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A model for strategic bidding in combined transmission and wholesale energy markets

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A Model for Strategic Bidding in Combined Transmission and Wholesale Energy Markets

by

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

A MODEL FOR STRATEGIC BIDDING IN COMBINED TRANSMISSION AND WHOLESALE ENERGY MARKETS

Sanket Gupte

ABSTRACT

Motivated by deregulation in major service sectors like airlines, banking and telecommunication, the electric industry is undergoing a major transformation. However due to design inefficiencies, restructuring of the power sector, so far, has not been a major success. A lack of comprehensive quantitative models has resulted in the inability of the market designers to evaluate market performance and develop successful market designs. A comprehensive model should include market features like two-settlement system, transmission congestion, financial transmission rights (FTRs), demand elasticity, demand-side bidding and other market rules.

The contribution of this thesis includes development of an exhaustive modeling framework that includes the above mentioned market features and also development of a computationally effective solution methodology. The market designers would use this methodology in the development of alternative conceptual market design frameworks, and also for assessing the impact of various market rules on market performance.

The noncooperative bidding behavior of the generators in both FTR and energy markets are modeled as nonzero-sum stochastic games. Since the bidding strategies in the FTR and energy games are dependent on each other and jointly impact the market performance, a two-tier learning approach is developed. Players (e.g. generators) first bid in the FTR market. FTR bids are then taken into account in the process of selecting bids in the energy market. The FTR bids and the energy bids together decide the market equilibrium and the resulting performance. This performance measure is then used to evaluate success of FTR bidding strategy. Several example power networks are studied to expose the modeling and learning based solution approach.

CHAPTER 1

INTRODUCTION

Experience from deregulation of major service sectors like, airlines, banking, and telecommunications shows that competition is the most effective way to establish sustained incentives to keep costs and prices down. Under competition, productivity grows, costs and prices decrease, and innovation and product diversity flourish. Motivated by the deregulation in other industries, the electric power industry in the US and worldwide is undergoing a major transformation. It is changing from a vertically integrated industry in which the generation, transmission and distribution system were owned by a single entity to the unbundling of the above services. However, due to design inefficiencies, the restructuring has not been a major success (e.g., failure of the California market) and many states have reached a standstill in their restructuring program [2]. The main purpose of this research is to develop a comprehensive methodology for designing economically sustainable competitive electricity markets. In the subsequent sections, a brief overview of restructured power market elements is given.

1.1 Elements of a Deregulated Power Industry

The basic constituents of any restructured electricity industry are the market participants, forward and spot markets, transmission network, and ancillary services, which are discussed here in brief.

1.1.1 Market Participants

The market participants in a deregulated power market include the generating companies, retailers and an independent system operator. The generators compete among themselves in the energy market to supply power with the objective of maximizing their expected pay-offs. The retailers impart demand elasticity by supplying price-sensitive demand bids in the energy market. On the other hand, both the generators and the retailers compete in the transmission rights market. The system operator determines the locational prices and the subsequent power flows using the supplier and retailer bids. The objective of the system operator is to minimize the cost of meeting the demand while adhering to security and reliability constraints.

1.1.2 Forward and Spot Markets

Trading for power delivered in any particular instant of time begins often years in advance and continues till the moment of time, the actual time at which power flows out of a generator and into a load. This is accomplished by a sequence of overlapping markets, the earliest of which is a bilateral market that trades in long-term forward contracts, known as bilateral contracts. Bilateral trading stops at least one day prior to the real time. At that time, the system operator holds a day-ahead (DA) market. This is often followed by hour-ahead and real-time (RT) markets. All of these markets except the RT market are considered as forward markets. In this research, bilateral contracts, DA and RT markets are considered.

Bilateral contracts implemented through *Contracts for Differences* (CFDs) completely insulate market participants from the real time market price volatility for the contracted quantities. A detailed explanation of CFDs is given in Chapter 4. The forward markets are financial markets in the sense that the delivery of power is optional and the seller's real obligation is financial. Any power that is sold in the forward market but not delivered in RT has to be purchased at the spot price of energy. This system of forward and RT markets is known as the two-settlement system that is explained in more detail in Chapter 4.

1.1.3 Transmission Network

Transmission network consist of high-voltage power lines that connect different locations. Transmission lines have capacity limits which must be enforced to protect the lines and the stability of the system. When these limits are binding, that is when traders would like to use more capacity than is safely available, transmission is a scarce resource. Congestion is a consequence of network constraints and can result in an overall increase in the cost of power delivery. Hence, in order to facilitate efficient utilization of scarce network capacity and hedge traders from the fluctuations in congestion prices, transmission rights are defined. The three approaches that are used for hedging transmission costs are physical transmission rights, capacity reservations, and financial transmission rights (FTRs). In this research, FTRs are modeled and are explained next.

Financial transmission rights entitle the holder to be paid only the difference in locational prices between the specified nodes of power injection and withdrawal, but do not confer the right to transmit power. FTRs are directional and may be defined either as obligations or options. The obligation holders will be entitled to payments when the locational difference in prices is positive and will be obligated to make payments when the locational difference is negative. The option holders will be entitled to payments when the locational difference in prices is positive but will not be obligated to make payments when the locational difference is negative. FTRs are obtained through an auction mechanism, which is described in Chapter 5.

1.1.4 Ancillary Services

Ancillary services are provided by the system operator and are concerned with the dispatch, trade and delivery of power. Some of the ancillary services include real power balancing, voltage stability, transmission security, and financial trade enforcement, etc. Because the role of the system operator is very important in most of the market architectures, understanding the ancillary services is crucial to evaluating any proposed market design.

1.2 How the Market Works

The power market works as a sequence of FTR and energy markets, as depicted in Figure 1. In the FTR market, participants compete with each other by supplying quantity and price bids for the transmission rights. The FTR auction selects the winning bids that provide the highest valued use of the network. This auction is conducted on a monthly basis. The participants then compete in the energy market given their allocation of FTRs. In the energy market, market participants can purchase or sell energy through a DA market, RT market or through bilateral contracts. For the DA market, the system operator holds an auction 24 hours prior to the actual day in which the suppliers and consumers submit their bids. Based on these bids and other system constraints, such as transmission constraints, the system operator determines the quantities and financially binding locational prices for the suppliers for each hour by solving the nonlinear Optimal Power Flow (OPF) and Unit Commitment (UC) problems. The real time market prices and quantities are determined by the actual supply and demand conditions. The RT market is settled by pricing deviations from day-ahead quantities and prices. In addition to what is described above, most power markets operate with some additional market rules imposed by the system operator.

The following are such rules that are observed by the Pennsylvania-New Jersey-Maryland (PJM) market participants.

- Market sellers that own capacity resources must submit offers into the day-ahead market, unless the resource is unavailable for outage.

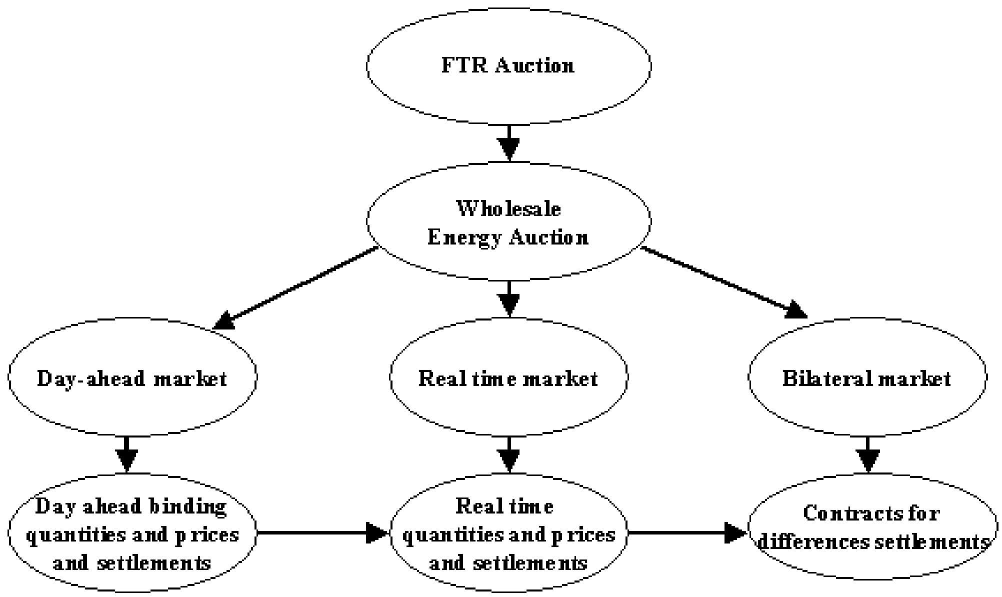

Figure 1.1. Transmission and Energy Market Elements

- Generation offers must not exceed $1000/MWh.
- Internal bilateral transactions may be designated as day-ahead or balancing market schedules.

1.3 Market Power

All of the major markets experienced spot market price volatility after their initial restructuring [3]. For example, California market experienced high variations in the spot prices due to demand inelasticity, price caps at the retail level, and lack of multi-settlement methods to promote long-term contracts. This resulted in market power making it possible for the market participants to involve in gaming [4] [5].

Market power is the seller's ability to profitably maintain prices above competitive levels for a significant period of time. The two key elements of the market power strategy are quantity withholding (producing at a level lower than the capacity) and financial withholding (pricing at a level higher than the marginal cost) [6]. There are both empirical and theoretical studies that have proven the existence of market power in the restructured power markets. The California Independent System Operator (CAISO) developed a price cost mark-up index and provided empirical evidence from previous data that market power was the reason for at least one-third of the increased prices during summer of 2000 [4].

1.4 Brief Description of the Problem

The objective of this thesis is to develop a comprehensive methodology for designing competitive electricity markets. Market features such as two-settlement system, FTR auctions, demand elasticity, and demand-side bidding, which are key elements of a successful market design are considered. An expected contribution of this research would be to build a framework, which could be used by market designers to evaluate alternative market designs and also to assess the impact of various market rules on market performance. The proposed model is a system wide tool and not intended for individual generators to optimize their bids. However, the generators would also be to use the model to learn market behavior and improve their bidding strategies. For example, this model would assist in obtaining the equilibrium bidding strategies in the FTR auction using the equilibrium profits obtained in the energy market as the performance measure. This model could also assist the generators in deciding the equilibrium combination of bilateral and day-ahead bidding quantities. Using this model, the generators could also analyze various market scenarios while preparing their bids.

1.5 Motivation for Research

The primary reasons for restructuring failures are: 1) inadequacy of comprehensive models incorporating features such as real time pricing, two-settlement system, congestion management rules, demand elasticity, and demand side bidding ([5], [7], [8], [9], [10]), 2) use of simplified economic models, such as Cournot, Bertrand, and Stackelberg models ([11], [12], [13]), and 4) evolving nature of the market itself [7]. All of the above factors resulted in the inability of the market designers to evaluate market performances and develop successful market designs. Joskow [4] notes that "responsive generators need to be in a position to evaluate alternative design frameworks and approve those that are likely to perform well." Hence there is a critical need to develop a scientific basis for identifying the ideal market design based on theoretical and experimental studies.

1.6 Proposed Design Strategy

The proposed methodology models the competitive bidding behavior of the generators and the retailers in both the FTR and energy markets as a non-zero sum stochastic game. Since the stochastic process underlying the bidding process can be shown to be a Markov chain, and the players are competitive, the bidding problem in the FTR market is modeled as a Competitive Markov Decision Process (CMDP). The energy game and its associated unit commitment (UC) and optimal power flow (OPF) problem [14] for scheduling and pricing of power in the energy market is solved using a two-stage CMDP and nonlinear programming (NLP) model. A simulation based on stochastic optimization approach, known as Reinforcement Learning (RL) ([15],[16]), is used as the solution methodology. Since RL uses simulation as its modeling tool, this model can incorporate most of the complex features of restructured power markets. Also an RL based simulation approach will be able to accommodate evolving alternative market designs. Recently [17] has developed convergence analysis for an RL algorithm for average reward irreducible stochastic games.

1.7 Thesis Organization

The organization of this thesis is as follows: Chapter 2 reviews the prior work in the area of restructured power markets, Chapter 3 explains the basic concepts of Markov Decision Process, Reinforcement Learning etc., Chapter 4 describes market features such as two-settlement and bilateral transactions. Chapter 5 illustrates the mechanism of the

FTR auctions. Chapter 6 gives a detailed problem description and assumptions along with the proposed modeling approach.

CHAPTER 2
LITERATURE REVIEW

The electric power industry has undergone a fundamental transformation in institutional structure from regulated private monopoly to an open access competitive environment. The role of decision-making has been shifted from vertically integrated utilities to profit maximizing horizontally independent power producers [3]. Many prominent economists, operation researchers, and engineers have been instrumental in the development of alternative conceptual frameworks for electric power restructuring. According to Power Systems Energy Engineering Research Center (PSERC), some of the important research areas in power market restructuring are market design, auctions, and market power. The primary focus of this thesis lies in the market design area, which attempts to develop a scientific basis for developing an ideal market design. The essential features of an ideal market design are discussed here followed by a review of existing models for power markets.

2.1 Framework of an Ideal Market Design

In addition to a short-term spot market with bid-based security constrained dispatch with nodal prices, Hogan [7] stresses that two-settlement system and FTRs be incorporated as key elements of competitive electricity markets. Regional Transmission Organization's (RTO) millennium order also recommends the above necessary elements for restructured power markets. In addition to these features, many researchers ([18], [19], [20], [21], [22], [23], [24], [25]) have stressed the importance of demand-side bidding. This ideal market structure encompassing all the features is relatively new and dynamic, hence there is no comprehensive model addressing all the issues.

2.1.1 Two-settlement System

PJM [18] emphasizes that the purpose of two-settlement system (that is forward and spot market settlements) is to enhance the robust and competitive electricity market. It also provides increased price certainty to the market participants by allowing them to commit to forward energy prices and submit price -sensitive demand bids in the day-ahead market. Joskow [4] points out that a large fraction of consumer demand covered by long term bilateral contracts can protect consumers from the volatility of the spot prices. These contracts also reduce the incentives suppliers have to exercise the market power when supplies get tight. Stoft [6] points out that a two-settlement system preserves the real time incentives for the market participants. He states that when the RT (real time) market is settled by pricing deviations from forward contracts at the RT price, suppliers and customers each have the same performance incentives in real time as if they had traded all their power in the RT market. Song et al. [26] model the bidding decision problem in the day-ahead and the spot market as a Markov Decision Process (MDP). Kamat et al. [27] analyze the welfare properties of two-settlement systems in the presence of network uncertainty and market power. In particular, they examine the extent to which a two-settlement system with zonal aggregation in the forward market facilitates forward trading, as well as the welfare and distributional implications of having such zonal aggregation in the presence of market uncertainty.

2.1.2 Transmission Rights

The move towards a competitive electric power industry has pointed out the critical situation of transmission congestion on the network. Limitations in the transmission grid in the short run may constrain long-distance movement of power and thereby impose a higher marginal cost in certain locations [7]. Thus transmission congestion gives rise to spatial differences in energy prices and also an adverse incentive to the system operator as the revenues collected from the customers will substantially exceed the payments to generators ([7],[18]). California Independent System Operator (CAISO) stresses that a critical component of any market based congestion management system is the definition of transmission rights that is complicated by network externalities due to loop flows

Hogan [7] suggests that a convenient solution to the above mentioned problems would be to re-distribute the congestion revenues through a system of long-run financial transmission rights (FTRs). Hogan et al. [28] point out that the FTRs would be functionally and financially equivalent to the Federal Energy Regulatory Commission (FERC) proposed point-to-point transmission capacity reservations. But Oren [29] argues that centralized implementation of passive FTRs will not provide adequate compensation for transmission rights holders and will result in inefficient dispatch and market power for the generators. Stoft [30] provides a counter-argument to Oren's conclusion and proves that under certain "excess capacity" conditions, financial transmission rights curb market power. Joskow et al. ([31], [32]) study the impact of allocation of financial and physical transmission rights on market power. [31], [32], [33] conclude that the effect of rights depend upon numerous factors including the configuration of the underlying market power problems (location of buyer and seller) and the microstructure of the market for transmission rights. Chao et al. [34] propose flow based systems as a potentially efficient method of trading rights and that does not require centralized optimization. They point out that flow based transmission rights will facilitate an efficient market design that is consistent with the new procedures outlined by North American Electric Reliability Council (NERC). Though FERC has recently endorsed the merit of having flowgate transmission rights (FGRs), if not exclusively, then in conjunction with point-to-point FTRs, there is a lot of debate surrounding the subject. Andrew [35] suggests that FGR systems when implemented in large grids may not capture all the congestion costs in the system. CAISO explains the several serious concerns inherent in a FGR based system. Seabron [36] presents a new method of trading point-to-point transmission rights based on the principles of unequal exchange rates between different point-to-point transmission rights. Raikar et al. [37] propose an alternative congestion management mechanism based on the novel Interruptible Physical Transmission contracts which guarantee physical access for the market participants to the transmission network and also provide financial incentives for the bilateral contract holders to forfeit the physical access to the transmission network. A hybrid model that combines the LMP hourly energy market with a forward transmission rights market based on FGR is proposed in [38], [39].

Hogan [40] proposes an auction mechanism for allocating FTRs. He points out that a straightforward adaptation of an optimal power flow dispatch model provides a formulation of a concurrent auction model for selecting long-term capacity awards based on the willingness to pay. The power flow formulation selects the combination of feasible contracts that would provide the highest valued use of the network. Financial transmission rights can be defined as obligations or options. CAISO stresses that the ISO define some rights as options, as long as it provides at least some rights as options. It points out that in an ideal scenario the ISO should offer both obligations and options and allow the market to determine the mix that best meets its commercial needs. PJM is currently investigating the implementation of FTR auction for options [18]. A FTR auction for both point-to-point obligations and options is similar to an economic dispatch problem [41]. But in FTR auction for options, evaluating a contingency and constraint condition requires solving an unconstrained optimal power flow for the worst case impact. This increases the complexity of the model and hence success with this auction model has not yet been demonstrated. On the other hand, a FTR auction for flowgate obligations or options is more complicated and it is not like an economic dispatch problem. In this model, there could be a large number of flowgates in the real grid that greatly complicates any construction of hedges. Also the required flowgate amounts to hedge any transaction change frequently with changing dispatch restrictions. A hybrid model with point-to-point and flowgate obligations and options can produce a computational challenge and it is not clear whether this auction model could be solved for a realistic grid. Hobbs et al.

[42] propose an auction-based process that allows the market participants to acquire and reconfigure the financial transmission rights. The paper shows that by allowing flowgate and point-to-point obligations and options to be reconfigured and exchanged, the market can decide what combination of financial rights are most useful to the market participants.

2.1.3 Demand-Side Bidding

The main motivation in deregulating the power industry was to improve its performance by exposing customers to cost-based price signals and hence FERC has also recommended large-scale demand side bidding programs. In the absence of demand-side bidding, the retail customers are shielded from exposure to the great variability of the energy prices. PJM [18] outlines an important fact that price-sensitive demand bids in the day-ahead market provide increased price certainty to the wholesale buyers. [19], [20], [21] emphasize that demand-side bidding will reduce the level and volatility of electricity prices. Carlos [22] states that one sided markets do not work well and market power is exacerbated by lack of demand side response. Johnsen et al. [23] also illustrate the fact that market power is mitigated by an active demand side. Cowart [24] states that demand side initiatives will provide a solution to price spikes , market power and reliability. Sally [25] confirms the importance of demand side bidding in making the markets more competitive.

Next we review the various approaches for modeling the restructured power markets.

2.2 Models for the Restructured Power Markets

The existing models in the literature for designing competitive electricity markets can be broadly classified as models that study market power by various approaches, such as empirical, mathematical, forecasting, simulation, and case study, which are reviewed here.

2.2.1 Mathematical Models

In competitive electricity markets, since the market participants compete against each other to maximize their benefits, game theory becomes a natural tool to study market behavior. Game theory has been widely used to understand a participant's behavior in deregulated environments [11], [43], [44], [45], [46], [47]. The notion of Nash equilibrium is applied to understand the likely behavior of rational firms in deregulated markets [11], [13]. Hobbs et al. [48] present a gaming model for markets with transmission constraints. [11], [13] model the restructured scenario as an oligopoly and argue that the simplistic Cournot and Bertrand models are not realistic enough to model the electricity markets. Klemperer and Meyer [49] choose a supply function approach and prove for a symmetric market structure that firms could sustain prices well above their marginal costs. Puller [50] characterizes two pricing models (static and dynamic), and proves by using both the models that in an industry with entry barriers, firms could sustain prices well above their marginal production costs exerting market power. [51] models the competition among POOL participants as a non-cooperative game with incomplete information and solves for the Cournot based Nash equilibrium to arrive at the optimal bidding strategy. Guan et al. [52] show that under certain market conditions, the suppliers independently withhold capacities and cause price spikes. Song et al. [26] model the problem as a Markov Decision Problem from the supplier side.

2.2.2 Price Based Models

Schweppe et al. [53] developed an operational approach for implementing deregulated competitive spot markets in the electric power industry. Their approach combines the economic theory with the physical laws that govern the working of the power networks. Hogan [10] shows the importance of explicitly considering the network externalities due to loop flows and stresses that nodal pricing methods will alleviate market power problems during congestion to a great extent. Mount [54] argues that a discriminatory price auction instead of an uniform price auction will result in price responsive supply curves.

2.2.3 Empirical Models and Case Studies

Wolak [55] provides statistical evidence for the fact that market mix, market structure and market rules play a very important role in the volatility of the spot price. Borenstein [56] points out that price cost mark-up index and the Herfindahl-Hisrchmann Indices (HHI's) indices are not capable of detecting market power under dynamic conditions when the supply and demand becomes tight. CAISO provides empirical evidence from the past data that market power was the reason for at least one third of the increased market clearing prices during summer 2000 [8]. Hirst et al. [57] emphasize the role of real time pricing as a measure to relieve the market power problem.

It can be concluded from the above available literature that there is a need for an exhaustive model including the real market features of two-settlement system, financial transmission rights and demand side bidding. This work intends to develop such a comprehensive framework for the analysis of market performance and this can be considered as one of the major contributions of this thesis.

CHAPTER 3

BASIC CONCEPTS

3.1 Introduction

In this chapter, basic concepts of Markov decision process (MDP), game theory, Competitive Markov decision process (CMDP), and reinforcement learning (RL) are explained.

3.2 Markov Decision Processes (MDPs)

A Markov decision process is a stochastic process described by the following elements: decision epochs, states, actions, transition probabilities and rewards. At each decision epoch, a decision maker takes an action and the system reaches a new state with a certain probability that is termed as transition probability. The decision maker receives a reward that may be positive or negative when the system moves to a new state. A decision rule assigns an action to each state while a policy is a collection of such decision rules over the state space.

Let

$$\mathbf{X} = \{X_n : n \in \mathcal{N}, X_n \in \mathcal{E}\} \tag{3.1}$$

represent the underlying Markov chain of a MDP, where X_n denotes the system state at the n^{th} decision making epoch, $\mathcal{E}$ denotes the state space, and $\mathcal{N}$ denotes the set of integers. At any decision making epoch n, where $X_n = i \in \mathcal{E}$, the decision maker chooses an action $A_n = a \in A_i$, where A_i denotes the set of possible actions in state i. Let $p(i, a, j)$ represent the probability of moving from state i to state j under action a. Let

$r : \mathcal{E} \times A \to \Re$, represent a reward function where $\Re$ denotes the real line, and $r(i, a)$ is the expected reward for taking action a in system state i. The transition probabilities and rewards are assumed to be stationary.

The solution algorithms for the MDPs, such as policy and value iteration, find the optimal *stationary deterministic policy* π^*, where $\pi^* : \mathcal{E} \to A$. The key idea of a stationary policy is that it is independent of time and is a nonrandomized policy that depends only on the current state of the process. The concepts of *gain, bias, Bellman's optimality equation, and average reward value iteration* which will be used in this thesis are explained next.

3.2.1 The Gain and Bias

The *gain* for a system in steady state modeled as MDP, is defined as the average reward per period for a given policy. For a system starting in an arbitrary state i and thereafter following policy π, gain is given as

$$\rho^\pi = \lim_{N \to \infty} \frac{1}{N} E_i^\pi \left\{ \sum_{n=1}^{N} r(X_n, A_n) \right\} = \psi r \tag{3.2}$$

where ψ denotes the limiting probability of the underlying Markov chain $\mathbf{X}$, and r is the reward vector $r(i, a) : i \in \mathcal{E}, a \in \pi$. The *bias* is defined as the expected total difference between the reward and the average reward. Hence, the bias in an MDP starting in state i and thereafter following policy π is given as

$$h^\pi(i) = E_i^\pi \left\{ \sum_{n=1}^{\infty} [r(X_n, A_n) - \rho^\pi] \right\} \tag{3.3}$$

3.2.2 Bellman's Optimality Equation for Average Reward Markov Decision Processes

The Bellman's optimality equation expresses a relationship between the value of a state and the values of its successor states. It states that the value of the start state must equal the discounted value of the expected next state, plus the reward expected along the path. The Bellman's optimality equation for average reward MDPs can be stated in component notation as follows. For policies with bounded rewards, there exist a scalar ρ^* and function $R^* \in V$ (where V is the space of bounded real valued functions on $\mathcal{E}$) for which

$$R^*(i) = \max_{a \in A_i} \left\{ r(i,a) - \rho^* + \sum_{j \in \mathcal{E}} p(i,a,j)(a) R^*(j) \right\} \tag{3.4}$$

3.2.3 Basic Concepts of Game Theory

Game theory studies the behavior of *rational players* in interaction with other *rational* players. Players are considered to be *rational* if they maximize their objective functions given their beliefs about the environment. Players act in an environment where other players' decisions influence their payoffs. Game theory can be considered as a method of analyzing the choice of strategies of agents in social situations. The concept of strategy as a complete plan of action provides an approach for modeling behavior that takes informational as well as dynamic characteristics of the environment into account.

3.2.4 Zero Sum and Non-Zero Sum Games

Games can be classified based on payoff structure as zero sum games and non-zero sum games. A *two player zero-sum game* is a game in strategic form such that

$$p_1(s_1, s_2) + p_2(s_1, s_2) = 0, \qquad \forall\ s_1 \in \mathcal{S}_1, s_2 \in \mathcal{S}_2 \tag{3.5}$$

where p_1, p_2 are the payoff functions of two players and $\mathcal{S}_1$ and $\mathcal{S}_2$ are the pure strategy sets of the two players.

From the above definition, it is seen that zero sum games are strictly competitive which means that what one player gains the other loses. In non-zero sum games some outcomes are more favorable to all players than others. Some outcomes may even yield a positive pay-off and others a negative pay-off for every player. This introduces a certain common interest among players to attain such more favorable outcomes even if they are not the most favorable outcomes for everyone. Such games are non-strictly competitive since they have both competitive and cooperative elements.

3.2.5 Pure and Mixed Strategy

The concept of strategy is fundamental to game-theoretic analysis as it provides a complete plan to the player for how to play the game. When players play each strategy with probability one in a repeated game, then the players are said to have a pure strategy. A mixed strategy simply means that the players random choose a pure strategy. Thus a mixed strategy is a probability distribution on the set of pure strategies. The set of mixed strategies always includes all pure strategies because a pure strategy can be considered as a special case of a mixed strategy in which the respective pure strategy is played with probability one and any other pure strategy with probability zero.

3.2.6 Nash Equilibrium

A strategy combination in which each player plays a best response to the opponents' behavior constitutes a *Nash Equilibrium.* Formally it can be stated that a strategy combination $s^* \in \mathcal{S}$ is a *Nash equilibrium* if

$$p_i(s^*) \geq p_i(s_i, s^*_{-i}) \;\; \forall \; s_i \in \mathcal{S}_i, i \in \mathcal{N} \tag{3.6}$$

where N is the set of players. A game in strategic form has at least one Nash equilibrium if for each player $i \in \mathcal{I}$, the strategy set $\mathcal{S}_I$ is a nonempty compact and convex subset of a Eucledian space and the payoff function p_i is continuous and quasi-concave in s_i. Games with finite pure strategy sets lack convexity of strategy sets and quasi-concavity of payoff functions. On the other hand, games with mixed strategies arising from them satisfy these conditions.

3.3 Reinforcement Learning

Dynamic programming (DP) algorithms for finding optimal policies for MDPs, such as value iteration, policy iteration and linear programming require the entire the probability structures of the system (e.g. the one-step transition probability matrices, reward matrices, and the sojourn times). For problems with large state spaces, computation of these quantities can become almost impossible and hence obtaining an optimal solution using these methods is often quite difficult. In recent years, a novel approach based on simulation-based stochastic approximation, called Reinforcement Learning (RL) has become a topic of intense research. Convergent algorithms based on this method have been shown to obtain near-optimal policies for MDPs with a considerable reduction in computational complexity. Since RL uses simulation as its modeling tool, it can handle problems with complex reward and stochastic structures. RL is a computational approach to understanding goal directed learning and decision making. It is different from other computational approaches by its emphasis on learning from direct interaction with the environment, without relying on exemplary supervision or complete models of the environment.

There are four main subelements of a RL system other than the agent and the environment: a policy, a reward function, a value function, and optionally, a model of the environment. A policy is a mapping from perceived states of the environment to actions taken when in those states. A reward function defines the goal in the RL problem. It maps each perceived state of the environment to a reward, indicating the intrinsic desirability of the state. The objective of a RL agent is to maximize the total reward in the long run. The value of a state is the total amount of reward an agent can expect to accumulate over the future, starting from that state. It should be noted that rewards are basically given directly by the environment, but values must be estimated from the sequences of observations an agent makes over its entire lifetime.

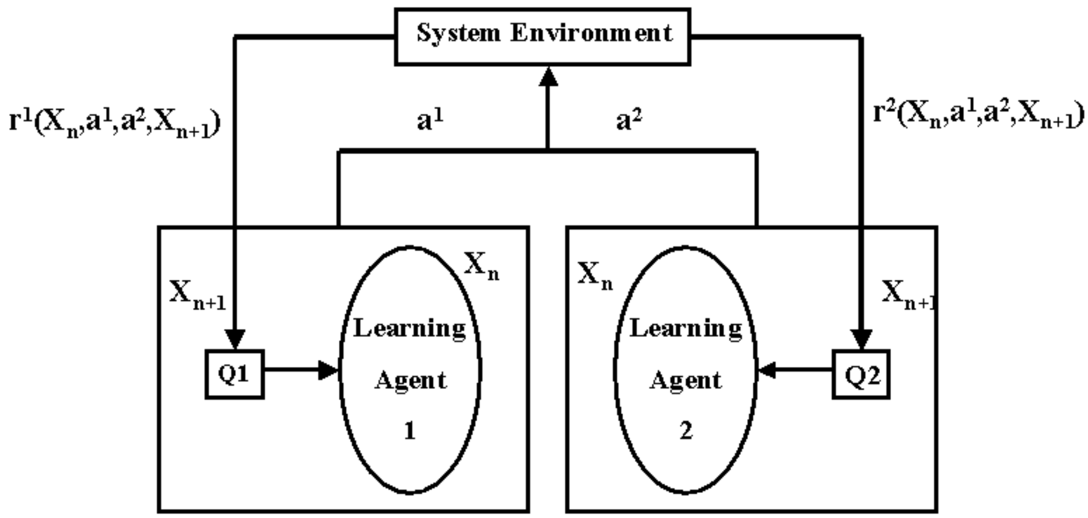

Figure 3.1. A Two-Agent Reinforcement Learning Model [1]

The agent and environment interact at each of the sequence of discrete time steps, $t = 0, 1, 2, 3, \cdots$. At each time step t, the agent receives some representation of the environment's *state*, $s_t \in \mathcal{S}$, where $\mathcal{S}$ is the set of possible states. Based on the given state, the agent selects an *action*, $a_t \in \mathcal{A}(s_t)$, where $\mathcal{A}_t$ is the set of actions available in state s_t. As a consequence of the action taken by the agent, it receives a numerical *reward*, $r_{t+1} \in \mathcal{R}$ and finds itself in a new state, s_{t+1}. The agent's policy is a mapping from states to probability of selecting each possible action.

A schematic representation for a 2-agent RL model is shown in Figure 3. Based on the system state X_n and and the reinforcement values for agent j ($Q^j(X_n = i)$), the jth agent takes an action a^j. The system, as a result of the actions chosen, evolves stochastically and results in the next system state (X_{n+1}) and reward (or punishment) for each agent ($r^j(X_n, a^j, X_{n+1})$). With these immediate rewards, the reinforcement function Q^j updates the new reinforcement values $Q^j(i)$ for the previous state ($X_n = i$). The optimal policy is determined by the steady state S values.

The two factors that determine the utility of an action are the immediate reward and the action value of the state to which a transition occurs as a result of that action. When a system visits a state for the first time, the agent chooses a random action since all the action values are equal. As the system revisits, the learning agent selects the action with highest (or lowest for minimization) action value. This is termed as a *greedy policy.* Sometimes, the agent by choosing an action other than that suggested by the greedy policy. The learning phase subsequently ends with one or more actions dominating in each state, which constitute the decision policy vector.

There are three different types of RL models that have been widely studied. In the *finite-horizon model*, the agent optimizes the expected reward for a finite number of steps, given by

$$E\left(\sum_{n=0}^{h} r_n\right), \tag{3.7}$$

where r_n is the scalar reward received from the n^{th} step of the horizon. Hence, it can be noted that the agents action on the first step is the *h-step optimal action*, on the second step *h-1 step optimal action*, and so on. The other two RL model types are *infinite horizon* models with *average reward* (3.8) and *discounted reward* (3.9) as their performance criterion, which are given as

$$\lim_{h\to\infty}\left(\frac{1}{h}\sum_{n=0}^{h} r_n\right), \tag{3.8}$$

and

$$E\left(\sum_{n=0}^{\infty} \gamma^n r_n\right), \tag{3.9}$$

where $\gamma(0 < \gamma < 1)$ is the discounting factor used per period. The performance measure used in this thesis is average reward that is explained next.

3.3.1 Average Reward RL

In most situations, discounting is inappropriate and hence it is logical to optimize the average reward per stage starting from state i, which is defined for any policy, any policy $\pi = (\pi_0, \pi_1, \cdots)$ by assuming that the limit exists where $r(i, a, j)$ is the player reward.

$$R^{\pi}(i) = \lim_{N \to \infty} \frac{1}{N} E\left[\sum_{k=0}^{N-1} (r(i_k, \pi_k, i_{k+1}) | i_0 = i)\right] \tag{3.10}$$

3.3.2 Model-Free RL

The model-based RL algorithms estimate the transition probabilities and rewrads using simulation. The curse of dimensionality which exists in model-based RL can be eliminated by model-free algorithms. Model-free algorithms can estimate action values from sample paths generated by simulation. These algorithms belong to a class of stochastic iterative algorithms for which the updating scheme is given as

$$Q_{new}(i,a) \ = (1-\alpha)Q_{old}(i,a) + \alpha\left[r_{imm}(i,a,j) - g^* + \max_b Q_{old}(j,b)\right], \tag{3.11}$$

where $Q_{new}(i,a)$ and $Q_{old}(i,a)$ are the new and old reinforcement values for state-action combination (i,a), α is the learning parameter, g^* is a scalar that could represent the average system performance measure.

3.4 Competitive Markov Decision Process (CMDP)

As compared to MDPs which are single agent decision processes, CMDPs or stochastic games are multi-agent decision making problems. In a CMDP, a player's payoff depends upon the decision taken by that player along with the decisions taken by the other players in the game. A stochastic game is a dynamic system that evolves along discrete time epochs $t = 0, 1, \cdots$. The state of the system at each time epoch is assumed to be one of a finite set $\in \mathcal{E}$. The process is governed by two agents referred to as player 1 and player 2. At each decision epoch, both players independently choose actions $a^1 \in A^1(i)$ and $a^2 \in A^2(i)$ and receives rewards $r^1(i, a^1, a^2)$ and $r^2(i, a^1, a^2)$ respectively. $A^1(i)$ denote set of actions available for player 1 in state i and $A^2(i)$ represents set of actions available for player 2 in state i. The stationary transition probabilities are given as

$$P(j|i,u,v) : P\left\{X^{t+1} = j|X^t = i, a^1(i) = u, a^2(i) = v\right\}, \tag{3.12}$$

for all $t = 0, 1, \cdots$. In (3.12), X^t represents the system state at any time t, u and v denotes the actions chosen by players 1 and 2 at time t respectively. The strategy set for player p can be given as

$$S^p = \{s^p(1), s^p(2), \cdots, s^p(|\mathcal{E}|)\}, \tag{3.13}$$

where

$$s^p(i) = (f^p(i,1), f^p(i,2), \cdots, f^p(i, |A^p(i)|)). \tag{3.14}$$

In (3.13), $s^p(i)$ is the strategy for player p in state i. In (3.14), $f^p(i,a)$ is the probability of player p choosing action a in state i. It is to be noted that for any player p and system state i,

$$\sum_{n=1}^{|A^p(i)|} f^p(i,n) = 1. \tag{3.15}$$

The strategy $s^p(i)$ defined in 3.14 is called a *mixed strategy*. A strategy is *pure strategy* if

$$f^p(i,a) \in \{0,1\} \qquad \forall a \in A^p(i), i \in \mathcal{E}. \tag{3.16}$$

3.4.1 Zero and Non-Zero Sum Stochastic Game

For a *zero sum* stochastic game, the sum of the rewards for all players for any state-action combination is equal to zero. For a zero sum stochastic game

$$r^1(i, a^1, a^2) + r^2(i, a^1, a^2) = 0 \qquad \forall a \in A^p(i), i \in \mathcal{E}. \tag{3.17}$$

When the left side of (3.17) sums to any other constant then the stochastic game is a *constant sum* game. On the other hand, if the left side of (3.17) is not restricted to zero or a constant then the stochastic game is a *general sum* game.

CHAPTER 4

CONCEPTS OF TWO-SETTLEMENT SYSTEM AND BILATERAL TRANSACTIONS

This chapter gives a detailed explanation of the two-settlement system, and bilateral transactions.

4.1 Two-Settlement System in PJM Market

The two-settlement system provides the PJM market participants with the option to participate in a forward market for electric energy in PJM. It consists of two markets, with separate financial settlement for each market.

4.1.1 Day-ahead Market

The day-ahead market is a forward market in which hourly clearing prices are calculated for each hour of the next operating day based on generation offers, demand bids, and bilateral transactions. The day-ahead schedule is developed using least-cost security constrained unit commitment and economic dispatch programs. The day-ahead market enables the participants to purchase and sell energy at financially binding day-ahead prices. Day-ahead congestion charges for bilateral transactions are based on the differences in locational marginal prices (LMPs) between the transaction's points of injection and withdrawal. The day-ahead scheduling process considers PJM reliability requirements and reserve obligations into the analysis. The resulting hourly schedules and LMPs at the various nodes represent binding financial commitments to the market participants.

4.1.2 Real-time Market

In the real-time market hourly clearing prices are determined by the actual system operations, as determined by the PJM state estimator. Load Serving Entities (LSEs) pay real-time LMP for any demand that exceeds their day-ahead scheduled quantities (and receive credit for demand deviations below their day-ahead scheduled quantities). Generators receive prices for any generation that exceeds their day-ahead scheduled quantities (and pay for generation deviations below their day-ahead scheduled quantities). All spot purchases and sales in the real-time market are settled at the real-time prices.

4.1.3 Purpose of Two-Settlement System

The purpose of two-settlement is to enhance the robust and competitive market in the PJM Control Area. It also provides increased price certainty to market participants by allowing them to perform the following activities:

- Commit to forward energy prices
- Submit price-sensitive demand bids in the day-ahead market
- Specify maximum congestion charge bids in the day-ahead market
- Submit increment offers or decrement bids in day-ahead market

4.1.4 Two-Settlement Market Rules

PJM has stated the following business rules for its market participants.

- Market sellers that own capacity resources must submit offers into the day-ahead market, unless the resource is unavailable due to an outage.
- If a capacity resource is not scheduled in the day-ahead market, then it may revise its offer and submit it into the balancing market or the unit may be self-scheduled.

- A capacity resource's last offer remains in effect until it is specifically superceded by another offer.
- Generation offers must not exceed \$1000/MWh.
- Offers for combined cycle units must make available either the schedule for the CT's or the schedule for the combined cycle unit.
- Generation offers and demand bids can be submitted up to seven days in future.
- Market buyers have a profile, maintained by PJM, that specifies the transmission zones or buses for which it is eligible to submit demand bids.
- A market buyer may submit demand bids for consumption in the next operating day. If the market buyer does not submit any day-ahead bids, then a 0 MW quantity is assumed.
- Price-sensitive bids, increment offers, and decrement bids must be consistent with the \$1000/MWh price cap.
- Internal bilateral transactions may be designated as day-ahead or balancing market in PJM internal bilateral transactions.

4.2 Bilateral Transactions

It is important to note the distinction between external and internal bilateral transactions. In PJM, external transaction bids and schedules are included as inputs in the unit commitment and optimal dispatch programs. On the other hand, internal bilateral transactions are used only to calculate financial settlements in the PJM markets.

4.2.1 External Transactions

Market participants that undertake external transactions have to make a series of decisions from the time that they make their transmission capacity reservation to the time that they submit their transaction schedule. Their decisions reflect important choices regarding: the injection and/or withdrawal locations for their transactions, the type of transmission service that they elect and whether or not they want to be elected in the two-settlement system. All external transactions are required to reserve and purchase transmission service over the PJM OASIS. Transmission customers may choose firm or non-firm point-to-point transmission service. Election of firm transmission service indicates that the transmission customer is willing to pay congestion charges. To hedge these charges, customers may elect to receive FTRs that correspond to their service. Customers taking non-firm service elect whether or not they are willing to pay congestion. The day-ahead market in PJM is used only to schedule transactions that are willing to pay congestion costs. Transactions that are not willing to pay congestion may not enter into day-ahead financial settlements and they are considered in the real-time balancing market.

4.2.2 Internal Bilateral Transactions

In PJM market, internal bilateral transactions are used only for calculating LMP settlements for the concerned parties to the transaction and are not used while scheduling the transmission system. The system operator has no information regarding the details of the contract. When these transactions are implemented through *Contracts for Differences* (CFDs), market participants are completely insulated from the volatility of the market price for the quantity under contract. The working of CFD can be explained with the following example. Consider a bilateral contract of 90 MW at \$10/MWh between a generator at node A and load at B. Also assume that the generator has 80 MW FTR from A to B. Let the real time LMP at nodes A and B be \$15/MWh and \$20/MWh respectively.

Assume that the generator supplies 125 MW to the network and the load draws a total of 100 MW. The set of financial transactions that take for this are as follows.

The system operator (SO) pays to the generator for the power and the congestion rent, which amounts to $125 \times 15 + (20-15) \times 80 =$ \$2275.

The SO receives a payment from the load for the amount of $100 \times 20 =$ \$2000.

The CFD settlement for the bilateral contract in this case requires the generator to pay the load an amount equal to (20-10) $\times 90 =$ \$900.

Thus it can be seen that the generator is hedged against congestion charges through FTR and the load is hedged against the spot market prices through the bilateral contract. In this thesis, only internal bilateral transactions are considered for modeling purposes.

CHAPTER 5
FTR AUCTIONS

5.1 Introduction

In an electric power network, the generating plants and customers are connected through a free-flowing grid of transmission and distribution lines. Transmission lines have thermal limits, reactive power, and stability limits which must be maintained in order to prevent the overheating of the wires and maintain the overall reliability of the system. These physical limits constrain the long-distance movement of power and hence, in periods of high demand, some of the lower cost generators may be “constrained off” and “out-of-merit” plants with higher costs are run. This phenomenon is termed as transmission congestion, which gives rise to spatial differences in energy prices. The cost of congestion or the transmission charge for moving energy from node X to node Y is simply the difference (positive or negative) in energy prices between the two nodes. There is no other congestion cost in the integrated locational energy market. Electricity markets use a well defined transmission rights auction to hedge the market participants from the volatility of the transmission charges.

5.2 Mechanism to Hedge Against Congestion Charges

According to CAISO, a transmission right is a property right that allows its holder to access a portion of the transmission capacity. Generally, a transmission property right consists of three components: 1) the right to receive financial benefits derived from the use of the capacity, 2) the right to use the capacity, and 3) the right to exclude others from accessing the capacity. Transmission rights can be defined as a combination of these three components. One approach to obtaining transmission rights is purely financial in nature. Such financial rights, also known as passive rights, provide market traders and other market participants an instrument for constructing financial hedges. The second approach combines financial benefits with capacity reservations or scheduling priority and is called the capacity-reservation approach. The third approach includes all three components and is known as the physical rights approach.

The definition of transmission rights further depends on how the transmission capacity is specified and measured. There are two common ways to specify the transmission capacity of the network. One way is to compute the point-to-point transfer capabilities, and the other is to specify the power flow carrying capacity for each link of the network.

The point-to-point definition is rooted in what has been commonly known as the contract path approach. However, the transfer capability between any two points in a network changes continuously as the pattern of flow changes. In contrast, the capacity of each link is determined by physical factors associated with the link and is generally insensitive to the power flow pattern. From the options discussed above, we can classify transmission rights in six possible ways: 1) point-to-point (PTP) financial rights, 2) flow based financial transmission rights (FTRs), 3) PTP capacity reservations, 4) flow based capacity reservations, 5) PTP physical rights, and 6) flow based physical rights. Transmission customers who acquire network transmission service are allocated FTRs on an annual basis up to their annual peak load. These FTRs are designated along paths from specific generators to their aggregated loads. The configuration of FTRs can be adjusted annually or when capacity resources are added or restricted. This research is focused on PTP financial transmission rights, which is further discussed next.

5.2.1 Point-to-Point Financial Transmission Rights

Ownership of PTP FTRs will entitle the holder to be paid the difference in the congestion components of the locational prices between the specific point or points of receipt and the specified point or points of injection. These payments may be subject to proration under some conditions. PTP FTRs are directional and may be defined either as obligations or options. PTP obligation holders are entitled to payments when the difference between the locational prices is positive, and are also obligated to make payments when the locational price difference is negative. PTP option holders will be entitled to payments when the difference in the locational prices is positive, but will not be obligated to make payments when the locational difference is negative. If a FTR holder transmits energy between two points, the congestion charges paid are matched by the congestion rent if the amount transmitted is less than or equal to the hedged quantity. In this way, an FTR holder can have price certainty on the delivery of energy scheduled, and the FTR holders are paid the applicable rents associated with the right, regardless of whether they schedule transmission service or not.

5.2.2 Simultaneous Feasibility

All FTRs outstanding at a given time must be simultaneously feasible. In other words, the transmission system under security-constrained conditions must be able to accommodate all the potential energy flows represented by an outstanding set of FTRs The system constraints used in modeling the FTR allocation process for feasibility will be consistent with the model used in determining the day-ahead and the spot energy market LMPs. FTRs are modeled as generation at the source (point of injection) and load at the sink (point of withdrawal). Simultaneous Feasibility Tests (SFT) are run for yearly, monthly, and weekly analysis periods, when network resource changes are submitted, and during the determination of the winning quotes for the FTR auction. SFT is carried out using a DC power flow algorithm which is a completely linear and non-iterative algorithm. The DC power flow calculates MW flows on transmission lines which are used to check the violation of the security constraints. The application of the SFT to the allocation or auction of FTR is intended to ensure that the congestion rents collected by the ISO will be sufficient to honor payment obligations to FTR holders. The congestion rent collections may nevertheless be insufficient to fund full payments to FTR holders if there are transmission outages that reduce transfer capability which was assumed in the SFT. In such circumstances, the ISO will prorate the transmission right payments.

5.3 Financial Transmission Right (FTR) Auction for Obligations

In this research work, FTR auction only for obligations, as practiced in the PJM market, is considered. An FTR auction for point-to-point obligations is similar to an economic dispatch problem. PJM is currently in the process of investigating FTR auction for options. The evaluation for simultaneous feasibility for options presents a significant increase in complexity [41], as there would be large number of option type FTRs and a very large number of constraints. The optimization over the constraint functions would require many evaluations and the combinatorics are expected to be daunting. Success with this auction model has not been demonstrated. Preliminary studies suggest that the auction for options might work for the DC-Load implementation in PJM, but the AC implementation in New York would be more of a challenge. In this thesis, FTR auction for obligations is considered for modeling purposes.

FTR auction allows the PJM market participants to submit bids to buy residual FTRs (remaining after initial allocation based on annual peak load) and to submit offers to sell existing FTRs. Each bid to buy FTRs states the maximum price in dollars per MW that the buyer is willing to pay for that FTR. It will pay no more than its bid, but may pay less. In the same manner, each bid to sell FTRs can define the minimum price in dollars per MW that the seller is willing to accept for that FTR. It will sell its FTR for no less than its bid, but it may receive more.

The purpose of the FTR auction is to facilitate a more robust and liquid market for FTRs. The FTR auction maximizes the efficiency of FTR trading by providing automatic reconfiguration of FTRs, while maintaining the simultaneous feasibility of the system. The

FTRs acquired in an FTR auction have a term of one month. They are available between any single bus or a combination of buses for which LMP is calculated. FTRs may be designated from injection and withdrawal locations outside of PJM. These FTRs hedge the holder against congestion payments to PJM when their energy delivery is consistent with the FTRs definition.

5.3.1 FTR Auction Business Rules

The following information summarizes PJM FTR auction business rules.

- Market participants cannot submit offers to sell FTRs that they do not own at submittal time.

- An FTR request that is approved by PJM but not confirmed by FTR customer by close of quoting period is deemed withdrawn. PJM makes best efforts to complete the processing of all transmission service requests involving FTRs that are submitted prior to close of auction quoting period.

- Any FTRs approved under firm transmission service at the close of the auction period that are defined for the auction month and not offered for sale in the auction are modeled as fixed injections in auction analysis.

- Auction quotes are financially binding.

- FTR auction revenues are distributed to the Regional Transmission Organizations (RTO's).

5.3.2 Selection of Winning Bids and Offers

The FTR auction clears based on maximizing the net bid-based value of FTR bids and offers submitted into the auction. In the actual PJM FTR Auction, this clearing process is performed using a linear program that models all security constraints including

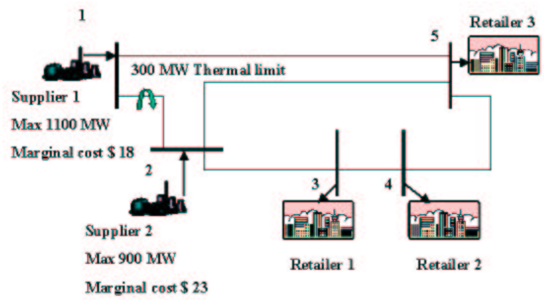

Figure 5.1. A Sample 5 Bus Network (Adopted from PJM Website)

both normal ratings and single contingency events. A simplified ratio approach is discussed here that works well when there is only a single binding transmission limitation. The selection process is based on calculating the cost effectiveness ratio for each bid and offer submitted into the auction. The cost effectiveness ratio calculated by dividing the price bid or sell offer by the flow sensitivity of the FTR on the constrained transmission line. The flow sensitivity is the portion of the FTR MW quantity that flows on the constrained line. The following steps are used for awarding the bids.

- Award bids from highest to lowest cost effectiveness until all FTR capability is utilized.
- Compare sell offer cost effectiveness to the cost of last marginal bid. If cost effectiveness of sell offer is favorable to marginal bid cost effectiveness, sell offer is awarded.
- Additional bids are awarded to consume the FTR capability made available during Step 2
- Repeat Steps 1, 2 and 3 until all FTR capability is utilized.

After the clearing quantities are obtained using the above procedure, the clearing prices are calculated based on the marginal FTR and the flow sensitivities of each FTR path relative to the marginal FTR path flow sensitivity. The following example, available on PJM website, illustrates the FTR bid selection process. In this example, a sample five

Table 5.1. Calculating Cost Effectiveness and Effect on the Capability of Constrained Line E-D

Path	MW Quote	Quote Price	Sensitivity	Cost Effectiveness	Effect on E-D Capability
Buy Quotes					
E-B	10	$ 4.00	0.2629	$ 16.21	2.6
A-D	40	$ 5.00	0.3685	$ 13.57	14.7
E-C	10	$ 4.00	0.3209	$ 12.46	3.2
A-D	10	$ 4.00	0.3685	$ 10.86	3.7
Sell Quotes					
E-C	10	$ 2.00	-0.3209	-$ 12.46	-3.2
A-D	10	$ 6.00	-0.3685	-$ 16.28	-3.7

bus network as shown in Figure 11 is considered. In this case, FTRs are allocated to the market participants based on their annual peak load. FTR auction is conducted for 10 MW remaining capacity on line E-D after initial allocation.

The FTR buy bids are as follows:

- $5/MW Bid for 40 MW A-to-D FTR
- $4/MW Bid for 10 MW E-to-B FTR
- $4/MW Bid for 10 MW A-to-D FTR
- $4/MW Bid for 10 MW E-to-C FTR

The FTR sell offers are as follows:

- $2/MW Sell Offer for 10 MW E-to-C FTR
- $6/MW Sell Offer for 10 MW A-to-D FTR

Given these bids, the cost effectiveness ratio and the effect on Line E-D capability are calculated as explained earlier and shown in Table 1. The quotes are then listed in descending order of cost effectiveness. For example, the cost effectiveness for the 10 MW E-B quote is calculated as $4.00/0.2629 = 16.21$. The effect of this bid on E-D capability is calculated as $0.2629 \times 10 = 2.6$.

Table 5.2. Calculating Feasible Quantities for the Winning Quotes

Quote	Effect on Line E-D	Remaining Capability on Line E-D	Portion of Quote Awarded
Buy 10 MW from Line E-B	2.6	7.4 MW	10 MW buy (10 MW buy quote)
Buy 40 MW from Line A-D	7.4	0 MW	7.4/0.3685=20 MW buy (40 MW buy quote)
Sell 10 MW from Line E-C	-3.2	3.2 MW	10 MW sell (10 MW sell quote)
Buy 40 MW from Line A-D (20 MW Remaining	3.2	0 MW	3.2/0.3685=8 MW buy 8 MW + 20 MW = 28 MW buy (40 MW buy quote)

Table 5.3. Clearing Price Calculation

Source	Sink	Portion of FTR that flows on Line E-D	Clearing Price Calculation
A	D	0.3685	\$5.00 (A-D is the Marginal FTR Path)
E	B	0.2629	\$5.00 $\times$0.2629/0.3685=\$3.57
E	C	0.3209	\$5.00 $\times$0.3209/0.3685=\$4.35

The feasible quantities for the winning quotes are calculated by performing steps 1, 2 and 3 as described earlier. As shown in Table 2, the 10 MW E-B quote having the highest cost effectiveness is first considered for allocation. The entire 10 MW quote is awarded as the remaining capability on Line E-D (10 -2.6 = 7.4) is greater than zero. The 40 MW A-D quote is considered next and only 7.4/0.3685 (sensitivity of line A-D)=20 MW is awarded since the remaining capability on Line E-D is zero. Next, the sell quote of 10 MW from E-C is considered as it has a more favorable cost effectiveness as compared to A-D. The additional capability made available by the sell offer is utilized by awarding 8 MW of the 40 MW buy offer from A-D. It should be noted that A-D is the marginal FTR path. Next the clearing price of path ij is calculated as:

(Marginal FTR path) $*$(Marginal Path sensitivity / Sensitivity of path ij).

For example, the clearing price of E-B is calculated as \$5.00 $\times$0.2629/0.3685=\$3.57.

The clearing price calculations are illustrated in Table 3. The final auction results are tabulated in Tables 4 and 5.

Table 5.4. Auction Results for Buy Bids

FTR Buy Bids	Quotes Cleared
\$5/MW Bid for 40 MW A-to-D FTR	28 MW @ \$ 5.00/MW
\$4/MW Bid for 10 MW E-to-B FTR	10 MW @ \$ 3.57/MW
\$4/MW Bid for 10 MW A-to-D FTR	0 MW
\$4/MW Bid for 10 MW E-to-C FTR	0 MW

Table 5.5. Auction Results for Sell Quotes

FTR Sell Offers	Quotes Cleared
\$2/MW Sell Offer for 10 MW E-to-C FTR	10 MW @\$ 4.35/MW
\$6/MW Sell Offer for 10 MW A-to-D FTR	0 MW

The next chapter presents a detailed problem definition and a modeling framework for the FTR auction described in this chapter.

CHAPTER 6

FTR AUCTION MODEL FORMULATION

This chapter presents a detailed FTR auction problem description along with the assumptions taken into consideration. Then a competitive Markov decision problem (CMDP) model for the bidding behavior of the suppliers in the FTR auction is presented.

6.1 Problem Definition and Assumptions

The problem considered here is to determine the competitive equilibrium bidding strategies in a FTR auction by considering the equilibrium profits realized in the energy market as the performance measure. In this thesis, it is assumed that FTRs can be acquired only by the suppliers and not by the load serving entities (LSEs), which is also assumed to hold for the energy game. This assumption is made solely to restrict the size of the problem for computational purposes without sacrificing the generality of the modeling approach. A sound bidding strategy is needed for purchasing FTRs, for the following reasons. If the bid price is too low, sufficient FTRs may not be allocated resulting in the supplier paying

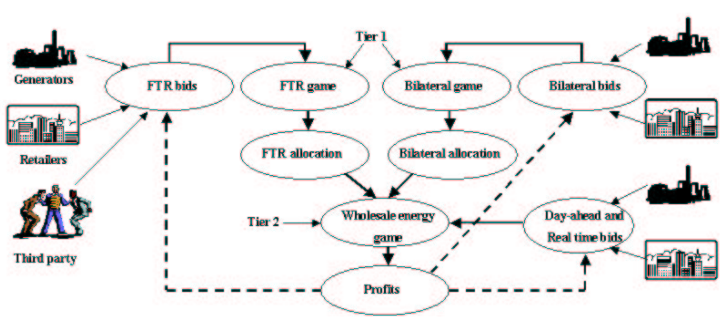

Figure 6.1. Two-tier Modeling Framework

high congestion costs. On the other hand, bidding too high will likely win ownership of the auctioned FTR, but may mean loss of profit.

Market participants in their efforts to bid for FTRs should take into account two important factors that are discussed next. One of these factors is the estimated price differentials between the supply node and the load nodes, for which an accurate prediction of future locational prices is important. Another important factor is the anticipated total supply quantity as it ideally represents the amount of power that needs to be hedged against the congestion costs.

6.2 Modeling Approach

As discussed earlier, we consider three major noncooperative components of the power market, namely FTR auction, bilateral contracts, and wholesale energy bidding in the day ahead (DA) and real time (RT) markets. The interdependence of these components are critical to the decision making processes of the participants. In our modeling approach, we adopt the following structure. The participants make bidding decisions in the FTR auction and bilateral energy markets, and subsequently use FTR and bilateral allocations in formulating their DA and RT bidding strategies. The individual profits realized by the participants are the combined effect of the decisions made by the participants in all three markets. These profits serve as the measure of performance for the participant's decisions. Thus, the DA and RT game has embedded in it the FTR and the bilateral contract games. Since the decisions for these three games are naturally separated in time, we model the power market with a two tiered structure as shown in Figure **??**. In the upper tier we will consider two parallel games, the FTR auction and the bilateral contract. The lower tier will account for the DA and RT game in which the upper tier decisions will be used as inputs.

Next, we present a competitive Markov decision problem (CMDP) model for the bidding behavior of the competing suppliers in the FTR auction.

6.2.1 CMDP Model for the FTR Auction

Let the number of suppliers and the loads be denoted by N and M respectively. Let $\mathcal{G}$ and $\mathcal{L}$ denote the sets of suppliers and loads respectively and $\mathcal{B}$ denotes the set of buses in the network. Let the system state at the t^{th} decision epoch be given by $X^t = \{\mathrm{q}^t, p^t\}$, where $q^t = (q_1^t, q_2^t, \cdots, q_N^t)$ and q_s^t denotes the total forecasted supply quantity of the s^{th} supplier, $s \in \mathcal{G}$. The forecasted supply quantities are considered to be the same as the average of the actual energy supplied in the $(t-1)^{th}$ decision epoch. Also, let matrix p^t $=(p_{ij}^t)$, where p_{ij}^t represents the anticipated price difference between buses i and j, where $i, j \in \mathcal{B}$. The elements of p^t are obtained from the average of the actual price differences in the $(t-1)^{th}$ decision epoch. We discretize the forecasted supply quantity for each decision epoch between its minimum ($q_{\min}$) and maximum ($q_{\max}$) possible values in Q discrete steps. Similarly, the forecasted nodal price differences are considered to vary between a minimum ($p_{\min}$) and maximum ($p_{\max}$) and are discretized in P steps. Then the cardinality of the system state space ($\mathcal{E}$) can be given as $\mid \mathcal{E} \mid = (Q^N \times P^b)$, where $b = 1/2(\mid \mathcal{B} \mid^2$ - $\mid \mathcal{B} \mid)$ represents the number of upper triangular elements of p^t and $\mid \mathcal{B} \mid$ is the cardinality of the set of buses.

Let the decision vector at the t^{th} epoch be given by $D^t = \{\mathcal{D}_l^t : l \in \mathcal{G} \cup \mathcal{L}\}$, where $\mathcal{D}_l^t$ is the decision vector of participant l and given as $\mathcal{D}_l^t = \{Q_l^t, P_l^t\}$. The element $Q_l^t = \{Q_l^t(i,j) : i, j \in \mathcal{B}\}$ denotes the symmetric matrix (with diagonal elements being zero) of FTR bid quantities of participant l for all nodes i and j. Similarly, $P_l^t = \{P_l^t(i,j) : i, j \in \mathcal{B}\}$ represents the FTR bid price matrix. We discretize the bid quantity in U steps between zero and the average of the actual energy supplied as identified in the current state. Also, the bid price is discretized in V steps between zero and the average of the actual nodal price differences as indicated in the current state. To restrict the action space to a finite number, we discretize the bids between the two limits as described above. However, this model is not restricted in its scope and can accommodate bids outside the assumed limits. The cardinality of the complete decision space for the l^{th} participant for any given epoch t,

D_l^t can be given as $\mid D_l^t \mid = (U^b \times V^b)$, where b is the number of upper triangular elements of matrices Q_l^t and P_l^t.

We next define the stochastic processes that underlie the FTR market and develop their properties. Define $\mathcal{X} = \{X^t : t \in \mathbf{N}\}$, where $\mathbf{N}$ is the set of integers, as the system state process. Assuming that the system state variables q^t, and p^t are discrete valued, the discrete parameter random process $\mathcal{X}$ can be shown to be a Markov chain. The decision process involves selection of bid quantities and prices for each decision epoch by the participants. The decision process can be defined as $\mathcal{D} = \{D^t : t \in \mathbf{N}\}$, where $D^t = \{D_l^t : l \in \mathcal{G} \cup \mathcal{L} = (1, 2, \cdots, M + N)\}$ is the decision vector for the t^{th} epoch. Since the decision vectors D_l^t by the participants are chosen in a competitive manner, the combined process given by $\mathcal{X}$ and $\mathcal{D}$ is a competitive Markov decision process (CMDP).

In the next chapter, we present a Reinforcement Learning (RL) based solution methodology for obtaining the equilibrium strategies for the market participants in both the transmission and energy markets.

CHAPTER 7
SOLUTION METHODOLOGY

In this chapter, we present a Reinforcement Learning (RL) based solution methodology for the FTR auction problem discussed in Chapter 6.

7.1 Two-tier Solution Framework for the Model

A two-tiered RL based solution framework for the proposed CMDP model is presented in this section. A schematic diagram of the solution framework depicting the flow of information between the various modules is shown in Figure 7.1.

In line with the modeling approach, the FTR and bilateral games in tier 1 while the DA and RT games are taken into account in tier 2. The interaction of the various modules in both the tiers is discussed next. The RL module in tier 1 generates the bids for the FTR and bilateral markets for the participants. Based on the bids, FTR and bilateral quantities and prices are allocated. These allocations serve as inputs to the RL module in tier 2, which decides on the DA and RT bids for each generator using the forecast of the next epoch's (day's) demand and prices (which make up the system state at the current epoch). This set of actions together with the simulated load vector is sent to the OPF module. The OPF output i.e., the DA and RT quantities and prices for each demand and supply node is sent to the forecasting and revenue calculation blocks in tier 2. The RL block in tier 2 then updates the R-value matrix of each supplier using the information received from the revenue calculation block. If the stopping criterion of convergence of R-values is not reached, RL block decides on the next set of actions for the suppliers. This cycle of Simulation $\rightarrow$ OPF $\rightarrow$ RL $\rightarrow$ Simulation continues until stable R-values for all the

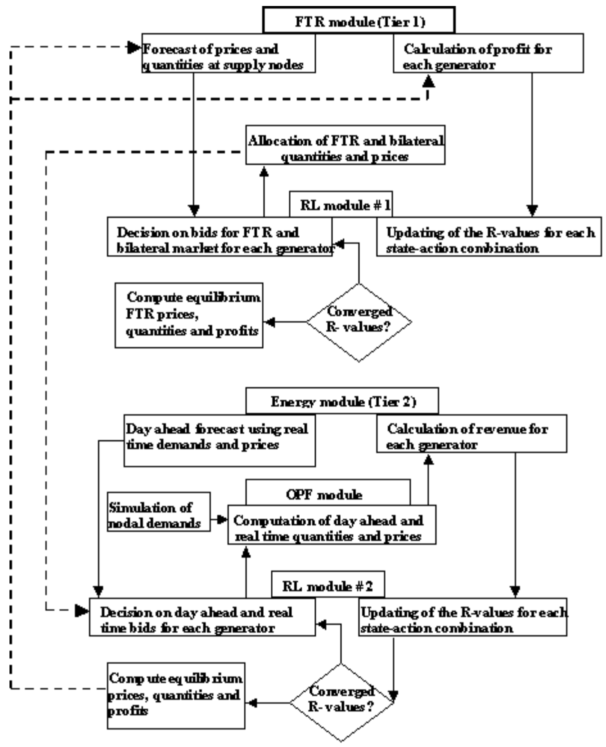

Figure 7.1. A Schematic of the Learning Based Solution Framework

state and action combinations are obtained. The stable values dictate the learned policy, which is then simulated to assess the equilibrium energy prices and quantities and the corresponding profits of the suppliers. This information is then sent to the forecasting and profit calculation blocks in tier 1. The RL module in tier 1 works in a similar manner to its counterpart in tier 2 and subsequently learns the equilibrium policy and the corresponding equilibrium FTR allocations and profits.

7.1.1 A RL Algorithm for Finding Equilibrium for FTR Auction

In what follows, the average reward RL algorithm for solving the non-zero sum average reward FTR auction game is presented. But, before formal presentation of the algorithm, a step-by-step description of the algorithm is given. In this algorithm, the decision making process is embedded within a system simulation program. The program simulates the actions of the players and the resulting system transitions, and also generates the corresponding system response (rewards). The decision making component of the algorithm then uses the system responses to learn the R values that constitute the equivalent matrix games. These matrix games are then solved to obtain the Nash equilibrium policies and values. The step numbers used below correspond exactly to the step numbers of the algorithm presented.

1. As a first step, the following variables are initialized: the R-value matrices for each player for each state, the average reward values for the players, the count for the number of visits to each state-action combination , the input parameters for two different learning rates and the exploration rate.

2. Assume that at the iteration count $m <$ MaxSteps, the system state is s. MaxSteps is the termination criterion.

   (a) Each player i, with the probability value of one minus the current exploration rate for chooses Nash action for the current matrix game $R^i(s)$. All of the remaining actions are chosen with equal proportions of the exploration probability. Uniform (0,1) random variables are generated for selecting action choices for the players according to the above probabilities.

   (b) The system is simulated with the chose actions and subsequently the system reaches a new state s'. The immediate rewards from the action choices of the players are generated.

   (c) At this time, the Nash equilibrium policy for each player (π^i_{m*}) for the stage matrix game $R^i(s')$ is obtained and also the Nash equilibrium value for each player ($Val^i(\pi^i_{m*})$) is computed.

   (d) The counts for the number of visits to each state-action combination, and the learning parameters are updated.

   (e) The R values for the stage matrix game for the most recent state-action combination ($R^i(s, a^1, \cdots a^N)$) are updated using a learning scheme. Also updated are the players' average reward values G^i. This type of a dual updating scheme is called a *two time-scale updating* procedure.

(f) Update the current system state as s' and the iteration count as $m+1$.

(g) If the current iteration count is less than MaxSteps, the algorithm continues at Step 2(a), else it moves to Step 3.

3. Start a fresh simulation of the system with the Nash equilibrium policies for individual stage games and estimate the rewards of the players.

We now give a formal description of the RL algorithm.

7.1.1.1 RL Algorithm

1. Let iteration or decision epoch count $m = 1$. Initialize for all players $i \in \mathcal{N}$ $=\{1, 2, \cdots N\}$, the R-value matrices as $R^i(s) = 0$ and the average reward values as $G^i = 0$ for all states $s \in S$. Set the visit frequency for the tuple $(s, a^1, \cdots a^N)$ as $n(s, a^1, \cdots a^N) = 0$, where $a^i \in A^i(s)$. Start the system simulation.

2. While $m <$ MaxSteps do

   (a) For each player $i \in \mathcal{N}$, with probability $(1-\gamma_m)$, choose a Nash action $a^i \in A^i(s)$ in state s for the stage matrix game $R^i(s)$. With a probability of γ_m choose a random (exploratory) action from the set $A^i(s)\backslash a^i$.

   (b) Simulate the chosen actions till the system reaches the next decision epoch. Let the system state at that epoch be s', and $r^i(s, s', a^1, \cdots a^N)$ be the immediate reward for player i earned as a result of actions $(a^1, \cdots a^N)$ chosen in state s. The immediate reward for player i is considered to be the equilibrium profit realized in the energy market as a result of the chosen actions. Note that, players do not see the actions of the other players.

(c) Calculate the Nash equilibria for the stage matrix game $R^i(s')$ for the new state s' and all $i \in \mathcal{N}$. Choose for each player an equilibrium policy π^i_{m*} based on a given scheme and calculate the Nash equilibrium value $Val^i(\pi^i_{m*})$.

(d) $n(s, a^1, \cdots a^N) \leftarrow n(s, a^1, \cdots a^N) + 1$. Update the learning parameters as: $\alpha_m = 1/n(s, a^1, \cdots a^N)$, and $\beta_m = 1/m$.

(e) For each player i update the R values of the stage game matrices $R^i(s, a^1, \cdots a^N)$ and the G^i values as follows:

$$
\begin{aligned}
R^i(s, a^1, \cdots a^N) \; &= (1 - \alpha_m) R^i(s, a^1, \cdots a^N) \\
&+ \alpha_m \{ r^i(s, s', a^1, \cdots a^N) \\
&- G^i + Val^i(\pi^i_{m*}) \} . \\
G^i \; &= (1 - \beta_m) G^i \\
&+ \beta_m \left[\tfrac{r^i(s, s', a^1, \cdots a^N) + tG^i}{t+1} \right] .
\end{aligned}
$$

(f) Set $s \leftarrow s'$, and $m \leftarrow m + 1$.

(g) If $m <$ MaxSteps, go to step $2(a)$, else go to step 3.

3. Simulate the system with the final form of R matrices $R^i(s)$ for all $i \in \mathcal{N}$, $s \in S$, and estimate the average reward for the players.

The RL algorithm was implemented on a sample 5 bus power network and the results obtained are discussed in the next chapter.

CHAPTER 8

RESULTS AND CONCLUSIONS

In this chapter, the results of the numerical study carried out on a sample power network are discussed.

8.1 Numerical Study

The two tier solution framework was tested on a sample 5 bus power network. The objectives of this study were 1) to implement the modeling and solution framework, 2) to demonstrate the ability of the framework in evaluating alternative market configurations and, 3) to identify the critical factors affecting market performance. The example network consisting of two suppliers and three retailers is shown in Figure 8.1. The details (capacitance, inductance, etc.) of the 5 bus network are identical to the tutorial problem that is currently available under the PJM 101 Training Materials on the PJM website. The figure shows the maximum capacities and the marginal costs of the suppliers and the transmission limit of 300 MW on the line connecting Bus 1 and Bus 2.

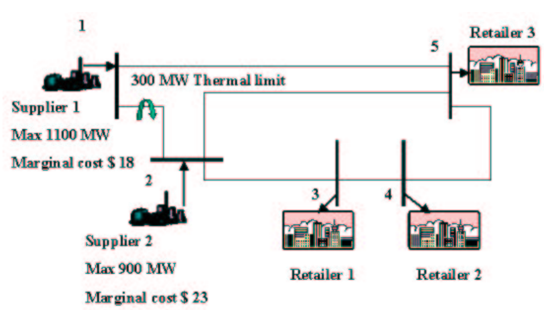

Figure 8.1. A 2-Supplier and 3 Retailer Network (adopted from PJM website)

Table 8.1. Average Outcomes for Ideal Market for Case A Where Supplier 1 Cannot Fulfill the Entire Demand

	LMP	Qty	FTR qty	FTR price
Sup 1	18.68	881	265.78	3.58
Sup 2	24.14	522	180.67	3.58

Table 8.2. Average Outcomes for Realistic Market for Case A Where Supplier 1 Cannot Fulfill the Entire Demand

	LMP	Qty	FTR qty	FTR price
Sup 1	30.68	723	198.89	1.92
Sup 2	34.08	677	287.98	1.92

Two different base demand scenarios at the load nodes are simulated. In the first scenario (Case A), where the lower priced supplier #1 cannot fulfill the entire demand, the base demands at Bus 3, Bus 4, and Bus 5 are 450 MWh, 500 MWh, and 600 MWh respectively. In the second scenario (Case B), Supplier #1 is capable of fulfilling the entire demand and the base demands are 300 MWh, 350 MWh, and 400 MWh respectively. The load variances at the nodes are considered to be 45, 40 and 55 MWh^2 respectively, and a demand elasticity factor of 2.5 is assumed. The suppliers compete for FTRs on Line 1-2 by submitting quantity and price bids.

8.1.1 Results

To illustrate the capability of the RL based solution framework in finding the equilibrium in combined energy and transmission markets, the methodology was implemented on two different types of wholesale energy markets: 1) an ideal market where the suppliers bid at their marginal prices and 2) a realistic market where the suppliers compete with both prices and quantities. Both of these market conditions were tested on two different base load scenarios (Case A and Case B) mentioned above. Note that, in both market conditions the suppliers bid competitively for FTRs.

Tables 8.1, 8.2, 8.3 and 8.4 show the average equilibrium energy and FTR quantities and prices for both suppliers in both market conditions. Following observations on the

Table 8.3. Average Outcomes for Ideal Market for Case A Where Supplier 1 Can Fulfill the Entire Demand

	LMP	Qty	FTR qty	FTR price
Sup 1	18.84	710	320.34	4.12
Sup 2	26.23	193	82.31	4.12

Table 8.4. Average Outcomes for Realistic Market for Case A Where Supplier 1 Can Fulfill the Entire Demand

	LMP	Qty	FTR qty	FTR price
Sup 1	28.53	399	110.67	2.01
Sup 2	33.04	442	152.67	2.01

FTR market can be made from the results: 1) total average FTR allocation depends on the demand; Case A has higher FTR allocation than Case B, 2) in the ideal market, the average price (LMP) differential between the buses (1 & 2) is higher than the realistic market resulting in higher FTR prices; i.e., competitive energy markets lower FTR prices, and 3) the FTR prices are significantly lower than the actual price differential across the constrained line indicating the presence of gaming in the FTR market.

In the following section, a set of designed experiments is conducted to assess the impact of various network parameters on the FTR auction and the combined FTR and energy market performance. The impact is measured through FTR prices, FTR quantities, and equilibrium profits of the suppliers.

8.1.2 Assessment of Factors Affecting FTR Auction

To identify the factors that affect FTR auction a comprehensive modeling framework combining both FTR and energy markets is required. This model provides such a framework which is exploited in evaluating the power network factors that might significantly impact the outcome of the FTR auction. A 2^{6-2} fractional factorial experiment. The factors examined along with their levels are as follows.

- Congestion constraint(A), 300(Low), 350(High)
- Demand Elasticity Factor(B) 1.5(Low),2.5(High)

- Load Variance(C) 45(Low),55(High)
- Base Load at bus 3(D) 400(Low),450(High)
- Base Load at bus 4 (E) 450(Low),500(High)
- Base Load at bus 5 (F) 550(Low),600(High)

Due to the high computational time involved in evaluating a combined FTR and energy market scenario, only a single replication of the fractional factorial experiment was conducted.

In order to assess the error sum of the square, a half-normal probability plot [58] of the factor effects was obtained. The factor effects falling on or near the line joining the origin and the 50^{th} percentile point were combined to get the error estimate.

Three separate sets of experiments were conducted using three different response variables: 1) equilibrium average FTR quantity allocation 2) equilibrium average FTR price 3) equilibrium profit of the suppliers. The first two responses indicate the direct effect of the factors on the FTR auction. The third response variable illustrates the impact of the factors on the combined FTR and energy market performance. For all the three experiments, generating relations used were I=ABCE and I=BCDF.

8.1.2.1 Experiment #1 with Equilibrium FTR Quantity as Response Variable

The sixteen treatment combinations for the 2^{6-2} experiment that were run had the following responses: (1)(189.4), ae(205.13), bef(175), abf(176.51), cef(227.71), acf(221.45), bc(153.56), abce(201.31), df(210.27), adef(242.82), bde(181.21), abd(168.83), cde(203.37), acd(189.33), bcdf(166.82) and abcdef(243.43).

After plotting the half normal plot, it was found that the main factors A, B, D, E, and F, and the interactions BD and AE appear away from the line and are perhaps significant in affecting the equilibrium average FTR quantity. The effects on or near the line are combined for an estimate of error sum of the squares.An analysis of variance (ANOVA) was conducted which showed that only the main factors A (congestion constraint), B (demand elasticity factor), E (base demand at bus 4), and F (base demand at bus 5) are significant. The above conclusions are somewhat intuitive, since it is expected that congestion constraint and the base demands should impact the FTR quantities. However, the significance of demand elasticity factor makes an interesting observation. It is also interesting to note that demand variance, which was perceived to be critical, turned out to be inconsequential.

8.1.2.2 Experiment #2 with Equilibrium FTR Price as Response Variable

The sixteen treatment combinations and the corresponding single replicate responses are as follows: (1)(1.06), ae(1.43), bef(1.21), abf(1.33), cef(1.18), acf(1.89), bc(1.13), abce(1.25), df(1.13), adef(2.21), bde(1.95), abd(1.87), cde(2.01), acd(1.95), bcdf(1.88) and abcdef(1.92).

The half normal plot indicated that the factors A (Congestion constraint), D(Base Load at bus 3), AD (interaction between Congestion Constraint and Base Load at bus 3) and AB (Interaction between Congestion Constraint and Demand Elasticity) lie away from the line and are perhaps significant in affecting the equilibrium average FTR price.

From the ANOVA, we conclude that only the main factors A (Congestion constraint) and D (Base Load at bus 3) are significant. It is to be noted that the line congestion constraint (factor A) affects the equilibrium FTR price. This, together with our earlier observation of congestion constraint affecting FTR quantity, suggest that separate optimal FTR bidding strategies should be developed for varying levels of the congestion constraint.

8.1.2.3 Experiment #3 with Equilibrium Profit of Supplier 2 as Response Variable

The sixteen treatment combinations and the corresponding single replicate responses are as follows: (1)(8558.73), ae(9294.82), bef(9101.90), abf(9833.01), cef(10267.13), acf(9954.81), bc(10105.68), abce(10267.01), df(11834.41), adef(9939.20), bde(9434.11), abd(11859.8), cde(10244.59), acd(8992.28), bcdf(10876.21) and abcdef(1.92).

The half normal plot showed that the factors C (Load Variance), D (Base Load at bus 3), E (Base Load at bus 4), F (Base Load at bus 5), AB (interaction between Congestion Constraint and Demand Elasticity), BD (interaction between Demand Elasticity and Base load at node 3), AF (interaction between Congestion Constraint and Base load at node 5) and ABD (interaction between Congestion Constraint, Demand Elasticity, and Base load at node 3) were found to be significant in affecting the equilibrium profit of supplier 2. From the ANOVA, we conclude that only the main factors D (Base Load at bus 3), E (Base Load at bus 4) and BD (interaction between Demand Elasticity and Base load at node 3) are significant. A similar factorial designed experiment and analysis was carried out for equilibrium profit of supplier 1 as the response variable and it was found out that only the main factor D (Base Load at bus 3) was significant. It is to be noted that the equilibrium profits of the suppliers were not affected by the variations in the congestion constraint. This suggests that the learning algorithm was able to effectively adjust hedging strategies (FTR) against varying congestion levels to be able to maintain the profit level.

8.2 Conclusions

A novel modeling framework for deregulated electric power market and its RL based solution methodology is presented. The modeling framework is comprehensive since its scope includes noncooperative bidding in both energy and transmission markets, two settlement system for the energy market, bilateral contracts and its associated contract for differences, demand elasticity, and consideration of existing market rules. The RL based solution approach makes it computationally viable to solve nonzero sum average reward stochastic games that characterize bidding in both FTR and energy markets.

This research work presents the first attempt to obtain equilibrium strategies in combined transmission and energy markets. The methodology learns bidding strategies in the FTR market using the corresponding equilibrium profits from the energy markets as the performance measure. As a result, the learning process yields equilibrium strategies for both markets and a true assessment of the corresponding energy prices. These prices could be used as an indicator for the competitiveness of the market (i.e., the extent of market power). As shown through the study of sample networks, the methodology presents a useful tool for identifying critical factors affecting market behavior.

8.3 Areas of Future Research

In this work, FTR auction only for obligations is considered. A logical extension to this would be the FTR auction for both obligations and options. There is tremendous scope in examining the allocation of FTR using OPF. Another challenging area would be to exploit the methodology for evaluating various auction mechanisms in the power market. The consideration of demand-side bidding would be an interesting area of research. Various existing market configurations can also be tested using this framework.

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