

2010

Evaluation of wholesale electric power market rules and financial risk management by agent-based simulations

Nanpeng Yu
Iowa State University

Follow this and additional works at: <https://lib.dr.iastate.edu/etd>

 Part of the [Electrical and Computer Engineering Commons](#)

Recommended Citation

Yu, Nanpeng, "Evaluation of wholesale electric power market rules and financial risk management by agent-based simulations" (2010). *Graduate Theses and Dissertations*. 11672.
<https://lib.dr.iastate.edu/etd/11672>

This Dissertation is brought to you for free and open access by the Iowa State University Capstones, Theses and Dissertations at Iowa State University Digital Repository. It has been accepted for inclusion in Graduate Theses and Dissertations by an authorized administrator of Iowa State University Digital Repository. For more information, please contact digirep@iastate.edu.

Evaluation of wholesale electric power market rules and financial risk
management by agent-based simulations

by

Nanpeng Yu

A dissertation submitted to the graduate faculty
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

Major: Electrical Engineering

Program of Study Committee:
Chen-Ching Liu, Co-major Professor
Leigh Tesfatsion, Co-major Professor
Venkataramana Ajjarapu
Lizhi Wang
Dan Nordman

Iowa State University

Ames, Iowa

2010

Copyright © Nanpeng Yu, 2010. All rights reserved.

DEDICATION

I would like to express my deep and sincere gratitude to my major professors, Dr. Chen-Ching Liu and Dr. Leigh Tesfatsion. I would like to thank professor Liu for his guidance, patience and continuous support throughout my Ph.D. studies at Iowa State University. I am grateful to him for providing me financial support to attend technical conferences and introducing industry experts to me to collaborate on research projects. His leadership skills, professional accomplishments and dedication to education has been a tremendous source of inspiration for me. I would also like to thank professor Tesfatsion for her invaluable advice and inspiring encouragement throughout this research and writing of this thesis. She was very generous in sharing her time to discuss not only research ideas but also career development with me. I am immensely motivated by her persistent pursuit of perfection in research and teaching.

I greatly appreciate my committee members, Dr. Lizhi Wang, Dr. Dan Nordman and Dr. Ajjarapu Venkataramana for providing valuable suggestions and comments.

I am grateful to my parents Zuguang Yu and Qi Liang, and my dear wife Juan Li for their unconditional support, love and encouragement without which I would not have been able to complete this work.

It is my pleasure to thank Jim Price from California ISO for sharing his industry experience and providing enlightening discussions.

The author acknowledges the financial support of Power Systems Engineering Research Center (PSERC) and Electric Power Research Center (EPRC).

TABLE OF CONTENTS

| | |
|---|-----|
| LIST OF TABLES | vi |
| LIST OF FIGURES | vii |
| ABSTRACT | ix |
| CHAPTER 1. INTRODUCTION | 1 |
| 1.1 Research Problem Statement | 1 |
| 1.2 Background Context and Motivation | 2 |
| 1.3 Literature Review | 6 |
| 1.3.1 Evaluating Electric Power Markets Rules and Analyzing Strategic Bidding Behaviors | 6 |
| 1.3.2 Financial Risk Management and Bilateral Contract Negotiation in Restructured Electric Power Markets | 8 |
| 1.4 Contribution of this Dissertation | 10 |
| 1.5 Thesis Organization | 11 |
| CHAPTER 2. EVALUATION OF WHOLESALE ELECTRIC POWER MARKET RULES | 12 |
| 2.1 Nomenclature | 12 |
| 2.2 Local Market Power: Problem Description | 14 |
| 2.3 Problem Formulation | 14 |
| 2.3.1 Multi-agent System Structure | 15 |
| 2.3.2 GenCo Agent Model | 15 |
| 2.3.3 Load Serving Entity Model | 17 |

| | | |
|-------|---|----|
| 2.3.4 | Market Operator Model | 17 |
| 2.4 | Proposed Multi-agent Approach | 20 |
| 2.4.1 | Software Implementation of Multi-Agent System | 20 |
| 2.4.2 | Learning Behavior of Agents Who Own Generation | 22 |
| 2.5 | Numerical Studies | 25 |
| 2.5.1 | Test System | 25 |
| 2.5.2 | Evaluation of CAISO Market Power Mitigation Rules | 26 |
| 2.5.3 | Effects of LSE Owning Generation Resources | 30 |
| 2.6 | Summary | 33 |

CHAPTER 3. FINANCIAL RISK MANAGEMENT IN WHOLESALE POWER

| | | |
|----------------|--|-----------|
| MARKETS | | 34 |
| 3.1 | Nomenclature | 34 |
| 3.2 | Financial Risk Management Basics | 35 |
| 3.2.1 | Definition of Risk | 35 |
| 3.2.2 | Financial Risk Management as a Four-Stage Process | 36 |
| 3.3 | Risk-Management Tools and Methods | 38 |
| 3.3.1 | Tools for Modeling Risk Factors | 38 |
| 3.3.2 | Construction of Risk Measures | 39 |
| 3.3.3 | Supplemental Tools: Stress Testing | 41 |
| 3.4 | Financial Bilateral Contract Negotiation: Problem Description | 42 |
| 3.5 | Analytical Formulation of a Financial Bilateral Contract Negotiation Problem | 44 |
| 3.5.1 | The GenCo's Perspective | 45 |
| 3.5.2 | The LSE's Perspective | 48 |
| 3.5.3 | Effects of GenCo and LSE Price Estimation Bias on Expected Price and Perceived Risk | 49 |
| 3.6 | Nash Bargaining Theory Approach | 51 |
| 3.6.1 | Nash Bargaining Theory: General Formulation | 51 |

| | | |
|-------------------------------|---|-----------|
| 3.6.2 | Application of Nash Bargaining Theory to the Bilateral Contract Negotiation Problem for GenCo G and LSE L | 53 |
| 3.7 | Computational Experiments | 55 |
| 3.7.1 | Five-Bus Test Case and Experimental Design | 55 |
| 3.7.2 | Experimental Findings | 59 |
| 3.8 | Summary | 62 |
| CHAPTER 4. | CONCLUSION | 64 |
| 4.1 | Summary Assessment of Dissertation Contributions | 64 |
| 4.2 | Limitations of the Proposed Methods and Further Research Directions | 65 |
| APPENDIX A. | Proof of Theorem 1 in Section 3.5.3 | 67 |
| APPENDIX B. | Proof of Theorem 2 in Section 3.6.2 | 70 |
| BIBLIOGRAPHY | | 88 |

LIST OF TABLES

| | | |
|-----------|--|----|
| Table 1.1 | Total generation capacity within each ISO/RTO region in 2008 | 4 |
| Table 2.1 | Q-Learning parameters | 24 |
| Table 2.2 | Installed capacity in different areas of CAISO | 26 |
| Table 2.3 | Key information from GenCo agent 7 and 8's updating Q-table | 27 |
| Table 2.4 | LSEs detailed information | 31 |
| Table 3.1 | Daily average load for the five-bus test case during the contract month ("June") | 58 |
| Table 3.2 | Autocorrelation function for daily average load for the five-bus test case during the contract month ("June") | 59 |
| Table 3.3 | Effects of risk-aversion factors on the contract amount M and strike price S determined through Nash bargaining | 59 |
| Table 3.4 | Effects of biases in LMP estimates on the contract amount M and strike price S determined through Nash bargaining | 61 |

LIST OF FIGURES

| | | |
|------------|---|----|
| Figure 2.1 | Structure of the multi-agent platform for electricity DAM | 20 |
| Figure 2.2 | Message flowing sequence in the multi-agent platform for electricity DAM | 21 |
| Figure 2.3 | 225-Bus WECC Model - Details of California | 25 |
| Figure 2.4 | Percent total market payment increase in the unmitigated and mitigated scenarios compared to the competitive benchmark | 28 |
| Figure 2.5 | Percent total generation cost increase in the unmitigated and mitigated scenarios compared to the competitive benchmark | 29 |
| Figure 2.6 | Percent largest unit's profit increase in the unmitigated and mitigated scenarios compared to the competitive benchmark | 30 |
| Figure 2.7 | 9-Day average bidding markup of generator 7 in unmitigated and mitigated scenario when owned by LSE or GenCo agent | 31 |
| Figure 2.8 | Total market payment and total generation cost percentage increase in four scenarios compared to the competitive benchmark | 32 |
| Figure 3.1 | Illustration of a major drawback of VaR as a risk measure: VaR assigns the same risk to each depicted probability density function for loss . . . | 40 |
| Figure 3.2 | Relationships among the true and biased probability density functions for λ_{Σ} given biases $K_G > K_L > 0$ | 51 |
| Figure 3.3 | Type 1 utility possibility set U and barter set B for GenCo G and LSE L. The barter set is a right triangle | 55 |
| Figure 3.4 | Type 2 utility possibility set U and barter set B for GenCo G and LSE L. The barter set reduces to the non-contract threat point | 56 |

| | | |
|------------|--|----|
| Figure 3.5 | Type 3 utility possibility set U and barter set B for GenCo G and LSE L. The barter set is a right triangle | 57 |
| Figure 3.6 | Five-bus test case used for computational experiments | 57 |
| Figure 3.7 | GenCo net earnings histogram given a fixed GenCo risk-aversion factor $A_G = 1$ and varying values for the LSE risk-aversion factor A_L | 60 |
| Figure 3.8 | LSE net earnings histogram given a fixed GenCo risk-aversion factor $A_G = 1$ and varying values for the LSE risk-aversion factor A_L | 60 |
| Figure 3.9 | Lower boundary for the no-contract region in the plane of possible nor- malized price biases $(K_L/E(\lambda_\Sigma), K_G/E(\lambda_\Sigma))$ under three alternative combinations of the risk-aversion factors (A_L, A_G) | 62 |
| B.1 | Supporting graph for proving that the slope of V_2 at the threat point is larger than $-\frac{1+A_L}{1+A_G}$ when the slope of V_1 at the threat point is smaller than $-\frac{1+A_L}{1+A_G}$ | 84 |
| B.2 | Type 1 utility possibility set U and barter set B for GenCo G and LSE L. The barter set is a right triangle. | 85 |
| B.3 | Type 2 utility possibility set U and barter set B for GenCo G and LSE L. The barter set reduces to the non-contract threat point. | 85 |
| B.4 | Type 3 utility possibility set U and barter set B for GenCo G and LSE L. The barter set is a right triangle. | 86 |

ABSTRACT

As U.S. regional electricity markets continue to refine their market structures, designs and rules of operation in various ways, two critical issues are emerging. First, although much experience has been gained and costly and valuable lessons have been learned, there is still a lack of a systematic platform for evaluation of the impact of a new market design from both engineering and economic points of view. Second, the transition from a monopoly paradigm characterized by a guaranteed rate of return to a competitive market created various unfamiliar financial risks for various market participants, especially for the Investor Owned Utilities (IOUs) and Independent Power Producers (IPPs). This dissertation uses agent-based simulation methods to tackle the market rules evaluation and financial risk management problems.

The California energy crisis in 2000-01 showed what could happen to an electricity market if it did not go through a comprehensive and rigorous testing before its implementation. Due to the complexity of the market structure, strategic interaction between the participants, and the underlying physics, it is difficult to fully evaluate the implications of potential changes to market rules. This dissertation presents a flexible and integrative method to assess market designs through agent-based simulations. Realistic simulation scenarios on a 225-bus system are constructed for evaluation of the proposed PJM-like market power mitigation rules of the California electricity market. Simulation results show that in the absence of market power mitigation, generation company (GenCo) agents facilitated by Q-learning are able to exploit the market flaws and make significantly higher profits relative to the competitive benchmark. The incorporation of PJM-like local market power mitigation rules is shown to be effective in suppressing the exercise of market power.

The importance of financial risk management is exemplified by the recent financial crisis.

In this dissertation, basic financial risk management concepts relevant for wholesale electric power markets are carefully explained and illustrated. In addition, the financial risk management problem in wholesale electric power markets is generalized as a four-stage process. Within the proposed financial risk management framework, the critical problem of financial bilateral contract negotiation is addressed. This dissertation analyzes a financial bilateral contract negotiation process between a generating company and a load-serving entity in a wholesale electric power market with congestion managed by locational marginal pricing. Nash bargaining theory is used to model a Pareto-efficient settlement point. The model predicts negotiation results under varied conditions and identifies circumstances in which the two parties might fail to reach an agreement. Both analysis and agent-based simulation are used to gain insight regarding how relative risk aversion and biased price estimates influence negotiated outcomes. These results should provide useful guidance to market participants in their bilateral contract negotiation processes.

CHAPTER 1. INTRODUCTION

1.1 Research Problem Statement

U.S. regional electricity markets continue to refine their market structures, designs and rules of operation in various ways. There are ongoing debates over new market design issues such as how to design market power mitigation (MPM) rules, how to properly implement a retail electricity market, and how to effectively incorporate ancillary service (AS) markets. Although much experience has been gained and costly and valuable lessons have been learned, there is still a lack of a systematic platform for evaluation of the impact of a new market design from both engineering and economic points of view.

The transition from a monopoly paradigm characterized by a guaranteed rate of return to a competitive market created various unfamiliar financial risks for various market participants, especially for the Investor Owned Utilities (IOUs) and Independent Power Producers (IPPs). Facing the new and evolving market and regulatory environment, most IOUs and IPPs have not been able to set up a general risk management framework that can facilitate their decision making with regard to day-ahead market trading, bilateral contract negotiation and generation investment.

This research is intended to provide a systematic framework and general methodology to address these two challenging issues. Specifically, the purpose of this research is *to develop a systematic platform to evaluate the impact of existing or new market designs from both engineering and economic points of view and to provide market participants with a unified methodology that could facilitate their management of financial risk.*

A more detailed motivation for the intended research is provided in the next section.

1.2 Background Context and Motivation

The electricity supply chain can be divided into three segments: generation, transmission and distribution. Under the U.S. electricity sector's legacy industry structure, within a defined geographical area, all three segments are typically owned by a utility that has been either investor-owned and state-regulated, or owned by the local municipality [1]. These utilities in turn had de facto exclusive franchises to supply electricity to residential, commercial and industrial retail consumers within their service areas [2]. Many of these vertically integrated utilities are control area operators that are responsible for operating portions of the synchronized AC networks in the U.S., subject to rules established by regional reliability councils and a variety of bilateral and multilateral operating agreements [3]. Under the old regulatory structure, the state or municipal governments regulate the electricity retail rates in such a way that utility shareholders are guaranteed a reasonable return on their investments. In this regulatory framework, the risks associated with utilities' generation investments and bilateral contracting decisions are not borne by themselves but by their retail customers [4].

Until the beginning of 1970, the old vertically integrated monopoly model functioned quite well. The improved technology and further exploitation of economics lowered the electricity prices in real terms and kept nominal prices largely unchanged over the 1960s [5]. Since then the change in a number of fundamental factors and the occurrences of a series of incidents contributed to the accumulation of dissatisfaction toward the vertically integrated monopoly model. On the technology front, the development of more efficient generating technologies such as combined-cycle gas turbines reduced economies of scale and cut the lead-time for adding new generating capacity [6]. This leads to a question on the legitimacy of generation sector's natural monopoly status. The first and second oil price shocks during 1973-1974 and 1979 have drove electricity prices up 26% in 1974 and 19% 1980 respectively. The increased safety regulations due to the Three Mile Island nuclear power plant in 1979, together with unexpected construction overruns and higher-than-anticipated operating costs and disposal costs have increased the costs of nuclear power [1]. However, under the monopoly model, electricity customers still had to pay for the decisions to build the nuclear power plants. During

the same period, the disparity in electricity prices within the U.S. began to rise which is partly due to the bad investments in some regions. All these events and changes have leveled up the political and social pressures to reform the electricity industry.

The reform goal has been to create new institutional arrangements for the electricity sector that provide long-term benefits to society. It is also to ensure that an appropriate share of these benefits goes to consumers through prices that reflect the efficient economic cost of supplying electricity and service quality attributes that reflect consumer valuation [2]. It is projected that those benefits will be realized through providing the proper price signal to stimulate technology innovation, better investment and consumption decisions.

Since the late 1980s, restructuring initiatives have been gradually taken to reform the electricity industry. The Public Utility Regulatory Policies Act of 1978 defined a new class of energy producers named Qualified Facilities which typically own co-generators or renewable resources. This federal law introduces some competition on the generation side by requiring utility companies to purchase energy from the qualified independent power producers at avoided cost rates which tend to be favorable to the qualified facilities.

The Energy Policy Act of 1992 established a new category of electricity producer called the exempt wholesale generator that is allowed to enter the wholesale electricity market to sell power to utilities. The law also mandated Federal Energy Regulatory Commission (FERC) to provide these generators with open access to the national power transmission grids.

In response to the mandate, FERC made two landmark Orders 888 [7] and 889 [8] which require the owners of transmission facilities to make transmission services available on the open market and establish Open Access Same-time Information System (OASIS) which provides customers and potential open access transmission customers with information that will enable them to obtain open access non-discriminatory transmission service. FERC also suggested the concept of an Independent System Operator as one way to satisfy the requirement of providing non-discriminatory access to transmission.

To overcome the existing barriers and impediments to achieving fully competitive electricity markets, and to promote efficiency in wholesale power markets, FERC issued Order 2000 [9].

The order encouraged voluntary formation of Regional Transmission Organizations (RTOs) to administer the transmission grid on a regional basis throughout North America and required all public utilities that own, operate or control interstate electric transmission to participate in a Regional Transmission Organization (RTO).

To clarify the Standard Market Design proposed in a Notice of Proposed Rulemaking (NOPR) issued in Aug 2002, FERC issued a white paper [10] titled “Wholesale Power Market Platform” that lays out key design elements that are needed for the success of well functioning wholesale markets. This design recommends the operation of wholesale power markets by Independent System Operators (ISOs) or RTOs using locational marginal pricing to price energy by the location of its injection into or withdrawal from the transmission grid [11].

After nearly 30 years of restructuring and reforms, the U.S. electricity industry has made a lot of progress towards a well-functioning competitive market. However, there have also been some major setbacks in the reform process that are painful but costly lessons to learn. Thanks to FERC’s “open access” Orders 888 and 889, transmission owning utilities in the U.S. now have made available reasonably standardized cost-based transmission service tariffs to support the provision of transmission service and provide easily available real-time information about the availability and prices of transmission service on their networks [12]. FERC’s Order 2000 has fostered the formation and expansion of ISOs/RTOs. Table 1 indicates that as of 2008, over 50% of the generating capacity in the U.S. is operating within an ISO/RTO.

Table 1.1 Total generation capacity within each ISO/RTO region in 2008

| ISO/RTO | Total Installed Capacity (MW) |
|--------------------------------|-------------------------------|
| ISO-New England | 31,088 |
| New York ISO | 38,900 |
| California ISO (CAISO) | 52,000 |
| SPP (RTO) | 57,765 |
| ERCOT | 75,504 |
| PJM (RTO) | 164,895 |
| Midwest ISO (MISO) | 170,000 |
| ISO/RTO Total | 590,152 |
| Total U.S. Generating Capacity | 1,109,017 |

Various regulations in the reform process have gradually eliminated the entry barrier and encouraged Independent Power Producers (IPPs) to enter the electricity market to compete with investor owned utilities. More generating capacity has been built in the United States between 2000 and 2004 than in any earlier 5-year period [13]. IPPs have sponsored the largest portion of the dominated generation additions (gas-fired generation) in this period.

In spite of the progress made towards well-functioning competitive electricity markets, some problems have emerged in the reform progress. Those problems and challenges are faced by not only regulators and ISOs but also market participants such as IOUs and IPPs.

A textbook example of electricity market restructuring that went wrong is the California market. The California energy crisis in 2000-01 showed what could happen to an electricity market if it did not go through a comprehensive and rigorous test before its implementation. California's market design departed from the regulator's blue book, and included complicated rules that basically ignored the fundamentals of how a power system operates [5]. The required reliance on a spot market in place of having a mix of short and long-term contracts, and a congestion pricing system that did not properly handles intra-zonal congestion, created a market design that was vulnerable to market manipulation. The combination of a poor market design, shortage of generation capacity and available power imports, the abuse of market power by market participants and over-divestiture of generator by the three major IOUs, resulted in the collapse of California market. The crisis rendered two major IOUs insolvent, led to rotating blackouts on eight days in Winter and Spring of 2001 and also left California with huge state budget deficits.

Facing an unfamiliar and evolving market and regulatory environment, IOUs and IPPs have also shown signs of inability to handle the new challenges, especially the novel task of financial risk management in wholesale power markets. Given the market entry opportunities, many IPPs have joined the wholesale power market to compete with IOUs and municipal utilities. However, it is essential to have a clear understanding of the way a wholesale power market operates in the presence of strategic interaction among market participants. Without a systematic methodology to manage financial risk in wholesale power markets, poor decisions

could be made. Being excessively optimistic regarding their predicted hours of dispatch and the predicted persistence of low natural gas prices, on the national level the IPPs over invested in combined cycle gas turbine (CCGT) plants from 2001-2004. Without employing a comprehensive risk management plan that properly hedges the risks associated with the operation and investment of the CCGT plants, some IPPs had to face financial difficulties in the following years. The three big IOUs in the California sold almost all of their fossil-fuel plants by 2000. This over-divestiture has taken away the IOUs' ability to hedge against the risks associated with volatile wholesale electricity prices. Together with a fixed retail rate put in by regulators, these decisions rendered two of three IOUs insolvent when the wholesale market prices rose above the fixed retail price and remained there for an extended period of time.

To date, regulators are still pondering over the question of how to design a competitive power market that achieves both efficacy and fairness. The electricity market participants are still striving to develop effective decision support and risk management tools that could assist day-ahead energy market trading, negotiation of bilateral contracts and expansion of generation units and transmission networks. The difficulties with market design issues and risk management problems arise from the complex interactions among strategic behaviors of market players, various layers of market structure, and the complex underlying physical network.

1.3 Literature Review

1.3.1 Evaluating Electric Power Markets Rules and Analyzing Strategic Bidding Behaviors

The literature on the interaction between strategic bidding and market designs can be categorized into two approaches: equilibrium analysis and agent-based simulation. In the equilibrium analysis approach, oligopoly models such as Bertrand, Cournot, and supply function equilibrium (SFE) are used to model the stylized strategic behavior of market participants. Younes and Ilic [14] modeled the oligopolistic competition in the electricity market with SFE and Bertrand models. They recognized that inelastic load and low transmission capacities may

give generators incentives to strategically constrain the network and profit from the high prices in isolated submarkets. Yao et al. [15] examined the two-settlement electricity market taking into account congestion, demand uncertainty and system contingencies with a Cournot model showing that it results in lower spot equilibrium prices at most buses than a single settlement. Li and Shahidehpour [16] analyzed the strategic bidding behavior and potential market power of generation companies with SFE model. Their conclusion is that setting a lower price cap is a proper measure for mitigating market power in an electricity market. Niu et al. [17] modeled the electric firms' bidding behaviors with a SFE model, and studied the effects of forward contracts on the ERCOT market. They found that a high volume of forward contracts decreases the incentive of major market players to raise real-time market prices. Liu et al. [18] studied the impact of learning behavior of generation companies on electricity-spot-market equilibrium under repeated linear supply-function bidding. The result is that under certain conditions the overall learning behavior will reduce market-clearing prices while in some other conditions the results are just the contrary.

Although the equilibrium analysis yielded some useful results in the oligopoly electricity market, it may oversimplify the complicated market mechanism [19]. The accumulated bidding experience from interacting with other market participants in repeated auctions may change the perception a player has of others [20]. The advantage of a learning algorithm is that it could capture the market dynamics and provide better insights into market behaviors. In the agent-based approach, variations of reactive reinforcement learning and anticipatory reinforcement learning have been used to model the behaviors of generation companies. The learning algorithm that Bunn and Oliveira designed [19] for generators shares the same essence with reactive reinforcement learning algorithm. The average reward γ -greedy reinforcement learning (RL) method was used in [21] to model the learning and bidding processes of generation companies. These generation companies are incorporated in a nonzero sum stochastic game model to assess day-ahead (DA) market power in different auction mechanisms. The average reward γ greedy reinforcement learning method is a RL method that uses average reward in the updating process and parameter γ to balance the exploration and exploitation. The learning

configuration for generation companies in [22] is a version of stochastic reactive reinforcement learning developed by Roth and Erev [23]. A test bed was built to investigate the effects of demand-bid price sensitivity and supply-offer price caps on locational marginal prices (LMPs). Yu et al. [24] modeled generation companies as Q-Learning agents. The results demonstrated that Q-Learning facilitates the GenCo agent exploiting the market in the absence of a MPM process. Several papers [25, 26, 27, 28] have investigated the use of agent-based simulation to evaluate electricity market rules.

1.3.2 Financial Risk Management and Bilateral Contract Negotiation in Restructured Electric Power Markets

Within the field of power economics, only a few researchers to date have studied the bilateral contract negotiation process. Khatib and Galiana [29] propose a practical process in which the bargainers take both benefits and risks into account. They claim that their proposed process will lead to agreement on a mutually beneficial and risk-tolerable forward bilateral contract. Song et al. [30] and Son et al. [31] analyze bidding strategies in a bilateral market in which GenCos submit bids to loads. Necessary and sufficient conditions for the existence of a Nash equilibrium in bidding strategies are then derived.

In a series of three studies, Kockar et al. [32, 33, 34] examine three important questions focusing on mixed pool/bilateral trading. In the first two studies the authors study the effects on portfolio performance of varying the relative level of pool versus bilateral trading given various curtailment strategies for firm and nonfirm bilateral contracts. In the third study the authors propose an incremental procedure to unbundle and price various services offered in an electricity market that permits both pool and bilateral trades.

Although the number of studies focusing on bilateral contract negotiation in electric power markets is small, a large number of researchers in power economics have examined the related topics of risk management and portfolio optimization. Only a small sampling of the literature will be noted here.

Regarding risk management in wholesale electric power markets, Liu and Wu [35] propose

a sequential optimization method to solve an electric energy allocation problem from the perspective of a profit-seeking GenCo facing an action-conditioned *probability density function* (*pdf*) for profits. They assume the GenCo's willingness to accept reductions in return in order to achieve reductions in risk is expressible in terms of a "return-risk utility function" with return measured by expected profit and risk measured by profit variance. Li et al. [36] use the same form of return-risk utility function to investigate the properties of a risk-constrained bidding strategy for financial transmission rights. Botterud et al. [37] compare and contrast the use of different objective functions for the evaluation of the bidding strategies of wind power producers, including a return-risk utility function with risk measured by conditional-value-at-risk. Shahidehpour [38, Chpt. 7] provide a general introduction to risk analysis in power markets with a particular stress on the use of value-at-risk measures.

Risk management issues arising in retail electricity markets are also analyzed in a number of studies. Bartelj et al. [39] study expected profit and conditional-value-at-risk outcomes for a retail supplier under alternative price volatility and retail contract maturities. Carrión et al. [40] propose a risk-constrained stochastic programming framework to decide which forward contracts a retailer supplier should offer its retail customers, and at what price. The retailer supplier's objective is assumed to be the maximization of expected profit given a prespecified level of risk. Gabriel et al. [41] propose a stochastic optimization model as a guide for the contractual arrangements of a retail supplier that takes into account both expected net return and risk exposure for the supplier. A "third way" approach to the design of retail utilities, between vertical integration and full divestment, is proposed by Chao et al. [42] based in part on principles of risk management.

Regarding portfolio optimization, Bjorgan et al. [43] identify a preferred portfolio of contracts by using efficient frontier theory. Tanlapco et al. [44] compare direct and cross-hedging strategies for a GenCo that uses future contracts to manage its risk. The authors show that, for all four spot markets they study, a hedging strategy that uses electricity future contracts yields lower risk than a cross-hedging strategy, all else equal. Denton et al. [45] analyze the risks encountered by electric energy asset operators in the short, intermediate and long term. Real

option models and stochastic optimization techniques are proposed to measure and manage these risks. Using computer simulations, Das and Wollenberg [46] assess a GenCo's risk associated with random forced outages in a day-ahead and spot energy market. Bjorgan et al. [47] examine the pricing of electricity contracts that allow flexible scheduling of electric energy based on the principle of no-arbitrage. Arbitrage opportunities and an optimized scheduling policy link the contract price to the spot price.

Finally, regarding reviews and tutorials, Dahlgren et al. [48] provide a comprehensive literature review of risk assessment in electric energy trading. Deng and Oren [49] present a thorough review of electricity financial instruments as well as general approaches to the pricing of these instruments. Liu et al. [50] survey risk management techniques widely used in the financial field and discuss their application to electric power markets. Yu et al. [51] discuss alternative definitions and measures of risk. They also examine and concretely illustrate the complicated and risky strategic decision making required of modern power traders operating in interlinked financial and physical energy markets.

1.4 Contribution of this Dissertation

This dissertation is focused on the development of an integrated framework for assessing the performance of electricity market rules and risk management methodologies for the electricity market participants. The original contributions of this dissertation are summarized as follows:

1. Proposed a flexible and integrative methodology and software platform capable of evaluating new electric market designs from both engineering and economic points of views. This allows the regulators and policy makers to conduct a comprehensive and rigorous testing before implementing new market design features. With this innovative methodology and simulation tool at hand, costly mistakes such as the California energy crisis may be avoided.

2. This dissertation is one of the first to utilize the proposed agent-based simulation methodology and platform to study a realistic market design feature in a large scale test system. Specifically, before its implementation, the effectiveness of market power mitigation (MPM) rule proposed by CAISO is evaluated in a realistic 225-bus WECC system. The simulation

results provide regulators with insights into how well the MPM rule is able to suppress implicit price collusion among pivotal GenCos with market power.

3. Developed a unified methodology, a four-stage process, to facilitate market participants' management of financial risk in wholesale electric power markets. It helps the market participants to restructure and retool their risk management practices in an evolving and volatile market environment.

4. Constructed an analytical and computation model to analyze the financial bilateral contract negotiation problem between a GenCo and a LSE within the proposed financial risk management framework. The model is capable of predicting the negotiation results under varied conditions and identifying circumstances in which the two parties might fail to reach an agreement. The insights gained regarding how relative risk aversion and biased price estimates influence negotiated outcomes provide valuable guidance to market participants in their bilateral contract negotiation process.

1.5 Thesis Organization

The remainder of this dissertation is organized as follows. Chapter 2 presents the methodology for the evaluation of electric power market rules, based on the results of Yu et al. [52]. A flexible and integrative method to assess market designs through agent-based modeling is presented. As a case study, realistic simulation scenarios are constructed for evaluation of the proposed PJM-like market power mitigation rules currently in use by the California Independent System Operator (CAISO). Chapter 3 presents the problem formulation and results on financial risk management in wholesale electric power markets, based on the results of Yu et al. [51, 53]. In Chapter 3, basic financial risk management concepts relevant for wholesale electric power markets are carefully explained and illustrated. Solving financial risk management problem in wholesale electric power markets is generalized as a four-stage process. Within the proposed financial risk management framework, the critical problem of financial bilateral contract negotiation is addressed. Finally, Chapter 4 provides a summary of this dissertation contribution and briefly discusses the proposed future research directions.

CHAPTER 2. EVALUATION OF WHOLESALE ELECTRIC POWER MARKET RULES

The California energy crisis in 2000-01 showed what could happen to an electricity market if it did not go through a comprehensive and rigorous testing before its implementation. Due to the complexity of the market structure, strategic interaction between the participants, and the underlying physics, it is difficult to fully evaluate the implications of potential changes to market rules. This research presents a flexible and integrative method to assess market designs through agent-based modeling. Realistic simulation scenarios are constructed for evaluation of the proposed PJM-like market power mitigation rules of the California electricity market. Simulation results show that in the absence of market power mitigation, GenCo agents facilitated by Q-learning are able to exploit the market flaws and make significantly higher profits relative to the competitive benchmark. The incorporation of PJM-like local market power mitigation rules is shown to be effective in suppressing the exercise of market power.

2.1 Nomenclature

| | |
|------------------|---|
| i | GenCo agent index. |
| j | LSE index. |
| AS_{jh} | Average per MW consumed ancillary services price charged to load serving entity j at hour h . |
| c_i^B | Multiplier of the supply offer for GenCo i . |
| c_i^{res} | Bidding price for spinning reserve capacity of unit i . |
| $c_i^{reg,up}$ | Bidding price for regulation up capacity of unit i . |
| $c_i^{reg,down}$ | Bidding price for regulation down capacity of unit i . |

| | |
|---------------------|---|
| $C_k(h)$ | LMP of real power on load bus k at hour h . |
| C_{jh}^G | LMP of real power at hour h for LSE j 's unit. |
| $C_{jh}^{reg,up}$ | Marginal price of regulation up at hour h . |
| $C_{jh}^{reg,d}$ | Marginal price of regulation down at hour h . |
| C_{jh}^{res} | Marginal price of spinning reserve at hour h . |
| F_{max}^l | Thermal limit of transmission line l . |
| GSF_{l-k} | Generation shift factor to line l from bus k . |
| I | Set of GenCo agents. |
| L_{jh} | Total MW load of LSE j at hour h . |
| N_b | Number of buses in the system. |
| N_l | Number of lines in the system. |
| P_{jh}^{G*} | MW power output scheduled at hour h . |
| $P_{jh}^{reg,up*}$ | Reserved capacity for regulation up at hour h . |
| $P_{jh}^{reg,d*}$ | Reserved capacity for regulation down at hour h . |
| P_{jh}^{res*} | Reserved capacity for spinning reserve at hour h . |
| P_k | Net power injection at bus k . |
| P_{gk} | Total MW power generation at bus k . |
| P_{ih}^G | Unit i MW power generation at hour h . |
| P_{dk} | Total MW demand at bus k . |
| $P_{ih}^{reg,down}$ | Unit i regulation down capacity reserved at hour h . |
| $P_{ih}^{reg,up}$ | Unit i regulation up capacity reserved at hour h . |
| P_{ih}^{res} | Unit i spinning reserve capacity reserved at hour h . |
| $P_{Lk}(h)$ | MW load of load bus k at hour h . |
| R_j | Retail rates of LSE j 's serving area. |
| R_i^{reg} | Regulation ramp rates of unit i . |
| R_i^{res} | Operating reserve ramp rates of unit i . |
| R_i^{oper} | Operational ramp rates of unit i . |

| | |
|----------------|---|
| $Rg_h^{req,d}$ | System's requirement for regulation down at hour h . |
| $Rg_h^{req,u}$ | System's requirement for regulation up at hour h . |
| Rs_h^{req} | System's requirement for spinning reserve at hour h . |
| τ | Delivery time requirement for ancillary service. |

2.2 Local Market Power: Problem Description

Local market power has been known as an issue for electricity markets due to limited transmission capabilities, lack of economical electricity storage devices and short-term inelasticity of demand. During certain peak hours, electricity markets can be temporarily isolated into several sub-regions by N-1 and transmission thermal limit constraints. Hence, generators that possess potential local market power could leverage it to make profits through either economical or physical withholding. Furthermore, generation companies can repeatedly play in similar market scenarios and learn over time to compete less aggressively [54, 55]. Pivotal generation companies might be able to elicit collusive strategies from others by punishing un-cooperative bidding behaviors. To address the problem of local market power, various types of *market power mitigation (MPM)* rules have been proposed and implemented in the industry. However, the effectiveness of those rules against strategic bidding market players with learning capabilities has not been extensively investigated. In general, the field of strategic bidding in an electricity market will remain an open research area for some time.

2.3 Problem Formulation

An electricity DAM is composed of interacting units: market operator, generation companies and load serving entities. Each of them has its own goal to achieve and will not only react to changes in the market condition but also try to exert some degree of influence in the market environment. An important attribute of the DAM is that it exhibits properties arising from the interaction in the market that are not properties of the individual units themselves. Therefore, to evaluate the effectiveness of market rules of the DAM, a MAS is proposed that models the complex market dynamics among the traders. The problem formulation is motivated by

CAISO's market design.

2.3.1 Multi-agent System Structure

The DAM is modeled as a MAS with three types of interacting agents: GenCo agents, load serving entities (LSEs), and a market operator (MO). The DAM works as follows. Before day D begins, MO gathers the load prediction data from LSEs, and publishes the forecasted zonal load data for day D+1. On the morning of day D, LSEs submit their demand bids and possibly supply offers; GenCo agents submit their supply offers for DAM to MO. The MO then performs MPM and runs the market clearing software. Refer to section 2.3.4 where details of MPM and the market clearing software are discussed. The market-clearing software determines the hourly dispatch schedules to minimize the cost of purchasing energy and 100% of the AS requirement and the corresponding LMPs for energy and AS. In this MAS, MO could also perform the AS evaluation based on the market clearing results by simulating the AGC performance of the interconnected power system [56]. At the end of the process, MO sends the dispatch schedules, LMPs and settlement information to GenCo agents and LSEs for day D+1.

2.3.2 GenCo Agent Model

GenCo agents sell bulk power to DAM. For simplicity, it is assumed that each GenCo agent has only one generation plant. However, this model can be extended to permit GenCo agents with multiple generation plants. Suppose the MW power output of generator i at some hour h is P_{ih}^G . For generator i , the variable production cost at hour h is represented by a quadratic form:

$$C_i(P_{ih}^G) = a_i \cdot P_{ih}^G + b_i \cdot (P_{ih}^G)^2 \quad (2.1)$$

In the above equation, a_i and b_i are given constants. By taking derivatives on both sides of (2.1), the marginal cost function for generator i is obtained, i.e.,

$$MC_i(P_{ih}^G) = a_i + 2 \cdot b_i \cdot P_{ih}^G \quad (2.2)$$

On each day D, the GenCo agent submits to DAM a supply offer for day D+1 that includes two components. The first component is its reported marginal cost function given by:

$$MC_i(P_{ih}^G) = c_i^B [a_i + 2 \cdot b_i \cdot P_{ih}^G] \quad (2.3)$$

Notice that there are other alternatives to exert market power through submitting reported marginal cost functions, e.g., adding a constant term or allowing both the slope and intercept of the reported marginal cost function to be decision variables.

In this research, it is assumed that the GenCo could exercise market power only through economical withholding. However, the modeling methodology can be extended to allow the GenCo to consider a combination of both economical and physical withholding.

The second component is its reported bidding price for AS including its bidding price for spinning reserve capacity c_i^{res} , regulation up capacity $c_i^{reg,up}$, and regulation down capacity $c_i^{reg,down}$. To provide regulation up or spinning reserve ancillary service, the units have to be synchronized and able to deliver the reserved capacity within 10 minutes. The difference is that to provide regulation up ancillary service, the unit must be able to receive AGC signals. This is not a requirement for providing spinning reserve ancillary service. Each generator is assumed to have a set of benchmark bidding prices for AS. The reported prices of AS are calculated as the benchmark price plus a markup which was a decision variable for the generation company. There are several AS offer price mark-ups that GenCos could choose from. The Q-learning algorithm illustrated in section 2.4.2 allows the GenCos to learn from past bidding experience and to decide which mark-ups combination is most profitable under each market condition. It is assumed that the bidding markups for spinning reserve capacity and regulation up capacity are identical for the same unit. In addition, the bidding markup for regulation down capacity is assumed to be zero. Suppose on day D, GenCo agents submit their supply offers for day D+1 to MO, and the market clearing program calculates LMPs for real power and AS, and

dispatch schedules. Then GenCo agent i 's net earnings on day D+1 is obtained by summing over the 24-hour net earnings on that day.

2.3.3 Load Serving Entity Model

LSEs purchase bulk power from the DAM to serve load. It is assumed that some LSEs also have generation units. If a LSE is a net buyer, then its motivation in offering its generation would be to reduce the cost of energy and AS. Suppose the set of buses where LSE j serves loads is L_j . On day D, LSE j submits a fixed load profile for day D+1. The load profile specifies 24 hours of MW power demand $P_{Lk}(h)$, $h=0...23$, at each of its load buses $k \in L_j$. Suppose, LSE j submits its own generator j 's reported offer price for spinning reserve capacity c_j^{res} , regulation up capacity $c_j^{reg,up}$, regulation down capacity $c_j^{reg,down}$ and reported marginal cost function $MC_j(P_{jh}^G) = c_j^B[a_j + 2 \cdot b_j \cdot P_{jh}^G]$ to the DAM for day D+1. Then LSE j 's profit on day D+1 is obtained by summing over the 24-hour net earnings on that day, i.e.,

$$\begin{aligned} \pi_{jD+1} = & \sum_{h=0}^{23} [P_{jh}^{G*} C_{jh}^G + P_{jh}^{reg,up*} C_{jh}^{reg,up} + P_{jh}^{reg,d*} C_{jh}^{reg,d} + P_{jh}^{res*} C_{jh}^{res} - C_j(P_{jh}^{G*}) + L_{jh} R_j \\ & - \sum_{k \in L_j} P_{Lk}(h) C_k(h) - L_{jh} AS_{jh}] \end{aligned} \quad (2.4)$$

The average per MW consumed ancillary services price charged to LSE j at hour h , AS_{jh} is calculated by dividing the total cost of procuring all ancillary services at hour h by the total amount of load at hour h .

2.3.4 Market Operator Model

Every day, upon receiving demand bids and supply offers, MO performs MPM and clears day-ahead energy and AS market simultaneously. The Local Market Power Mitigation (LMPM) is intended to limit the exercise of local market power by generation owners in load pockets. The basic idea is to identify which generators are dispatched up to relieve congestion on non-competitive paths (e.g. interfaces to load pockets). Generators that have been identified will be subject to mitigation since they have the potential to exercise local market power. If those

generation units' supply offer is higher than default proxy bids, then energy offers will be reduced to the default level. Specifically, the MPM process includes three steps. In the first step, MO runs the market clearing software and clears the market with only competitive network constraints. In CAISO, Path 15, Path 26, Inter-ties, and interfaces to certain generation pockets are pre-defined as competitive network constraints. The first step is called competitive constraint run (CCR). In the second step, MO clears the market with all constraints enforced. This step is called all constraint run (ACR). In the third step, the CCR market clearing result is compared with that of the ACR. If a generation unit is incremented between CCR and ACR, the unit will be mitigated per the MPM process. In other words, mitigation applies to the units that are dispatched up by the ACR compared to the CCR. If generation unit's offer subject to mitigation is higher than cost based default proxy bids (modeled as marginal cost + 10% in this study), then energy offers are reduced to the level of proxy bids. Those mitigated bids serve as inputs to the actual day-ahead market clearing. In reality, a method to calculate the default proxy bids is based on the unit's variable cost. Under this variable cost option, the default bids will be calculated based on the incremental heat rate curve (for gas fueled units) multiplied by the gas price index or incremental cost rate curve (for non-gas fueled units), plus an operations and maintenance adder [57]. This quantity multiplied by 110% will be used as the default proxy bid.

The market operator runs a market clearing software to determine the hourly dispatch schedules and LMPs of energy and AS. The market clearing software clears the bid-in supply with bid-in demand and procures 100% of AS requirement with minimum cost. The objective is to minimize the 24-hour total purchasing cost, which is formulated as:

$$\min \sum_{h=1}^{24} \left\{ \sum_{i \in I} c_i^B [a_i + 2 \cdot b_i \cdot P_{ih}^G] + C_i^{res} P_{ih}^{res} + C_i^{reg,up} P_{ih}^{reg,up} + C_i^{reg,down} P_{ih}^{reg,down} \right\} \quad (2.5)$$

s.t.

$$P_k - P_{gk} + P_{dk} = 0, k = 1, \dots, N_b \quad (2.6)$$

$$\left| \sum_{k=1}^{N_b} GSF_{l-k} \cdot P_k \right| \leq F_{max}^l, l = 1, \dots, N_l \quad (2.7)$$

$$P_{ih}^G + P_{ih}^{res} + P_{ih}^{reg,up} \leq P_i^{max}, i \in I, \forall h \quad (2.8)$$

$$P_{ih}^G - P_{ih}^{reg,down} \geq P_i^{min}, i \in I, \forall h \quad (2.9)$$

$$0 \leq \left(\frac{P_{ih}^{reg,up}}{R_i^{reg}} + \frac{P_{ih}^{res}}{R_i^{res}} \right) \leq \tau, i \in I, \forall h \quad (2.10)$$

$$P_{ih}^{reg,down} \leq R_i^{reg} \tau, i \in I, \forall h \quad (2.11)$$

$$\sum_{i=1}^I P_{ih}^{reg,up} \geq Rg_h^{reg,u} \forall h \quad (2.12)$$

$$\sum_{i=1}^I P_{ih}^{reg,down} \geq Rg_h^{reg,d} \forall h \quad (2.13)$$

$$\sum_{i=1}^I (P_{ih}^{res} + P_{ih}^{reg,up}) \geq Rs_h^{reg} + Rg_h^{reg,u}, \forall h \quad (2.14)$$

$$P_{ih}^G - P_{ih-1}^G \leq R_i^{oper} 60, i \in I, \forall h \quad (2.15)$$

$$P_{ih-1}^G - P_{ih}^G \leq R_i^{oper} 60, i \in I, \forall h \quad (2.16)$$

The optimization problem of (2.5) is subject to real power balance constraints at each bus (2.6), thermal limit constraints for each line (2.7), upper and lower generation capacity constraints (2.8 - 2.9), and ramp rate constraints (2.10 - 2.11). There are also system wide reliability requirements constraints (2.12 - 2.14), and power schedule constraints between hours (2.15 - 2.16). In the case that a generation unit has reserved capacity for both regulation up and spinning reserve AS, it has to be able to deliver both within 10 minutes. That is why there is a combined constraint on both regulation up and spinning reserve AS in (2.10). In procuring upward AS, the MO could substitute a higher quality AS type to meet the requirement of a lower quality AS type if it is economically desirable to do so in the optimization process. Regulation up AS is considered to have a higher quality than spinning reserve AS. Therefore, there is an individual constraint on minimum amount of regulation up AS (2.12), and a combined constraint on minimum amount of both regulation up and spinning reserve AS

(2.14). The optimization problem is solved by CPLEX which is capable of handling large-scale power systems problems. A CPLEX Java interface is implemented in this project to facilitate the sharing of data between the programs.

2.4 Proposed Multi-agent Approach

2.4.1 Software Implementation of Multi-Agent System

When using an agent-based approach to solve a problem, a number of domain independent issues must be addressed, such as how to allow agents to communicate [58]. JADE, a widely-used agent-oriented middleware, provides the domain independent infrastructure which allows developers to focus on the construction of key logics. Since JADE is written in Java, it benefits from a large set of programming abstractions which greatly facilitate the development of MAS. JADE fully complies with the FIPA specifications which are maintained by the standards organization for agents and MAS. Based on the above considerations, JADE is chosen to be the middleware on which the proposed MAS was implemented.

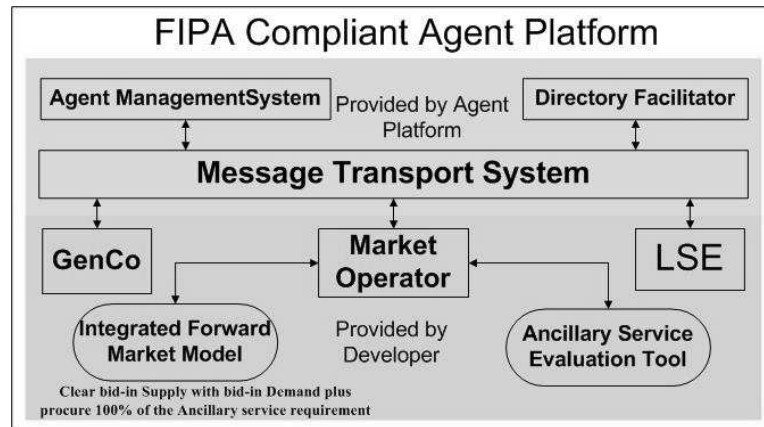


Figure 2.1 Structure of the multi-agent platform for electricity DAM

The structure of the multi-agent platform is depicted in Fig 2.1. JADE provides two utility agents: the agent management system (AMS) and directory facilitator (DF) and an inter-agent messaging system through which the agents communicate with each other. The AMS allocates agent identifiers (AIDs) to each agent that registered with it, and provides a "white page"

service, where an agent can ask for the address of another. The DF provides a "yellow page" service, where agents register the services they provide, and an agent can ask for all agents to provide a particular service.

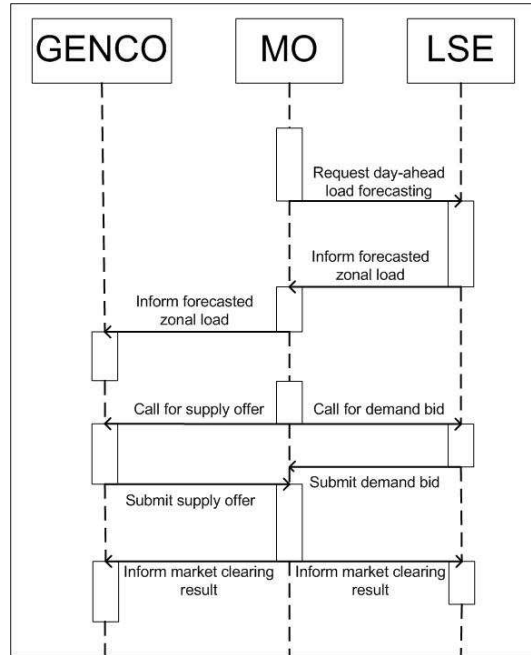


Figure 2.2 Message flowing sequence in the multi-agent platform for electricity DAM

MO, GenCo agents and LSEs are developed fully in Java in this research. Fig 2.2 demonstrates the message flowing sequence in the multi-agent platform to help explain the daily sequence of tasks of MO, GenCo agents and LSEs. A GenCo agent's daily sequence of tasks is implemented as follows: collecting forecasted zonal load data posted by MO, submitting supply offers to MO, collecting market settlement information posted by MO and adjusting its bidding strategy based on the Q-learning algorithm. MO starts the day by collecting forecasted load data from LSEs, and posting the MO forecasted zonal load data. Upon receiving the supply offers and demand bids, it performs MPM followed by market clearing. Afterwards, it posts the market clearing information and uses an AS evaluation tool to test the system frequency performance under hypothesized disturbances. The sequence of actions taken by the LSEs is: report forecasted load data to MO, submit demand bid to MO, and collect the

market settlement information from MO.

2.4.2 Learning Behavior of Agents Who Own Generation

The learning behavior of agents with generation units is modeled by Q-Learning. Q-Learning, developed by Watkins [59], is a form of anticipatory reinforcement learning that allows agents to learn how to act in a controlled Markovian domain. A controlled Markovian domain implies that the environment is Markovian in the sense that the state transition probability from any state x to another state y only depends on x , y and the action a taken by the agent, and not on the historical information. It works by successively updating estimates for the Q-values of state-action pairs. The Q-value $Q(x, a)$ is the expected discounted reward for taking action a at state x and following an optimal decision rule thereafter. The estimates of Q-values will be updated based on the reward received immediately after an action has been taken at each time step. As time moves on, series of Q-value estimates will be formed. If the series of estimates of Q-values converge to the correct Q-values, the optimal action to take in any state is the one with the highest Q-value.

The Q-learning agent moves around a discrete finite world, choosing one action from its finite action domain at every time step. In the n^{th} step the agent observes the current system state x_n , selects an action a_n , receives an immediate payoff r_n , and observes the next system state y_n . The agent then updates its Q-value estimates using a learning parameter α_n and a discount factor γ [59] as follows:

If $x = x_n$ and $a = a_n$,

$$Q_n(x, a) = (1 - \alpha_n)Q_{n-1}(x, a) + \alpha_n[r_n + \gamma V_{n-1}(y_n)] \quad (2.17)$$

Otherwise,

$$Q_n(x, a) = Q_{n-1}(x, a) \quad (2.18)$$

where

$$V_{n-1}(y) \equiv \max_b \{Q_{n-1}(y, b)\} \quad (2.19)$$

The way Q-Learning is implemented for an agent with generation unit(s) is as follows. A step in the electricity DAM environment means a trading day. The agent views the DAM as a complex system with different states. The perceived system state by an agent with generation unit(s) on day D is defined as a vector with two elements which are variables related to the zone where the agent's unit is located. The first element is predicted day D+1's daily average zonal load level. The second element is the average LMP level of the most recent day that has a similar average load level as day D+1. Each zone's zonal daily average load is divided into M_L levels. For each zonal daily average load level, there are M_P LMP levels. Hence the cardinality of each agent's state space is $M_L \times M_P$.

For an agent i , selecting an action means submitting a specific supply offer to the MO. The supply offer of the agent is defined as a vector with two elements. The first element is the bidding markup for the real power c_i^B that has M_B possible values. The second element is the bidding price for regulation up capacity $c_i^{reg,up}$ that has M_R possible values. The action domain of an agent is defined as the set of all possible actions that has a dimension of $M_B \times M_R$. To limit the dimension of the action domain for agents, it is assumed that the bidding markups for spinning reserve capacity and regulation up capacity are identical for the same unit. In addition, the bidding markup for regulation down capacity is assumed to be zero.

The Q-learning algorithm does not specify how to choose an action at each time step. An action a in state x is selected according to the Gibbs/Boltzmann distribution given in equation (2.20) which depends on the Q-values.

$$P_D(x, a) = \frac{e^{Q(x,a)/T_d}}{\sum_{b \in AD_i} e^{Q(x,b)/T_d}} \quad (2.20)$$

In equation (2.20), AD_i is the action domain of the agent, and T_d is a "temperature" parameter that models a decay over time according to the formula given in Table 2.1. In this paper the Gibbs/Boltzmann distribution is chosen because, by setting proper parameters, it ensures a sufficient exploration while still favoring actions with higher Q-value estimates.

The parameters that are used in the numerical study are set according to Table 2.1.

According to equation (2.20), when $Td = +\infty$, every action has an equal probability of

Table 2.1 Q-Learning parameters

| γ | α | ω | T_d | M_L | M_P | M_B | M_R |
|----------|----------------------|----------|-------------------------|-------|-------|-------|-------|
| 0.7 | $1/T_{(x,a)}^\omega$ | 0.77 | $const \times N_d^{-6}$ | 4 | 3 | 5 | 3 |

being chosen. As T_d gradually decreases over time, the action with a higher Q-value estimate will have a higher probability to be chosen. By using the Gibbs/Boltzmann distribution to select actions, the Q-learning agents are able to try a variety of actions when there was not much historical bidding information to learn from. As time moves on, it also allows agents to progressively favor those that appear to be the best actions. In this way, a trade-off between exploration and exploitation is made.

Consider the beginning of each day D . An agent first makes a prediction of the system state based on published load forecasting data and historical LMP data, which is represented by x . It next chooses an action according to the process illustrated above. Having chosen an action a , the agent will submit its supply offer and possibly demand bids to the MO. Once the market is cleared, the agent will receive its reward, which is the profit for day $D+1$. Then the agent uses this reward to update its Q-value estimates according to equations (2.17) to (2.19). In the generator model, the Q-value estimates of the state-action pairs are updated by the Q-learning algorithm.

In Table 2.1, $T_{(x,a)}^\omega$ is the number of times action a has been taken in state x . N_d is the number of days that have been simulated. ω should be chosen to obtain a suitable decay for the learning parameter α . γ should be assigned a value that strikes an appropriate balance between immediate reward and expected reward in the future. The choice of these parameter values depends on the specific application. Since the application of this paper is in a dynamic multi-agent learning environment and the simulation only runs for 184 days, the γ and ω parameters are set so that the agents are able to extract enough information from the limited historical bidding experience and learn at a relatively fast pace from the environment.

2.5 Numerical Studies

2.5.1 Test System

A 225-bus WECC system developed in this project is used as the test market. The system model, which is extended from a 179-bus model used in CAISO planning studies [60], represents the essentials of the CAISO area. The system block diagram is shown in Fig. 2.3, where blocks with a thick dashed outline represent constrained load and generation pockets, and thick solid lines denote simplified network constraints, which are used as illustrations in CAISO's Congestion Management Reform Project, which predated market redesign and technology upgrade (MRTU).

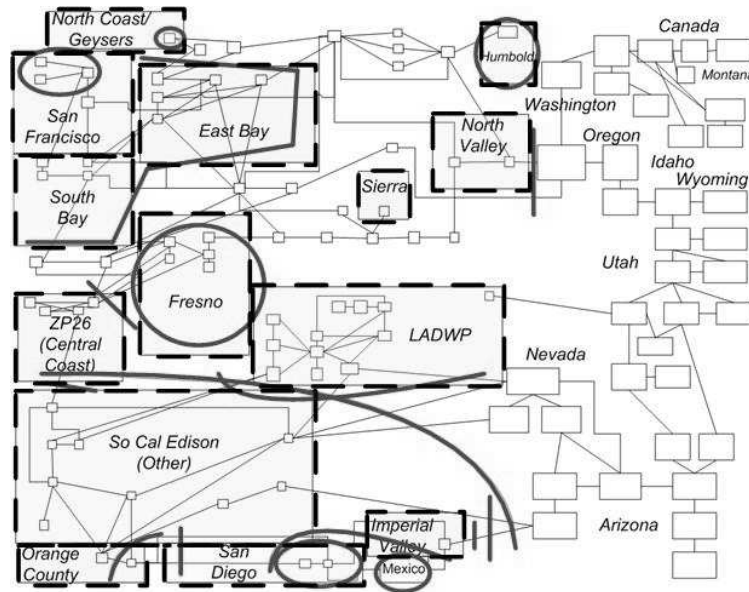


Figure 2.3 225-Bus WECC Model - Details of California

Inside the CAISO area, 23 aggregated thermal generators are modeled as GenCo agents that bid strategically into the market. A total of 15 aggregated hydroelectric and other renewable energy generators are modeled by time-varying outputs according to historical resource availability. Outside the CAISO area, resources represented as 22 generators produce net imports into the CAISO area. The hourly time-varying data reflect a six-month period of operations from May 1 2004 to Oct 31 2004, and include area loads for 11 local areas within the CAISO

as well as net exports into a separate control area that is surrounded by the CAISO control area. The system peak demand is 44209.2 MW. The installed capacities in different areas of CAISO are listed in Table 2.2. Due to confidentiality, names of the areas are not shown in the table.

Table 2.2 Installed capacity in different areas of CAISO

| | | | | | | | |
|-------------------------|------|-------|------|------|------|------|----|
| Area | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| Installed Capacity (MW) | 4146 | 2644 | 196 | 1223 | 4010 | 7371 | 42 |
| Area | 8 | 9 | 10 | 11 | 12 | 13 | |
| Installed Capacity (MW) | 395 | 17842 | 3577 | 255 | 903 | 4669 | |

2.5.2 Evaluation of CAISO Market Power Mitigation Rules

To demonstrate the exercise of market power by Q-Learning agents and evaluate the effectiveness of the MPM rules, the following three scenarios are simulated. The first scenario is a competitive benchmark where every GenCo agent bids its marginal cost. The second scenario is an unmitigated scenario where every GenCo agent bids strategically into the market according to the Q-learning rules in the absence of MPM. The third scenario is a mitigated scenario where every GenCo agent still bids strategically into the market, but is subject to the MPM specified in subsection 2.3.4.

In every scenario, 15 simulation runs, each with a different random seed, are performed. The average results are reported in Fig. 4-6.

To illustrate how Q-learning facilitates the exercise of market power and implicit collusion of large GenCo agents, two pivotal GenCo agents from the SCE area are chosen for a case study. GenCo agents 7 and 8 together have a capacity of 7685 MW, which comprises of 64% of the area's generation capacity.

For simulation run 1 of the unmitigated scenario and mitigated scenario, key information from the Q-tables of GenCo agent 7 and 8 on August 10th are illustrated in Table 2.3.

As can be seen from Table 2.3, in the unmitigated scenario, both GenCo agents are in state

Table 2.3 Key information from GenCo agent 7 and 8's updating Q-table

| | Unmitigated Scenarios | | | Mitigated Scenarios | | |
|---------|-----------------------|--|-------------------------------|---------------------|--|-------------------------------|
| | state | Action Index with the Highest Estimate Q-value | Bidding Markup for Real Power | State | Action Index with the Highest Estimate Q-value | Bidding Markup for Real Power |
| GenCo 7 | 12 | 11 | 12% | 12 | 7 | 8% |
| GenCo 8 | 12 | 7 | 8% | 12 | 4 | 4% |

12. This state is encountered when the forecasted day D+1's load level is high and most recent similar load level day's LMP is also high. In state 12, the highest Q-value estimate for GenCo 7 is given by action 11 which corresponds to a 12% bidding markup for real power. Similarly, for GenCo 8, the highest Q-value estimate is given by action 7 which corresponds to an 8% bidding markup for real power. The highest possible bidding markup for real power is set to be 16% and the lowest is set to be 0%. From equation (2.20), an action that has a higher Q-value estimate will have a higher probability to be selected. Q-learning method has helped GenCo 7 and 8 to favor high markup actions when there is more potential to exercise their market power. In addition, it is shown that those two Q-learning GenCo agents are capable of implicitly colluding with each other by setting relatively high bidding markup together which will successfully drive up the price. However, the highest possible bidding markup, 16%, is not very attractive to the two pivotal GenCo agents. Indeed, although the LMPs are further driven up, they will lose part of their previously profitable generation schedule to two other relatively smaller generation companies in the area. This result extends the conclusion from [61], in that the condition of having the same demand in every trading period is not necessary. Even in a rapidly changing market environment, large generation owners who interact with each other in similar scenarios easily learn to implicitly collude even without having to know others' historical bidding data.

In the mitigated scenario, both GenCo agents are also in state 12 on Aug 10th. This time, the highest Q-value estimate for GenCo 7 is given by action 7 which correspond to an 8% bidding markup for real power. The highest Q-value estimate for GenCo 8 is given by action

4 which corresponds to a 4% bidding markup for real power. Comparing to the unmitigated case, the favorite actions' bidding markups are lower for both GenCo agents. This result shows that the MPM helped to break the high markup collusion of the two pivotal suppliers and successfully suppressed the Q-learning GenCo's potential to exert market power.

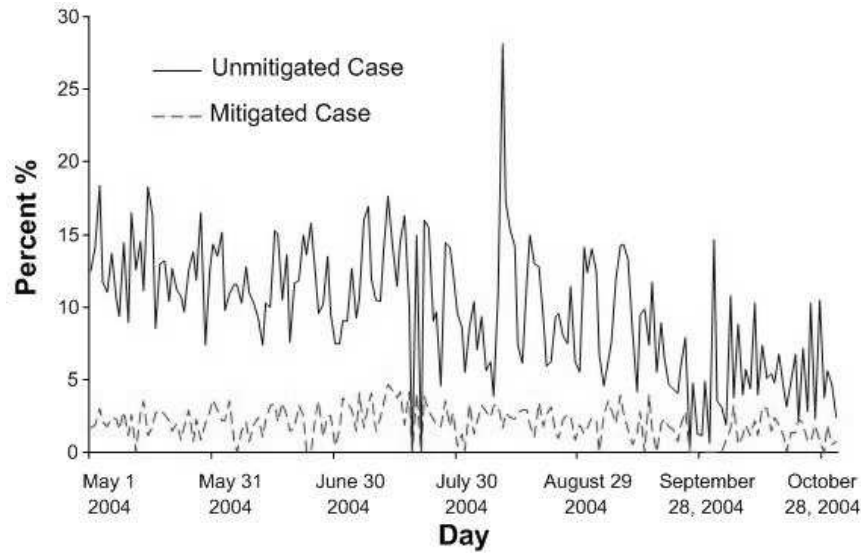


Figure 2.4 Percent total market payment increase in the unmitigated and mitigated scenarios compared to the competitive benchmark

As shown in Fig. 2.4, the total market payment in the unmitigated scenario is significantly higher than that of the competitive benchmark. With the help of Q-Learning, the GenCo agents are able to exploit the market together and gain an average of 9.7 percent increase in total market payment comparing to the competitive benchmark. However, the total market payment in the mitigated scenario is slightly higher than that of the competitive benchmark. Facilitated by the MPM rules, the MO effectively reduced the percentage increase in total market payment to only 2 percent. The lower average load level and less congestion leads to a relatively low percentage increase of total market payment from August to the October compared to June and July.

Fig. 2.5 demonstrates the percentage increase of total generation cost in the mitigated and unmitigated scenario, compared to the competitive benchmark. The simulation result shows that the total generation cost increase in the unmitigated scenario is about 1.5 percent higher

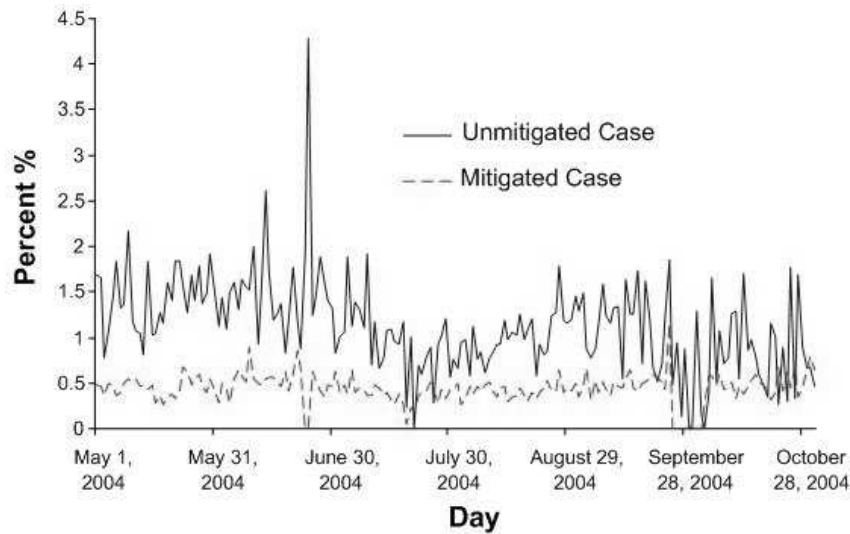


Figure 2.5 Percent total generation cost increase in the unmitigated and mitigated scenarios compared to the competitive benchmark

than that of the competitive benchmark. The strategic bidding of the GenCo agents' results in extramarginal capacity being cleared, and inframarginal capacity left not dispatched. The reduction of market efficiency is caused by the market power collectively exercised by the GenCo agents. The total generation cost increase in the mitigated scenario is only about 0.5 percent higher than that of the competitive benchmark. This result shows that the MPM rules not only suppressed the exercise of market power, but also enhanced market efficiency by bringing the total generation cost closer to marginal cost revenues, compared to the unmitigated scenario's outcome.

The largest unit's profit percentage increase in the unmitigated and mitigated scenarios, compared to the competitive benchmark, is depicted in Fig. 2.6. The largest GenCo agent's profit increase, which is 47.9 percent above the competitive benchmark, is significantly higher than the average increase of all other GenCo agents. This shows the Q-learning algorithm did help the GenCo agent realize that the huge size of its unit does provide a higher potential to exercise market power. In the mitigated scenario, the strategic bidding of generators is not beneficial to the largest GenCo agent at all. In some situations, the strategic bidding behavior will even lead to a lower profit compared to the competitive benchmark. The MPM rules being

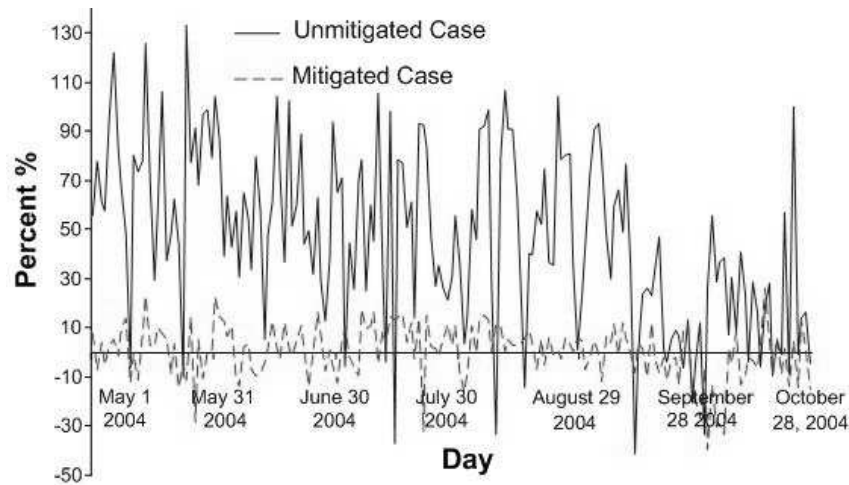


Figure 2.6 Percent largest unit's profit increase in the unmitigated and mitigated scenarios compared to the competitive benchmark

examined did reasonably well in discouraging the exercise of market power.

2.5.3 Effects of LSE Owning Generation Resources

It is common in agent modeling studies of electric markets to have separate agents for GenCo agents vs. LSEs, and rare to have the same agents both buying and selling electricity. However, in CAISO, a number of LSEs also own or control generation. The results of this study demonstrate the importance of accounting for this type of LSE.

To examine the bidding behaviors of LSEs that own generation resources and their impacts on suppressing the GenCos' collective market power, it is assumed that five major LSEs have their own generation units. Details of study inputs about LSEs' service areas, their units' capacity, and peak load is listed in Table 2.4. It is assumed that each LSE serves a peak load of twice its unit's capacity. To provide the desired test scenarios, this distribution of load among LSEs is more uniform than the actual CAISO market, in which one LSE dominates each of three transmission areas that also contain smaller municipal utilities and customers served by competitive retail energy service providers.

The simulation is carried out in four scenarios categorized by whether mitigation rules exist and whether some generation units are owned by LSEs. 15 simulation runs are performed in

Table 2.4 LSEs detailed information

| | Area Peak Load (MW) | Generation Unit Owned | Unit Capacity (MW) | Peak Load to Serve (MW) |
|-------|---------------------|-----------------------|--------------------|-------------------------|
| LSE A | 16280.3 | Generator 7 | 3718 | 7436 |
| LSE B | 16280.3 | Generator 8 | 3967 | 7934 |
| LSE C | 7002.0 | Generator 18 | 2628 | 5256 |
| LSE D | 6977.8 | Generator 20 | 1478 | 2956 |
| LSE E | 6977.8 | Generator 22 | 1314 | 2628 |

each scenario and the average results are reported below.

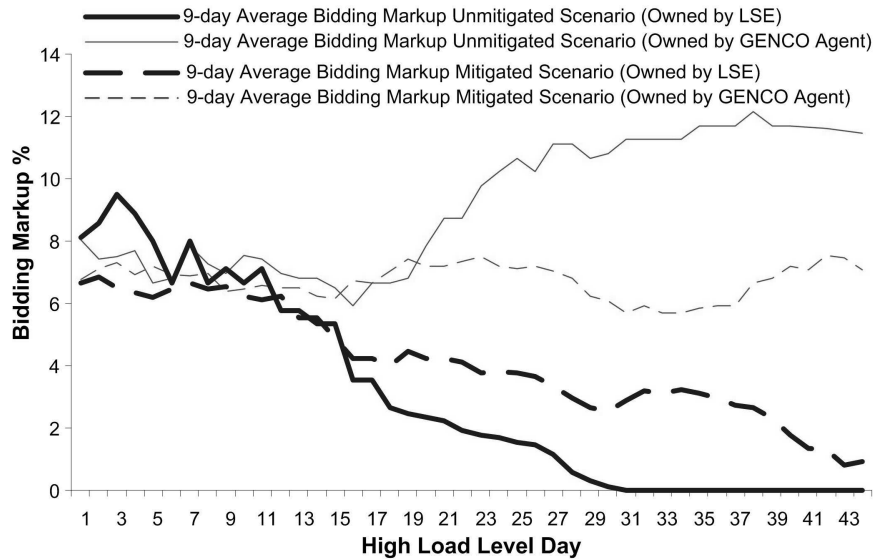


Figure 2.7 9-Day average bidding markup of generator 7 in unmitigated and mitigated scenario when owned by LSE or GenCo agent

As shown in Fig. 2.7, generator 7, for example, quickly learned to bid at a lower markup in the unmitigated scenario when it is owned by a LSE and the load level is high. The LSE also learned the same strategy to reduce the cost of energy and AS in the mitigated scenario, however, at a slower rate. In the unmitigated scenario where generator 7 is owned by a GenCo agent, Q-Learning helped it learn to bid at a higher markup during high load days. In the mitigated scenario, the GenCo agent learned a similar strategy except that the actual bidding markup can not exceed 10% due to the existence of MPM rules. The bidding markup of other

generators in Table 2.4 also exhibits similar patterns in the four simulation scenarios.

A conclusion from these simulation results is that if the generation capacity of a LSE is smaller than the LSE's total load, it will tend to bid at its generation unit's true marginal cost. However, if a generation company owns the same generator, it will tend to bid at a much higher markup.

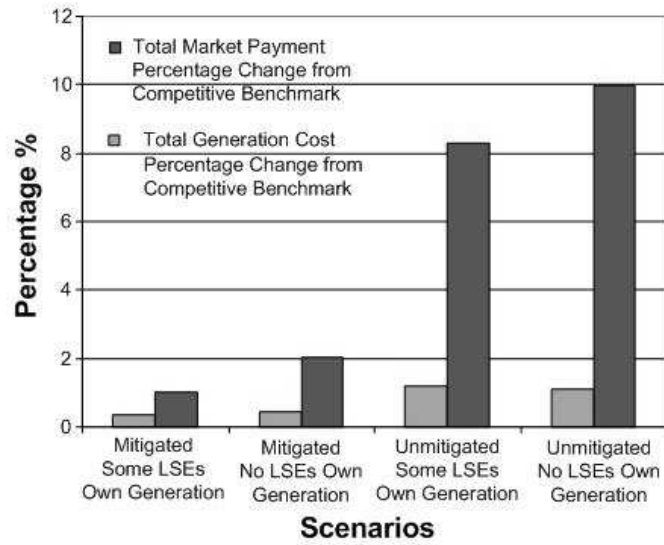


Figure 2.8 Total market payment and total generation cost percentage increase in four scenarios compared to the competitive benchmark

The total market payment and total generation cost percentage increase from competitive benchmark in the four scenarios are shown in Fig. 2.8. The simulation results show that both MPM procedure and the LSEs' ownership of generation units contribute to reductions in total market payment and total generation cost. In the mitigated scenario, on average the total profit of the group of generators that are not owned by LSEs is about 1.5% lower when some LSEs own generation units compared to the case when LSEs do not own any generation units. In the unmitigated scenarios, the reduction in profit is about 1.1% on average. Therefore, the generation resources that are owned or managed by LSEs are useful for reduction of market power during peak hours to the GenCo agents.

2.6 Summary

This chapter presented a multi-agent simulation approach to the evaluation of electricity market rules. It is found that the agent-based simulation approach empowered by Q-Learning agents is able to capture the dynamic interaction between strategic bidding market participants. The simulation result in the unmitigated scenarios shows that, even in a rapidly changing market environment, major generation owners who interact with each other in similar scenarios easily learn to implicitly collude even without having to know others' historical bidding data. This is achieved by anticipating each other's impact on market prices. The simulation results in a mitigated scenario show that the LMPM rules proposed by CAISO perform reasonably well against Q-Learning agents and enhance the market efficiency. It is also shown that when LSEs with generation resources are net buyers in the market, they pose effectively countervailing market power against the GenCo agents. A drawback of the Q-Learning model for GenCo agents is that it may suffer from the curse of dimensionality if there are too many decision variables. This weakness can be overcome by designing a learning algorithm for electricity market participants that combines the strength of both Q-Learning and Artificial Neural Networks.

Further research is needed on the development of the proposed multi-agent platform to enable the negotiation between GenCo agents and LSEs on bilateral contracts and study the effects of forward contracts on DAM. In addition, it is desirable to incorporate marketers into the model who trade energy but who do not own generation or serve load, and to examine the impacts of virtual bidding on electricity markets.

CHAPTER 3. FINANCIAL RISK MANAGEMENT IN WHOLESALE POWER MARKETS

3.1 Nomenclature

| | |
|-----------------|--|
| $Bus\ i$ | Location of GenCo and LSE in a financial bilateral contract negotiation. |
| P_G | GenCo's fixed hourly output (MW) for its power plant. |
| A_G | GenCo's risk-aversion factor. |
| A_L | LSE's risk-aversion factor. |
| K_G | Price bias affecting probability measure Q_G . |
| K_L | Price bias affecting probability measure Q_L . |
| E^P | Expected value calculated using true probability measure P . |
| E^G | Expected value calculated by GenCo using biased probability measure Q_G . |
| E^L | Expected value calculated by LSE using biased probability measure Q_L . |
| α | Confidence level for GenCo and LSE. |
| $CVaR_\alpha^P$ | Conditional value-at-risk calculated using true probability measure P . |
| $CVaR_\alpha^G$ | Conditional value-at-risk calculated by GenCo using biased probability measure Q_G . |
| $CVaR_\alpha^L$ | Conditional value-at-risk calculated by LSE using biased probability measure Q_L . |
| T | Contract period (hours). |
| M | Contract amount per hour (MW). |
| M^R | Lower bound for negotiated contract amount. |
| M^U | Upper bound for negotiated contract amount. |

| | |
|------------------|--|
| S | Contract strike price (\$/MWh). |
| S^R | Lower bound for negotiated strike price. |
| S^U | Upper bound for negotiated strike price. |
| u_G | GenCo's return-risk utility function. |
| u_L | LSE's return-risk utility function. |
| π_G | GenCo net earnings. |
| π_L | LSE net earnings. |
| π_G^0 | GenCo net earnings if no contract is signed. |
| π_L^0 | LSE net earnings if no contract is signed. |
| λ_Σ | Sum of LMP realizations at bus i during contract period. |

3.2 Financial Risk Management Basics

3.2.1 Definition of Risk

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

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

Researchers focusing on risk management in wholesale power markets typically do not provide a clear definition of "risk." An exception is Liu and Wu [50], who define risk to be "the hazard to which a market participant is exposed because of uncertainty." This definition clearly reflects the two previously mentioned common elements. However, it does not include

the idea of anticipation or expectation as a benchmark.

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

3.2.2 Financial Risk Management as a Four-Stage Process

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

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

These four stages are explained more carefully below.

Stage 1: Identification and Modeling of Financial Risk Factors

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

Consider a risk manager attempting to manage a portfolio of assets for a profit-maximizing GenCo facing two sources of risk: a variable electric energy demand level D , and a variable fuel price level F . Suppose for simplicity that D and F can only take on two values, High

(denoted by 1) or Low (denoted by 0). The sample space Ω consisting of all possible outcome pairs (D_i, F_j) for D and F then takes the form $\Omega = \{(1, 1), (1, 0), (0, 1), (0, 0)\}$. Define \mathcal{F} to be the collection of all subsets of Ω , including the empty set. The two risk factors D and F can then be modeled by defining an appropriate joint probability measure P on \mathcal{F} .

Additional discussion of this stage is provided in Section 3.3.1.

Stage 2: Derivation of a Loss Function

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

Stage 3: Risk Measure Selection

The third risk-management stage typically involves the choice of an appropriate risk measure for characterizing overall portfolio risk for the particular situation at hand. This risk-measure selection process could involve comparative consideration of several candidate risk measures, such as return-rate variance, Value-at-Risk and Conditional Value-at-Risk. The definitions and derivations of these commonly used risk measures are discussed in Section 3.3.2.

Stage 4: Portfolio Optimization

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

3.3 Risk-Management Tools and Methods

This section provides additional details regarding the tools and methods used to implement the four-stage risk management process outlined in Section 3.2.2.

3.3.1 Tools for Modeling Risk Factors

In the financial industry, three methods are commonly used to model risk factors in any given time period. These methods are the “analytical variance-covariance method,” “historical simulation,” and “Monte Carlo analysis” [62].

The *analytical variance-covariance approach*, also called the *parametric approach*, assumes that changes in risk factors follow a multivariate normal distribution. In practice, the unconditional or conditional mean vector and covariance matrix of the assumed multivariate normal distribution are estimated based on historical data for risk-factor changes. The main advantages of this method are the simplicity of the analytical solution and its speed of calculation. The main drawback is that the normality assumption can be problematic.

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

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

3.3.2 Construction of Risk Measures

In theory, the probability density function of the loss function for a portfolio of assets provides complete information about its risk. However, portfolio managers have found these probability density functions too cumbersome and complex for practical applications. Instead, they have preferred to construct simpler measures of portfolio risk that can be reduced to the reporting of a single number. Although single-number measures clearly lose a great deal of information through aggregation, the issue is whether they adequately serve the risk-management purposes of portfolio managers [63]. Three such single-number measures are briefly reviewed below.

In traditional finance, following the work of Markowitz [64], the measurement of risk for a portfolio of assets was primarily associated with the variance of the portfolio's return rate. Although variance is a well-understood concept and is easy to use analytically, it has some major drawbacks [65]. The most important drawback is that variance does not distinguish between positive and negative deviations from the mean. Consequently it is not conceptually compatible with definitions of risk that focus solely on negative (unfavorable) deviations.

Beginning in the 1990s, alternative measures of portfolio risk have increasingly been adopted in financial practice. As discussed at length in [66]-[72], two of the best-known measures are "VaR" and "CVaR."

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

To put this definition in more rigorous mathematical form, consider a *probability space* (Ω, \mathcal{F}, P) where Ω is a space of points called the *sample space*, \mathcal{F} is a sigma-field of subsets of Ω , and P is a probability measure on \mathcal{F} . Singleton subsets $\{\omega\}$ of Ω , assumed to be elements of \mathcal{F} , are called elementary events. Define $q = (x_1, x_2, \dots, x_n)$ to be a given portfolio, where x_n denotes the amount of money invested in the n th asset. Let L_q denote the *loss function*

of portfolio q , where L_q maps Ω into the real line \Re . Define $A_{L_q}(l) \equiv \{\omega \in \Omega : L_q(\omega) > l\}$, and assume $A_{L_q}(l) \in \mathcal{F}$ for each l . The *Value at Risk (VaR)* for portfolio q at confidence level $\alpha \in [0, 1]$ is then defined to be

$$\text{VaR}_\alpha(L_q) = \inf\{l \in \Re : P(A_{L_q}(l)) \leq 1 - \alpha\}. \quad (3.1)$$

Since its inception, VaR has been widely used by corporate treasurers and fund managers as well as by financial institutions. It has also been incorporated into the Basel II capital-adequacy framework, an agreement among regulators on how to calculate the minimum regulatory capital requirements for banks. In spite of its popularity, however, VaR suffers from several theoretical deficiencies. First, as a simple quantile of the loss distribution, it does not provide any information about the severity of the losses when the loss exceeds the quantile level. This problem is illustrated in Fig. 3.1. Although the two depicted portfolios have the same risk level as measured by $\text{VaR}_\alpha(L_q)$, the portfolio on the right is clearly riskier due to its larger potential losses.

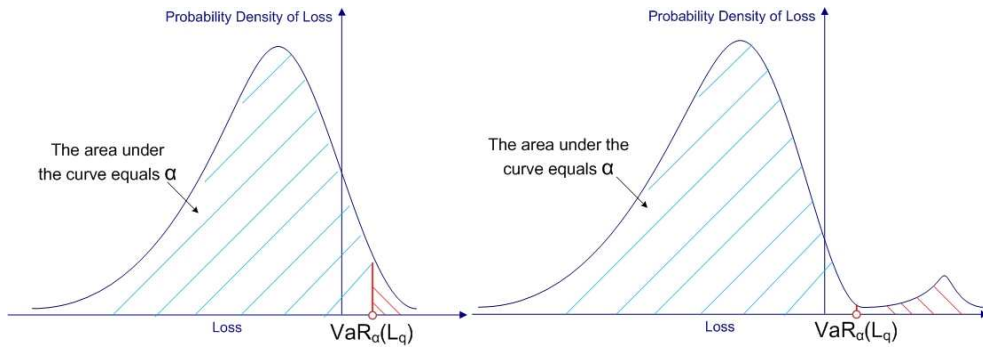


Figure 3.1 Illustration of a major drawback of VaR as a risk measure: VaR assigns the same risk to each depicted probability density function for loss

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

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

$$\text{CVaR}_\alpha(L_q) \equiv E(L_q \mid \{\omega \in \Omega : L_q(\omega) \geq \text{VaR}_\alpha(L_q)\}) . \quad (3.2)$$

Equivalently, CVaR can be written as:

$$\text{CVaR}_\alpha(L_q) = \frac{1}{1 - \alpha} \int_{\bar{A}_{L_q}(\text{VaR}_\alpha(L_q))} L_q(\omega) dP(\omega) , \quad (3.3)$$

where

$$\bar{A}_{L_q}(l) \equiv \{\omega \in \Omega : L_q(\omega) \geq l\} . \quad (3.4)$$

To see the distinction between VaR and CVaR more clearly, refer again to Fig. 3.1. For the given confidence level α , the CVaR measure assigns heavier risk to the right-hand distribution because the expected loss over the loss range $l \geq \text{VaR}_\alpha(L_q)$ is greater for this distribution. In contrast, VaR assigns the same risk value $\text{VaR}_\alpha(L_q)$ to each depicted distribution.

As established in [69], CVaR has four properties required for a coherent risk measure: subadditivity, positive homogeneity, monotonicity and translation invariance. Moreover, in contrast to VaR, CVaR is convex with respect to portfolio positions, a major practical advantage of CVaR over VaR in applications.

3.3.3 Supplemental Tools: Stress Testing

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

As discussed at greater length in [70], the rationale for using stress testing is that risk measures derived from historical data might not adequately reflect possible future risks. For

example, a portfolio manager might be concerned about the occurrence of a shock that he believes is more likely to occur in the future than the historical data suggest, or about shocks that he believes would substantially alter the historically observed correlation patterns among asset returns upon which his current risk-factor model is based.

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

3.4 Financial Bilateral Contract Negotiation: Problem Description

Costly lessons learned from the California energy crisis in 2000-01 were that overreliance on spot markets can lead to extremely volatile prices as well as a market design vulnerable to gaming. The bilateral contracts for longer-term trades that were disallowed by the California regulators could have reduced spot price volatility, discouraged gaming behaviors by power traders, and provided a much-needed risk-hedging instrument for the three largest investor-owned utilities.

Today, bilateral contracting either through negotiation (forward trading) or through organized public exchanges (futures trading) is a critical feature of most countries’ wholesale electric power market designs. This critical feature helps to ensure competitive and transparent prices and to countervail the exercise of market power.

In fact, bilateral contracting is the most frequent and preferred form of trade arrangement in many electricity markets. Examples include the continental European electricity market, the Texas (ERCOT) wholesale power market, the Nordic electricity market, and the Japanese electric power exchange [73]. Traders in these markets routinely hedge their price risks by

signing bilateral contracts. A common example of such a contract is a *Contract-For-Difference (CFD)* that specifies a strike price (\$/MWh) at which a particular MW amount is to be exchanged at a particular reference location during a particular contract period. If the actual price at the reference location differs from the strike price, the advantaged party is required to “make whole” the disadvantaged party by paying the difference [51, Section V.A].

Given the prominent role played by negotiated bilateral contracts in power markets, a crucial question is how the parties to such contracts successfully negotiate the terms of their contracts. The negotiation process can be extremely complicated, involving considerations of both risk management and strategic gaming.

In particular, a participant in a bilateral contract negotiation will typically be concerned not only with expected net benefit but also with *risk*, i.e., the possibility of adverse deviations from expected net benefit. Consequently, the participant will presumably try to negotiate a contract that achieves a satisfactory trade-off between expected net benefit and risk in accordance with its risk preferences.

In addition, such a participant will typically also be concerned with reactive and anticipatory strategic gaming. If the other party offered that, how should I respond; and if I offer this, what will the other party do? From a game theoretic perspective, each party to a negotiation must always keep in mind that a strategy of trying to unilaterally improve its own return at the expense of the other party will typically be self-defeating [74]. Although a party could stubbornly insist on pushing the point of agreement in its favor, this effort will be in vain if the other party then decides to walk away. A typical bilateral contract negotiation process involves elements of both cooperation and competition [75].

Moreover, these considerations of risk and strategic gaming can arise across several distinct markets at the same time. For example, many generation companies in the ISO New England simultaneously participate in an exchange market for bilateral contracts, a day-ahead energy market, a financial transmission rights market, and a capacity market. The contractual position of a generation company in any one of these markets can strongly affect its behavior in the other three markets, as well as its bargaining position in future contractual negotiations. A

classic example is given by Stoft [76]: a generation company that has bilaterally contracted to sell 90% of its power output has only a 10% incentive to raise the price it receives in the day-ahead energy market in comparison to an identically structured generation company with no bilateral contracts.

This study analyzes a negotiation process between a *generation company (GenCo)* and a *load-serving entity (LSE)* for a financial¹ bilateral contract, taking into account considerations of risk management, strategic gaming, and multi-market interactions. Nash bargaining theory is used to model a Pareto-efficient settlement point for this negotiation process. The model predicts negotiation results under varied conditions and identifies circumstances in which the two parties might fail to reach an agreement. In particular, both analytical and computational studies are used to gain insight regarding how negotiated outcomes depend on the relative risk preferences of the GenCo and the LSE, and on the degree to which their price estimates are biased. These results should provide useful guidance to GenCos and LSEs engaged in actual bilateral contract negotiation processes.

3.5 Analytical Formulation of a Financial Bilateral Contract Negotiation Problem

This section develops a simple but informative analytical modeling of a GenCo G and an LSE L attempting to negotiate the terms of a financial bilateral contract in order to hedge price risk in a day-ahead energy market with congestion managed by locational marginal pricing. Both G and L are located at the same bus, so the price risk they face arises from their uncertainty regarding future outcomes for the LMP at their common bus.

As clarified below, each participant G and L is assumed to express their preferences over possible terms for their negotiated contract by means of a return-risk utility function. Also, each participant is assumed to know the utility function of the other participant. Thus, ex-

¹In U.S. ISO-managed electric power markets such as the Midwest ISO [77], a bilateral transaction that involves the physical transfer of energy through a transmission provider's region is referred to as a *physical bilateral transaction*. A bilateral transaction that only transfers financial responsibility within and across a transmission provider's region is referred to as a *financial bilateral transaction*. A financial bilateral contract between a GenCo and an LSE provides more flexibility to both parties since the contract terms are not subject to the GenCo's physical constraints.

pressed in standard game theory terminology, the negotiation process between G and L is a two-player cooperative game with a commonly known payoff matrix.

The day-ahead energy market in which G and L participate entails core features of actual restructured day-ahead energy markets in the U.S. Specifically, during each operating day D a market operator runs *DC optimal power flow (DC-OPF)* software to determine hourly dispatch schedules and LMPs for the day-ahead energy market on day D+1. For simplicity, it is assumed that each GenCo reports its true cost and capacity conditions to the ISO, i.e., GenCos do not formulate strategic supply offers in an attempt to exercise market power. The DC-OPF software is implemented as in Yu et al. [52] except that, for simplicity, the ancillary services aspects are omitted.

3.5.1 The GenCo's Perspective

For concreteness, GenCo G is assumed to own a single nuclear power plant located at bus i . For safety reasons, the production of the nuclear power plant is set at a fixed level P_G (MW) per hour at which its outage risk is effectively zero. Since the nuclear power plant's production level is fixed, G is not allowed to bid strategically in the day-ahead energy market.²

For simplicity, it is assumed that G has a long-term supply contract for uranium fuel (solid ceramic fuel pellets), implying its fuel costs per MW of production are essentially fixed. The total variable production cost (\$/h) for G's nuclear power plant in any hour h is given by

$$TVC(P_G) = aP_G + bP_G^2 \quad (3.5)$$

Under the above assumptions, the only risk facing G is price risk induced by the variability of the LMP outcomes at its own bus i . In an attempt to reduce its price risk, suppose G enters into a financial bilateral contract negotiation with an LSE L also located at bus i .

In particular, suppose G and L attempt to negotiate the hourly contract amount M (MW) and strike price S (\$/MWh) for a *contract-for-difference (CFD)* over a specified contract period from hour 1 to hour T . Let LMP_i^h denotes the LMP realized at bus i for any hour h during

²The assumption of a nuclear power plant is simply for illustration purposes. All that is needed for the analysis below is that the power plant has a fixed output.

the contract period. Under the terms of this CFD, if LMP_i^h differs from the strike price S , then the advantaged party must compensate the disadvantaged party. For example, if S exceeds LMP_i^h , then the advantaged buyer L must pay to the disadvantaged seller G an amount $[S - LMP_i^h] \cdot M$; and conversely.

After signing a CFD with hourly contract amount M and strike price S , the combined net earnings of G from its day-ahead energy market sales and its CFD, conditional on any given realization of LMP_i^h values over the CFD contract period from hour 1 to hour T , are given by

$$\begin{aligned} \pi_G(M, S) = & \sum_{h=1}^T [LMP_i^h \cdot P_G - TVC(P_G)] \\ & + \sum_{h=1}^T [(S - LMP_i^h) \cdot M] \end{aligned} \quad (3.6)$$

Let the net earnings attained by G from its day-ahead energy market sales be denoted by

$$\pi_G^0 \equiv \sum_{h=1}^T [LMP_i^h \cdot P_G - TVC(P_G)] , \quad (3.7)$$

and let

$$\lambda_\Sigma \equiv \sum_{h=1}^T LMP_i^h . \quad (3.8)$$

Then G 's net earnings function (3.6) can equivalently be expressed as

$$\pi_G(M, S) = \pi_G^0 + [T \cdot S - \lambda_\Sigma] \cdot M \quad (3.9)$$

Note that the time-value of money is not considered in G 's net earnings function (3.6). The introduction of a discount rate could easily be incorporated to obtain a standard present-value representation for intertemporal net earnings without changing the analysis below. However, for expositional simplicity, it is assumed that the contract period T for the CFD under study here is of such short duration that the discount rate across all hours of T can be set to zero.

GenCo G is a profit-seeking company that negotiates contract terms in an attempt to attain a favorable tradeoff between expected net earnings and financial risk exposure. To accomplish this, it makes use of a *return-risk utility function* to measure its relative preferences over return-risk combinations.

The best-known example of a return-risk utility function is the *mean-variance utility function* traditionally used in finance to evaluate portfolios of financial assets (e.g., stock holdings). For example, given a stock portfolio q with market value p_t at time t , the “mean” of q at time t is interpreted to be the expectation of q 's one-period return rate $R(t, t+1) = [p_{t+1} - p_t]/p_t$ and the “variance” of q at time t is interpreted to be the variance of this return rate. Often mean-variance utility functions are specified in a simple parameterized linear form: $U(\text{mean}, \text{variance}) = \text{mean} - A \cdot \text{variance}$.

Modern finance has moved away from the use of variance as a measure of financial risk for two key reasons. First, the return rates for many financial instruments appear to have “thick-tailed” pdfs, in the sense that the second moment (hence variance) does not exist. Second, in financial contexts, upside deviations from expected returns are desirable; only downside deviations satisfy the intuitive idea that “riskiness” should refer to the possibility of “adverse consequences.”

Consequently, in place of variance, modern financial researchers now frequently measure the financial risk of an asset portfolio in terms of “one-tail” measures such as *value-at-risk (VaR)* and *conditional-value-at-risk (CVaR)*. Basically, for any given confidence level α , the VaR of a portfolio is given by the smallest number l such that the probability that the loss L in portfolio value exceeds l is no greater than $(1-\alpha)$. In contrast, the CVaR of a portfolio is defined as the *expected* loss L in portfolio value during a specified period, conditional on the event that L is greater than or equal to VaR. Thus, CVaR informs a portfolio holder about expected loss conditional on the occurrence of an unfavorable event rather than simply indicating the probability of an unfavorable event. See Yu et al. [51] for a more detailed discussion of the meaning of VaR and CVaR, and the conceptual and technical advantages of CVaR relative to VaR.

In this study the return-risk utility function of GenCo G is assumed to have the following parameterized linear form:

$$\begin{aligned} u_G(E^G(\pi_G), CVaR_\alpha^G(-\pi_G)) \\ = E^G(\pi_G) - A_G \cdot CVaR_\alpha^G(-\pi_G) \end{aligned} \quad (3.10)$$

In (3.10), $E^G(\pi_G)$ denotes G's expected net earnings, and $CVaR_\alpha^G(-\pi_G)$ denotes the CVaR associated with G's "loss function," i.e., the negative of G's net earnings function (3.6), conditional on any given confidence level α . The parameter A_G in (3.10) is G's *risk-aversion factor* that determines G's preferred tradeoff between expected net earnings and risk exposure as measured by CVaR.

3.5.2 The LSE's Perspective

On each day D the LSE L submits a demand bid to purchase power at bus i from the day-ahead energy market for day $D+1$ in order to service retail customer load at bus i on day $D+1$. This demand bid consists of a 24-h load profile. The retail customers at bus i pay L a regulated rate f (\$/MWh) for electric power.

At the end of day D the LSE is charged the price LMP_i^h (\$/MWh) for its cleared demand for hour h of day $D+1$, where LMP_i^h is the LMP determined by the market operator for bus i in hour h via DC-OPF. Any deviation between L's cleared demands and its actual demands for day $D+1$ are resolved in the real-time market for day $D+1$ using real-time market LMPs.

The risk faced by L on each day D thus arises both from its uncertainty regarding its actual demand and from its uncertainty regarding the prices it will be charged for its cleared demand and for deviations from its cleared demand. As detailed in Section 3.5.1, it is assumed that L attempts to partially hedge its price risk at bus i by entering into a negotiation with GenCo G at bus i for a CFD contract over a given contract period from hour 1 to hour T. The negotiable terms of this CFD consist of a contract amount M (MW) and a strike price S (\$/MWh).

Suppose L and G have signed a CFD for a contract amount M at a strike price S. Let P_{Li}^h denote L's cleared day-ahead market demand at bus i for any hour h during the contract period. Then the combined net earnings of L from its day-ahead energy market purchases and its CFD, conditional on any given realization of LMP_i^h values over the CFD contract period

from hour 1 to hour T, are given by

$$\begin{aligned} \pi_L(M, S) = & \sum_{h=1}^T [P_{Li}^h \cdot (f - LMP_i^h)] \\ & + \sum_{h=1}^T [(LMP_i^h - S) \cdot M] \end{aligned} \quad (3.11)$$

As was done for G, let the net earnings of L from its day-ahead energy market purchases be denoted by

$$\pi_L^0 \equiv \sum_{h=1}^T [P_{Li}^h \cdot (f - LMP_i^h)] \quad (3.12)$$

Then, using (3.8), the net earnings function (3.11) for L can equivalently be expressed as

$$\pi_L(M, S) = \pi_L^0 + [\lambda_\Sigma - T \cdot S] \cdot M \quad (3.13)$$

Finally, similar to G, it is assumed that L uses a return-risk utility function to represent its preferences over combinations of expected net earnings and risk. In particular, it is assumed L's utility function takes the following parameterized linear form:

$$\begin{aligned} u_L(E^L(\pi_L), CVaR_\alpha^L(-\pi_L)) \\ = E^L(\pi_L) - A_L \cdot CVaR_\alpha^L(-\pi_L) \end{aligned} \quad (3.14)$$

In (3.14), $E^L(\pi_L)$ denotes L's expected net earnings, and $CVaR_\alpha^L(-\pi_L)$ denotes the CVaR associated with L's "loss function," i.e., the negative of its net earnings function (3.11), conditional on any given confidence level α . The parameter A_L in (3.14) is L's *risk-aversion factor* that determines L's preferred tradeoff between expected net earnings and risk exposure as measured by CVaR.

3.5.3 Effects of GenCo and LSE Price Estimation Bias on Expected Price and Perceived Risk

This section examines how biases in the probability density functions (pdfs) used by GenCo G and LSE L to represent their uncertainty about the LMP outcomes at their bus i affect their price expectations and perceived risk exposure. These results will be used in Section 3.7 to

determine how these biases affect the outcomes of the financial bilateral contract negotiation process between G and L.

As seen in (3.9) and (3.13), the net earnings of G and L depend on prices only through the LMP summation term λ_Σ . Consequently, in considering biased price estimates, it suffices to consider biases in the pdfs used by G and L for λ_Σ .

Suppose the true uncertainty in λ_Σ over the contract period can be represented by a probability measure P defined over a sigma-field \mathcal{F} of measurable subsets of a sample space Ω of elementary events, i.e., by the probability space (Ω, \mathcal{F}, P) . Suppose, instead, that G and L perceive this uncertainty to be described by probability spaces $(\Omega, \mathcal{F}, Q_G)$ and $(\Omega, \mathcal{F}, Q_L)$, respectively, where Q_G and Q_L differ from P by constant additive bias terms K_G and K_L as follows:

$$Q_G(\lambda_\Sigma + K_G) = P(\lambda_\Sigma) \quad (3.15)$$

$$Q_L(\lambda_\Sigma + K_L) = P(\lambda_\Sigma) \quad (3.16)$$

Let the corresponding pdfs for λ_Σ under the three different probability measures P , Q_G , and Q_L be denoted by $f_P(\lambda_\Sigma)$, $f_{Q_G}(\lambda_\Sigma)$, and $f_{Q_L}(\lambda_\Sigma)$. These probability measures and corresponding pdfs satisfy the following relationships:

$$dP(\lambda_\Sigma) = f_P(\lambda_\Sigma)d\lambda_\Sigma \quad (3.17)$$

$$dQ_G(\lambda_\Sigma) = f_{Q_G}(\lambda_\Sigma)d\lambda_\Sigma \quad (3.18)$$

$$dQ_L(\lambda_\Sigma) = f_{Q_L}(\lambda_\Sigma)d\lambda_\Sigma \quad (3.19)$$

It follows from these relationships that

$$f_{Q_G}(\lambda_\Sigma + K_G) = f_P(\lambda_\Sigma) \quad (3.20)$$

$$f_{Q_L}(\lambda_\Sigma + K_L) = f_P(\lambda_\Sigma) \quad (3.21)$$

Figure 3.2 illustrates relationships (3.20) and (3.21) for a particular configuration of biases.

Making use of the above relationships, the effects of the bias terms K_G and K_L on the expectation and CVaR for λ_Σ can be determined. These effects are summarized in the following theorem, whose proof is provided in Appendix A.

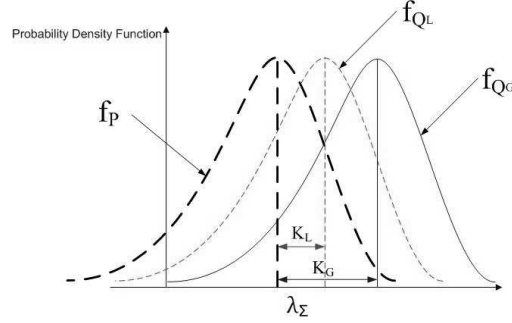


Figure 3.2 Relationships among the true and biased probability density functions for λ_Σ given biases $K_G > K_L > 0$

Theorem 1: Given any confidence level $\alpha \in (0, 1)$, the expectation and $CVaR_\alpha$ measure for λ_Σ under the true probability measure P and the biased probability measures Q_G and Q_L satisfy the following relationships:

$$E^G(\lambda_\Sigma) = E^P(\lambda_\Sigma) + K_G \quad (3.22)$$

$$CVaR_\alpha^G(\lambda_\Sigma) = CVaR_\alpha^P(\lambda_\Sigma) + K_G \quad (3.23)$$

$$E^L(\lambda_\Sigma) = E^P(\lambda_\Sigma) + K_L \quad (3.24)$$

$$CVaR_\alpha^L(\lambda_\Sigma) = CVaR_\alpha^P(\lambda_\Sigma) + K_L \quad (3.25)$$

3.6 Nash Bargaining Theory Approach

Section 3.6.1 reviews Nash bargaining theory in general form. Nash bargaining theory is then specialized in Section 3.6.2 to the financial bilateral contract negotiation problem set out in Section 3.5.

3.6.1 Nash Bargaining Theory: General Formulation

Consider two utility-seeking players attempting to agree on a settlement point $\mathbf{u} = (u_1, u_2)$ in a compact convex *utility possibility set* $U \subseteq \mathbb{R}^2$. If the two players fail to reach an agreement, the default outcome is a *threat point* $\zeta = (\zeta_1, \zeta_2)$ satisfying $\zeta \in U$ and

$$U \cap \{\mathbf{x} \in \mathbb{R}^2 : x_j > \zeta_j \text{ for } j = 1 \text{ or } j = 2\} \neq \emptyset \quad (3.26)$$

Let the set of all bargaining problems (U, ζ) satisfying the above assumptions be denoted by D . For each $(U, \zeta) \in D$, define the *barter set* as follows:

$$B(U, \zeta) \equiv U \cap \{x \in \mathfrak{R}^2 : x \geq \zeta\} \quad (3.27)$$

Nash [78] defined a *bargaining solution* to be any function $f: D \rightarrow \mathfrak{R}^2$ that assigns a unique outcome $f(U, \zeta) \in B(U, \zeta)$ for every bargaining problem $(U, \zeta) \in D$. Nash proved that there is a unique bargaining solution which satisfies the following four axioms (see [79]).

Axiom 1. Invariance Under Positive Linear Affine Transformations: If a bargaining problem (U, ζ) is transformed into a bargaining problem (U', ζ') by taking $u'_j = \alpha_j u_j + \beta_j$ and $\zeta'_j = \alpha_j \zeta_j + \beta_j$, where $\alpha_j > 0$, then $f_j(U', \zeta') = \alpha_j f_j(U, \zeta) + \beta_j$.

Axiom 2. Symmetry: If a bargaining problem (U, ζ) is symmetric, in the sense that $\zeta_1 = \zeta_2$ and $(u_1, u_2) \in U$ if and only if $(u_2, u_1) \in U$, then $f_1(U, \zeta) = f_2(U, \zeta)$. The symmetry axiom basically says that, if the utility possibility set is symmetric, and the two participants have the same threat point, then the two participants achieve the same utility outcomes.

Axiom 3. Independence of Irrelevant Alternatives: If (U, ζ) and (U', ζ) are bargaining problems with $U \subset U'$, and $f(U', \zeta) \in U$, then $f(U, \zeta) = f(U', \zeta)$. The independence of irrelevant alternatives axioms states that the outcome of a bargaining game does not change if the bargainers are given additional bargaining points that are not then selected.

Axiom 4. Pareto-Efficiency: If (U, ζ) is a bargaining problem with $u, u' \in U$ and $u' > u$, then $f(U, \zeta) \neq u$. The Pareto-efficiency property requires that the bargaining solution not be strictly Pareto-dominated by another possible bargaining point.

The four axioms make Nash bargaining solution a fair, efficient and hence desirable outcome of general bargaining processes.

Specifically, for any given bargaining problem $(U, \zeta) \in D$, Nash's bargaining solution $f^*(U, \zeta) \equiv (u_1^*, u_2^*) \in B(U, \zeta)$ is determined as the unique solution to the following problem: maximize $(u_1 - \zeta_1)(u_2 - \zeta_2)$ with respect to $(u_1, u_2) \in U$ subject to $u_1 \geq \zeta_1$ and $u_2 \geq \zeta_2$. Hereafter the function f^* will be referred to as the *Nash Bargaining Solution (NBS)*.

Note that Nash's original bargaining theorem summarized above assumes utility possibility sets that are non-empty, compact, and convex. As shown in [80], however, this theorem can

readily be extended to the broader class of bargaining problems for which the barter sets are non-empty, closed, and “corner concave” in the sense of having a concave northeast boundary. Interestingly, as will be shown in Section 3.6.2, the barter sets for the particularly class of bargaining problems analyzed in this study are always non-empty, compact (hence closed), and convex (hence corner concave) even though the underlying utility possibility sets need not be convex.

3.6.2 Application of Nash Bargaining Theory to the Bilateral Contract Negotiation Problem for GenCo G and LSE L

Consider once again the financial bilateral contract problem set out in Section 3.5. GenCo G and LSE L at a common bus i are engaged in a negotiation for a contract-for-difference (CFD) at bus i .

Suppose G and L use Nash bargaining theory in an attempt to negotiate the contract amount M and strike price S for this CFD. The threat point ζ for the negotiation is given by the utility levels attained by G and L if no contract is signed:

$$\zeta_1 \equiv u_G(E^G(\pi_G^0), CVaR_\alpha^G(-\pi_G^0)) \quad (3.28)$$

$$\zeta_2 \equiv u_L(E^L(\pi_L^0), CVaR_\alpha^L(-\pi_L^0)) \quad (3.29)$$

Suppose, also, that the feasible negotiation ranges for M and S are nonempty closed intervals: $M^R \leq M \leq M^U$, and $S^R \leq S \leq S^U$. In general, the lower bound M^R for M could be any nonnegative value. However, the setting $M^R = 0$ that yields the largest utility possibility set is used in the analysis below for better graphical visualization.

The utility possibility set U for G and L’s CFD bargaining problem is given by the set of all possible utility outcomes (3.10) and (3.14) for G and L as M and S vary over their feasible negotiation ranges. The barter set for this bargaining problem (U, ζ) then takes the form $B \equiv \{(u_G, u_L) \in U : u_G \geq \zeta_1, u_L \geq \zeta_2\}$. Finally, the Nash bargaining solution for this

bargaining problem is calculated as follows:

$$\begin{aligned} \max_{(u_G, u_L) \in U} & (u_G - \zeta_1)(u_L - \zeta_2) \\ \text{s.t.} & u_G \geq \zeta_1 \text{ and } u_L \geq \zeta_2 \end{aligned} \quad (3.30)$$

Notice that since the Nash bargaining solution satisfy Pareto-Efficiency Axiom, the solution points are restricted to the north east corner of the barter set which is the right triangle's longest edge as shown in figure 3.3 and 3.5. Therefore, the optimization problem illustrated above is reduced to a quadratic programming problem.

The following Theorem 2, proved in Appendix B, establishes that the barter set B for this CFD bargaining problem is always convex even though the utility possibility set U can fail to be convex. As shown in the proof of Theorem 2, the exact shape of the barter set B depends on the relationships among the partial derivatives of $CVaR_\alpha^L$ with respect to M , A_G , A_L , λ_Σ , K_L and K_G .

Theorem 2: Suppose the previously given restrictions on the CFD bargaining problem for G and L all hold. Suppose, also, that the lowest possible strike price S^R is less than S^{R^} as defined in (3.31), and that the highest possible strike price S^U is greater than S^{U^*} as defined in (3.32). Then the Nash barter set B for the CFD bargaining problem for G and L is a non-empty, compact, convex subset of \mathfrak{R}^2 . Specifically, the barter set B is a compact right triangle when conditions (3.33) and (3.34) both hold (cf. fig. 3.3); the barter set B reduces to the no-contract threat point when inequality (3.34) does not hold (cf. fig. 3.4); and the barter set B is a compact right triangle when (3.33) does not hold but (3.34) holds (cf. fig. 3.5).*

$$\begin{aligned} S^{R^*} = \min & \left(\frac{E(\lambda_\Sigma) + A_G CVaR(\lambda_\Sigma) + (1 + A_G)K_G}{T(1 + A_G)}, \right. \\ & \frac{E(\lambda_\Sigma) - A_G CVaR(-\lambda_\Sigma) + (1 + A_G)K_G}{T(1 + A_G)}, \\ & \left. \frac{E(\lambda_\Sigma) + (1 + A_L)K_L - A_L CVaR(-\lambda_\Sigma)}{T(1 + A_L)} \right) \end{aligned} \quad (3.31)$$

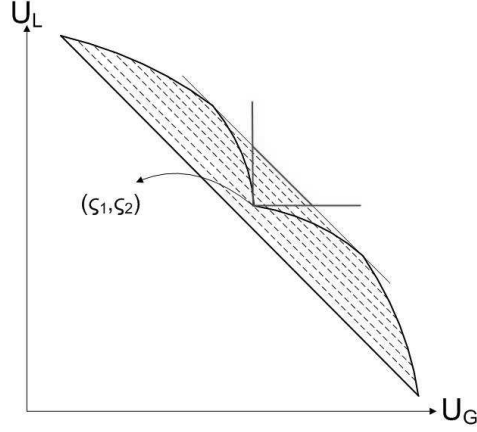


Figure 3.3 Type 1 utility possibility set U and barter set B for GenCo G and LSE L . The barter set is a right triangle

$$S^{U^*} = \max\left(\frac{E(\lambda_\Sigma) + A_G CVaR(\lambda_\Sigma) + (1 + A_G)K_G}{T(1 + A_G)}, \frac{E(\lambda_\Sigma) - A_G CVaR(-\lambda_\Sigma) + (1 + A_G)K_G}{T(1 + A_G)}, \frac{E(\lambda_\Sigma) + (1 + A_L)K_L + A_L CVaR(\lambda_\Sigma)}{T(1 + A_L)}\right) \quad (3.32)$$

$$\frac{dCVaR_\alpha^L(-\pi_L(M, S^L))}{dM} \Big|_{M=M^U} > \frac{A_G - A_L}{A_L[1 + A_G]} E^P(\lambda_\Sigma) - \frac{A_G[1 + A_L]}{A_L[1 + A_G]} CVaR_\alpha^P(\lambda_\Sigma) + \frac{1}{A_L} K_L - \frac{1 + A_L}{A_L} K_G + TS \quad (3.33)$$

$$\frac{dCVaR_\alpha^L(-\pi_L(M, S^L))}{dM} \Big|_{M=0} < \frac{A_G - A_L}{A_L[1 + A_G]} E^P(\lambda_\Sigma) + \frac{A_G[1 + A_L]}{A_L[1 + A_G]} CVaR_\alpha^P(-\lambda_\Sigma) + \frac{1}{A_L} K_L - \frac{1 + A_L}{A_L} K_G + TS \quad (3.34)$$

3.7 Computational Experiments

3.7.1 Five-Bus Test Case and Experimental Design

This section reports on computational CFD bargaining experiments conducted using a modified version of the benchmark five-bus test case presented in [81]. As depicted in Fig 3.6,

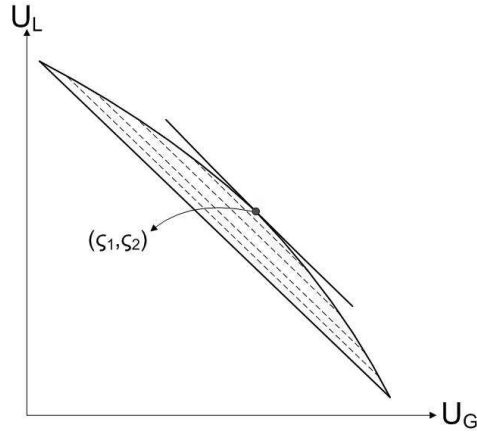


Figure 3.4 Type 2 utility possibility set U and barter set B for GenCo G and LSE L . The barter set reduces to the non-contract threat point

the key changes are the addition of a GenCo G_6 at Bus 3 that owns and operates a nuclear power plant at Bus 3, and a more detailed modeling of LSE 2 at Bus 3.

More precisely, G_6 is assumed to have the characteristics of the profit-seeking risk-averse GenCo G described in Section 3.5.1, and LSE 2 is assumed to have the characteristics of the profit-seeking risk-averse LSE L described in Section 3.5.2. To hedge their price risk at Bus 3, G_6 and LSE 2 enter into a negotiation process for a CFD. As in Section 3.6.2, this CFD negotiation process is modeled as a Nash bargaining problem, and outcomes are obtained via a Nash bargaining solution as in (3.30).

The two types of experiments reported below examine how the outcomes of this CFD bargaining problem are affected by systematic variations in structural conditions. The first set of experiments investigates the effects of absolute and relative changes in the risk-aversion factors A_G and A_L for G_6 and LSE 2, assuming zero price bias. The second set of experiments investigates the effects of absolute and relative changes in the price bias factors K_G and K_L affecting the estimates formed by G_6 and LSE 2 for λ_Σ , the sum of LMPs at Bus 3 during the CFD contract period, conditional on particular risk aversion settings. For simplicity, these price bias factors are assumed to be proportional to λ_Σ .

As in Section 3.5.1, G_6 's nuclear power plant is assumed to have a quadratic *total variable*

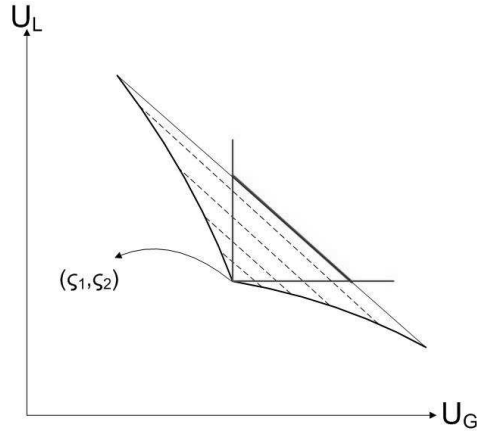


Figure 3.5 Type 3 utility possibility set U and barter set B for GenCo G and LSE L . The barter set is a right triangle

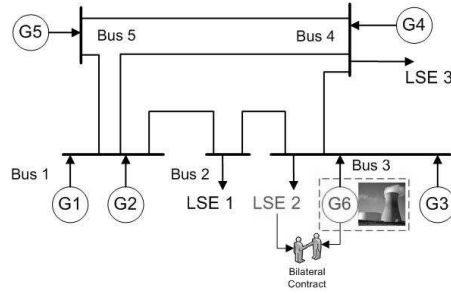


Figure 3.6 Five-bus test case used for computational experiments

cost (TVC) function given by (3.5). The parameters characterizing this TVC function are set as follows: $b = 0.005$ and $a = 10.0$. G_6 's fixed output P_G is set at 300 MW/h. The regulated retail resale rate f for LSE 2 is set at \$25/MWh. Also, the confidence level α for all CVaR evaluations for both GenCo G_6 and LSE 2 is set at 0.95. All line capacities, reactances, and cost and capacity data for GenCos G_1 through G_5 are set as in the benchmark five-bus test case from [81].

The CFD contract period for G_6 and LSE 2 is assumed to be one month, "June." The "true" daily average load during this month was generated via a truncated multivariate normal distribution. To make the case study more realistic, the parameters for the mean vector and covariance matrix for this distribution were estimated from MISO load data for June 2006 [82]. The daily average load and load autocorrelation function used for sample generation are

Table 3.1 Daily average load for the five-bus test case during the contract month (“June”)

| | | | | |
|-----------|-----------|-----------|-----------|-----------|
| June 1 | June 2 | June 3 | June 4 | June 5 |
| 337.01 MW | 319.10 MW | 285.94 MW | 268.12 MW | 318.61 MW |
| June 6 | June 7 | June 8 | June 9 | June 10 |
| 329.53 MW | 335.84 MW | 336.94 MW | 316.81 MW | 270.06 MW |
| June 11 | June 12 | June 13 | June 14 | June 15 |
| 250.76 MW | 297.36 MW | 310.81 MW | 322.45 MW | 338.52 MW |
| June 16 | June 17 | June 18 | June 19 | June 20 |
| 360.43 MW | 341.99 MW | 312.55 MW | 351.49 MW | 349.64 MW |
| June 21 | June 22 | June 23 | June 24 | June 25 |
| 363.59 MW | 367.08 MW | 336.56 MW | 300.43 MW | 285.71 MW |
| June 26 | June 27 | June 28 | June 29 | June 30 |
| 329.89 MW | 335.36 MW | 336.34 MW | 337.69 MW | 336.93 MW |

provided in Tables 3.1 and 3.2. The variance of the daily average load was set at 834.5748 MW^2 . The hourly load was approximated by multiplying the daily total load by an hourly load weight factor equal to the load weight factor for the historical data.

Using the above modeling for hourly loads, 1000 sample paths were generated for hourly DC-OPF dispatch and LMP solutions for the day-ahead energy market over the contract month.³ To reduce the sample space and corresponding sample generation time and number of runs necessary for Monte Carlo simulation, recourse was made to an efficient stratified sampling technique, *Latin Hypercube Sampling (LHS)* [83].

Given each experimental treatment, i.e., each setting for (A_G, A_L, K_G, K_L) , these 1000 sample paths were used to formulate the return-risk utility functions (3.10) and (3.14) for G6 and LSE 2 as functions of the contract amount M and strike price S . The feasible negotiation ranges for M and S were set as follows:⁴ $M \in [0, 600]$, and $S \in [15, 25]$. The unique Nash bargaining outcomes for M and S were then determined.

³These sample paths are available upon request from N. Yu.

⁴As required by Theorem 2, it can be shown that the setting $S^R = 15$ is smaller than S^{R^*} in (3.31) and the setting $S^U = 25$ is greater than S^{U^*} in (3.32) for each tested configuration for (A_G, A_L, K_G, K_L) .

Table 3.2 Autocorrelation function for daily average load for the five-bus test case during the contract month (“June”)

| | | | | | |
|----------|----------|----------|----------|----------|----------|
| Lag 0 | Lag 1 | Lag 2 | Lag 3 | Lag 4 | Lag 5 |
| 1.00000 | 0.68366 | 0.22233 | -0.09257 | -0.16865 | -0.04008 |
| Lag 6 | Lag 7 | Lag 8 | Lag 9 | Lag 10 | Lag 11 |
| 0.18943 | 0.36306 | 0.28063 | 0.12285 | 0.00094 | -0.05240 |
| Lag 12 | Lag 13 | Lag 14 | Lag 15 | Lag 16 | Lag 17 |
| -0.05279 | -0.03001 | -0.00707 | 0.00596 | 0.00903 | 0.00644 |
| Lag 18 | Lag 19 | Lag 20 | Lag 21 | Lag 22 | Lag 23 |
| 0.00251 | -0.00028 | -0.00137 | -0.00125 | -0.00065 | -0.00011 |
| Lag 24 | Lag 25 | Lag 26 | Lag 27 | Lag 28 | Lag 29 |
| 0.00017 | 0.00022 | 0.00015 | 0.00005 | -0.00001 | -0.00004 |

3.7.2 Experimental Findings

3.7.2.1 Risk-Aversion Treatment

This section examines the effects of changes in the risk-aversion factors A_G and A_L assuming zero price bias ($K_G = K_L = 0$).

Table 3.3 Effects of risk-aversion factors on the contract amount M and strike price S determined through Nash bargaining

| $A_G \backslash A_L$ | 0.5 | 1 | 2 |
|----------------------|-------------------------|-------------------------|-------------------------|
| 0.5 | \$19.84/MWh 300.0 MW | \$19.93/MWh 284.4 MW | \$20.02/MWh 271.0 MW |
| 1 | \$19.74/MWh 300.0 MW | \$19.81/MWh 300.0 MW | \$19.88/MWh 291.8 MW |
| 2 | \$19.64/MWh 300.0 MW | \$19.71/MWh 300.0 MW | \$19.77/MWh 300.0 MW |

Table 3.3 reports the Nash bargaining outcomes for the contract amount M and strike price S as A_G and A_L are systematically varied from 0.5 to 2.0. Moving from top to bottom in each column of Table 3.3, the negotiated strike price S systematically decreases as A_G 's risk-aversion factor A_G is increased, holding fixed the risk-aversion factor A_L for LSE 2. Conversely, moving

from left to right in each row, the negotiated strike price S systematically increases as LSE 2's risk-aversion factor A_L is increased, holding fixed the risk-aversion factor A_G for G6.

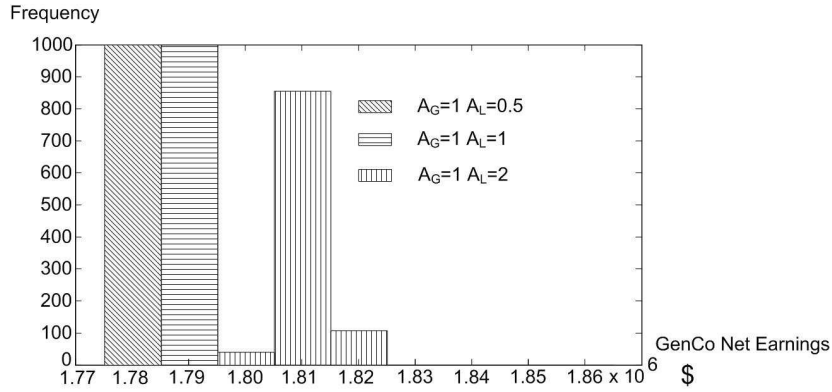


Figure 3.7 GenCo net earnings histogram given a fixed GenCo risk-aversion factor $A_G = 1$ and varying values for the LSE risk-aversion factor A_L

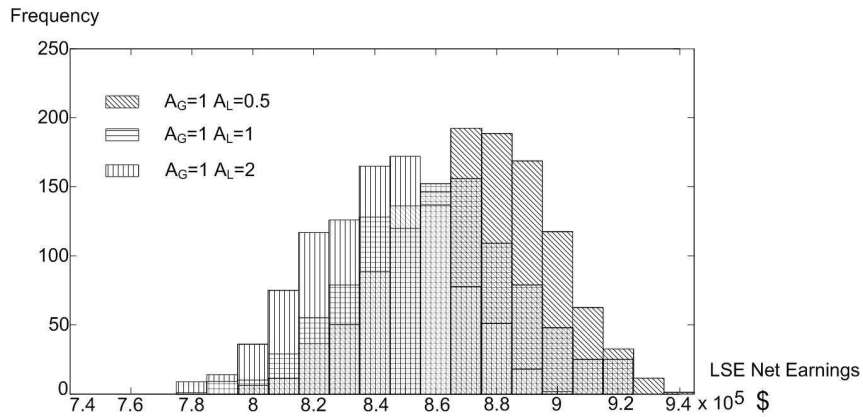


Figure 3.8 LSE net earnings histogram given a fixed GenCo risk-aversion factor $A_G = 1$ and varying values for the LSE risk-aversion factor A_L

In summary, all else equal, as each trader becomes more risk averse the negotiated strike price moves in a direction that favors the other trader. Interestingly, the negotiated outcomes for both M and S are seen to depend on the absolute levels as well as on the relative levels of the risk-aversion factors A_G and A_L .

Figs.3.7 and 3.8 display the effects of changes in the risk-aversion factor A_L for LSE 2

on the post-contract net earnings histograms for G6 and LSE 2, respectively, assuming the risk-aversion factor A_G for G6 is fixed at 1.0. As LSE 2 becomes more risk averse, its net earnings histogram shifts to the left, an unfavorable shift for LSE 2. On the other hand, the net earnings histogram for G6 shifts to the right, a favorable shift for G6. These net earnings findings provide additional support for the conclusion previously drawn from the more aggregated findings reported in Table 3.3: namely, an increase in risk aversion for one party to the CFD bargaining process, all else equal, results in a worse outcome for this party and a more favorable outcome for the other party.

3.7.2.2 LMP Bias Treatment

Experiments were conducted to determine the effects of changes in the price bias factors K_G and K_L for each risk-aversion treatment (A_G, A_L) in Table 3.3. Due to space limitations, only the price bias results for $A_G = A_L = 1$ are reported below.⁵

Table 3.4 Effects of biases in LMP estimates on the contract amount M and strike price S determined through Nash bargaining

| $K_L \backslash K_G$ | $-0.01E(\lambda_\Sigma)$ | 0 | $0.01E(\lambda_\Sigma)$ |
|--------------------------|--------------------------|-------------------------|-------------------------|
| $-0.01E(\lambda_\Sigma)$ | \$19.60/MWh 300.0 MW | \$19.73/MWh 282.8 MW | \$19.85/MWh 263.4 MW |
| 0 | \$19.71/MWh 300.0 MW | \$19.81/MWh 300.0 MW | \$19.93/MWh 284.4 MW |
| $0.01E(\lambda_\Sigma)$ | \$19.81/MWh 300.0 MW | \$19.91/MWh 300.0 MW | \$20.01/MWh 300.0 MW |

Table 3.4 reports Nash bargaining outcomes for the contract amount M and strike price S as the price bias factors K_G and K_L are each systematically varied from $-0.01E(\lambda_\Sigma)$ to $0.01E(\lambda_\Sigma)$. The no-bias case $K_G = K_L = 0$ provides a useful benchmark of comparison. Relative to this benchmark, if LSE 2 underestimates λ_Σ , then the strike price S decreases; and if LSE overestimates λ_Σ , then S increases. Conversely, relative to this benchmark, if G6

⁵The price bias results for the other risk-aversion treatments are qualitatively similar.

underestimates λ_Σ , then S decreases; and if G6 overestimates λ_Σ , then S increases.

Also, moving from the lower-left to the upper-right cell of Table 3.4—that is, letting K_G increase and K_L decrease together—the contract amount M is seen to systematically decrease.

Additional simulations were also conducted to search for combinations of the normalized price-bias factors $K_G/E(\lambda_\Sigma)$ and $K_L/E(\lambda_\Sigma)$ such that the negotiated contract amount M was zero, implying a no-contract outcome. These no-contract regions are depicted in fig. 3.9 for three alternative specifications for the risk-aversion factors. As seen, for each risk-aversion case the boundary of the no-contract region in the $(K_L/E(\lambda_\Sigma), K_G/E(\lambda_\Sigma))$ plane is a line and the no-contract region is the half-plane bounded below by this no-contract line. An important observation from fig. 3.9 is that the no-contract region shrinks in size as the traders become more risk averse.

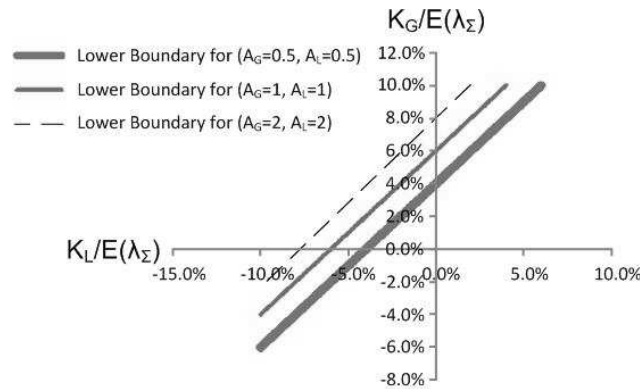


Figure 3.9 Lower boundary for the no-contract region in the plane of possible normalized price biases $(K_L/E(\lambda_\Sigma), K_G/E(\lambda_\Sigma))$ under three alternative combinations of the risk-aversion factors (A_L, A_G)

3.8 Summary

This study analyzes Nash bargaining settlement outcomes for a contract-for-difference (CFD) negotiation between a GenCo and an LSE facing price risk from uncertain LMP out-

comes at a common bus location. Using both analysis and computational experiments, it is shown that differing levels of risk aversion and biases in LMP estimations have systematic effects on the negotiated contract amount and strike price, hence also on the post-contract net earnings distributions for the GenCo and LSE. In addition, the circumstances in which the two parties fail to reach an agreement is identified. These results could be used by market participants in practice to aid their understanding of factors determining outcomes in bilateral negotiation processes.

Future studies will consider more general contract negotiation problems involving both financial and physical energy contracts between wholesale power market traders located at possibly different buses. In this case full hedging of price risk can require traders to combine CFDs with additional instruments, such as financial transmission rights, to take into account LMP separation across buses due to transmission congestion.

CHAPTER 4. CONCLUSION

4.1 Summary Assessment of Dissertation Contributions

This dissertation addresses two challenging issues related to wholesale power markets. The first issue is the development of software platforms permitting the systematic experimental study of power market performance. The second issue is how GenCos might best undertake short-run financial risk management in restructured wholesale power markets operating under LMP.

Chapter 2 discusses in some detail the collaborative development of a systematic methodology and software platform capable of evaluating new market designs from both engineering and economic points of views. The software platform consists of a software implementation of a multi-agent system on an agent-oriented middleware, known as the *Java Agent Development Framework (JADE)*. This platform fully complies with *Foundation for Intelligent Physical Agents (FIPA)* standards and also allows extensions that facilitate the development of complete agent-based applications.

As a case study, this software platform is used to study the market power mitigation (MPM) rule implemented by CAISO, based on a similar rule used by PJM. The effectiveness of this MPM rule is evaluated in the context of a realistic 225-bus WECC system with real heat rate data and hourly time-varying load data and with strategic GenCos who have learning capabilities permitting them to adaptively adjust their supply offers in a changing market environment. In particular, an anticipatory reinforcement learning algorithm, Q-learning, is used to model the supply offer behaviors of the GenCos. The simulation results provide insights into how well the MPM rule is able to suppress implicit price collusion among pivotal GenCos with market power.

Chapter 3 proposed a four-stage process to manage financial risk in wholesale electric power markets. The specific tools and techniques needed in the four-stage process are carefully discussed. This integrated and unified financial risk management framework can facilitate GenCos and LSEs in their decision making with regard to day-ahead energy market trading, Financial Transmission Rights (FTRs) auction participation, and bilateral contract negotiations.

The proposed financial risk management framework is utilized to analyze the financial bilateral contract negotiation process between a GenCo and a LSE in a wholesale electric power market with congestion managed by LMP. Nash bargaining theory is used to model a Pareto-efficient settlement point. The model predicts negotiation results under varied conditions and identifies circumstances in which the two parties might fail to reach an agreement. Both analysis and simulation are used to gain insight regarding how relative risk aversion and biased price estimates influence negotiated outcomes. The results derived from this study provide useful guidance to market participants in their bilateral contract negotiation processes.

4.2 Limitations of the Proposed Methods and Further Research Directions

The limitations of the proposed methods and the potential research directions that they point to are as follows.

In Chapter 2, the Q-learning algorithm that is tailored to model the generation unit's bidding strategies can only be applied to GenCo agents that own one generation plant. In the future, coordinated learning schemes and decision strategies need to be developed for GenCos agents that own multiple generation plants. In addition, the systematic methodology and simulation platform presented in Chapter 2 is not only capable of evaluating market designs at wholesale level but also analyzing market design issues at retail level. The lack of demand-side participation in the electric power markets and the resulting market inefficiency clearly calls for further research on retail market designs and its integration with wholesale electric power market.

In Chapter 3, the financial bilateral contract negotiation problem is restricted to the case where the GenCo and LSE are located at the same bus and facing the same price risk. The

bilateral contract negotiation problem illustrated in Chapter 3 can be extended to consider not only financial but also physical bilateral contracts between market participants that are located at possibly different buses in the power system network. In this case full hedging of price risk can require traders to combine CFDs with additional instruments, such as financial transmission rights, to take into account LMP separation across buses due to transmission congestion. In addition, the supply offer strategies of the GenCo and its opponents in the day-ahead energy market could be incorporated into the negotiation problem framework. Another extension would be to study a contract negotiation process among multiple GenCos and LSEs.

APPENDIX A. Proof of Theorem 1 in Section 3.5.3

The proof of Theorem 1 follows directly from the proofs for Propositions 1–3, below.

Proposition 1: The expected values for λ_Σ derived under the three probability measures P , Q_G , and Q_L satisfy (3.22) and (3.24).

Proof of Proposition 1: The expected value of λ_Σ derived under Q_G (with pdf f_{Q_G}) is given by

$$\begin{aligned} E^G(\lambda_\Sigma) &= \int_{-\infty}^{+\infty} \lambda_\Sigma f_{Q_G}(\lambda_\Sigma) d\lambda_\Sigma \\ &= \int_{-\infty}^{+\infty} \lambda_\Sigma f_P(\lambda_\Sigma - K_G) d\lambda_\Sigma \end{aligned} \quad (\text{A.1})$$

Introducing the change of variables $\lambda'_\Sigma = \lambda_\Sigma - K_G$,

$$\begin{aligned} E^G(\lambda_\Sigma) &= \int_{-\infty}^{+\infty} (\lambda'_\Sigma + K_G) f_P(\lambda'_\Sigma) d\lambda'_\Sigma \\ &= \int_{-\infty}^{+\infty} \lambda'_\Sigma f_P(\lambda'_\Sigma) d\lambda'_\Sigma + K_G \int_{-\infty}^{+\infty} f_P(\lambda'_\Sigma) d\lambda'_\Sigma \\ &= E^P(\lambda_\Sigma) + K_G \end{aligned} \quad (\text{A.2})$$

It can similarly be shown that $E^L(\lambda_\Sigma) = E^P(\lambda_\Sigma) + K_L$. QED

Proposition 2: The VaR values for λ_Σ derived under P , Q_G , and Q_L satisfy

$$\text{VaR}_\alpha^G(\lambda_\Sigma - K_G) = \text{VaR}_\alpha^P(\lambda_\Sigma) \quad (\text{A.3})$$

$$\text{VaR}_\alpha^L(\lambda_\Sigma - K_L) = \text{VaR}_\alpha^P(\lambda_\Sigma) \quad (\text{A.4})$$

Proof of Proposition 2: $\text{VaR}_\alpha^G(\lambda_\Sigma)$ and $\text{VaR}_\alpha^P(\lambda_\Sigma)$ are defined as follows:

$$\begin{aligned} \text{VaR}_\alpha^G(\lambda_\Sigma) &\equiv \inf\{\Lambda \in \mathfrak{R} : Q_G(\lambda_\Sigma > \Lambda) \leq 1 - \alpha\} \\ &= \inf\{\Lambda \in \mathfrak{R} : \int_{\Lambda}^{+\infty} f_{Q_G}(\lambda_\Sigma) d\lambda_\Sigma \leq 1 - \alpha\} \end{aligned} \quad (\text{A.5})$$

$$\begin{aligned}
VaR_\alpha^P(\lambda_\Sigma) &\equiv \inf\{\Lambda \in \mathfrak{R} : P(\lambda_\Sigma > \Lambda) \leq 1 - \alpha\} \\
&= \inf\{\Lambda \in \mathfrak{R} : \int_\Lambda^{+\infty} f_P(\lambda_\Sigma) d\lambda_\Sigma \leq 1 - \alpha\}
\end{aligned} \tag{A.6}$$

It follows from the definition of $VaR_\alpha^G(\lambda_\Sigma)$ that

$$\begin{aligned}
VaR_\alpha^G(\lambda_\Sigma - K_G) &= \inf\{\Lambda \in \mathfrak{R} : Q_G(\lambda_\Sigma - K_G > \Lambda) \leq 1 - \alpha\} \\
&= \inf\{\Lambda \in \mathfrak{R} : Q_G(\lambda_\Sigma > \Lambda + K_G) \leq 1 - \alpha\} \\
&= \inf\{\Lambda \in \mathfrak{R} : \int_{\Lambda+K_G}^{+\infty} f_{Q_G}(\lambda_\Sigma) d\lambda_\Sigma \leq 1 - \alpha\} \\
&= \inf\{\Lambda \in \mathfrak{R} : \int_{\Lambda+K_G}^{+\infty} f_P(\lambda_\Sigma - K_G) d\lambda_\Sigma \leq 1 - \alpha\}
\end{aligned} \tag{A.7}$$

Introducing the change of variables $\lambda'_\Sigma = \lambda_\Sigma - K_G$,

$$\begin{aligned}
VaR_\alpha^G(\lambda_\Sigma - K_G) &= \inf\{\Lambda \in \mathfrak{R} : \int_\Lambda^{+\infty} f_P(\lambda'_\Sigma) d\lambda'_\Sigma \leq 1 - \alpha\} \\
&= VaR_\alpha^P(\lambda_\Sigma)
\end{aligned} \tag{A.8}$$

It can similarly be shown that $VaR_\alpha^L(\lambda_\Sigma - K_L) = VaR_\alpha^P(\lambda_\Sigma)$. QED

Proposition 3: The CVaR values for λ_Σ derived under P , Q_G , and Q_L satisfy (3.23) and (3.25).

Proof of Proposition 3: Let Y denote any real-valued random variable measurable with respect to a probability space $(\Omega, \mathcal{F}, \mu)$. Let $\alpha \in (0, 1)$, and let A denote the measurable subset of points $\omega \in \Omega$ such that $Y(\omega) \geq VaR_\alpha^\mu(Y)$, which implies (by definition of VaR) that $\mu(A) = [1 - \alpha]$. Then $CVaR_\alpha^\mu(Y)$ is defined as follows:

$$CVaR_\alpha^\mu(Y) \equiv \frac{1}{1 - \alpha} \int_A Y d\mu(Y) \tag{A.9}$$

Recall that f_{Q_G} is the pdf corresponding to the probability measure Q_G . It follows that

$$\begin{aligned}
CVaR_\alpha^G(\lambda_\Sigma) &= \frac{1}{1 - \alpha} \int_{VaR_\alpha^G(\lambda_\Sigma)}^{+\infty} \lambda_\Sigma f_{Q_G}(\lambda_\Sigma) d\lambda_\Sigma \\
&= \frac{1}{1 - \alpha} \int_{VaR_\alpha^P(\lambda_\Sigma + K_G)}^{+\infty} \lambda_\Sigma f_P(\lambda_\Sigma - K_G) d\lambda_\Sigma
\end{aligned} \tag{A.10}$$

Introducing the change of variables $\lambda'_\Sigma = \lambda_\Sigma - K_G$,

$$\begin{aligned}
& CVaR_\alpha^G(\lambda_\Sigma) \\
&= \frac{1}{1-\alpha} \int_{VaR_\alpha^P(\lambda_\Sigma + K_G) - K_G}^{+\infty} (\lambda'_\Sigma + K_G) f_P(\lambda'_\Sigma) d\lambda'_\Sigma \\
&= \frac{1}{1-\alpha} \int_{VaR_\alpha^P(\lambda_\Sigma)}^{+\infty} \lambda'_\Sigma f_P(\lambda'_\Sigma) d\lambda'_\Sigma \\
&\quad + \frac{1}{1-\alpha} K_G \int_{VaR_\alpha^P(\lambda_\Sigma)}^{+\infty} f_P(\lambda'_\Sigma) d\lambda'_\Sigma \\
&= CVaR_\alpha^P(\lambda_\Sigma) + K_G
\end{aligned} \tag{A.11}$$

It can similarly be shown that $CVaR_\alpha^L(\lambda_\Sigma) = CVaR_\alpha^P(\lambda_\Sigma) + K_L$. QED

APPENDIX B. Proof of Theorem 2 in Section 3.6.2

This section provides a proof for Theorem 2 making use of four lemmas. For expositional simplicity, throughout this appendix the α subscripts on all VaR and CVaR expressions are omitted, as are the P -superscripts for all expectations, VaR, and CVaR expressions calculated using the true probability measure P .

Lemma 1: $CVaR^L(-\pi_L(M, S))$ is convex in M for any $S \in [S^R, S^U]$.

Proof of Lemma 1: Let $S \in [S^R, S^U]$ be given. To prove that $CVaR^L(-\pi_L(M, S))$ is convex in M , we need to show that, for arbitrary M_1, M_2 , and $0 < \lambda < 1$, the following inequality holds,

$$\begin{aligned} & CVaR^L(-\pi_L(\lambda M_1 + [1 - \lambda]M_2), S) \\ & \leq \lambda CVaR^L(-\pi_L(M_1, S)) + (1 - \lambda)CVaR^L(-\pi_L(M_2, S)) \end{aligned} \quad (B.1)$$

Using the convexity of CVaR we have,

$$\begin{aligned} \text{right} &= \lambda CVaR^L(-\pi_L^0 - M_1(\lambda_\Sigma - TS)) \\ & \quad + (1 - \lambda)CVaR^L(-\pi_L^0 - M_2(\lambda_\Sigma - TS)) \\ & \geq CVaR^L(-\lambda\pi_L^0 - \lambda M_1(\lambda_\Sigma - TS) \\ & \quad - (1 - \lambda)\pi_L^0 - (1 - \lambda)M_2(\lambda_\Sigma - TS)) \\ & = CVaR^L(-\pi_L^0 - [\lambda M_1 + (1 - \lambda)M_2](\lambda_\Sigma - TS)) \\ & = \text{left} \end{aligned} \quad (B.2)$$

QED

Lemma 2: Given any contract amount $M \in [M^R, M^U]$, varying the strike price S from S^R to S^U maps under (3.10) and (3.14) into a straight line in U with slope $-[1 + A_L]/[1 + A_G]$.

Proof of Lemma 2: Using (3.9) and (3.13), we have

$$\pi_G(M, S + \Delta S) - \pi_G(M, S) = TM\Delta S \quad (\text{B.3})$$

$$\pi_L(M, S + \Delta S) - \pi_L(M, S) = -TM\Delta S \quad (\text{B.4})$$

Taking expectations on each side of equations (B.3) and (B.4),

$$E^G \pi_G(M, S + \Delta S) - E^G \pi_G(M, S) = TM\Delta S \quad (\text{B.5})$$

$$E^L \pi_L(M, S + \Delta S) - E^L \pi_L(M, S) = -TM\Delta S \quad (\text{B.6})$$

It follows immediately from the definition of CVaR (see Lemma 3) that CVaR is translation-equivariant, i.e. $CVaR(Y + c) = CVaR(Y) + c$. Thus

$$\begin{aligned} CVaR^G(-\pi_G(M, S + \Delta S)) \\ &= CVaR^G(-\pi_G(M, S) - TM\Delta S) \\ &= CVaR^G(-\pi_G(M, S)) - TM\Delta S \end{aligned} \quad (\text{B.7})$$

Rearranging the terms in the above equation, we have

$$\begin{aligned} CVaR^G(-\pi_G(M, S + \Delta S)) - CVaR^G(-\pi_G(M, S)) \\ &= -TM\Delta S \end{aligned} \quad (\text{B.8})$$

Similarly, we have

$$\begin{aligned} CVaR^L(-\pi_L(M, S + \Delta S)) - CVaR^L(-\pi_L(M, S)) \\ &= TM\Delta S \end{aligned} \quad (\text{B.9})$$

The utility functions for GenCo G and LSE L are defined in (3.10) and (3.14). Using these definitions, together with relationships (B.5), (B.6), (B.8), and (B.9), we have

$$\begin{aligned} u_G(E^G(\pi_G(M, S + \Delta S)), CVaR^G(-\pi_G(M, S + \Delta S))) \\ - u_G(E^G(\pi_G(M, S)), CVaR^G(-\pi_G(M, S))) \\ &= TM\Delta S[1 + A_G] \end{aligned} \quad (\text{B.10})$$

and

$$\begin{aligned}
& u_L(E^L(\pi_L(M, S + \Delta S)), CVaR^L(-\pi_L(M, S + \Delta S))) \\
& \quad - u_L(E^L(\pi_L(M, S)), CVaR^L(-\pi_L(M, S))) \\
& \quad \quad = -TM\Delta S[1 + A_L]
\end{aligned} \tag{B.11}$$

It follows that

$$\frac{du_G}{dS} = TM[1 + A_G] \tag{B.12}$$

$$\frac{du_L}{dS} = -TM[1 + A_L] \tag{B.13}$$

Integrating both sides of equations (B.12) and (B.13) with respect to S, we have

$$u_G + C_1 = TM[1 + A_G]S + C_2 \tag{B.14}$$

$$u_L + C_3 = -TM[1 + A_L]S + C_4 \tag{B.15}$$

Multiply equations (B.14) and (B.15) by $[1 + A_L]$ and $[1 + A_G]$, respectively, and add the resulting expressions. After rearranging terms,

$$\begin{aligned}
& [1 + A_L]u_G + [1 + A_G]u_L \\
& = -[1 + A_L]C_1 + [1 + A_L]C_2 - [1 + A_G]C_3 + [1 + A_G]C_4
\end{aligned} \tag{B.16}$$

Totally differentiating this expression, it follows that

$$\frac{du_L}{du_G} = -\frac{1 + A_L}{1 + A_G} \tag{B.17}$$

QED

Lemma 3: With the strike price fixed at the lowest possible level, S^R , the contract amount interval from M^R to M^U maps under (3.10) and (3.14) into a concave curve in the utility possibility set U .

Proof of Lemma 3: Using (3.9),

$$\begin{aligned}
& E^G \pi_G(M + \Delta M, S) - E^G \pi_G(M, S) \\
&= \Delta M [TS - E^G(\lambda_\Sigma)] \\
&= \Delta M [TS - E(\lambda_\Sigma)] - \Delta M K_G \\
&\equiv -\Delta\delta - \Delta M K_G
\end{aligned} \tag{B.18}$$

Similarly,

$$\begin{aligned}
& E^L \pi_L(M + \Delta M, S) - E^L \pi_L(M, S) \\
&= \Delta M [E^L(\lambda_\Sigma) - TS] \\
&= \Delta M [E(\lambda_\Sigma) - TS] + \Delta M K_L \\
&= \Delta\delta + \Delta M K_L
\end{aligned} \tag{B.19}$$

The rest of the proof will be divided into two cases that cover all possibilities.

Case 1: $M > P_G$

$$\begin{aligned}
& CVaR^G(-\pi_G(M, S)) \\
&= CVaR^G(-P_G \lambda_\Sigma + COST - M[TS - \lambda_\Sigma]) \\
&= CVaR^G((M - P_G)\lambda_\Sigma + COST - TM S) \\
&= (M - P_G)CVaR^G(\lambda_\Sigma) + COST - TM S
\end{aligned} \tag{B.20}$$

Therefore, we have

$$\begin{aligned}
& CVaR^G(-\pi_G(M + \Delta M, S)) - CVaR^G(-\pi_G(M, S)) \\
&= \Delta M CVaR^G(\lambda_\Sigma) - \Delta M TS \\
&= \Delta M [CVaR(\lambda_\Sigma) - TS] + \Delta M K_G \equiv \Delta\varepsilon_1 + \Delta M K_G
\end{aligned} \tag{B.21}$$

Now,

$$\begin{aligned}
& \Delta u_G \equiv \\
& u_G(E^G(\pi_G(M + \Delta M, S)), CVaR^G(-\pi_G(M + \Delta M, S))) \\
& \quad - u_G(E^G(\pi_G(M, S)), CVaR^G(-\pi_G(M, S))) \\
& \quad = -\Delta\delta - \Delta MK_G - A_G(\Delta\varepsilon_1 + \Delta MK_G)
\end{aligned} \tag{B.22}$$

Now calculate the (right) derivative of u_G with respect to M :

$$\begin{aligned}
\frac{du_G}{dM} &= \lim_{\Delta M \rightarrow 0^+} \frac{\Delta u_G}{\Delta M} \\
&= \lim_{\Delta M \rightarrow 0^+} \left\{ \frac{\Delta M [TS - E(\lambda_\Sigma) - K_G]}{\Delta M} \right. \\
& \quad \left. + \frac{-A_G \Delta M [CVaR(\lambda_\Sigma) + K_G - TS]}{\Delta M} \right\} \\
&= TS - E(\lambda_\Sigma) - K_G - A_G CVaR(\lambda_\Sigma) - A_G K_G + TA_G S
\end{aligned} \tag{B.23}$$

Integrate both sides of the above equation and rearrange the terms we have,

$$\begin{aligned}
u_G &= [TS - E(\lambda_\Sigma) - A_G CVaR(\lambda_\Sigma) \\
& \quad + TA_G S - (1 + A_G)K_G]M + C_5 \\
&= C_6 M + C_5
\end{aligned} \tag{B.24}$$

From (B.24), M can be viewed as a function of u_G . We can thus calculate the derivative of u_L with respect to u_G as follows:

$$\begin{aligned}
\frac{du_L}{du_G} &= \frac{du_L}{dM} \cdot \frac{dM}{du_G} \\
&= \left[\frac{dE^L(\pi_L(M, S))}{dM} - A_L \frac{dCVaR^L(-\pi_L(M, S))}{dM} \right] \frac{1}{C_6}
\end{aligned} \tag{B.25}$$

Taking the derivative of each side of (B.25) with respect to u_G , we have

$$\begin{aligned}
\frac{d^2 u_L}{du_G^2} &= \frac{1}{C_6} \left[\frac{d^2 E^L(\pi_L(M, S))}{dM^2} \frac{dM}{du_G} \right. \\
& \quad \left. - A_L \frac{d^2 CVaR^L(-\pi_L(M, S))}{dM^2} \frac{dM}{du_G} \right] \\
&= \frac{1}{C_6^2} \left[\frac{d^2 E^L(\pi_L(M, S))}{dM^2} \right. \\
& \quad \left. - A_L \frac{d^2 CVaR^L(-\pi_L(M, S))}{dM^2} \right]
\end{aligned} \tag{B.26}$$

Taking the expectation and then the derivative with respect to M on each side of equation (3.11), we get

$$\frac{dE^L(\pi_L(M, S))}{dM} = E(\lambda_\Sigma) + K_L - TS \quad (\text{B.27})$$

Then obviously we have

$$\frac{d^2E^L(\pi_L(M, S))}{dM^2} = 0 \quad (\text{B.28})$$

Now equation (B.26) can be reduced to the following:

$$\frac{d^2u_L}{du_G^2} = -A_L \frac{1}{C_6^2} \frac{d^2CVaR^L(-\pi_L(M, S))}{dM^2} \quad (\text{B.29})$$

As shown in Lemma 1, $CVaR^L(-\pi_L(M, S))$ is convex in M . Consequently,

$$\frac{d^2CVaR^L(-\pi_L(M, S))}{dM^2} \geq 0 \quad (\text{B.30})$$

It follows that

$$\frac{d^2u_L}{du_G^2} = -A_L \frac{1}{C_6^2} \frac{d^2CVaR(-\pi_L(M, S))}{dM^2} \leq 0 \quad (\text{B.31})$$

Therefore, for Case 1 the curve of points (u_G, u_L) traced out in U space as M varies from M^R to M^U is concave.

Case 2: $M \leq P_G$

$$\begin{aligned} & CVaR^G(-\pi_G(M, S)) \\ &= CVaR^G(-P_G\lambda_\Sigma + COST - M(TS - \lambda_\Sigma)) \\ &= CVaR^G(-\lambda_\Sigma(P_G - M) + COST - TM S) \\ &= (P_G - M)CVaR^G(-\lambda_\Sigma) + COST - TM S \end{aligned} \quad (\text{B.32})$$

Therefore, we have

$$\begin{aligned} & CVaR^G(-\pi_G(M + \Delta M, S)) - CVaR^G(-\pi_G(M, S)) \\ &= -\Delta M CVaR^G(-\lambda_\Sigma) - \Delta M TS \\ &= -\Delta M [CVaR(-\lambda_\Sigma) + TS] + \Delta M K_G \\ &\equiv \Delta \varepsilon_2 + \Delta M K_G \end{aligned} \quad (\text{B.33})$$

Now,

$$\begin{aligned}
\Delta u_G &\equiv \\
&u_G(E^G(\pi_G(M + \Delta M, S)), CVaR^G(-\pi_G(M + \Delta M, S))) \\
&\quad - u_G(E^G(\pi_G(M, S)), CVaR^G(-\pi_G(M, S))) \\
&= -\Delta\delta - \Delta MK_G - A_G(\Delta\varepsilon_2 + \Delta MK_G)
\end{aligned} \tag{B.34}$$

Now calculate the (right) derivative of u_G with respect to M .

$$\begin{aligned}
\frac{du_G}{dM} &= \lim_{\Delta M \rightarrow 0^+} \frac{\Delta u_G}{\Delta M} \\
&= \lim_{\Delta M \rightarrow 0^+} \left\{ \frac{\Delta M [TS - E(\lambda_\Sigma) - K_G]}{\Delta M} \right. \\
&\quad \left. + \frac{A_G \Delta M [CVaR(-\lambda_\Sigma - K_G) + TS]}{\Delta M} \right\} \\
&= TS - E(\lambda_\Sigma) + A_G CVaR(-\lambda_\Sigma) + TA_G S - (1 + A_G)K_G
\end{aligned} \tag{B.35}$$

Integrate both sides of the above equation and rearrange the terms we have,

$$\begin{aligned}
u_G &= [TS - E(\lambda_\Sigma) + A_G CVaR(-\lambda_\Sigma) \\
&\quad + TA_G S - (1 + A_G)K_G]M + C_7 \\
&= C_8 M + C_7
\end{aligned} \tag{B.36}$$

Similar to the derivation in Case 1, the second derivative of u_L with respect to u_G can be calculated as

$$\frac{d^2 u_L}{du_G^2} = -A_L \frac{1}{C_8^2} \frac{d^2 CVaR^L(-\pi_L(M, S))}{dM^2} \tag{B.37}$$

Given the inequality relationship in (B.30), we have

$$\frac{d^2 u_L}{du_G^2} = -A_L \frac{1}{C_8^2} \frac{d^2 CVaR^L(-\pi_L(M, S))}{dM^2} \leq 0 \tag{B.38}$$

Therefore, for Case 2 the curve of points (u_G, u_L) traced out in U space as M varies from M^R to M^U is once again concave. QED

Before moving onto Lemma 4, additional derivations are provided with regard to Δu_L , which will be used in the following Lemma.

As is well known, $CVaR$ is convex in the following sense: For arbitrary (possibly dependent) random variables Y_1, Y_2 and λ with $0 < \lambda < 1$, $CVaR(\lambda Y_1 + (1 - \lambda)Y_2) \leq \lambda CVaR(Y_1) + (1 - \lambda)CVaR(Y_2)$. Hence we have,

$$\begin{aligned}
& CVaR^L(-\pi_L(M, S)) - \Delta\varepsilon_2 - \Delta MK_L \\
&= CVaR^L(-\pi_L^0 - M(\lambda_\Sigma - TS)) \\
&\quad + \Delta M(CVaR(-\lambda_\Sigma - K_L) + TS) \\
&= CVaR^L(-\pi_L^0 - M(\lambda_\Sigma - TS)) \\
&\quad + CVaR^L(-\lambda_\Sigma \Delta M + TS \Delta M) \\
&= 2\left\{ \frac{1}{2} CVaR^L(-\pi_L^0 - M(\lambda_\Sigma - TS)) \right. \\
&\quad \left. + \frac{1}{2} CVaR^L(-\lambda_\Sigma \Delta M + TS \Delta M) \right\} \\
&\geq 2\left[CVaR^L\left(\frac{1}{2}(-\pi_L^0 - M(\lambda_\Sigma - TS))\right) \right. \\
&\quad \left. + \frac{1}{2}(-\lambda_\Sigma \Delta M + TS \Delta M) \right] \\
&= CVaR^L(-\pi_L^0 - (M + \Delta M)(\lambda_\Sigma - TS)) \\
&= CVaR^L(-\pi_L(M + \Delta M, S)) \tag{B.39}
\end{aligned}$$

Rearranging the terms in the above equation, we have

$$\begin{aligned}
& CVaR^L(-\pi_L(M + \Delta M, S)) - CVaR^L(-\pi_L(M, S)) \\
&\quad + \Delta MK_L \equiv -\Delta\varepsilon'_2 + \Delta MK_L \\
&\leq -\Delta\varepsilon_2 = \Delta M[CVaR(-\lambda_\Sigma) + TS] \tag{B.40}
\end{aligned}$$

Hence, Δu_L can be derived as,

$$\begin{aligned}
& \Delta u_L \equiv \\
& u_L(E^L(\pi_L(M + \Delta M, S)), CVaR^L(-\pi_L(M + \Delta M, S))) \\
& \quad - u_L(E^L(\pi_L(M, S)), CVaR^L(-\pi_L(M, S))) \\
& = \Delta\delta + \Delta MK_L + A_L \Delta\varepsilon'_2 \tag{B.41}
\end{aligned}$$

Similar to inequality (B.39) we have,

$$\begin{aligned}
& CVaR^L(-\pi_L(M + \Delta M, S)) + \Delta\varepsilon_1 + \Delta MK_L \\
&= CVaR^L(-\pi_L(M + \Delta M, S)) \\
&\quad + [CVaR(\lambda_\Sigma) + K_L - TS]\Delta M \\
&= 2\left\{ \frac{1}{2}CVaR^L(-\pi_L(M + \Delta M, S)) \right. \\
&\quad \left. + \frac{1}{2}CVaR^L(\Delta M(\lambda_\Sigma - TS)) \right\} \\
&\geq 2CVaR^L\left(\frac{1}{2}(-\pi_L^0 - (M + \Delta M)(\lambda_\Sigma - TS)) \right. \\
&\quad \left. + \Delta M\lambda_\Sigma - TS\Delta M\right) \\
&= CVaR^L(-\pi_L^0 - M(\lambda_\Sigma - TS)) \\
&= CVaR^L(-\pi_L(M, S))
\end{aligned} \tag{B.42}$$

Rearranging the terms in the above equation, we have

$$\begin{aligned}
& CVaR^L(-\pi_L(M + \Delta M, S)) - CVaR^L(-\pi_L(M, S)) \\
&\quad + \Delta MK_L \equiv -\Delta\varepsilon'_1 + \Delta MK_L \\
&\geq -\Delta\varepsilon_1 = -\Delta M[CVaR(\lambda_\Sigma) - TS]
\end{aligned} \tag{B.43}$$

Hence, Δu_L can be derived as,

$$\begin{aligned}
& \Delta u_L \equiv \\
& u_L(E^L(\pi_L(M + \Delta M, S)), CVaR^L(-\pi_L(M + \Delta M, S))) \\
& \quad - u_L(E^L(\pi_L(M, S)), CVaR^L(-\pi_L(M, S))) \\
& = \Delta\delta + \Delta MK_L + A_L\Delta\varepsilon'_1
\end{aligned} \tag{B.44}$$

Lemma 4: If S^R is less than S^{R} as defined in (3.31), then with the strike price fixed at S^R , as the contract amount M increases, u_G decreases and u_L increases. If S^U is greater than S^{U*} as defined in (3.32), then with the strike price fixed at S^U , as the contract amount M increases, u_G increases and u_L decreases.*

Proof of Lemma 4:

Part 1: Proof that if S^R is less than S^{R^*} as defined in (3.31), then with the strike price fixed at S^R , as the contract amount M increases, u_G decreases and u_L increases.

As shown in equation (B.41), $\Delta u_L = \Delta\delta + \Delta MK_L + A_L\Delta\varepsilon'_2$. As given in equation (B), $\Delta\varepsilon'_2 \geq \Delta\varepsilon_2 + \Delta MK_L$. Hence, we have

$$\Delta u_L \geq \Delta\delta + \Delta MK_L + A_L(\Delta\varepsilon_2 + \Delta MK_L) \quad (\text{B.45})$$

After substituting $\Delta\delta$ and $\Delta\varepsilon_2$ into the above equation, we see that inequality (B.45) is equivalent to

$$\begin{aligned} \Delta u_L \geq & \Delta M [E(\lambda_\Sigma) - \\ & TS^R + K_L - A_L CVaR(-\lambda_\Sigma) - A_L TS^R + A_L K_L] \end{aligned} \quad (\text{B.46})$$

Since, S^R is less than $\frac{E(\lambda_\Sigma) + (1+A_L)K_L - A_L CVaR(-\lambda_\Sigma)}{T(1+A_L)}$, and $A_L > -1$, it can be shown that the right hand side of the above inequality is greater than 0.

Therefore, with the strike price fixed at S^R , as the contract amount M increases, u_L increases.

The rest of the proof will be divided into two cases that cover all possibilities.

Case 1: $M > P_G$

As shown in equation (B.24), $u_G = C_6 M + C_5$. Since $S^R < \frac{E(\lambda_\Sigma) + A_G CVaR(\lambda_\Sigma) + (1+A_G)K_G}{T(1+A_G)}$, and $A_G > -1$, $C_6 < 0$. Hence, in Case 1, with the strike price fixed at S^R , when M increases, u_G decreases.

Case 2: $M \leq P_G$

As shown in equation (B.36), $u_G = C_8 M + C_7$. Since $S^R < \frac{E(\lambda_\Sigma) - A_G CVaR(-\lambda_\Sigma) + (1+A_G)K_G}{T(1+A_G)}$, and $A_G > -1$, $C_8 < 0$. Hence, in case 2, with the strike price fixed at S^R , when M increases, u_G decreases.

Part 2: Proof that if S^U is greater than S^{U^*} as defined in (3.32), then with the strike price fixed at S^U , as the contract amount M increases, u_G increases and u_L

decreases.

As shown in equation (B.44), $\Delta\delta + \Delta MK_L + A_L\Delta\varepsilon'_1$. As given in equation (B), $\Delta\varepsilon'_1 \leq \Delta\varepsilon_1 + \Delta MK_L$. Hence, we have

$$\Delta u_L \leq \Delta\delta + \Delta MK_L + A_L(\Delta\varepsilon_1 + \Delta MK_L) \quad (\text{B.47})$$

After substituting $\Delta\delta$ and $\Delta\varepsilon_1$ into the above equation, we see that inequality (B.47) is equivalent to

$$\begin{aligned} \Delta u_L \leq \Delta M [E(\lambda_\Sigma) - \\ TS^U + K_L + A_L CVaR(\lambda_\Sigma) - A_L TS^U + A_L K_L] \end{aligned} \quad (\text{B.48})$$

Since, S^U is greater than $\frac{E(\lambda_\Sigma) + (1+A_L)K_L + A_L CVaR(\lambda_\Sigma)}{T(1+A_L)}$, and $A_L > -1$, it can be shown that the right hand side of the above inequality is smaller than 0.

Therefore, with the strike price fixed at S^U , as the contract amount M increases, u_L decreases.

The rest of the proof will be divided into two cases that cover all possibilities.

Case 1: $M > P_G$

As shown in equation (B.24), $u_G = C_6 M + C_5$. Since $S^U > \frac{E(\lambda_\Sigma) + A_G CVaR(\lambda_\Sigma) + (1+A_G)K_G}{T(1+A_G)}$, and $A_G > -1$, $C_6 > 0$. Hence, in Case 1, with the strike price fixed at S^U , when M increases, u_G increases.

Case 2: $M \leq P_G$

As shown in equation (B.36), $u_G = C_8 M + C_7$. Since $S^R > \frac{E(\lambda_\Sigma) - A_G CVaR(-\lambda_\Sigma) + (1+A_G)K_G}{T(1+A_G)}$, and $A_G > -1$, $C_8 > 0$. Hence, in case 2, with the strike price fixed at S^U , when M increases, u_G increases.

QED

Lemma 5: Consider the following two conditions:

$$\frac{du_L(M, S^L)}{du_G(M, S^L)} \Big|_{M=0} < -\frac{1 + A_L}{1 + A_G} \quad (\text{B.49})$$

$$\frac{du_L(M, S^L)}{du_G(M, S^L)} \Big|_{M=M^U} > -\frac{1 + A_L}{1 + A_G} \quad (\text{B.50})$$

Inequality (B.50) is equivalent to inequality (3.33), and inequality (B.49) is equivalent to inequality (3.34).

Proof of Lemma 5:

Part 1: Proof that inequality (B.50) is equivalent to inequality (3.33)

Inequality (B.50) implies $M > P_G$. Substituting equation (B.27) into (B.25), we have

$$\frac{du_L}{du_G} = [E(\lambda_\Sigma) + K_L - TS - A_L \frac{dCVaR^L(-\pi_L(M, S))}{dM}] \frac{1}{C_6} \quad (\text{B.51})$$

After substituting C_6 into the above equation, we see that inequality (B.50) is equivalent to

$$\begin{aligned} & \frac{E(\lambda_\Sigma) + K_L - TS - A_L \frac{dCVaR^L(-\pi_L(M, S))}{dM}}{E(\lambda_\Sigma) - TS + A_G CVaR(\lambda_\Sigma) - TA_G S + (1 + A_G)K_G} \\ & > -\frac{1 + A_L}{1 + A_G} \end{aligned} \quad (\text{B.52})$$

Rearranging the terms in the above equation, we have

$$\begin{aligned} & \frac{du_L(M, S^L)}{du_G(M, S^L)} \Big|_{M=M^U} > -\frac{1 + A_L}{1 + A_G} \Leftrightarrow \\ & \frac{dCVaR^L(-\pi_L(M, S^L))}{dM} \Big|_{M=M^U} > \frac{A_G - A_L}{A_L(1 + A_G)} E(\lambda_\Sigma) \\ & - \frac{A_G(1 + A_L)}{A_L(1 + A_G)} CVaR(\lambda_\Sigma) + \frac{1}{A_L} K_L - \frac{1 + A_L}{A_L} K_G + TS \end{aligned} \quad (\text{B.53})$$

Part 2: Proof that inequality (B.49) is equivalent to inequality (3.34)

Inequality (B.49) implies $M \leq P_G$. Similar to equation (B.51), we now have

$$\frac{du_L}{du_G} = [E(\lambda_\Sigma) + K_L - TS - A_L \frac{dCVaR^L(-\pi_L(M, S))}{dM}] \frac{1}{C_8} \quad (\text{B.54})$$

After substituting C_8 into the above equation, we see that inequality (B.49) is equivalent to

$$\begin{aligned} & \frac{E(\lambda_\Sigma) + K_L - TS - A_L \frac{dCVaR^L(-\pi_L(M, S))}{dM}}{E(\lambda_\Sigma) - TS - A_G CVaR(-\lambda_\Sigma) - TA_G S + (1 + A_G)K_G} \\ & < -\frac{1 + A_L}{1 + A_G} \end{aligned} \quad (\text{B.55})$$

Rearranging the terms in the above equation, we have

$$\begin{aligned} \frac{du_L(M, S^L)}{du_G(M, S^L)} \Big|_{M=0} < -\frac{1+A_L}{1+A_G} \Leftrightarrow \\ \frac{dCVaR^L(-\pi_L(M, S^L))}{dM} \Big|_{M=0} < \frac{A_G - A_L}{A_L(1+A_G)} E(\lambda_\Sigma) \\ + \frac{A_G(1+A_L)}{A_L(1+A_G)} CVaR(-\lambda_\Sigma) + \frac{1}{A_L} K_L - \frac{1+A_L}{A_L} K_G + TS \end{aligned} \quad (\text{B.56})$$

QED

Theorem 2: Given the stated restrictions on the CFD bargaining problem for G and L , and given that the lowest strike price S^R is less than S^{R^} as defined in (3.31) and the highest strike price S^U is greater than S^{U^*} as defined in (3.32), the Nash barter set B for this problem is a non-empty, compact, convex subset of \mathbb{R}^2 , as follows:*

- Case 1.** *The barter set B is a compact right triangle when conditions (3.33) and (3.34) both hold, cf. fig. 3.3.*
- Case 2.** *The barter set B reduces to the no-contract threat point when inequality (3.34) does not hold, cf. fig. 3.4.*
- Case 3.** *The barter set B is a compact right triangle when (3.33) does not hold but (3.34) holds, cf. fig. 3.5.*

Proof of Theorem 2:

Before considering the shape of the utility possibility set U , first consider the following two curves. The first curve V_1 is the locus of points (u_G, u_L) traced out in U as M varies from M^R to M^U , given a sufficiently small lowest strike price S^R . The second curve V_2 is the locus of points (u_G, u_L) traced out in U as M varies from M^R to M^U , given a sufficiently large highest strike price S^U .

As proved in Lemma 3, the curve V_1 is concave in U . Similarly, it can be proved that V_2 is also concave in U . Moreover, as proved in Lemma 4, with the strike price fixed at S^R , as M increases, u_G decreases and u_L increases. Similarly, if the strike price is fixed at S^U , as M increases, u_G increases and u_L decreases. Therefore, at each point along V_1 and V_2 the slope

is negative. Note, as proved in Lemma 2, given any contract amount $M \in [M^R, M^U]$, varying the strike price S from S^R to S^U maps under (3.10) and (3.14) into a straight line in U with slope $-[1 + A_L]/[1 + A_G]$. Hence, connecting the points on V_1 and V_2 that have the same contract amount M , we have straight lines with a slope of $-[1 + A_L]/[1 + A_G]$. In addition, every single point on these straight lines belongs to U .

The proof of Theorem 2 will be divided into three parts corresponding to the three possible cases in the statement of the theorem.

Case 1:

When following the proof below, please refer to fig. B.2. As shown in Lemma 5, when conditions (B.49) and (B.50) both hold, the slope of V_1 at the threat point is smaller than $-\frac{1+A_L}{1+A_G}$; and, when $M = M^U$, the slope of V_1 is greater than $-\frac{1+A_L}{1+A_G}$. Therefore, since V_1 is concave, the slope of V_1 must steadily increase from below $-\frac{1+A_L}{1+A_G}$ to over $-\frac{1+A_L}{1+A_G}$ as M increases from 0 to M^U , and u_G correspondingly decreases.

By following steps similar to that of Lemma 3, it can be shown that V_2 is also concave. Moreover, the slope of V_2 at the threat point is larger than $-\frac{1+A_L}{1+A_G}$. This statement can be proved by contradiction. Assume that, when the slope of V_1 at the threat point is smaller than $-\frac{1+A_L}{1+A_G}$, the slope of V_2 at the threat point is also smaller than $-\frac{1+A_L}{1+A_G}$. This situation is plotted in fig. B.1. Pick a point Z on V_1 above the straight line with a slope of $-\frac{1+A_L}{1+A_G}$ which passes the threat point. By construction, Z takes the form $Z = (u_L(M', S^R), u_G(M', S^R))$. According to Lemma 2, the point $(u_L(M', S^U), u_G(M', S^U))$ on V_2 together with Z must be on a straight line with a slope of $-\frac{1+A_L}{1+A_G}$. Therefore, the point $(u_L(M', S^U), u_G(M', S^U))$ on V_2 must be above the straight line with a slope of $-\frac{1+A_L}{1+A_G}$ that passes through the threat point. However, since the initial slope of V_2 is smaller than $-\frac{1+A_L}{1+A_G}$, and V_2 is concave, no point on V_2 is above this straight line. This contradicts Lemma 2, which completes the proof.

As proved in Lemma 2, all the points that belong to the utility possibility set U are on parallel lines with one end on V_1 and with a slope of $-[1 + A_L]/[1 + A_G]$. Hence, the typical utility possibility set U for Case 1 is as shown in fig. B.2.

Since the slope of V_1 gradually increases from below $-\frac{1+A_L}{1+A_G}$ to above $-\frac{1+A_L}{1+A_G}$, there exists

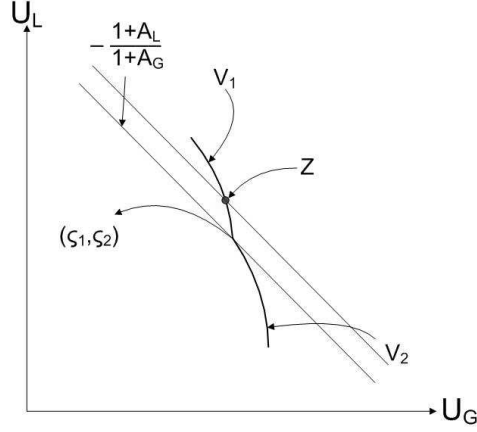


Figure B.1 Supporting graph for proving that the slope of V_2 at the threat point is larger than $-\frac{1+A_L}{1+A_G}$ when the slope of V_1 at the threat point is smaller than $-\frac{1+A_L}{1+A_G}$.

a contract amount M^* that satisfies $\frac{du_L(M^*, S^R)}{du_G(M^*, S^R)} = -\frac{1+A_L}{1+A_G}$.

Using the results proved in Lemma 2, M^* should also satisfy $\frac{du_L(M, S^U)}{du_G(M, S^U)} = -\frac{1+A_L}{1+A_G}$. Define $X = (u_L(M^*, S^R), u_G(M^*, S^R))$, and define $Y = (u_L(M^*, S^U), u_G(M^*, S^U))$. Suppose that $[1 + A_L]u_G(M^*, S^R) + [1 + A_G]u_L(M^*, S^R) = C^1$.

Since V_1 is concave, it follows from the initial slope and end slope that all the points (u_G, u_L) on V_1 satisfy $[1 + A_L]u_G + [1 + A_G]u_L \leq C^1$. As proved in Lemma 2, all the points that belongs to U are on parallel lines with one end on V_1 and with a slope of $-\frac{1+A_L}{1+A_G}$. Hence, all the points in U except the points on the straight line between X and Y satisfy $[1 + A_L]u_G + [1 + A_G]u_L \leq C^1$.

Now draw a horizontal line and a vertical line from the threat point. As shown in fig. B.2, let I denote the point where the vertical line intersects with the straight line between X and Y , and let J denote the point where the horizontal line intersects with the straight line between X and Y . By definition, the right triangle $I\zeta J$ constitutes the Case-1 barter set, which is clearly non-empty, compact, and convex.

Case 2:

When following the proof below, please refer to fig. B.3. Suppose that $[1 + A_L]\zeta_1 + [1 + A_G]\zeta_2 = C^2$. As shown in Lemma 5, when condition (B.49) fails to hold, $\frac{du_L(M, S^R)}{du_G(M, S^R)} \Big|_{M=0} \geq -$

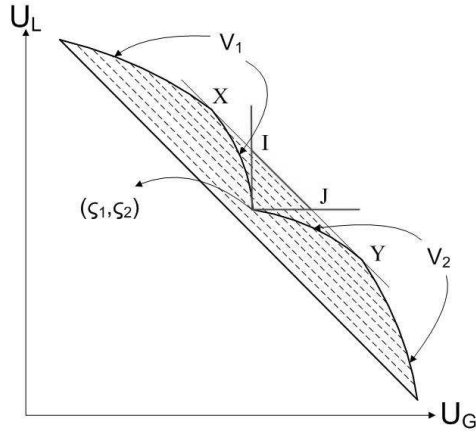


Figure B.2 Type 1 utility possibility set U and barter set B for GenCo G and LSE L . The barter set is a right triangle.

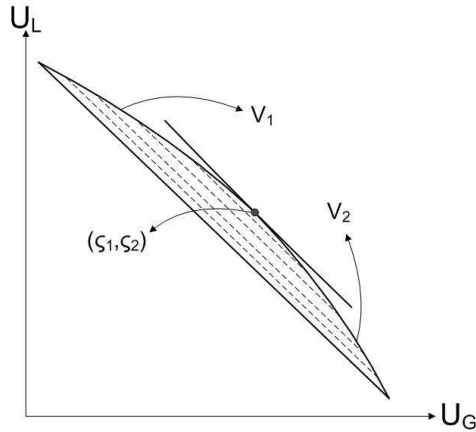


Figure B.3 Type 2 utility possibility set U and barter set B for GenCo G and LSE L . The barter set reduces to the non-contract threat point.

$$\frac{1+A_L}{1+A_G}$$

Because V_1 is concave, all the points (u_G, u_L) on V_1 satisfy $[1 + A_L]u_G + [1 + A_G]u_L \leq C^2$. As proved in Lemma 2, all the points that belong to the utility possibility set U are on parallel lines with one end on V_1 and with a slope of $-[1 + A_L]/[1 + A_G]$. Hence, all the points in the utility possibility set U satisfy $[1 + A_L]u_G + [1 + A_G]u_L \leq C^2$.

Therefore, the threat point is the only point in the utility possibility set U that satisfies both $u_G \geq \zeta_1$ and $u_L \geq \zeta_2$. This can be proved by contradiction. Suppose there is another point (u'_G, u'_L) in U apart from the threat point that satisfies both $u'_G \geq \zeta_1$ and $u'_L \geq \zeta_2$. Then,

Now draw a horizontal line and a vertical line from the threat point. Let the point where the vertical line intersects with the straight line between N and W be denoted by I , and let the point where the horizontal line intersects with the straight line between N and W be denoted by J . As shown in fig. B.4, the right triangle $I\zeta J$ constitutes the Case-3 barter set B by definition. Clearly B is non-empty, compact, and convex.

QED

BIBLIOGRAPHY

- [1] S. Borenstein and J. Bushnell, "Electricity restructuring: Deregulation or reregulation?" *Regulation, The Cato Review of Business & Government*, vol. 23(2), pp. 46–52, Spring, 2000.
- [2] P. Joskow, "Lessons learned from electricity market liberalization," *The Energy Journal*, vol. 29, special issue 2, pp. 9–42, 2008.
- [3] P. Joskow, "The difficult transition to competitive electricity markets in the United States," *Electricity Deregulation: Where To From Here?* (J. Griffin and S. Puller, eds.), Chicago, University of Chicago Press.
- [4] H. Chao, "Global electricity transformation: The critical need for integrated market design and risk management research," *Energy*, vol. 31, issues. 6-7, pp. 923–939, May-Jun. 2006.
- [5] W. Hogan, "Electricity market restructuring: Reforms of reforms," *Journal of Regulatory Economics*, vol. 21, no. 1, pp. 103–132, 2002.
- [6] P. Joskow, "Restructuring, competition and regulatory reform in the U.S. electricity sector," *Journal of Economic Perspectives*, vol. 1, no. 3, pp. 119–138, summer, 1997.
- [7] FERC Order No. 888, Promoting Wholesale Competition Through Open Access Non-discriminatory Transmission Services by Public Utilities; Recovery of Stranded Costs by Public Utilities and Transmitting Utilities, [On-line]. Available: <http://www.ferc.gov/legal/maj-ord-reg/land-docs/order888.asp>.

- [8] FERC Order No. 899, Open Access Same-Time Information System (formerly Real-Time Information Networks) and Standards of Conduct, [On-line]. Available: <http://www.ferc.gov/legal/maj-ord-reg/land-docs/order889.asp>.
- [9] FERC Order No. 2000, Regional Transmission Organizations, Docket No.RM99-2-000, [On-line]. Available: <http://www.ferc.gov/legal/maj-ord-reg/land-docs/RM99-2A.pdf>.
- [10] FERC White Paper, Wholesale Power Market Platform, April 28, 2003, [On-line]. Available: http://www.hks.harvard.edu/hepg/Standard_Mkt_dsgn/FERC_White_paper_042803.pdf.
- [11] J. Sun and L. Tesfatsion, "Dynamic testing of wholesale power market design: An open-source agent-based framework," *Computational Economics*, vol. 30, no. 3, pp. 191-327, 2007.
- [12] P. Joskow, "Markets for power in the United States: An interim assessment," *The Energy Journal*, vol. 27, no. 1, pp. 1-35, 2006.
- [13] FERC, "2004 state of the markets report," Office of Market Oversight and Investigations, Jun. 2005.
- [14] Z. Younes and M. Ilic, "Generation strategies for gaming transmission constraints: Will the deregulated electric power market be an oligopoly?," *Decision Support Syst.*, vol. 24, no. 34, pp. 207-222, 1999.
- [15] J. Yao, I. Adler, and S. Oren, "Modeling and computing two-settlement oligopolistic equilibrium in a congested electricity network," *Operations Research*, vol. 56, pp. 34-47, 2008.
- [16] T. Li and M. Shahidehpour, "Market power analysis in electricity markets using supply function equilibrium model," *IMA Journal of Management Mathematics*, vol. 15, no. 4, pp. 339-354, 2004.

- [17] H. Niu, R. Baldick, and G. Zhu, "Supply function equilibrium bidding strategies with fixed forward contracts," *IEEE Trans. Power Systems*, vol. 20, no. 4, pp. 1859–1867, Nov. 2005.
- [18] Y. F. Liu, Y. X. Ni, and F. F. Wu, "Impacts of suppliers' learning behaviour on market equilibrium under repeated linear supply-function bidding," *IEE Proc.-Gener. Transm. Distrib.*, vol. 153, no. 1, pp. 44–50, Jan, 2006.
- [19] D. W. Bunn and F. S. Oliveira, "Agent-based simulation: An application to the new electricity trading arrangement of England and Wales," *IEEE Transactions on Evolutionary Computation*, vol. 5, no. 5, pp. 493–503, Oct. 2001.
- [20] M. H. Rothkopf, "Daily repetition: A neglected factor in the analysis of electricity auctions," *Electricity J.*, vol. 12, pp. 61–70, Apr. 1999.
- [21] V. Nanduri and T. K. Das, "A reinforcement learning model to assess market power under auction-based energy pricing," *IEEE Trans. Power Systems*, vol. 22, no. 1, pp. 85–95, Feb. 2007.
- [22] H. Li, J. Sun, and L. Tesfatsion, "Effects of price-sensitive demand and price cap on LMP volatility and separation in restructured wholesale power markets," Working Paper, ISU Economics Department, in progress.
- [23] I. Erev and A. Roth, "Predicting how people play games: reinforcement learning in experimental games with unique, mixed strategy equilibria," *The American Economic Review*, vol. 88, no. 4, pp. 848–881, 1998.
- [24] N. P. Yu, C. C. Liu, and L. Tesfatsion, "Modeling of suppliers' learning behaviors in an electricity market environment," *Proc. 14th Int. Conference on Intelligent System Applications to Power Systems (ISAP)*, pp. 1–6, Nov. 2007.

- [25] I. Praça, C. Ramos, Z. Vale, and M. Cordeiro, “A new agent-based framework for the simulation of electricity markets,” in *Proc. of IEEE/WIC Int. Conf. on Intelligent Agent Technology 2003*, pp. 469–473. Oct. 2003.
- [26] D. Bunn and F. Oliveira, “Evaluating individual market power in electricity markets,” *Annals of Operations Research*, vol. 121, no. 1-4, pp. 57–77, July. 2003.
- [27] J. Bower and D. Bunn, “A model-based comparison of pool and bilateral market mechanisms for electricity trading,” *Energy Journal*, vol. 21, no. 3, July. 2000.
- [28] M. North, G. Conzelmann, V. Koritarov, C. Macal, P. Thimmapuram, and T. Veselka, “E-laboratories: agent-based modeling of electricity markets,” in *Proc. of 2002 American Power Conference*, Chicago, IL, USA, April. 2002.
- [29] S. El. Khatib and F. D. Galiana, “Negotiating bilateral contracts in electricity markets,” *IEEE Trans. on Pow. Sys.*, vol. 22(2), pp. 553–562, 2007.
- [30] H. Song, C.-C. Liu, and J. Lawarrée, “Nash equilibrium bidding strategies in a bilateral electricity market,” *IEEE Trans. on Pow. Sys.*, vol. 17(1), pp. 73–79, 2002.
- [31] Y. S. Son, R. Baldick, and S. Siddiqi, “Re-analysis of ‘Nash equilibrium bidding strategies in a bilateral electricity market’”, *IEEE Trans. on Pow. Sys.*, vol. 19(2), pp. 1243–1244, 2004.
- [32] F. D. Galiana, I. Kockar, and P. C. Franco, “Combined pool/bilateral dispatch — Part I: Performance of trading strategies,” *IEEE Trans. on Pow. Sys.*, vol. 17(1), pp. 92–99, 2002.
- [33] I. Kockar and F. D. Galiana, “Combined pool/bilateral dispatch — Part II: Curtailment of firm and nonfirm contracts,” *IEEE Trans. on Pow. Sys.*, vol. 17(4), pp. 1184–1190, 2002.

- [34] P. C. Franco, I. Kockar, and F. D. Galiana, “Combined pool/bilateral dispatch — Part III: Unbundling costs of trading services,” *IEEE Trans. on Pow. Sys.*, vol. 17(4), pp. 1191–1198, 2002.
- [35] M. Liu and F. F. Wu, “Managing price risk in a multimarket environment”, *IEEE Trans. on Pow. Sys.*, vol. 21(4), pp. 1512–1519, 2006.
- [36] T. Li and M. Shahidehpour, “Risk-constrained FTR bidding strategy in transmission markets,” *IEEE Trans. on Pow. Sys.*, vol. 20, no. 2, pp. 10014–10021, 2005.
- [37] A. Botterud, J. Wang, R.J. Bessa, H. Keko, and V. Miranda, “Risk management and optimal bidding for a wind power producer,” *Proceedings of the IEEE Power and Energy Society General Meeting*, Minneapolis, Minnesota, USA, July, 2010.
- [38] M. Shahidehpour, H. Yamin, and Z. Li, *Market Operations in Electric Power Systems: Forecasting, Scheduling, and Risk Management*, Wiley Interscience, New York, NY, 2002.
- [39] L. Bartelj, A.F. Gubina, D. Paravan, and R. Golob, “Risk management in the retail electricity market: The retailer’s perspective,” *Proceedings of the IEEE Power and Energy Society General Meeting*, Minneapolis, Minnesota, USA, July, 2010.
- [40] M. Carrión, A. J. Conejo, and J. M. Arroyo, “Forward contracting and selling price determination for a retailer,” *IEEE Trans. on Pow. Sys.*, vol. 22(4), pp. 2105–2114, 2007.
- [41] S. A. Gabriel, A. J. Conejo, M. A. Plazas, and S. Balakrishnan, “Optimal price and quantity determination for retail electric power contracts,” *IEEE Trans. on Pow. Sys.*, vol. 21(1), pp. 180–187, 2006.
- [42] H. P. Chao, S. Oren, and R. Wilson, “Alternative pathway to electricity market reform: A risk-management approach,” *Proc.*, 39th Hawaii Int’l Conf. on System and Science, 2006.
- [43] R. Bjorgan, C.-C. Liu, and J. Lawarrée, “Financial risk management in a competitive electricity market,” *IEEE Trans. on Pow. Sys.*, vol. 14(4), pp. 1285–1291, 1999.

- [44] E. Tanlapco, J. Lawarrée, and C.-C. Liu, "Hedging with future contracts in a deregulated electricity industry," *IEEE Trans. on Pow. Sys.*, vol. 17(3), pp. 577–582, 2002.
- [45] M. Denton, A. Palmer, R. Masiello, and P. Skantze, "Managing market risk in energy," *IEEE Trans. on Pow. Sys.*, vol. 18(2), pp. 494–502, 2003.
- [46] D. Das and B. F. Wollenberg, "Risk assessment of generators bidding in a day-ahead market," *IEEE Trans. on Pow. Sys.*, vol. 20(1), pp. 416–424, 2005.
- [47] R. Bjorgan, H. Song, C.-C. Liu, and R. Dahlgren, "Pricing flexible electricity contracts," *IEEE Trans. on Pow. Sys.*, vol. 15(2), pp. 477–482, 2000.
- [48] R. Dahlgren, C.-C. Liu, and J. Lawarrée, "Risk assessment in energy trading," *IEEE Trans. on Pow. Sys.*, vol. 18(2), pp. 503–511, 2003.
- [49] S. Deng and S. Oren, "Electricity derivatives and risk management," *Energy, The International Journal*, vol. 31, pp. 940–953, 2006.
- [50] M. Liu and F. F. Wu, "A survey on risk management in electricity markets," *IEEE Proc., Power & Energy Soc. GM*, June 2006.
- [51] N. P. Yu, A. Somani, and L. Tesfatsion, "Financial risk management in restructured wholesale power markets: Concepts and tools," *IEEE Proc., Power & Energy Soc. GM*, 2010, to appear.
- [52] N. P. Yu, C. C. Liu, and J. Price, "Evaluation of market rules using a multi-agent system method," *IEEE Trans. on Pow. Sys.*, vol. 25(1), pp. 470–479, 2010.

- [53] N. P. Yu, L. Tesfatsion, and C. C. Liu, “Financial bilateral contract negotiation in wholesale electric power markets using Nash bargaining theory,” Working Paper No. 10032, Economics Department, Iowa State University, Ames, IA, September 2010.
- [54] S. Borenstein and J. Bushnell, “An empirical analysis of the potential for market power in California’s electricity industry,” *Journal of Industrial Economics*, vol. 47(3), pp. 285–323, Sep. 1999.
- [55] J. Bushnell and F. A. Wolack, “Regulation and the leverage of local market power in the California electricity market,” (May 2, 2000). Competition Policy Center. Paper CPC00-013. [On-line]. Available: <http://repositories.cdlib.org/iber/cpc/CPC00-013>
- [56] J. Roy, A. Bose, and J. Price, “Effect of ancillary service market design on control performance of power systems,” *Proceedings of 2008 Power System Computation Conference (PSCC)*.
- [57] CAISO Business Practice Manual for Market Instruments, Appendix D, Calculation of Default Energy Bids, Version 1, March 26, 2009. [On-line]. Available: <http://www.caiso.com/17ba/17baa8bc1ce20.html>
- [58] F. Bellifemine, G. Caire, and D. Greenwood, *Developing Multi-Agent Systems with JADE*, John Wiley & Sons, Feb. 2007.
- [59] C. Watkins, “Learning from delayed rewards,” Ph.D. Thesis, University of Cambridge, England, 1989.
- [60] J. Jung, C. C. Liu, S. Tanimoto, and V. Vital, “Adaptation in load shedding under vulnerable operating conditions,” *IEEE Trans. on Pow. Sys.*, vol. 17(4), Nov. 2002.
- [61] T. Mount, “Investment performance in deregulated markets for electricity: A case study of New York state,” Cornell University, Sep. 2007. [On-line]. Available: <http://www.appanet.org/files/PDFs/StudyMountEMRIreportNYISOCapacity09-07.pdf>
- [62] P. Penza and V. K. Bansal, *Measuring Market Risk with Value at Risk*. Wiley, 2000.

- [63] S. Focardi and C. Jonas, *Risk Management: Framework, Methods, and Practice*. Frank J. Fabozzi Associates, 1998.
- [64] H. Markowitz, "Portfolio selection," *The Journal of Finance*, vol. 7(1), pp. 77–91, March 1952.
- [65] A. J. McNeil, R. Frey, and P. Embrechts, *Quantitative Risk Management: Concepts, Techniques and Tools*. Princeton U Press, 2005.
- [66] P. Artzner, F. Delbaen, J. M. Eber, and D. Heath, "Coherent measures of risk," *Mathematical Finance*, vol. 9(3), 1999.
- [67] T. J. Linsmeier and N. D. Pearson, "Value-at-risk," *Financial Analysts Journal*, vol. 56(2), pp. 47–67, 2000.
- [68] S. Uryasev, "Conditional value-at-risk: Optimization algorithm and applications," *Financial Engineering News*, pp. 1–5, 2000.
- [69] G. Pflug, *Some Remarks on the Value-at-Risk and the Conditional Value-at-Risk*. Kluwer Academic Publishers, 2000.
- [70] P. Christoffersen, *Elements of Financial Risk Management*. Academic Press, 2003.
- [71] M. Crouhy, D. Galai, and R. Mark, *The Essentials of Risk Management*. McGraw-Hill, 2005.
- [72] J. C. Hull, *Options, Futures, and Other Derivatives*, 7th ed. Prentice Hall, May 2008.
- [73] F. Sioshansi and W. Pfaffenberger, eds., *Electricity Market Reform: An International Perspective*. Elsevier, 2006.
- [74] J. G. Gross, *The Economics of Bargaining*. Basic Books, 1969.
- [75] H. Gintis, *Game Theory Evolving*. Princeton University Press, 2000.
- [76] S. Stoft, *Power System Economics*. Wiley, 2002.

- [77] MISO, *BPM 003 - Energy Markets Instruments*, [On-Line]. Available: <http://www.midwestmarket.org/>
- [78] J. Nash, "The bargaining problem," *Econometrica*, vol. 18, no. 2, pp. 155-162, 1950.
- [79] M.J. Osborne and A. Rubinstein, *Bargaining and Markets*, Academic Press, San Diego, CA, 1990.
- [80] L. Tesfatsion, "Pure strategy Nash bargaining solutions," *Discussion Paper*, No. 75-61, Nov, 1975, Center for Economic Research, Department of Economics, University of Minnesota.
- [81] J. Sun and L. Tesfatsion, "Dynamic testing of wholesale power market designs: An open-source agent-based framework," *Computational Economics*, vol. 30, no. 3, pp. 291-327, 2007.
- [82] Market Reports: Historical LMPs, [On-line]. Available: http://www.midwestiso.org/publish/Folder/10b1ff_101f945f78e_-75e70a48324a?rev=1.
- [83] M. D. McKay, R. J. Beckman, and W. J. Conover, "A Comparison of Three methods for selecting values of input variables in the analysis of output from a computer code," *Technometrics*, vol. 21, no. 2, pp. 239-245, 1979.