the market price of the fuel at the point of delivery plus transportation costs. Depending upon its proximity to coal, gas pipelines, and oil distribution centers, each utility will choose a combination of activities for generating electricity that minimizes costs and allow them to diversify their energy services portfolio. Figure 2.3 represents a typical energy market structure.

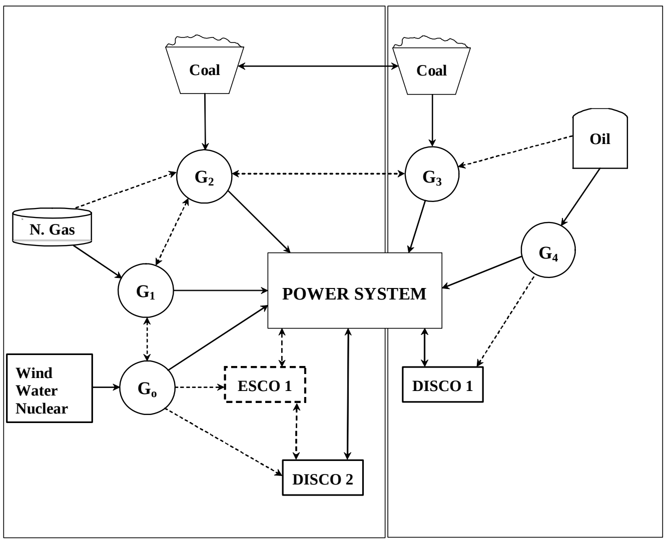

Figure 2.3 Representative structure integration of the industries in the energy market

A. Static I-O Model

The static I-O model is characterized for one stage on which everything is needed to produce everything. There exist applied problems, which, by their nature, are purely static.

This type of problem is one that involves the *state* of the economy and not process of change [11, 12].

The structure of each productive sector is represented by an appropriately defined vector of structural coefficients that describes quantitatively the relationship between the inputs from sector *i* required to support one unit of output of sector *j*, which can be expressed in matrix form as follows:

$$x = Mx + d \tag{1}$$

The equation (1) implies that internal demand plus final demand must be satisfied. Rearranging equation (1) yields:

$$\left(I - M\right)x = d \tag{2}$$

Assuming that $\left(I - M\right)^{-1}$ exists, then:

$$x = \left(I - M\right)^{-1} d \tag{3}$$

since $x \geq 0$ is required to yield economic interpretation, then $d \geq 0$ and $\left(I - M\right)^{-1} \geq 0$

The Leontief system is often used to compute the economic impact of a given change in final demand. The initial conditions and the stimulus are propagated through the economy as each producer places orders for changes in inputs. Note that total production must equal the sum of the final demands plus all intermediate stage demands, which can be represented as:

$$x = d + Md + M^2 d + M^3 d + \ldots \tag{4}$$

Comparing with the input-output relation above:

$$\left(I - M\right)^{-1} = I + M + M^2 + M^3 + \ldots \tag{5}$$

Notice the triple effect throughout the economy. Using the vector of prices, *p*, for the various products, equilibrium is found when:

$$p\left[\left(I - M\right)x - d\right] = 0 \tag{6}$$

B. Dynamic I-O Model

Dynamic I-O model derives from the static through consideration of rates of change over time of industry interdependences. Dynamic model reflects changes in time and take into account model components that are constantly changing as a result of previous actions or future expectations.

A primary distinction of a static model versus dynamic model is the scope of examining intra-period relationships. Dynamic economic modeling involves an understanding of how phenomena within an interval are related to activities outside the interval yet within the period of study [13].

$$\left(I - A\right)x_t - B\left(x_{t+1} - x_t\right) = y_t \tag{7}$$

It is assumed that there are none changes in technology such as coefficients of A and B matrices remain constant over time.

VI. STATIC I-O IN THE ENERGY MODEL

The production chain of the generation and delivery of electricity to consumers includes fuel transportation, generation, transmission and distribution of electricity through a transmission network. The optimization problem can be formulated mathematically as:

$$\text{Minimize} \quad \sum_{h=1}^{m}\sum_{s=1}^{r} b_{hs}x_{hs} + \sum_{h=1}^{m}\sum_{k=1}^{m} g_{hk}w_{hk} + \sum_{h=1}^{m}\sum_{k=1}^{m}\sum_{s=1}^{r} c_{hks}t_{hks}$$

$$\text{Subject to} \quad \sum_{s=1}^{r} x_{hs} + \sum_{k=1}^{m}\left(w_{kh} - w_{kh}\right) \geq d_h \tag{8}$$

$$a_{hs}x_{hs} - \sum_{k=1}^{m}\left(t_{khs} - t_{hks}\right) \leq f_{hs}$$

$$x_{hs} \leq X_{hs}$$

$$x_{hs},\, w_{hk},\, t_{hks} \geq 0$$

The objective function minimizes the production costs of each unit, the different fuel transportation costs, and transaction costs among participants. Transaction costs not necessarily refers to bilateral contracts of commodities but also financial. Constraints represent electricity balance, fuel balance, upper bounds, and minimum capability.

The model takes into consideration fuel networks, but transportation costs are bearing for final consumers in each market. Moreover, we assume that networks externalities are internalized in each market by means of commodity prices.

Since Leontief Model allows to representing intermediate products and services for the different sectors is possible to value each one of this products or services. The model can capture the revenue/cost for electricity production as well as Ancillary Services.

VII. ILLUSTRATIVE EXAMPLE

The following examples illustrate the impact of the fuel markets in the electricity market, by using the Leontief Model. The energy market is consisted of oil, coal, natural gas, and electricity markets for sake of simplicity.

In the electricity Market, 4 GENCOs compete for supplying the demand of 2 Distribution Companies, DISCOs (See Figure 2.3). GENCOs are participating in Power Exchange and their decisions are focused in level of production and time. For simplicity we assume that each GENCO produce energy base on one fuel type.

The trading period demand is 53 MWh. Table 2.1 shows the complementary information of the system and the optimal generation output. Since prices are imposed directly from fuel markets and transportation fuel cost in our model, GENCO 3 presents the larger production cost and hence its output is zero.

Table 2.1 Fuel type, fuel costs, capacity and optimal output generation

GENCO	Fuel	Cost M-$/M-KWh	Capacity (MW)	Output (MW)
1	N. Gas	280	22	22
2	Coal	310	25	25
3	Coal	420	20	0
4	Oil	380	30	6

Figure 2.4 represents the energy markets interaction in a matrix form. Fuel markets are linked trough GENCOs production to Electricity Market. In addition, given that our examples do not consider transactions among fuel markets and in order to make clear partial equilibrium, elements off the diagonal are displayed as zero in Figure 2.4.

Oil Market			
	Coal Market		
		Natural Gas Market	
			Electricity Market

Figure 2.4 Seller Energy market structure in matrix representation

The next section presents an extensive example of the previous one; we will extend our study for 32 (every 15 minutes) trading periods. The demand pattern is depicted in Figure 2.5.

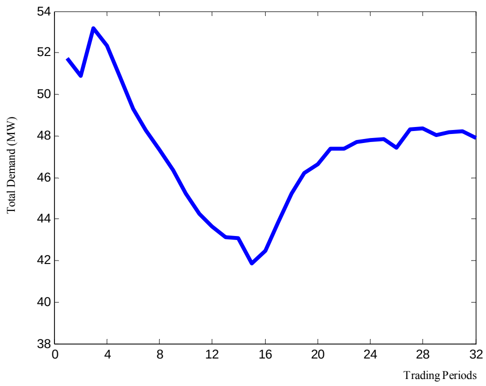

Figure 2.5 Demand pattern

Figure 2.6 shows the fuel prices. Fuel prices are considered to be settled hourly.

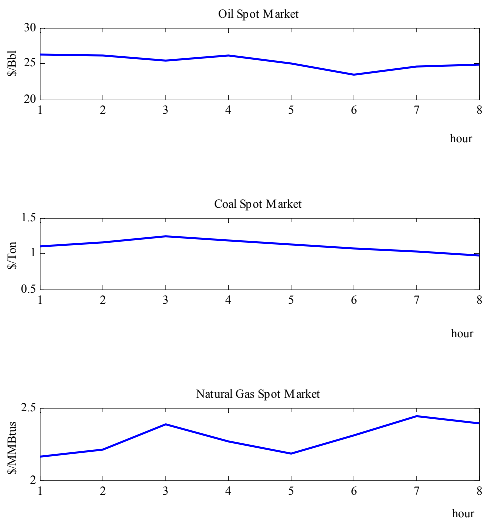

Figure 2.6 Fuel spot prices

From Figure 2.6 we can observe how fuel prices are correlated. Prices of Oil and Coal are negatively correlated, prices of Oil and Natural Gas are positively correlated and prices of Coal and Natural Gas are negatively correlated.

Variation in fuel spot prices will reach the electricity market almost instantaneously, since storability of fuel has been neglected, and therefore this would modify GENCOs' strategies in the very short run.

Figure 2.7 presents the generation output for the 32 trading periods. We can observe how output changes when fuel prices change. For instance, GENCO 4 resulted to be the cheapest and therefore produces during the 32 periods. It happens because GENCO 4 presents the lower production costs even when input prices vary. However, this is not the case for the others. Given that GENCO 2 and 3 uses coal as input their behavior is positively correlated. GENCO 2 has lower production cost that GENCO 3, and hence GENCO 3 produces after GENCO 2 reaches its maximum limit. It occurs during the last 8 periods.

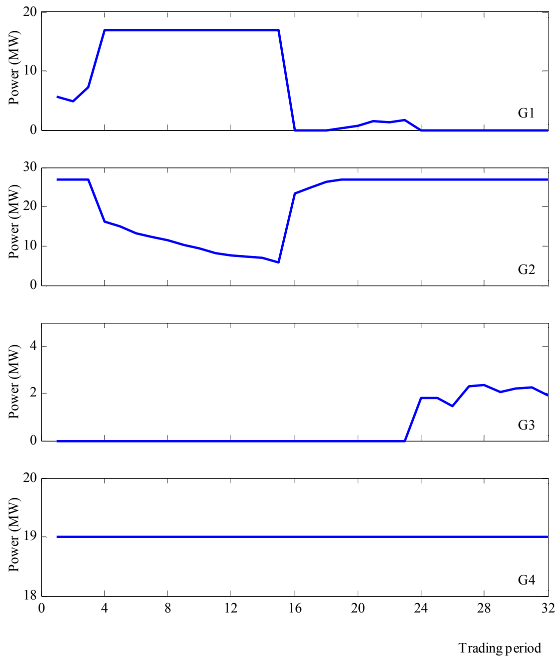

Figure 2.7 Generation outputs

During periods 4 and 18 prices in coal increases whereas prices in Natural Gas decreases –negatively correlated. As consequence of these price variations, GENCO1 produces its maximum power and GENCO 2 supplies the remaining demand. Throughout periods 19 to 24 GENCO 1 produces small amount of power due to fuel prices variations -at that time results the marginal unit.

The analysis allows us to observe the impact of fuel prices in the GENCOs' strategies for participating in the electricity spot market. In our model we consider that unit commitment, UC, is part of GENCOs' own strategies and GENCOs are participating to supply the market demand, this is a decentralized market structure.

The next example illustrates the effect of storage in the electricity market. The storage of electricity is economically impractical; therefore storage has to be done in terms of fuel. The example considers 3 periods and the 4 GENCOs compete for demand in the market. This analysis considered initial storage and none final volume restriction. Each GENCO has a maximum capacity of 40 MWs. Table 2.2 reports the information used in this simulation.

Table 2.2 Fuel prices and demand for the 3 periods

Time Period	Oil ($/bbl)	Coal ($/ton)	Natural Gas ($/MMBTUs)	Demand (MW)
1	26.21	1.10	2.164	120
2	26.16	1.16	2.210	150
3	25.45	1.24	2.383	80

Assuming fuel prices settled daily, the solution is presented in Table 2.3. Whereas Table 2.4 presents results assuming fuel prices settled hourly.

Table 2.3 Powers at each period (period = 1day)

Time Period	GENCO 1 (MW)	GENCO 2 (MW)	GENCO 3 (MW)	GENCO 4 (MW)
1	40	40	40	0
2	40	40	40	30
3	40	0	40	0

Table 2.4 Powers at each period (period = 1hr)

Time Period	GENCO 1 (MW)	GENCO 2 (MW)	GENCO 3 (MW)	GENCO 4 (MW)
1	40	40	40	0
2	30	40	40	40
3	0	40	0	40

From tables 2.3 and 2.4, we can observe how prices affect GENCOs' production. The use of storage provides flexibility for producing electricity. But, the use of storage is usually driven in contrary directions by reliability and economic considerations. Reliability recommends high storage capacity, whereas economics suggest low inventories, since inventories represents an investment of capital.

Until now, we considered GENCOs produce based on a single sort of fuel and they just participate producing/selling electricity. However, in order to survive in the competitive market GENCOs must to diversify their energy production, based on fuel portfolio. Hence our analysis can be trap as a company consisting of 4 units with a diversified fuel portfolio. Moreover, GENCOs would be able to participating selling fuel. Figure 2.8 represent GENCOs' I-O market participation. Electricity Market can be consisted of Power Exchange as well as several ancillary services.

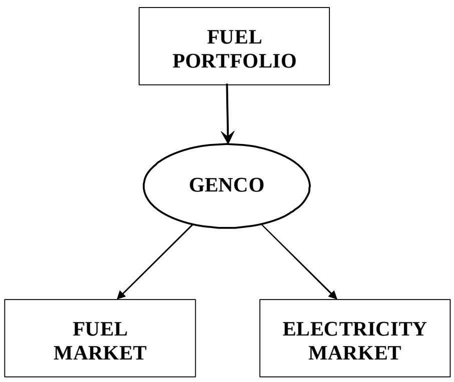

Figure 2.8 GENCOs' I-O market participation

VIII. CONCLUSIONS

This paper addresses market interactions in the electricity supply chain by means of I-O model. Partial equilibrium is considered for each market and its integration is represented by prices which embodied independent externalities. Hence, the constraints imposed in the electricity market by the other markets would influence the collapse of the Electricity Market. Evidently, it is important to define the markets to be included and why they are included.

Nowadays, electricity markets have been decomposed into several markets, for instance, Power Exchange and Ancillary Services market. Our discussion has been focused just in the Power Exchange market, but ancillary services are provided such the power system allows the transactions committed in the market. GENCOs will need to find a value for each of the ancillary services which contribute to the economic profit every trading period.

GENCOs' best marketing strategy is not only based on outputs but also on inputs, where both are driven by markets forces. The expected profit is the contribution of the several products of services in where GENCOs are participating and this has to be positive. However, it is possible that GENCOs incurs in negative profits during trading periods. However the net expected profit should be positive. The estimation of the future cash stream is difficult given the future uncertainty, but it is only necessary to estimate it with enough accuracy to justify future investments. Future Cash Flow can be estimated by using I-O model given that it allows to representing and valuating intermediate products and services for the different sectors.

In the examples presented we considered static conditions for each interval. Therefore, the use of static conditions as well as partial equilibrium permit us to observe the big picture of the interrelation markets in the production chain of the generation and delivery of electricity to final consumers by using Leontief model.

IX. ACKOWLEDGMENT

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X. REFERENCES

[1] Gerald B. Sheblé, *Computational Auction Mechanisms for Restructured Power Industry Operation*, Kluwer Academic Publisher, 1999.

[2] Brian R. Binger and Elizabeth Hoffman, *Microeconomics with Calculus*, Harper Collins Publishers, 1998.

[3] Eugene Silberberg and Wing Suen, *The Structure of Economics: A mathematical Analysis*, Irwin McGraw Hill.

[4] Jean-Michel Guldmann, Fahui Wang, "Optimizing the natural gas supply mix of local distribution utilities," *European Journal of Operational Research*, pp. 598-612.

[5] Michael E. Porter, *Competitive Strategy: Techniques for Analyzing Industries and Competitors*, Free Press 1998.

[6] Henk de Swaan Arons and Philip Waalewinjn, "A knowledge Base Representing Porter's Five Forces Model," *Proceedings CIMCA'99*, Viena 1999.

[7] Hau L. Lee, Corey Billington, "Material management in decentralized supply chains," *Operations Research* Vol. 41, Issue 5, Sept.–Oct., 1993. pp. 835-847.

[8] Robert S. Pindyck, The Dynamics of Commodity Spot and Futures Markets: A Primer, Massachusetts Institute of Technology, Cambridge, May 16, 2001.

[9] Jeffrey C. Williams and Brian D. Wright, *Storage and commodity markets*, Cambridge University Press, 1991.

[10] Gerald B. Sheblé, "Decision Analysis Tools for GENCO Dispatchers," *Trans. on Power Systems*, Vol. 14 No 2, May 1999. pp. 745-749.

[11] Gerald L. Thompson and Sten Thore, *Computational Economics: Economic Modeling with Optimization Software*, The Scientific Press Series, 1992.

[12] Robert Doftman, Paul A. Samuelson, and Robert M. Solow, *Linear Programming and Economic Analysis*.

[13] Heinz D. Kurz and Neri Salvadori, "The Dynamic Leontief Model and the Theory of Endogenous Growth," *Twelfth International Conference on Input-Output Techniques*, New York, 18-22 May 1998.

[14] Thomas Gloria, "An Approach to Dynamic Environmental Life-Cycle Assessment by Evaluating Structural Economic Sequences," Ph.D. Thesis, TUFTS University, May 2000.

CHAPTER 3 MODELING ENERGY MARKET DYNAMICS USING DISCRETE EVENTS SYSTEM SIMULATION

A paper submitted in the International Journal of Energy

G. Gutiérrez-Alcaraz, and Gerald B. Sheblé

3.1 Abstract

This paper proposes the use of Discrete Event System Simulation to study the interactions among fuel and electricity markets and consumers, and the decision-making processes of fuel companies (FUELCOs), generation companies (GENCOs), and consumers in a simple artificial energy market. In reality, since markets can reach a stable equilibrium or fail, it is important to observe how they behave in a dynamic framework. We consider a Nash-Cournot model in which marketers are depicted as Nash-Cournot players that determine supply to meet end-use consumption. Detailed engineering considerations such as transportation network flows are omitted, because the focus is upon the selection and use of appropriate market models to provide answers to policy questions.

Index Terms—Cournot model, energy market modelling, market dynamics

3.2 Introduction

The electricity industry operates by means of a supply chain that extends from generating station to end-users. Each link in the chain is crucial to the chain's integrity. Actors at each level, organized as markets, make decisions that have ramifications throughout the chain. The quality of any given decision depends on the quality of the knowledge available to the decision-maker. As a result, the dissemination of accurate information is critical if the supply chain is to operate effectively [1][2]. Conventional optimization techniques are no longer adequate to answer important questions about the stability and dynamic evolution of each supply chain activity because the behavior of each market participant is unknown.

In recent years, the total number of available energy models has grown tremendously and the models themselves vary considerably. The question arises about how to select the model most suited to a specific purpose. A classification scheme will provide insights about the differences and similarities, thus facilitating the selection of the appropriate methodology [27]. Several models have been developed for policy analysis, forecasting, and to support global or local energy planning in an effort to better understand the interplay between the macro-economy and energy use. Generally, these models focus on a long-term planning horizon and their underlying methodology is based on macro-economic approaches and market equilibrium models.

In general, the energy market has been studied separately because liberalization of the different markets (i.e. natural gas, coal, oil, etc) has occurred sequentially. Consequently, the markets present varying levels of maturity. Methodologies and tools developed for these previously liberalized markets are being applied to today's electricity market. Market models for natural gas are numerous and varied. GRIDNET is a detailed model of the North American natural gas system but from the gas transactions and operational perspective [28]. The Gas Systems Analysis Model (GSAM) is another North American natural gas market model with a very detailed supply side representation consisting of over 17,000 production reservoirs with about 200 variables each. The Natural Gas Transmission and Distribution Module (NGTDM) simulates market equilibrium prices, flows, and quantities using a heuristic algorithm; previous versions of NGTDM used a linear programming formulation for computing market equilibria [29]. These models provided detailed level analyses based on a competitive market assumption and cover many aspects of the North American system.

Energy models have been developed to support local energy planning and recently to observe the effects of interdependencies in the case of terrorist attacks [3][4][5]. However, analyses to date have focused mainly on the interrelation between the energy sector and the larger economy over time. A useful example is the computer-based National Energy Modeling System (NEMS) in the United States that models energy markets driven by the fundamental economic interactions of supply and demand [6]. Additional large-scale energy models include Electricity Markets Complex Adaptive Systems (EMCAS) and Energy and Power Evaluation Program (ENPEP) [7][8]. EMCAS is an agent-based modeling system used to simulate various market operating rules [7], while ENPEP is a set of integrated energy, environmental, and economic analysis and planning tools [8]. A supply chain network perspective for electric power production, supply, transmission, and consumption is presented in [9]. Various decision-makers operating in a decentralized manner such as generation companies, transmission companies and market consumers are modeled. A novel electric power supply chain network model with fuel supply markets that captures both the economic network transactions in energy supply chains and the physical network transmission constraints in the electric power network is reported in [30]. The theoretical derivation and analyses use the theory of variational inequalities. In [10] the authors present market integration and agent participation in a multiple-market framework using the Leontief model. Static conditions for each interval and partial equilibrium analysis are considered. [11] shows how to replace the inter-industry component of the Leontief model by a few surrogate constraints corresponding to the industries associated with the sector of interest.

A generalized network flow model of a national, integrated energy system that incorporates production, storage, and transportation of coal, natural gas, and electricity in a single mathematical framework for a medium-term analysis has been reported in [12][13]. The model focuses on the economic interdependencies of the integrated system along with a detailed characterization of their functionalities (supply, demand, storage, and transportation) within a single analytical framework that allows for their simultaneous study.

This paper provides a dynamic model to study the interactions among fuel and electricity markets and consumers, and the decision-making processes of fuel companies (FUELCOs), generation companies (GENCOs), and consumers in a simple artificial energy market. We construct a simple artificial energy market to: (1) maintain tractability; (2) obtain theoretical results; and (3) develop intuitions about economic complexity. We assume the existence of hourly spot electricity and fuel markets where few producers compete to supply markets demand. The problem is formulated using Discrete Event System Simulation (DESS), also known as discrete control theory. DESS differs from agent-based computational simulation methods such as Multiagent Resource Allocation (MARA) in that time is represented in discrete quanta or units called *ticks*. Participant behaviors that occur within a tick are reported in aggregate as a tick-final state. The aggregation of behaviors across ticks decreases the elevated importance of individualistic participant traits that confound agent-based simulations when environments with few participants are examined. With DESS, it is possible to retain a focus on select variables or participant behaviors and these behaviors are seen to vary smoothly with time [14][15]. In our model, decision-makers, FUELCOs and GENCOs, utilize adaptive expectations to forecast their competitors' actions [16]. When companies are willing to make trade-offs between present and future profits, it is critical to incorporate learning strategies in the decision-making. For example, GENCO *i* may understand so little about its rival's past actions and the underlying rationales that GENCO *i* comes to believe ("static assumption") and accept that the circumstances it observes in the immediate past will repeat themselves. Adaptive expectations posit that future values may be calculated on the basis of previous values.

The paper is organized as follows: Section II describes the energy market supply chain and the role of information in the new market environment. Section III describes the energy market model considered in the development of its mathematical formulation. In Section IV, a case study is used to present our model using numerical data. Section V details a sensitivity analysis and Section VI discusses computational issues. Section VII offers conclusions and suggestions for future research.

3.3 Energy Market Supply Chain

Energy models generally tend towards an economic equilibrium between consuming and producing sectors: Raw materials flow in one direction; orders and money in the other; and the flow of information in both directions. These flows of capital, raw materials, and information link the individual components of the system to form a supply chain.

In today's liberalized markets where it is possible that end-users can also be suppliers, information and commodities can flow in both directions as shown in Figure 3.1.

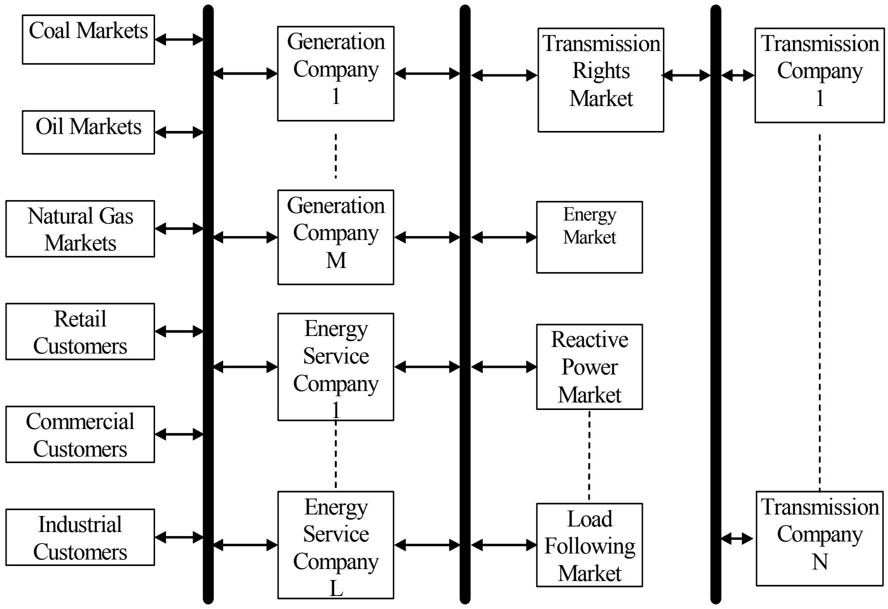

Figure 3.1 Schematic information flowing in the electricity supply chain

The new electricity markets allow consumers to sell power back to the market through contractual agreements that are usually components of demand-side management programs. Although some utilities are wary of demand-side programs that may affect revenue, in most cases, both the short- and long-term savings from demand-side programs outweigh costs.

3.4 Energy Model

Dynamic simulations allow the researcher to observe system changes over time so that s/he may understand how the system is likely to evolve, predict probable future system behaviors, and determine how to influence probable future behaviors [17][18].

This section describes the dynamic model developed to study the interactions between two FUELCOs, two GENCOs, and an aggregated consumer within the following markets: (1) A fuel market for GENCOs, and (2) an electricity market and (3) a fuel market for consumers (Figure 3.2 below). Time is considered to be discrete [19]. In the discrete form, system state space model is:

$$X(k+1) = A(k)X(k) + B(k)U(k)$$
$$Y(k) = C(k)X(k) + D(k)U(k) \tag{1}$$

Where k is the time period index, $X(k)$ is the vector of state variables, $U(k)$ is the vector of input variables, $Y(k)$ is the vector of output variables and A, B, C, D are system matrices function of k [14].

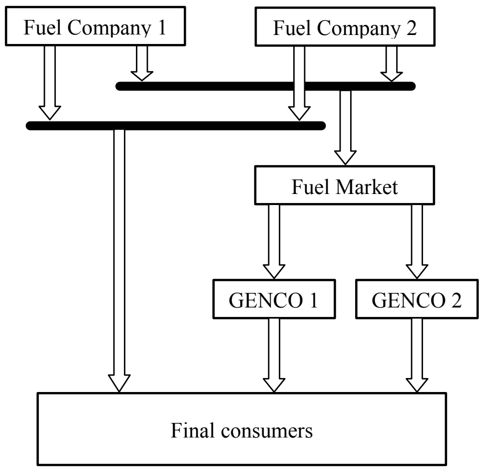

Figure 3.2 An energy market system

A. Consumer decision-making

The consumer wants to minimize the total cost of energy:

$$\underset{\{q^{fc}, q^{ec}\}}{Min} \ P^{fc}q^{fc} + P^{ec}q^{ec} \tag{2a}$$

$$s.\ to \ \ h^{ec}q^{ec} + h^{fc}q^{fc} \geq Heat \tag{2b}$$

$$q^{ec} \geq Q^{ec}_{\min} \tag{2c}$$

$$q^{fc} \geq Q^{fc}_{\min} \tag{2d}$$

where P^{fc} is the price in the consumer fuel market, q^{fc} is the fuel quantity the consumer purchased, P^{ec} is the price in the consumer electric market, and q^{ec} is the electricity quantity the consumer purchased, h^{fc} is the heat coefficient of fuel, h^{ec} is the heat coefficient of electricity, Heat is the minimum amount of heat the consumer needs, $Q^{ec}_{\min}$ is the minimum requirement for electricity, and $Q^{fc}_{\min}$ is the minimum requirement for fuel. Consumption of fuel and electricity depends on fuel and electricity prices. The substitution effect of fuel and electricity is included.

B. FUELCOs' decision-making

The two FUELCOs want to maximize total profit in both the fuel and consumer fuel markets:

$$\underset{\{q^{fc},q^{f}\}}{Max}\ \pi_i^f(k) = P^{fc}(k)q_i^{fc}(k) + P^f(k)q_i^f(k) - FC\left[q_i^{fc}(k) + q_i^f(k)\right] \tag{3}$$

where P^f is the inverse demand function in the fuel market, q_i^f is the fuel quantity in the fuel market, and *FC* is the fuel production cost function. The FUELCOs' decisions are based on their estimates of each other's actions in both markets. We assume that both GENCOs know the inverse demand function. Consider that P^{fc} is a linear final-consumers fuel market-demand function given by $P^{fc}(k) = a^{fc} - b^{fc}\left(Q^{fc}(k)\right)$ where $Q^{fc}(k) = \left(q_i^{fc}(k) + \hat{q}_j^{fc}(k)\right)$, a^{fc}, b^{fc} are fuel market consumers' demand parameters, and $\hat{q}_j^{fc}(k)$ is fuel consumer *i's* estimate of fuel consumer *j's* output at period *k*. Similarly for the fuel market, $P^f\left((k)\right) = a^f - b^f\left(Q^f(k)\right)$, where $Q^f(k) = q_i^f(k) + \hat{q}_j^f(k)$, a^f, b^f are fuel market demand parameters, and $\hat{q}_j^f(k)$ is FUELCO *i's* estimate of FUELCO *j's* output at period *k*.

When the fuel production function is linear, the fuel market and consumer fuel market are decoupled.

$$\underset{\{q^{fc},q^{f}\}}{Max}\,\pi_i^f(k)=\left[a^{fc}-b^{fc}\left(q_i^{fc}(k)+\hat{q}_j^{fc}(k)\right)\right]q_i^{fc}(k)+\left[a^{f}-b^{f}\left(q_i^{f}(k)+\hat{q}_j^{f}(k)\right)\right]q_i^{f}(k) \\ -FC\left[q_i^{fc}(k)+q_i^{f}(k)\right] \tag{4}$$

Assuming that the fuel production is quadratic, the fuel market and consumer fuel market are coupled:

$$\underset{\{q^{fc},q^{f}\}}{Max}\,\pi_i^f(k)=\left[a^{fc}-b^{fc}\left(q_i^{fc}(k)+\hat{q}_j^{fc}(k)\right)\right]q_i^{fc}(k)+\left[a^{f}-b^{f}\left(q_i^{f}(k)+\hat{q}_j^{f}(k)\right)\right]q_i^{f}(k) \\ -c_{f0}-c_{f1}\left[q_i^{f}(k)+q_i^{fc}(k)\right]-c_{f2}\left[q_i^{f}(k)+q_i^{fc}(k)\right]^2 \tag{5}$$

where c_{f0}, c_{f1}, c_{f2} are coefficients of the production cost function

According to the first order condition, we have:

$$\frac{\partial\pi_i^f(k)}{\partial q_i^f(k)}=a^f-2b^fq_i^f(k)-b^f\hat{q}_j^f(k)-c_{f1}-2c_{f2}\left[q_i^f(k)+q_i^{fc}(k)\right]=0 \tag{6}$$

$$\frac{\partial\pi_i^f(k)}{\partial q_i^{fc}(k)}=a^{fc}-2b^{fc}q_i^{fc}(k)-b^{fc}\hat{q}_j^{fc}(k)-c_{f1}-2c_{f2}\left[q_i^f(k)+q_i^{fc}(k)\right]=0 \tag{7}$$

Therefore, the FUELCOs will employ adaptive expectation and effective forecasting techniques to help them to learn from the past and to make more “profitable” decisions [20][21]. Under adaptive expectation, the FUELCOs adjust the output expectation of their competitors according to each competitor’s output and the forecasting error in the last period. As an example, when FUELCO *i* adopts adaptive expectation in two markets, it yields:

$$\hat{q}_j^f(k) = \hat{q}_j^f(k-1) + \beta_j^f\left(q_j^f(k-1) - \hat{q}_j^f(k-1)\right) \tag{8}$$

$$\hat{q}_j^{fc}(k) = \hat{q}_j^{fc}(k-1) + \beta_j^{fc}\left(q_j^{fc}(k-1) - \hat{q}_j^{fc}(k-1)\right) \tag{9}$$

Where β is adjusting coefficient and $\beta \in [0,1]$.

By substituting these expectations into the profit, we can obtain the optimal fuel output in two markets for FUELCO *i*:

$$\begin{aligned}\frac{\partial \pi_i^f(k)}{\partial q_i^f(k)} = a^f &- 2b^f q_i^f(k) - b^f \hat{q}_j^f(k-1) - b^f \beta_j^f q_j^f(k-1) \\ &+ b^f \beta_j^f \hat{q}_j^f(k-1) - c_{f1} - 2c_{f2}\left[q_i^f(k) + q_i^{fc}(k)\right] = 0\end{aligned} \tag{10}$$

$$\begin{aligned}\frac{\partial \pi_i^f(k)}{\partial q_i^{fc}(k)} = a^{fc} &- 2b^{fc} q_i^{fc}(k) - b^{fc} \hat{q}_j^{fc}(k-1) - b^{fc} \beta_j^{fc} q_j^{fc}(k-1) \\ &+ b^{fc} \beta_j^{fc} \hat{q}_j^{fc}(k-1) - c_{f1} - 2c_{f2}\left[q_i^f(k) + q_i^{fc}(k)\right] = 0\end{aligned} \tag{11}$$

Simplifying previous equations (see appendix A for details), we can now express them as:

$$q_i^f(k) = s_i^{f0} + s_i^{f1} q_j^f(k-1) + s_i^{f2}\hat{q}_j^f(k-1) + s_i^{f3} q_i^{fc}(k) + s_i^{f4}\hat{q}_i^{fc}(k) \tag{12}$$

$$q_i^{fc}(k) = s_i^{fc0} + s_i^{fc1} q_i^f(k) + s_i^{fc2}\hat{q}_i^f(k) + s_i^{fc3} q_j^{fc}(k-1) + s_i^{fc4}\hat{q}_j^{fc}(k-1) \tag{13}$$

Where $s_{if0}, s_{icf0}, s_{if1}, s_{icf1}, s_{if2}, s_{icf2}, s_{if3}, s_{icf3}, s_{if4}$, and s_{icf4} are constants determined by fuel production cost function, fuel market demand, consumer fuel market demand, and expectation parameters.

The fuel markets for GENCOs and for consumers are represented in matrix form (equations 8, 9, 10 and 13) by the following system state space equations:

$$\begin{bmatrix} q_{f1}(k+1) \\ q_{fc1}(k+1) \\ q_{f2}(k+1) \\ q_{fc2}(k+1) \\ \hat{q}_{f1}(k+1) \\ \hat{q}_{fc1}(k+1) \\ \hat{q}_{f2}(k+1) \\ \hat{q}_{fc2}(k+1) \end{bmatrix} = \begin{bmatrix} 0 & 0 & s_{1f3} & s_{1f1} & 0 & s_{1f4} & s_{1f2} & 0 \\ s_{1cf1} & 0 & 0 & s_{1cf3} & s_{1cf2} & 0 & 0 & s_{1cf4} \\ s_{2f1} & 0 & 0 & s_{2f3} & s_{2f2} & 0 & 0 & s_{2f4} \\ 0 & s_{2cf3} & s_{2cf1} & 0 & s_{2cf2} & s_{2cf4} & 0 & 0 \\ \beta_{f1} & 0 & 0 & 0 & 1-\beta_{f1} & 0 & 0 & 0 \\ 0 & \beta_{fc1} & 0 & 0 & 0 & 1-\beta_{fc1} & 0 & 0 \\ 0 & 0 & \beta_{f2} & 0 & 0 & 0 & 1-\beta_{f2} & 0 \\ 0 & 0 & 0 & \beta_{fc2} & 0 & 0 & 0 & 1-\beta_{fc2} \end{bmatrix} \begin{bmatrix} q_{f1}(k) \\ q_{fc1}(k) \\ q_{f2}(k) \\ q_{fc2}(k) \\ \hat{q}_{f1}(k) \\ \hat{q}_{fc1}(k) \\ \hat{q}_{f2}(k) \\ \hat{q}_{fc2}(k) \end{bmatrix} + \begin{bmatrix} s_{1f0} \\ s_{1cf0} \\ s_{2f0} \\ s_{2cf0} \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

$$\begin{bmatrix} p_f(k) \\ p_{fc}(k) \end{bmatrix} = \begin{bmatrix} -b_f & 0 & -b_f & 0 & \vline & [0] \\ 0 & -b_{fc} & 0 & -b_{fc} & \vline & \end{bmatrix} \begin{bmatrix} q_{f1}(k) \\ q_{fc1}(k) \\ q_{f2}(k) \\ q_{fc2}(k) \\ \hat{q}_{f1}(k) \\ \hat{q}_{fc1}(k) \\ \hat{q}_{f2}(k) \\ \hat{q}_{fc2}(k) \end{bmatrix} \quad (14)$$

C. GENCOs decision-making

The GENCOs' objective is to maximize profits. Assuming a linear electricity market-demand function given by $P^e(k) = a^e - b^e\left(Q^e(k)\right)$ where $Q^e(k) = q_i^e(k) + \hat{q}_j^e(k)$, a^e, b^e are electricity market demand parameters, the profit of GENCO i is:

$$\underset{\{q_i^e\}}{Max}\ \pi_i^g(k) = P^e(k)q_i^e(k) - c_{ei1}q_i^e(k) - c_{ei0} \tag{15}$$

Assuming the GENCOs use adaptive expectations to estimate their competitor's actions [20] and according to the first order condition, we have

$$q_i^e(k+1) = \frac{a^e - c_{ei1}}{2b^e} - \frac{1}{2}\hat{q}_j^e(k) \tag{17}$$

Where $\hat{q}_{ej}(k) = \hat{q}_{ej}(k) + \beta_j\left(q_{ej}(k) - \hat{q}_{ej}(k)\right)$. Substituting in (16), reduces it to:

$$q_i^e(k+1) = \frac{a^e - c_{ei1}}{2b^e} - \frac{\beta_j^e}{2}q_j^e(k) - \frac{1-\beta_j^e}{2}\hat{q}_j^e(k) \tag{17}$$

To describe GENCOs' decision dynamics with adaptive expectation, choose $q_{e1}(k), q_{e2}(k), \hat{q}_{e1}(k)$, and $\hat{q}_{e2}(k)$ as state variables and market price as the output. The electricity market can then be represented by the following system (16)-(17). In the discrete-time linear system we have:

$$\begin{bmatrix} q_{e1}(k+1) \\ \hat{q}_{e1}(k+1) \\ q_{e2}(k+1) \\ \hat{q}_{e2}(k+1) \end{bmatrix} = \begin{bmatrix} 0 & 0 & -\beta_2/2 & (\beta_2-1)/2 \\ \beta_1 & 1-\beta_1 & 0 & 0 \\ -\beta_1/2 & (\beta_1-1)/2 & 0 & 0 \\ 0 & 0 & \beta_2 & 1-\beta_2 \end{bmatrix} \begin{bmatrix} q_{e1}(k) \\ \hat{q}_{e1}(k) \\ q_{e2}(k) \\ \hat{q}_{e2}(k) \end{bmatrix} + \begin{bmatrix} \frac{a_e - c_{e11}}{2b_e} \\ 0 \\ \frac{a_e - c_{e21}}{2b_e} \\ 0 \end{bmatrix}$$

$$p_e(k) = \begin{bmatrix} -b_e & 0 & -b_e & 0 \end{bmatrix} \begin{bmatrix} q_{e1}(k) \\ \hat{q}_{e1}(k) \\ q_{e2}(k) \\ \hat{q}_{e2}(k) \end{bmatrix} + a_e \tag{18}$$

Since fuel price is a function of the fuel output of both companies in the fuel market, and it changes production cost for the GENCOs, it is a critical factor in GENCOs' decision-making; therefore production cost for both GENCOs can be represented as:

$$\mathrm{cost}_i = c'_{ei1} p^{fc} q_i^e(k) - c'_{ei0} p^{fc}. \tag{19}$$

Next, we assume that the fuel price, for GENCOs, is given and is constant during their profit maximizing problem. Thus, we need only to modify the cost coefficient of the GENCOs' production costs in the electricity market. The second term in the previous system is modified as:

$$\begin{bmatrix} \dfrac{a^e - c'_{e11}\left[a^f - b^f\left(q_1^f(k) - q_2^f(k)\right)\right]}{2b^e} \\ 0 \\ \dfrac{a^e - c'_{e12}\left[a^f - b^f\left(q_1^f(k) - q_2^f(k)\right)\right]}{2b^e} \\ 0 \end{bmatrix} \tag{20}$$

We note that although fuel market outputs and electric market inputs are related, they are not necessarily equal because fuels such as gas and coal can be stored efficiently. Therefore, the total inventory of fuel is introduced as:

$$q_{inv}^{f}\left(k+1\right)=q_{1}^{f}\left(k\right)+q_{2}^{f}\left(k\right)-h_{1}q_{1}^{e}\left(k\right)-h_{2}q_{2}^{e}\left(k\right)+q_{inv}^{f}\left(k\right) \tag{21}$$

where h_1 and h_2 are the heat rates of GENCO1 and GENCO2, and q_{inv}^{f} is the quantity in inventory.

D. Energy market model

We can obtain the energy market system model by incorporating the consumer decision model, the fuel market model, and the electricity market model. The state variables are $q_1^e\left(k\right)$, $q_2^e\left(k\right)$, $q_1^f\left(k\right)$, $q_1^{fc}\left(k\right)$, $q_2^f\left(k\right)$, $q_2^{fc}\left(k\right)$, $\hat{q}_1^e\left(k\right)$, $\hat{q}_2^e\left(k\right)$, $\hat{q}_1^f\left(k\right)$, $\hat{q}_1^{fc}\left(k\right)$, $\hat{q}_2^f\left(k\right)$, $\hat{q}_2^{fc}\left(k\right)$, and $\hat{q}_{inv}^f\left(k\right)$. The energy market system can then be represented by the state space equations 22:

$$\begin{bmatrix} q_1^e(k+1) \\ q_2^e(k+1) \\ q_1^f(k+1) \\ q_1^{fc}(k+1) \\ q_2^f(k+1) \\ q_2^{fc}(k+1) \\ \hat{q}_1^e(k+1) \\ \hat{q}_2^e(k+1) \\ \hat{q}_1^f(k+1) \\ \hat{q}_1^{fc}(k+1) \\ \hat{q}_2^f(k+1) \\ \hat{q}_2^{fc}(k+1) \\ q_{inv}^f(k+1) \end{bmatrix} = \begin{bmatrix} 0 & -\beta_2/2 & 0 & 0 & 0 & 0 & 0 & (\beta_2-1)/2 & 0 & 0 & 0 & 0 & 0 \\ -\beta_1/2 & 0 & 0 & 0 & 0 & 0 & (\beta_1-1)/2 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & s_{1f3} & s_{1f1} & 0 & 0 & 0 & 0 & s_{1f4} & s_{1f2} & 0 & 0 \\ 0 & 0 & s_{1cf1} & 0 & 0 & s_{1cf3} & 0 & 0 & s_{1cf2} & 0 & 0 & s_{1cf4} & 0 \\ 0 & 0 & s_{2f1} & 0 & 0 & s_{2f3} & 0 & 0 & s_{2f2} & 0 & 0 & s_{2f4} & 0 \\ 0 & 0 & 0 & s_{2cf3} & s_{2cf1} & 0 & 0 & 0 & 0 & s_{2cf4} & s_{2cf2} & 0 & 0 \\ \beta_1 & 0 & 0 & 0 & 0 & 0 & 1-\beta_1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \beta_2 & 0 & 0 & 0 & 0 & 0 & 1-\beta_2 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \beta_1^f & 0 & 0 & 0 & 0 & 0 & 1-\beta_1^f & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \beta_1^{fc} & 0 & 0 & 0 & 0 & 0 & 1-\beta_1^{fc} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \beta_2^f & 0 & 0 & 0 & 0 & 0 & 1-\beta_2^f & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \beta_2^{fc} & 0 & 0 & 0 & 0 & 0 & 1-\beta_2^{fc} & 0 \\ -h_1 & -h_2 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} q_1^e(k) \\ q_2^e(k) \\ q_1^f(k) \\ q_1^{fc}(k) \\ q_2^f(k) \\ q_2^{fc}(k) \\ \hat{q}_1^e(k) \\ \hat{q}_2^e(k) \\ \hat{q}_1^f(k) \\ \hat{q}_1^{fc}(k) \\ \hat{q}_2^f(k) \\ \hat{q}_2^{fc}(k) \\ q_{inv}^f(k) \end{bmatrix} + \begin{bmatrix} \frac{a^e-c_{e11}}{2b^e} \\ \frac{a^e-c_{e21}}{2b^e} \\ s_{10} \\ s_{1c0} \\ s_{20} \\ s_{2c0} \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

$$
\begin{bmatrix} P^{e}(k) \\ P^{f}(k) \\ P^{fc}(k) \end{bmatrix} = \left[\begin{array}{cccccc|c} -b^{e} & -b^{e} & 0 & 0 & 0 & 0 & \\ 0 & 0 & -b^{f} & 0 & -b^{f} & 0 & [0] \\ 0 & 0 & 0 & -b^{fc} & 0 & -b^{fc} & \end{array}\right] \begin{bmatrix} q_e^1(k) \\ q_e^2(k) \\ q_1^f(k) \\ q_1^{fc}(k) \\ q_2^f(k) \\ q_2^{fc}(k) \\ \hat{q}_1^e(k) \\ \hat{q}_2^e(k) \\ \hat{q}_1^f(k) \\ \hat{q}_1^{fc}(k) \\ \hat{q}_2^f(k) \\ \hat{q}_2^{fc}(k) \\ q_{inv}^f(k) \end{bmatrix} + \begin{bmatrix} a^{e} \\ a^{f} \\ a^{fc} \end{bmatrix} \tag{22}
$$

Using the energy market system models developed above, assists us in more effectively study and analysis of overall market performance and the interactions among market participants.

E. N-FUELCOS and N-GENCOS Case

In the previous sections we have developed the energy market equations for a specific number of players (2 GENCOS and 2 FUELCOS). In this section we generalize the expressions for .N number of FUELCOs and N number of GENCOs.

N FUELCOs

Recalling that FUELCOs want to maximize total profit from fuel and consumer fuel markets, then the profit of the FUELCO *i* at period *k* is equal to its revenue minus its production cost; mathematically its optimization problem can be formulated as:

$$
\underset{\{q^{fc},q^{f}\}}{Max}\ \pi_i^f(k) = P^{fc}(k)q_i^{fc}(k) + P^{f}(k)q_i^{f}(k) - FC\left[q_i^{fc}(k) + q_i^{f}(k)\right] \tag{23}
$$

Substituting P^{fc} , P^{f} and FC we have:

$$\underset{\{q^{fc},q^{f}\}}{Max}\,\pi_i^f\left(k\right)=\left[a^{fc}-b^{fc}\left(q_i^{fc}\left(k\right)+\sum_{\substack{j=1\\ i\neq j}}^{N}\hat{q}_j^{fc}\left(k\right)\right)\right]q_i^{fc}\left(k\right)+\left[a^{f}-b^{f}\left(q_i^{f}\left(k\right)+\sum_{\substack{j=1\\ i\neq j}}^{N}\hat{q}_j^{f}\left(k\right)\right)\right]q_i^{f}\left(k\right)$$
$$-c_{f0}-c_{f1}\left[q_i^f\left(k\right)+q_i^{fc}\left(k\right)\right]-c_{f2}\left[q_i^f\left(k\right)+q_i^{fc}\left(k\right)\right]^2 \quad (24)$$

Where $Q^{fc}\left(k\right)=q_i^{fc}\left(k\right)+\sum_{\substack{j=1\\ i\neq j}}^{N}\hat{q}_j^{fc}\left(k\right)$ and $Q^{fc}\left(k\right)=q_i^{f}\left(k\right)+\sum_{\substack{j=1\\ i\neq j}}^{N}\hat{q}_j^{f}\left(k\right)$

According to the first order condition, we have:

$$\frac{\partial\pi_i^f\left(k\right)}{\partial q_i^f\left(k\right)}=a^f-2b^f q_i^f\left(k\right)-b^f\sum_{\substack{j=1\\ i\notin j}}^{N}\hat{q}_j^f\left(k\right)-c_{f1}-2c_{f2}\left[q_i^f\left(k\right)+q_i^{fc}\left(k\right)\right]=0 \quad (25)$$

$$\frac{\partial\pi_i^f\left(k\right)}{\partial q_i^{fc}\left(k\right)}=a^{fc}-2b^{fc} q_i^{fc}\left(k\right)-b^{fc}\sum_{\substack{j=1\\ i\notin j}}^{N}\hat{q}_j^{fc}\left(k\right)-c_{f1}-2c_{f2}\left[q_i^f\left(k\right)+q_i^{fc}\left(k\right)\right]=0 \quad (26)$$

$$\hat{q}_j^f\left(k\right)=\hat{q}_j^f\left(k-1\right)+\beta_j^f\left(q_j^f\left(k-1\right)-\hat{q}_j^f\left(k-1\right)\right) \quad (27)$$

$$\hat{q}_j^{fc}\left(k\right)=\hat{q}_j^{fc}\left(k-1\right)+\beta_j^{fc}\left(q_j^{fc}\left(k-1\right)-\hat{q}_j^{fc}\left(k-1\right)\right) \quad (28)$$

Substituting (27) and (28) into (25) and (26) yields:

$$\frac{\partial\pi_i^f\left(k\right)}{\partial q_i^f\left(k\right)}=a^f-2b^f q_i^f\left(k\right)-b^f\sum_{\substack{j=1\\ i\notin j}}^{N}\hat{q}_j^f\left(k-1\right)-b^f\sum_{\substack{j=1\\ i\notin j}}^{N}\beta_j^f q_j^f\left(k-1\right)$$
$$+b^f\sum_{\substack{j=1\\ i\notin j}}^{N}\beta_j^f\hat{q}_j^f\left(k-1\right)-c_{f1}-2c_{f2}\left[q_i^f\left(k\right)+q_i^{fc}\left(k\right)\right]=0 \quad (29)$$

$$\frac{\partial \pi_i^f(k)}{\partial q_i^{fc}(k)} = a^{fc} - 2b^{fc} q_i^{fc}(k) - b^{fc} \sum_{\substack{j=1 \\ i \notin j}}^{N} \hat{q}_j^{fc}(k-1) - b^{fc} \sum_{\substack{j=1 \\ i \notin j}}^{N} \beta_j^{fc} q_j^{fc}(k-1)$$
$$+ b^{fc} \sum_{\substack{j=1 \\ i \notin j}}^{N} \beta_j^{fc} \hat{q}_j^{fc}(k-1) - c_{f1} - 2c_{f2}\left[q_i^f(k) + q_i^{fc}(k)\right] = 0 \tag{30}$$

Simplifying previous equations, we can now express them as:

$$q_i^f(k) = s_i^{f0} + \sum_{\substack{j=1 \\ i \notin j}}^{N} s_i^{f1} q_j^f(k-1) + \sum_{\substack{j=1 \\ i \notin j}}^{N} s_i^{f2} \hat{q}_j^f(k-1) + s_i^{f3} q_i^{fc}(k) + s_i^{f4} \hat{q}_i^{fc}(k) \tag{31}$$

$$q_i^{fc}(k) = s_i^{fc0} + s_i^{fc1} q_i^f(k) + s_i^{fc2} \hat{q}_i^f(k) + \sum_{\substack{j=1 \\ i \notin j}}^{N} s_i^{fc3} q_j^{fc}(k-1) + \sum_{\substack{j=1 \\ i \notin j}}^{N} s_i^{fc4} \hat{q}_j^{fc}(k-1) \tag{32}$$

N GENCOs

The profit of the GENCO i, at period k, is defined as:

$$Max\ \pi_i^g(k) = P^e(k) q_i^e(k) - c_{ei1} q_i^e(k) - c_{ei0} \tag{33}$$

Assuming the GENCOs use adaptive expectations to estimate their competitor's actions [20] and according to the first order condition, we have

$$q_i^e(k+1) = \frac{a^e - c_{ei1}}{2b^e} - \frac{1}{2} \sum_{\substack{j=1 \\ i \notin j}}^{N} \hat{q}_j^e(k) \tag{34}$$

where $\hat{q}_j^e(k) = \hat{q}_j^e(k) + \beta_j^e\left(q_j^e(k) - \hat{q}_j^e(k)\right)$. Substituting in (34), reduces it to:

$$q_i^e(k+1) = \frac{a^e - c_{ei1}}{2b^e} - \frac{1}{2} \sum_{\substack{j=1 \\ i \notin j}}^{N} \beta_j^e q_j^e(k) - \frac{1}{2} \sum_{\substack{j=1 \\ i \notin j}}^{N} \left(1 - \beta_j^e\right) \hat{q}_j^e(k) \tag{35}$$

$$q_{inv}^{f}\left(k+1\right)=\sum_{j=1}^{N}q_{j}^{f}\left(k\right)-\sum_{j=1}^{N}h_{j}q_{j}^{e}\left(k\right)+q_{inv}^{f}\left(k\right) \tag{36}$$

3.5 Case Study

This section presents numerical examples from our model.

Consider that demand in fuel market is given by $P^f = 6 - Q^f$ while demand in electric market is $P^e = 10 - Q^e$. Demand in consumer fuel market is $P^{fc} = 5 - Q^{fc}$. Production cost for fuel companies is $C_i^f = 0.6\left(q_i^f\right)^2 + 3q_i^f + 2$; the production cost for both GENCOs is $C_i^e = 3q_i^e + 2$. The demand data has been taken from references [24, 25] and modified. All of the companies utilize adaptive expectations with $\beta = 0.9$. The heat rate for GENCOs is assumed as 0.2 (To simplify this discussion, we omitted delivery costs, transportation costs, etc.)

The price dynamics in fuel market, consumer fuel market and electricity market shown in Figure. 3.3 represents the necessary adjustments between players and markets. We can observe that the system market is stable from an economic and physics perspective. In economic terms, equilibrium refers to market equilibrium, i.e. the equality of supply and demand, whereas in physics it describes a system's resting state.

We can observe that all three markets experience different dynamic transition processes (nevertheless, all are stable once the equilibrium price-quantity is reached and consumers do not change preferences in consumption). The highest market's price is the price of electricity and the lowest market's price is the price for fuel consumers. Table I presents the equilibrium for each market.

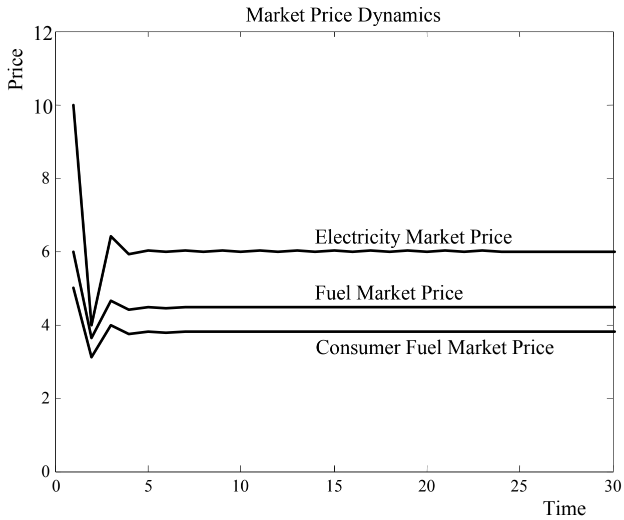

Figure 3.3 Energy market price dynamics

TABLE I

MARKET EQUILIBRIUM

MARKET	PRICE	QUANTITY
ELECTRICITY	6.0000 ($/MWh)	4.0000 MW
FUEL	4.4567 ($/MWh)	1.8760
FUEL CONSUMERS	3.7901 ($/MWh)	1.2098

The model provides unique market equilibria for each market considered rather than unique individual consumer solutions. As noted previously, since consumers are considered in aggregate. They are taken into account at the aggregate level in the market equilibrium solutions.

Market quantity summarizes the combined contributions of each participant by market. Given the parameters for this simulation (same production costs for each participant within each market type, same β for all participants, two participants per market), the contribution of each participant is half of the market quantity.

In the next scenario, we consider the case in which the (1) fuel market and (2) aggregate consumer fuel demand are similar. The new equilibrium for each market is shown in Figure 3.4. We observe that the market clearing prices converge slightly faster.

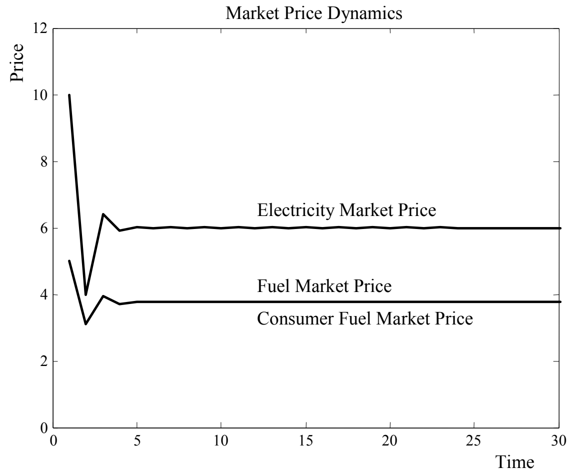

Figure 3.4 Energy market price dynamics with similar curves in the fuel and fuel consumers markets

Table II presents the new equilibrium for each market.

TABLE II

MARKET EQUILIBRIUM

MARKET	PRICE	QUANTITY
ELECTRICITY	6.0000 (\$/MWh)	4.0000 MW
FUEL	3.7654 (\$/MWh)	1.234566
FUEL CONSUMERS	3.7654 (\$/MWh)	1.234566

We observe that the electricity market price is the same as in the previous case. The market prices of fuel and fuel consumers are equal but different with respect to the previous case because the similar market demand curves are considered for both markets. No changes to the other parameters were made; therefore, each participant contributes half of the total market quantity to their respective market (e.g. each FUELCO contributes half of the total fuel market quantity).

The next case considers a simplified large market with 18 GENCOS. For illustrative purposes only the electricity market has been modified. The market demand parameters are given in Table III.

TABLE III

DEMAND PARAMETERS

PARAMETERS	ELECTRICITY	FUEL	CONSUMER
a^e	10		
b^e	0.1		
a^f		5	
b^f		1	
a^{fc}			8
b^{fc}			1

The production cost for each GENCOs is $C_i^e = 4q_i^e + 2$. All of the companies utilize adaptive expectations with $\beta = 0.2$. The heat rate for GENCOs is assumed as 0.3. Markets price dynamics are reported graphically in Figure 3.5 and numerically in Table IV.

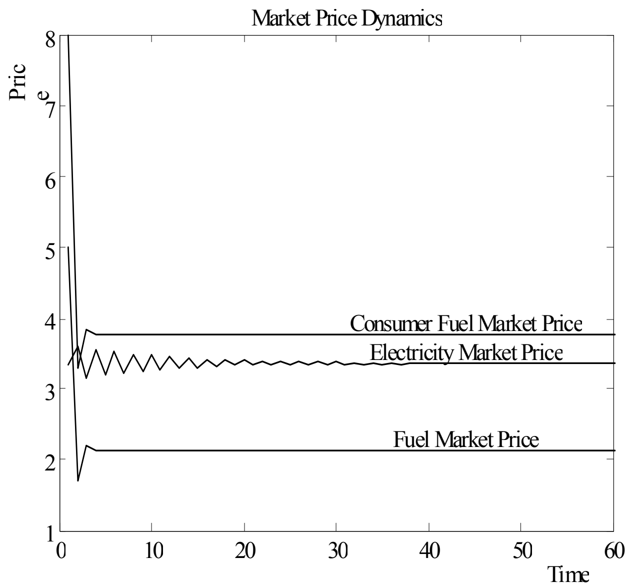

Figure 3.5 Energy market price dynamics: 18 GENCOs with similar cost curves

TABLE IV

MARKET EQUILIBRIUM: 18 GENCOS WITH SIMILAR COST CURVES

MARKET	PRICE	QUANTITY
ELECTRICITY	3.3684 ($/MWh)	66.6 MW
FUEL	2.1311 ($/unit)	1.6 units
FUEL CONSUMERS	3.7675 ($/unit)	4.2 units

Next, we assume that production costs are different from GENCO to GENCO. The production cost data, shown in Table V, is used arbitrarily for illustrative purposes.

TABLE V

GENCOS' COST DATA

	GENCO																	
Parameters	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
c_{ei1}	3.10	2.75	3.20	2.90	2.80	3.33	3.30	2.70	3.15	3.23	2.96	3.06	3.19	2.88	2.94	3.07	2.79	2.93
c_{ei0}	5	6	5	7	4	6	4	3	5	5	6	5	7	4	6	4	3	5

Markets price dynamics are reported graphically in Figure 3.6 and numerically in Table VI.

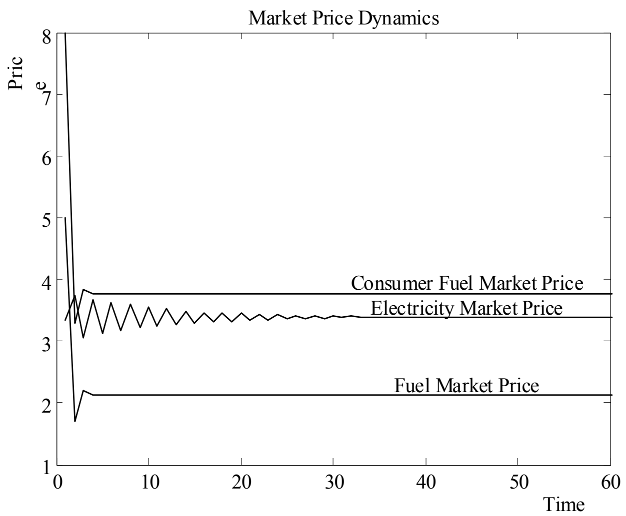

Figure 3.6 Energy market price dynamics: 18 GENCOs with different cost curves

TABLE VI

MARKET EQUILIBRIUM: 18 GENCOS WITH DIFFERENT COST CURVES

MARKET	PRICE	QUANTITY
ELECTRICITY	3.3831 ($/MWh)	65.6 MW
FUEL	2.1311 ($/unit)	1.6 units
FUEL CONSUMERS	3.7675 ($/unit)	4.2 units

The GENCOs' outputs are reported numerically in Table VII.

There is a unique price for each market but the quantities produced for each GENCO and FUELCO differ, given that their production costs differ. For instance, GENCO's 8 output is 6.80 MW and GENCO's 6 output is 0.5 MW because GENCO 8 has the lowest production costs whereas GENCO 6 has the highest production cost. FUELCO market quantities do not change because market demand remains constant (similarly for consumers).

TABLE VII

GENCOS' OUTPUTS

		Quantity (MW)
GENCO	1	2.80
	2	6.30
	3	1.80
	4	4.80
	5	5.80
	6	0.50
	7	0.80
	8	6.80
	9	2.30
	10	1.50
	11	4.20
	12	3.20
	13	1.90
	14	5.00
	15	4.40
	16	3.10
	17	5.90
	18	4.50

3.6 Parameter Dependency

A different choice of parameters will influence market outcomes. Market equilibrium depends on all system parameters except fixed cost, i.e. c_{ei0} parameters. For β values close to zero we observe less frequent oscillatory behavior in market equilibrium. Additionally, as long as β increases, the market price decreases in all markets and consequently, market quantity decreases. The traditional Cournot equilibrium is achieved when both coefficients are 1. Any other combination of adjusting coefficients will fall between monopoly and Cournot models, and eventually one GENCO will act as leader in the market.

For explanatory purposes we consider the case of an electricity market with two GENCOs. The intersection of the two reaction functions, equation (17), determines the market equilibrium in the Cournot model. This equilibrium represents a Nash equilibrium if each GENCO believes the other will not change output regardless of what its competitor does.

Figure 3.7 portrays the reaction functions for the two GENCOs in a specific period. Here we observe that the classic Cournot outcome is achieved when both adjusting coefficients are set to 1, point A. Monopoly occurs when one of the adjusting coefficients is set to 1 and the other is equal to zero, whereas the Bertrand outcome, perfect competition, is achieved when the adjusting coefficients are set to 0, point B.

This analysis is extended to the other markets.

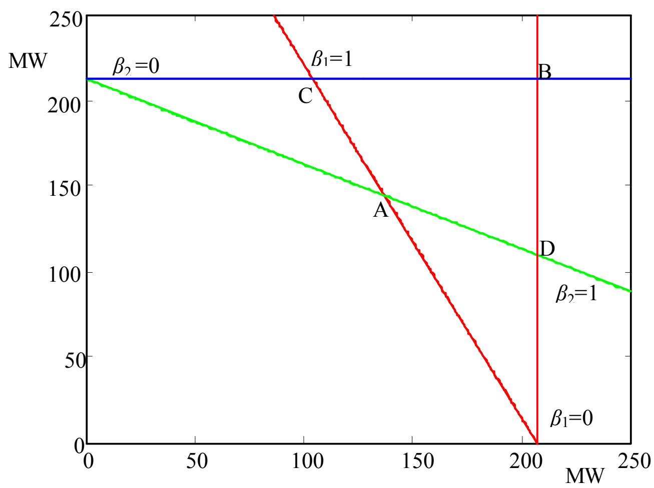

Figure 3.7 Equilibrium market factible region

We note that storage does not affect market dynamics. Heat rates have direct impacts on inventory. As long as the combination of both heat rates increases, storage is more "negative" because storage in our model is only a balance equation in the entire energy market. Hence, the model does not guarantee that storage will be zero in the long-term. In the real world, however, storage will influence GENCOs' decision-making, and therefore must be integrated in their optimization problem.

In reality, markets can reach a stable equilibrium or fail. Market stability can also be affected by participants' behavior. High demand produces higher prices, but spikes are also due to congestion/reliability issues. Nonetheless, since we are assuming the existence of hourly spot trading markets, the reliability aspect, transmission and transportation network contingency, is not reflected immediately. This aspect also may make the markets unstable.

To prove stability we apply Greshgoring theorem to the A matrix. According to the theorem, every eigenvalue of a matrix lies in a circle centered at diagonal elements a_{ii} with radius of $R_i = \sum_{\substack{j=1 \\ j \neq i}}^{n} \left| a_{ij} \right|$. The radius is calculated as:

$$R_i = \sum_{\substack{j=1 \\ j \neq i}}^{n} \left| a_{ij} \right| < 1$$

Therefore the eigenvalues lie in a circle centered at a_{ii} with a radius less than one. This area is a subset of the unit, circle. Hence the system is stable.

3.7 Computational issues

The energy model is currently prototyped as a Matlab® code using DLSIM routine to solve the discrete state space system. The energy market simulation is solved on a Pentium 4, 2.8 MHz with 512 MB of RAM. The solution time is 3 s for both simulations reported in Tables I and II. Since the energy market formulation is a representation of a linear set of equations [22], we use it to validate our model. Both models reach the same solution in all cases reported; however, using a linear set of equations model results in much less computational effort given that the dynamic model requires a time domain simulation. Time simulation needs to be specified as part or input data. Additionally we use a modified model reported in [25] for validating the two market segments, electricity and fuel markets.

The dimension of a large energy model is not trivial [24]. Similar problems exist when the dynamic model becomes larger [23]. The application of decomposition methods, sparsity techniques, and parallel processing should be the subject of future research efforts.

The estimation of the adaptive expectations coefficients is a separate problem. Several approaches can be used to estimate each parameter for each market player, e.g., data mining, neural nets, and forecasting.

3.8 Conclusions and future research

In this paper, we have proposed a dynamic game-theoretic energy model based on Discrete Event System Simulation that can be used to study general market behaviors and dynamics. Our energy market consists of fuel, electricity, and consumer fuel markets.

In the proposed model, decision-makers (electricity producers and consumers) utilized adaptive expectations to forecast their competitors' actions. A valuable extension of this work would include consideration of other decision-making behaviors such as naïve, forward expectations, forward adaptive expectations, and adaptive moving average.

The model also assumes that GENCOs understand the inverse demand function, and that when they do not know the actual demand function, they will estimate it. The effects on their expectations can be included in the demand function, but are beyond the scope of this paper.

Using DESS to model the markets provides unique market information, such as market stability, achievability of equilibrium, and dynamic transition processes. We suggest that incorporating the findings of a DESS approach can improve market design, market monitoring, and assist in defining appropriate market control schemes.

The model presented omits some constraints that would be considered in production-level simulation. Constraints such as transmission limits on each market network and upper limits in generating unit companies will be reported in future publications.

3.9 References

[1] de Kok A.G. and Graves S.C.. Handbooks in Operations Research and Management Science, Supply Chain Management: Design, Coordination and Operation. Elsevier, 2004.

[2] Lee H. L., Billington C. Material Management in Decentralized Supply Chains. Operations Research 1993; 41(5):835-847.

[3] Rinaldi S. M. Modeling and Simulating Critical Infrastructures and Their Interdependencies. In: Proceedings of the 37th Hawaii International Conference on System Sciences HICSS, 2004.

[4] Lev B. Energy Models and Studies. North-Holland Publishing Company, 1983.

[5] Hafkamp W.A. Economic-Environmental Modelling in a National-Regional System. North Holland Publishing Company, 1984.

[6] The National Energy Modeling System: An Overview 2003, Energy Information Administration Office of Integrated Analysis and Forecasting. See also: http://www.eia.doe.gov/oiaf/aeo/overview/index.html

[7] EMCAS, Center for Energy, Environmental, and Economic Systems Analysis, Argonne National Laboratory, Argonne, Illinois. See also: http://www.dis.anl.gov/CEEESA/EMCAS.html

[8] ENPEP, Center for Energy, Environmental, and Economic Systems Analysis, Argonne National Laboratory, Argonne, Illinois. See also: http://www.dis.anl.gov/CEEESA/ENPEPwin.html

[9] Nagurney A., and Matsypura D. A Supply Chain Network Perspective for Electric Power Generation, Supply, Transmission, and Consumption. In: Proceedings of the International Conference in Computing, Communications and Control Technologies, Austin, Texas, vol. VI, p.127-134.

[10] Gutierrez-Alcaraz G., Sheblé G.B. Spot Fuel Markets' Influence on the Spot Electricity Market Using Leontief Model. In: Proceedings of the 2003 IEEE Bologna Power Tech, Bologna Italy, June 2003.

[11] Dantzing G. B. On the Reduction of an Integrated Energy and Interindustry Model to a Smaller Linear Program. The Review of Economics and Statistics, 58(2): 248-250.

[12] Quelhas, A.; Gil, E.; McCalley, J. D.; Ryan, S. M.A. Multiperiod Generalized Network Flow Model of the U.S. Integrated Energy System: Part I—Model Description. IEEE Trans. On Power Systems 2007; 22(2):829 – 836.

[13] Quelhas, A.; McCalley, J. D.A Multiperiod Generalized Network Flow Model of the U.S. Integrated Energy System: Part II—Simulation Results. IEEE Trans. On Power Systems 2007; 22(2): 837 – 844.

[14] Banks J., Carson J., Nelson B., and Nicol D. Discrete-event System Simulation. Prentice Hall, 2005.

[15] Garrido J. M. Object-oriented Discrete event Simulation with Java: A Practical Introduction. Kluwer, 2001

[16] Yang W. Short-term electric market dynamics and generation company decision-making in new deregulated environment. Ph.D. dissertation, Dept. Elec. Eng., Iowa State University, 2003.

[17] Bather, J. Decision Theory: An Introduction to Dynamics Programming and Sequential Decisions. Wiley, 2000.

[18] Basar T. A Dynamic Games Approach to Controller Design: Disturbance Rejection in Discrete-time. IEEE Trans. on Automatic Control 1991; 36(8): 936–952.

[19] Chen C. Linear System Theory and Design. Oxford University Press, 1998.

[20] Sterman J. D. Business dynamics: systems thinking and modeling for a complex world. McGraw-Hill, 2000.

[21] Makridakis S., Andersen A., Carbone R., Fildes R., Hibon M., Lewandowski R., Newton J., Parzen E., Winkler R. The Forecasting accuracy of major time series methods. New York: Wiley, 1984

[22] Soto-Reyes L., Gutierrez-Alcaraz G. Energy Market Model Competition: A Discrete Event System Simulation Equivalent, 2007 IEEE Power Engineering Society General Meeting, Tampa, Florida, USA, June 2007.

[23] Tovar C., Multiperiod Energy Market Competition, B.S. thesis (in progress), Instituto Tecnologico de Morelia.

[24] Steven A. G., Jifang Z., Supat K. A large-scale complementary model of the North American natural gas market, Energy Economics 2005; 27:639 – 665.

[25] Gerald L. T., Sten T. Computational Economics: Economic Modeling with Optimization Software, The Scientific Press Series, 1992.

[26] Matlab R2007b, The MathWorks, Inc, Sept. 2007. USA.

[27] Nicole van Beeck. Classification of Energy Models, Research Memorandum 777, Tilburg University, Faculty of Economics and Business Administration.

[28] Brooks R. E. Optimizing Complex Natural Gas Models. http://rbac.com/Articles/OptimizingComplexNaturalGasModels/tabid/66/Default.aspx

[29] Gabriel A. S., Kydes A. S.., Whitman P. The National Energy Modeling System: A Large-Scale Energy-Economic Equilibrium Model, Operations Research, Vol. 49, No. 1, January-February 2001, pp. 14-25

[30] Matsypura D., Anna Nagurney A., Liu Z. Modeling of Electric Power Supply Chain Networks with Fuel Suppliers via Variational Inequalities, *International Journal of Emerging Electric Power Systems*, Vol. 8, No. 1, Article 5. http://www.bepress.com/ijeeps/vol8/iss1/art5.

Appendix A

This appendix details the coefficient *k*'s for expressions (12) and (13)

Recalling (10)

$$q_{fi}(k) = \frac{a_f - b_f \hat{q}_{fj}(k-1) - b_f \beta_{fj} q_{fj}(k-1) + b_f \beta_{fj} \hat{q}_{fj}(k-1) - c_{f1} - 2c_{f2} q_{fci}(k)}{2\left(b_f + 2c_{f2}\right)}$$

Hence

$$q_{fi}\left(k\right)=s_{if0}+s_{if1}q_{fj}\left(k-1\right)+s_{if2}\hat{q}_{fj}\left(k-1\right)+s_{if3}q_{fci}\left(k\right)+s_{if4}\hat{q}_{fci}\left(k\right)$$

Where $s_{if0}=\dfrac{a_f-c_{f1}}{2\left(b_f+c_{f2}\right)}$; $s_{if1}=\dfrac{-b_f\beta_{fj}}{2\left(b_f+c_{f2}\right)}$; $s_{if2}=\dfrac{b_f\left(\beta_{fj}-1\right)}{2\left(b_f+c_{f2}\right)}$; $s_{if3}=\dfrac{-2c_{f2}}{2\left(b_f+c_{f2}\right)}$; $s_{if4}=0$

From (11)

$$2\left(b_{fc}+c_{f2}\right)q_{fci}\left(k\right)=a_{fc}-b_{fc}\hat{q}_{fcj}\left(k-1\right)-b_{fc}\beta_{fcj}q_{fcj}\left(k-1\right)+b_{fc}\beta_{fcj}\hat{q}_{fcj}\left(k-1\right)-c_{f1}-2c_{f2}q_{fi}\left(k\right)$$

$$q_{fci}\left(k\right)=\frac{a_{fc}-b_{fc}\hat{q}_{fcj}\left(k-1\right)-b_{fc}\beta_{fcj}q_{fcj}\left(k-1\right)+b_{fc}\beta_{fcj}\hat{q}_{fcj}\left(k-1\right)-c_{f1}-2c_{f2}q_{fi}\left(k\right)}{2\left(b_{fc}+c_{f2}\right)}$$

Hence

$$q_{fci}\left(k\right)=s_{icf0}+s_{icf1}q_{fi}\left(k\right)+s_{icf2}\hat{q}_{fi}\left(k\right)+s_{icf3}q_{fcj}\left(k-1\right)+s_{icf4}\hat{q}_{fcj}\left(k-1\right)$$

Where $s_{icfo}=\dfrac{a_{fc}-c_{f1}}{2\left(b_{fc}+c_{f2}\right)}$; $s_{icf1}=\dfrac{-2c_{f2}}{2\left(b_{fc}+c_{f2}\right)}$; $s_{icf2}=0$; $s_{icf3}=\dfrac{-b_{fc}\beta_{fcj}}{2\left(b_{fc}+c_{f2}\right)}$; $s_{icf4}=\dfrac{b_{fc}\left(\beta_{fcj}-1\right)}{2\left(b_{fc}+c_{f2}\right)}$

CHAPTER 4 I-O MODEL IN THE ELECTRICITY MARKET: A GENCOS PERSPECTIVE

A paper published in the 35th North American Power Symposium

Guillermo Gutiérrez-Alcaraz, *Member, IEEE*, and Gerald B. Sheblé, *Fellow, IEEE*

Abstract

The restructured electricity industry moves toward more competitive environment in where the decentralized decision making model is persuaded in order to attain efficiency in commodity transactions. In the vertical integrated industry the decisions of production were centralized attaining minimum costs by executing global optimization approaches. In the restructured electric industry, under the assumption of liquid market, Generation Companies (GENCOs) would decide whether to produce energy, sell fuel, shut down the plant, or/and participate in fuel and electricity markets, depending upon the market spot prices. The effort in such decisions is to manage effectively and efficiently the product flow in the strategically planned supply chain. These changes in the energy sector in terms of trade between participants, seller and buyers, needs for energy modeling, either as a stand-alone or within the context of a complete system. The Input-Output model allows quantifying interrelationship among fuel markets and electricity market from the GENCOs viewpoint. Because the spot market settles hourly, the open static input-output model is considered in this document.

Index Terms—Energy markets, Input-Output method

I. INTRODUCTION

The restructured electricity industry keep moving toward more competitive environment where decentralized decision making is strongly encourage to attain efficiency in commodity transactions. In general, increased competition delivers increased benefits to society. Competitive markets provide lower prices, better quality, and more innovation than monopolistic markets [1,2].

Traditionally, business between electric utilities was conducted trough bilateral contracts or multiple interchange transactions. In the new framework of deregulation, a commodity wholesale electricity marketplace characterizes the electric industry. This new environment has changed drastically the objective of electricity producing companies. In the vertical integrated industry, utilities were obligated to meet all the demand for customers in a certain region at fixed rates. Therefore, the traditional understanding of risk was entirely about operational risk that might lead to supply of electricity falling below demand. Nowadays, risk does not only refer to operational risk but also price risk, and financial risk. Derivatives products such as options, futures or swap contracts have become a standard risk management tool that enables risk sharing and thus facilities the efficient allocation of capital to productive investment opportunities [3].

This paper focuses in GENCOs' participation in a market environment driven by market forces –supply and demand. The open static Input-Output, OSI-O, model illustrates the market interaction, input markets as well as output market, from GENCOs point of view. Due to the operation of the spot market (discrete and sequential snapshots) and short–term forecasting participation in the electricity market (unit commitment) OSI-O model provides enough accuracy to capture changes in both sides of the supply chain.

Some commodities or services provided by GENCOs are not interdependent, however for sake of simplicity, we assume they are. This assumption will permit the decomposition of ancillary markets and others, from a GENCOs' viewpoint. Under the same assumption, an independent stream cash flow associated to each commodity can be obtained. An additional consideration is a complete decentralized and liquid market. Thus, GENCOs would decide what and when to produce -voluntary participation. Exchange exists for every commodity traded and auction is the market clearing price mechanism.

The rest of the document is organized as follow: The next section discusses the decentralization production decision making in the new electric industry. Section III presents the Input-Output theory developed by Leontief. The Open I-O model is briefly described in section IV. In section V, the I-O model in the energy market is discussed. A case of study is given in Section VI. Conclusions and future work are presented in section VII.

II. PRODUCTION DECENTRALIZATION

Segmentation of the vertical integrated electric industry into a horizontally integrated set of companies make production decisions, by each one of the independent GENCOs, are decentralized. This new paradigm has introduced much uncertainty in the production-supply chain. The traditional understanding of risk under vertical integrated model was referred to the obligation of meet the demand at any moment. A fixed rate of return was established as payback. The operation of the GENCOs was centralized and a single decision maker allocated the energy services by minimized total production costs.

Nowadays, the performance of the utility depends of the market forces in input suppliers and output customers. In addition they must compete strategically with other market producers [4,5]. Market forces will dictate the equilibrium price-quantity, subject to operational constraints. It is also possible that some of those constraints, operational constraints proper of the power system, would be relaxed by the introduction of demand and interrupted power programs.

In a competitive market, no externalities exist and GENCOs goal is to maximize expected profits. Externalities must be internalized by the same participants into their market strategies in order to attain an optimal decision making. Optimal decision making refers to units output allocated on the frontier production function. Therefore, GENCOs, or other firms, out of the frontier do not make an efficient use of their inputs indicating that their performance might be improved by changing management procedures.

III. THE INPUT-OUTPUT THEORY

Wassily Leontief developed the Input-Output, I-O, theory which is a linear approximation of the Walrasian model that allows the general theory of equilibrium to be applied [1,6,7]. Economic I-O analysis is a method to systematically quantify the interrelationships among various productive sectors of an economy sector in which goods are produced in those sectors by main of primary factors. The economic system may be as large as a nation or as small as the economy of a municipality area. The structure of each industry's production process is represented by an appropriately defined vector of technical coefficients that describes quantitatively the relationship between the inputs it absorbs and the output it produces. The interdependence among the sectors of the given economy is described by a set of linear equations expressing the balance between the total input and the aggregate output of each commodity and service produced and used in the course of one or several periods of time [7].

In I-O analysis, a fundamental assumption is that the inter-industry flows from i to j depend entirely on the total output of sector j. From this concept then a ratio of input/output termed a technical coefficient is formulated. Thus, there is an explicit definition of a linear relationship between input and output and there are no economies of scale (ES), rather the Leontief model represents constant return to scale (CRTS). Here the coefficients are the economic production function from sector i to sector j, which equates to the ratio of intermediate input to total output in value terms. This is equivalent to the fraction of price of commodity i / price commodity j, and the corresponding technical coefficient ratio: physical quantity of input from sector i / total physical quantity of sector j.

Static models are confined to a single point in time and are concern with changes in social behavior, such as price and demand. On the other hand, dynamic models reflects changes in time and take into account model components that are constantly changing as a result of previous actions or future expectations [1,6,7,8,9].

Static I-O analysis describes the economic system in terms of mutually interrelated and structural conditioned, simultaneous flows of commodities and services. The Dynamic I-O model includes the same assumptions of the static model within a time period.

In the Walrasian system of equilibrium, the static economy is in equilibrium, when all the individuals in it are choosing quantities they prefer to produce and to consume. Thus, for a given system, there are always a set of prices and a set of quantities that separately and simultaneously satisfies the technical structure of production. In the static I-O model the general principles of equilibrium are exploited to arrive at quantities produced based on the exogenously determined quantities of final demand [1,7]. Thus, for the static I-O model, as intermediate production converges, the system is expected to achieve a new equilibrium. At this new equilibrium the static I-O model intrinsically represents the market clearing mechanisms of the Walrasian model [1,7].

IV. OPEN STATIC I-O MODEL

In the open static I-O model final demand is exogenously determined. Given the final demand by the economy of all sectors, it is desired to compute for each sector the gross output necessary to cover final demand. It can be expressed in matrix form as follows:

$$(I-M)X = d \tag{1}$$

where $X =$ vector of total output

$I =$ Identity matrix

$M =$ *nxn* matrix of input/output coefficients

$d =$ vector of final demand

if $|I-M| \neq 0$ then $(I-M)^{-1}$ exists, and the unique solution is given by

$$x = (I-M)^{-1} d \tag{2}$$

The elements of M are:

$$m_{ij} = \frac{X_{ij}}{X_j}$$

where $X_{ij} =$ Intermediate input delivery from i o j

$X_j =$ Gross output of j

V. I-O IN THE ENERGY MARKET

With deregulation of electricity markets, Generation Companies must compete in a market environment where their decisions focus on activities over a day-to-day, month-to-month basis. The effort in such decisions is to manage effectively and efficiently the product flow in the strategically planned supply chain. These changes in the energy sector in terms of trade between participants, seller and buyers, needs for energy modeling, either as a stand-alone or within the context of a complete system.

Generation Companies who competes vigorously with each other in seeking to maximize their individual financial return must take their own market participation's decisions. Competition between suppliers will drive down prices, but not supplier will be willing to sell at less than the variable cost. The competitive equilibrium is described by the optimal solution to an appropriate constrained optimization problem. Minimization of transportation cost is a necessary condition for competitive equilibrium if such cost were not minimized otherwise an extra profit could be earned by appropriate relocation of supplies [10].

The traditional understanding of risk in vertical integrated industry was entirely about operational risk that might lead to supply of electricity falling below demand. Nowadays, there is a volatile market price instead of a fixed rate at which electricity is provided. In addition, the markets for input products like coal or gas are liberalized, with the effect that fuel prices become volatile too [11].

The power play may be made base upon the so-called Spark Spread a calculated value that compares wholesale electric prices to wholesale fuel prices to determine whether to operate the electric power plant or sell its fuel in the wholesale market. The practicality of applying the spark spread formula is limited due to the lack of liquidity of certain electricity options [11].

It is possible to consider additional products that the GENCO can sell, i.e. ancillary service, pollution rights, heating service. In the energy market, auctions are used for finding the equilibrium price-quantity each trading period for the different products or services. Hence, prices for every service must be provided by the market in order the GENCOs would find a value for each of the products and services contributing to the economic profit. The I-O model is a spatial model of the flow of fuels to the generation plants as well as services offered. Thus GENCOs must build a portfolio of contracts for fuel purchases in order to control fuel cost and a portfolio of services offered in the electricity market. Operating a portfolio of fuel types GENCOs add more flexibility in generation. However, to build such portfolio requires taking into account all potential fuel contracts characteristics, transportation contracts, storage/consumption commodity, among other uncertainty factors [12]. GENCOs' output would be diversified in similar fashion.

Figure 4.1 depicts GENCOs' input portfolio as well as output portfolio. GENCOs sell energy under mill pricing and customers buy energy at delivery price. Transmission Company collects transportation costs.

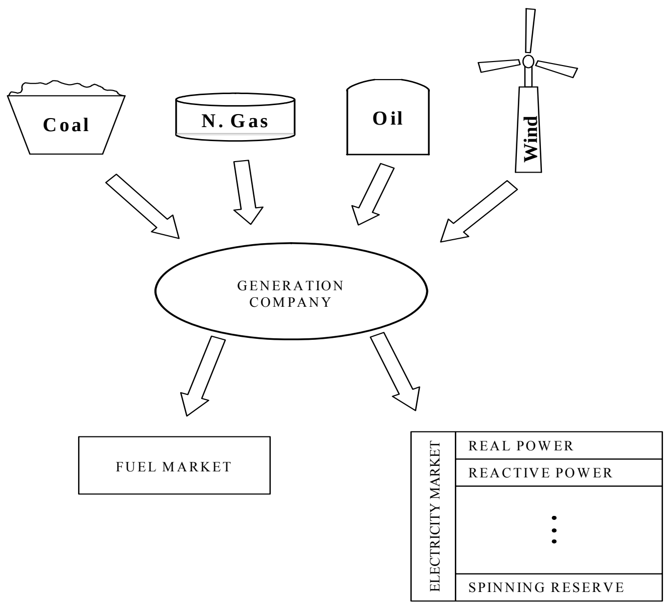

Figure 4.1 I-O GENCOs' participation in the Energy Market structure inn

The decision to produce depends strongly on market prices, fuel and electricity. Hence, if $S_t > C(P_G)$ then $P_G \neq 0$, where S_t is the spot price of electricity at time *t*, $C(P_G)$ is the production cost, constant, and P_G is the power produced at time *t*.

The GENCOs' profit at period *t* is then $\pi = P_G\left[S_t - C(P_G)\right]$

Environment plays an important role in the energy industry given that it will impose additional constraints to the participants –especially coal plants. Environmental constraint can be relaxed by buying rights to pollute in an environmental market. The matrix structure of the industry markets and environmental markets is shown in Figure 4.2.

Fuel Market		
	Environmental Market	
		Electricity Market
		• Real Power • Reactive Power • … • Spinning Reserve

Figure 4.2 Matrix representation of the Energy market structure

Figure 4.3 presents the spot market equilibrium for the 24 trading periods in the primary market (day-ahead). The submitted bids are collected in a sealed order book and are sorted according to the price and aggregated to get a market demand and supply curve for every trading period.

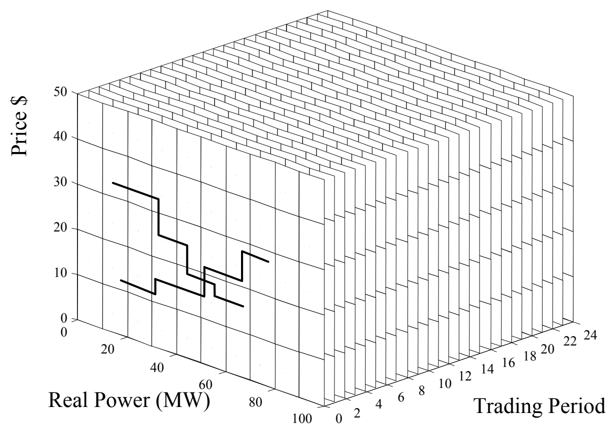

Figure 4.3 Primary market equilibrium for every trading period

The revenue cash flow stream associated to primary market for a generation unit is shown in Figure 4.4. Zero values in the cash flow diagram depicted in Figure 4.4 represent time off, banking generation status, or participation in other markets.

In case of different products are sold, these produce additional revenues. The same argument holds for emission rights, which might be an additional product that the GENCOs could sell.

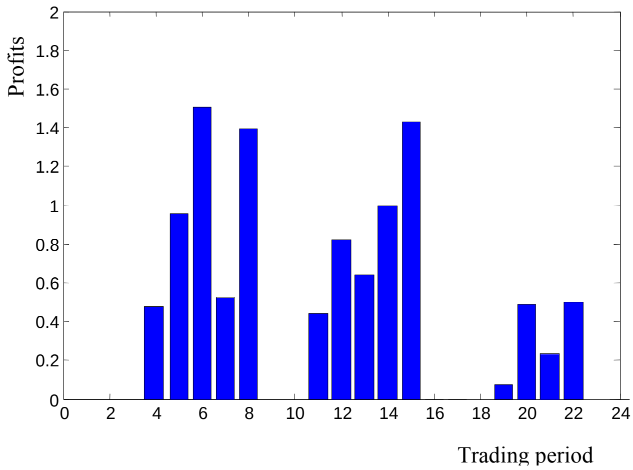

Figure 4.4 Seller Revenue stream cash flow

The net expected profit at period *t* is then:

$$E(\pi) = P_G\left[S_t - C(P_G)\right] + other\ products + pollution\ rights$$

VI. CASE OF STUDY

A three generation unit portfolio was considered for the problem formulation. Oil, coal, natural gas, and electricity markets constitute the energy market. Participation in the electricity market is restricted to the primary market in this numerical example. Their generation unit characteristics are shown in Table 4.1 as well as fuel spot prices.

Table 4.1 Generation data

Unit	Fuel	Operating Cost M-$/M-KWh	Rate of transformation (TBTU/$KWh)	Fuel Cost
1	N. Gas	16.325	0.01100	2.164 $/MMBTU
2	Coal	31.818	0.01144	1.100 $/ton
3	Oil	1.0780	0.01200	26.21 $/bbl

Table 4.2 shows the output power solution for a trading period demand of 68 MWh.

Table 4.2 Optimal output

Unit	Capacity (MW)	Output (MW)
1	10	--
2	40	38.000
3	30	30.000

The results show that unit 3 produces the maximum amount of power whereas unit 1 result the most expensive due to the fuel spot price and transportation cost.

VII. CONCLUSIONS

This paper reports the open static I-O model in the GENCOs decision making process for strategic participation in the energy market. A discrete model is considered given the characteristics of the day-ahead spot market.

The I-O model, by evaluating intermediate goods in the production-supply chain permits to observe the added-value of these goods. Therefore, a better approximation on the stream cash flow must be expected.

Decentralized optimization is attained when GENCOs decide when and what to produce. However, in order to achieve such condition a liquid market in generation was assumed.

VIII. ACKNOWLEDGMENT

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IX. REFERENCES

[1] Tjalling C. Koopmans, Editor, Activity Analysis of Production and Allocation Proceedings of a Conference, John Wiley & Sons, Inc., New York, 1951.

[2] Rebecca M. Blank, "When Can Public Policy Makers Rely on Private Markets," NBER Working Paper Series. April 1999.

[3] Jonh C. Hull, Options, *Futures, and Other Derivatives*, Fourth Edition, Prentice Hall, 2000.

[4] Michael E. Porter, *Competitive Strategy: Techniques for Analyzing Industries and Competitors*, Free Press 1998.

[5] Guillermo Gutierrez, Gerald B. Sheble, "Spot Fuel Markets' Influence on the Spot Electricity Market Using Leontief Model," *Proc. of the IEEE Bologna PowerTech 2003 Conference*, June 2003, Bologna, Italy.

[6] Gary J. Koehler, Andrew B. Whinston and Gordon P. Wright, *Optimization over Leontief Substitution Systems*, North-Holland/American Elsevier, 1975.

[7] Ronald E. Miller and Peter D. Blair, *Input-Output Analysis: Foundations and Extensions*, Englewood Cliffs, NJ: Prentice-Hall, Inc. 1985.

[8] Robert Doftman, Paul A. Samuelson, and Robert M. Solow, *Linear Programming and Economic Analysis, 1986.*

[9] Thomas Gloria, "An Approach to Dynamic Environmental Life-Cycle Assessment by Evaluating Structural Economic Sequences," Ph.D. Thesis, TUFTS University, May 2000.

[10] Gerald L. Thompson and Sten Thore, *Computational Economics: Economic Modeling with Optimization Software*, The Scientific Press Series, 1992.

[11] J. Hlouskova, M. Jeckle, S. Kossmeier, M. Obersteiner, A. Schnabl, "Real Option Models and Electricity Portfolio Optimisation," Institute of Advanced Studies, Vienna, July 2001.

[12] Jean-Michel Guldmann, Fahui Wang, "Optimizing the natural gas supply mix of local distribution utilities," *European Journal of Operational Research*, pp. 598-612.

CHAPTER 5 GENCOS' PARTICIPATION IN THE UNBUNDLED ENERGY MARKET

A paper published in the 2004 IEEE PES Power Systems Conference & Exposition

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Abstract

In this document we analyze market producers' participation in the new unbundled energy market. The electricity market is in the process of unbundling the ancillary services. In a fully unbundled electricity market more extensive analysis needs to be performed given that market participation is not restricted to electricity production. Ancillary services were bundled within the integrated generation and transmission services in the vertical integrated industry. Instead of being bundled with generation and transmission, the individual services are now uniquely identified in the competitive markets. In this new market environment, the decision making process can be seen as an activity analysis problem. Market participants will need to determine the most probable and profitable future market actions based on the last known market data and market projection.

Index Terms—Activity Analysis, Ancillary Services.

I. NOMENCLATURE

The following nomenclature will be used throughout the present work:

$i, j = 1 \ldots m$ regions
$s = 1 \ldots r$ fossil fuel types
$d_i^t =$ Demand in region i at period t
$f_{hs} =$ Supply of fuel in region i at period t

g_{ij} =Unit cost of power loss due to interchange transactions
k^{t}_{ijs} =Number of BTU's of fuel s sent from region i to region j
P^{t}_{ij} =Active power transacted from region i to region j at period t
x^{t}_{is} =Amount of electricity for region i produced by burning fuel s
c_{ijs} =Per unit shipping cost of sending fuel s from region i to region j
a^{t}_{is} =Amount of fuel s need to produce one unit of electricity in region i
b_{is} =Unit operating costs for producing electricity in region i from fuel s
X^{t}_{is} =Upper bound of x^{t}_{is}

II. INTRODUCTION

With liberalization of fuel markets and the electric industry, the production-supply chain is almost fully decentralized. This new environment presents a wide range of opportunities for market sellers as well as market consumers. At the same time, this condition exposes producers and consumers to higher levels of risk.

Risk does not only refer to physical problems eventually leading to an electricity shortage but also to price risk and therefore financial risk.

The energy market has had been studied separately because the liberalization of the different markets (i.e. natural gas, coal, oil, etc) have had taken place in a sequential manner. Consequently, markets present different levels of maturity. The development of methodologies and tools developed in the former markets then has been applied to the new liberalized markets.

The electric industry is the latest to be deregulated. This new environment is increasing pressure on generation companies to attain productive efficiency. The economic operation of a Generation Company (GenCo) requires that expenditures for fuel be minimized over a period of time. In today's electric spot market, the time horizon is a day-ahead and the analysis is executed by each GenCo whishing to maximize profits. In the past, GenCos used to sign long term fuel contacts to prevent high variations due to unexpected events. Take-or–pay contract probably was other financial option offered to producers to reduce uncertainty on fuel delivery. Fuel can be contracted for purchase in a number of ways, allowing the generator to increase security of supply of primary fuel. The optimal contract length depends on market information, as future economic environment becomes more certain, the length of contracts decreases [1][3].

In addition to these new changes in the fuel markets, the electricity market is in the process of unbundling the ancillary services (AS)**.** Ancillary Services are necessary to make electricity energy market reliable and transactions deliverable. AS were bundled within the integrated generation and transmission in the vertical integrated industry. Instead of being bundled with generation and transmission, the individual services are now uniquely identified in the competitive markets.

Many of these services can be traded on an exchange-based market. Thus, it is envisioned that an independent market exists for each one of the services or commodities offered. In fully unbundled electric market, market participants would be facing higher level of uncertainty than in current market models.

Therefore, GenCos are immersing in a multi-market multi-product decision environment. GenCos will need to determine future market actions based on the last known market data.

Extensive work has been done in the electric load forecast and spot fuel prices and its impact in the decision making process for GenCos [2]. On the other hand, substantial work has been done in scheduling fuel deliveries for the different fuel types (Coal, Natural Gas, Oil, etc.) in competitive and noncompetitive environments [3][4][5][6]. The decision making process for GenCos is constrained to operational minimum up/down unit's times. Hence, the solution of scheduling units in the production of electricity is commonly solved by the traditional UC approach. Production costing models have been used in the electric industry to forecast the cost of producing electricity [7][8]. Real power is the commodity of interest. However, the economic principles governing the pricing of active power can be applied to reactive power. Other AS are taken into consideration since the probabilistic production cost consists of two components: operating cost and outage costs [7][9].

Energy models have been developed to support local energy planning and recently to observe interdependencies effects in case of terrorist attacks. However, analysis is focused manly on the interrelation between the energy sector and the rest of the economy in the long term.

In [10] the author presents a dynamic model for a GenCo involved in fuel and electricity market. The underlying problem is consumer heating problem -consumer demand is met either by fuel or electricity, while electricity is generated by fuel. In previous papers [11] the authors have described the use of Leontief model in the energy market in which GenCos have been the focus of analysis. The studies were done considering participation only in the electric energy market and observing the interrelationship with fuel markets. This work extends previous work by considering GenCos participation in the electricity unbundled market (energy and AS). Competitor's reactions are not taken into account, instead cooperation among them is considered.

By decomposing the energy market it is possible to observe other market's effects in the final commodity price as well as to identify the sources of risk. To manage risk effectively, the market participant needs to insure that it has a transaction management infrastructure that captures accurate and timely information regarding the entire set of business activities performed. Incorrect, untimely, and improperly analyzed information often leads to suboptimal solutions for the profit-maximizing player. The financial implications of relying on outdated or incorrect information in bidding can be enormous.

In this document we analyze market producers' participation in the new unbundled energy market. Market producers will need to determine the most probable and profitable future market actions based on the last known market data. The market participants will use a much quicker analysis of the system's status for next hour pricing. Forecasting the status of the system is necessary for the short term operation. Determining the value of the certain information can simplify some of the analysis by using concentrating on the most cost effective research. Then, they would extend the expected market participation for the next days (up to one week) and adapt their decision according new information is collected.

In the problem formulation we assume that the demand for every service is constant over any given trading period. Some of these services need to be satisfied locally. The analysis is restricted to a single snapshot. Additional services, such transmission rights can also be traded in spot market, but these are beyond the scope of this paper. The 24 hours decision is accompanied with a UC in order to consider start up/down costs, min/max up/down times, and min/max on/off times.

The rest of the document is organized as follow: The next section discusses the decentralization production decision making in the new energy market with emphasis in the electric industry. The energy model is then presented. A static model is considered in this document considering discrete and sequential snapshots decisions in the spot market. The model is formulated and solved by using linear programming. A case of study is presented and discussed. Finally, conclusions are presented.

III. DECENTRALIZED ENERGY MARKETS

Under market completeness and perfectly competitive assumptions, centralized and decentralized designs attain the same result. This is the primal-dual equivalence of first-best implementations when competition makes the first best incentive compatible.

In the electric industry and under the same assumptions of competitiveness, the traditional unit commitment (UC) schedule can be obtained by optimizing the self-commitment of each unit separately at market prices. The objective of the optimization is to schedule hourly generation such that generation costs are minimized. The traditional UC achieve units' time coordination. In a new environment market, such coordination needs to be attained in a different fashion since each player is voluntarily participating. An illustrative representation of the above discussed issue is shown in Figure 5.1.

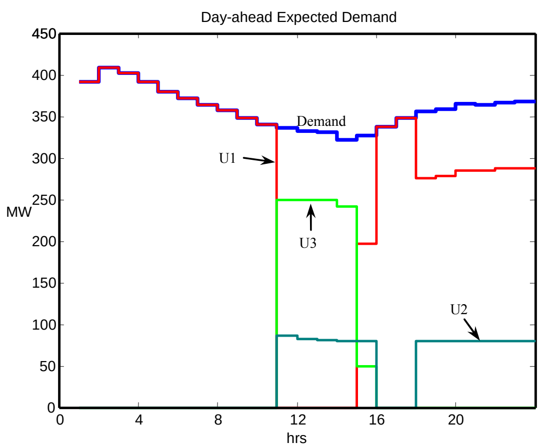

Figure 5.1 Seller Conventional UC solution

The spot market clearing price (MCP) for the day-ahead is shown in Figure 5.2. Even when centralized UC is executed, the existence of spark prices would be present. It can be seen that a substantial increment in price occurs during period 11 to period 15, as a result of unit's operational time constraints. This represents a hockey-stick supply curve from period 10 to period 11. Such effect would be present also when a generation or transmission line outage occurs. Additionally, there exist different marginal units along the day. By assuming that transmission system losses are not significant and there are no transmission constraints activated, the electric energy price would be strongly correlated to the marginal unit fuel cost. Electricity is typically stored in the form fuel inventories at power plants. For existing plants, the storage costs are usually less than or equivalent to the costs of storing other energy fuels; however, the addition of new storage capacity can be very capital intensive. The high cost of new capacity also means that there are disincentives to building spare power capacity.

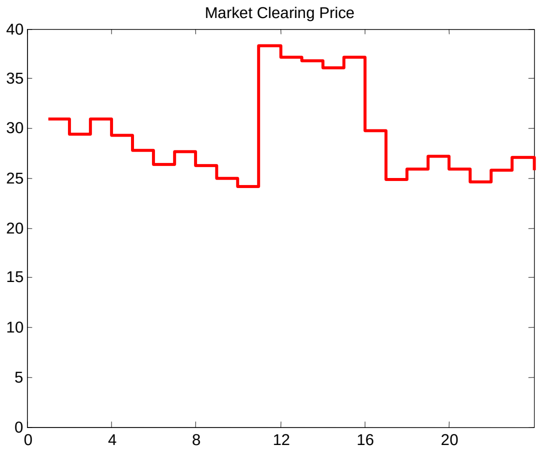

Figure 5.2 Hourly Market Clearing Prices

In a competitive market, market participants will have the freedom to decide in which market to participate base on market price information. It implies that the market producer should seek to optimize its assets value in the spot market using all the various products that he can offer.

The power play may be made base upon the so-called Spark Spread a calculated value that compares wholesale electric prices to wholesale fuel prices to determine whether to operate the electric power plant or sell its fuel in the wholesale market.

In this new competitive energy market, the decision making process from a GenCo's viewpoint can be seen as an activity analysis problem [12][13].

An activity consist of the combination of certain qualitatively defined commodities in fixed qualitative ratios as inputs to produce as outputs certain other commodities in fixed quantitative ratios to the inputs [13][14]. Any possible state of production can be represented by a linear combination of basic activities with nonnegative coefficients [15].

IV. THE ENERGY MODEL

The optimal purchase of fuel is an important problem for electric power producers in the new liberalized energy industry. Producers pursue their private self interests by observing and achieving strategic decisions in the whole energy market, fuel and electricity market. In the present and evolving energy market, it is necessary to simultaneously, over time and over space, clears regional markets.

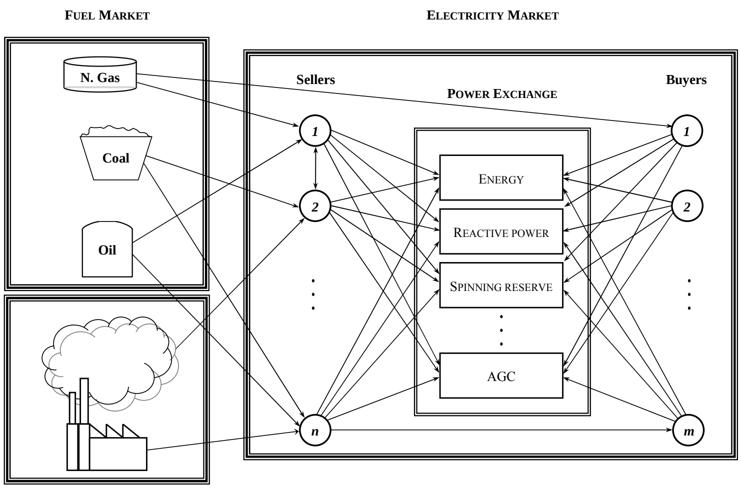

Figure 5.3 Energy market

The model takes into consideration fuel networks and transmission networks. The objective function takes the linear form

$$min\sum_{i=1}^{m}\sum_{s=1}^{r}b_{is}x_{is}^{t}+\sum_{i=1}^{m}\sum_{j=1}^{m}g_{ij}P_{ij}^{t}+\sum_{i=1}^{m}\sum_{j=1}^{m}\sum_{s=1}^{r}c_{ijs}k_{ijs}^{t} \tag{1}$$

In our case, the objective function to be minimized is the total production costs. The constraints are limitations on the unknown variables.

$$\sum_{s=1}^{r}x_{is}^{t}+\sum_{i=1}^{m}\left(P_{ij}^{t}-P_{ji}^{t}\right)\geq d_{i}^{t} \tag{2}$$

$$a_{is}^{t}x_{is}^{t}-\sum_{k=1}^{m}\left(w_{kis}^{t}-w_{kis}^{t}\right)\leq f_{is} \tag{3}$$

$$\sum_{s=1}^{r}x_{is}^{t}\leq X_{si}^{t}-SR_{i}^{t} \tag{4}$$

$$\sum_{s=1}^{r}q_{is}^{t}\leq Q_{i}^{t} \tag{5}$$

$$x_{is}^{t},P_{ij}^{t},k_{ijs}^{t}\geq 0 \tag{6}$$

Constraints (2) represent the balance of each service within local markets and exchanges. Constraints (3) require that the amount of fuel s shipped in region *i* less the amount of fuel shipped out of region *i* is at most the amount of fuel that region *i* has. Constraints (4) and (5) represent the spinning reserve and reactive power balance in each region while constraints (6) are nonnegative conditions.

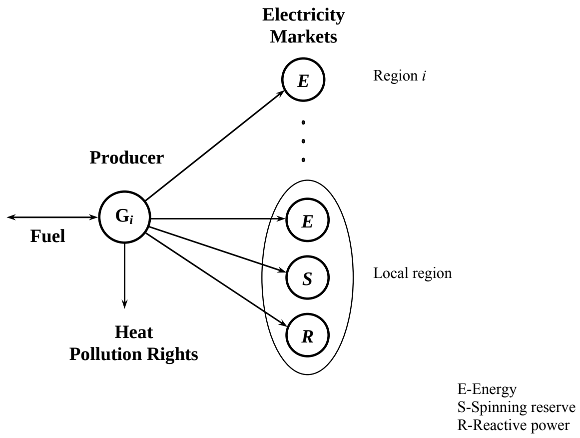

Figure 5.4 Network representation of GenCo's participation in the energy market

Figure 5.4 shows the network flow representation of the different activities/services in which the GenCo is involved. In this new environment, GenCos are able to sell fuel instead of producing electricity. GenCo compares wholesale electric prices to wholesale fuel prices to determine whether to operate the electric power plant or sell its fuel in the wholesale market. Regarding the electricity market, a GenCo would be able to participate in the provision of energy or any of the AS. Hence, the Generator unit is a multi-product device per se. GenCos will need to find a value for each of the products contributing to the net economic profit. The Gross operating profit is the sum of a series of multi-product revenues. The observation of information from each market would be essential in their decision-making process.

V. CASE OF STUDY

A two areas interconnected systems is considered. Each area has three major markets within the electricity market: energy, reactive power, and spinning Reserve. The reactive and reserve markets must be met for the energy to be traded. The system has four GenCos competing for supplying the demand distributed in both areas (regions). Control areas are interconnected by a transmission tie line. The unit parameters are shown in Table I. The market demand per region, for each independent service is shown in the Table II.

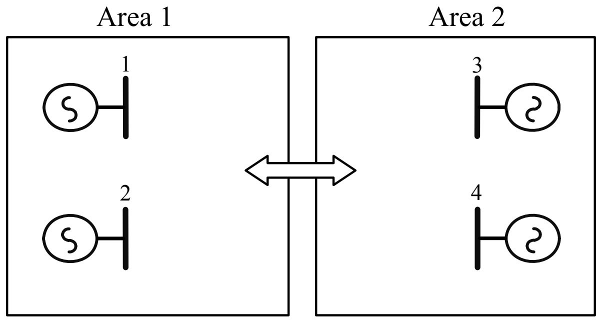

Figure 5.5 Two areas interconnected system

TABLE I

Unit parameters

Unit	Fuel	P_{max} (MW)	Operating Cost (M$/MWh)	Rate of Transformation (TBTU/$MWh)
Gen 1	Coal	260.0	8	0.01144
Gen 2	Oil	180.0	6	0.01200
Gen 3	Coal	120.0	10	0.01100
Gen 4	Oil	80.0	8	0.01200

TABLE II

Markets demand per area

	Energy (MW)	Reserve (MW)	Reactive Power (MVAr)
Area 1	200	20	160
Area 2	300	30	100

Per unit fuel shipping costs and unit cost of power loss when sending from region *i* to *j* are displayed in Table III.

TABLE III

Shipping costs for fuel and transmission losses

From	To	Oil (M$/TBTUs)	Coal (M$/TBTUs)	Electricity (M$/MWh)
R 1	R 2	0.1	0.2	2.5
R 2	R 1	0.1	0.2	2.5

R1 = Region 1; R2 = Region 2

For sake of simplicity, all units have the same real and reactive capability curve in percentages of real capability. The capability curve is shown in Figure 5.6.

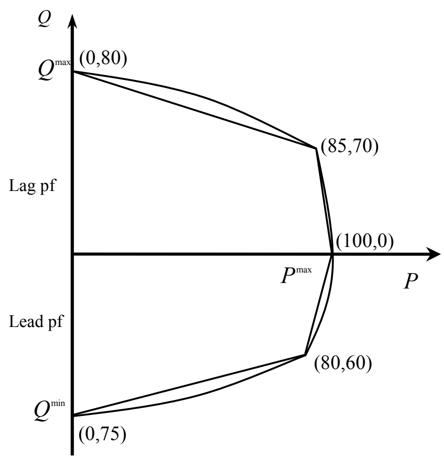

Figure 5.6 Generating capability curve (real and reactive power)

TABLE IV

Supply of fuels

From	To	Oil (TBTUs)	Coal (TBTUs)
R 1	R 2	0.90	2.55
R 2	R 1	1.20	1.65

The electric energy price in R1 is 8.00 $/MWh whereas in R2 this is 10.5 $/MWh. Note that the imputed price in R2 is 8.00 + 2.5 = 10.5. This is the cost of generating electricity in R1 and shipping it to R2. Optimal service allocation of each generating unit is shown in Table V.

TABLE V

Market participants outputs

	Energy (MW)	Reserve (MW)	Reactive Power (MVAr)
Gen 1	222.902	30.00	160.000
Gen 2	107.098		-
Gen 3	102.098	20.00	83.543
Gen 4	67.902		16.457
Total	500.000	50.000	260.000

From Table V we can observe that local demand will have to be satisfied in order to allow interchanges. Without transmission constraints between areas, the markets are integrated; cheap electric energy flows from Area 1 to Area 2 given that electricity is more expensive in Area 2. Gen 1 is participating in the three different services. Hence, the gross profit of Gen 1 is the sum of cash flows.

In addition of electricity transactions between areas, fuel is also transacted. This transaction in fuel is the result of fuel requirements from Gen 2. However, in this new environment, we will see more frequently fuel transactions between GenCos when selling fuel is more profitable than producing electricity.

VI. CONCLUSIONS

Market-based generation scheduling problems in different geographical markets were studied. Participation in additional market products was also studied. Competitor's actions were neglected in the analysis. A linear programming approach to the optimal activity analysis has been applied on a small system example.

Modeling tools that take into account the complexities of the multiple services of the unbundled industry and the independent reactions of the participants in this environment will assist in efforts to manage for the present and plan for the future. The integration of optimization and financial models as well as managerial decision-making approaches would permit market participants to develop strategies for mechanisms that operate on a daily basis.

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REFERENCES

[1] Baye, Michael, Managerial Economics & Business Strategy, 4th edition. Irwin McGraw-Hill. 2003.

[2] Gerald B. Sheblé, "Decision Analysis Tools for GENCO Dispatchers," *IEEE Trans. on Power Systems*, Vol. 14 No 2, May 1999. pp. 745-749.

[3] J.W. Lamont, D.J. Lubash, "Daily power system fuel optimization using a network flow algorithm," *Proc. of the Twenty-First Annual North-American Power Symposium*, pp. 12–20, Oct. 1989.

[4] Fred N. Lee, "The Coordination of Multiple Constrained Fuels," *IEEE Trans. On Power Systems*, Vol. 4 No. 3, pp. 1208-1218, Aug. 1989.

[5] Samer Takriti, Benedikt Krasenbrink, and Lilian S.-Y. Wu, "Incorporating Fuel Constraints and Electricity Spot Prices into the Stochastic Unit Commitment Problem," *Operations Research*, Vol. 48, No. 2, March-April 2000. pp. 268-280.

[6] L. A Twisdale and J. Chu, "A Decision Methodology for Coal Inventory Optimization," *IEEE Trans on Power Apparatus and Systems*, Vol. PAS-98, No. 6, pp. 1947–1957, Nov.-Dec. 1979.

[7] Laurence D. Kirsch, Robert L. Sullivan, Theresa A. Flaim, Joseph J. Hipius, Margaret G. Krantz, "Developing marginal costs for real-time pricing," *IEEE Trans on Power Systems*, Vol. 3, No. 3, pp. 1133–1138, Aug. 1988.

[8] Fen-Ru Shih and Mainak Mazumdar, "An analytical formula for the mean and variance of marginal costs for a power generation system," *IEEE Transactions On Power Systems*, Vol. 13, No. 3, pp. 731 – 737, Aug. 1998.

[9] R. Ghajar and R. Billinton, "Comparison of Alternative Techniques for Evaluating the Marginal Outage Cost of Generating Systems," *IEEE Transactions on Power Systems*, Vol. 8, No. 4, pp. 1550–1556, Nov. 1993.
[10] Weiguo Yang, "Short-term electric market dynamics and generation company decision-making in new deregulated environment," Ph.D. dissertation, Dept. Elec. Eng., Iowa State University, 2003.
[11] Guillermo Gutierrez, Gerald B. Sheble, "Spot Fuel Markets' Influence on the Spot Electricity Market Using Leontief Model," *Proc. of the IEEE Bologna PowerTech 2003 Conference*, June 2003, Bologna, Italy.
[12] Tjalling C. Koopmans, Editor, *Activity Analysis of Production and Allocation Proceedings of a Conference*, John Wiley & Sons, Inc., New York, 1951.
[13] Gerald L. Thompson and Sten Thore, *Computational Economics: Economic Modeling with Optimization Software*, The Scientific Press Series, 1992.
[14] Ronald E. Miller, Karen R. Polenske, and Adam Z. Rose, *Frontiers of Input-Output Analysis*, Oxford University Press, 1989.
[15] Enrique Castillo, Antonio J. Conejo, Pablo Pedregal, Ricardo Garcia, and Natalia Alguacil, *Building and Solving Mathematical Programming Models in Engineering and Science*, John Wiley & Sons, Inc. 2002.

CHAPTER 6 REAL OPTION DATA REQUIEREMENTS OF POWER SYSTEM DATA FOR COMPETITING BIDDING

A paper published in the 37 Hawaii International Conference on System Sciences

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Abstract

The interaction of markets and the power system network is stronger based on real options analysis than on traditional single event net present value analysis. The optionality of network restrictions due to congestion increases the importance of network information beyond the values found with traditional net present value for bidding. This paper demonstrates the importance of option analysis in the bidding process. The value of high volatility, due to network congestion and to network operating restrictions, leads to larger valuations. As always, larger uncertainty leads to larger values when opportunities can be recognized in advance. This paper shows how such information can be used in the bidding process.

1. Introduction

The deregulation of electric industry has created many changes and challenges in the complete energy sector. The industry is facing with the responsibility for many pricing decisions in an environment that is highly volatile. This new market-driven environment has originated the necessity of new economic institutions and the use of financial tools has been introduced to manage risks associated with the operation of the whole energy market. Real Options (RO) which can be evaluated in similar way to financial options, have been introduced in the energy market, because it explicitly accounts for the flexibility of operating/investing real assets. RO, as well as financial option, is the right but not the obligation to buy or sell an underlying commodity [1][2].

Traditional Discounted Cash Flow (DCF) methods cannot value management's ability to make decisions in the future. Strategic planning offers a view that values multiple opportunities and competitive issues [1][2]. The strategic approach appreciates the dynamic complexity of the future whereas the DCF approach is a passive management strategy [1].

The complex interactions and interdependencies among electricity market participants are similar to those studied in game theory. However, the different existing markets force Generation Companies (GenCos) to make strategic marketing decisions regarding the operation of the generating resources and the specific rules under which each different market operates will influence decisions made by market participants.

The electricity market consists in several markets, i.e. one market for each ancillary service (AS). Some commodities/services are highly correlated either because they are good complements produced by the same provider or due to lack of market liquidity.

Transmission access is imperative in the determination of bidding strategies. Frequently, transmission effect is neglected in bidding models and hence any solution given under such assumption is not optimal. According to [3][4] bidding strategies are affected by the interaction between operational constraints and other factors such as market design rules, price uncertainty, and non-convexity of costs. Reference [5] concludes that operational characteristics affect the valuation of a power plant to different extents depending of the operation efficiency of the power plant and the assumptions about electricity and fuel prices.

The optionality of network restrictions due to congestion increases the importance of network information beyond the values found with traditional net present value for bidding. This paper focused on operational decisions due to network operating restrictions supported by RO models. The bidding optimal decision takes into consideration the transmission system.

The rest of the paper is organized as follows: Multiple markets and interrelation between them are discussed in section 2. In section 3, uncertainty and correlation among different commodities or services in the electricity market is emphasized. Decision Support Systems (DSS) involve a number of analytical tools. Financial derivatives, RO, and the Porter's five forces model are presented in Section 4. Information required for optimal bidding is discussed in section 5. Section 6 gives some observations about application of RO in transmission investment and its impact on bids. Finally, section 7 summarizes the problems involve in the electricity market.

2. Multiple Markets

The new electricity market is only one piece on the energy market. The energy market is composed by fuel markets, transportation markets, and pollution markets. The Figure 6.1 shows in a matrix representation the different markets involve in the energy market.

Oil Market				
	Coal Market			
		Natural Gas Market		
			Environmental Market	
				Electricity Market

Figure 6.1 Matrix representation of the energy market structure

Fuel markets and wholesale electricity market are linked trough electricity production companies. This link is physical as well as financial. In a market-oriented environment, such link is modeled financially rather than physically.

In the electricity market, additional services, needed to support a reliable delivery of electric energy are or can be traded on an exchange-based market since supportive services are unbundled in this new environment [6]. Thus, it is envisioned that an independent market exists for each one of the services or commodities offered. There are 24 independent hourly auctions for each service concurrent with the 24 independently energy auctions [6].

Because of imbalances in the electric system a real time market is required. Real time market would improve the ability of electricity demand to respond to wholesale spot prices. Reduction in spot prices will decrease total costs of meeting demand and volatility of spot prices during critical periods. Forward market reflects short term future system conditions. In the forward market, prices are determined at the time of the contract but the transactions occur at some specific date in the future. The settlement of forward contracts can be either physical or financial. Physical contracts consider an obligation of the generation company to fulfill the specified amount of energy at the hours and network node arranged at the fixed price agreed. Financial Contracts do not imply a physical energy transaction but a cash flow.

Futures contracts eliminate the credit risk of forward contracts. In a futures contract, the counterparty is always the exchange-clearing house. The exchange guarantees that the term of the contract would be honored at maturity [7]. In the swap market, contract position can be closed with an exchange of physical or financial substitutions. The trader may find another trader who will accept delivery and end the trader's delivery obligation. Figure 6.2 represents schematically the electricity-derivative markets.

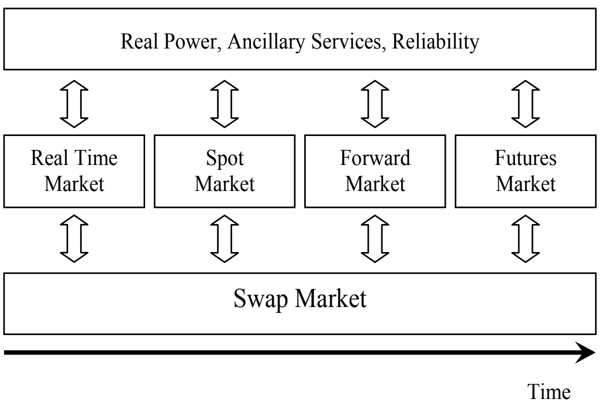

Figure 6.2 Electricity-derivatives market

The energy market is geographically distributed. Raw material and intermediate goods are bought from one location and used as inputs for activities in another.

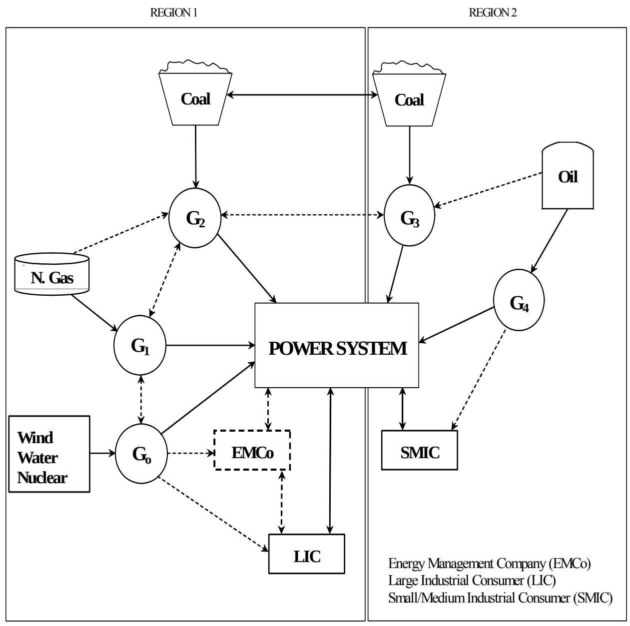

Figure 6.3 Representative structure integration of the industries in the energy market

In our context, fuels flow from fuel locations to the generation utilities, where electricity is produced and transmitted to demand centers towards transmission lines. Unit fuel costs consist of the market price of the fuel at the point of delivery plus transportation costs. Typical energy market structure is shown in Figure 6.3.

Every market clears independently base on market forces. In the electricity market, auctions are used for finding the equilibrium price-quantity for the different products or services. The submitted bids are collected in a sealed order book and are sorted according to the price and aggregated to get a market demand and supply curve for every trading period. Every trading period may take several iterations to find the Market clearing price during the bidding process. This process is required in order to match the business transactions into the system. The market clearing price discovery is shown in Figure 6.4.

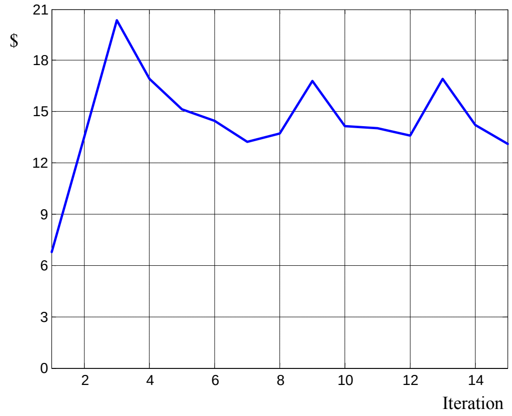

Figure 6.4 Market clearing price discovery

Figure 6.5 presents the spot market equilibrium for the 24 trading periods in the primary electricity market.

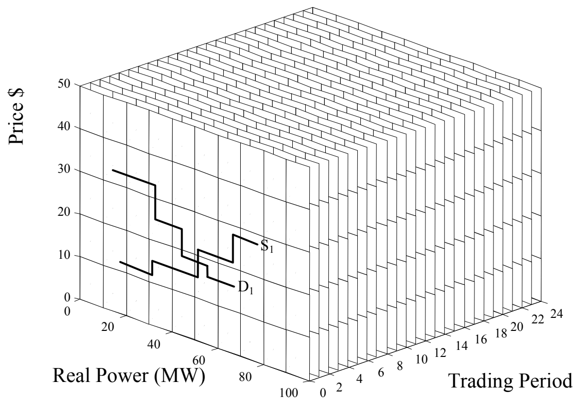

Figure 6.5 Market Clearing Price for the 24 auctions

The CFD for a given generation unit participating in the primary market is shown in Figure 6.6. Negative values in the CFD represent time off, banking generation status, or participation in other markets since availability of the unit implies certain variable costs.

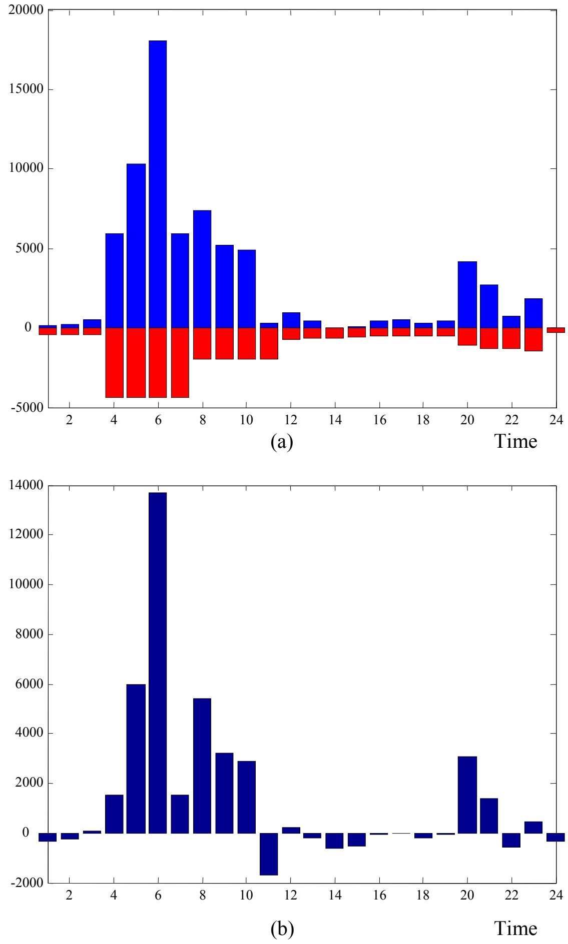

Figure 6.6 Day-ahead Cash Flow Diagrams: (a) Revenues and Costs (b) Profit per period

The Gross operating profit is the sum of a series of multi-product hourly revenues under the consideration of mutually exclusive services.

3. Uncertainty and Correlation

The decomposition of several markets in the electricity market itself is not well accepted and such decomposition has not been fully implemented in a decentralized fashion either because of the high correlation among the different services or due to lack of market liquidity. Instead, complementary mechanisms to quantify associated costs in the short-term have been implemented.

One of these complementary mechanisms is the opportunity costs for the reactive power service provided by a generator. Technically, reactive power support must achieve two objectives: voltage regulation and reactive spinning reserve in order to preserve adequate quality and security margins. Both services can be traded independently. However, these services are highly correlated with the energy market when the same device is the provider. In such case, those services are seen as substitutes by the device.

Reserves present similar conditions with the previous case. Reserve, as well as reactive power, is traded in advance and the use of it depends on the later system conditions. Generator can participate concurrently in several markets from which it can have additional revenues.

The correlation among the different services involve in the electricity market are nonlinear. Therefore prices in the different commodities are influenced by uncertainties associated to the electric system state variables which defined its operating point. Monte Carlo simulation seems viable to model plenty of probabilistic scenarios as way to include uncertainties in the power system [8].

Figure 6.7 represents the inference diagram for GenCos market participation selection. A generator can participate concurrently is several markets. However, such participation is limited by the operational constraints either of the unit itself and/or the power system.

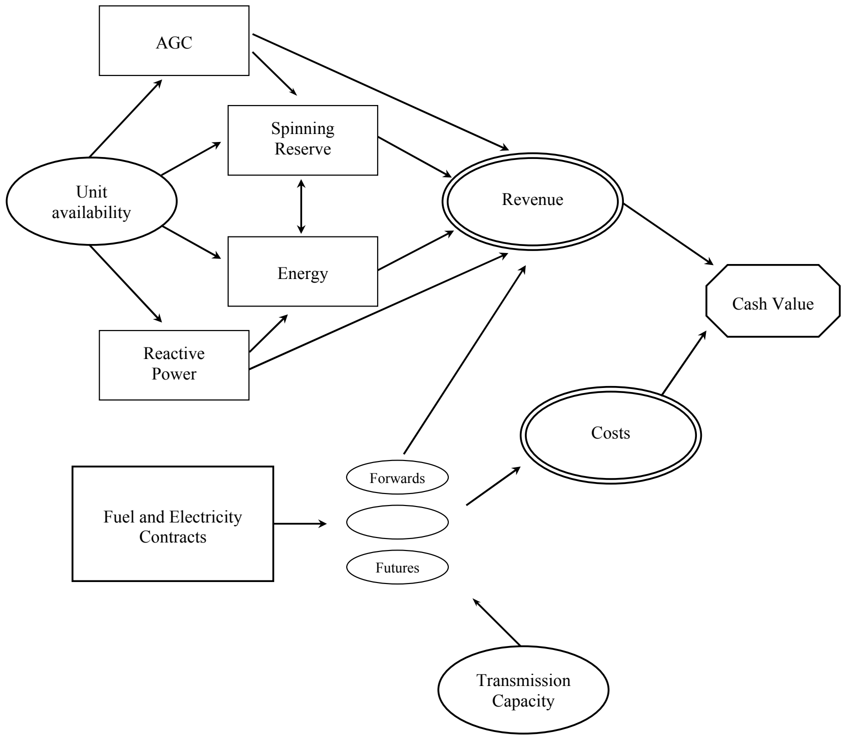

Figure 6.7 Inference diagram for Market Participation selection

4. Decision Support Tools

Competitive wholesale electricity markets are complex, with multiple interdependent products sold on different time frames and differentially priced at different geographic locations. Modeling tools that take into account the complexities of the multiple products of the unbundled industry and the independent reactions of the many participants in the new industry, Decision Support Systems, will assist in efforts to manage in the present and plan for the future.

A DSS involves a number of analytical tools Conventional optimization techniques, statistical econometric and statistical analysis, financial tools, and data system, among others. Financial tools, Real Option Analysis, and Input-Output model are presented in this section.

4.1 Financial Tools

Over the past two decades, the financial markets have experienced an impressive expansion in terms of securities issued and traded. Additionally, financial markets have become more and more interconnected allowing almost continuous trading. Derivatives products such as options, futures or swap contracts have become a standard risk management tool that enables risk sharing and thus facilities the efficient allocation of capital to productive investment opportunities [7]. The new restructured electric industry is using these financial tools to hedge against the risk involve in the spot market.

Trading has been executed in the electricity market without standardized contracts. Trading was firstly introduced by bilaterally where the two parties decide the contractual arrangements. Nowadays, markets do not have a standardized contract as other exchanges have [9][10][11]. This lack of standardized contracts makes difficult the trading process.

Salient features of the commodity traded have to be clearly specified as the contract for any commodity that is openly traded [9][10][11]. Four basic terms are commonly included in a contract:

1. Description of the goods: type, quantity, and quality
2. Delivery time
3. Price
4. Time and means of payment

These terms are considered essential because they cannot be easily implied by law they are the necessary parameters to the contractual relationship. Every contract should provide for these terms. Standardizing contract will help the market by increasing liquidity and transparency.

Long-term contracts (forward or bilateral) have been used to lock prices; price risk is removed, in absence of options and other financial derivatives. However, but before entering into long-term contracts, the company must evaluate the benefits that it expects to obtain from it. The optimal contract length reflects an economic trade-off between the marginal cost and marginal benefits of extending the length of the benefit. The optimal contract length also depends on market information, as future economic environment becomes more certain, the length of contracts decreases [12].

4.2 Real options

The application of RO to valuing managerial flexibility has been critical to gains made in many risky ventures. There exist a number of methods that can be used to value RO. One method is to value a security relative to the value of a portfolio of other traded securities [1][2]. Another approach is using a binomial option value method [1][2]. Monte Carlo (MC) simulation is another method to model a statistically significant number of logically constructed future scenarios. Embedded decision rules can make choices in the simulated scenarios, playing the role of active managers who would be making decisions based on information available at the time. Imperfect or delayed decision-making can also be modeled, limiting potential overestimates of achievable returns.

The following are some of many RO

- Option to abandon. The possibility to stop investing and liquidate existing assets
- Option to switch. Redistribute resources or change inputs
- Option to contract. The flexibility to reduce the rate of output
- Option to expand. An option to defer part of the scale of investment.

These options can also be rolled into a consolidated framework that allows for the many alternatives to be analyzed in a complimentary fashion.

Example:

Consider a decision maker is faced with an opportunity to invest I_o = \$ 104 in a given project whose value in each period will either move up by 60 % or down by 20 % depending on market price underlying variations. A year later the project will have an expected value of \$160 if the market price moves up or \$80 if it moves down. There is an equal probability that the price of the underlying commodity will move up or down in a period *t*. Let *S* be the price of twin security that is treated in financial markets and has the same risk characteristic with the real project under consideration. The project and the twin security have an expected rate of return of 20 %. The risk free interest rate is of 5 %

Assume that the value of the project, V_t, and its twin security price, S_t, move through the time as follows:

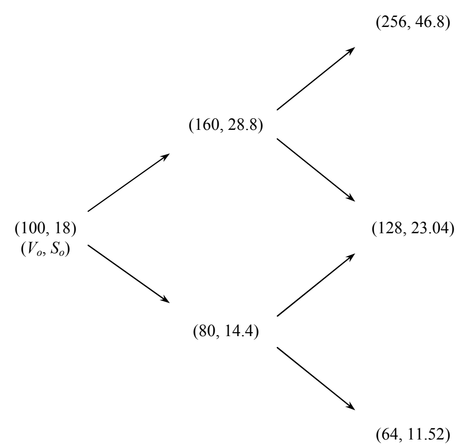

Figure 6.8 Option valuation tree

The pair (V_o, S_o) represents a current gross project value of \$ 100 million and a spot commodity price of \$ 18. Under Net Present Value (NPV) analysis, the current gross project value would be obtained first by discounting the project's end-of –period values using the expected rate of return of the project's twin security as the appropriate discount rate, i.e., V_o = (0.5x160 + 0.5x80)/(1+0.2) = 100. The project's NPV is given by: NPV = V_o - I_o = -4

The same solution can be obtained from its expected future values discounted at the riskless rate, *r*. In such a risk-neutral world, the current value of the project, E, is given by:

$$E = \frac{pE^{+} + (1-p)E^{-}}{1+r}$$

where $p = \dfrac{(1+r)S - S^{-}}{(S^{+} - S^{-})}$

$$p = \frac{(1.05*18) - 14.4}{(28.8 - 14.4)} = 0.3125$$

Observe that the value for *p* is distinct from the actual probability *q*, and can be used to determine expected cash flows which can be properly discounted at the risk free rate. For example:

$$V_o = \frac{(0.3125*160) + (0.6875*80)}{(1.05)} = 100$$

We next illustrate how RO can enhance the value of the opportunity to abandon the project. Abandonment options analysis not only provides and estimates the value of optimal abandonment, but it also indicates when the abandonment should be implemented. Continuing with the example, now let the project's current savage value \$90.

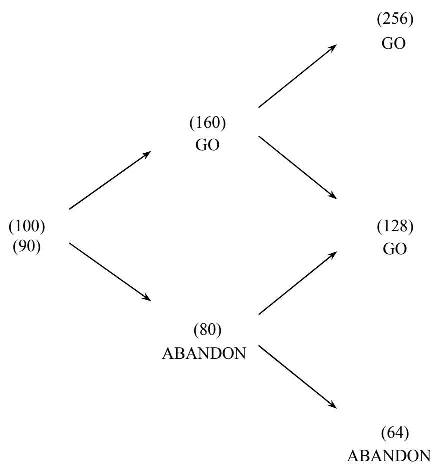

Figure 6.9 Abandonment option valuation tree

Figure 6.9 shows the binomial lattice calculation. If prices decline substantially or the operation does poorly for some reason, management does not have to continue incurring the fixed cost, abandon may be the best option.

4.3 Porte Five Forces Model

In the market oriented environment aggressiveness will depend on different factors such as number of competitors, competitor's strategies, market substitutes, among others. Those factors are represented in the Porter's five forces model [13][14].

The Porter's model brings the big picture to evaluate the potential profit of an industry in a competitive environment. These five forces are:

1) Barriers to entry
2) Rivalry among existing competitors
3) Substitutes
4) Power of Buyers
5) Power of Suppliers

Each of those five forces collectively impacts the potential profit and jointly determines the intensity of the industry competition and profitability. In order to analyze the specific activities through which firms can create a competitive advantage, it is useful to model the firm as a chain of value-creating strategies taking in consideration the five forces. The goal of these strategies is to create value that exceeds the cost of providing the product or service, thus generating a profit margin.

Evidently, there is a need for a mechanism through which these five forces can be integrated together. Supply chain management is a strategy through which such integration can be accomplished. The value chain describes the full range of required activities to bring a product or service from conception, through the intermediary phases of production, delivery to final consumers [15][16].

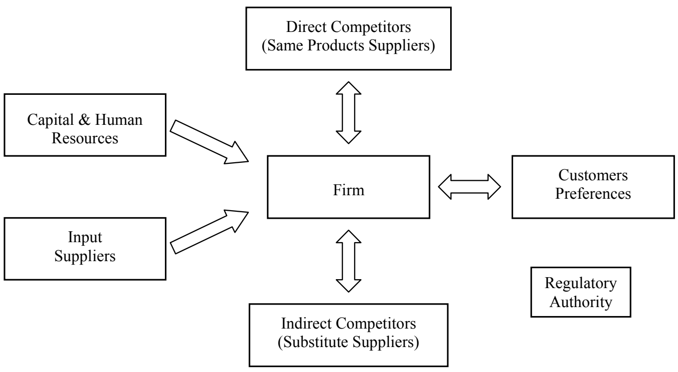

Figure 6.10 Porter’s five forces

5. Information required for optimal bidding

In the context of electricity producing firms, real options theory can be used as a method of identifying and quantifying the contingent decisions embedded in owning generation assets and financial positions that the company owns.

The value of high volatility, due to small change to transmission congestion and to network operating restrictions, leads to larger valuations.

Strategic market decision is usually performed towards optimal bidding process. Transmission effects are frequently neglected in bidding models. The optimal bidding strategy is function of several factors: generator status, commodity/services market prices, transmission constraints, participants' strategies, force outages, and operational market rules.

Some of the abovementioned factors are independent of market reaction and participants' strategies. Market uncertainty is represented by commodity prices whereas transmission constraints and forced outages generally are technical uncertainties. Generation status is a self-dependent constraint that must be considered in order to avoid physical operational inconsistencies. These market and technical uncertainties will impact GenCos' bidding strategies.

Investing on information will reduce uncertainty. Reduction on uncertainty can be quantified in present value and added up. After new information is brought, the GenCo's decision is driven by the new expectation. This new expectation is conditional to the kind of new information. Lack of information tends to perform suboptimal operation and development decisions.

Market information provided by exchanges is displayed in the commodity prices. Different prices exist on the extraction/delivery points due to transmission costs and constraints. The trading of forward contracts distorts partially commodity prices, *imperfect information*.

The organization of the market itself would play an important role in market information. Spot market equilibrium, price and quantity, is provided by the power exchange, additional information such as the aggregate supply and demand curves can also by provided. Market information would or would not be part of the exchange fees [17].

As an example consider the following case. A Generation Company is competing to sell energy and reactive power support. As long as the transmission system becomes congested reactive power is positively correlated to energy as well as the other supportive services (for sake of simplicity considerer just Energy and Reactive Power). Suppose that prices will either move up or down by 20 % in period one and 30 % in period two, depending on market price underlying variations and transmission operational conditions.

The up and down factors are different over the two time periods. Consequently the binomial lattice will not longer be recombined as it is shown in Figure 6.11.

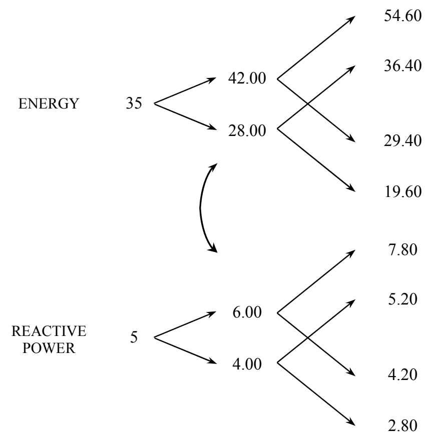

Figure 6.11 Lattice evolution of the underlying

Under the assumption of mutually exclusive services, the two graphs will be independent; the net profit is then the sum up of the different services provided by the GenCo.

Consider the spot price of \$ 40.00 and \$ 5.50 for energy and reactive power respectively. Additionally, assume the risk free interest rate is of 10 %.

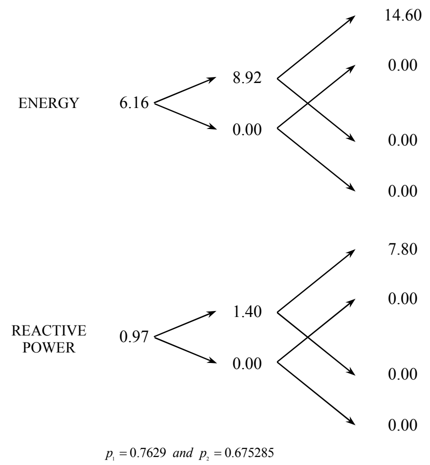

Figure 6.12 Lattice option valuation

Figure 6.12 shows the option valuation binomial tree. The binomial option valuations results to be greater than the NPV for both commodities providing an additional value.

$$\text{energy bid added value} = 6.16 - 5.00 = \$1.16$$
$$\text{reactive power added value} = 0.97 - 0.50 = \$0.47$$

6. Observations

Nowadays, transmission network remains highly regulated in almost all the markets. In the vertical integrated industry the decisions of new investments in generation and transmission were made jointly attaining reliability and social welfare issues. However a decentralized market model such investment must be done independently. Generation location will be persuaded to install new capacity close to consumer centers delaying new investment in transmission lines. On the other hand, expanding the transmission system would decrease generator profits. When new investments are made in generation, although it would modify system's power flows, transmission would reallocate revenue costs among participants. Modification on power flows would modify revenue costs of the transmission system.

Investors in generation can evaluate a potential project at a particular location, estimate expected economic profits, and then decide whether it is attractive to risk its capital. After the power plant is placed in operation, profits will depend on how the plant is operated. Transmission is inherently different. The extent to which a transmission element is used in real-time depends on the electrical parameters and the overall system flows, not the price charged for the service.

Incorporation of Flexible AC Transmission (FACT) devices could be an alternative for expansion in the transmission system. Investments in generation rather than transmission seem more attractive for market participants. Transmission improvements would remove the natural monopoly character of the wholesale power market in most locations or would not. Distributed Generation (DG) is a clear example of expansion in the generation sector. The lack of reactive power support of DG, i.e. reactive power for voltage control, will open the door for investment in reactive power devices needed to maintain real power transactions.

The growth of transmission grid requires transmission companies to make ex-ante contracts based on the expected usage to finance projects. Transmission expansion investments would underwrite the usage of equipment subject to the long term commitments to which distribution and generation companies are bound by the rules of network expansion to maintain a fair market place.

7. Summary

In this document we have discussed different aspects that must be considered for GenCos competitive bidding under liquid energy market condition.

Two of the main sources of uncertainty in the electricity market are market and technical uncertainties. Lack of information would jeopardize firms' goal, profits maximization, in a market-oriented paradigm. Consideration of technical uncertainties in a real option modeling would be capture in the adaptive bidding process.

Operational real options are a flexible tool for real assets able to enhance GenCos strategic decisions in multiple markets. Generators are a multi-product investment project per se. Hence, GenCos will need to find a value for each of the products contributing to the net economic profit. Additivity of individual option values is feasible when market decomposition participations are independent and options do not rely on the same underlying.

8. References

[1] Eduardo S. Schwartz, Lenos Trigeorgis, *Real Options and Investment under Uncertainty: Classical Readings and Recent Contributions*, MIT Press, 2001.

[2] Johnathan Mun, *Real Options Analysis: Tools and Techniques for Valuating Strategic Investments and Decisions*, John Wiley & Sons, Inc. 2002.

[3] Rajesh Rajaraman and Fernando Alvarado, *Optimal Bidding Strategy in Electricity Markets Under Uncertainty Energy and Reserve Prices*, PSERC Report, April 2003.

[4] R. Rajaraman, L. Kirsch, F. L. Alvarado and C. Clark, Optimal Self-Commitment Under Uncertain Energy and Reserve Prices. In B.F. Hobbs, M.H. Rothkopf, R.P. O'Neill, and H.-P. Chao, eds., *The Next Generation of Unit Commitment Models*, International Series in Operations Research & Management Science, Kluwer Academic Publishers, Boston/Dordrecht/London, 2001.

[5] Shi-jie Deng and Samuel Oren, “Incorporating Operational Characteristics and Starup Cost in Option-Based Valuation of Power Generation Capacity”, *Probability in the Engineering and Informational Sciences* (PEIS), April, 2003.

[6] Harry Singh, “Auctions for Ancillary Services,” *Decision Support Systems*, January 1999. pp. 183-191.

[7] Jonh C. Hull, *Options, Futures, and Other Derivatives, Fourth Edition*, Prentice Hall, 2000.

[8] Guillermo Gutiérrez-Alcaraz, Noe Navarrete, J. Horacio Tovar-Hernández, Claudio R. Fuerte-Esquivel, Ricardo Mota-Palomino, “Analysis of Probabilistic Short Run Marginal

Cost Using Monte Carlo Method," *61st American Power Conference*, Chicago Illinois, USA, April 1999.

[9] NYMEX web Site defining the terms and conditions of contracts traded: http://www.nymex.com/.

[10] CBOT web site defining the terms and conditions of the contracts traded: http://www.cbot.com/cbot/.

[11] CME web site defining the terms and conditions of the contracts traded: http://www.cme.com/market/index.html.

[12] Baye, Michael, *Managerial Economics & Business Strategy*, 4th edition, Irwin McGraw-Hill. 2003

[13] Michael E. Porter, *Competitive Strategy: Techniques for Analyzing Industries and Competitors*, Free Press 1998.

[14] Henk de Swaan Arons and Philip Waalewinjn, "A knowledge Base Representing Porter's Five Forces Model," *Proceedings CIMCA'99*, Viena 1999.

[15] Thomas Gloria, *An Approach to Dynamic Environmental Life-Cycle Assessment by Evaluating Structural Economic Sequences*, Ph.D. Thesis, TUFTS University, May 2000.

[16] Hau L. Lee, Corey Billington, "Material management in decentralized supply chains", *Operations Research* Vol. 41, Issue 5, Sept.–Oct., 1993. pp. 835-847.

[17] European Energy Exchange www.exx.de

CHAPTER 7 GENCO'S SELF-SCHEDULING: REAL OPTION APPROACH

A paper published in the 36th North American Power Symposium

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Abstract

With the electricity market aperture, Energy Market is becoming every day more unified. Nowadays, there is a volatile market price at which electricity is provided. Price volatility is increasing for fuel inputs due to market restructuring. This means that Generation Companies (GenCos) under deregulated market structure faces a lot more uncertainty than under the traditional vertical integrated structure. But the new environment also offers benefits to the GenCos. Under the assumption that a liquid market exists, GenCos can decide the amount of electricity to produce to maximize profit according to the risk desired. Daily operation for maximizing expected profits for generation assets in a dynamic competitive electricity market still relies on the traditional Unit Commitment (UC) solution. In this document we formulate the real option optimal self-scheduling for a GenCo market participant. Participation in the electricity market is focused on two spot markets: energy and reserves. According to the fuel prices, GenCos would decide level of participation in the electricity or fuel markets. Stochastic UC is considered for scheduling different units using different fuel inputs. It is also shown that by participating in the environmental market, GenCos would be able to increase level of production.

I. NOMENCLATURE

Through this paper, we use the following notation:

T	= Total umber of periods
n	= Total number of units
t	= Hour index
u_{it}	= Binary decision variable indicating whether the unit i at period t is up or down
x_{it}	= State variable indicating the length of time that the unit i has been up or down at period t
π_i	= Gross expected profit of GenCo i
P_t^E	= Energy spot price at period t
P_t^S	= Spinning reserve spot price at period t
P_t^F	= Fuel spot price at period t
S_t	= Spinning reserve at period t
D_t	= Demand required at period t
Z_i	= Maximum power ramp-up increment of unit i
W_i	= Maximum power ramp-down decrement of unit i
R_t	= Revenue of unit i at period t
y_t^+	= Amount of purchased allowances at period t
y_t^-	= Amount of sold allowances at period t
EA	= SO_2 maximum hourly emission allowances
$Su(u_{it})$	= Start-up costs of unit i at period t
$Sd(u_{it})$	= Shutdown costs of unit i at period t
$Pg_{i,t}$	= Active power generation of unit i at period t
$C_t(Pg_{it})$	= Operation cost of unit i at period t
$H_t(Pg_{it})$	= Heat rate of unit i
$Pg_{it}^{\min}, Pg_{it}^{\max}$	= Lower and upper generation limit of unit i
$E\left(R_t, C_t\left(Pg_{i,t}\right)\right)$	= European production option

II. INTRODUCTION

With deregulation of the electric industry different market models have been implemented. Three groups of market models are identified [1]: centralized, decentralized, and hybrid models. Centralized models were favored initially because they imitate vertically integrated operations, being a natural step towards more decentralized market design. Under this framework, a System Operator (SO) wields a rigid control over the wholesale electricity market. Due to the complexity of the bulk power system, the SO is also responsible for providing supportive services. Decentralized models are based on an Exchange where a Market Operator (MO) is in charge of market activities. A single entity may execute System and Market activities or two independent entities would be responsible to separately handle the responsibilities of market-making and network operations. Under market completeness and perfectly competitive assumptions, centralized and decentralized designs could attain the same result. This is the primal-dual equivalence of first-best implementations when vigorous competition makes the first best incentive compatible [1]. But this primal-dual equivalence fails in practice since markets are imperfectly competitive and poorly synchronized. On the other hand centralized designs request accurate data, which private market participants are reluctant to provide creating market inefficiencies. Hybrid models are created to alleviate previous concerns.

The tendency of wholesale electricity markets keeps moving towards a decentralized market structure. Decentralized market economies characterized by price-taking consumers and firms are supported by price systems. Price summarizes part of the information. Knowing the price, consumers are supposed to know how to choose their consumption bundle, without knowing others' behavior or the set of scarce resources. In real-world decentralized market economies, price is not enough for coordinating the supplies and demands of private agents since many of them in such markets are price setters. Market protocols, market institutions, and supportive policies to reduce the number of multiple market equilibrium, play an important role for establishing rules through a collaborative process to ensure that the markets operate fairly and efficiently.

In the electric industry, power exchange (PX) is a centralized market that trades energy as Power Pool does. These two entities play market roles in the decentralized and centralized models mentioned above. However, differences between them exist in the way they constrain market participants' strategies. Indeed, participants' market strategies in Pool model are more restricted given that an overall optimization of operational decisions is executed. On the other hand, PX completes reliance on "voluntary participation."

The criticism against PX is that it does not consider the Unit Commitment (UC) problem. Hence, it is argued that self-scheduling does not fully internalize inter-temporal considerations. But, inter-temporal effects are not exclusive of electricity markets and these can be controlled by using additional markets likewise in agricultural commodities. In addition, SO remain wary of reliance on markets to ensure reliability. From the SO's point of view reliability seems precarious because voluntary participation could jeopardize real-time operations.

In electricity markets, instantaneous supply and demand must always be in balance. This creates the need to hold reserves to balance instantaneous variations in load. The existing market models handled this problem in two different ways with possible variations.

1) Obligatory participation in the provision of the spinning reserve service.
2) An independent market exists wherein the spinning reserve is traded.

The mathematical formulation in a centralized model (obligatory participation) calls for spinning reserve as an additional constraint. This constraint can be treated as a global constraint or indexed to each unit. The latest would result in a better reserve distribution over the system, but not necessarily at the minimum cost. The earlier formulation ties both services: energy and reserve.

On the other hand, when an independent market exists, each supplier is responsible for its own decisions on what and how to bid into the energy and AS markets. Bidders bear all the risks of poor decisions and might be faced with suboptimal or even impossible operation of their units. Given that the SO does not control or direct dispatch of generation units, the SO would decide to purchase more AS, i.e. reserves, than centralized systems do. As consequence additional costs are incurred unless mechanisms for allocating different levels of security exist.

In this document we formulate the real option optimal self-scheduling for a GenCo market participant. Participation in the electricity spot market is focused on two different markets: energy and reserves. GenCos offer power in block contracts in hourly independent trading periods for each commodity; this implies that the market supply curves have the form of a step function. The intersection of the aggregate supply and aggregate demand curves determine the Market Clearing Price (MCP). All bids accepted at prices lower than the MCP are paid at the MCP instead of their bid prices. The used spinning reserve is fully paid the same as unused. Therefore, the optimization program is formulated as a set of European options. Environmental constraints are included in the formulation. It is also shown that by participating in the environmental market, GenCos would be able to increase profits.

The reminder of the document is as follows. In the next section, the constrained UC is briefly reviewed. In Section IV the UC problem is formulated on the Real Options framework. The formulation considers operational constraints. Numerical examples are presented in the subsequent section. The last section presents the conclusions of the present work.

III. CONSTRAINED UNIT COMMITMENT

The economic operation of an electric power system requires that expenditures for fuel be minimized over a period time. When there is limitation on energy resources, it can complicate the short-term unit scheduling. In response, a short term fuel constrained UC need to be executed [2]. UC must take into account what happened in the past and what will happen in the future. In order to prevent high variations in prices due to unexpected events, GenCos used to sign fuel contracts with the fuel supplier.

In the past, the take-or–pay contract probably was the simplest financial option offered to producers to reduce uncertainty on fuel delivery. Take-or-pay fuel contract is an agreement in which utility agrees to use a specified minimum amount of fuel during a given period of time or failing to use the specified amount it agrees to pay the minimum penalty. Another alternative was to get involved in long-term contracts. This was an option for base-load generation units. Nowadays, long-term contracts have been used to lock prices; price risk is removed, in absence of options and other financial derivatives. But before entering into long-term contracts, the company must evaluate the benefits that it expects to obtain from it. The optimal contract length reflects an economic trade-off between the marginal cost and marginal benefits of extending the length of the benefit. A graphical representation of optimal length contracts is shown in Figure 7.1.

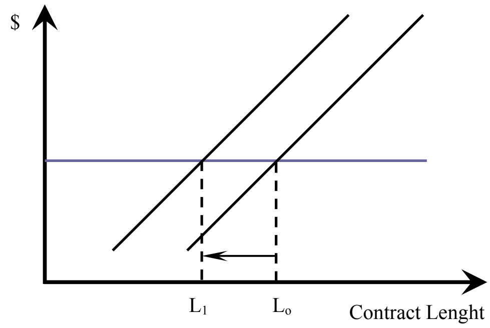

Figure 7.1 Optimal Length Contract

With the liberalization of fuel markets, the merit-order for the scheduling of generating units is not any longer guaranteed. Fuel can be contracted for purchase in a number of ways, allowing the generator to increase security of supply of primary fuel. However, there are limits to the flexibility of supply that a generator can achieve. The optimal contract length also depends on market information, as future economic environment becomes more certain, the length of contracts decreases [3]. Take-or-pay contracts and limitations associated with the gas delivery system are explicitly considered in determining the short-term UC strategy. A method for coordinating multiple constraints fuels which compete with one another is presented in [4]. The proposed method is general enough such that it can be used to solve many fuel constrained decision problems often encountered by the utility industry in its operation/planning activities.

The market permits GenCos to make more optimal decisions in committing to often expensive solutions. Hence, given that GenCos wish to maximize profits in the new restructured electric industry, it is necessary to redefine the UC problem. Richter et al. [5] formulate the UC problem as maximization profit program. Buyers purchase reserves per contract. Samer et al. [6] presents a stochastic model for scheduling the generation units of an electric utility while taking power trading and fluctuations in fuel and electricity prices into consideration. The model accounts for fuel constraints.

The emission allowances trading gives flexibility to generating units on the treatment of pollution constraints. In this document we treat these constraints as European options.

IV. UC: REAL OPTIONS FRAMEWORK

UC has been used in the vertical integrated electric industry for scheduling units to meet the demand at minimum cost. For day-ahead market, the total profit maximization with all the technical and economic constraints becomes generation scheduling program for GenCos in the deregulated environment with impacts of competitor's decisions and market conditions. Hence, UC will be a key tool for GenCo's optimal marketing decision.

Real options (RO) have become an important tool in valuation of generation assets in the electric industry [7][8][9]. RO is a term that has been created to identify the value inherent in a physical asset that is derived from some future contingent decision. RO is an extension of financial options to tangible assets [10]. Therefore, RO like financial options, give an owner the right but not the obligation, to take action [10][11]. The optimization program is formulated as a set of European options since they are exercised at maturity time *t,* where *t* represents the hourly trading period.

Electricity market prices are an important input to the profit-based UC algorithm; they are used to determine the expected revenue. The forecast of remaining demand and forecasted spot prices are calculated for each hour by another routine not described here.

The optimization program is to maximize the expected profit from the generation assets, energy and reserve, subject to operational constraints, over a period of time. Then, the UC program in the real option framework is formulated as the following mixed-integer programming problem:

Maximize the expected profits

$$\max\left\{E\left[\sum_{i}^{n} E\left(R_t, C_t\left(Pg_{i,t}\right)\right) - Su\left(u_{it}\right) - Sd\left(u_{it}\right)\right]\right\} \tag{1}$$

where

$$E\left(R_t, C_t\left(Pg_{i,t}\right)\right) = \left(P_t^E \cdot Pg_{i,t} + P_t^S \cdot S_{i,t} - C_t\left(Pg_{i,t}\right)\right) \cdot u_{it}$$

subject to the following constraints.

Demand constraint: At every period the residual demand would be estimated, so

$$\sum\nolimits_{i=1}^{n} Pg_{i,t} \cdot u_{it} \le D_t \qquad \forall\, t = 1,\ldots,T \tag{2}$$

Spinning Reserve: reserve residual demand would be estimated at every period, then

$$\sum\nolimits_{i=1}^{n} S_{i,t} \le S_R \qquad \forall\, t = 1,\ldots,T \tag{3}$$

Ramp-up constraints: From one time instant to the next the unit cannot increase its output above a maximum increment; this yields

$$Pg_{i,t+1} - Pg_{i,t} \le Z_i \qquad \forall\, t = 1,\ldots,T \tag{4}$$

Ramp-down constraints: A unit cannot decrease its output power above a maximum power decrement. Therefore

$$Pg_{i,t} - Pg_{i,t+1} \le W_i \qquad \forall\, t = 1,\ldots,T \tag{5}$$

Unit capacity constrain: Any unit at any time should operate within operational limits, then

$$Pg_{i,t}^{\min} \le Pg_{i,t} \le Pg_{i,t}^{\max} \tag{6}$$

State transition constraints: The length of time the unit has been off or on-line.

$$x_{it} = \begin{cases} \min\left(t_i^{on}, x_{t+1} + 1\right) & if \ u_{it} = 1 \\ \max\left(t_i^{off}, x_{t+1} - 1\right) & if \ u_{it} = 0 \end{cases} \quad (7)$$

Unit status constraint: The unit can be either on or off, then

$$u_{it} = \begin{cases} 1 & if \ \ 1 \le x_{i,t-1} < \ t_i^{on} \\ 0 & if \ \ -1 \ge x_{i,t-1} > -t_i^{off} \end{cases} \quad (8)$$

The power production cost function is given by:

$$C_{i,t}\left(Pg_{i,t}\right) = \begin{cases} P_t^F \cdot \left(a_i + b_i Pg_{i,t} + d_i Pg_{i,t}{}^2\right) & if \ Pg_{i,t} > 0 \\ 0 & if \ Pg_{i,t} = 0 \end{cases} \quad (9)$$

where $F \in \{Oil, Coal, N.Gas\}$

In the following section emission allowances is discussed. The emission constraint and how it is relaxed with the use of the emission market is also presented.

V. EMISSION ALLOWANCES

Emission markets arose as a consequence of the imposition of controls on nitrogen and sulfur oxides (NOx, SOx) through the Clean Air Act. The Act established nationwide limits on SO_2 emissions and allocated emission credit to generators. The Act permits the free exchange of allowance credits while meeting environmental restrictions. A method for coordinating sulfur dioxide emission allowance trading, energy and spinning reserve transactions, and consumption of take-or-pay fuels in the context of generation dispatching is presented in [12].

Environmental constraints would be relaxed by getting involved in pollution rights market [13]. The GenCo will have to take positions in the emission market and decide whether to exercise it or not depending on the marginal benefits at given period of time. In this document, we are modeling the pollution rights as European options as well, given that the trading period for electricity is considered hourly.

A convex function for trading allowance is considered for the local system. The incremental cost function of emission allowances is shown in Figure 7.2 in where $y > 0$ represents local system purchases allowances from the external market and $y < 0$ denotes the local system sells emission allowances to the external market [12]. The sales of emissions represent extra revenue.

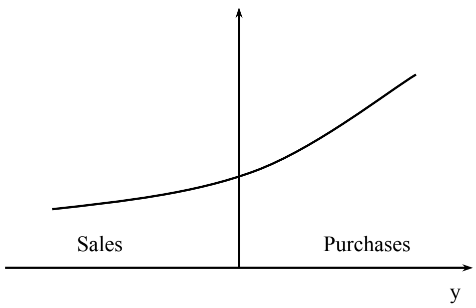

Figure 7.2 Incremental cost emission allowances function

The emission constraint included in the formulation is given by:

$$H_t\left(Pg_{it}\right) - y_t \leq EA \tag{10}$$

When a generating unit is scheduled to dispatch based on spot market and the emission constraints are activated, the trading of emission allowances would allow them to increase production level if the marginal benefit of producing is greater than the value of the pollution right.

In this work, the previous condition is represented as European option, which mathematically is described by:

$$\max\left(S_T - X, 0\right) \tag{11}$$

This reflects the fact that the option will be exercised if $S_T > X$. A graphical representation of previous situation is depicted in Figure 7.3.

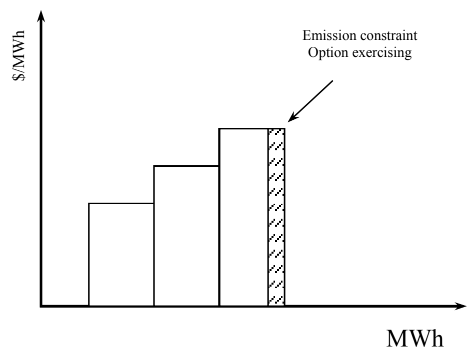

Figure 7.3 Representation of the emission constraint and emission option

The effect on the optimal commitment decision will be determined by the dependence between the prices of electricity and the prices of fuel and emission rights.

VI. NUMERICAL EXAMPLES

In this section simple examples are presented. In these examples, the time horizon is 3 hours with hourly trading periods. The generation system has 3 units. Three different fuels are available for consumption by the 3 generating units. The unit parameters are given in Table I.

TABLE I

Unit parameters

Unit	1	2	3
Fuel	Coal	N. Gas	Oil
a ($/h)	300.00	200.00	5.00
b ($/MWh)	21.75	12.01	1.22
c ($/MW^{2}h)	0.002400	0.001956	0.00001685
P_{min} (MW)	50	20	50
P_{max} (MW)	300	50	420
Min up (h)	2	3	2
Min down (h)	1	1	1
Max Ramp up	100	100	50
Max Ramp down	100	100	50

Developing the forecasted data is an important topic, but beyond the scope of this paper. For the results presented in this section, the forecasted load and prices are taken to be those shown in Table II. The transmission system is neglected in the optimization program. Fuel prices are considered to follow a random walk and are shown in Table III.

TABLE II

Forecasted demand and prices

Period	D_t	S_t	P_t^E	P_t^S
1	508.70	50.87	24.22	21.5
2	531.70	53.17	26.60	23.2
3	523.20	52.32	25.31	22.9

TABLE III

Forecasted fuel prices

	Fuel Type		
Period	Coal $/Ton	N. Gas $/MMBTUs	Oil $/bbl
1	0.978	2.116	27.731
2	1.027	2.073	26.899
3	1.078	2.033	27.705

The first example illustrates the self-scheduling real option approach. The impact of trading allowances is neglected. The second example takes into consideration trading emission allowances and shows the effect on firm's profits improvements.

The unit scheduling neglecting environmental constraints is presented in Table IV.

TABLE IV

Unit status

Period	Coal	N Gas	Oil
1	1	0	0
2	1	0	0
3	1	0	0

The generation outputs produced at every period are displayed in Table V.

TABLE V

Units' output committed

Period	U1		U2		U3	
	D	S	D	S	D	S
1	100	0	0	0	0	0
2	100	0	0	53.17	0	0
3	50	0	0	0	0	0

From Table V it can be observed that Unit 1 is restricted to produce 100 MW in the first and the second period due to the Ramp Up constraint. The Spot price covers its average costs. Units 2 and 3 are not producing given that the Spot price is very low. However, they may decide to participate in the reserve market. In order to evaluate the participation in this market, they need to forecast the probability of being call. Assume that the probability to be call is 70%, just in period 2 the U2 will be willing to sell in the reserve market.

TABLE VI

Unit profits

Period	U1	U2	U3
1	63.5145	0.0	0.0
2	603.5375	1233.5	0.0
3	2.8020	0.0	0.0
Total	669.8540	1233.5	0.0

Additional profit can be obtained if during the periods of non emission violation those are sold to the emission markets or are swapped with other market players.

In this second example, it is assumed that coal-fired unit emits SO_2 at rate of 0.001 Ton/MBTU and the SO_2 emission of the gas-fired and oil units are neglected. The results are shown in Tables VII and VIII.

TABLE VII

Unit status

Period	Coal	N Gas	Oil
1	1	0	0
2	1	0	0
3	1	0	0

TABLE VIII

Units' output committed

Period	U1		U2		U3	
	D	S	D	S	D	S
1	100	0	0	0.00	0	0
2	100	0	0	53.17	0	0
3	50	0	0	0.00	0	0

In the second case, the constraint in emission does not allow that the Coal unit produces its maximum capacity. This constraint is relaxed by trading emission allowances. In our formulation it implies to exercise an option. Definitely, even when the solution in production is similar profits are higher in the first case, this, because emission constraints were not considered nor the cost of emission options. In order to producers increase their output, the exercise of pollution options were required.

VII. CONCLUSIONS

The optimal UC program has been formulated in Real Option Framework. The market participation was considered in the provision of two different services: Electric Energy and Reserve.

The formulation of the optimization program is simple but consistent with the hourly sequential auctions in the spot market.

The use of emission rights would allow GenCos to relax emission constraints. These rights are also model as European options.

Electricity markets have been maturing and a growth in the use of financial derivatives is expected. Thus, a better understanding of financial and economic theory would be helpful to manage risk.

The effect on the optimal committed decision will be determined by the dependence between the prices of electricity and the prices of fuel and emission rights.

Real Options can dynamically adapt while operational constraints are considered since it can be seen as dynamic optimization portfolio.

REFERENCES

[1] Robert Wilson, Market Architecture, Technical Report, Stanford University, 1999.

[2] Fred N. Lee, "A Fuel Constrained Unit Commitment Method," *IEEE Trans. On Power Systems*, Vol. 4 No. 3, pp. 1208-1218, Aug. 1989.

[3] Baye, *Michael, Managerial Economics & Business Strategy*, 4th edition. Irwin McGraw-Hill. 2003.

[4] Fred N. Lee, "The Coordination of Multiple Constrained Fuels," *IEEE Trans. On Power Systems*, Vol. 4 No. 3, pp. 1208-1218, Aug. 1989.

[5] Charles W. Richter and Gerald B. Sheble, "A Profit-Based Unit Commitment GA for the Competitive Environment," *IEEE Trans. On Power Systems*, Vol. 15, No. 2, May 2000. pp. 715-721.

[6] Samer Takriti, Benedikt Krasenbrink, and Lilian S.-Y. Wu, "Incorporating Fuel Constraints and Electricity Spot Prices into the Stochastic Unit Commitment Problem," *Operations Research*, Vol. 48, No. 2, March-April 2000. pp. 268-280.

[7] Chung-Li Tseng, "Exercising Real Unit Operational Options under Price Uncertainty," IEEE Power Engineering Society Winter Meeting, 2000, Vol. 1, pp. 436 – 440, Jan. 2000

[8] J. Hlouskova, M. Jeckle, S. Kossmeier, M. Obersteiner, A. Schnabl, Real Option Models and Electricity Portfolio Optimisation, Institute for Advanced Studies, Vienna July 2001.

[9] Shi-jie Deng and Samuel Oren, "Incorporating Operational Characteristics and Startup Cost in Option-Based Valuation of Power Generation Capacity", *Probability in the Engineering and Informational Sciences* (PEIS), April, 2003.

[10] Johnathan Mun, *Real Options Analysis: Tools and Techniques for Valuating Strategic Investments and Decisions*, John Wiley & Sons, Inc. 2002.

[11] Steve Grenadier, "Option Exercise Games: An Application to the Equilibrium Investment Strategies of firms," *The review of Financial Studies*, Summer 2002 Vol. 15, No. 3, pp. 691-721

[12] Fred N. Lee, James Liao, Arthur M. Breiphol, "Coordination of SO_2 Emission Allowance Trading, Energy and Spinning Reserve Transactions, and consumption of Take-or-Pay Fuels," *IEEE Trans. On Power Systems*, Vol. 9, No. 3, pp. 1243-1251, Aug. 1994.

[13] http://www.evomarkets.com

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CHAPTER 8 DECENTRILIZED ELECTRICITY MARKET PRICE DYNAMICS

A paper published in the 2004 IEEE Power Engineering Society General Meeting

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Abstract

The fundamental Walrasian model of resource allocations can be replaced by a decentralized dynamical model. In a decentralized dynamic model, price plays the role of control and coordination of players' actions. Economic market dynamics is commonly studied from the stability viewpoint. Market price over a period of time is determined by the interaction of the market supply and market demand. Movements between equilibrium must be explained utilizing comparative static analysis. But, when time is explicit in the system, dynamic analysis must replace the latter method. The ability of the system to successfully navigate between points of equilibrium is known as dynamic stability. In this document, price market dynamics is emphasized as the bidding iterative process associated to each trading period. Additional properties can be studied under the dynamic framework in order to achieve market efficiency. Controllability, observability, and reachability may help to monitor market dynamics. Market monitoring covers financial and physical market activities. Numerical examples are provided to illustrate the market dynamics properties. Finally, some related issues are discussed and conclusions are presented

II. INTRODUCTION

The fundamental Walrasian model of resource allocations can be replaced by a decentralized dynamical model. In a decentralized dynamic model, price plays the role of control and coordination of non-cooperative players' actions.

Economic market dynamics is commonly studied from the stability viewpoint. Under pure perfect competition condition, market price over a period of time is determined by the interaction of the market supply and market demand [1]. However, this may require several rounds before the aggregate demand and aggregate supply intersects [2].

Movements between equilibrium must be explained utilizing comparative static analysis. But, when time is explicit in the system, dynamic analysis must replace the latter method. The movement between equilibrium points is a function of time. The ability of the system to successfully navigate between points of equilibrium is known as dynamic stability [3].

System theory has been used for economists to study inter-temporal resources allocation on competitive market environment since system theory studies transitions and changes in variables with time. Controllability, from the System Operator (SO) viewpoint, makes him able to adjust market performance by adjusting market system state variables. On the other hand, observability is associated with market information. In this context, controllability and observability system’s properties may help to identify market dynamic behavior, monitoring the market, in order to prevent market inefficiencies or market abuse.

Currently, electricity markets are composed of multilateral and spot markets. Multilateral contracts are direct agreements between participants, whereas spot trading is executed by using exchanges, similarly to other commodities. Then, the market is not completed informed. The market may be observable or may not. In either case, it is convenient that market participant actions be verifiable, market monitoring.

Effective market monitoring is needed to prevent gamming, market power, or market inefficiencies. FERC Order 2000 and FERC Order on standard market design (SMD) identify market monitoring as a basic function [4].

Market monitoring can be sorted on financial and physical market activities. Financial monitoring includes monitoring of supply and demand conditions and market performance, monitoring of market power exercise, and monitoring of market participants’ activities and transactions. Physical monitoring takes account of generation and transmission outages, availability indices (generation and transmission), among others [4].

Little work on electricity market dynamics is reported in the literature. Power system market modeling by differential algebraic equations and eigenvalue techniques is reported in

[5]. In references [7][8] market dynamics is modeled by using a discrete linear system model. The model is a closed-loop dynamic system in which previous and current information are use as a feedback signal. Two types of suppliers' decision making processes are presented: decision making under weighted moving average expectation and decision making under adaptive expectation. In [9] the authors developed a dynamic game base on a dynamic system in which generators are players. Generators learn the market and evaluate their next bids by using available market information, past prices, and private information.

Several assumptions constitute the framework of the present document: Market partial analysis, the market equilibrium price-quantity is defined only for the spot market, market demand is negatively-sloping linear function, and the transmission system is neglected.

This work studies the electric price spot market dynamics. The cornerstone of market dynamics is control theory. Price market dynamics is emphasized as the bidding iterative process associated to each trading period. Common definitions in the jargon of system theory, such as controllability, observability, and reachability are introduced in section III. In this document, market controllability and observability are seen from the Market Operator/System Operator (MO/SO) point of view. If the market is controllable, then it is possible to adjust market system state variables in order to adjust market performance. However, to adjust the market involves costs, intervention costs. If the market is observable, the MO can know the transition process of the market state variables. Market structure is described in section IV. Numerical examples are presented in section V to illustrate price market dynamics. Market Monitoring issues are briefly discussed in section VI. Finally, some conclusions are drawn in section VII.

III. MARKET DYNAMICS: CONTROL THEORY

In decentralized markets, the information on the allocation problem is split over the system. Price summarizes part of the information. Knowing the price, consumers are supposed to know how to choose their consumption bundle, without knowing neither the others consumers behavior nor the set of scarce resources.

System theory has been used for economists to study intertemporal resources allocation on competitive market environment. One of the advantages of the system theory approach is that it can be more easily adapted to explain noncompetitive commodity markets.

In the discrete form, system state space model is:

$$\begin{aligned} X(k+1) &= A(k)X(k) + B(k)U(k) \\ Y(k) &= C(k)X(k) + D(k)U(k) \end{aligned} \tag{1}$$

A. Controllability

A linear system is said to be controllable if, for initial state $x(0) = x_0$ there exists some input sequence of finite length that drives the state vector to any final state x_1. Controllability of the system is determined by matrices A and B [10]. Controllability can be determined by testing if the controllability matrix (CO) has rank n, where n is the dimension of the state space.

$$CO = \begin{bmatrix} B & AB & \dots & A^{n-1}B \end{bmatrix} \tag{2}$$

$$\rho(CO) = Rank(CO) = n \quad \rightarrow \quad controllable$$

B. Observability

Analogously, a linear system is said to be observable if, for any unknown initial state $x(0)$ there exists a finite integer $k_1 > 0$ such that the knowledge of the input sequence and output sequence $y(k)$ from k=0 to k_1 suffices to determine uniquely the initial states. Observability involves the matrices A and C [10]. The system is observable, if and only if the observability matrix (OB) has full rank (Rank (OB) = n)

$$OB = \begin{bmatrix} C \\ CA \\ \vdots \\ CA^{n-1} \end{bmatrix} \quad (3)$$

C. Reachability

A state is said to be reachable from the origin, if given $x(0)=0$ there exist a finite time interval $[0,T]$ and an input $\{u(t), t \in [0,T]\}$ such that $x(T)=\bar{x}$

IV. MARKET STRUCTURE

The complex interactions and interdependencies among electricity market participants are similar to those studied in game theory [11][12]. However, the different existing markets: day-ahead and forward, force Generation Companies (GenCos) to make strategic marketing decisions regarding the operation of the generating resources. The specific rules under which each different market operates will influence decisions made by market participants.

In what follows, dynamic Cournot model under naïve and forward expectations is considered. Players adjust their bids depending upon the “state” of the market. The MO is the auctioneer who collects supply bids, update prices and send it back to suppliers. Suppliers adjust bids and pass them to MO. This process is repeated until demand is satisfied for every trading period. Agents’ flow information is schematically represented in Figure 8.1. GenCos are the suppliers whereas Distribution Companies (DisCos) and Energy Management Companies (EMCos) are the consumers.

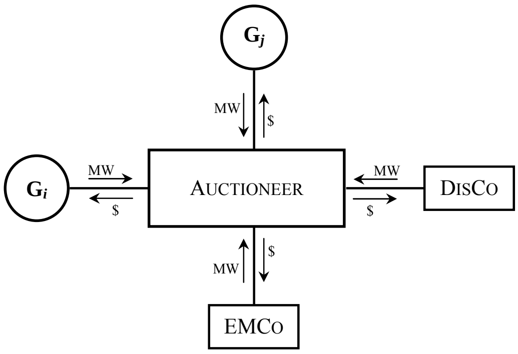

Figure 8.1 Agents' flow information in a decentralized electricity market

Consider the linear market-demand function given by:

$$p(Q(k)) = a - bQ(k) \tag{4}$$

where $Q(k) = q_1(k) + q_2(k)$

At period k, the profit of the GenCo i is:

$$\pi_i(k) = \left(p\left(Q(k)\right) - c_i\right)q_i(k) \tag{5}$$

Without loss of generality assume equal production cost and initial conditions equal to zero.

Solving for each GenCo their optimization problem, under the assumption of players behave naively, we obtain the industry output:

$$Q(k) = \frac{2(a-c)}{3b} \tag{6}$$

and the market price is:

$$p_t^c = \frac{a + \sum_{i=1}^{Ng} c_i - p_{t-1}}{\left(N_g + 1\right)} \tag{7}$$

There exists only one steady state equilibrium point given by:

$$p^* = \frac{a + \sum_{i=1}^{Ng} c_i}{\left(N_g + 1\right)} \tag{8}$$

Similarly, for the forward expectation case, we set up their optimization problem and solve for players' outputs, it yields:

$$q_i\left(k\right) = \frac{a-c}{2b} - \frac{\left(1-\lambda_j\right)}{2} q_j\left(k-1\right) \tag{9}$$

The reaction functions are given by:

$$q_i\left(k\right) = \frac{a-c}{2b}\left(\frac{1+\lambda_j}{2}\right) + \left(\frac{1-\lambda_j}{2}\right)\left(\frac{1-\lambda_i}{2}\right) q_i\left(k-1\right) \tag{10}$$

Change in output at period *k* with respect owns expectations are negative, except when other agent's expectation coefficient equals 1. The change in output at period *k* with respect past output, is always positive, except when own expectation coefficient equals 1.

$$\frac{\partial q_i\left(k\right)}{\partial q_i\left(k-1\right)} = \frac{\left(1-\lambda_i\right)}{2}\frac{\left(1-\lambda_j\right)}{2} > 0 \quad \forall \lambda \in \left\{-1 < \lambda < 1\right\} \tag{11}$$

When the expected coefficients are all equal to 1 the Bertrand outcome is achieved. On the other hand, when expected coefficients are all zero, the Cournot outcome is reached. For

$\lambda_i \neq \lambda_i \in 0 \leq \lambda \leq 1$ the Leader-Follower are attained. Figure 8.2 portrays the different possible outcomes with $a = 115,\ b = 2,$ and $c = 0.$

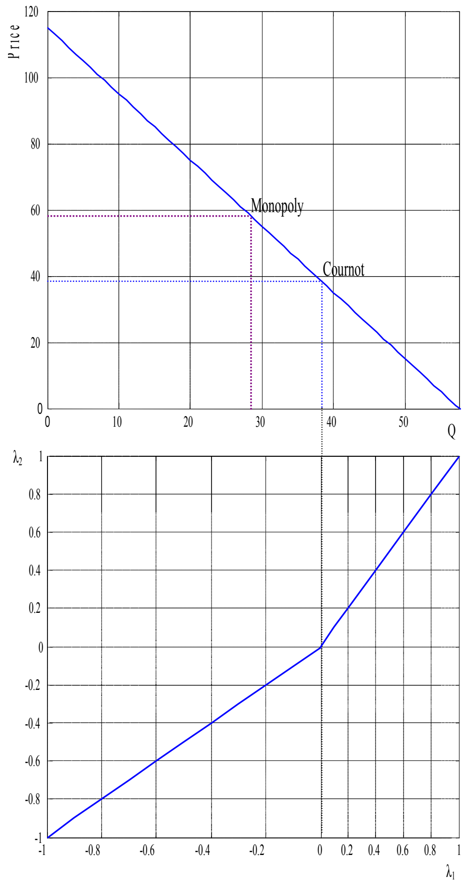

Figure 8.2 Expected agents' impact on market equilibrium

The generalized steady state equilibrium industry output and market price under naïve and forward expectations for n players and different production costs are given by the expressions shown in Table I.

TABLE I.

STEADY STATE EQUILIBRIUM MARKET

	NAIVE	FORWARD
PRICE	$p^c = \dfrac{a + \sum_{i=1}^{Ng} c_i}{\left(N_g + 1\right)}$	$p^c = a - \dfrac{\sum_{i=1}^{Ng} \left(\dfrac{a - c_i}{2}\right)\left(\dfrac{1 + \lambda_i}{2}\right)}{1 - \prod_{i=1}^{Ng} \dfrac{\left(1 - \lambda_i\right)}{2}}$
QUANTITY	$Q^c = \dfrac{N_g a - \sum_{i=1}^{Ng} c_i}{\left(N_g + 1\right) b}$	$Q^c = \dfrac{\sum_{i=1}^{Ng} \left(\dfrac{a - c_i}{2b}\right)\left(\dfrac{1 + \lambda_i}{2}\right)}{1 - \prod_{i=1}^{Ng} \dfrac{\left(1 - \lambda_i\right)}{2}}$

Whether central optimization models or centralized auction mechanism are use to clear the market, it is known the difficulties of allocating units with exact cost or bids results on degenerated solutions [13][14]. From the dynamics point of view, this represents that the market is not controllable neither observable. However, the market reaches the equilibrium which is also a Nash Equilibrium [11][12].

Under the current market-rules of the day-ahead market, price is determined at the beginning of every period (24 periods). The price prevails constant in each of these periods. Graphically, this is represented in Figure 8.3 for three succeeding periods.

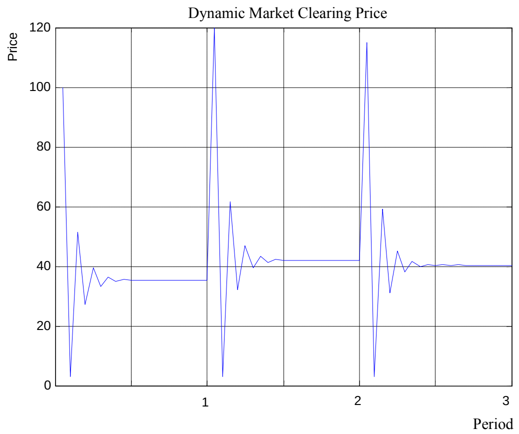

Figure 8.3 Multi-period dynamic market clearing price

The dynamics represents the necessary bidding rounds between players and auctioneer, in order to reach market clearing price.

Figure 8.4 presents the dynamic price discovery for a given trading period under a naïve expectation. This is the dynamic effect shown in Figure 8.3 on supply-demand curves representation. The quantity supplied in the initial period is short, producing a relative large price where it intersects the demand curve. This large price intersecting the supply curve calls forth in the next period a large supply. The production and price keep moving until equilibrium is reached.

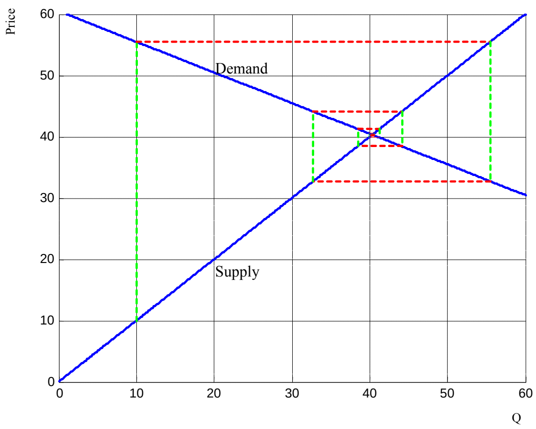

Figure 8.4 Market equilibrium convergence process for a *t* trading period

This process is carried out every trading period. GenCos' actions become strategically linked.

V. NUMERICAL EXAMPLES

This section presents some numerical examples of the models above described. This version is for a single period and single market without generation upper limits. With out loss of generality this idea could be extended to cover the energy market, as well as fuel and environmental markets. Nevertheless, we will concentrate only in the electricity sector.

For sake of simplicity two players compose the market. First, GenCo 1 and GenCo 2 compete to supply the market under Cournot naïve expectation. Subsequently, Cournot under forward expectation is simulated.

Three cases are considered under agents' naïve expectations. Production costs are equal in case I. In cases II and III production cost of GenCo 2 had increased. Demand and production cost parameters are shown in Table II. Simulation results are presented in Table III.

TABLE II

DEMAND AND PRODUCTION COST PARAMETERS

Parameters	CASE I	CASE II	CASE III
a	115	115	115
b	2	2	2
c_1	4	4	4
c_2	4	6	8

TABLE III

MARKET DYNAMICS PROPERTIES UNDER NAÏVE EXPECTATIONS

q_1 (MW)	18.50	18.8333	19.1666
q_2 (MW)	18.50	17.8333	17.1667
Controllable	No	Yes	Yes
Observable	No	No	No
Stable	Yes	Yes	Yes

From Table III, we can observe that the system market is stable. When cost are equal, market equilibrium is reached, but the system is not controllable. On the other hand, when costs are different the system market is controllable. However, in both cases the market is not complete observable. Price dynamics is shown in Figure 8.5.

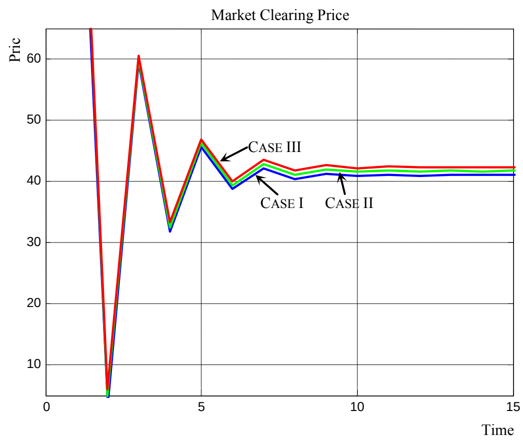

Figure 8.5 Market dynamics clearing price (naïve expectations)

GenCos under forward expectations is studied next. Four cases are considered. Combination of production costs and forward expectations constitutes the four-case analysis. GenCos parameters and market dynamic properties are shown in Table IV.

TABLE IV

DEMAND AND PRODUCTION COST PARAMETERS

Parameters	CASE I	CASE II	CASE III	CASE IV
a	115	115	115	115
b	2	2	2	2
c_1	4	4	4	4
c_2	4	6	6	6
λ_1	0	0.2	0.4	0.4
λ_2	0	0.2	0.4	0.6

Table V shows the market equilibrium under different conditions. From the same table, we can observe that in first column the equilibrium market is the same as naïve expectation outcome, shown previously in Table III.

TABLE V

MARKET DYNAMICS PROPERTIES UNDER FORWARD EXPECTATIONS

q_1 (MW)	18.50	19.3452	19.9725	20.9574
q_2 (MW)	18.50	18.5119	19.2582	18.9628
Controllable	No	Yes	Yes	Yes
Observable	No	No	No	Yes
Stable	Yes	Yes	Yes	Yes

Figure 8.6 shows the dynamic price for all cases. From the same graph, we observe that as long as the forward expectation is adjusted through their coefficient λ price dynamics converges faster, reaching different industry output between Cournot-Bertrand market equilibriums range. Consequently, the market presents multiple equilibriums based on the agents' expectation. Some of these are socially better than others.

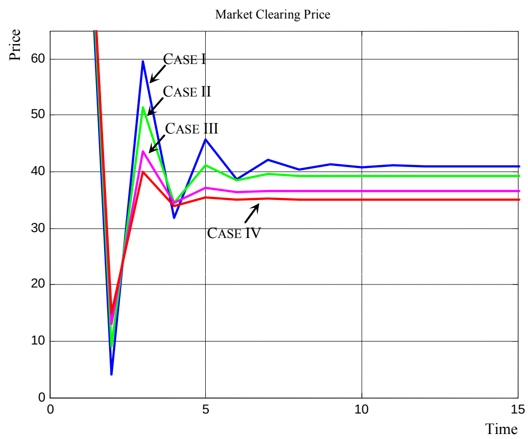

Figure 8.6 Market dynamics clearing price (forward expectations)

From the same Figure 8.6 we observe that market clearing price converge faster as coefficient factors get close to 1 which from market point of view, players are price takers instead of prices setters.

VI. MARKET MONITORING

In a decentralized market, prices do not only just clear market but fulfill additional functions under the new information economics.

From the simulations previously shown, important market monitoring information is obtained from the dynamic modeling. The system is most of the time complete unobservable. Because the system consists of two state variables, one state is observable. These dynamic properties need to be evaluated by SO/MO to decide whether intervention is necessary. On the other hand, there are few cases in which the system is not complete controllable. One case result when GenCos have same production costs, besides the forward expectation is zero, becoming the classical Cournot market equilibrium. Additional results showed that this condition prevails when forward expectations and production costs are the same for both GenCos. Market outcome is stable in all the cases reported. However, the system is unstable when both expected coefficients reach -1, becoming oscillatory.

VII. CONCLUSIONS

This paper reports dynamic market price discovery in a decentralized energy market. Two-GenCo market was considered for dynamic simulation and analysis.

Market dynamics price discovery represents the bidding process in a closed loop dynamic system. In a decentralized market, price dynamics depends on strategic agents' bids. Agents' decisions are made base on current available information, public and private.

Forward expectations incorporate private past information to the strategic decision of GenCos during the bidding process. GenCos also are able to incorporate other agents expected behavior into the reaction functions.

The dynamic properties should be considered by MO/SO in short term market monitoring.

VIII. REFERENCES

[1] Ariel Rubestein and Asher Wolinsky, "Decentralized Trading, Strategic Behaviour, and the Walrasian Outcome," *Review of Economics Studies*, 1990, vol. 57, issue 1, pp. 63-78.
[2] Mordecai Ezekiel, "The Cobweb Theorem," *The Quarterly Journal of Economics*, Vol. 52, No. 2, pp. 255-280, Feb. 1938.
[3] Walter C. Labys, Dynamic Commodity Models: Specification, Estimation, and Simulation, Lexington Books, 1973.
[4] A. F. Rahimi and A.Y. Sheffrin, "Effective market monitoring in deregulated electricity markets," *IEEE Trans. on Power Systems,* Vol. 18, No. 2, pp. 486- 493, May 2003.
[5] F. Alvarado, "The Stability of Power Systems Markets," *IEEE Trans. on Power Systems*, Vol. 14, No. 2, pp. 505-511, May 1999.
[6] F. Alvarado, The Dynamics of Power Systems Markets, Technical Report PSERC-97-01, Power Systems Engineering Research Consortium (PSERC), The University of Wisconsin, March 1997.
[7] Weiguo Yang and Gerald B. Sheble, "Power Market Stability under Price Expectations Models," in Proc of the *32nd North American Power Symposium*, Vol. 2, Waterloo Canada, October 2000. pp. 9-22 – 9-27.
[8] Weiguo Yang, "Short-term electric market dynamics and generation company decision-making in new deregulated environment," Ph.D. dissertation, Dept. Elec. Eng., Iowa State University, 2003.
[9] Poonsaeng Visudhiphan and Marija D. Ilic, "Dynamic games-based modeling of electricity markets," in *Proc. of the 1999 IEEE Winter Meeting, Power Engineering Society*, Vol. 1, pp. 274 -281, Jan.-Feb. 1999.
[10] Chi-Tsong Chen, *Linear System Theory and Design*, Oxford University Press.
[11] Oz Shy, Industrial Organization Theory and Applications, The MIT Press, 1998.
[12] Jean Tirole, The Theory of Industrial Organization, The MIT Press.
[13] Gerald B. Sheblé, Computational Auction Mechanisms for Restructured Power Industry Operation, Kluwer Academic Publisher, 1999.
[14] Somgiat Dekrajangpetch, Gerald B. Sheble, Antonio J. Conejo, "Auction implementation problems using Lagrangian relaxation," *IEEE Trans. on Power Systems*, Vol. 14 No. 1, pp. 82 -88, Feb. 1999.

CHAPTER 9 ELECTRICITY MARKET PRICE DYNAMICS: MARKOV PROCESS ANALYSIS

A paper published in the 8th International Conference on Probabilistic Methods Applied to Power Systems, PMAPS 2004

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Abstract

Market dynamics have been studied with emphasis on price stability. Dynamic market pricing in a purely competitive environment for a given trading period is determined by the interaction of the supply and demand with the information available to each. The scheduling of a generation is determined according to a Generation Company's (GENCOs) perception of the expected future conditions. Future conditions include equipment availability and competitor play. These decisions, which attempt to maximize profits, and the resulting interactions represents a major source of electric market dynamics. Profits in any period depend on level of efficiency as well as on the levels of efficiency of other competing GENCOs. Incorrect, untimely, and improperly analyzed information often lead to suboptimal solutions for the profit maximizing player. This paper analyzes market price dynamics by using Markov Process (MP) modeling. An example application is presented as would be conducted by information seeking players to maximize profit. Key issues with applying Markov chains to different market conditions are identified. The key economic pricing signals, representing different forces, are examined as a basis of influencing these key decisions by each player.

I. INTRODUCTION

A. Background

Dynamic market pricing in a competitive fluctuating business environment is determined by the interaction of the supply and demand with the information available to each player. Demand is highly dependent on changes in basic variables that describe the state of the economy. To model demand processes, the use of a set of states of the world has been suggested in where each state includes the relevant information about demand [1].

The sellers' goal is to follow a dynamic market strategy that brings the best expected total profit over a given period of time. Sellers' dynamic market strategy involves implicitly a dynamic pricing policy. Hence, they need to balance the trade-off between current and futures revenues in setting the prices. Incorrect, untimely, and improperly analyzed information would lead to suboptimal solutions. The financial implications of relying on outdated or incorrect information can be enormous. Signals from the market must be processed by the seller as time progresses to choose actions that increase profits.

B. Literature

Decentralized price systems can lead to efficient allocation of resources. Electricity market design trends toward a decentralized self-scheduling model. A centralized auctioneer, Power Exchange (PX), is seen as the fictitious Walrasian Auctioneer in the Walrasian General Equilibrium model [2]. PXs normally provide bidding trading in contracts for power delivery during a particular hour of the next day, called day-ahead or spot market. The usual trading method varies from a daily single-side auction to double-side auction for every hour to match transactions at a uniform price [3]. In decentralized markets, price is adjusted dynamically based on the response of market supply-demand. GENCOs offer energy into the market at prices offered based on estimated future conditions. As market participants, GENCOs in single-side or double-side decentralized models, are not price takers but price setters. The aggregate quantity of electricity offered is a nondecreasing function of price. Depending on market rules, GENCOs may offer power in block contracts. This implies that the market supply curve has the form of a step functions. Similarly, buyers may make bids into the market at prices that they are willing to pay. The aggregate demand curve is a decreasing step function of price. The market clearing price is commonly determined by the intersection of these demand-supply curves. In addition, the market clearing price must incorporate consideration of any transmission constraints. When the bulk system does not have transmission constraints, the spot market price of electricity can be computed by successively dispatching generation with the lowest price until the demand is met.

Price dynamics can be analyzed from the bidding strategy that each player develops to maximize profits. A bidding decision is formulated as a Markov Process as reported in [4]. Those authors used bidding decisions to determine the price and amount of electricity for a supplier assumed to be risk-neutral. The same authors in [5] developed a systematic method to calculate transition probabilities and rewards for the Markov Decision Process model. All other suppliers are modeled by their bidding parameters with corresponding probabilities. The optimal strategy is calculated to maximize the expected reward over a planning horizon. The authors considered a simplified market in where the suppliers' bids are chosen from the cheapest until the load in that period is met. For all units that are called into operation, the last selected bid price defines the spot price in that load period. Security constraints and other market characteristics are neglected. The no-arbitrage-pricing principle is applied to the pricing of flexible electricity contracts in [6]. Pricing of flexible contracts involves a scheduling policy. By representing the spot price with an appropriate stochastic process, the scheduling policy can be found using stochastic dynamic programming. The mathematics of finding optimal bidding strategies in multi-period electricity market auctions of energy and reserve markets is presented in [7] and [8]. Generator costs, operating constraints, and exogenous price uncertainties are fully taken into consideration within the approach. These authors studied strategies for generators making offers into wholesale electricity markets when both demand and competing generators behavior is unknown but represented by a probability distribution in [9]. Their analysis is restricted to markets in which the supply of power in a given time interval is defined by generators of power in the form of offers of energy blocks. Market dynamics with interaction among participants is modeled in [10] by using a discrete linear system model. The model is a closed-loop dynamic system in which current and previous information are use as a feedback signal into decision support systems.

Price market dynamics is emphasized as the bidding iterative process associated to each trading period in game theory framework by using difference equations [11].

C. Paper Contribution and Structure

This paper analyzes market price dynamics by using a Markov Process (MP). A single snap shot is considered in order to identify not only the different scenarios but also the various services (products) that a GENCO might consider selling when determining the optimal scheduling of units.

The following section presents the market assumptions. Then, the Discrete Time Markov Process is presented. Key issues with applying Markov chains to different market conditions are identified. Key economic pricing signals, representing different market forces, are examined as a basis of influencing these key decisions of each player. The incorporation of demand side bidding introduces more uncertainty to the suppliers. Demand side bidding for electric energy is presented next. Finally, problems involved in the market price dynamics are summarized.

II. MARKET FRAMEWORK: ASSUMPTIONS

Several assumptions set up the framework of the present model. Model assumptions follow. The market is operated as an open auction. Each hourly auction is independently solved by the central agency. There are 24 sequential auctions that constitute the day-ahead spot market. A discrete-time model is considered given the hourly trading periods of the electricity spot market. The discrete nature of the model is well suited to study the day-ahead market dynamic trading process. Future demand and possible competitors' actions, including price and quantity for each period, are forecasted by each player. For sake of simplicity, but without loss of generality, energy is the unique commodity traded in the market. Supply-side bidding for energy is assumed in this paper. Demand side bidding for energy is included. It is noted that service operations are typically interested in customer retention. Additional services are also mentioned as the various markets form a complex interaction of services.

Several assumptions follow. Sequential decisions are made at the beginning of each trading period. The system successfully moves between equilibrium points (market equilibrium exists for every trading period). The ability of the system to successfully move between points of equilibrium is an assumption of dynamic stability [12]. Figure 9.1 shows graphically this condition, as the supply and demand curves at two trading periods are explicitly represented.

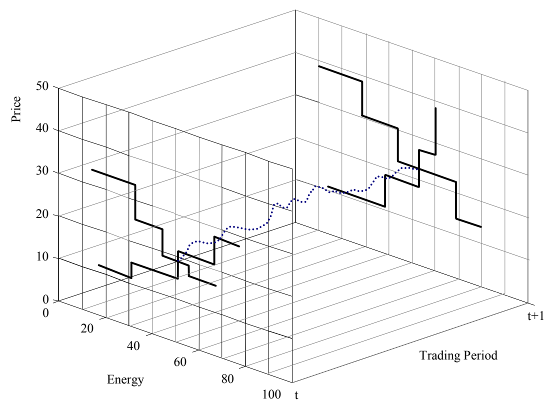

Figure 9.1 Market Price Dynamic Stability

Form Figure 9.1, observe that price fluctuations occur. This is common as the real time supply and demand balance. In this analysis, the transition between one point and another is assumed to be a straight line. Once the equilibrium is reached at given trading period it remains constant until new trading period is started.

III. MARKOV PROCESS: DISCRETE TIME

A Markov Process is a stochastic process characterized by the Markov property that the distribution of the future process depends only on the current state, not on all of the historical values [13]. The Discrete Time Markov Process (DTMP) that characterizes the process captures its evolution among states of over time by its transition probability distribution function, including the conditional probabilities. The generality of the MP framework makes it attractive for engaging in sequential decision-making problems under uncertainty.

Consider a process, observed at time periods $t = 0,1,...,n$ to be in one of the states $i \in S$. The transition probability between state i to state j at time n-1 is the probability $P[X_n = j \mid X_{n-1} = i]$ where X_n denotes the process at time n.

The one step probability transition matrix P is defined as:

$$P = \begin{bmatrix} p_{0,0} & p_{0,1} & \cdots & p_{0,j} \\ p_{1,0} & p_{1,1} & \cdots & p_{1,j} \\ \vdots & \vdots & \ddots & \vdots \\ p_{i,0} & p_{i,1} & \cdots & p_{i,j} \end{bmatrix} \tag{1}$$

Each row of the probability transition matrix represents the transition flow out of the corresponding state. Each column of it represents the transition flow into the state. As the accumulative transition flow out of each state must be 1, the rows of matrix P must sum to 1.

When the market dynamic environment is unknown, the transient probabilities can be estimated by using Decision Analysis, Monte Carlo Simulation or Reinforcement learning algorithms [14].

The optimal expected profit generated at period k moving from state i to state j is given by

$$\pi_k(i,j) = \max\left\{ P_{(i,j,s)}\left(P_{Gi}^k p_E^k - C\left(P_{Gi}^k\right)\right)\right\} \tag{2}$$

where $P_{(i,j,s)}$ is the transition probability of state s from state i to state j, P_{Gi}^k is the amount of active power generation of unit i at period k, p_E^k is the energy spot price at period k, and $C_i\left(P_{Gi}^k\right)$ represents the production costs of unit i.

This is a dynamic optimization program, over a specific time horizon, given by:

$$\Pi^* = \sum_{k=1}^{T} \pi_k(i,j) \tag{3}$$

where T is the horizon period of interest and Π^* is the total expected profit over the desired horizon.

The players data mine market behavior of competitors by comparing actual market outcomes with forecasted outcomes. The estimated information is updated each period [15]. The players expect a reinforcement signal from the environment indicating whether or not the latest move was in the right direction. The optimal prediction about the market is beyond the scope of this paper.

Two types of uncertainties, common in electric markets, are embedded in the transient matrix. These uncertainties are market uncertainty and system uncertainty. Market uncertainty is linked corresponding to different electricity market clearing prices and market demand. It is assumed, in this paper, that each player observes the demand process. At the beginning of period i, each player has exact information about the history of the market demands and prices. However, to include market condition uncertainty, the player does not necessarily know the exact state of demand at each period. Technical uncertainties, related directly with the bulk system such as transmission constraints, transmission lines outages, and generation outages, are included. Other technical uncertainties could be included. Transmission capacity is the only technical uncertainty considered in this presentation. A graphic representation of both uncertainties considered in our model is depicted in Figure 9.2.

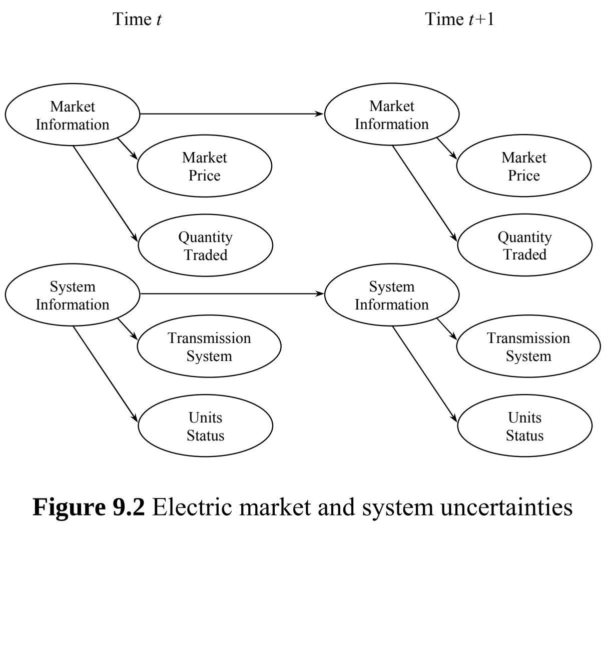

Figure 9.2 Electric market and system uncertainties

Other market information has to be observed and forecasted by market participants (i.e. fuel market prices, weather). Fuel is the main price factor in the production of electricity. Fuel price alter the market strategy for a market participant at a given period of time and may be embedded in the transition probability between states. Even though spot fuel prices are public information, a player has to decide the fuel price to index in the bid as part of their market strategy as many fuel contracts are only loosely indexed to the spot market.

Ancillary services (AS) play an important role in a player's decision in decentralized markets. The lack of reactive power will reduce the amount of energy transferred through the power system is a common example. If such information is mined by a player, that player may make additional revenues, by probably exercising market power based on the locational characteristic of reactive power.

IV. MARKET STATES

Key economic pricing signals are a basis of influence on key decisions of each player.

The scheduling of a generation unit, for a GENCO, is based on a perception of expected future conditions, including equipment availability and competitors play. Profits in any period depend on the level of efficiency of the individual players as well as on the efficiency levels of other competitive players. The simple rule is that it is profitable to sell if the spot market price is higher than the production costs. Thus, the production costs for each block of electric energy has to be estimated. The production costs have to include all available information about each unit and all technical requirements.

Each player's goal is to follow a dynamic market strategy that brings the best expected total profit over a given period of time. This is a highly demanding task. The player needs to balance the trade-off between present and future revenue in setting all prices. Each player has to account the state of market demand and transmission system operation.

Players need adaptive mechanisms that respond to the information revealed by agents through all markets. The different market states are represented in the transition matrix in which the market state is strongly dependent on the past state. Changes in market state may include both market and technical uncertainties observed by each market participant.

In a decentralized market design, price summarizes this information. Transmission system capacity information is embedded in the Locational Marginal Price (LMP). Market participants should have access to transmission system information. This information is needed to forecast the market state. Perfect information is not available as the contractual (trading) information is not revealed. LMP provides more than locational information based on transmission system losses and congestions. LMP provides insights to production fuel type dominance. Observing fuel prices in their respective markets and the price of electricity, enable a player to identify price at a given point of time. Such a dependency is shown by spark contracts. Such contracts are beyond the scope of this paper [16].

Generally, high demand conditions drive high prices, not only because the transmission system is more congested, but also because more expensive units are operating.

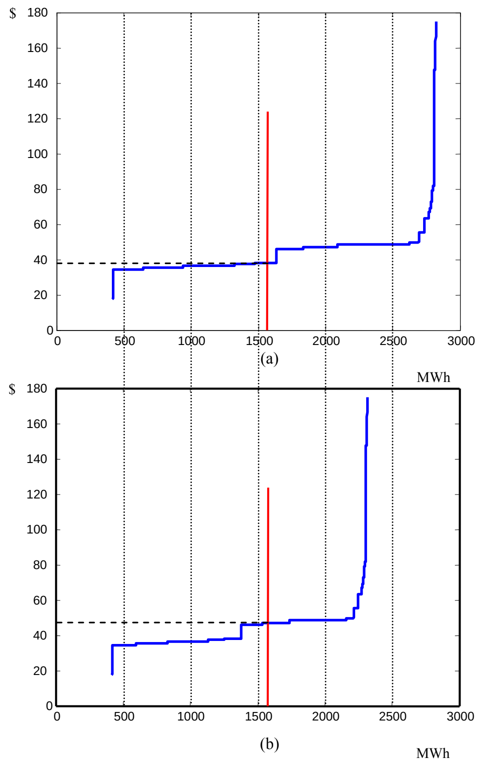

Figure 9.3 Hockey-stick supply curve

A price signal from the markets indicating whether the latest strategic moves were in the right direction is expected by players in order to make the next decision. This is a reinforcement signal. When this reinforcement signal is not observed in the current information or it is not assimilated, a player may end with a bad outcome. It is necessary to distinguish between a bad outcome and bad decision. Bad outcome does not necessarily imply that a bad decision was chosen. It may happen for instance when a market "*hockey-stick*" supply curve is observed. A "*hockey-stick*" curve is an abrupt change in the demand in either a severe increase or decrease of demand. Then, a GENCO might expect a similar demand curve in the next period. The *hockey-stick* supply curve may be the result of a unit outage or transmission congestion, just to name two common causes. Such changes in price signals require all players to know in detail the reason behind supply curve change. An example of the effect of unit outage supplying the demand is depicted in. This outage leads to a shrinking of the supply curve and by consequence an increment in the market clearing price. It can be observed that the price is below \$40 in (a) and then it goes around \$50 in (b).

Information in the electricity markets as well as fuel markets must be updated between each equilibrium points. It is necessary, in more rigorous studies, to model the actual trading frequencies when the markets and the information are not synchronized as in these first order models. This paper extends the decision analysis approach to a Markov Model approach.

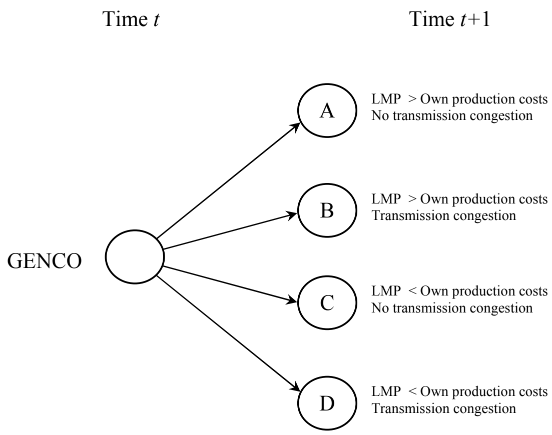

Figure 9.4 An example of a discrete Markov Chain

As depicted in Figure 9.4, when transitioning from period *t* to period *t+1*, there is a chance of transitioning to state A, B, C, or D. Each one of the states may represent the expected outcome which can be obtained by using Decision Analysis or Monte Carlo Simulation [17][18]. In State A and C the system is not congested. But in state A the LMP is higher than the GENCOs bid whereas in state C the opposite is true. Similar scenarios are defined for states B and D.

The transient probability matrix, according with these 4 states shown in the previous graph is given by:

$$P = \begin{bmatrix} p_{A,A} & p_{A,B} & p_{A,C} & p_{A,D} \\ p_{B,A} & p_{B,B} & p_{B,C} & p_{B,D} \\ p_{C,A} & p_{C,B} & p_{C,C} & p_{C,D} \\ p_{D,A} & p_{D,B} & p_{D,C} & p_{D,D} \end{bmatrix} \tag{4}$$

The LMP is strongly dependent of the market participant prices and the transmission system congestion. At the moment of congestion, occurs the price increases abruptly. The price and the respective density function (PDF) for a fictitious GENCO expectation on LMP due to congestion effect is shown in Figure 9.5. Because we are considering discrete variables instead of continuous, the probability mass function (PMF) is also shown in Figure 9.5 (b).

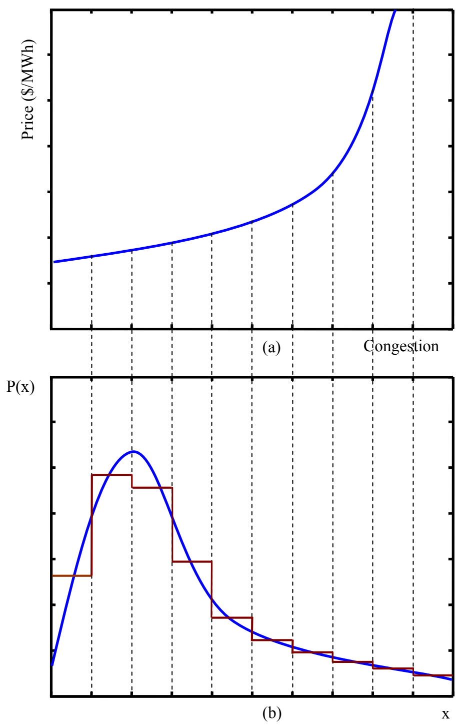

Figure 9.5 Expected delivery energy price considering congestion effect (a) and the associated PDF and PFM (b)

V. NUMERICAL EXAMPLE

Consider the following illustrative example. Each state *k* of the market is characterized by a discrete, price-dependent probability function. In order for a GENCO to sell, the price of energy has to be acceptable. It means that spot market price must be greater than the price they are willing to sell. In each state, GENCO does know some information about other GENCOs such as physical location, fuel inputs, among others. However, the GENCO does not know how those other GENCOs are going to bid.

It is assumed for this simple model that at every period fuel price remains constant. For sake of illustration the 4 states used on the course of this document are considered. The analysis is executed for the next trading period -the next hour.

In order to solve the MP problem, we need to have complete knowledge of the transient probabilities $P_{(i,j,s)}$. The transient probability for the 4 different states was obtained after performing Monte Carlo simulations. The six-bus system from [19] was considered for the analysis. In these simulations, other uncertainties were modeled such as line and generation outages. The expected market information is listed in Table I.

The 4 states summarize a series of feasible scenarios to occur. The respective probability associated to each state is the transient probability. The state probabilities are displayed in Table II.

TABLE I

EXPECTED: DEMAND, SPOT PRICES, AND POWER COMMITED

Current Demand	Low Demand	High Demand
350 MW	340 MW	370 MW
19 $/MWh	18 $/MWh	21 $/MWh
50 MW	45 MW	60 MW

TABLE II

STATE AND ASSOCIATED TRANSIENT PROBABILITY

State	Transient Probability
A	0.678
B	0.152
C	0.094
D	0.076

The transient probability displayed on Table II represents the market clearing price likelihood at given state in the next trading period. Therefore, state A is 67.8 % likely expected while state C has a 9.4 % probability of occurrence. Both cases consider that the transmission system is uncongested. Similarly, the other two states, B and D, have 15.2 % and 7.6 % probability of occurrence respectively. In addition these two scenarios consider the effect of transmission congestion. In these scenarios, transmission congestions blocks the optimal strategy given that this unit does not have market power. If it were possible for market power to be achieved because of transmission congestion, a GENCO would be able to manipulate the locational marginal price resulting in a substantial increment in profits.

VI. DEMAND SIDE BIDDING

Some of the existing markets do not allow the buyers to bid. Hence, demand is inelastic and the market equilibrium is achieved by successively dispatching generation with the lowest price until the demand is met.

The incorporation of demand side bidding introduces more dynamics components into the market model but may lead to more stable market operation. Buyers face similar uncertainties to what supplier face. Hence, buyers would be able to decide how much to consume based on the observed price. This could avoid or reduce the possibility of a hockey-stick supply curve and, consequently, prices spike.

A market participant, seller or buyer, has a choice of multiple markets into which different services could be bought, sold, or resold. Specifically, a GENCO could decide to allocate its output to the energy market or to one of the operating reserves markets. The observation of information from each market would be essential in the decision-making process for every market participant. For instance, an increase in electric prices could entice the buyer to respond by decreasing consumption.

VII. SUMMARY AND OBSERVATIONS

This paper focuses on analyzing market price dynamics by using Markov processes an observing the different market states. The analysis was carried out from the supplier's viewpoint in where players face the problem of setting the right price for services that would maximize gross profits. Nevertheless, buyers face similar problems and consequently the analysis can be easily extended.

A single snapshot was considered for this analysis. Sequential analysis would be repeated for a given time horizon to more accurately depict market play. Market participants need to adaptively adjust market strategies as soon as each new piece of information is gathered and understood.

Given that MP is based on current information the existence of bad outcomes, not bad decisions, may result when market information is not properly digested. This is true for all good decision whether computed using extensive models, or simple closed form solutions.

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REFERENCES

[1] Suresh P. Sethi and Feng Cheng, "Optimality of (s,S) Policies in Inventory Models with Markovian Demand," *Operations Research*, Vol. 45, No. 6, pp. 931-939, Nov. - Dec. 1997.

[2] Samuel Bowles and Herbert Gintis, "Walrasian Economics in Retrospect," *The Quarterly Journal of Economics*, Vol. 115, No. 4, pp. 1411 – 1439, November 2000.

[3] Gerald B. Sheble, *Computational Auction Mechanisms for Restructured Power Industry Operation*, Kluwer Academic 1999.

[4] Chen-Ching Liu, Haili Song, Lawarree, J., and Dahlgren, R., New methods for electric energy contract decision making, *in the Proc. of International Conference on Electric Utility Deregulation and Restructuring and Power Technologies, DRPT 2000*, pp. 125-129, April 2000.

[5] Haili Song, Chen-Ching Liu, Jacques Lawarrée, and Robert W. Dahlgren, "Optimal Electricity Supply Bidding by Markov Decision Process," *IEEE Trans. on Power Systems*, Vol. 15 No. 2, pp. 618-624, May 2000.

[6] Roger Bjorgan, Haili Song, Chen-Ching Liu, Robert Dahlgren, "Pricing flexible electricity contracts," *IEEE Trans. on Power Systems*, Vol. 15, No. 2, pp. 477-482, May 2000.

[7] Rajesh Rajaraman and Fernando Alvarado, Optimal Bidding Strategy in Electricity Markets Under Uncertain Energy and Reserve Prices, PSERC Publication 03-05 April 2003.

[8] Rajaraman, R., L.D. Kirsch, F.L. Alvarado, and C. Clark, 2001, "Optimal self-commitment under uncertain energy and reserve prices," in B. F. Hobbs et al., ed.: *Next Generation of Electric Power Unit Commitment Models*. International Series in Operations Research and Management Science (Kluwer Academic Publishers, Boston).

[9] Anderson, Edward J. & Philpott, A.B. "Optimal offer construction in electricity markets." *Mathematics of Operations Research*, 27 (1), pp. 82-100, 2002.

[10] Weiguo Yang, "Short-term electric market dynamics and generation company decision-making in new deregulated environment," Ph.D. dissertation, Dept. Elec. Eng., Iowa State University, 2003.

[11] Guillermo Gutiérrez-Alcaraz, Gerald B. Sheblé, "Decentralized Electricity Market Price Dynamics," accepted to be presented at *IEEE 2004 General Meeting Power Engineering Society*, Denver Colorado, USA.

[12] Walter C. Labys, *Dynamic Commodity Models: Specification, Estimation, and Simulation*, Lexington Books, 1973.

[13] Athanasios Papoulis, *Probability, Random Variables, and Stochastic Process*, McGraw Hill, Third Edition.
[14] C.V.L. Raju, Y. Narahari, and K. Ravikumar, "Reinforcement Learning Applications in Dynamic Pricing of Retail Markets," *in the Proc. of the IEEE International Conference on E-Commerce (CEC'03)*.
[15] J. S. Meditch, *Stochastic Optimal Linear Estimation and Control*, McGraw Hill Series in Electronic Systems, 1969.
[16] Shijie Deng, Blake Johnson, and Aram Sogomonian, "Spark Spread Options and the Valuation of Electricity Generation Assets," *in the Proc. of the 32nd Hawaii International Conference on System Sciences, 1999.*
[17] Kneale T. Marshall, Robert M. Oliver, *Decision Making and Forecasting*, McGraw Hill series in Industrial Organization and Management Science, 1995.
[18] Masaaki Kijima, *Stochastic Processes with Applications to Finance*, Chapman & Hall/CRC, 2003.
[19] Allen J. Wood, B. F. Wollenberg, *Power Generation Operation and Control*, Second Edition published by John Wiley and Sons, New York, January 1996
[20] Robert Dahlgren, Liu Chen-Ching Liu, Jacques Lawarree, "Risk Assessment in Energy Trading," *IEEE Trans. on Power Systems*, Vol. 18, No. 2, pp. 503-511, May 2003

CHAPTER 10 ELECTRICITY MARKET DYNAMICS: OLIGOPOLISTIC COMPETITION

A paper published in the Electric Power Systems Research

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Abstract

Presently, electricity markets are characterized by a small number of suppliers with distributed resources. These market suppliers can easily be identified because their geographic location is known. Essentially, two or three of them compete for leading the market whereas the rest of them follow. Hence, it is necessary to study the market structure as ologopolistic competition rather than perfect competition. This paper studies market producer decisions in a dynamic sequential framework by using discrete event system simulation (DESS) also known as discrete control theory. Two-player ologopolistic market structure is presented in this paper.

1. Introduction

Electricity markets are at the core of restructuring process. The traditional electricity supply or value chain is altered by restructuring with the same activities as when it was vertically integrated: transmission, generation, distribution, and commercialization. However, the new structure has revolved the way of making business.

Risk for market instability is one of the main concerns in a dynamic market. Market instability may result from disruption in any physical infrastructure, i.e. electricity, natural gas, petroleum, of the supply chain or any market inefficiencies.

Several methods have been utilized to model electric market economic dynamics. Decision analysis, game theory, stochastic simulation, adaptive agent systems, and systems theory are some in the list. Decision analysis, DA, allows a decision maker to focus on what is important rather than what is already known. DA is an iterative process of gaining insight and promoting creative alternatives to help decision makers make better decisions [1]. Game theory has been extensively applied to study dynamic economic and political conflicting situations [2]. Stochastic simulation uses computer techniques to imitate a model numerically in order to estimate the desired true characteristics of a system having random input components. Adaptive Agent Systems distinguished by its ability of learning as time progress can simulate very complex decision making process. Discrete event system simulation (DESS) also known as discrete control theory has also been applied to study economic models in dynamic framework [3]. However, the potential of DESS has not fully investigated. This paper studies market producer decisions in a dynamic sequential framework by DESS.

Market dynamics focused on power market instability is presented in [4, 5]. The paper shows a situation where the removal of congestions makes the market unstable. The impact of various policies on the dynamic behavior of power system markets is also reported. In [6] and [7] a closed-loop dynamic system in which previous and current information are use as a feedback signal for modeling market dynamics. A model of an electricity generation bidding system has been analyzed in [8]. The model is formulated as a control problem. A dynamic game base on a dynamic system in which generators are players is developed in [9]. Generators learn the market and evaluate their next bids by using available market information, past prices, and private information. In [10] a generalized approach for a two-player market model under naïve and forward expectations is analyzed. In this document the authors extend the previous work reported in [10]. Generation capacity limits and contingency effects, partial o total loss of generation, are included in the model.

The rest of the paper is organized as follows: in the next section market dynamics is established in a DESS framework. A two-GENCO model under quantity competition is then presented. A set of simple numerical examples are presented to illustrate the points at hand. Finally, conclusions are listed.

2. Market dynamics: discrete event system simulation

Control theory has become a standard mathematical tool for economists. Optimal control theory and dynamic programming are two sides of the same coin and lead to equivalent solutions for deterministic analysis [3]. Dynamic programming is used to solve problems of sequential decision making as optimal control does [14]. The process of making decisions can be seen as to find an optimal control policy.

A decentralized spot electricity market based on auctions, exhibit characteristics of discrete system problems [13]. The Market Equilibrium, price and quantity, it is found every training period. It implies that every trading period GENCOs will need to make a new decision. These decisions would be supported based on forecasted market information and current available information. Thus, the market is modeling by using difference algebraic equations [11].

3. Market dynamics under quantity competition

3.1. Market equilibrium

Consider the linear market-demand function given by:

$$p\left(Q(k)\right) = a - bQ(k) \tag{1}$$

where $p\left(Q(k)\right)$ is inverse market demand, $Q(k)$ is the total market output, a and b are constants. Total market output is $Q(k) = P_{G_1}(k) + P_{G_2}(k)$ where $P_{G_i}(k)$ is the GENCOs i's contribution. At period k, the profit of the GENCO *i* is:

$$\pi_i(k) = \left(a - b\left(P_{G_1}(k) + P_{G_2}(k)\right) - c_i\right)P_{G_i}(k) \tag{2}$$

where c_i is the production cost of GENCO *i*.

The first order condition to maximize profits is:

$$\frac{\partial \pi_i(k)}{\partial P_{G_i}} = a - c_i - 2bP_{G_i}(k) - bP_{G_j}(k) = 0 \tag{3}$$

GENCO i should set output to maximize profit considering the output decision of competitor. Under naïve expectation, GENCO i believes that GENCO j will not change its output such as:

$$P_{G_j}(k) = P_{G_j}(k-1) \tag{4}$$

Therefore at period k GENCO i setups its output as:

$$P_{G_i}(k) = \frac{a - c_i}{2b} - \frac{P_{G_j}(k-1)}{b} \tag{5}$$

The market system can be represented by the following 2nd-order system:

$$\begin{bmatrix} P_{G_1}(k+1) \\ P_{G_2}(k+1) \end{bmatrix} = \begin{bmatrix} 0 & -1/2 \\ -1/2 & 0 \end{bmatrix} \begin{bmatrix} P_{G_1}(k) \\ P_{G_2}(k) \end{bmatrix} + \begin{bmatrix} (a-c_1)/2b \\ (a-c_2)/2b \end{bmatrix} \tag{6}$$

$$p^E(k+1) = \begin{bmatrix} -b & -b \end{bmatrix} \begin{bmatrix} P_{G_1}(k) \\ P_{G_2}(k) \end{bmatrix} + [a] \tag{7}$$

where $p^E(k+1)$ is the electricity price at period k+1.

Under naive expectation, market system is always stable, even though A has one eigenvalue with real part.

3.2. Generation upper limits

In traditional Cournot analysis players choose quantities simultaneously. In addition, each firm presumes no reaction on the part of the other firms to a change in its output. Now, considering that GENCO *j* has a capacity constraint $P_{G_j}^{\max}$

$$P_{G_i}\left(k\right)=\frac{a-c_i}{2b}-\frac{P_{G_j}^{\max}}{b} \tag{8}$$

The capacity-constrained price game potentially will appear if players get informed [12].

3.3. Contingency: loss of generation

The step system response is considered in this work for modeling generation contingency -partial or total loss of generation. The step response is defined as the response of a system to a step input [11].

By simulating loss of generation, market vulnerability is studied. Market vulnerability problems means the activities of the market participant, market mechanism, and rules problems in the power market that lead to market failure, make the power market inefficient, instable or even crash.

In terms of electric system operating states, the first objective of system operation is to keep the system running all the time. Least cost operation was secondary to this primary objective. From economic perspective this implies new market equilibrium with additional costs.

3.4. Real time market

The real time electricity market under normal conditions requires satisfying the demand-supply balance at any moment. It implies that some generators will be modifying its output to follow demand variations.

As restructuring of the electric industry unfolds, GENCOs decide individual whether, or when, they wish to produce. The generation company decision making process includes forecasting of demand and competitors actions. This forecasting is stochastic and is modeled as random variable.

3.5. Numerical examples

This section presents some numerical examples. The demand parameters for all the cases reported are $a = 115,$ and $b = 2.$

Table 1

Production costs and market equilibrium

CASE		PRICE ($/MWh)	P_{G_1} (MW)	P_{G_2} (MW)	$P_{G_1} + P_{G_2}$ (MW)
I	$c_1 = c_2 = 4$	41.0000	18.500	18.500	37.000
II	$c_1 = 6 > c_2 = 4$	41.6667	17.833	18.833	36.666
III	$c_1 = c_2 = 4$	44.5000	15.0000	20.2500	35.250
IV	$c_1 = 6 > c_2 = 4$	44.5000	15.0000	20.2500	35.250
V	$c_1 = 4 < c_2 = 6$	45.5000	15.0000	19.7500	34.750
VI	$c_1 = c_2 = 4$	49.0000	15.0000	18.0000	33.000
VII	$c_1 = 6 > c_2 = 4$	49.0000	15.0000	18.0000	33.000
VIII	$c_1 = 4 < c_2 = 6$	49.0000	15.0000	18.0000	33.000

The two first cases presented in Table 1 do not consider capacity limits. Hence these cases represent the traditional Cournot equilibrium with two players and linear demand function. Case I considers similar marginal production cost, whereas in case II an increase of GENCO 1's marginal cost is represented. Figure 10.1 shows the GENCOS's reaction functions. The effect of increasing the marginal cost of GENCO 1 in the quantity market equilibrium is also depicted. The intersection of the two reaction functions represents a Nash Equilibrium if each firm believes the other firm will not change output regardless of what that firm does (Table 2).

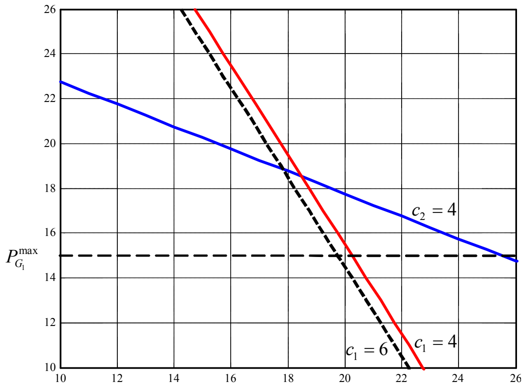


Figure 10.1 Effect of an increase in GENCO 1's marginal cost and capacity limit

Observe that increasing GENCO 1's marginal cost results in reaching new market equilibrium, this is consistent with the result presented in Table 1. The standard Nash equilibrium is also reached even when maximum generation limit is reached. It happens even when one of the GENCOs reaches its maximum limit, under the assumption that other player does not have full information. If it was not the case, the other player will exercise market power.

Cases III to V show the effect that GENCO 1 reaches its maximum limit, $P_{G_1}^{max} = 15\,MW$. In case III and case IV the same market equilibrium is obtained. The effect on increasing the marginal cost of GENCO 1 does not change the market equilibrium. However, when the increment in marginal costs occurs on GENCO 2, new market equilibrium is found. The new market equilibrium shows higher price and lower quantity.

The last three cases consider the effect when both GENCOs reach their maximum production limits. GENCO 2's maximum limit for these cases is $P_{G_2}^{max} = 18\,MW$. In Figure 10.2 the market equilibrium is depicted when both GENCOs reaches their upper generation limit. The price is always determined by the total market generation.

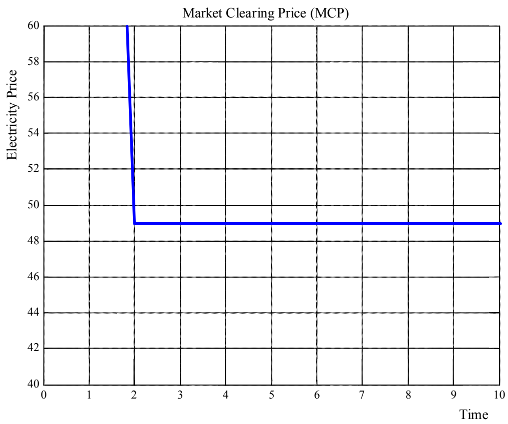


Figure 10.2 Effect of both GENCO's maximum capacity in the MCP

In all the cases when marginal productions are the same, the system is not observable neither controllable. On the other hand, when GENCOs' marginal production costs are slightly different the system becomes controllable but remains unobservable.

Table 2 summarizes the system's properties, controllability and observability for all the cases.

Table 2

Production costs and market equilibrium

CASE	LIMITS		CONTINGENCY		DEMAND		PRICES	
I	NO	NO	NO	NO	NO	NO	NO	NO
II	YES	NO	YES	NO	YES	YES	YES	YES
III	NO	NO	NO	NO	NO	NO	NO	NO
IV	YES	NO	YES	NO	YES	YES	YES	YES
V	YES	NO	YES	NO	YES	YES	YES	YES
VI	NO	NO	NO	NO	NO	NO	NO	NO
VII	YES	NO	YES	NO	YES	YES	YES	YES
VIII	YES	NO	YES	NO	YES	YES	YES	YES
PROPERTY	C	O	C	O	C	O	C	O

O=Observability; C=Controllability

The following example portrays a contingency effect on market equilibrium. The contingency is simulated as a step function after the market reaches equilibrium. Only four out of the eight previous cases are presented in Figure 10.3.

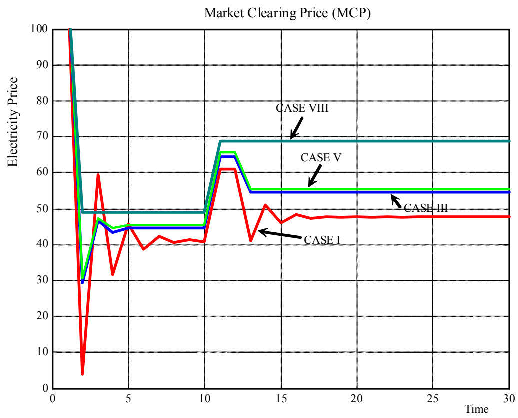


Figure 10.3 Effect of generation contingency

Observe a change in market equilibrium in Figure 10.3. When upper limits on generation are neglected, as in case I, a longer transitory oscillatory process is observed. The examples reported consider full loss of generation as well as partial loss.

When total generation is lost from GENCO 1, two possible scenarios can happen: GENCO 2 does or does not reach its upper generation limit. In the first scenario, monopoly equilibrium is found. In the second scenario, depending on the GENCO 2's upper limit, the new market equilibrium will be above the monopoly equilibrium.

Given the demand responsiveness, new market equilibrium is reached in any of the two different scenarios. Hence the use or derivative markets would play an important role for producers and consumer. The demand responsiveness can be interpreted as part of demand side programs. Derivative markets and demand side response may prevent market vulnerability problems.

The next example considers the demand variations over time and the response of market suppliers. Four cases are considered for explanatory purposes. Market equilibriums are shown in Figure 10.4.

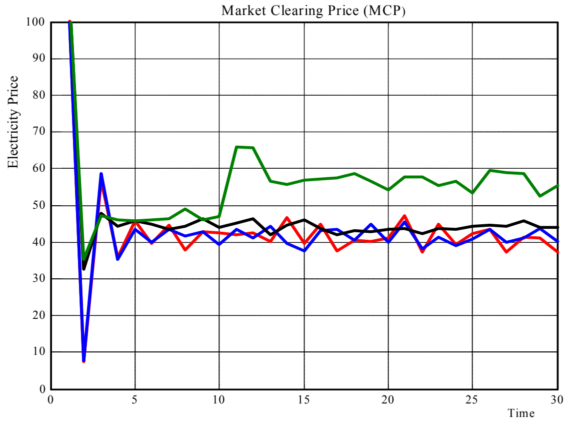


Figure 10.4 Effect of real time load variation

Generation outputs for each case are depicted in Figure 10.5.

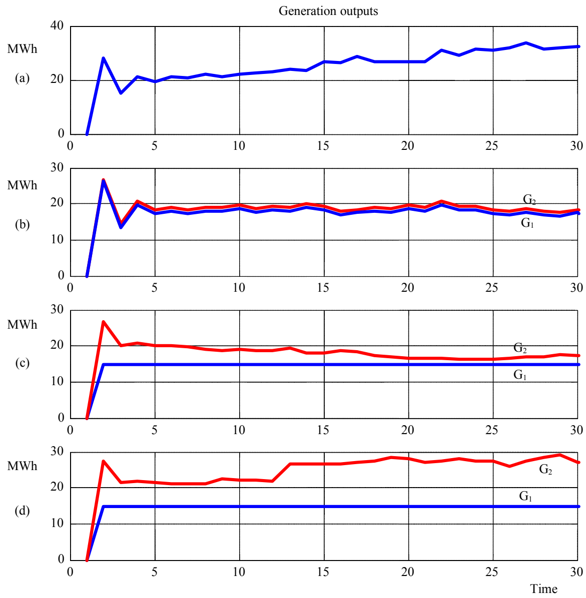


Figure 10.5 Effect on generation

Given that both GENCOs have equal production marginal costs and generation limits are neglected, both are producing the same amount of power which is displayed in Figure 10.5(a). Unlike Figure 10.5 (a) and (b) exhibits GENCO's output when GENCO 2 has a higher marginal production costs. In Figure 10.5 (c), the effect of GENCO 1's upper limits is presented. GENCO 2 is the marginal unit and it supplies the remained market demand. Figure 10.5(d) additionally simulates, with respect Figure 10.5 (c), a substantial increment in demand. Hence, we observe a jump on generation after period 12. The net generation in each case above presented implies different demand.

The next simulation considers fuel price variation. Fuels during some time interval are positively correlated and then become negatively correlated as it can be observed in Figure 10.6.

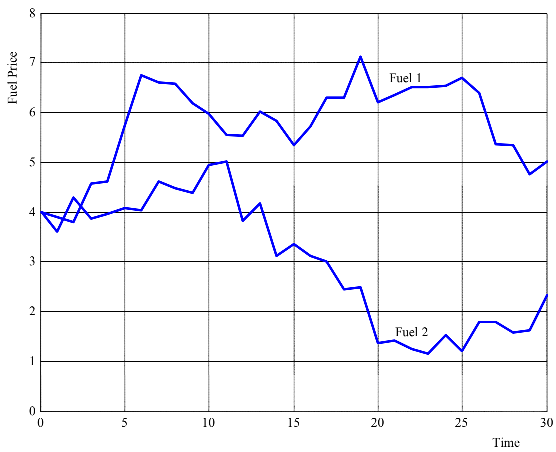


Figure 10.6 Input prices

Due to fuel price variations, change in GENCOs' outputs and market equilibrium is expected. Figure 10.7 presents the GENCOs' output for time simulation.

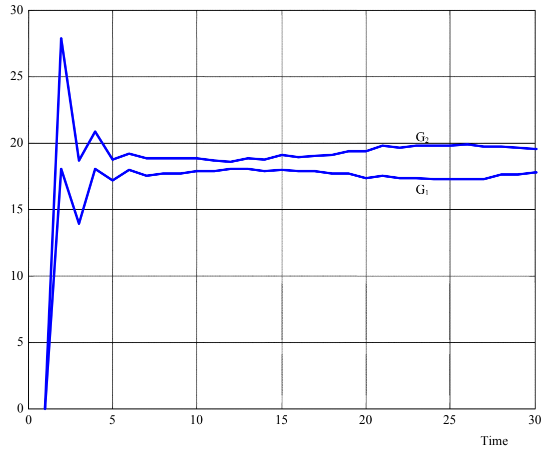


Figure 10.7 Effect of real time generation

Because of prices' negative correlation, it is clear than cheap generation offset expensive generation. In this particular example, it can be observed how GENCO 2 increases production while GENCO 1 decreases it. This effect is more visible during the last periods.

The market clearing price is displayed in Figure 10.8. The price does not remain constant due to changes in GENCOs output. Nevertheless, the electricity price does not experience spark ups/downs, even when fuel prices are very volatile (Fuel 1 increases around 80 % whereas Fuel 2 decreases around 70%). The overall effect of fuel high volatility on electricity price results in smooth price performance.

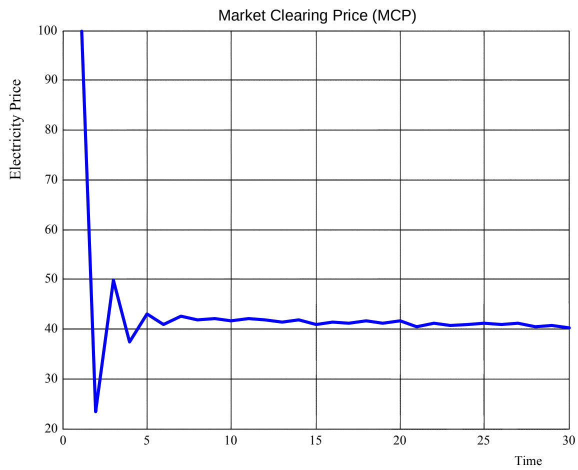


Figure 10.8 Real time market clearing price

Previous simulations have shown the traditional Cournot model neglecting players' adaptive and learning strategies from the dynamic market. The system's properties, controllability and observability [11], do not change when a generation limit is reached, neither when a contingency occurs. In any case, the system economy is stable.

4. Conclusions

This paper reports market dynamics in a two-GENCO market model. The market clearing price is defined by the output they players are committed to the market.

When GenCos' marginal production costs are equal, the system is unobservable and uncontrollable. However, if these are different, the system becomes controllable but not observable. In all the cases reported, the system's properties, controllability and observability, do not change when a generation limit is reached, neither when a contingency occurs.

In all the simulations, the standard Cournot Nash equilibrium is found. It happens even when one of the GENCOs reaches its maximum limit, under the assumption that other player does not have full information. If it was not the case, the other player will exercise market power.

References

[1] David C. Skinner, Introduction to Decision Analysis: A Practitioner's Guide to Improving Decision Quality, Probabilistic Publishing, Second Edition, 1999.

[2] A. Haurie, and J. B. Krawczyk, An Introduction to Dynamic Games, available at http://ecolu-info.unige.ch/

[3] Mario J. Miranda and Paul L. Fackler, Applied Computational Economics and Finance, The MIT Press, September 2002.

[4] F. Alvarado, The Dynamics of Power Systems Markets, Technical Report PSERC-97-01, Power Systems Engineering Research Consortium (PSERC), The University of Wisconsin, March 1997.

[5] F. Alvarado, The Stability of Power Systems Markets, IEEE Trans. on Power Systems, Vol. 14, No. 2, pp. 505-511, May 1999.

[6] Weiguo Yang and Gerald B. Sheble, Power Market Stability under Price Expectations Models, in Proc of the *32nd North American Power Symposium*, Vol. 2, Waterloo Canada, October 2000. pp. 9-22 – 9-27.

[7] Weiguo Yang, "Short-term electric market dynamics and generation company decision-making in new deregulated environment," Ph.D. dissertation, Dept. Elec. Eng., Iowa State University, 2003.

[8] A. Syothert and I. MacLeod, "Competitive Bidding as a Control Problem, IEEE Trans on Power Systems, Vol. 15, No. 1, pp. 88-94. Feb. 2000.

[9] Poonsaeng Visudhiphan and Marija D. Ilic, "Dynamic games-based modeling of electricity markets," in *Proc. of the 1999 IEEE Winter Meeting, Power Engineering Society*, Vol. 1, pp. 274 -281, Jan.-Feb. 1999.

[10] Guillermo Gutierrez-Alcaraz and Gerald B. Sheble, "Decentralized Electricity Market Price Dynamics," *IEEE Power Engineering Society General Meeting*, Denver Colorado, June 2004.

[11] Chi-Tsong Chen, *Linear System Theory and Design*, Oxford University Press, August 1998.

[12] Jean Tirole, The Theory of Industrial Organization, The MIT Press, January 1998.

[13] Gerald B. Sheblé, Computational Auction Mechanisms for Restructured Power Industry Operation, Kluwer Academic Publisher, 1999.

[14] A. Alj and A. Haurie, Dynamic Equilibria in Multigeneration Stochastic Games, *IEEE Trans. on Automatic Control*, Vol. 28, No. 2, pp. 193–203. Feb 1983.

[15] T. Basar, "A Dynamic Games Approach to Controller Design: Disturbance Rejection in Discrete-time," *IEEE Trans. on Automatic Control*, Vol. 36, No. 8, pp. 936–952. Aug. 1991

CHAPTER 11 SEQUENTIAL TIME-STEP GENERATION COMPANIES DECISIONS IN OLIGOPOLISTIC ELECTRICITY MARKET

A paper published in the Electric Power Systems Research

Guillermo Gutiérrez-Alcaraz

Abstract

This paper studies the production decisions of Generation Companies (GENCOs) which are fully engaged in oligopolistic electricity markets. The model presented is based upon the static equilibrium model solved sequentially in time. By decomposing the problem in time, each time-step is solved independently using a Cournot-like market model. The time dimension is divided into discrete, one-hour time-steps. The model also incorporates the effects of technical and temporal constraints such as time on/off and ramp up/down. Since GENCOs tend toward repetitive decision-making, they can more easily learn from the market. The concept of forward expectations and the lessons derived from the market are introduced, and several numerical examples are provided.

Keywords: Cournot Model, Electricity Markets, Oligopolistic Competition.

1. Introduction

In a market-driven environment, a power generating utility solves the self-unit commitment problem to obtain an optimal bidding strategy [1]. Ideally, its optimal policy is designed to reap the maximum expected profit. In reality, however, the environment in which decisions (and decision-making policies) are made is often defined by the operational and technical constraints of the utility’s generating units, its short-term financial requirements, or other restrictions.

The easiest way to model the dynamic behavior of market players is to replicate static snapshot of single periods [2]. The single-period models then provide the basis for multi-period models. In the single-period Cournot model each firm wants to maximize profits by deciding its optimal decision output. In the multi-period extension of the Cournot model, each firm wants to maximize its discount profits by selecting the optimum output levels for each time period [2, 3].

Most of the work applied to the electricity market analysis reported in the literature covered a single period. At the beginning most of these models were constructed as single-node generation-only models [4]. Later, basic representations and linear DC transmission network were introduced for modeling spatiality [5,24-26]. Recently, AC network representation has been incorporated in a non-linear programming problem in order to systematically study for the impacts of network constraints on the market equilibrium [6].

Since GENCOs operate in a sequential-period market where, in each period, simultaneous output decisions are made, in most market scenarios, it may not be enough to maximize gain in the current and next period. Therefore, the GENCOs will seek to maximize total gain over the next several periods. However, not knowing (or being unaware of) their competitors' future output decisions will make it difficult for any one GENCO to predict its rivals' behavior [7,8]. Faced with this difficulty, a GENCO may adjust its own output expectation of the current period according to both the output of the last period and the expected output in the next subsequent period. In addition, each GENCO will probably rely upon other information it gathers over time, especially the data which will most likely influence its present choice. In other words, when the same bidder plays the same opponents multiple times, we would expect that the bidding agents will adjust their own behaviors to maximize their profits [8]. A procedure to identify multi-period equilibria in an electricity market is important for market regulators who may use it for market monitoring [9]. A multi-period equilibrium in a pool-based electricity market that may include minimum profit constraints for on-line generating units is analyzed in Ref. [23]. An oligopoly with spatially dispersed generators and consumers and with multiperiod demand is modeled in Ref. [4]. A dynamic sequential framework by using DESS is reported in Ref. [10]; that analysis focuses on the dynamics within a single period.

We can also expect that forward expectations will accompany the learning process [11,12]. This integration is crucial for two reasons: forward expectations teach a GENCO how its current stock valuation is affected (since stocks are the physical link between successive periods, and the valuation will transform expectations about future trading into desires to exchange current goods), and they are based on *available information,* i.e., the stream of past and present price-quantity signals [13]. In today's competitive, volatile markets, accurate modeling of both the operational and temporal constraints of all of its generating units may give a GENCO the "edge" over its competition. Conjectural variation method has been widely applied to estimate the strategic behavior in game-theoretical contexts in terms of imperfect information [14]. A conjectural variation-based learning model that can be used by a GENCO to improve its bidding performance is reported in Ref. [15]. Each firm learns and dynamically regulates its conjectures based upon the reactions of its rivals to its bidding according to the available information published in the electricity market. Unfortunately, these conjectural variation models have been criticized for the drawbacks of logical consistency and the possibility of abundant equilibria. The existence and uniqueness of consistent conjectural variation equilibrium in electricity markets is investigated in Ref. [16].

Even what appears to be an insignificant constraint can quickly alter a GENCO's market strategies [17]. For example, the strategic use of ramp rates beyond elastic limits in generation dispatch has been investigated in Ref. [18], because they incur ramping costs and also widen the possible range of energy delivery. A detailed formulation to model the power trajectories followed by a thermal unit during start-up and shut-down processes, as well as the ramping limitations when increasing or decreasing power is reported in Ref. [19].

The Cournot model still does not analyze significant electricity market issues including intertemporal considerations. In Ref. [20] intertemporal decisions related with maintenance decisions are reported. In an electricity market with only a few major competing GENCOs, maintenance plays a critical role that goes beyond traditional least-cost analysis. In this document the authors extend the previous work reported in Ref. [12]. A rigorous formulation of the ramping constraints reported in Ref. [11] has been implemented to analyze the effect of intertemporal constraints on a GENCO's decision-making process. The learning aspect, represented by forward expectations, is compared with the Cournot model without learning. A sensitivity analysis is performed to observe how the solution of the short-term equilibrium problem varies with the generation cost parameters, the demand parameters, and the adjusting coefficients.

The paper is organized as follows: Section 2 describes the electricity spot market model. Section 3 presents a set of numerical examples to illustrate the points at hand. Section 4 presents a parameter dependency analysis. Finally, our conclusions are given in Section 5.

2. Electricity market model

In this paper we consider a spot market operated on an hourly basis where each time-step is solved individually using the Cournot market model. A representation of this electric market is shown in Figure 11.1.

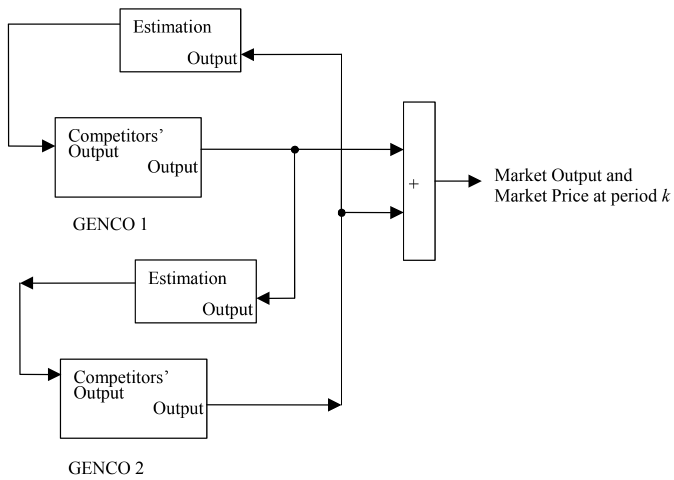


Figure 11.1 Electricity spot market model

Since GENCOs tend to make repetitive decisions, it is expected that they will learn from the market [22]. For each time period, GENCOs must form an expectation of their rivals' output in the subsequent period in order to determine their own corresponding profit-maximizing quantity for period k+1, and so on. The sequential decision-making process of GENCO 1 is depicted in Figure 11.2.

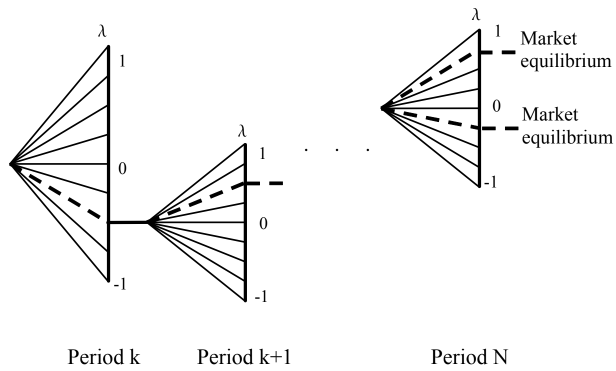


Figure 11.2 Sequential decision-making for GENCO 1

Consider the inverse linear market-demand function at period *k* given by:

$$P(Q) = a - bQ(k) \tag{1}$$

where $Q(k) = \sum_{i=1}^{n} q_i(k)$ and a and b are the market-demand function parameters.

We assume that a GENCO knows the inverse demand function, and that it must estimate the demand when it does not know the actual demand function. Its optimization program is to maximize the expected profit from its generation assets, energy and reserve, subject to operational constraints, over time. Mathematically, this can be expressed as:

$$\underset{q_i(k)}{Max}\ \pi_i(k) = P\left(q_i(k) + \hat{q}_j(k)\right)q_i(k) - C_i\left(q_i(k)\right) \tag{2}$$

where $\hat{q}_j(k) = \lambda_j q_j(k-1) + (1-\lambda_j)q_j(k)$, $\hat{q}_j(k)$ represents GENCO *j*'s expectation of the decisions made by GENCO *i*, $q_j(k-1)$ is GENCOs *j*'s decision output at period $(k-1)$, λ_j is the adjustment coefficient for GENCO *j*, and $\lambda_2 \in [-1 < \lambda_2 \leq 1]$.

Subject to the following constraints:

Ramp-up constraints: From one time instant to the next the unit cannot increase its output above a maximum increment; this yields

$$q_i(k+1) - q_i(k) \le Z_i \qquad \forall\, k = 1,\ldots,K \tag{3}$$

where Z_i is the maximum power ramp-up increment of unit *i*

Ramp-down constraints: A unit cannot decrease its output power above a maximum power decrement. Therefore

$$q_i(k) - q_i(k+1) \le W_i \qquad \forall\, k = 1,\ldots,K \tag{4}$$

where W_i is the maximum power ramp-down decrement of unit *i*

Unit capacity constraint: Any unit at any time should operate within operational limits, then

$$q_i^{MIN} \le q_i \le q_i^{MAX} \qquad \forall i = 1,\ldots,n \tag{5}$$

q_i^{MIN} and q_i^{MAX} are the lower and upper generation limit, respectively, of unit *i*

State transition constraints: The length of time the unit has been off or on-line.

$$x_{ik} = \begin{cases} \min\left(t_i^{on}, x_{k+1} + 1\right) & \text{if } u_{ik} = 1 \\ \max\left(t_i^{off}, x_{k+1} - 1\right) & \text{if } u_{ik} = 0 \end{cases} \tag{6}$$

where x_{ik} is a state variable indicating the length of time that unit *i* has been up or down at period *k*, and u_{ik} is a binary decision variable indicating whether unit *i* at period *k* is up or down.

Unit status constraint: The unit can be either on or off, then

$$u_{ik} = \begin{cases} 1 & if \quad 1 \le x_{i,k-1} < \quad t_i^{on} \\ 0 & if \quad -1 \ge x_{i,k-1} > -t_i^{off} \end{cases} \tag{7}$$

The GENCO *i* production cost function is given by:

$$C_i\left(q_i\left(k\right)\right) = d_i + e_i q_i\left(k\right) + f_i q_i^2\left(k\right) \qquad \forall i = 1,\ldots 2 \tag{8}$$

where d_i, e_i, and f_i are the production cost factors.

Temporarily ignoring operational and temporal constraints and solving the problem as if they did not exist, then:

$$\underset{q_i(k)}{Max}\ \pi_i\left(k\right) = P\left(q_i\left(k\right) + \hat{q}_j\left(k\right)\right)q_i\left(k\right) - d_i - e_i q_i\left(k\right) - f_i q_i^2\left(k\right) \tag{9}$$

The first-order condition is:

$$\frac{\partial \pi_i}{\partial q_i\left(k\right)} = a - 2bq_i\left(k\right) - b\lambda_j q_j\left(k-1\right) + b\left(1-\lambda_j\right)q_j\left(k\right) - e_i - 2f_i q_i\left(k\right) = 0 \tag{10}$$

For the two players, in matrix form we have:

$$\begin{bmatrix} 2\left(b+f_1\right) & b\left(1-\lambda_2\right) \\ b\left(1-\lambda_1\right) & 2\left(b+f_2\right) \end{bmatrix} \begin{bmatrix} q_1\left(k\right) \\ q_2\left(k\right) \end{bmatrix} = \begin{bmatrix} a-e_1-b\lambda_2 q_2\left(k-1\right) \\ a-e_2-b\lambda_1 q_1\left(k-1\right) \end{bmatrix} \tag{11}$$

A representation of this electric market is shown in Figure 11.3.

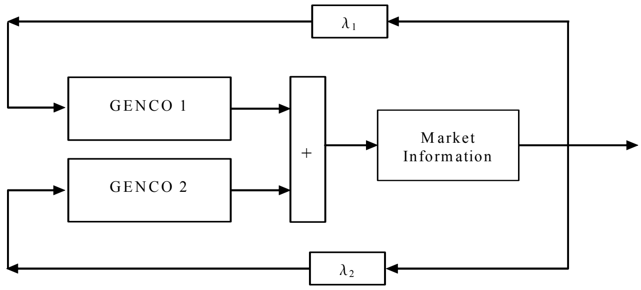


Figure 11.3 Two-GENCO electricity market equivalent

Solving for $q_1(k)$ and $q_2(k)$ yields:

$$q_1(k) = \frac{2(b+f_2)(a-e_1-b\lambda_2 q_2(k-1)) - b(1-\lambda_2)(a-e_2-b\lambda_1 q_1(k-1))}{4(b+f_1)(b+f_2)-b^2(1-\lambda_1)(1-\lambda_2)} \tag{12}$$

$$q_2(k) = \frac{2(b+f_1)(a-e_2-b\lambda_1 q_1(k-1)) - b(1-\lambda_1)(a-e_1-b\lambda_2 q_2(k-1))}{4(b+f_1)(b+f_2)-b^2(1-\lambda_1)(1-\lambda_2)} \tag{13}$$

If the GENCOs do not know the inverse demand function, they must estimate the demand. Assume that GENCO *i*'s estimate is $P(Q) = a_i - b_i Q(k)$, $i = 1,\ldots,2$. Then, the system becomes:

$$\begin{bmatrix} 2(b_1+f_1) & b_1(1-\lambda_2) \\ b_2(1-\lambda_1) & 2(b_2+f_2) \end{bmatrix} \begin{bmatrix} q_1(k) \\ q_2(k) \end{bmatrix} = \begin{bmatrix} a_1-e_1-b_1\lambda_2 q_2(k-1) \\ a_2-e_2-b_2\lambda_1 q_1(k-1) \end{bmatrix} \tag{14}$$

2.1 Generation upper limits

If GENCO 1 has a capacity constraint, its profit maximization decision becomes:

$$\begin{aligned} &Max\ \pi_1(k) = P(Q(k))q_1(k) - C_1(q_1(k)) \\ &S.\ to \qquad q_1 \le q_1^{MAX} \end{aligned} \tag{15}$$

We construct the new function:

$$L = P\big(Q(k)\big)q_1(k) - c_1\big(q_1(k)\big) - \mu\big(q_1(k) - q_1^{MAX}\big) \qquad (16)$$

where μ is a Lagrange multiplier.

The first-order conditions are:

$$\frac{\partial L}{\partial q_1(k)} = a - e_1 - 2(b + f_1)q_1(k) - bq_2(k) - \mu = 0 \qquad (17)$$

$$\frac{\partial L}{\partial \mu} = q_1(k) - q_1^{MAX}(k) = 0 \qquad (18)$$

In the two-player market model, the resulting set of equations is:

$$\begin{bmatrix} 2(b+f_1) & b(1-\lambda_2) & -1 \\ b(1-\lambda_1) & 2(b+f_2) & 0 \\ 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} q_1(k) \\ q_2(k) \\ \mu \end{bmatrix} = \begin{bmatrix} a - e_1 - b\lambda_2 q_2(k-1) \\ a - e_2 - b\lambda_1 q_1(k-1) \\ q_1^{MAX}(k) \end{bmatrix} \qquad (19)$$

A similar procedure is applied when the lower limit is bounded.

The intersection of the two reaction functions, equations (12) and (13), determines the market equilibrium in the Cournot model. This equilibrium represents a Nash equilibrium if each GENCO believes the other will not change output regardless of what its competitor does. The standard Nash equilibrium is also reached even when maximum generation limit is reached (which we can observe in a situation where one GENCO reaches its maximum limit under the assumption that its competitor lacks complete information). If this was not the case, the other GENCO will exercise market power.

Figure 11.4 portrays the reaction functions for the two GENCOs at specific period. Here we observe that the upper generating limit of any unit is not reached given that such limits are above the market equilibrium, $q_1 = 141.53$ and $q_2 = 143.83$. If a generating upper limit is reached, the new market equilibrium is determined at the intersection point between the reaction function and the generating unit's upper limit. Therefore, the limit will restrict the pure Cournot equilibrium.

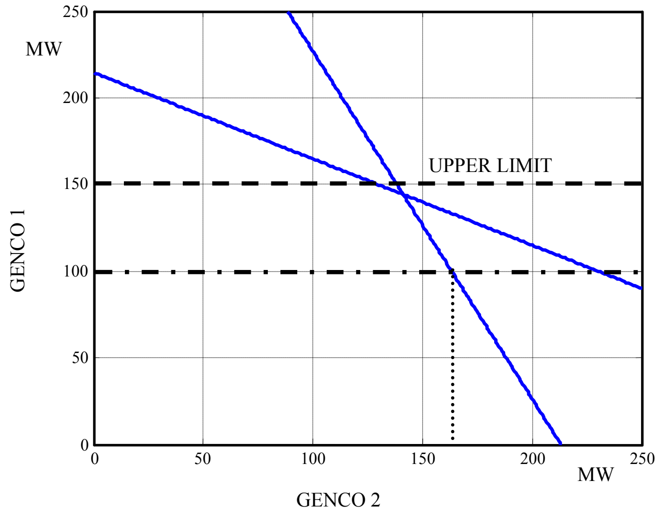


Figure 11.4 Effect of capacity limit in market equilibrium

From Figure 11.4, we also observe that the upper limit will never be reached under demand and cost production parameters: if the upper limit is 100 MW instead of 150 MW, the new equilibrium is $q_1 = 100$ and $q_2 = 164.53$, as shown.

2.2 Time on/off and ramp up/down constraints

The increment or decrement of the generation level of a unit over any two successive on-line periods (excluding start-up and shut-down periods) is bounded by the ramp-up (RU) and ramp-down (RD) limits respectively as shown in Figure 11.5. Temporal constraints and ramp up/down are incorporated in our model from [19].

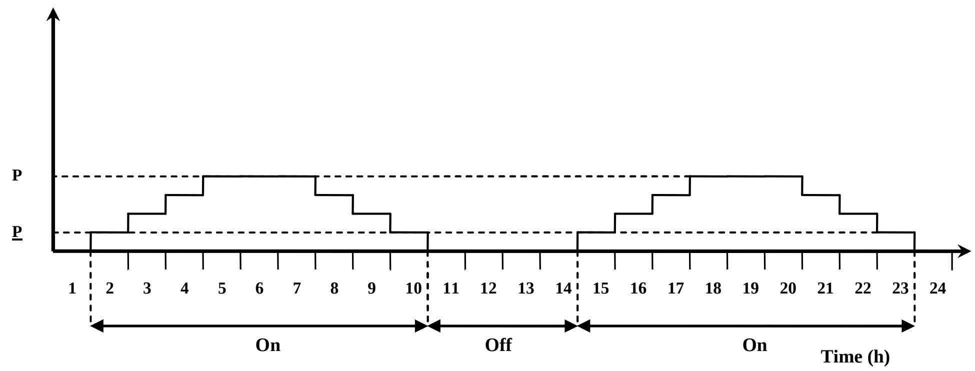


Figure 11.5 Seller Illustration of ramp up/down and maximum/minimum constraints

3. Numerical examples

This section presents three numerical examples of the model described above. In each case the Cournot model is executed twice: without and with learning. The production cost data shown in Table 1 has been taken from Ref. [1] and modified.

Table 1 Producers' data

GENCO	d_i (\$)	e_i (\$/MW)	f_i (\$/MW^2)	q_i^{MIN} (MW)	q_i^{MAX} (MW)	t_i^{On} (h)	t_i^{Off} (h)	$Ramp\,Up_i^{MAX}$ (MW)	$Ramp\,Down_i^{MAX}$ (MW)
1	820	9.023	0.00113	0	150	16	6	40	30
2	400	7.654	0.00160	0	300	12	4	50	30

The expected demand function parameters for each period of the day-ahead market are listed in Table 2. The same demand function is retained for the three cases.

Table 2 Expected demand function parameters for the day-ahead market

Period	a	b	Period	a	b
1	185	0.42	13	148	0.22
2	190	0.35	14	330	0.5
3	210	0.46	15	135	0.25
4	120	0.34	16	180	0.43
5	130	0.40	17	168	0.35
6	140	0.62	18	160	0.36
7	195	0.34	19	198	0.49
8	150	0.20	20	175	0.30
9	180	0.37	21	190	0.48
10	240	0.42	22	140	0.60
11	230	0.99	23	150	0.52
12	160	0.28	24	130	0.20

The forward expectation adjusting factors for each period of the day-ahead market are listed in Table 3 (obtaining the adjusting coefficients is an important topic, but beyond the scope of this paper). These parameters must be estimated for each GENCO; they can be found utilizing several methods (e.g., data mining, neural nets, and forecasting approaches) [21].

Table 3 Forward expectation adjusting coefficient

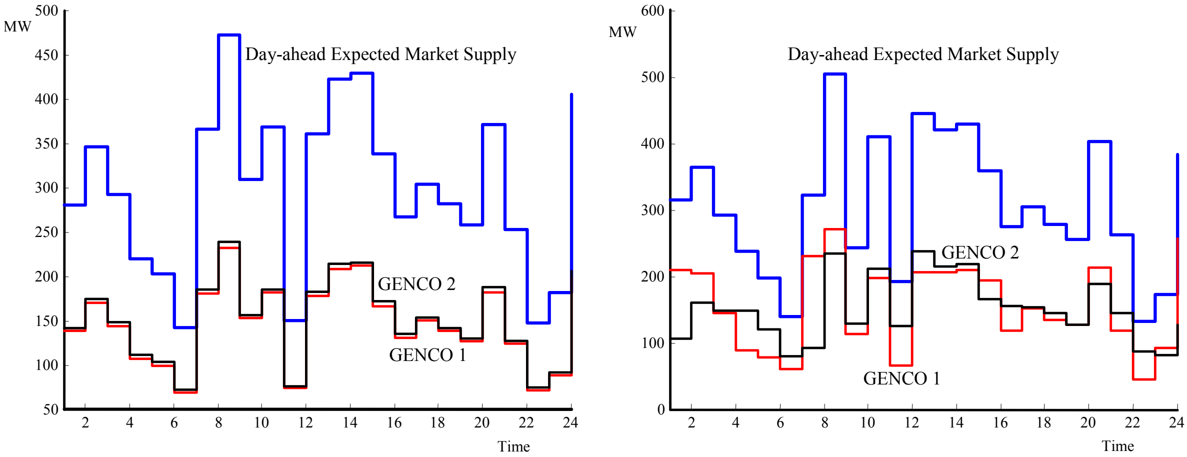
Period	λ_1	λ_2	Period	λ_1	λ_2	Period	λ_1	λ_2
1	0.0	1.0	9	0.6	1.0	17	0.0	-1.0
2	-1.0	1.0	10	0.8	0.7	18	0.0	0.7
3	0.0	0.0	11	-0.7	-0.4	19	0.9	0.2
4	-1.0	0.9	12	1.0	1.0	20	0.4	1.0
5	-0.9	1.0	13	0.3	0.2	21	-0.3	-0.1
6	-0.3	0.3	14	0.8	-0.8	22	0.0	0.7
7	-0.8	0.5	15	-0.9	-0.9	23	-0.4	1.0
8	0.7	0.5	16	-0.4	0.4	24	-0.6	0.8

Case A. In this case, operational and temporal constraints are omitted. The market equilibrium is found for each trading period individually. The expected market supply and the expected outputs of the two GENCOs for each period of the day-ahead are reported in Table 4 and graphically depicted in Figure 11.6.

Table 4 Expected GENCOs' outputs: Case A

PERIOD	GENCO 1	GENCO 2	GENCO 1	GENCO 2
1	138.51	141.60	209.21	106.32
2	170.95	174.62	205.05	159.69
3	144.58	147.40	144.58	147.40
4	107.40	111.26	89.33	147.82
5	99.62	102.92	77.20	119.55
6	69.66	71.81	59.89	79.28
7	180.88	184.64	230.30	91.98
8	232.44	238.69	270.24	233.79
9	152.71	156.21	113.98	128.75
10	182.14	185.18	198.02	210.81
11	73.93	75.27	65.87	125.51
12	177.97	182.54	206.43	238.43
13	208.30	214.04	205.35	215.35
14	212.98	215.51	209.90	218.87
15	166.01	171.14	193.04	165.23
16	131.42	134.44	118.98	155.44
17	150.01	153.71	151.73	152.85
18	138.45	142.05	134.37	144.09
19	127.57	130.23	127.40	127.19
20	182.77	187.03	212.63	189.13
21	124.67	127.39	118.22	144.75
22	71.98	74.20	45.31	87.51
23	89.46	92.00	91.70	81.62
24	199.14	205.47	256.29	127.83

By comparing columns 1 and 2 with columns 3 and 4 in Table 4, we observe that each GENCO's contribution to the market is the same when both adjusting coefficients equal 0 (this occurs at period 3). Hence this case represents the traditional Cournot equilibrium with two players and a linear demand function. The equilibrium is more competitive when both coefficients are positive; the opposite occurs when both coefficients are negative [17]. Each market equilibrium is a Nash equilibrium since neither GENCO will change its output if the other does not change, given the current information.



(a) (b)

Figure 11.6 GENCOs' expected outputs (a) without learning and (b) with learning: Case A

From Figure 11.6 (a) we can observe that the GENCOs' outputs differ slightly. The differences between their outputs are due only to different production costs. We see that GENCO 1 is more costly and therefore its output is lower. However, when learning is introduced, the outputs of the two GENCOs differ because of production costs *and* because of the adjusting factor involved in each one's decisions as shown in Figure 11.6 (b).

The market price for each period as displayed in Figure 11.7 is determined by the total market generation.

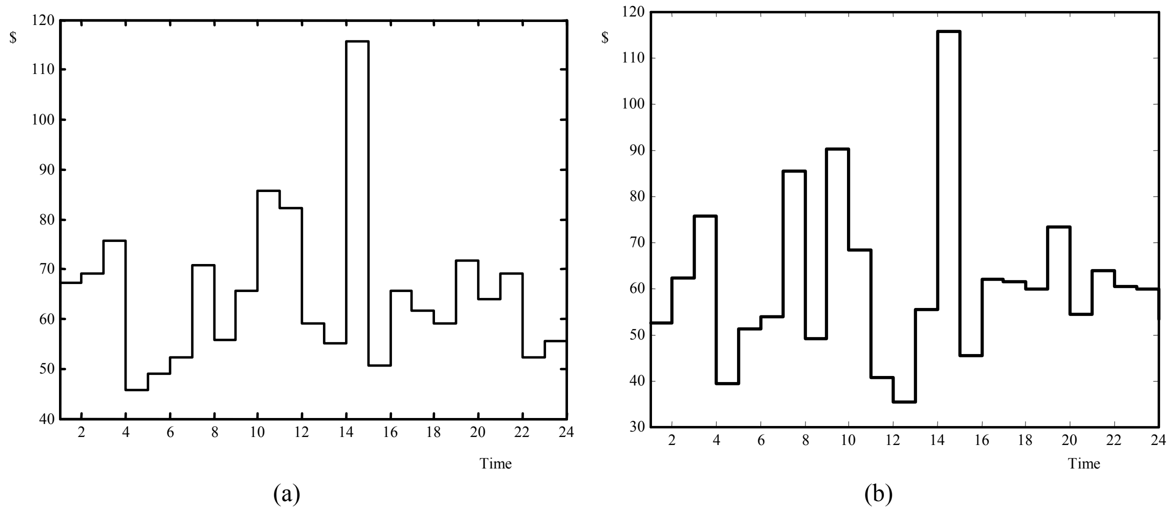
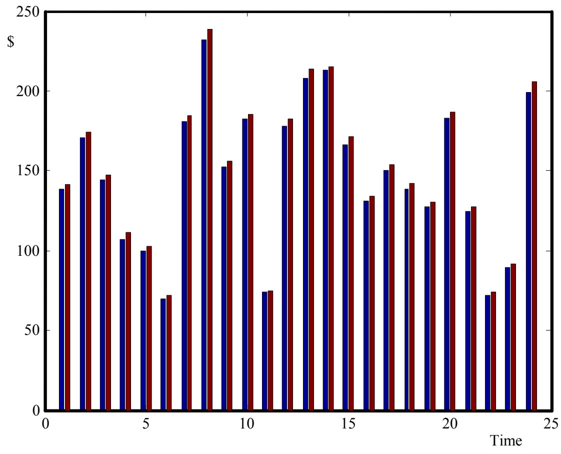


Figure 11.7 Market-clearing prices (a) without learning and (b) with learning: Case A

From Figure 11.7 (a), the lowest market price occurs at period 5 and at period 13 in Figure 11.7(b). In the first case, it is due only to the market demand and production cost parameters. In the second case, the adjusting factors play an important role such that the market equilibrium reaches the perfect competitive outcome in that specific period.

Figure 11.8 shows the profits for each GENCO at each period. Figure 11.8(a) shows that profits are quite similar (the differences occur because the GENCOs' outputs differ slightly). However, profits vary more when the learning effect is considered. Moreover, in some cases (i.e. periods 1, 2, 7, 8, and 24), GENCO 1's profits are higher due to the adjusting factors.



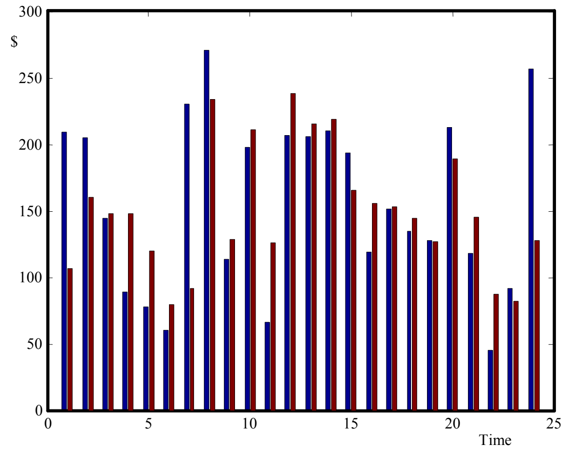


Figure 11.8 InProfits per period per GENCO (a) without and (b) with learning: Case A

Table 5 summarizes the total revenues, total costs, and net profits over the 24 periods.

Table 5 Total revenues, total costs and net profits: Case A

GENCO	Total Revenue ($)	Total Cost ($)	Net profit ($)
1	232080	52207	179873
2	237410	38257	199153
1	231610	54149	177461
2	220000	38094	181906

From Table 5 we observe that net profits are higher for both GENCOs when learning is not included. This indicates that the traditional Cournot outcome is even greater because the coefficients selected were not the optimum values.

Case B. In this case, maximum/minimum on/off times and operational limits are considered. The new expected market supply and the new expected GENCOs' outputs for each period of the day-ahead are presented in Table 6.

Table 6 Expected GENCOs' outputs: Case B

	NO LEARNING		LEARNING	
PERIOD	GENCO 1 (MW)	GENCO 2 (MW)	GENCO 1 (MW)	GENCO 2 (MW)
1	138.51	141.60	150.00	135.87
2	150.00	185.07	150.00	214.61
3	144.58	147.40	144.58	147.40
4	107.40	111.26	89.33	147.82
5	99.62	102.92	77.20	119.55
6	69.66	71.81	59.89	79.28
7	150.00	200.04	150.00	164.08
8	150.00	279.75	150.00	251.75
9	150.00	157.56	113.98	128.75
10	150.00	201.22	150.00	215.60
11	73.93	75.27	65.87	125.51
12	150.00	196.49	150.00	238.43
13	150.00	0.00	150.00	0.00
14	150.00	0.00	150.00	0.00
15	150.00	0.00	150.00	0.00
16	150.00	0.00	150.00	0.00
17	0.00	228.54	0.00	228.54
18	0.00	211.12	0.00	211.12
19	0.00	193.91	0.00	193.91
20	0.00	278.17	0.00	278.17
21	0.00	189.63	0.00	189.63
22	0.00	110.14	0.00	110.14
23	89.46	92.00	80.40	80.47
24	150.00	229.95	150.00	209.15

Here we can see that GENCO 1 reaches its upper limit of generation in several periods and that market equilibrium is found for each period even when GENCO 1 reaches its upper limit. Table 6 also shows that there is one shut-down for each GENCO. Each time that a GENCO goes "off," the market supply becomes the GENCO's online output. Maximum up and minimum down times are met throughout the timespan. The remaining operational constraints are satisfied.

By comparing Table 4 with Table 6, we observe that the GENCOs' outputs differ only for the periods in which the upper limit is reached, in addition to the shutdown periods. A graphic representation of the two outputs with and without the learning effect is shown in Figure 11.9.

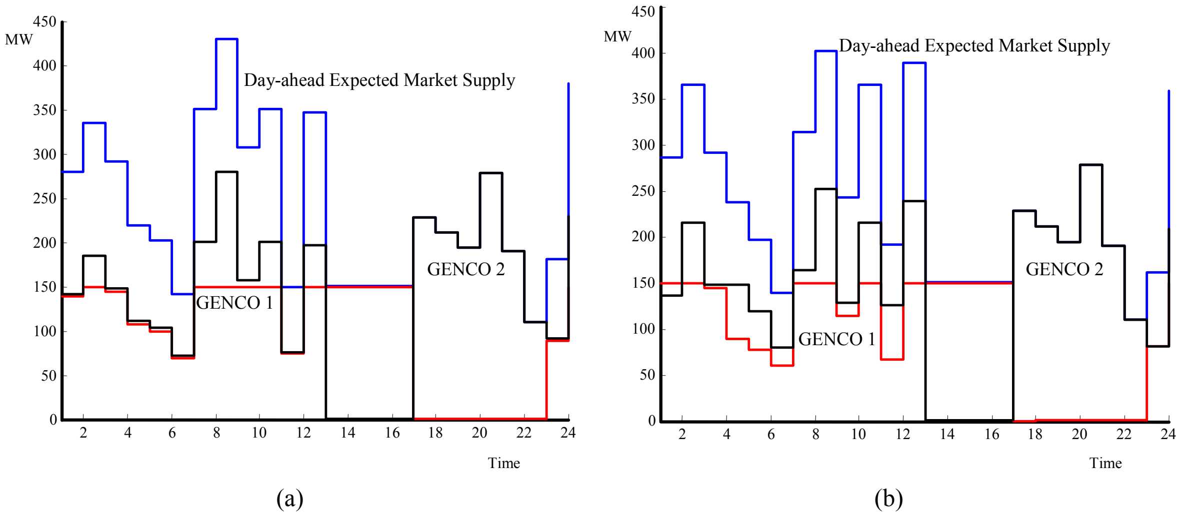


Figure 11.9 GENCOs' expected outputs (a) without learning and (b) with learning: Case B

Figure 11.9 shows that each time a GENGO is off, the market supply becomes the GENCO's online output. In addition, we observe that GENCO 1 reaches its upper generating limit in several periods even when GENCO 2 is off.

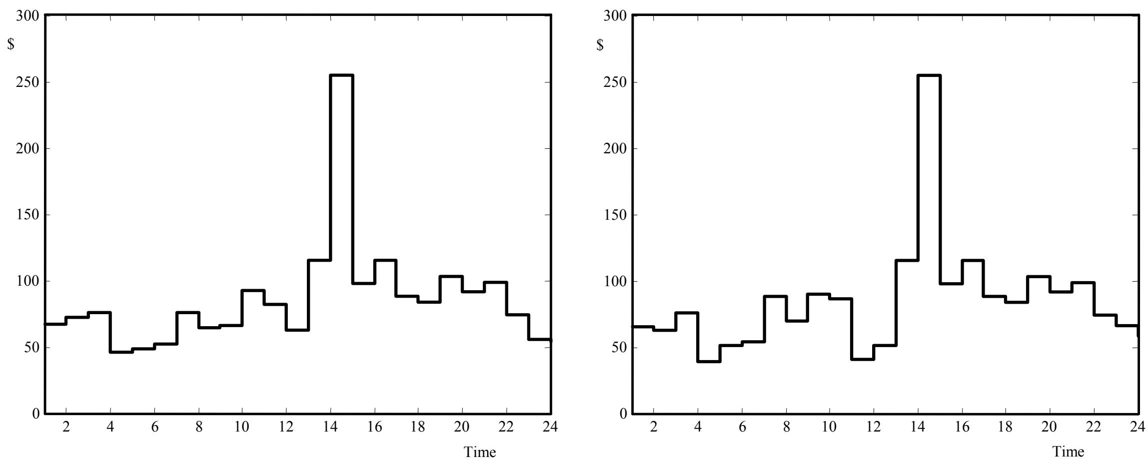
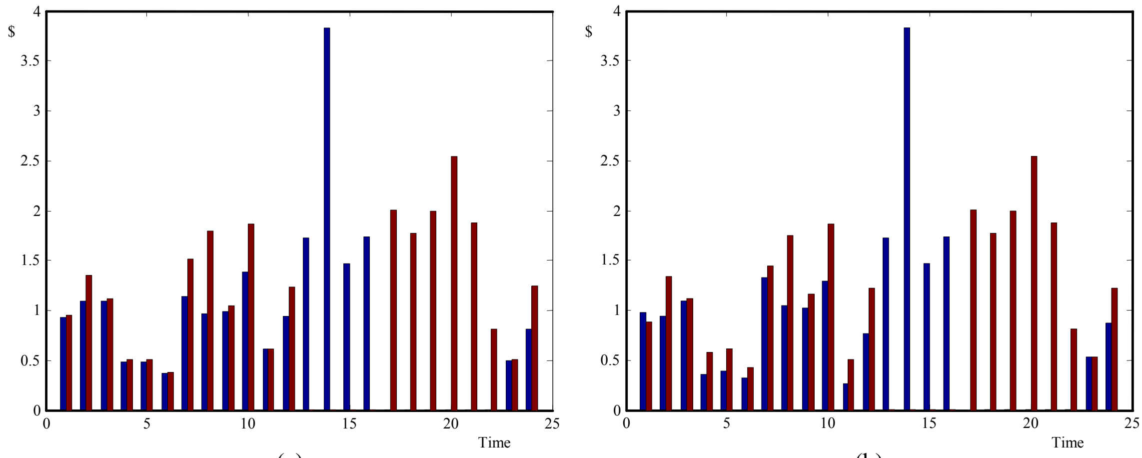


Figure 11.10 Market-clearing prices (a) without learning and (b) with learning: Case B



(a) (b)

Figure 11.11 Profits per period per GENCO (a) without and (b) with learning: Case B

During those periods when only one unit is on and it reaches its upper limit, the learning aspect affects the market equilibrium. The market equilibrium is still a Nash equilibrium. The capacity-constrained price game potentially will appear if the players become informed.

Table 7 Total revenues, total costs and net profits: Case B

GENCO	Total Revenue	Total Cost	Net profit
1	205480	41463	164017
2	256490	36698	219792
1	199530	40614	158916
2	256840	37221	219619

Similar to Table 5, the net profits are higher when learning is not considered. However, GENCO's 2 profits increase substantially while GENCO's 1 profits decrease. Changes in profits occur because the units went off for several periods. During periods when only one unit is supplying the market, a GENCO's profits at day's end are higher than when all of its units are online for all the periods.

Case C. This case accounts for temporal and operational constraints. The expected GENCOs' outputs for the day-ahead are presented in Table 8.

Table 8 Expected GENCOs' outputs: Case C

	NO LEARNING		LEARNING	
PERIOD	GENCO 1 (MW)	GENCO 2 (MW)	GENCO 1 (MW)	GENCO 2 (MW)
1	138.51	141.60	150.00	135.87
2	150.00	185.07	150.00	214.61
3	140.74	155.07	125.99	184.61
4	110.74	125.07	95.99	154.61
5	99.62	102.92	77.20	124.61
6	69.11	72.92	54.53	94.61
7	109.11	122.92	94.53	213.89
8	149.11	150.00	134.53	150.00
9	150.00	120.00	113.98	120.00
10	150.00	90.00	150.00	90.00
11	120.00	60.00	120.00	60.00
12	150.00	30.00	150.00	30.00
13	120.00	0.00	120.00	0.00
14	90.00	0.00	90.00	0.00
15	60.00	0.00	60.00	0.00
16	30.00	0.00	30.00	0.00
17	0.00	50.00	0.00	50.00
18	0.00	100.00	0.00	100.00
19	0.00	150.00	0.00	150.00
20	0.00	200.00	0.00	200.00
21	0.00	189.63	0.00	189.63
22	0.00	159.63	0.00	159.63
23	40.00	129.63	40.00	129.63
24	80.00	179.63	80.00	264.92

Here we observe that the commitment schedule differs from the two previous cases. There is one shut-down for each GENCO. In addition, ramp up and ramp down constraints occur (seen in the GENCOs' outputs). In Case B above, once the unit reached its maximum time online, it goes off (this also occurs when it reaches its maximum offline time). However, in Case C, before the unit goes off, the ramp down constraint begins working so that the unit decreases its output for several periods before it finally goes off.

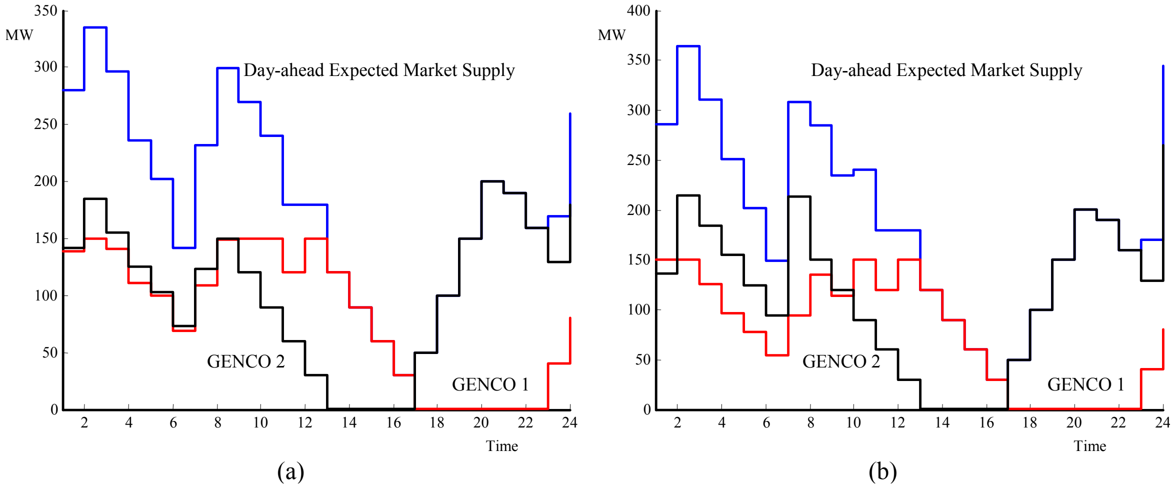


Figure 11.12 GENCOs' expected outputs (a) without learning and (b) with learning: Case A

As seen in Figure 11.12, the commitment schedule differs with respect to the two previous cases. There is one shut-down for each GENCO. The market-clearing price as displayed in Figure 11.13 differs considerably due to the ramp up and ramp down constraints.

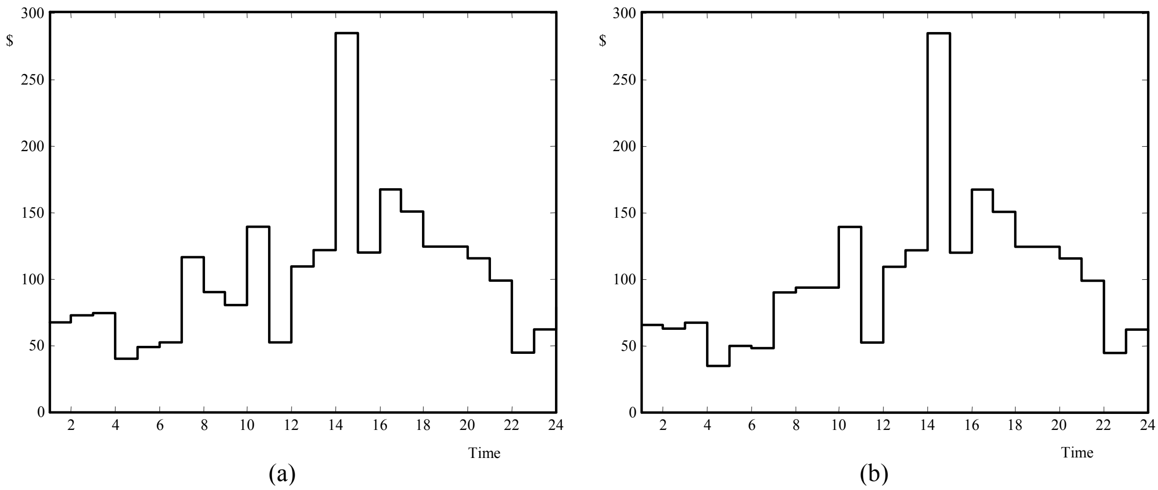
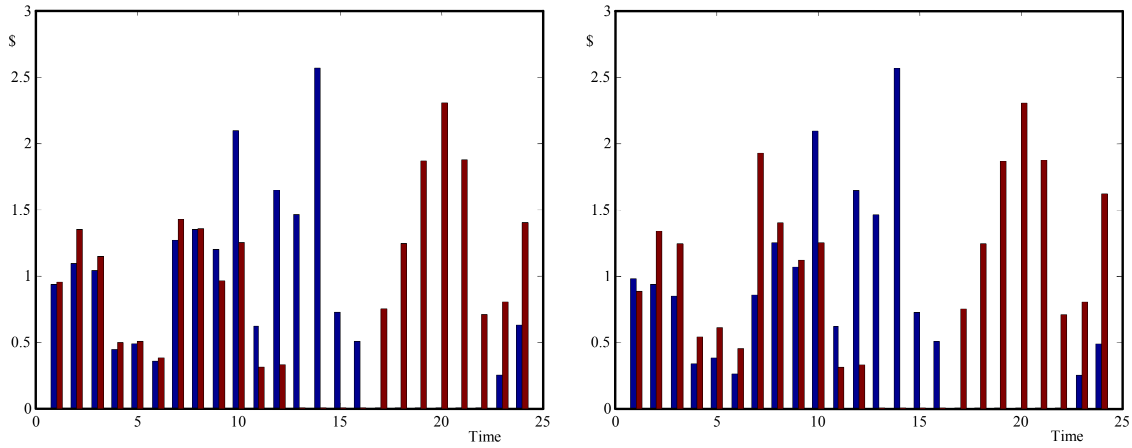


Figure 11.13 Market-clearing prices (a) without learning and (b) with learning: Case C



(a) (b)

Figure 11.14 Profits per period per GENCO (a) without and (b) with learning: Case C

Table 9 Producer's revenues, costs and profits: Case C

GENCO	Total Revenues ($)	Total Costs ($)	Net Profits ($)
1	186360	37608	148752
2	214070	29419	184651
1	172330	36494	135836
2	225600	31903	193697

In the situation depicted, GENCO 2 makes the highest profits with and without learning. Moreover, GENCO 2's profits are higher when the learning aspect is considered via the use of adjusting factors. However, the inclusion of ramp up and ramp down reduces its profits with respect to Case B.

Table 10 summarizes total expected revenues, total expected costs, and net expected profits for each GENCO for each case.

Table 10 Producers' revenues, costs and profits

GENCO	Total Revenues ($)	Total Costs ($)	Net Profits ($)	CASE
1	232080	52207	179873	A
2	237410	38257	199153	
1	231610	54149	177461	
2	220000	38094	181906	
1	205480	41463	164017	B
2	256490	36698	219792	
1	199530	40614	158916	
2	256840	37221	219619	
1	186360	37608	148752	C
2	214070	29419	184651	
1	172330	36494	135836	
2	225600	31903	193697	

Table 10 reveals that net profits differ from case to case. In all cases, GENCO 2 earns higher profits, with Case B resulting in the most favorable conditions. The table also shows that the benefits differ with the incorporation of additional constraints, operative generation limits, and ramping constraints.

4. Parameter dependency

A different choice of parameters will influence market outcomes. Market equilibrium depends on all system parameters except fixed-cost parameters.

Adjusting factors assume a key role in the determination of market equilibrium since they modify the reaction functions. By changing the adjusting factors, we can find a factible region. The factible region is determined by the extreme maximum values reached by the adjusting factors. For instance, when both factors equal 1, it represents the maximum market quantity which is in essence the Bertrand outcome. The intersection of reaction functions still determines the market equilibrium. On the other hand, when both factors approach -1, the lower market quantity bound is established. Graphically this factible region is represented by the shadowed area depicted in Figure 11.15. We note that any combination of adjusting factors will fall within the factible region.

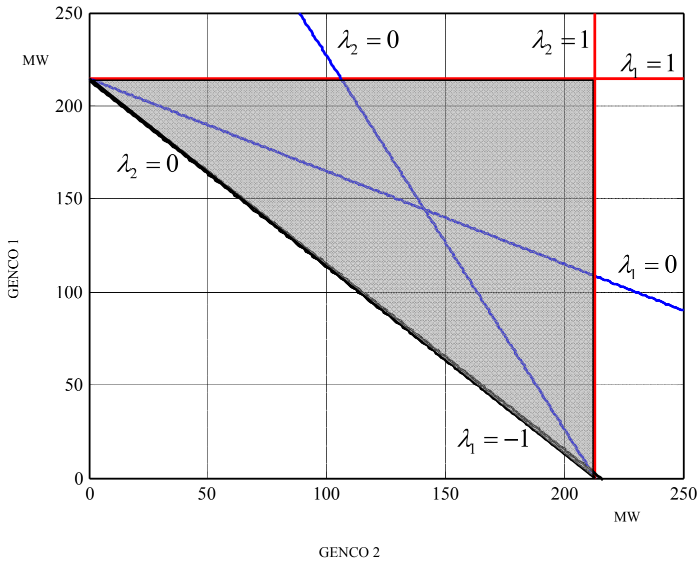


Figure 11.15 Equilibrium market factible region

It is well known that changes in market-demand function parameters will increase or decrease the factible region. For instance market demand "shifts up" when increasing parameter *a* and keeping everything else constant. Consequently, the factible region increases. If parameter *b* decreases, and everything else is kept constant, the market demand also shifts up and therefore the factible region increases.

5. Conclusions

This paper studies the production decisions of GENCOs in an oligopolistic electricity market solved by sequential market equilibriums. The formulation of sequential market equilibriums is represented by an independent linear set of equations with unique solutions when temporal constraints are omitted. Operational and temporal constraints have been included in the model. Once the temporal constraints are considered, the independent time-steps solutions are coordinated by the supervision of the maximum/minimum on/off time constraints.

The model elaborated in this paper was reduced to a two-player model to facilitate the analysis and make it relatively easy to identify the results derived a priori. The model can be extended to an n-player model in a single-node. Under this condition, the problem can be reduced to a two-player model. To reduce a two-player model we can use a composite of the generation production cost curves, and reduce our own generation units and the rival units to one composite unit. The Cournot game results if all the adjusting coefficients equal zero, $\lambda = 0$. When all of the GENCOs' adjusting coefficients are equal to 1, the market equilibrium moves to the Bertrand outcome; monopoly is reached when they tend to -1.

The solution of the short-term equilibrium problem varies with the generation cost parameters, the demand parameters, and the adjusting coefficients. A numerical example that illustrates the impact of the ramping process shows that the benefits will differ with the incorporation of ramping constraints.

Modeling the repetition of static snapshot with learning effect in the decision-making process is an alternative method to analyze the dynamic behavior of the market players. We incorporated learning by using forward expectations. In the examples given, these coefficients are assumed to be known. However, they must be estimated for each GENCO utilizing methods such as data mining, neural nets, and forecasting.

The issue of transmission network effect merits further research. Currently, we are applying it to our model and will report the results in further publications.

Appendix A. List of symbols

k Index for the number of time intervals in hours

i Index for the number of GENCOs

$P(Q)$= Inverse linear market demand at period k

$Q(k)$= Total market output at period k

$q_i(k)$= Output from player i at period k

$\hat{q}_j(k)$ GENCO j's expectation of the decisions made by GENCO I at period k

$\pi_i(k) =$ Profit of GENCO i at period k

$C_i(q_i(k)) =$ Production cost function of GENCO i

$q_i^{MIN} =$ Minimum output of the GENCO i

q_i^{MAX} Maximum output of the GENCO i

$t_i^{Off} =$ Minimum time off of the GENCO i

t_i^{On} Maximum time on of the GENCO i

$a, b =$ Market-demand parameters

$d_i, e_i, f_i =$ Coefficients of production cost function $C_i(q_i(k))$

$\lambda_j =$ Adjustment coefficient for GENCO j

$Z_i =$ Maximum power ramp-up increment of unit i

$W_i =$ Maximum power ramp-down decrement of unit i

$x_{ik} =$ State variable indicating the length of time that the unit i has been up or down at period k

$u_{ik} =$ Binary decision variable indicating whether the unit i at period k is up or down

$\mu =$ Lagrange multiplier

References

[1] The next generation of Electric Power Unit Commitment Models, Edited by Benjamin F. Hobbs, Michael H. Rothkopf, Richard P. O'Neill and Hung-po Chao, Kluwers' international series.

[2] James Friedman, Oligopoly Theory, Cambridge Surveys of Economic Literature, Cambridge University Press, 1983.

[3] Jean Tirole, The Theory of Industrial Organization, The MIT Press.

[4] Wei JY, Smeers Y, "Spatial Oligopolistic Electricity Models with Cournot Generators and Regulated Transmission Prices," Operations Research, Vol. 47, No. 1, Jan-Feb 1999, pp. 102-112.

[5] Christopher J. Day, Benjamin F. Hobbs, and Jong-Shi Pang, "Oligopolistic competition in power networks: A conjectured supply function approach," IEEE Trans. On Power Systems 17 (3): 597-607 Aug 2002.

[6] Guillermo Bautista, Miguel F. Anjos, and Anthony Vannelli, "Formulation of Oligopolistic Competition in AC Power Networks: An NLP Approach," IEEE Trans. On Power Systems, Vol. 22, No. 1, Feb. 2007, pp. 105-115.

[7] A. Alj and A. Haurie, "Dynamic Equilibria in Multigeneration Stochastic Games," IEEE Trans. On Automatic Control, Vol. 28, No. 2, pp. 193–203. Feb 1983.

[8] J. D. Liu, T. T. Lie, and K. L. Lo, "An Empirical Method of Dynamic Oligopoly Behavior Analysis in Electricity Markets," IEEE Trans. On Power Systems, Vol. 21, No. 2, May 2006.

[9] Barquin J, Centeno E, Reneses J, "Medium-term generation programming in competitive environments: a new optimisation approach for market equilibrium computing," IEE Proceedings-Generation Transmission and Distribution 151 (1): 119-126 JAN 2004.

[10] Gutierrez-Alcaraz G, Sheble GB, "Electricity market dynamics: Oligopolistic competition," Electric Power Systems Research, Vol. 76, Jun 2006, pp. 695-700.

[11] Weiguo Yang, "Short-term electric market dynamics and generation company decision-making in new deregulated environment," Ph.D. dissertation, Dept. Elec. Eng., Iowa State University, 2003

[12] A. Vidales-Vazquez and G. Gutierrez-Alcaraz, "Sequential Time-Step Oligopolistic Electricity Market Competition with Forward Expectations," IEEE 2007 Power Engineering Society General Meeting, Tampa, Florida, USA, June 2007.

[13] Gian Italo Bischi and Michael Kopel, "Equilibrium selection in a Nonlinear Duopoly Game with Adaptive Expectations," Journal of Economic Behavior and Organization, Vol. 46, 2001, pp. 73-100.

[14] Gyochi Iwata, Measurement of Conjectural Variations in Oligopoly, Econometrica, Vol. 42, No. 5, Sep 1974, pp. 947-966.

[15] Yiqun Song, Yixin Ni, Fushuan Wen, and Felix F. Wu, Conjectural variation based learning model of strategic bidding in spot market, Electrical Power and Energy Systems, Vol. 26, 2004, pp. 797-804.

[16] Youfei Liu, Y.X. Ni, Felix F. Wu, and Bin Cai, Existence and uniqueness of consistent conjectural variation equilibrium in electricity markets, Electrical Power and Energy Systems, Article in Press.

[17] Tellef Juell Larsen, Ivar Wangensteen, and Terje Gjengedal, "Sequential Timestep Unit Commitment," IEEE Power Engineering Society Winter Meeting 2001, Vol. 3, Jan-Feb 2001, pp. 1524 – 1529.

[18] G. B. Shrestha, Kai Song, and L. Goel, "Strategic Self-Dispatch Considering Ramping Costs in Deregulated Power Markets," IEEE Trans. On Power Systems, Vol. 19, No. 3, Aug 2004, pp. 1575–1581.

[19] Jose M. Arroyo and Antonio J. Conejo, "Modeling of Start-Up and Shut-Down Power Trajectories of Thermal Units," IEEE Trans. On Power Systems, Vol. 19, No. 3, Aug 2004, pp. 1562-1567.

[20] Chattopadhyay D, "A Game Theoretic Model for Strategic Maintenance and Dispatch Decisions," IEEE Trans. On Power Systems, Vol. 19, No. 4, Nov 2004, pp. 2014-2021.

[21] Keith Cuthbertson, "Modelling Expectations: A Review of Limited Information Estimation Methods," Bulletin of Economic Research No. 42, Vol. 1, pp. 1-34, 1990.

[22] Paul W. B. Atkins, Robert E. Wood, and Philip J. Rutgers, The effects of feedback format on dynamic decision making, Organizational Behavior and Human Decision Processes, Vol. 88, 2002, pp. 587-604.

[23] Raquel Garcia-Bertrand and Antonio J. Conejo, "Multi-Period Near-Equilibrium in a Pool- Based Electricity Market Including On/Off Decisions," Networks and Spatial Economics, Vol. 5, No. 4, Dec 2005, pp. 371–393.

[24] Youfei Liu and Felix F. Wu, "Impacts of Network Constraints on Electricity Market Equilibrium," IEEE Trans. On Power Systems, Vol. 22, No. 1, Feb. 2007, pp. 126-135.
[25] Wang X, Li YZ, Zhang SH, "Oligopolistic Equilibrium Analysis for Electricity Markets: A Nonlinear Complementarity Approach," IEEE Trans. On Power Systems, Vol. 19, No. 3, Aug. 2004, pp. 1348-1355.
[26] Younes Z, Ilic M, "Generation strategies for gaming transmission constraints: will the deregulated electric power market be an oligopoly?," Decision Support Systems, Vol. 24, Jan 1999, pp. 207-222.

CHAPTER 12 OPERATIONAL PLANNING CONSTRAINED BY FINANCIAL REQUIEREMENTS

A paper published in the Electricity Transmission in Deregulated Markets: Challenges, Opportunities, and Necessary R&D Agenda

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Abstract

This paper focuses on the future cash revenue flows required for an expected stock profile. It is these future cash flow requirements that determine the bidding strategy implemented by a Generation Company, GENCO. Based on forecasted information of competitors' product consumptions, forecasted demand, forecasted fuel prices, and expected transmission capabilities, each GENCO makes output decisions. Two cases of study are presented.

I. INTRODUCTION

The objective of the expansion decision process is to maximize the profit in future periods commensurate with the risk and return expected by each company within an industry window. Each generation company, GENCO, has a given production cost, market niche and competitive advantage as a portfolio to maximize its profit in future periods. As it is the GENCOs' production that drives the risk and return profile, each competitive player needs to know the other competitor's strategic decisions to set bidding profiles and thus, maximize profit. Each GENCO potentially uses different techniques to forecast the competitor's decisions (product mix) when trying to determine its own production mix.

The input consists of forecasts of competitor's products based on historical consumption, the forecasted demand, the forecasted prices of each fuel type, and the expected transmission capabilities. While not all information has an impact in each future period, some, such as transmission capability, have a dramatic impact for a short period with profound price movements.

The dynamic simulation focuses on the interactions between competitors and the resulting option value of the generation asset. Each GENCO in the market starts with an initial state based on the type of asset owned, the capital requirements, and the operational costs. Each GENCO then finds output decisions based on expectations of the major factors as listed previously. Each GENCO adjustments its bidding decisions accordingly. There may be or may not be equilibrium after interactions occur. The uncertainties of these factors are modeled as real options to properly value the assets into the future periods.

Real Option Analysis, ROA, has been use for valuating generation assets in a market environment. First models neglected operational unit's constraints, such as ramp up/down and maximum time on/off, becoming a pure financial modeling. Neglecting operational constraints may have a significant impact on value the generation assets [1]. When these constraints are taken into consideration, the valuation problem is path-dependent. Hence, the decision to turn on or off the generating unit not only depends of fuel and electricity prices but also on unit's status. Several methodologies have been proposed for handling the technical unit's constraints. Tseng et al. [2] apply Monte Carlo simulation in the option pricing. Doug Gardner and Yiping Zhuang [1] use stochastic dynamic programming instead. These, as well as other reported papers make emphasis in modeling the electricity price and fuel prices [3][4].

Considering operational characteristics seems similar to the traditional unit commitment, which finds the optimal scheduling strategy. However, what ROA does, is to determine the optimal bidding strategy rather than the optimal schedule. Under specific conditions, these two objectives can be equivalent.

With the unbundling of the electric power industry, the generation unit has become a multi-product device. Generation owners may have additional means of generating revenues. Rajaraman et al. in [5] describes the multi-period optimal bidding strategy for a generator under exogenous uncertain energy and reserve prices. Finding the optimal market-responsive generator commitment and dispatch policy in response to exogenous uncertain prices for energy and reserves is analogous to exercising a sequence of financial options [6].

The optimal bidding is deficient if additional factors are neglected, for example transmission congestion and competitor's behavior. Rajaraman et al. in [5] treats transmission congestions by modeling locational prices that are consistent with the structure of the transmission congestion and the transmission network. Shi-jie et al. in [7] and [8] also use locational prices for valuating transmission assets. They refer to price difference between two points as locational spreads.

This paper focuses on the future cash revenue flows required for an expected stock profile [9] (as determined by Capital Assets Pricing Model, CAPM, Arbitrage Pricing Theory, APT, etc.). It is these future cash flow requirements that determine the bidding strategy implemented by a GENCO. For simplicity's sake, the future cash flows are dependent on a single commodity, electric energy, although a generating unit is a multi-product device. The remainder of the paper is organized as follows. The next section presents the CAPM. Next, ROA in the electric power industry is introduced. A linear programming mathematical model is then presented. Numerical example follows. The final section concludes the paper.

II. CAPITAL ASSET PRICING METHOD (CAPM)

CAPM is an important tool used to analyze the relationship between risk and rate of return [9][10]. An average-risk stock is defined as one that tends to move up and down in step with the general market as measured by some index such as the Dow Jones Industrials, the S&P 500, or the New York Stock Exchange Index [11].

If a stock is in equilibrium, then its required rate of return, r, must be equal to its expected rate of return, $\hat{r}$. Further, its required return is equal to a risk free rate, r_f, plus a risk premium, whereas the expected return on a constant growth stock is the stock's dividend yield D_1/P_o, plus its expected growth rate, g.

$$r = r_f + \left(r_m - r_f\right)\beta = \frac{D_1}{P_o} + g = \hat{r} \tag{1}$$

Figure 12.1 shows the security market line, SML, as a function of risk (β). The riskless return has a β=0, where the SML crosses the expected return axis.

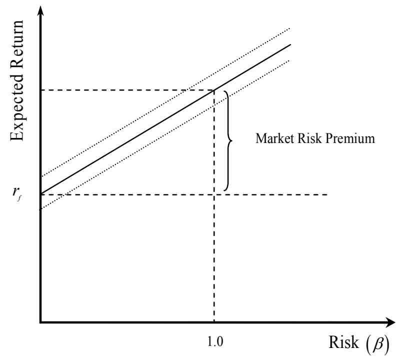

Figure 12.1 The security market line

β indicates how sensitive a security's returns are to changes in the return on the market portfolio. If a security's β=1.0, its return tend to track the market portfolio.

If the market portfolio increases/decreases by 10%, the stock also tends to move up/down by 10%. If a stock has a β < 1.0, it will tend to rise/fall less than the market. For instance, assume a stock has a β=0.5. If the market portfolio increases by 10%, the stock will tend to move up only 5%.

A stock with β > 1.0 will rise/fall more than the market. For example, a stock with a β=1.5 will tend to rise/fall by 15% when the market portfolio increases/decreases 10%.

The utility's forecasted market clearing price is essential in its market strategy. Price variations are the result of competitors' interaction and system conditions. Competitors' decisions are strongly correlated with input price variations. Even when the forecasted prices reflect the normal stochastic variations in system operating conditions, the forecasted prices may not be accurate enough to guarantee a winning decision. The producer has to live with the uncertainty of negative profits. Possible losses may occur due to the difference between the spot price at delivery time and the forecasted price.

There exist two basic models that can be used to determine the risk management benefits of alternative strategies. The first is to conduct a historical analysis and determine how a given strategy would have performed had it been employed in the past. Historical information would be used to simulate the future cash flows. The second method would be conducted a forward-looking analysis by forecasting future system and market variables.

The planning of scheduling for a GENCO will determine the future cash flows. These need to recover costs, fixed and variable, plus an additional expected return.

Operational constraints of the generating units, the interest rate, forecasted electricity and fuel prices error deviation, among others, will create a SML bandwidth instead of a strict SML, as depicted in Figure 12.1.

III. REAL OPTIONS ANALYSIS

Real options have become an important tool on valuation of power generation asset. Real options represent opportunities to act which provide their holder with the right, but not the obligation, to exchange the value of the cash flow stream of underlying asset against the value of the cash flow stream of an exercise asset [12].

The financial concepts applied to the electricity market results in the spark spread option. The spark spread option is based on the difference between the electricity price, p_E^t, and the price of a particular fuel, p_F^t, used to generate it [8]. The spark spread payoff associated with a specific heat rate, H is defined as:

$$payoff = p_E^t - Hp_F^t \tag{2}$$

A generation asset's value over a period of time is commonly estimated by a series of European call spark spread options.

$$\sum_{t=1}^{T} E\left(p_E^t, p_F^t, T\right) = \sum_{t=1}^{T} \max\left(p_E^t - Hp_F^t, 0\right) \tag{3}$$

Each period has an associated cost and revenue. It is common practice to distribute the fixed costs within the existing periods. It means that fixed costs are periodized over its useful economic life. Fixed costs as well as variable costs must be covered during the periods when bids are accepted by the market. For instance, when the fixed costs are covered during the fist periods seems more favorable, but this is disputable given that profits strongly depend on spot prices, which may be higher in later periods. However, selling during the earliest period with a lower profit provides additional flexibility since they have extra periods to adapt their strategy base on new market information. Hence there exists a trade-off of when to scheduling output becoming a timing problem.

Real Options could be used to take the uncertainty due to different factors such as uncertainty about an opponent's bid, uncertainty about future demand, and uncertainty about future failures and inefficiencies in power plant operation, and uncertainty about congestion on transmission lines, and reduce all these uncertainties to a single number.

IV. MODEL AND SOLUTION

How can a GENCO gauge the expected cash flows of revenue that would result from a specific strategy? These cash flows are not exogenous at all. The future cash flows depend upon future scheduling decisions, however the fixed cost are certain to be incurred and those have to be recover.

Consider that any quantity produced can be sold in the spot market in the subsequent periods as long as it is priced competitively. The optimization problem is formulated as a maximizing linear program.

$$\underset{P_G^t}{Maximize} \ \sum_{t=1}^{T} \left(P_G^t p_E^t - C\left(P_G^t\right) \right) \Big/ \left(1+r\right)^t \tag{4}$$

$$S.to \quad HP_G^t \leq D^t \qquad \forall t = 1,\ldots,T \tag{5}$$

$$P_E^t \geq H \cdot p_F^t \qquad \forall t = 1,\ldots,T \tag{6}$$

$$P_G^t \geq 0 \qquad \forall t = 1,...,T \tag{7}$$

where the P_G^t is the electric power generated at period *t*, $C\left(P_G^t\right)$ represents the fix and variable cost, D^t is the demand at period *t*, and $\left(1+r\right)^t$ is the time value of money, and H a matrix of output coefficients. It is assumed a linear relationship between input and output transformation. This assumption permits to model GENCO's bid in block contracts. The formulation also assumes that there is no limitation on fuel supply.

The cost function is given by the equation:

$$C\left(P_G^t\right) = a + bP_G^t \tag{8}$$

where *a* represents the fixed cost and *b* is the variable costs of production.

A network flow interpretation of the mathematical model is depicted in Figure 12.2.

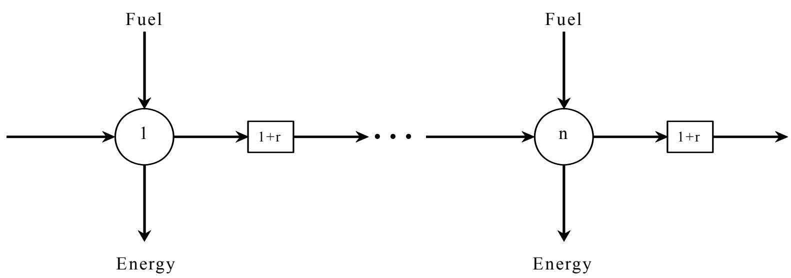

Figure 12.2 N-periods production decision network flow

The previous diagram portrays the spark spread option. This option adds value to the power generation assets when the contracted fuel is sold back to the fuel market or swapped, which is beyond the scope of this paper.

It is possible to include additional inputs in the described model permitting to market participants adaptively adjust market strategies as soon as each new piece of information is available.

V. CASE STUDIES

In this section numerical examples are presented. A GENCO is designing the bidding strategy for the next 4 periods. Fixed cost, variable production cost, and an expected rate of return must be recovered. Historical market information was taken from a random electric utility [13].

For the purpose of this example, forecasted electricity spot prices for the upcoming periods are assumed known. Except as noted elsewhere, all other parameters values used are listed in Table I and Table II. Fuel price is assumed constant for all the periods.

TABLE I

EXPECTED DEMAND AND EXPECTED ELECTRICITY PRICES

Period	Demand (MWh)	Price
1	500	20.0
2	600	24.3
3	550	26.5
4	580	28.0

TABLE II

BASE CASE PARAMETER VALUES

Parameter	Value
P_G^{MAX} (MW)	50
a ($)	120
b ($/MWh)	1.0
r_f (%)	8
r_M (%)	12
β	1.2
Fuel ($)	21

The expected rate of return is calculated as follows:

$$\hat{r} = 8\% + (12\% - 8\%) * 1.2$$

$$\hat{r} = 12.8\%$$

With the previous information, the optimization program gives the results shown in Table III:

TABLE III

OPTIMAL FORWARD POWER COMMITTED

Period	Power (MWh)
1	0
2	50
3	50
4	50

Prices, committed power, and revenues are shown in Figure 12.3.

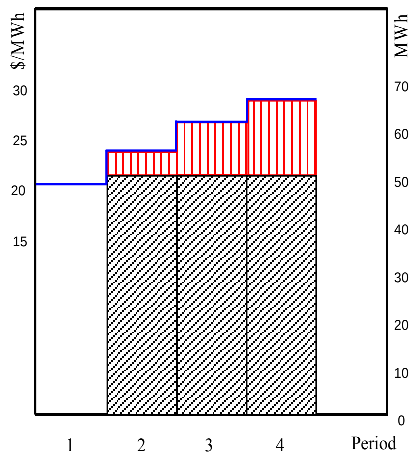

Figure 12.3 Expected price of electricity and committed power: case I

From Figure 12.3, we can observe that expected price of electricity is lower than the production costs at period 1. It implies that GENCO is not selling energy in such period. The subsequent periods, expected prices seem more favorable allowing him to sell its energy. No selling power in period 1 generates negative profits which are transfer to next periods.

In order to recover the cost acquired at those periods, GENCO will need to raise the bidding price in subsequent periods. This can be done basically in two different ways: distributing in two or more periods or in a single period. Distributing in more than two periods seems more credible which also distribute the risk. However, such decision will depend much on market information. The most disruptive factor that leads to violation of theoretical predictions is information uncertainty on the part of market participants.

From the same we also observed the price difference between the electricity expected market price and the expected selling price. This information is also provided for the optimization program and is presented in Table IV.

TABLE IV

PRICE DIFFERENCE AT EACH PERIOD

Period	1	2	3	4
Difference ($)	-	2.549	3.832	4.324

Note that the values take in consideration the time value of the money. For instance, the expected market price at period 2 is $24.3

In this case, it was possible to allocate forward contracts such as the future cash flows recover all the cost and the expected return. However, there exists always the possibility that this condition does not happen. Two alternatives need to be considered: To reduce the expected return or to increase bid prices.

Now, consider that the price in period 1 = $23.6 and in period 2 = $20.3. The optimal solution is shown in Table V.

TABLE V

OPTIMAL FORWARD POWER COMMITED WITH NEW EXPECTED PRICES OF ELECTRICITY

Period	Power (MWh)
1	50
2	0
3	50
4	50

From Table V we can see that due to lower expected price of electricity at period 2, GENCO's decision is not to sell. Thus, GENCO is incurring in negative profits at that period. The negative profits are essentially the periodized fixed costs. Form the unit's operational viewpoint, it can be said that the unit is banking. Prices as well as committed power and revenues for the 4 periods are shown in Figure 12.4.

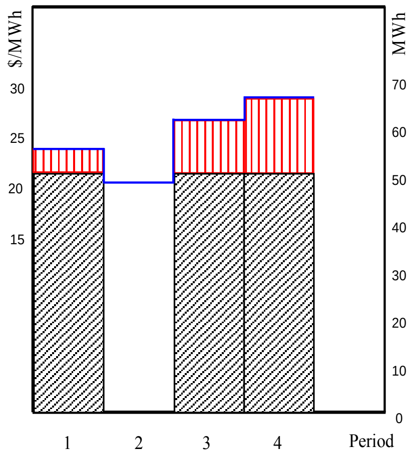

Figure 12.4 Expected price and committed power: case II

The future profits per period for both cases are shown in Table VI.

TABLE VI

FUTURE EXPECTED PROFITS

Period	Case I ($)	Case II ($)
1	-	115.248
2	129.678	-
3	191.604	191.604
4	216.188	216.188
NPV	10.526	10.78

From Table VI we observe that the NPVs are different. The difference is due to time value of money between selling today (period 1) and selling tomorrow (period 2) since the values at period 3 and 4 are the same. In both cases, the fixed costs are fully recovered.

VI. UNCERTAINTY

Simple capital budgeting analysis, based on the assumption of a given time flows of receipts, is perfectly valid if future production plants are known. However, this assumption neglects futures events introducing substantial uncertainty in the decision making process. Uncertainty is best thought of as representing a spectrum of unknown situations, ranging from perfect knowledge of the likelihood of all the possible outcomes at one end to no knowledge of the likelihood of possible outcomes at the other.

By taking in consideration uncertainty, the company will gain a flexibility option allowing him to modify operations depending on how conditions develop as time progresses.

Decision trees have been a traditional tool for analyzing and valuating embedded options when uncertainty is considered. Setting up a decision tree forces the GENCOS´s decision maker to consider embedded options.

In this document we basically are evaluating a single path of the decision tree. The branch at each new node, assumes the same rate of return and external variables are forecasted with accuracy, price of electricity.

Our approach, LP optimal committed power for multiple time periods can be expanded by using the decision tree. For each path, we form a LP problem to forecast the optimal decision that maximizes profits.

The introduction of uncertainty for fuel and electricity price for a given period *t* can be graphically represented as follows:

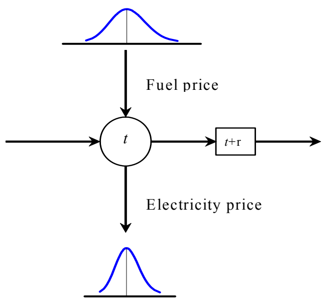

Figure 12.5 Expected fuel and electricity price at period *t*

Other exogenous variables can be modeled similarly to fuel or electricity price variables depending whether it is a input or output variable. Additionally, different rate of return inter-period would also be simulated

VI. SUMMARY

GENCOs operational planning is not only constrained for its technical operational limits and fuel inventory, but also for the financial requirements.

A GENCOs financial requirement is the expected rate of return within a specific period of time. According with CAPM in order to increase the expected rate of return, GENCOs portfolio will be exposing to higher risk.

By committing forward contracts in the earliest deadline, the company will gain a flexibility option allowing him to modify operations depending on how conditions develop as time progresses. One of these options is to modify financial requirements, expected rate of return, in order to obtain a higher profit.

In order to reduce risk in the allocation on forward contracts a less expected return may be chosen otherwise the expected electricity price must be higher.

Another alternative would be to increment the number of periods. This generally is an option for investment decisions. However, for operational decision this condition is not available; bookkeeping time is fixed usually quarterly.

The previous analysis can be applied to any price taker forward contract, intermediate load unit, or contracts within a bandwidth at the money from financial option viewpoint. Peak generators need as well as any other unit to recover the full cost in a certain period of time. This justify why for some periods electricity prices experience sparks unless other allocating mechanism helps GENCOs to recover all the costs smoothly.

An intertemporal LP optimization program has been proposed in this document. The problem is formulated as deterministic optimization problem since a single path of a decision tree is evaluated. However, the incorporation of uncertainty was discussed and it is issue of future work.

REFERENCES

[1] Doug Gardner and Yiping Zhuang, "Valuation of Power Generation Assets: A Real Option Approach," *Algo Research Quarterly*, 3/2000, Vol. 3, No 3, pp. 9-20. December 2000.

[2] Tseng, C. and G. Barz, "Short-Term Generation Asset Valuation: A Real Options Approach," *Operations Research*, Vol. 50, No. 2, pp. 297-310. March-April 2002.

[3] Shi-jie Deng and Samuel Oren, "Incorporating Operational Characteristics and Startup Cost in Option-Based Valuation of Power Generation Capacity", *Probability in the Engineering and Informational Sciences (PEIS)*, April, 2003.

[4] M. Hsu. Spark Spread Options are Hot!. *Electricity Journal*, 11(2): 1998.

[5] Rajesh Rajaraman and Fernando Alvarado, "Optimal Bidding Strategy in Electricity Markets Under Uncertainty Energy and Reserve Prices," PSERC Report, April 2003.

[6] R. Rajaraman, L. Kirsch, F. L. Alvarado and C. Clark, "Optimal Self-Commitment under Uncertain Energy and Reserve Prices," in B.F. Hobbs, M.H. Rothkopf, R.P. O'Neill, and H.-P. Chao, eds., *The Next Generation of Unit Commitment Models*, International Series in Operations Research & Management Science, Kluwer Academic Publishers, Boston/Dordrecht/London, 2001.

[7] S. Deng, B. Johnson, A. Sogomonian, "Exotic Electricity Options and the Valuation of Electricity Generation and Transmission Assets," Research Report #PSERC 98-13, 1998.

[8] Shi-jie Deng, Blake Johnson, Aram Sogomonian, "Spark Spread Options and the Valuation of Electricity Generation Assets", in P*roc. of the 32nd Hawaii International Conference on System Sciences*, 1999.

[9] Don Dayanandra, Richard Irons, Steve Harrison, John Herbohn, and Patrick Rowland, *Capital Budgeting: Financial Appraisal of Investment Projects*, Cambridge University Press, 2002.

[10] Kevin Dowd, *Beyond Value at Risk: The New Science of Risk Management*, John Wiley & Sons, August 1999.

[11] http://www.nymex.com

[12] Johnathan Mun, *Real Options Analysis: Tools and Techniques for Valuating Strategic Investments and Decisions*, John Wiley & Sons, Inc. 2002.

[13] http://www.finance.yahoo.com

[14] Damien C. Sansom and Tapan K. Saha, Energy Constrained Generation Dispatch based on price Forecasts Including Expected Values and Risk, in *Proc. 2004 General Meeting*, Denver Colorado, USA. June 2004.

[15] J. Kumar and G.B. Sheble', "A Framework for Transaction Selection Using Decision Analysis Based Upon Risk and Cost of Insurance," *in Proc. of the 26th annual North American Power Symposium*, Kansas State University, KS, pp. 81-90, 1994.

CHAPTER 13 THE VALUE OF TECHNICAL INFORMATION IN THE UNBUNDLED ELECTRICITY MARKET

A paper published in the 10th International Conference on Probabilistic Methods Applied to Power Systems, PMAPS 2008

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Abstract

For many years, the electric power industry treated electricity as a unique commodity sold to costumers. Nowadays, the new electricity industry has identified several key ancillary services. Under this new scenario, the producer's primary goal is the selection of services in which to participate via assessing the potential profits as part of the decision-making. Purchasing additional information can help reduce uncertainty and identify the optimum market scenarios. However, it will require market participants to analyze both perfect and imperfect information. The price that the decision maker may be willing to pay to resolve an uncertainty depends on the value of the information. This paper will investigate the identification and value of technical system information available for purchase from system operators.

I. INTRODUCTION

In a fully unbundled electric market, market participants (MPs) consumers and/or producers- face a higher level of uncertainty than in current market models. MPs need to forecast both the residual demand for electric energy and the residual demand for each ancillary service (AS). These unbundled markets provide opportunities for MPs to observe the different services, selecting those that will be most profitable at a given time.

Many AS can be traded on an exchange-based market. It is envisioned that an independent market will exist for each service or commodity offered. Twenty-four independent hourly auctions for each service will concur with the twenty-four independent energy auctions [1].

When an independent market exist for each AS, MPs are solely responsible for their choice of product and bids. Therefore, a primary objective is to quantify the potential profits of the service selected. MPs may reduce uncertainty and risk by purchasing additional information from the system operator (SO). The potential flexibility gained directly relates to the information's value. Value is defined as the maximum amount a decision-maker will pay to resolve an uncertainty [2].

The SO's technical information is available for purchase by all MPs. The technical data includes: line impedances and capacities, real and reactive power nodal demands, and the parameters of switch capacitors and reactor banks. This paper investigates the expected value of the SO's technical information from the perspective of the producer MP. We calculate the value of system information using a production costing approach. The model considers fuel price fluctuations indexed by the total MP bid probability density function. The overall model simulates typical generation and network scenarios to assess the technical and financial risks associated with the range of possible market decisions. We use Decision Tree Analysis (DTA) to compute the value of the information available for purchase.

Production costing models are used in the electric industry to forecast the cost of producing electricity [3][4][5]. Real power is the commodity of interest. However, the economic principles governing the pricing of active power also apply to reactive power. Other AS must be considered since the probabilistic production cost approach consists of operating cost and outage costs [3][6][7]. However, this issue is questionable since customers would be able to select the level of reliability in the unbundled electric market. In [8] the production costing approach was employed to analyze the risk of short-term system operational planning in the presence of electric load forecast uncertainty and in [9] to forecast electricity price statistical information necessary in the valuation of future and other electricity derivatives. Production costing models have been also used to forecast the electricity system's marginal costs [10].

In this paper a producer MPs (Generation companies –GenCos) offer power or any other service in block contracts; this implies that the market supply curve has the form of a step function. Similarly, buyers may make bids into the market at the prices they are willing to pay. The aggregate demand curve is a decreasing step function of price. The market clearing price (MCP) is commonly determined by the intersection of these demand-supply curves.

II. VALUE OF INFORMATION

A decentralized market environment presents a wide range of opportunities for sellers and consumers while at the same time it exposes them to higher levels of risk.

In essence, risk is subject to empirical measurement, while uncertainty is non-quantifiable. Thus, in a risk situation it is possible to indicate the chances of the realized value of a variable falling within stated limits. Stated limits can be described by the fluctuations around the average of a probability distribution function (PDF). In situations of uncertainty, the fluctuations of a variable are such that they cannot be described by a PDF. Hence, risk and uncertainty are best thought of as representing a spectrum of unknown situations ranging from perfect knowledge of the likelihood of all the possible outcomes at one end to no knowledge of the likelihood of possible outcomes at the other [11].

We observe that it is not the real-world situation itself which is either *risky* or *uncertain*, but simply the information available to decision-makers which defines it as such. All actual project outcomes are unknown since they occur in the future and are subject to influence by any number of variables, each of which may take different values.

Analysis of energy sales in a decentralized market may be undertaken in terms of *optimistic* or *pessimistic* assumptions about power demand levels. There are two approaches used to consider the associated returns. The first is based on prediction of future power demands under different scenarios. The second is based on modeling the outcomes through a PDF of future power demand. In both approaches, there is nothing inherently different about the circumstances of the decisions; only the data available to the MP making the decisions is different (i.e. the decisions have different levels of risk). The longer the forecasting period of participation the higher the uncertainty involved. This condition can be represented by the cone of uncertainty shown in Figure 13.1.

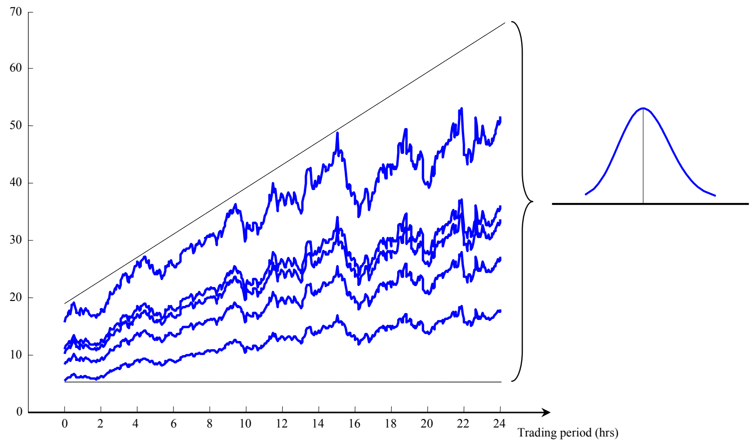

Figure 13.1 GenCos' cone of uncertainty on the day-ahead market

It is possible to reduce this staggering range by obtaining additional information. A cost/benefit comparison can decide whether or not to purchase the additional information.

The value of additional information under different scenarios is determined by using DTA. DTA is a sequential representation of decisions and uncertainties which represent all paths the decision-maker might follow through time [2][11]. The outcome of the decision tree is the expected value. The expected value of the decision tree with uncertainty is the sum of all the potential consequences multiplied by their associated probabilities:

$$EV_i = \sum_{j=1}^{n} \left(\mathrm{Prob}_j \cdot val_j \right) \tag{1}$$

where i = Node to be evaluated
j = Index of nodes connected to i
n = Number of nodes connecting node i
$Prob$ = Probability of the branch connecting node j and i
val = Valuation of node j

When one or more services are provided for the same GenCo the correlation of these services should be modeled. The correlation among the different services offered in the electricity market is nonlinear. For instance, from a generator point of view, reactive power is a complement output of active power, which makes complex to decompose those commodities

A schematic representation of the decision tree for 24 periods is shown in Figure 13.2. The different uncertainties modeled concern only operational uncertainties.

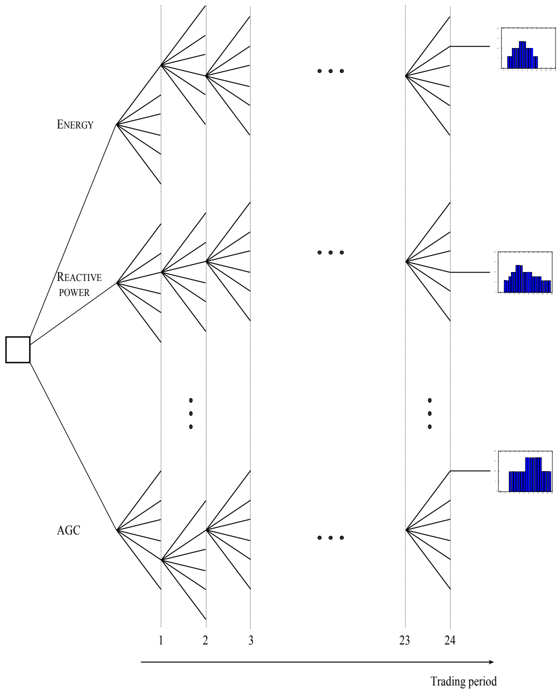

Figure 13.2 Multi-product Electricity market decision tree

Monte Carlo Simulation is applied given the simplicity of adding multiple uncertainties and viability of model plenty of probabilistic scenarios [2]. The simulation process should include a reasonable number of samples, each representing a system-operating state.

In the real world each producer sorts the probabilities and alternatives chronologically or by other criteria (i.e. level of risk). A number of uncertainties are displayed in Figure 13.3.

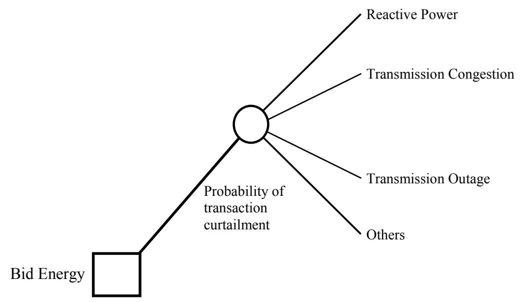

Figure 13.3 Decision tree for valuating information at period *t*

For illustrative purposes, consider the case of a GenCo that bids into the energy market and assume that the forecasted residual demand for energy has been estimated. The GenCo wants to discover whether the amount of power at the willing price to sell can or cannot be delivered. It bids 100 MWh at \$26/MWh on peak demand. It is able to sell more, but transmission congestion is a concern. The expected profits are \$2,600. However, the expected profit could be \$2,800 if the GenCo knows that 120 MW is the maximum power the system can handle without any congestion. Thus, the value of perfect information (VOPI) is:

(VOPI) is: $VOPI = \$2,800 - \$2,600 = \$200.$

Transmission access is imperative in the determination of electric energy delivery. The optionality of network restrictions due to congestion increases the importance of network information.

The PDFs associated with electric energy demand in each bus differ due to network parameters, load conditions, non-linear correlation between services, etc. For the sake of simplicity but with loss of generality, assume there is no correlation between these PDFs at each bus. Thus, each bus has a different PDF for each service, as represented in Figure 13.4.

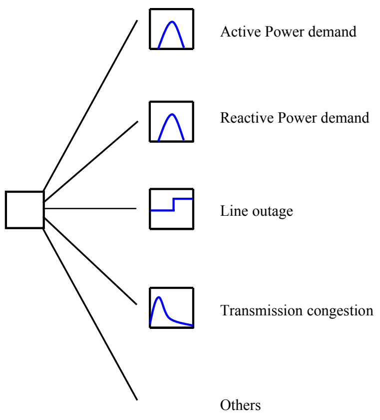

Figure 13.4 Probability distribution system at bus *i* for the different services

Normal PDF is considered for active and reactive power demand. Since a line can only be in two states, “in” or “out”, the uniform PDF is considered. Transmission congestion PDF depends on the state of the system and the network configuration. This implies that each GenCo may face different PDFs for transmission congestion.

The MP’s task is to discover the most important variables affecting the decision outcome. The usual form of representing the impact on outcome value and choice of policy is a tornado diagram [2].

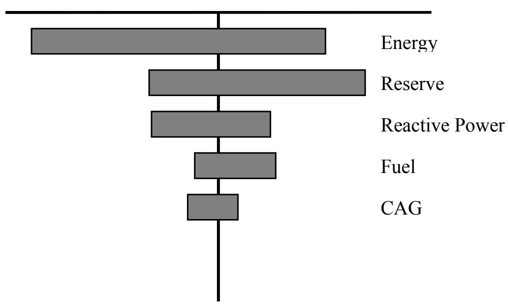

Figure 13.5 Example tornado diagram

For each of the most significant uncertainties, it is necessary to assess a PDF. The probability for uncertain represents the best state of knowledge about uncertainty.

It is helpful to think of the SO as the “container” of system operation information (nodal demand, status of transmission lines, maintenance records, etc.) available for sale. As the holder and seller, the SO must assess the willingness of MPs to buy its information. In turn, MPs must weigh the value of the SO’s information against the alternatives. Often, specific new information about key uncertainties will alter GenCo’s production decision. If this is the case, the new information has a value which can be calculated prior to making its final decision.

Due to the spatial distribution of the power system, not all MPs will be willing to buy the SO’s information. Therefore, the SO must consider the possibility of selling different information especially to players that do not have market power.

The existence of other AS and operating changes in units supplying demand introduce nonlinearities in electricity prices. Because of the lack of information on AS prices, MPs must use historical data to disaggregate and estimate them. One alternative is to use conventional optimization tools. For instance, in the case of reactive power ancillary service, Optimal Power Flow can be used for solving past scenarios along with the information purchased from the SO.

III. ILUSTRATIVE CASE STUDY

Case studies were performed using the modified five-node system [12] depicted in Figure. 13.6. The test system bid data is given in Table I. Additional data is provided in Appendix A.

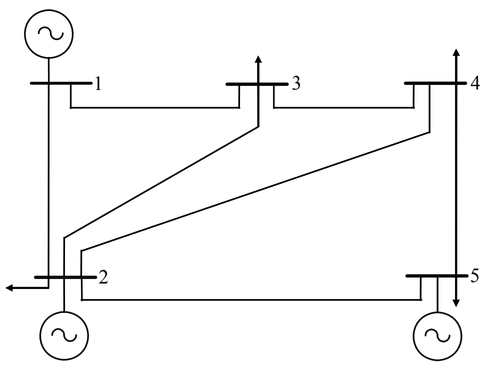

Figure 13.6 Five-nodes System

The simulation process uses 1,000 samples to obtain a PDF. Each sample represents one power system operating state. This sampling set was generated considering as random variables nodal loads, availability of generating units, and transmission lines. The only constraints on transactions are transmission limits.

TABLE I

NODAL LOADS' BID AND SUPPLY'S BID DATA

	Demand	Supply	
Node	MWh @ $/MWh	**MWh @ $/MWh**	
1	- @ 28	170@34	**GenCo 1**
2	20 @ 41	110@29	**GenCo 2**
3	195 @ 37		
4	140 @ 45		
5	**60 @ 36**	**140@25**	**GenCo 3**

The nodal PDF for the active power demand is displayed in matrix form in Figure 13.7. A similar matrix exists for reactive power demand.

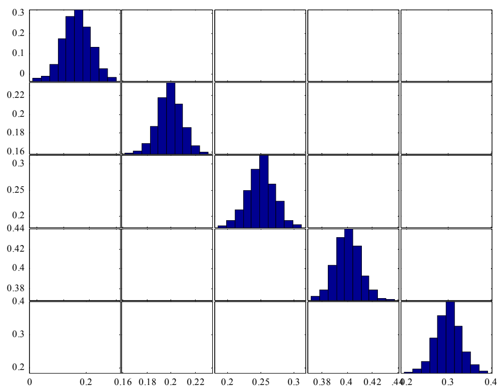

Figure 13.7 Nodal active power demand PDF

The SO solves the auction given the information submitted by both parties.

When transmission congestion does not exist we observe that demand is fully satisfied by the supply side. The transmission losses are also covered by the existing supply. The reserve is settled in an independent market.

The power flows through the system are shown in Table II.

TABLE II

REAL POWER FLOWS

Element	MW	Max (MW)
1	101.21	100
2	63.07	100
3	52.76	100
4	168.78	150
5	-32.56	30
6	-55.07	80
7	-44.69	40
Losses	29.29 MW	

Nodal voltage magnitudes are within the ±10%.

Now, let's analyze the following two cases:

Case 1: Consider the transmission limits

Case 2: Assume the transmission limits in elements 5 and 7 are 33MW and 45 MW respectively.

Having additional information about system operations may enable GenCo 3 to bid more accurately.

When transmission limits are violated, the power produced by GenCo 3 cannot be sold. Indeed, the maximum power it can sell is 130 MW instead of the 140 MW it is bidding. With this information GenCo 3 may be able to save money by reducing the level of production and fuel consumption.

On the other hand, GenCo 1 and/ or GenCo 2 will also benefit by having this information and can bid greater amounts of power. The system overall will also benefit by operating more economically.

The expected profit for GenCo 3 with perfect information is:

$$E^{P}\left(\pi\right)=130MWh*\$35\ /\ MWh=\$4,550$$

The expected profit without perfect information is:

$$E\left(\pi\right)=140MWh*\$35\ /\ MWh=\$4,900$$

Then, the value of perfect information (VOPI) is:

$$VOPI=\$4,550-\$4,900=-\$350$$

In the second case, the transmission limits have been relaxed and almost all the power from GenCo 3 can be delivered. Around 2 MW cannot be delivered. Then, the expected profit with perfect information is:

$$E^{P}\left(\pi\right)=138MWh*\$35\ /\ MWh=\$4,830$$

and

$$VOPI=\$4,830-\$4,900=-\$70$$

Even when the costs of information are relatively low, the information may reduce uncertainty to such a minor extent that is not worth the investment.

IV. CONCLUSIONS

If the unbundled electricity market introduces more uncertainty, it also provides more ancillary services. Obviously, astute MPs can maximize profits but others will only stay in business by being able to observe the opportunities available from participation in all of the ancillary services. For example, a GenCo may well find it difficult to sell expensive active power, yet the same GenCo's reactive power may be needed by the system.

The identification and value of the SO's technical information was analyzed using the concept of "value of perfect information". We observe that the value of imperfect information can prove more useful since imperfect sources are more often available. The value can be calculated by adding an uncertainty to the decision tree.

This paper only valued the technical information based on transmission constraints. However, the lack of ancillary services may also jeopardize GenCOs' production deliveries. Reactive power and voltage control play critical roles in supporting the real power transfer across the grid. We will present these additional research results in a future paper.

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REFERENCES

[1] Harry Singh, "Auctions for Ancillary Services," Decision Support Systems, January 1999. pp. 183-191.
[2] David C. Skinner, *Introduction to Decision Analysis*, Probabilistic Publishing, Second Edition, 1999.
[3] Laurence D. Kirsch, Robert L. Sullivan, Theresa A. Flaim, Joseph J. Hipius, Margaret G. Krantz, "Developing marginal costs for real-time pricing," *IEEE Trans. on Power Systems*, Vol. 3, No. 3, pp. 1133–1138, Aug. 1988.
[4] M. Lin, Art Breipohl, Fred Lee, "Comparison of probabilistic production cost simulation methods," *IEEE Trans. on Power Systems*, Vol. 4, No. 4, pp. 1326–1334, Nov. 1989.

[5] Fen-Ru Shih and Mainak Mazumdar, "An analytical formula for the mean and variance of marginal costs for a power generation system," *IEEE Trans. on Power Systems*, Vol. 13, No. 3, pp. 731 – 737, Aug. 1998.

[6] R. Ghajar and R. Billinton, "Comparison of Alternative Techniques for Evaluating the Marginal Outage Cost of Generating Systems," *IEEE Trans. on Power Systems*, Vol. 8, No. 4, pp. 1550–1556, Nov. 1993.

[7] S.H. Zhang and Y.Z. Li, Concise method for evaluating the probability distribution of the marginal cost of power generation, *IEE Proc.-Gener. Transm. Distribu.*, Vol. 147, No. 3, pp. 137-142, May 2000.

[8] Andrew P. Douglas, Arthur M. Breipohl, Fred N. Lee, Rambabu Adapa, Risk Due to Load Forecast Uncertainty in Short Term Power System Planning," *IEEE Trans. on Power Systems*, Vol. 13, No. 4, pp. 1493 – 1499, Nov. 1998.

[9] Jorge Valenzuela and Mainak Mazumdar, Statistical Analysis of Electric Power Production Cost, IIE Transactions on Power Systems, Vol. 15, No. 2, pp. 668-674, 2000.

[10] Guillermo Gutiérrez-Alcaraz, Noe Navarrete, J. Horacio Tovar-Hernández, Claudio R. Fuerte-Esquivel, Ricardo Mota-Palomino, "Analysis of Probabilistic Short Run Marginal Cost Using Monte Carlo Method," *61 st American Power Conference*, pp. 924-929, 1999.

[11] Robert T. Clemen, Making Hard Decisions: An Introduction to Decision Analysis, Duxbury Press, second edition. 1997.

[12] Stagg and El-Abiad, Computer Methods in Power System Analysis, 1968.

APPENDIX A

TABLE AI

TRANSMISSION LINES DATA (P.U.)

Element	Sending Node	Receiving Node	R	X	y/2
1	1	2	0.02	0.06	**0.030**
2	1	3	0.08	0.24	**0.025**
3	2	3	0.06	0.18	**0.020**
4	2	4	0.06	0.06	**0.020**
5	2	5	0.04	0.12	**0.015**
6	3	4	0.01	0.03	**0.010**
7	**4**	**5**	**0.08**	**0.24**	**0.025**

CHAPTER 14 GENERAL CONCLUSIONS

14.1 Chapter overview

The electricity economic markets are a complex area of study. Due to incomplete information and occasional irrationality on the part of market participants, they have the potential to careen wildly away form theoretical predictions. Electric markets in particular, having been regulated for so long, have had a bumpy re-entry into the atmosphere of de-regulated capitalism. For all entities vested in the electric power industry, with this re-entry comes the need to protect themselves from risk as well as new opportunities for profit. This research work presented additional aspects on information requirements for improving strategic decision-making in the electricity market by proposing and developing theories and ideas that can be applied directly in algorithms. The main contributions of this dissertation as well as the future work are listed in this chapter.

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14.2 Contributions

Today's liberalized energy markets require the development of new methods and techniques in order to understand market prices, the impacts of fuel price volatility, and to design effective regulatory policies. Bearing these in mind, research on generation decisions/actions will assess and explain bidding strategies and their implications for asset valuation, developing sitting decisions, and contract strategies. This dissertation provide for in-depth analysis of strategic topics on generation asset management and energy markets. In depth studies and guidelines on these and other timely topics will result in robust insights for the generation asset managers concerned with advancing their understanding and response to critical strategic issues. The analysis was carried out from the supplier's viewpoint in where players face the problem of setting the right price for services that would maximize gross profits. Nevertheless, buyers face similar problems and consequently the analysis can be easily extended.

The specific contributions of this research can be summarized as follows:

1. Because the electricity sector is interrelated with fuel and emission markets, it is necessary to consider them in the design of market actions for the market participants. Hence, the Input-Output model is considered to decompose/integrate the energy market. The model also allows to the SO to monitor the electric market which is an extremely important aspect to be considered in a decentralized market environment.
2. The production decisions of GENCOs which are fully engaged in ologopolistic electricity need to be studied. A model based upon the static equilibrium model solved sequentially in time has been developed. By decomposing the problem in time, each time-step is solved independently using a Cournot-like market model. The time dimension is divided into discrete, one-hour time-steps.
3. The value of information is analyzed in the fist instance by the SO stepping in to the foot of producers. In order to solve this problem, a probabilistic model is considered. The system value of information is calculated by the analysis of the electric network using a Decision Tree Analysis and Monte Carlo method. Using these tools in combination will help maximize profit while minimizing risk and losses.
4. Decision support system (DSS) core tools are also proposed to help in the development of optimal market strategies for the different market participants.
5. Two models of an integrated electricity and fuel markets are presented. The first formulation is a closed form solution of the Cournot model represented by a set of linear equations. The second formulation is an equivalent of the first in a Discrete Event System Simulation (DESS) framework. The main advantage when formulating the energy market by using DESS is the possibility to study market dynamics.
6. In the electricity sector, our previous work has been extended by including a rigorous formulation of the ramping constraints has been implemented to analyze

the effect of intertemporal constraints on a GENCO's decision-making process. Once the temporal constraints are considered, the independent time-steps solutions are coordinated by the supervision of the maximum/minimum on/off time constraints. The learning aspect, represented by forward expectations, is compared with the Cournot model without learning. A sensitivity analysis is performed to observe how the solution of the short-term equilibrium problem varies with the generation cost parameters, the demand parameters, and the adjusting coefficients.

14.3 Future work

As future work, the following issues are considered:

1. The energy market models do not consider transportation costs and transportation networks, generating units' operational and temporal constraints. We suggest that future research should incorporate these and other constraints. Supplementary studies on specific risk, standardized contracts, the dynamism taking place in fuel procurement, and other factors will be initiated to the extend they directly and transparently support fuel portfolio development
2. In an unbundled electricity market, GENCOs may participate in the provision of different services. In this multi-product framework, a GENCO can be seen as a series of European call options or a combination of European and American options. The latter case is considering a market design for which services are compound of capacity and delivery payments. If each service is paid the same, even if not used, the resulting optimization program is expressed as a set of European options. Impulse control can be used for analyze the effect on the option exercise for the two-part bidding approach.
3. Modeling tools that take into account the complexities of the multiple services of the unbundled industry and the independent reactions of the participants in this

environment will assist in efforts to manage for the present and plan for the future. The integration of optimization and financial models as well as managerial decision-making approaches would permit market participants to develop strategies for mechanisms that operate on a daily basis.

4. Market monitoring can be sorted on financial and physical market activities. Financial monitoring includes monitoring of supply and demand conditions and market performance, monitoring of market power exercise, and monitoring of market participants' activities and transactions. Physical monitoring takes account of generation and transmission outages, availability indices (generation and transmission), among others. Market monitoring can be done under given conditions by using control theory for a two-player market structure. An extend need to be done in order to observe the power of control theory in market controllability and observability –market monitoring.
5. An intertemporal LP optimization program has been proposed in this thesis. The proposed approach, LP optimal committed power for multiple time periods can be expanded by using the decision tree. For each path, we form a LP problem to forecast the optimal decision that maximizes profits. The problem is formulated as deterministic optimization problem since a single path of a decision tree is evaluated. Then, the introduction of uncertainty for fuel and electricity price must be included.

REFERENCES

[1] Steven M. Rinaldi, "Modeling and Simulating Critical Infrastructures and Their Interdependencies," in Proceedings of the 37th Hawaii International Conference on System Sciences HICSS 2004.

[2] Lev B., Energy Models and Studies, North-Holland Publishing Company 1983.

[3] Hafkamp WA, Economic-Environmental Modelling in a National-Regional System, North Holland Publishing Company, 1984.

[4] The National Energy Modeling System: An Overview 2003, Energy Information Administration Office of Integrated Analysis and Forecasting. Available: http://www.eia.doe.gov/oiaf/aeo/overview/index.html

[5] EMCAS, Center for Energy, Environmental, and Economic Systems Analysis, Argonne National Laboratory, Argonne, Illinois. Available: http://www.dis.anl.gov/CEEESA/EMCAS.html

[6] ENPEP, Center for Energy, Environmental, and Economic Systems Analysis, Argonne National Laboratory, Argonne, Illinois. Available: http://www.dis.anl.gov/CEEESA/ENPEPwin.html

[7] Quelhas, A., Gil, E., McCalley, J. D.; Ryan, and S. M.A "*Multiperiod Generalized Network Flow Model of the U.S. Integrated Energy System: Part I—Model Description*," IEEE Trans. On Power Systems, Vol. 22, No. 2, May 2007, pp. 829 – 836.

[8] Quelhas, A. and McCalley, J. D., "*Multiperiod Generalized Network Flow Model of the U.S. Integrated Energy System: Part II—Simulation Results*," IEEE Trans. On Power Systems, Vol. 22, No. 2, May 2007, pp. 837 – 844.

[9] Dmytro Matsypura, Anna Nagurney , and Zugang Liu, Modeling of Electric Power Supply Chain Networks with Fuel Suppliers via Variational Inequalities, International Journal of Emerging Electric Power Systems, Vol. 8, No. 1, Article 5. Available at: http://www.bepress.com/ijeeps/vol8/iss1/art5

[10] Robert Wilson, Market Architecture, Technical Report, Stanford University, 1999.

[11] Gerald B. Sheblé, Computational Auction Mechanisms for Restructured Power Industry Operation, Kluwer Academic Publisher, 1999.

[12] Chen-Ching Liu, Haili Song, Lawarree, J., and Dahlgren, R., New methods for electric energy contract decision making, *in the Proc. of International Conference on Electric Utility Deregulation and Restructuring and Power Technologies, DRPT 2000*, pp. 125-129, April 2000.

[13] Haili Song, Chen-Ching Liu, Jacques Lawarrée, and Robert W. Dahlgren, "Optimal Electricity Supply Bidding by Markov Decision Process," *IEEE Trans. on Power Systems*, Vol. 15 No. 2, pp. 618-624, May 2000.

[14] Roger Bjorgan, Haili Song, Chen-Ching Liu, Robert Dahlgren, "Pricing flexible electricity contracts," *IEEE Trans. on Power Systems*, Vol. 15, No. 2, pp. 477-482, May 2000.

[15] Rajesh Rajaraman and Fernando Alvarado, Optimal Bidding Strategy in Electricity Markets Under Uncertain Energy and Reserve Prices, PSERC Publication 03-05 April 2003.

[16] Rajaraman, R., L.D. Kirsch, F.L. Alvarado, and C. Clark, 2001, "Optimal self-commitment under uncertain energy and reserve prices," in B. F. Hobbs et al., ed.: *Next Generation of Electric Power Unit Commitment Models*. International Series in Operations Research and Management Science (Kluwer Academic Publishers, Boston).

[17] Anderson, Edward J. & Philpott, A.B. "Optimal offer construction in electricity markets." *Mathematics of Operations Research*, 27 (1), pp. 82-100, 2002.

[18] Guillermo Gutiérrez-Alcaraz, Gerald B. Sheblé, "Decentralized Electricity Market Price Dynamics," *IEEE 2004 General Meeting Power Engineering Society*, Denver Colorado, USA.

[19] Dave Felzien, Bob Fesmire, and John Finney, "IT Requirements for Market Participant Interaction with ISOs/RTOs," *IEEE Trans. on Power Systems*, Vol. 18, No. 2, pp. 798-805, May. 2003

[20] Derek W. Bunn, Modelling prices in competitive electricity markets, John Wiley & Sons, 2004

[21] Peter C. Fusaro, Energy Risk Management: Hedging Strategies and Instruments for the International Energy Markets, McGraw-Hill 1998.

[22] Wei JY, Smeers Y, "Spatial Oligopolistic Electricity Models with Cournot Generators and Regulated Transmission Prices," Operations Research, Vol. 47, No. 1, Jan-Feb 1999, pp. 102-112.

[23] Barquin J, Centeno E, Reneses J, "Medium-term generation programming in competitive environments: a new optimisation approach for market equilibrium computing," IEE Proceedings-Generation Transmission and Distribution 151 (1): 119-126 JAN 2004.

[24] Raquel Garcia-Bertrand and Antonio J. Conejo, "Multi-Period Near-Equilibrium in a Pool- Based Electricity Market Including On/Off Decisions," Networks and Spatial Economics, Vol. 5, No. 4, Dec 2005, pp. 371–393.

[25] Christopher J. Day, Benjamin F. Hobbs, and Jong-Shi Pang, "Oligopolistic competition in power networks: A conjectured supply function approach," IEEE Trans. On Power Systems 17 (3): 597-607 Aug 2002.

[26] Youfei Liu and Felix F. Wu, "Impacts of Network Constraints on Electricity Market Equilibrium," IEEE Trans. On Power Systems, Vol. 22, No. 1, Feb. 2007, pp. 126-135.

[27] Wang X, Li YZ, Zhang SH, "Oligopolistic Equilibrium Analysis for Electricity Markets: A Nonlinear Complementarity Approach," IEEE Trans. On Power Systems, Vol. 19, No. 3, Aug. 2004, pp. 1348-1355.

[28] Younes Z, Ilic M, "Generation strategies for gaming transmission constraints: will the deregulated electric power market be an oligopoly?," Decision Support Systems, Vol. 24, Jan 1999, pp. 207-222.

[29] Guillermo Bautista, Miguel F. Anjos, and Anthony Vannelli, "Formulation of Oligopolistic Competition in AC Power Networks: An NLP Approach," IEEE Trans. On Power Systems, Vol. 22, No. 1, Feb. 2007, pp. 105-115.

[30] A. Alj and A. Haurie, "Dynamic Equilibria in Multigeneration Stochastic Games," IEEE Trans. On Automatic Control, Vol. 28, No. 2, pp. 193–203. Feb 1983.

[31] J. D. Liu, T. T. Lie, and K. L. Lo, "An Empirical Method of Dynamic Oligopoly Behavior Analysis in Electricity Markets," IEEE Trans. On Power Systems, Vol. 21, No. 2, May 2006.

[32] Dennis W. Carlton and Jeffrey M. Perloff, *Modern Industrial Organization*, PERASON Addison Wesley, Fourth Edition.

[33] Michael H. Riordan, Imperfect Information and Dynamic Conjectural Variations, The RAND Journal of Economics, Vol. 16, No.1, pp. 41-50, Spring 1985.

[34] Engelbert J. Dockner, A Dynamic Theory of Conjectural Variations, The Journal of Industrial Economics, No. 4, Vol. XL, pp. 377-395, December 1992.

[35] Morton I. Kamien and Nancy L. Schwartz, Conjectural Variations, The Canadian Journal of Economics, Vol. 16, No.2, pp. 191-211, May 1983.

[36] Martin K. Perry, Oligopoly and Consistent Conjectural Variations, The Bell Journal of Economics, Vol. 13, No. 1, pp.197-205, Spring,1982.

[37] Youfei Liu, Y.X. Ni, Felix F. Wu, and Bin Cai, Existence and uniqueness of consistent conjectural variation equilibrium in electricity markets, Electrical Power and Energy Systems, Article in Press.

[38] Yiqun Song, Yixin Ni, Fushuan Wen, and Felix F. Wu, Conjectural variation based learning model of strategic bidding in spot market, Electrical Power and Energy Systems, Vol. 26, 2004, pp. 797-804.

[39] S. Lopez de Haroa, P. Sanchez Martın, J. E. de la Hoz Ardiz, and J. Fernandez Caro, Estimating conjectural variations for electricity market models, European Journal of Operational Research 1 81(2007) 1322–1338.

[40] H. Chen, K. P. Wong, D. H. M. Nguyen, and C. Y. Chung, Analyzing Oligopolistic Electricity Market Using Coevolutionary Computation, *IEEE Trans. On Power Systems*, Vol. 21, No. 1, pp. 143-152. Feb. 2006.

[41] Keith Cuthbertson, "Modelling Expectations: A Review of Limited Information Estimation Methods," Bulletin of Economic Research No. 42, Vol. 1, pp. 1-34, 1990.

[42] Weiguo Yang, "Short-term electric market dynamics and generation company decision-making in new deregulated environment," Ph.D. dissertation, Dept. Elec. Eng., Iowa State University, 2003.

[43] Gian Italo Bischi and Michael Kopel, "Equilibrium selection in a Nonlinear Duopoly Game with Adaptive Expectations," Journal of Economic Behavior and Organization, Vol. 46, 2001, pp. 73-100.

[44] Tellef Juell Larsen, Ivar Wangensteen, and Terje Gjengedal, "Sequential Timestep Unit Commitment," IEEE Power Engineering Society Winter Meeting 2001, Vol. 3, Jan-Feb 2001, pp. 1524 – 1529.

[45] G. B. Shrestha, Kai Song, and L. Goel, "Strategic Self-Dispatch Considering Ramping Costs in Deregulated Power Markets," IEEE Trans. On Power Systems, Vol. 19, No. 3, Aug 2004, pp. 1575–1581.

[46] Jose M. Arroyo and Antonio J. Conejo, "Modeling of Start-Up and Shut-Down Power Trajectories of Thermal Units," IEEE Trans. On Power Systems, Vol. 19, No. 3, Aug 2004, pp. 1562-1567.

[47] Chattopadhyay D, "A Game Theoretic Model for Strategic Maintenance and Dispatch Decisions," IEEE Trans. On Power Systems, Vol. 19, No. 4, Nov 2004, pp. 2014-2021.

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