PSERC

Agent Modeling for Integrated Power Systems

Final Project Report

Power Systems Engineering Research Center

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Power Systems Engineering Research Center

Agent Modeling for Integrated Power Systems

Final Project Report

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Power Systems Engineering Research Center

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Executive Summary

Countries around the world continue to refine their electricity market structures in various ways. There are ongoing debates over market design issues, such as how to design effective market power mitigation rules, how to incorporate ancillary service markets, and how to properly implement a retail electricity market to encourage customer participation. Although valuable experience has been gained, there is a lack of a robust analysis platform for evaluating the effects of a new market design from both engineering and economic points of view.

The difficulty in creating such a platform arises from the interactions among strategic behaviors of market players, various layers of market designs, and the underlying physical network. A multi-agent system with a corresponding software platform would allow for robust analysis of the complex phenomena of an electricity market with its human decision-making in the context of market rules and a physical electric system.

In this research, multi-agent electricity market simulation tools were designed and implemented. Three market design areas were investigated: market power mitigation, ancillary service market design, and customer participation.

Part I: Multi-Agent System Modeling of Electricity Market and Its Application in Evaluation of Market Power Mitigation (work done at Iowa State University)

Local market power is an issue for electricity markets due to transmission capability bottlenecks, lack of economical electric energy storage devices, and short-term inelasticity of the customer demand. The generators that possess potential local market power could leverage it to gain profits, such as by actually withholding or proposing to withhold supply. To address the issue of local market power, various market power mitigation rules have been proposed and implemented in practice. However, there has been no systematic analysis of the effectiveness of those rules against strategic bidding of market players with learning capabilities in the context of an electric power system.

An agent-based market platform was designed and constructed to incorporate energy and ancillary service markets with market power mitigation rules. The agents were designed to make decisions to maximize their reward through reinforcement learning. The platform is based on JADE, a widespread agent-oriented middleware, and was programmed in JAVA. As a result of these features, the platform offers a rich set of programming abstractions and libraries that can facilitate new analysis applications. Important constraints were incorporated, such as ramp rates, reserves, and regulation requirements. Heat rate and fuel price data were used to create quadratic cost curves for the thermal generators. A PJM-like local market power mitigation process was implemented in the simulation platform. The resulting platform includes a 225-bus system model that resembles the structure of the Western Electricity Coordinating Council (WECC) grid and electricity market. The platform allows for load serving entities (LSEs) to also be generation owners.

The simulation results showed that without market power mitigation rules, large generation owners learn to *implicitly* exercise market power without knowing each other's bidding data. The PJM-like market power mitigation rules performed reasonably well against the supplier agents in enhancing market efficiency and discouraging the exercise of market power. The results also showed that generation resources owned by LSEs can counteract the exercise of market power by other suppliers during peak demand hours.

Part II: Effects of Ancillary Service Markets on Frequency and Voltage Control Performance of Deregulated Power Systems (work done at Washington State University)

The second research topic was the effect of different ancillary service market designs for frequency and voltage control on the control performance of power systems. Different market structures were created for the balancing (i.e., regulation) markets. The power system control used the standard automatic generation control (AGC) technique. Only the market structures were varied to study their effect on frequency control performance. By changing the market structure and incorporating generator ramp rates in the market design, a more desirable control performance was observed in the study.

Analyses showed that bilateral load following is viable within the conventional AGC framework. In this case, the control was modified to accommodate the market structure. Bilateral load following resulted in a faster frequency response as compared to separate, third party frequency control.

The feasibility of VAr markets was investigated. For voltage/VAr control, secondary control methods are still evolving and few markets are actually in operation. In this project, a new control method and new market structures were analyzed. In a comparative study of the feasibility of generator VAr markets, it proved difficult to avoid locational advantage (and hence, market power) for certain generators.

Part III: Power System Electricity Market Agent Model (work done at Cornell University and Smith College)

To examine the effect of active customer participation, the electricity market was modeled as a multi-agent system that included three types of agents: supplier, customer, and market. The market agent accepts and processes bids and offers according to market rules. The agents' responses to different market environments were simulated using Matlab.

The simulation results showed that suppliers and customers should learn as much as possible about the market environment and from historical data to maximize their benefits from participation. The simulation results also highlighted the importance of customer participation to deter the supplier market power, to lower electricity prices, to promote energy conservation, and to improve the system reliability.

The results emphasize the need for restrictive laws for the suppliers to protect customers as well as market integrity. In addition, customer participation was shown to be crucial from an environmental point of view. As customers become more familiar with the market mechanisms, they can indirectly improve overall market efficiency and energy conservation by simply minimizing their own expenditures.

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Part 1. Multi-Agent System Modeling of Electricity Market and its Application in Evaluation of Market Power Mitigation Rules

1.1 Introduction

1.1.1 Research Background, Motivation and Objective

Countries around the world continue to refine their electricity market structures in various ways. There are ongoing debates over new market design issues such as how to correctly design market power mitigation rules, how to properly implement a retail electricity market, how to effectively incorporate ancillary service markets, etc. Although years of experience has been gained, costly and valuable lessons have been learned, there is a lack of a systematic platform for evaluation of the impact of a new market design from both engineering and economic points of view. The difficulty arises from the complex interactions among strategic behaviors of market players, various layers of market designs, and the complex underlying physical network. Therefore, it is desirable to develop a multi-agent system based method and the corresponding software platform to model the complex phenomena of an electricity market [1].

Local market power has been known as an issue for electricity market due to limited transmission capabilities, lack of economical electricity storage devises and short-term inelasticity of demand. During certain peak hours, electricity markets can be temporarily isolated into several sub-regions by N-1 and transmission thermal limit constraints. Hence, the generators that possess potential local market power could leverage it to gain lucrative payment through either economical or physical withholding. The exaggerating factor is that electricity suppliers repeatedly play in similar market scenarios which may let them learn over time to compete less aggressively [2, 3]. Pivotal suppliers might be able to elicit collusive strategies from others by punishing un-cooperative bidding behaviors. To address the problem of local market power, various types of market power mitigation rules have been proposed and implemented in practice. However, the effectiveness of those rules against strategic bidding market players with learning capabilities has not been investigated.

The literature on the interaction between strategic bidding and market designs can be categorized into two approaches: equilibrium analysis and agent-based simulation. In the equilibrium analysis approach, oligopoly models such as Bertrand, Cournot, and supply function equilibrium (SFE) are used to model the stylized strategic behavior of market participants. Younes and Ilic [4] modeled the oligopolistic competition in electricity market with SFE and Bertrand model. They recognized that inelastic load and low transmission capacities may give the generators incentives to strategically constraint the network and profit from the high prices in isolated submarkets. Yao et al. [5] examined the two-settlement electricity market taking account of congestion, demand uncertainty and system contingencies with a Cournot model. They showed that two-settlement results in a lower spot equilibrium prices at most buses than a single settlement. Li and Shahidehpour [6] analyzed the strategic bidding behavior and potential market power of generation suppliers with SFE model. Their conclusion is that setting a lower price cap is a proper measure for mitigating market power in electricity market. Niu et al. [7] modeled the electric firms' bidding behaviors with SFE model, and studied the effects of forward contracts on ERCOT market. They found that a high volume of forward contracts decreases the incentive of major market players to raise real-time market prices. Liu et al. [8] studied the impact of learning behavior of electricity suppliers on electricity-spot-market equilibrium under repeated linear supply-function bidding. The result is that under certain conditions the overall learning behavior will reduce market-clearing price while in some other conditions the results are just the contrary.

Although the equilibrium analysis has yielded some useful results in the oligopoly electricity market, it may oversimplify the complicated market mechanism [9]. The accumulated bidding experience from interacting with other market participants in repeated auctions may change the perception a player has on others [10]. The advantage of a learning algorithm is that it could capture the market dynamics and provide better insights into the market behaviors. In the agent-based approach, variations of reactive reinforcement learning and anticipatory reinforcement learning have been used to model the behaviors of electricity suppliers. The learning algorithm that Bunn and Oliveira designed [9] for generators share the same essence with reactive reinforcement learning algorithm. The average reward γ-greedy reinforcement learning method was used in [11] to model the learning and bidding processes of suppliers. These suppliers are incorporated in a nonzero sum stochastic game model to assess day-ahead market power in different auction mechanism. The learning configuration for electricity suppliers in [12] is a version of stochastic reactive reinforcement learning developed by Alvin Roth and Ido Erev. Agents in the test bed investigate the effects of demand-bid price sensitivity and supply-offer price caps on LMPs. Yu et al. [13] modeled suppliers as Q-Learning agents. The results demonstrated that Q-Learning facilitates the supplier agent exploiting the market in the absence of a market power mitigation process.

1.1.3 Contents of this Part

Section 2 provides an introduction to multi-agent systems and a review of their applications to power systems. This section discusses the Foundation for Intelligent Physical Agents, a popular standard that is used in most industrial and commercial multi-agent system applications. A multi-agent system model of the Day-Ahead electricity market is presented. The market operator, load serving entities, and supplier agents' models are incorporated.

Section 3 provides a literature review of the multi-agent learning algorithms. Multi-agent learning algorithms are classified into three categories: Model-based approaches, Model-free approaches, and regret minimization approaches. In this research, Q-Learning, an anticipatory reinforcement learning technique is selected for the study of the electricity suppliers' learning behavior.

Section 4 presents an application of the proposed modeling methods on evaluating the PJM-like market power mitigation rules on a 225-bus system. Simulation results show that without market power mitigation rules, Q-learning supplier agents are capable of implicitly collude with each other and drive up the LMPs. The market power mitigation rules being examined did reasonably well in discouraging the exercise of market power and enhancing market efficiency. It is also shown that the generation resources that are owned by LSEs would be a source of countervailing market power during peak hours to the suppliers group.

Section 5 provides the key conclusions of this research and suggestions for the future work.

1.2 Multi-Agent System

1.2.1 Introduction

1.2.1.1 What is an Agent?

There is not a single definition of an agent that is universally accepted. However, the following definition from the Wooldridge and Jennings [14] is commonly adopted in the field. An agent is a computer system that is situated in some environment, and that is capable of autonomous action in this environment in order to meet its design objectives.

Note that the agent discussed here is actually a software entity. The two basic properties that an agent must have are autonomous, and situated. Autonomous means that a software agent must be able to operate without the direct intervention of people or other agents and has control over its own action and internal state. Situated means that a software agent is situated in some type of environment. These environments may be dynamic, unpredictable and unreliable.

According to Jennings and Wooldridge, to make an agent "intelligent", the software agent should be able to take flexible autonomous actions in order to meet its design objectives [15]. Flexible means an agent is reactive, proactive and social. By reactive, it is meant that the agent perceives its environment and responds in a timely fashion to changes that occur in the environment. By proactive, it is meant that the agent does not simply act in response to its environment but is able to achieve a goal by taking the initiative. By social, it is meant that in order to achieve its goals, the agent interact with people or other agents.

1.2.1.2 What is a Multi-Agent System?

A Multi-Agent System (MAS) is an organization of heterogeneous and self-motivated agents that interact with one another. The agents in MAS could have conflicting interests or they could coordinate with one another to accomplish the same mission.

1.2.1.3 When and Why are agents useful?

Reactive systems that maintain an ongoing interaction in some environment are inherently more difficult to design and implement [15]. One can classify these systems into three categories: open systems, complex systems, and ubiquitous computing systems. Some of the characteristics that these systems have are dynamic, highly complex, and unpredictable. With a better encapsulation, and modularity, the agent paradigm can develop a number of modular components that are specialized at solving a particular aspect of the complex, unpredictable system. In addition, with reactiveness and proactiveness, an agent can be relied upon to persist in achieving its goals, trying alternatives that are appropriate to the changing environment without continuous supervision and checking [16]. The Agent technology also helps to improve the efficiency of software development, especially when the data, control, expertise, or resources are physically or logically distributed.

1.2.1.4 Agent-Oriented Programming versus Object-Oriented Programming

Agent Oriented Programming has a higher level of encapsulation than Object Oriented Programming. An object encapsulates some state, and has some control over its own state in that it can only be accessed or modified via the methods that the object provides [15]. An agent encapsulates not only state, but also its own behavior. In contrast, an object does not encapsulate behavior: in other words, it has no control over the execution of its own methods. Note that the autonomous property of an agent allows it to have control over its own actions. Due to this distinction, one should not think of agents as invoking methods (actions) on agents. Rather, agents are requesting actions to be performed [15]. The agent itself could also decide whether to act upon the request.

1.2.1.5 Applications of Multi-Agent Systems in Power Engineering

The MAS technologies have been used for modeling and simulation of different aspects of power engineering. A major application is the simulation of restructured electricity market. With the embedded learning capabilities, agents that are autonomous, proactive and reactive are well suited for modeling of various market participants in the electricity market. It has been shown that a well-designed software agent can emulate the offer behavior of human agents [17]. Thomas et al. proposed to use software agents to test electricity markets [18]. Five standardized agents – four different types of speculators and a marginal cost offer agent are designed to compete with human subjects in a central auction market. A multi-agent trading platform for electricity contract market is constructed [19]. Customers' response under time-of-use electricity pricing is studied in a Multi-Agent system [20]. An agent-based model is designed in [21] to support decentralized generation expansion in electricity market.

Major challenges in the power system diagnostic and monitoring applications include how to handle large volumes of raw data from different sources, how to convert those raw data into meaningful information, and how to provide power engineers with correct information to support the decision making. These challenges could be overcome with the help of MAS technology. In [22], the authors designed and constructed the Protection Engineering Diagnostic Agents system (PEDA) for automated disturbance diagnosis. The PEDA system was implemented as an on-line post-fault analysis system for the Scottish Power Systems which significantly reduces the data retrieval, collection and interpretation burden on protection engineers. Condition Monitoring Multi-Agent System (COMMAS) for transformer condition monitoring was developed in [23]: the system is intended to provide decision support for operational engineers. A MAS was designed for fault detection, diagnostics, and prognostics of navy All-Electric Ships (AES) [24]. This fault diagnosis and prognosis tool will improve the reliability, availability, and survivability of AES, and support the drastic manning reduction requirements for future navy ships.

Nagata et al. suggests a multi-agent approach to restore a power system to a target network that has as many buses as possible [25]. In the proposed MAS, local bus agents formulate a restoration plan through negotiation, and then check the restoration plan with a global facilitator. In [26], a multi-agent-based approach for navy ship system electric power restoration is provided to restore the capacity as much as possible to serve the loads.

Through negotiation among three different types of agents, the system can perform the restoration work using local information without a central controller.

The distributed properties of MAS, and potential of local decision making make it better suited for certain control scenarios in a power system relative to conventional centralized control. There are some common features of those control scenarios. The system is highly complex so that optimum control is difficult to accomplish even with centralized control and the control decision making time is limited. For example, in microgrid control, the operation of micro-sources, storage devices, and controllable loads is highly complex. In [27], MAS approach was used to control the microgrid. In the proposed method, Microgrid Central Controller coordinates the local controllers and decides whether to connect to the main grid, whereas Local Controllers control the distributed energy resources, production and storage units, and some of the local loads. Jung et al. proposed an application of multi-agent system technologies for the development of strategic power infrastructure defense (SPID) system that is designed to prevent catastrophic failures and cascading sequences of events, an application of which is on adaptive load shedding [28].

1.2.2 The Foundation for Intelligent Physical Agents (FIPA)

FIPA was established in 1996 as an international non-profit association to develop a collection of standards relating to software agent technology [29]. FIPA was formally reincorporated in mid-2005 as a standards committee of the IEEE Computer Society, lending credibility to the use of FIPA as standards for industrial and commercial multi-agent system applications. FIPA standards govern the basics of an agent architecture, including agent lifecycle management, inter-agent message transport, message structure, inter-agent interaction protocols, and security. Users are left with the flexibility to design an agent that accomplishes its goals. The most important ideas of FIPA are agent communication, agent management, and agent architecture.

1.2.2.1 Agent Communication

The FIPA-Agent Communication Language (ACL) states the message representing actions or communicative acts that are called speech acts or performatives [29]. There are 22 performatives in communicative act library, which has 4 basis performatives: request, inform, confirm, and disconfirm. FIPA also standardizes a set of interaction protocols such as requests, query to coordinate multi-message actions. Different content languages can be employed to express the content of FIPA-ACL. The most popular language FIPA semantic language (SL) is standardized and specified in [30].

1.2.2.2 Agent Management

The second fundamental aspect of FIPA is addressed by agent management that establishes the logical reference model for creation, registration, location, communication, migration and operation of the agents. It specifies how a FIPA compliant agent can exist, operate and be managed. A FIPA compliant Agent Platform (AP) provides the physical infrastructure that consists of the machines, operating system, FIPA agent management components, the agents themselves, and any additional support software [29]. An AP has two utility agents: the Agent Management System (AMS) and the Directory Facilitator (DF). The

AMS is mandatory, as it allocates agent identifiers (AIDs) to each agent that registered with it, keeps track of the status of an agent, and terminates the life an agent when it deregistered. The DF is optional; it provides yellow page services that allow every agent to advertise its services on a non-discriminatory basis. An AP also provides a Message Transport Service (MTS) to transport FIPA-ACL messages between agents on the same platform or within different platforms.

1.2.2.3 Agent Architecture

The FIPA Abstract Agent Architecture provides a common, unchanging point of reference for FIPA-compliant implementations that capture the most critical and salient features of an agent system [31]. Most important mandatory items specified in the architecture are the ACL message structure, message transport, agent directory services, and service directory services. As described in Section 2.2.2, the communication between two agents relies on a message transport service that transports FIPA-ACL messages. As mentioned in Section 2.2.1 the structure of a message is a set of key values written in FIPA-ACL. The content of the message is expressed in a content language, such as FIPA-SL or FIPA KIF [31]. Essentially, the two directory services allow agents to register themselves or the services that they provide, and to search for specific agents for services.

1.2.3 Multi-Agent Approach to Day-Ahead Electricity Market Modeling

An electricity day-ahead market is composed of interacting units: market operator, electricity suppliers and load serving entities. Each one has its own goal to achieve and will not only react to the changes in the market condition but also try to exert some degree of influence in the market environment. An important attribute of the day-ahead market is that it exhibits properties arising from the interaction in the market that are not properties of the individual units themselves. Therefore, to evaluate the effectiveness of market rules of the day-ahead market, a multi-agent system is proposed that models the complex market dynamics among the traders.

The Day-Ahead electricity market is modeled as a multi-agent system with three types of interacting agents: supplier agents, load serving entities (LSEs), and a market operator (MO). The Day-Ahead Market works as follows. Before day D begins, MO gathers the load prediction data from LSEs, and publishes the forecasted zonal load data for day D+1. On the morning of day D, LSEs submit their demand bids and possibly supply offers; suppliers submit their supply offers for the Day-ahead Market to MO. During afternoon, MO performs market power mitigation and runs the market clearing software. The market-clearing software minimizes the cost of purchasing all the energy and 100% of the ancillary service requirement and then determines the hourly dispatch schedules, and locational marginal prices (LMPs) for energy and ancillary services. MO can also perform the ancillary service evaluation based on the market clearing results by simulating the AGC performance of the interconnected power system [32]. At the end of the process, MO sends the dispatch schedules, LMPs and settlement information to supplier agents and LSEs for day D+1.

1.2.3.1 Supplier Agent Model

Supplier agents sell bulk power to Day-ahead market. For simplicity, it is assumed that each supplier agent has only one generation plant. However, this model can be extended to permit suppliers with multiple generation plants. Suppose the set of supplier agents in the Day-ahead market is denoted by I, and the MW power output of generator i in some hour h is P_{ih}^G. For generator i, the hourly variable production cost $C_i(P_i^G)$ for production level P_i^G is represented by a quadratic form:

$$C_i(P_i^G) = a_i \cdot P_i^G + b_i \cdot (P_i^G)^2 \tag{1}$$

where a_i, b_i are given constants. By taking derivatives on both sides of (1), the marginal cost function for generator i is obtained, i.e.,

$$MC_i(P_i^G) = a_i + 2 \cdot b_i \cdot P_i^G \tag{2}$$

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

$$MC_i(P_i^G) = c_i^B(a_i + 2 \cdot b_i \cdot P_i^G) \tag{3}$$

The second component is its reported bidding price for ancillary services including its bidding price for spinning reserve capacity c_i^{res}, regulation up capacity $c_i^{reg,up}$, and regulation down capacity $c_i^{reg,down}$. Suppose on day D, supplier agents submit their supply offers for day D+1 to MO, and the market clearing program calculates locational marginal prices for real power and ancillary services, and dispatch schedules. Then supplier agent i's profit on day D+1 is obtained by summing over 24 hours the profits on that day.

1.2.3.2 Load Serving Entity Model

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

$$\pi_{jD+1} = \sum_{h=0}^{23} \begin{bmatrix} P_{jh}^{G*} C_{jh}^{G} + P_{jh}^{reg,u*} C_{jh}^{reg,u} + \\ P_{jh}^{reg,d*} C_{jh}^{reg,d} + P_{jh}^{res*} C_{jh}^{res} - C_j(P_{jh}^{G*}) \end{bmatrix}$$
$$+ \sum_{h=0}^{23} L_{jh}^{D+1} R_j - \sum_{h=0}^{23} \sum_{k \in L_j} P_{Lk}(h) C_k(h) - \sum_{h=0}^{23} L_{jh}^{D+1} AS_{jh}$$

where

C_{jh}^{G} LMP of real power at hour h for LSE j's unit

$C_{jh}^{reg,up}$ LMP of regulation up at hour h

$C_{jh}^{reg,d}$ LMP of regulation down at hour h

C_{jh}^{res} LMP of spinning reserve at hour h

P_{jh}^{G*} MW power output scheduled at hour h

$P_{jh}^{reg,up*}$ Cleared capacity for regulation up at hour h

$P_{jh}^{reg,d*}$ Cleared capacity for regulation down at hour h

P_{jh}^{res*} Cleared capacity for spinning reserved

R_{j} Retail rates of LSE j's serving area

L_{jh}^{D+1} Total MW load of LSE j at hour h

$C_{k}(h)$ LMP of real power on LSE j's load bus k at hour h

AS_{jh} Average AS price per MW load consumed at hour h

1.2.3.3 Market Operator Model

MO implements market power mitigation and market clearing procedures based on submitted supply offers and demand bids. The market power mitigation rule considered in this paper is similar to the one proposed for local market power mitigation process in CAISO. In the first run of pre-market clearing, MO clears the market with only competitive constraints enforced. The competitive constraints consist of the CAISO's pre-defined major interface branch groups. In the second run of pre-market clearing, it clears the market with all constraints enforced. Mitigation applies to the units that are dispatched up by the "all constraints" run of the pre-market clearing. If supplier offers subject to mitigation are higher than cost based default proxy bids (i.e., marginal cost + 10%), then energy offers are reduced to the level of cost-based default proxy bids.

The market operator runs a market clearing software to determine the hourly dispatch schedules and LMPs of energy and ancillary services. The objective is to minimize the 24-hour purchasing cost of both energy and ancillary services.

1.2.3.4 Software Implementation of Multi-agent System

When using an agent-based approach to solve a problem, there are a number of domain independent issues that must always be addressed, such as how to allow agents to communicate [29]. Java Agent Development Framework (JADE), being the most widespread agent-oriented middleware, provides the domain independent infrastructure which allows the developers to focus on the construction of key logics. Since JADE is written in Java, it benefits from a large set of programming abstractions which greatly facilitate the development of multi-agent systems. JADE fully complies with the Foundation for Intelligent Physical Agents (FIPA) specifications which is maintained by the standards organization for agents and multi-agent systems, the eleventh standards committee of IEEE.

The structure of the multi-agent platform is depicted in Figure 1. JADE provides two utility agents: the agent management system (AMS) and directory facilitator (DF) and an inter-agent messaging system through which the agents communicates with each other. The AMS allocates agent identifiers (AIDs) to each agent that registered with it, and provides a "white page" service, where an agent can ask for the address of another. The DF provides a "yellow pages" service, where agents register the services they provide, and an agent can ask for all agents to provide a particular service.

MO, supplier agents and LSEs are developed fully in Java in this research. A supplier agent's daily sequence of tasks is implemented as follows: collecting forecasted zonal load data posted by MO, submitting supplier offers to MO, collecting market settlement information posted by MO and adjusting of its bidding strategy based on Q-learning algorithm. MO starts the day by collecting forecasted load data from LSEs, and posting the MO forecasted zonal load data. Upon receiving all the supply offers and demand bids, it performs market power mitigation followed by market clearing. Afterwards, it posts the market clearing information and then uses ancillary service evaluation tool to test the system frequency performance under potential disturbances. The sequence of actions taken by the LSEs is: reports forecasted load data to MO, submits demand bid to MO, and collects the market settlement information from MO. If the LSE owns generation unit, it will adjust its bidding strategy according to Q-learning rules.

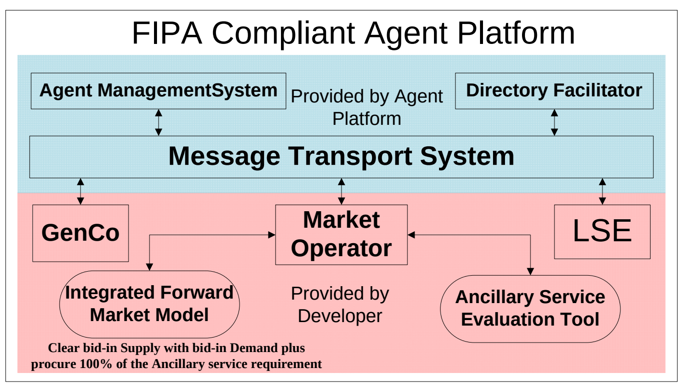


Figure 1: Structure of the Multi-agent Platform for Electricity Day-Ahead Market

1.2.3.5 Market Clearing Algorithm of Market Operator

The market clearing software clears the bid-in supply with bid-in demand and procures 100% of ancillary service requirement with minimum cost. The objective is to minimize the 24 hour total purchasing cost, which is formulated as:

$$\min \sum_{h=1}^{24} \left[\sum_{i \in I} \begin{array}{l} (c_i^B (a_i P_{ih}^G + b_i (P_{ih}^{G^2})) + c_i^{res} P_{ih}^{res} + \\ c_i^{reg,up} P_{ih}^{reg,up} + c_i^{reg,down} P_{ih}^{reg,dwon}) \end{array} \right] \tag{4}$$

Subject to

$$P_k - P_{gk} + P_{dk} = 0\,,\ k = 1,\ldots N_b \tag{5}$$

$$\left| H\delta \right| \le F_{\max} \tag{6}$$

$$P_{it}^{G} + P_{it}^{res} + P_{it}^{reg,up} \le P_i^{\max}, i \in I, \forall h \tag{7}$$

$$P_{it}^{G} - P_{it}^{reg,down} \ge P_i^{\min}, i \in I, \forall h \tag{8}$$

$$0 \le \left(\frac{P_{it}^{reg,up}}{R_{reg}} + \frac{P_{it}^{res}}{R_{res}} \right) \le \tau, i \in I, \forall h \tag{9}$$

$$P_{it}^{reg,down} \le R_{reg}\tau, i \in I, \forall h \tag{10}$$

$$\sum_{i=1}^{I} P_{it}^{reg,up} \ge Rg_t^{req,u}, \forall h \tag{11}$$

$$\sum_{i=1}^{I} P_{it}^{reg,down} \ge Rg_t^{req,d}, \forall h \tag{12}$$

$$\sum_{i=1}^{I} \left(P_{it}^{res} + P_{it}^{reg,up} \right) \ge Rs_t^{req} + Rg_t^{req,up}, \forall h \tag{13}$$

$$P_{i,t}^{G} - P_{i,t-1}^{G} \le R_i^{oper} 60, i \in I, \forall h \tag{14}$$

$$P_{i,t-1}^{G} - P_{i,t}^{G} \le R_i^{oper} 60, i \in I, \forall h \tag{15}$$

where

N_b	Number of buses in the system
P_k	Net power injection at bus *k*
P_{gk}	Total MW power generation at bus *k*
P_{dk}	Total MW demand at bus *k*
H	Line flow matrix
δ	Vector of voltage angle differences
$F_{\max}$	Vector of maximum line flows
$P_{ih}^{reg,down}$	Unit *i* regulation down capacity reserved at hour *h*
$P_{ih}^{reg,up}$	Unit *i* regulation up capacity reserved at hour *h*
P_{ih}^{res}	Unit *i* spinning reserve capacity reserved at hour *h*
τ	Delivery time requirement for ancillary service
R_i^{reg}	Regulation ramp rates of unit *i*
R_i^{res}	Operating reserve ramp rates of unit *i*
R_i^{oper}	Operational ramp rates of unit *i*
c_i^{res}	Bidding price for spinning reserve capacity of unit *i*

$c_i^{reg,up}$ Bidding price for regulation up capacity of unit i

$c_i^{reg,down}$ Bidding price for regulation down capacity of unit i

$Rg_h^{req,d}$ System's requirement for regulation down at hour h

$Rg_h^{req,u}$ System's requirement for regulation up at hour h

$Rs_h^{req,u}$ System's requirement for spinning reserve at hour h

The optimization problem of (4) is subject to real power balance constraints at each bus (5), thermal limit constraints for each line (6), upper and lower generation capacity constraints (7-8), and ramp rate constraints (9-10). There are also system wide reliability requirements constraints (11-13), and energy schedule constraints between hours (14-15). The optimization problem is solved by CPLEX which is capable of handling large-scale power systems problems. A CPLEX Java interface is built in this project to facilitate the sharing of data between the programs.

1.2.4 Summary

This section provides an introduction to the multi-agent system technology by answering several basic questions, i.e., what is an agent, what is a multi-agent system, when and why are agents useful. In subsection 1.2.1.4, the agent oriented programming is compared with object oriented programming. Subsection 1.2.1.5 is an overview of the applications of multi-agent system in four areas of power engineering field: Modeling and Simulation, Monitoring and Diagnostics, System Restoration and Reconfiguration, and System Controls. Some core concepts of the FIPA specifications are discussed in subsection 1.2.2.

With the multi-agent system technology, the Day-Ahead electricity market is modeled as a multi-agent system with three types of agents: supplier agents, LSEs, and the Market Operator. Since JADE is an implementation of FIPA specification, it was used to develop the proposed multi-agent system. The models for supplier agents, LSEs, and MO are presented in detail in subsection 1.2.3.1-1.2.3.3. The software implementation of the proposed multi-agent system model and the market clearing algorithm of market operator are presented in subsection 1.2.3.4 and 1.2.3.5 respectively.

1.3 Multi-agent Learning Algorithms

1.3.1 Introduction

A basic question that was often asked by researchers in the field of Artificial Intelligence (AI) is how to design a learning algorithm that allows a machine to learn about the environment in which it resides and to maximize its chances of success.

Insightful observations and tools from statistics, computer science, psychology, cognitive science, and logic are utilized to develop learning algorithms that are implemented on machines in different contexts. Some of the key algorithms developed for single-agent learning are Artificial Neural Networks (ANN), Bayesian Learning (BL), Computational

Learning Theory (CLT), Genetic Algorithms (GA), Analytical Learning (AL), and Reinforcement Learning (RL). The applications of these algorithms range from chess-play computer program Deep Blue that beats the world champion Garry Kasparov, to data mining programs that learn to approve bank loans to lower the bad loan rate, to autonomous cars that learn to drive safely from door to door.

In recent years, multi-agent learning takes the place of single-agent learning and becomes an important issue of learning that attracts the attention of many researchers in both computer science and game theory.

1.3.2 Literature Review

Three major classes of learning techniques were developed—the first one is representative of work in game theory, the second one is typical in AI, and the last one seems to have drawn equal attention from both communities [33]. The three approaches are model-based, model-free, and regret minimization approaches.

1.2.3.5 Model-based Approaches

In model-based learning algorithms, the presence of other decision making agents in the learning environment is taken into account. It usually begins with some models of the opponents' strategy, and then starts an iterative three-step learning process. First, it computes and plays the best action based on the model of opponents' strategies. Then, it observes the opponent's actions and updates the models of the opponents' strategies. Afterwards, it goes back to the first step.

The early model-based learning algorithm well known in game theory is called fictitious play. The model rests on traditional statistician's philosophy of basing future decisions on the relevant past history [34]. The opponent is assumed to pick an action at each turn according to a stationary probability distribution function (PDF). The algorithm keeps track of opponent's play, and chooses an action that is optimum against the estimates of the opponents' PDF based on the relative frequencies.

Fictitious play only allows the agent to exploit all the information that it has so far, and play the "optimum" action. The variants of fictitious play such as smooth fictitious play [35] and exponential fictitious play [36] allow the agent to explore other actions that is not "optimum".

1.2.3.5 Model-free Approaches

In model-free approaches, Q-Learning [37] allows agents to learn how to act in a controlled Markovian domain with unknown transition functions. A controlled Markovian domain implies that the environment is Markovian in the sense that state transition probabilities from state x to state y only depends on x, y and the action a taken by the agent, and not on other historical information. It works by successively updating estimates for the Q-values of state-action pairs. The Q-value $Q(x,a)$ is the expected discounted reward for taking action a at state x and following an optimal decision rule thereafter. Once these estimates have converged to the correct Q-values, the optimal action in any state is the one with the highest Q-value.

By the procedure of Q-Learning, in the n[th] step the agent observes the current system state x_n, selects an action a_n, receives an immediate payoff r_n, and observes the next system state y_n. The agent then updates its Q-value estimates using a learning parameter α_n and a discount factor γ [37] as follows:

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

$$Q_n(x,a) = (1-\alpha_n)Q_{n-1}(x,a) + \alpha_n[r_n + \gamma V_{n-1}(y_n)] \tag{16}$$

Otherwise,

$$Q_n(x,a) = Q_{n-1}(x,a) \tag{17}$$

where $V_{n-1}(y) \equiv \max_b \{Q_{n-1}(y,b)\}$ (18)

It is proven by Watkins in [38] that if (1) the state and action-values are discrete, (2) all actions are sampled repeatedly in all states, (3) the reward is bounded, (4) the environment is Markovian and (5) the learning rate decays appropriately, then the Q-value estimates converge to the correct Q-values with probability 1.

The Q-Learning algorithm can be extended to the multi-agent environment by redefine the Q-values as a function of all the agents' actions:

$$Q_n(x,\vec{a}) = (1-\alpha_n)Q_{n-1}(x,\vec{a}) + \alpha_n[r_n + \gamma V_{n-1}(y_n)] \tag{19}$$

However, in the contexts where the actions taken by other agents are unknown such as the electricity market, it is impossible to apply this variation of Q-Learning algorithm. Therefore, in the above stated contexts, the only option left is to extend the Q-Learning to the multi-agent environment by having each agent simply ignore the other agents and pretend the environment is Markovian. The theoretical proof of convergence to the correct Q-values no longer holds when an opponent adapts its strategy based on the past experience. It is reasonable to expect that such a strong convergence result no long holds, in a non-Markovian environment where each agent is learning others' strategy.

1.2.3.6 Regret Minimization Approaches

In the regret minimization model, agents adjust their strategies probabilistically. This adjustment is guided by "regret measures" based on observations of the past period [39]. The assumption made in this model is that each agent knows the past history of all other agents, as well as its own payoff matrix. An instance of the no-regret learning algorithm is presented below. The regret of agent i for playing the sequence of actions s_i instead of playing action a_j, given that the opponents played the sequence s_{-i} is defined as $r_i^t(a_j, s_i)$ [33].

$$r_i^t(a_j, s_i \mid s_{-i}) = \sum_{k=1}^{t} R(a_j, s_{-i}^k) - R(s_i^k, s_{-i}^k) \tag{20}$$

At each round, an agent may either continue choosing the same strategy as in the previous round, or switch to other strategies that have positive regret with a probability proportional to $r_i^t(a_j, s_i)$.

1.3.3 Modeling of Suppliers' Learning Behavior by Q-learning

The way Q-Learning is implemented for an agent with generation unit is as follows. The agent views the day-ahead market as a complex system with different states. Each zone's zonal daily average load is divided into M_L levels. For each zonal daily average load level, there are M_P LMP levels. The perceived system state by an agent with generation units on day D is defined as a vector of predicted day D+1's daily average zonal load level and most recent similar day's average LMP level. Hence, the cardinality of each agent's state space is $M_L \times M_P$.

The action domain of an agent is defined as a vector of bidding information. This vector consists of the bidding mark up for the real power c_i^B which has M_B possible values, and bidding price for regulation up capacity $c_i^{reg,up}$ which has M_R possible values. To limit the dimension of the action domain for agents, it is assumed that the bidding price for regulation up capacity is the same as that of spinning reserve and 3 times that of regulation down. The dimension of the action domain is given by $M_B \times M_R$.

Consider the beginning of each day D. An agent first makes a prediction of the system state based on published load forecasting data and historical LMP data, which is represented by x . It next chooses an action according to a Gibbs/Boltzmann probability distribution, i.e.,

$$p_D(x,a) = \frac{e^{Q(x,a)/T_D}}{\sum_{b \in AD_i} e^{Q(x,b)/T_D}} \tag{21}$$

where T_D , which depends on D, is a temperature parameter that models a decay over time.

Having chosen an action a , the agent will submit its supply offer and possibly demand bids to MO. Once the market is cleared, the supplier agent will receive its reward, which is the profit for day D+1. Then the agent will use this reward to update its Q-value estimates according to equations (16) to (18).

The parameters that are used in the numerical study are set according to Table 1:

Table 1: Q-Learning Parameters

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

where $T_{(x,a)}^{\omega}$ is the number of times action a has been taken in state x. ND is the number of days that have currently been simulated.

1.3.4 Summary

In this section, the multi-agent learning techniques are organized into three categories: model-based approaches, model-free approaches and regret minimization approaches. Fictitious play, Q-Learning, and no-regret learning are described as representative of each of the approaches. Both model-based and regret minimization approaches assume that each agent knows all other agents' historical actions. However, this assumption is not valid in the electricity market context. Therefore, Q-Learning in the model-free approaches is selected to model the learning behavior of electricity supplier agents. The application of Q-learning for supplier agents in an electricity market context is presented.

1.4 Numerical Studies and Simulation Result

1.4.1 Test System

The 225-bus WECC system that represents the essentials of the CAISO area is used as test case. A system block diagram is shown in Figure 2, where colored blocks represent load and generation pockets, and red lines denote simplified network constraints.

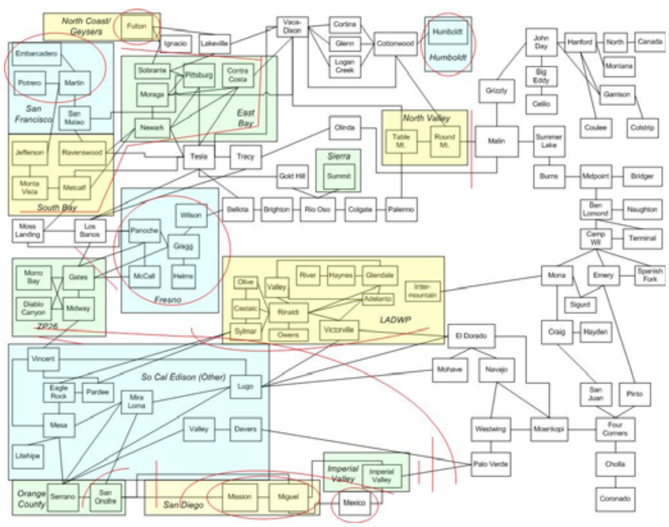


Figure 2: 225-Bus WECC Model – Details of California

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

Quadratic fuel cost curve for each of the 23 aggregated thermal generators is fitted from step function that represents the heat rates of the aggregated units in a least square sense. The fuel cost is assumed to be \$6/mcf. The two coefficients of the quadratic fuel cost curves are provided in Appendix A.

1.4.2 Evaluation of Market Power Mitigation Rules of CAISO

To demonstrate the exercise of market power by Q-Learning suppliers and evaluate the effectiveness of the market power mitigation rules, the following three scenarios are simulated. The first scenario is the competitive benchmark where every supplier agent bids their marginal cost. The second scenario is the unmitigated scenario where every supplier agent bids strategically into the market according to the Q-learning rules in the absence of market power mitigation. The third scenario is the mitigated scenario where every supplier agent still bid strategically into the market, however, this time subject to the market mitigation rule specified in Section III.

In every scenario, 15 simulation runs are performed and the average results are reported in figures 3-5.

To illustrate how Q-learning facilitates the exercise of market power and implicit collusion of large supplier agents, two pivotal suppliers from the SCE area are chosen as case study. Supplier 7 and 8 together has a capacity of 7685 MW which comprises of 64% of the generation capacities in the SCE area.

In simulation run 1 of the unmitigated scenario, supplier agent 7 and 8's updating Q-tables on August 10th are illustrated in Table 2 and 3.

Table 2: Supplier Agent 7's Updating Q-table

	Action Index						
State	1	…	5	…	11	…	15
…	…						
3	…	…	**3.23**	…	2.83	…	1.97
…	…						
6	**3.72**	…	3.68	…	3.38	…	2.88
…	…						
9	2.86	…	**4.47**	…	…	…	2.81
…	…						
12	…	…	10.03	…	**10.79**	…	…

Table 3: Supplier Agent 8's Updating Q-table

	Action Index						
State	1	2	3	…	7	…	12	…
…	…							
3	…	2.45	**3. 19**	…	2.28	…	2.42	…
…	…							
6	3.23	**3. 56**	…	…	2.84	…	3.27	…
…	…							
9	**4. 03**	1.92	…	…	2.98	…	3.59	…
…	…							
12	…	3.61	7.86	…	**11. 5**	…	4.71	…

When the area load is high and historical LMP is high on their generation bus, both supplier agents are in state 12. As shown in Table 2 and 3, after several experimental bidding, the highest estimated Q-values of both agents in state 12 are from relatively high action indices. This means that the two pivotal suppliers learned to coordinate with each other at high markups. The energy bid markup is 12% for supplier 7 and 8% for supplier 8. Therefore, it is shown that the Q-learning supplier agents are capable of implicitly collude with each other and drive up the LMPs successfully. However, the highest possible bidding markup is not so attractive to the two pivotal suppliers because although the LMPs are further driven up, they will lose part of previously profitable generation schedule to two other relatively smaller suppliers in the area. This result extends the conclusion from [17], in that the condition of same level of demand in every trading period is not necessary. Even in a rapid changing market environment, large generation owners who interact with each other in similar scenarios easily learn to implicitly collude even without knowing others' historical bidding data. This finding further supports the hypothesis in [18]: the generation argues for continued confidentiality because the resource owners do not need rapid release of bidding data to fall into tacit collusion.

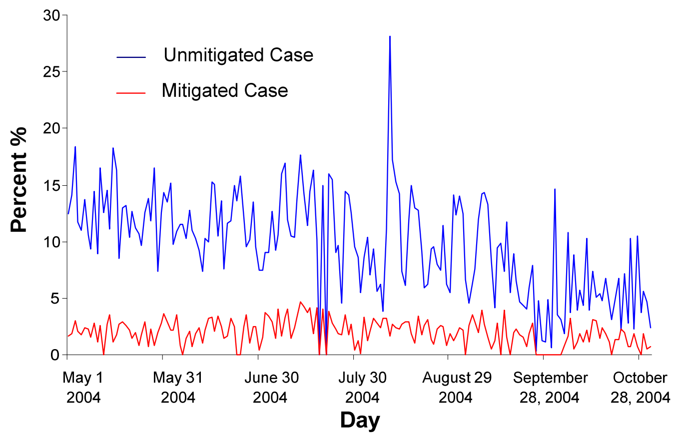


Figure 3: Percent Total Market Payment Increase in the Unmitigated and Mitigated Scenarios Comparing to the Competitive Benchmark

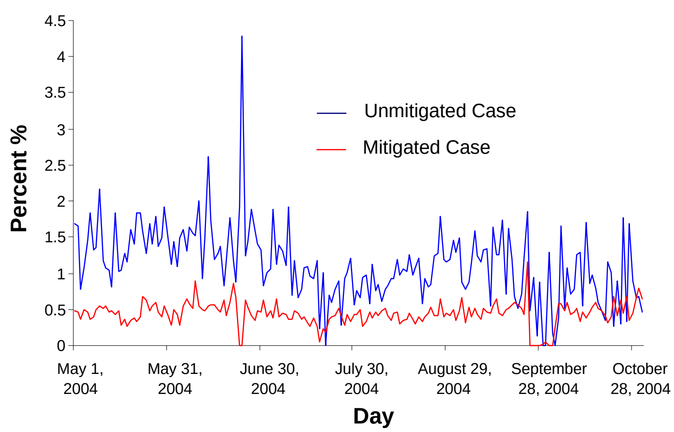


Figure 4: Percent Total Generation Cost Increase in the Unmitigated and Mitigated Scenarios Comparing to the Competitive Benchmark

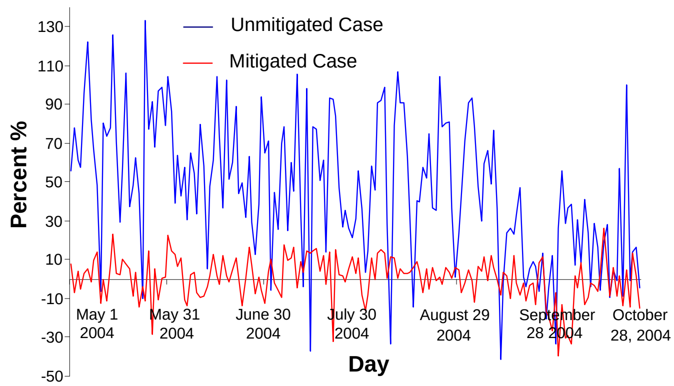


Figure 5: Percent Largest Unit's Profit Increase in the Unmitigated and Mitigated Scenarios comparing to the Competitive Benchmark

As shown in Figure 3, the total market payment in the unmitigated scenario is significantly higher than that of the competitive benchmark. With the help of Q-Learning, the supplier agents are able to exploit the market together and get an average of 9.7 percent increase in total market payment comparing to the competitive benchmark. However, the total market payment in the mitigated scenario is slightly higher than that of the competitive benchmark. Facilitated by the market power mitigation rules, the MO effectively reduced the percentage increase in total market payment to only 2 percent. The lower average load level and less congestion leads to relatively low percentage increase of total market payment from August to the October comparing to June and July.

Figure 4 demonstrates the percentage increase of total generation cost in the mitigated and unmitigated scenario comparing to the competitive benchmark. The simulation result shows that the total generation cost increase in the unmitigated scenario is about 1.5 percent higher than that of the competitive benchmark. The strategic bidding of the supplier agents result in extramarginal capacity being cleared, and inframarginal capacity left not dispatched. The reduction of market efficiency is caused by the market power collectively exercised by the supplier agents. The total generation cost increase in the mitigated scenario is only about 0.5 percent higher than that of the competitive benchmark. This result shows that the market power mitigation rules not only suppressed the exercise of market power but also enhance market efficiency by reducing the total generation cost comparing to the unmitigated scenario.

The largest unit's profit percentage increase in the unmitigated and mitigated scenarios comparing to the competitive benchmark is depicted in figure 5. The largest supplier agent's profit increase is significantly higher than that of the competitive benchmark. The average profit increase of 47.9 percent is well beyond the average payment increase for all the supplier agents. This shows Q-learning algorithm did help the supplier agent realize that the huge size of its unit does provide higher potential of market power to exercise. In the mitigated scenario, the strategic bidding of generators is not beneficial to the largest supplier agent at all. In some situation, the strategic bidding behavior will even lead to a lower profit comparing to the competitive benchmark. The market power mitigation rules being examined did reasonably well in discouraging the exercise of market power.

1.4.3 Effects of LSE Owning Generation Resources

To examine the bidding behaviors of LSEs that own generation resource and their impacts on suppressing the collective market power, it is assumed that five major LSEs have their own generation units. The detailed information about LSEs' serving area, their units' capacity, and peak load they serve is listed in Table 4. It is assumed that the peak load to serve for each LSE is twice its unit's capacity.

Table 4: LSEs Detailed Information

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

The simulation is carried out in four scenarios categorized by whether mitigation rules exist and whether some generation units are owned by LSEs. 15 simulation runs are performed in each scenario and the average results are reported below.

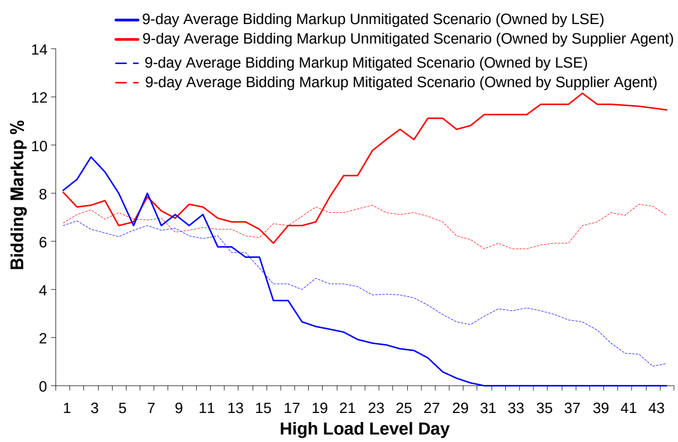


Figure 6: 9-day Average Bidding Markup of Generator 7 in Unmitigated or Mitigated Scenario When Owned by LSE or Supplier Agent

As shown in Figure 6, in unmitigated scenario if generator 7 is owned by a LSE, it quickly learned over time to bid at a lower markup when the load level is high. In the mitigated scenario, LSE also learned the same strategy to reduce the cost of energy and ancillary service however at a slower rate. In unmitigated scenario if generator 7 is owned by a supplier agent, Q-Learning algorithm helped it learn to bid at a higher markup during high load days. In the mitigated scenario, the generator learned a similar strategy except that the actual bidding markup cannot exceed 10% due to the existence of market power mitigation rules. The bidding markup of other generators in table 4 also exhibits similar patterns in the four simulation scenarios.

It is concluded from the above simulation results that if a generator is owned by a LSE, it will tend to reveal its true marginal cost. However, if it is owned by a supplier agent, it will tend to bid at a much higher markup. Hence, the generation resources that are owned by LSEs would be a source of countervailing market power during peak hours to the suppliers group.

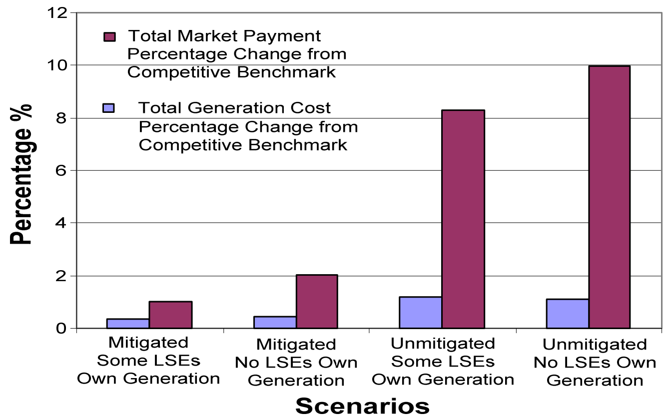


Figure 7: Total Market Payment and Total Generation Cost Percentage Increase in Four Scenarios Comparing to the Competitive Benchmark

The total market payment and total generation cost percentage increase from competitive benchmark in the four scenarios are shown in Figure 7. The simulation results show that both market power mitigation procedure and the LSEs' ownership of generation units contributes to reduction in total market payment and total generation cost. The market power mitigation procedure is more effective than LSEs' ownership of generation in suppressing collective market power and enhancing market efficiency.

1.5 Conclusions and Future Work

This section presents a multi-agent simulation approach on evaluating electricity market rules. It is found that the agent-based simulation approach empowered by carefully designed Q-Learning agents is able to capture the dynamic interaction between strategic bidding market participants. The PJM-like market power mitigation rules are shown to be effective in suppressing the exercise of market power and enhancing market efficiency at the same time. It is also shown that the generation resources that are owned by LSEs is a source of countervailing market power during peak hours to the suppliers group.

A drawback of the Q-Learning model for supplier agents is that it suffers from the curse of dimensionality. This weakness should be overcome in the future work by designing learning algorithm that combines the strength of both Q-Learning and Artificial Neural Networks.

Further research is needed on the development of proposed multi-agent platform to enable the negotiation process between supplier agents and LSEs on bilateral contracts and study what are the effects of forward contracts on day-ahead market. In addition, it is desirable to incorporate marketers into the model to examine the impacts of virtual bidding on electricity market.

Part 2. Effects of Ancillary Service Markets on Frequency and Voltage Control Performance of Deregulated Power Systems

2.1 Introduction

2.1.1 General

Ancillary services are those necessary to sustain the basic operation of power systems provided by generators and transmission control equipment. While the number of potential services is large, the following services are recognized in the major power systems as ancillary services and are asked from those who are capable of providing them:

- Energy imbalance equalization
- Frequency regulation
- Spinning reserve generation
- Supplementary reserve generation
- Reactive power supplied from generators
- Black start

The function of the frequency regulation service is to maintain the frequency of the system at the specified value. At the heart of frequency regulation is the Automatic Generation Control (AGC). Whenever there is a random variation in system load, the frequency and tie line interchanges deviate from its scheduled value. It is the AGC that senses the deviations and brings the values of frequency and tie line interchange back to normal by re-dispatching the generators under control. For safe operation of the power system, voltage at the network buses is required to be within certain admissible limits. The objective of secondary voltage control is to maintain the voltage over the network within these limits by managing the reactive power supplied by generators.

In a deregulated environment generation, transmission and distribution systems are owned by separate organizations. Competitive markets have been developed where Load Serving Entities (LSE) can buy energy from Independent Power Producers (IPP). Similar markets exist for ancillary services but the structures of such markets vary widely influenced by rules and regulations of the region. More often than not, these markets are designed to maximize the financial interest of certain parties, seldom paying attention to the engineering capabilities of the underlying power system. Here, in this work, it is shown that taking the engineering aspects of the network components into account may improve control performance of the system, which often influences the financial aspects in direct or indirect fashion.

2.1.2 Research Objective

The focus of this research is on balancing markets, which includes regulation and load following, and secondary voltage control markets to analyze the effect of different markets for these ancillary services on control performance of the power system. The primary objective is broken down into the following subtasks:

1. Studying the existing frequency and voltage control markets and the measure of control performance
2. Identifying the attributes that influences control performance of the system and possible improvements
3. Analyzing short and long term impacts of market structures under discussion

2.1.3 Outline

This part is organized in three sections as follows:

Section 2 analyzed the influence of regulation market structures on frequency control performance of a system. The comparative studies are presented to examine whether existing markets should be changed and exploiting available control options can result in a more desirable performance. In a separate section a method is presented to unify the responsibility of regulation and load following under classical Automatic Generation Control (AGC). The method described here uses the AGC system to dispatch both regulation and load following in real-time. Subsequently, feasibility of a competitive market for load following is discussed.

Section 3 studies secondary voltage control. In an attempt to capture the impact of VAr markets and associated secondary voltage control methods on voltage control capability in terms of controllability, performance and economics of the system, two methods of automatic secondary voltage control have been looked into in this work, voltage control by adjusting the reference voltage of generators and voltage control by adjusting the reactive power injection at the generator bus. Feasibility of competitive markets in VAr using the above mentioned generation based voltage control methods have been examined thereafter.

Appendix B illustrates the reduced WECC model which has been used for the simulations. Appendix C elucidates the method of dividing the network into a number of voltage-control areas.

2.2 Effects of Balance Markets on Frequency Control Performance

2.2.1 Preface

Regulation is one of the ancillary services (AS) traditionally provided by the generating units, under the jurisdiction of a balancing area (BA), to continually compensate for the difference between load and generation. After the advent of deregulation, there has been much effort to form competitive markets for regulation. These markets have usually been markets for capacity reserves and have variously been called regulation, balancing, load-following, frequency control or even combined with spinning reserve markets. For simplicity it is called the regulation market throughout this paper. While the method of frequency control and load following has to be precisely defined within an interconnection, the structures of the regulation markets vary greatly. In North America, some regulation reserve markets have been developed for secondary control. The payment is for capacity made available, up and down, fully dispatchable within 10 minutes [40], the energy supply being compensated at spot market rates. In some areas there is no separate regulation market and part of the spinning reserve is used for secondary frequency control. In England and Wales, where automatic secondary control is not used, there is a power exchange system with a 30-minute short-term market for balancing, operating one hour ahead of real time. There, only a few generators are called upon for frequency response replacing free governor action by all generators. Likewise, regulation markets exist in Australia, Nordic countries, continental Europe, China and other countries; however, the frequency performance standards are influenced heavily by regional policies and grid rules [40].

To design such markets financial factors have so far played more important roles than technical considerations. Besides there are other issues, which have come into discussion recently [41]-[43], e.g. the problems of involving more suppliers in the market or allocating payments to the participants which reflect the impact of each participant in the market. There also has been lack of insight about how solutions to such problems are going to affect the system as a whole.

In this chapter, a comparative analysis on the models of regulation markets is presented. It is assumed that the balancing authority has secondary control or Automatic Generation Control (AGC), i.e. uses tie-line bias control. A systematic control strategy is put forward to improve the frequency response.

In the next section the market models have been described. Section 2.3 has a brief description of the traditional AGC. In section 2.4 a case study on WECC 225-bus model has been presented and the effects of the markets on its control performance have been compared vis-à-vis.

2.2.2 Regulation Market

All markets can be designed with many variations and regulation markets are the same. To show how such variations can affect system performance, the structure of three example regulation markets are laid out in this section. These three are briefly described below.

A. A flat-rate regulation market – This is the most common type of regulation market that exists (the California market is described in [44]). The features are as follows:
    - 10-minute regulation market, i.e. any spinning unit under AGC control can bid the capacity it can make available in 10 minutes.
    - No distinction according to ramp rates of the generators.
    - Uniform second price payment i.e. all qualified suppliers are paid at the rate of Market Clearing Price (MCP).

B. A price based regulation market – The generators are paid based on the performance in the market.
    - 5-minute or 10-minute regulation market
    - Generators are categorized as fast or slow as per the ramp rates.
    - The fast ramp generators are paid according to the regulation MCP whereas slow ramp generators are paid according to their bid price as long as it is less than the regulation MCP.

C. A response based regulation market – Two separate markets for fast ramp regulation and slow ramp regulation.
   - 5-minute market for fast ramp regulation
   - 10-minute market for slow ramp regulation.
   - Generators are allowed to participate in the respective market which its ramp rate corresponds to.
   - Generators are paid at the rate of clearing price of the market they participate into.

All the generators participating in the regulation markets mentioned above are required to meet certain technical and operating requirements. Primary control by governor action is mandatory for participation. The full response of the bid capacity is required to be delivered in the dispatch interval (10 or 5 minutes as applicable). Thus the regulation bid capacity of each supplier is dependent on its ramp rate. This last point is very important since this establishes the connection between market outcome and consequent control performance.

To bid (as shown in Figure 8) in the markets, each supplier specifies three quantities in the bid: 1) capacity, 2) price in \$/MWh, and 3) operational ramp rate in MW/min. The markets are cleared for every dispatch interval during the trading interval ahead of real time.

The market may be formulated as single auction power pool (Figure 9) where only suppliers bid in the market or double auction power pool, where suppliers' bids are cleared against customers' offers [45]. Single auction pool is assumed for all markets considered.

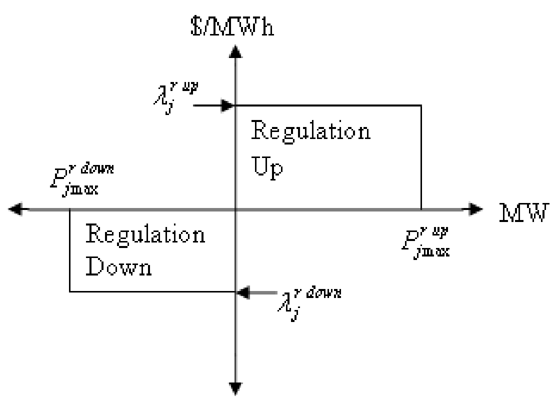


Figure 8: Regulation market bid

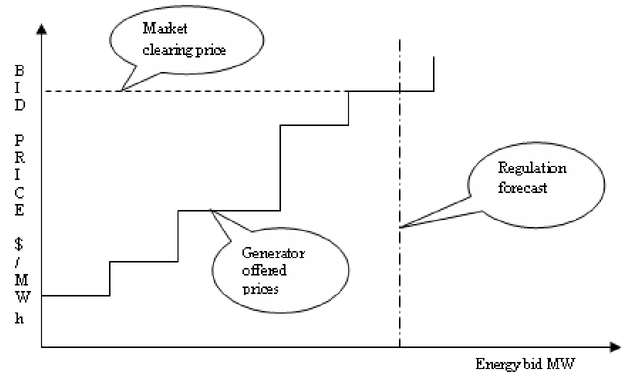


Figure 9: Market clearing in single auction pool

Type A market is most straightforward and followed at many places of North America and North Africa. The simple nature of such a market makes it attractive; however there is good reason for suppliers not to participate in such market as it does not differentiates among the participants and pays a flat price irrespective of their performance. Type B market on the other hand solves that problem and introduces the performance based pricing. The qualified generators receive market payment at the rate of their bid price except the fast ramp generators which are paid at the rate of MCP. Since the MCP is the maximum possible payment available in auction market, recipients get away with an amount of incentive for their service. Type C market is somewhat similar to the contingency reserve market, only the control here is on a longer time frame. The separation of fast and slow ramp generators makes it possible to call upon the appropriate service depending on the magnitude of the disturbance. It is also possible to use a combination of these services for cost effectiveness. There is no need of added incentive since separate markets would take care of it automatically.

2.2.3 Frequency Control

The function of the regulation market is to select a set of generators to provide the service and to allocate the amount of regulation each are supposed to provide at the time of need. The real-time regulation would be performed by Automatic Generation Control (AGC) to keep the frequency of the system within safe operating limits and the interchanges between the areas at the scheduled value.

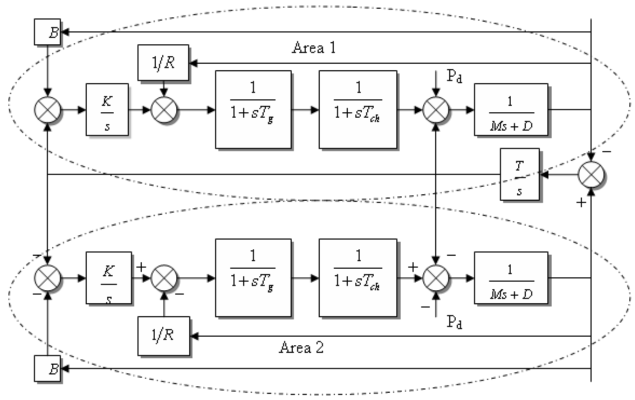


Figure 10: Classical ACG for two control areas

For the purpose of modeling it is assumed that the generators in a control area are tied together closely, electrically. As a result they oscillate together under minor disturbances. If the deviations in frequency and load are small enough, each control area can represented as the linear approximation [46] as shown in the Figure 10.

While modeling the individual generators (Figure 11), it is to be remembered that there are limits on the rate at which generators can move their output due to thermal and mechanical stress on the equipments. The ramp rate of hydro units are of the order of 100% of the rated capacity within minutes. However, the ramp rates of thermal units are limited and thermal turbines can be approximated as shown in Figure 12.

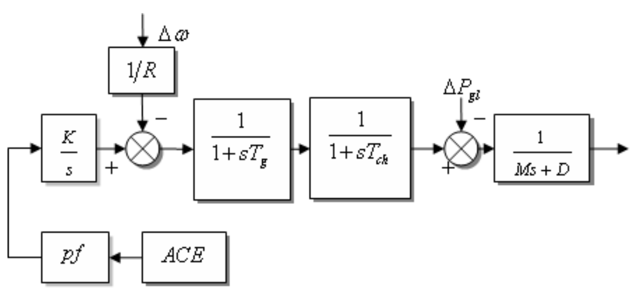


Figure 11: Model of generator with classical AGC

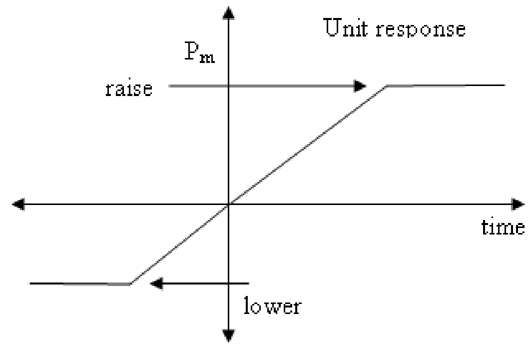


Figure 12: Output of rate limited units

The performance vector η is defined to express the frequency control performance of the markets described earlier as:

$$\eta = \begin{bmatrix} \Delta f_{max} \\ t_s \\ t_c \end{bmatrix} \qquad (2.1)$$

Where, Δf_{max} is the maximum deviation of system frequency after the disturbance, t_s, settling time is the time taken by AGC to bring the frequency back within safe limits, and t_c, crossover time is the time taken by ACE to cross zero for the first time after the disturbance.

2.2.4 WECC Case Study

The proposed markets have been simulated on a reduced WECC model with 225 buses where the California ISO (CAISO) and LADWP are represented in more detail than the rest. The network has been divided into three balancing areas (BA1 to BA3), which are summarized below in Table 5. All three areas are interconnected to each other with tie lines.

The markets are set up on area BA3 where all of the 40 generators submit their bid in the regulation market. The market goal is to procure 600MW up and 200MW down regulation capacity at a total load of 25000MW for the hour. The bid prices have been obtained from the generator cost curves which are of the form $C(P) = a + bP + cP^2$ and the dispatch level as per the Optimal Power Flow (OPF).

It may be pertinent to mention here that in reality the bids submitted by the participants depend on a large number of market factors. Also, the payment of bid price instead of the clearing price may change the way suppliers submit bids. Our assumption of bid price being same as the marginal cost of generation irrespective of the market is solely to present a comparative idea about the impact of different market structures in a common framework.

a) Market Settlement

i) Type A and B 10-minute markets

The outcome of settlement for 10-minute regulation market of type-A and type-B are same as far as the generators and contracted quantities are concerned. As expected the market payment for type-B is less than that of type-A. The final contracts are shown in Table 6. It can be observed that the procurement resulted in 6 contracts; the effective ramp rate of the system is 61 MW/min.

Table 5: Summary of Control Area Parameters

Area code	No. of generators	H (p.u.)	D (% per 1%f)
BA1	13	1685	1.06
BA2	9	637	0.26
BA3	40	1076	0.91

ii) Type B 5-minute market

The settlement of the type-B 5-minute regulation market is shown in Table 7 for the same market goal. 15 generators are contracted for regulation which is noticeably higher than the earlier case. The reason of higher number of generators being accepted in a 5-minute market is due to the fact that in a market with shorter dispatch interval the generators are able to bid less for a given ramp rate. The effective ramp rate for the system resulting from the market is 140 MW/min.

Table 6: 10-min market – Regulation contracts and prices

Gen#	Cost of generation c, b, a)	Contracted Regulation Up/Down (MW)	Contracted Regulation Ramp rate (MW/min)
6	(0.00378, 20, 0)	70, 0	7
8	(0.00224, 20, 0)	90, 0	10
15	(0.00343, 20, 0)	80, -80	8
16	(0.00768, 20, 0)	80, -80	8
17	(0.00193, 20, 0)	200, -40	20
20	(0.030600, 20, 0)	80, 0	8

ISO's burden from these contracts

Total payment	Type A: 23226.00 $/h
	Type B: 23113.20 $/h
Clearing Price Up	38.71 $/MWh
Clearing Price Down	22.03 $/MWh

iii) Type C market

Type C market is comprised of a 5-minute fast ramp market and a 10-minute slow ramp market. The markets are settled separately each procuring half of the regulation goal. The separate markets for fast ramp regulation and slow ramp regulation are shown in the Table 8 and Table 9. The two markets separately result in 8 contracts and total market payment is 23200.50 $/h.

Table 7: 5-minute market – Regulation contracts and prices

Gen#	Cost of generation (c, b, a)	Contracted Regulation Up/Down (MW)	Ramp rate (MW/min)
4	(0.00487, 20, 0)	100, 0	20
5	(0.00591, 20, 0)	15, 0	3
6	(0.00378, 20, 0)	35, 0	7
8	(0.00224, 20, 0)	30, 0	10
9	(0.00223, 20, 0)	30, 0	6
15	(0.00343, 20, 0)	40, -40	8
16	(0.00768, 20, 0)	40, -40	8
17	(0.00193, 20, 0)	100, -100	20
20	(0.0306, 20, 0)	40, -20	8
23	(0.00395, 20, 0)	40, 0	8
24	(0.00222, 20, 0)	25, 0	5
25	(0.01017, 20, 0)	40, 0	8
28	(0.00595, 20, 0)	30, 0	6
29	(0.00769, 20, 0)	20, 0	20
35	(0.04504, 20, 0)	15, 0	3

ISO's burden from these contracts

Total payment	23541 $/h
Clearing Price Up	39.70 $/MWh
Clearing Price Down	22.03 $/MWh

It is important to note here that the number of contracted generators changes as the market structure changes. The appropriateness of any particular market model for a region depends on certain factors. Apart from economic policies mandated by the market operator and regulatory organization, availability of resources and willingness of suppliers would play an important role to decide the right choice of market for a particular region. It can be seen by comparing the 5-minute and 10-minute markets of type-A and type B that a shorter dispatch interval results in an increase in the number of generators participating in AGC. Now, a direct impediment to form a 5-minute regulation market may simply be bid insufficiency, since everyone bids into the market only what they can deliver in 5 minutes. In such a scenario a reasonable choice would be to keep a 10-minute market overall and add a premium to the single market's regulation price for capacity that can be delivered in 5 minutes.

Table 8: 5-minute fast ramp regulation market

Gen#	Cost of generation (a, b, c)	Contracted Regulation	
		Up/Down (MW)	Ramp rate (MW/min)
4	(0.00487, 20, 0)	100, 0	20
8	(0.00224, 20, 0)	30, 0	10
17	(0.00193, 20, 0)	100, -100	20
30	(0.00600, 20, 0)	70, 0	20

ISO's burden from these contracts

Total payment	11700.30 \$/h
Clearing Price Up	39.70 \$/MWh
Clearing Price Down	22.03 \$/MWh

Table 9: 10-minute slow ramp regulation market

Gen#	Cost of generation (a, b, c)	Contracted Regulation	
		Up/Down (MW)	Ramp rate (MW/min)
6	(0.00378, 20, 0)	60, 0	3
15	(0.00343, 20, 0)	80, -80	8
16	(0.00768, 20, 0)	80, -20	8
20	(0.0306, 20, 0)	80, 0	8

ISO's burden from these contracts	
Total payment	11500.20 $/h
Clearing Price Up	38.71 $/MWh
Clearing Price Down	22.03 $/MWh

Besides, there are more choices available for controlling these generators to optimize the system frequency response. In the next section we will observe how these different markets and control systems can affect the system performance.

b) Performance consideration

Generators selected in the market as described above provide regulation and the AGC assigns regulation load to each selected generator according to some preset participation factors (pf) or regulation factors. There may be four ways to determine these participation factors.

- Equal participation factor for all units
- Proportional to ramp rate of the units
- Proportional to bid capacity of the units
- Inversely proportional to marginal cost of generation

The following cases demonstrate ways to determine participation factors and corresponding system response for a load disturbance of 1 p.u in BA3.

i) Type A & Type B 10-min markets

10-minutes markets of both type A and B have essentially same performance for the reason that the contracted generators are same in both cases. Depending on the method of determining the regulation participation the system response can vary. The following Table 10 summarizes the response of 10-minute market with four control schemes mentioned above that choose the participation factors differently.

Table 10: Performance comparison of four controls

Participation	Δf (%)	t_s (s)	t_c (s)
Equal	-0.1445	350	112
Ramp rate	-0.13	185	96
Bid capacity	-0.13333	225	92
1/Marginal cost	-0.14167	350	110

Noticeably, frequency response is best when the participation factors are proportional to ramp rate. The reason is, with such participation factor every generator is moved by an amount which is equal to $ramp\ rate \times dispatch\ interval$.

ii) Type B 10-min & 5-min markets

The different dispatch interval of the markets result in a difference in number of generators contracted and amount of service bought from each of them. A 10-minute market yields 6 contracts whereas a 5-minute market yields 15 contracts. Consequently the effective ramping capacity of the system is higher after the later comes into effect. As can be seen from the Figure 13, Figure 14, Figure 15 and Figure 16, the frequency response of the 5-minute market is faster for all the four participation methods.

The amount that a generator can bid in the market depends on the ramp rate of the generator. In case every generator gets its full bid capacity accepted in the market, 2nd and 3rd participation factors are essentially same. But a generator's bid may be partly accepted in the market. In that case the control system with 2nd participation method would be different than 3rd participation method.

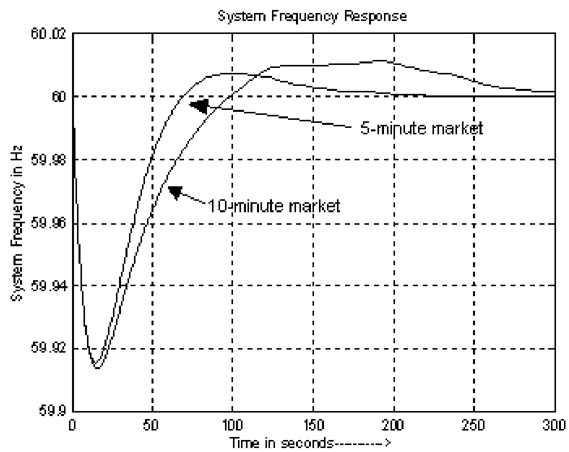


Figure 13: Frequency response with equal pf

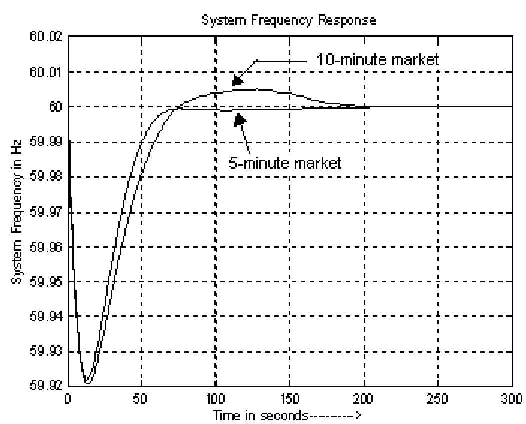


Figure 14: Frequency response with pf proportional to ramp rate

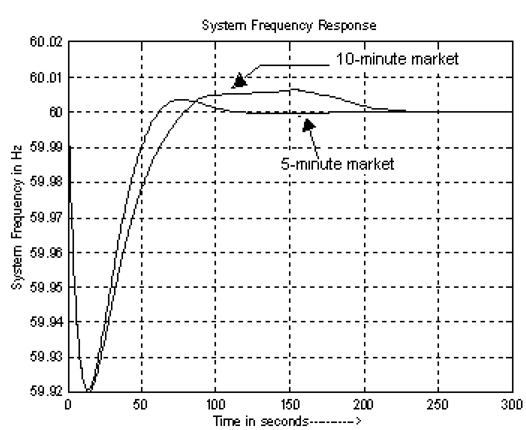


Figure 15: Frequency response with pf proportional to bid capacity

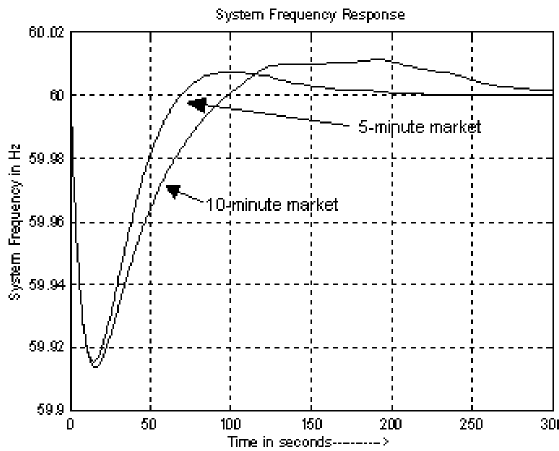


Figure 16: Frequency response with pf inversely proportional to marginal cost

The Table 11 shows the summary of the effect of four participation methods on a 5-minute market.

Table 11: Performance comparison of four controls

Participation	Δf (%)	t_s (s)	t_c (s)
Equal	-0.14167	220	76
Ramp rate	-0.13	150	100
Bid capacity	-0.13333	175	76
1/ Marginal cost	-0.14167	221.1	78

The crossover time is important in systems where ACE is expected to change signs within a certain time. In North America, NERC imposes statistical bounds on the value of ACE and the operators are responsible to maintain the values within these limits.

iii) Type C market

Unlike the previous two markets, type-C has separate markets for fast ramp and slow ramp regulation. To procure a certain amount of regulation from such a market one has to decide how much of fast and slow service are to be bought. Then there are multiple options available as to how to use them in time of need. For the purpose of our study we have procured half of the regulation from each of the fast and slow markets. While using the resources to follow the load we have looked into four scenarios using:

- Fast ramp only
- Slow ramp only
- Fast and slow together

- Immediate use of fast, then slow service

For a load disturbance of 1p.u, it is possible to bring the frequency back to normal with fast generators alone, as shown in Figure 17 and Figure 18a.

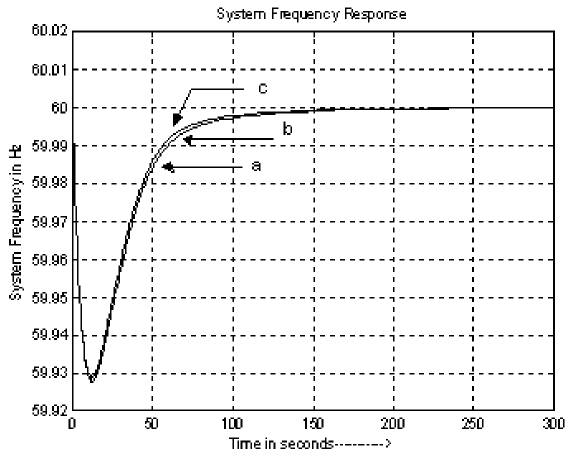


Figure 17: Regulation response with fast generators only with: a) Equal participation, b) Ramp rate based participation, c) Bid capacity based participation

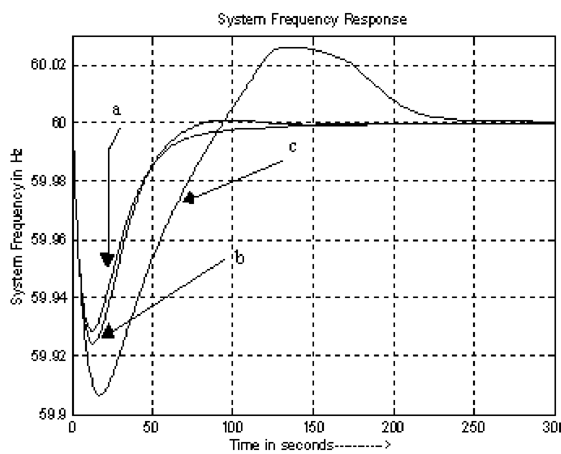


Figure 18: Regulation response with a) only fast, b) 50-50 fast & slow, c) only slow generators

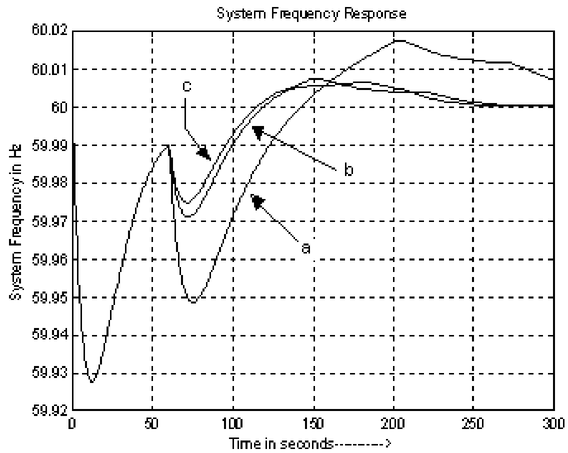


Figure 19: Regulation with fast response for 1minute and thereafter, a) slow only response, b) 25% fast–75% slow combination, c) 50% fast–50% slow response

If only slow generators are used instead, the recovery of frequency is very slow and takes a long time to settle down (Figure 18c). But combined together the fast and slow generators can recover the frequency quickly and smoothly (Figure 18b). The latter response is almost the same as in Figure 18a. which only uses the fast response generators.

In a typical case the operator may not wish to exhaust the fast service completely and call the slow resources to take up the remaining of the regulation load. Though the fast market is designed to sustain the service for 5 minute, for the simulation purposes some part of the fast resources are relieved after 1 minute of the occurrence of the disturbance. Figure 19 shows that a. if only slow generators are used for regulation after 1 minute the frequency response is quite slow, b. and c. if a combination fast and slow generators are used, is possible the recover the frequency within the dispatch interval. The response of case c. is smoother than that of b. because of more fast generators.

Together these cases show that the structure of the regulation market has a direct effect on the control performance of the system. Since the maximum amount of regulation that a generator can deliver in the market depends directly on its ramping capability, the amount of service (capacity) bought in the market also affects the system response. The more the procurement, the more would be the number of generators taking part in regulation, and better would be the frequency response. An increased participation of the generators with faster ramp rates can also be achieved by reducing the dispatch interval. The added advantage is more competition and less stress on generators.

Also it is necessary to incorporate some payment method which would reflect the effect of each supplier on the system performance. Splitting up the payment according to the ramp rates of the generators as in the type-B market can solve that issue.

Forming separate markets for fast ramp and slow ramp regulation service can open up a lot of possibilities. Not only does it differentiate among the suppliers as per their rate of response, but also the payment is decided in an easy and competitive manner.

It is necessary to say that the right choice of market will somewhat depend on the idiosyncrasies of a particular geographical region, e.g. availability of resource or capacity. Once a suitable market has been formed there are also certain choices available for control to optimize the performance. In a type-C market it is necessary to decide how much of fast and slow service to be procured and the historical profile of use of regulation in the area under consideration will play an important role in that division. Apart from that it is also possible to decide on the amount of each service to be used depending on the magnitude of the disturbance.

2.2.5 Remarks

In this section, it is demonstrated that the structure of the regulation market has a direct effect on the control performance of the system. Three different market structures were chosen to demonstrate the varying control performance on a reduced WECC system. Although the first market structure is similar to what is used by the California ISO today, the other two were chosen somewhat arbitrarily to show that control performance can be improved by providing more incentives for generators with better response (ramp) rates. However, the actual market structure will have to take into account the actual response rates of available generators. For example, whether a 5-min regulation market can actually be developed depends on the types and capacities of generators willing to be part of such a market. It is shown that price based or ramp rate based regulation markets can be formed to:

i) Increase competition
ii) Encourage generators with incentive
iii) Explore more control options to optimize performance

Existing regulation markets are flat priced and does not recognize the difference among suppliers or reward them appropriately. As the regulation market provides control, it is believed that such markets should make the necessary changes that are needed to elicit the best control performance possible.

2.2.6 Accommodating Third Party Load Following into Classical AGC

Regulation and load following, both addresses the time varying characteristics of balancing the generation and load under normal operating condition. While regulation matches the generation with minute-to-minute load change, load following uses the generation to meet hour-to-hour and daily variations of load [47]. Though restructured markets after deregulation recognize regulation and energy, load following is not a recognized service.

In a restructured power system independent competitive generating units are allowed to enter into bilateral transactions with Load Serving Entities (LSE) and industrial consumers. When these loads come online, Area Control Error (ACE) detects the change and accordingly units are dispatched by AGC. However, if the loads ramp up too fast, ACE becomes too large and it takes a long time for the frequency to recover. Hence, the larger the variation in load, the more it endangers the dynamic stability of the system. Also as an aftereffect of large values of ACE future regulation estimates are increased, which in turn increases the cost of procurement. For that reason it is desirable to quantify the load following requirement and keep the regulation procurement as low as possible.

Recent impetus for facilitating load following as an ancillary service has led to the conception of a new “AGC like” scheme [48] where a decentralized market for this ancillary service has been proposed, suggesting procurement of load following through bilateral contracts. Thus ISO is relieved from this burden and ultimate responsibility for performance is moved to the supplier.

In an alternative approach, load following can still be procured in a bilateral market while ISO will control response of each supplier to ensure acceptable performance. To incorporate this centralized control over bilateral exchange it is necessary to integrate third party load following with the usual AGC. In the next section, a method to provide load following service is presented in the existing framework of AGC by changing the method of calculation of ACE and unit error. Then a comparative study between the proposed method and the separate third party control shows the effectiveness of this method in terms of control performance of the system.

2.2.6.1 AGC with Third Party Load Following

Let us consider a power system where control areas are connected via tie lines. In classical AGC system the ACE after a disturbance is calculated from the change in scheduled interchange flows and frequency [46], [49] as follows:

$$ACE = \Delta P_{Tie} + B\Delta\omega$$

The change in tie line flow is nothing but the difference between the generation and load in the area given by:

$$\Delta P_{Tie} = \sum \Delta P_G - \sum \Delta P_L$$

The control signal to a unit is then given by:

$$u_t = pf \times (ACE_t + \int_0^{t-1} ACE_\tau d\tau)$$

The participation factors *pf* are empirical for a particular system.

Let us now assume that generators inside the control area enter into bilateral contracts with loads. For any generator with real power output P_{Gi} and bilateral load P_{Bi} the instantaneous unit control error (CE) is:

$$CE_i = P_{Gi} - P_{Bi} + \left(D_i + \frac{1}{R_i}\right)\Delta\omega$$

If the generator also takes part in regulation with a participation factor *pf* the instantaneous unit control error would be:

$$CE_i = P_{Gi} - \left(P_{Bi} + pf \times P_R\right) + \left(D_i + \frac{1}{R_i}\right)\Delta\omega$$

Now, taking sum over all the control errors inside the area we get:

$$\sum_{area} CE_i = \sum_{area} P_{Gi} - \left(\sum_{area} P_{Bi} + \sum_{area} pf \times P_R\right) + \sum_{area}\left(D_g + \frac{1}{R_g}\right)\Delta\omega$$

$$\sum_{area} CE_i \approx \sum_{area} P_{Gi} - \left(\sum_{area} P_{Bi} + \sum_{area} pf \times P_R \right) + \left(D_{area} + \frac{1}{R_{area}} \right) \Delta\omega$$

Hence $$\sum_{area} CE_i \approx \Delta P_{Tie} + B\Delta\omega$$

The signal to a participation unit can be written as: $u_t = CE_t + \int_0^{t-1} CE_\tau d\tau$

It can be seen that the ACE for an area in classical AGC system is equivalent to the sum of all the unit control errors in that area. Consequently it is possible to dispatch the bilateral load along with the regulation load simultaneously without changing the AGC control structure. Although it would be necessary to calculate the control error for each and every generator in that area and all the transactions with the generators have to be accounted for. It is also possible for the generators to take part in contracts across the control area boundary as would be demonstrated in the following simulation results.

2.2.6.2 Case Study

The control scheme has been simulated on an experimental three-area system as shown in Figure 20. The areas have two, three and four generators respectively. The summary of the three balancing areas are shown in Table 12. Bilateral contract of generator G3 is in area 3.

The frequency response of the system has been shown in Figure 21. For the sake of comparison the response of third party control [48] on the same system is also shown. It can be seen that the proposed scheme bring the frequency back to normal effectively. Comparing the response times of the two schemes mentioned, it can be seen that load following AGC is faster.

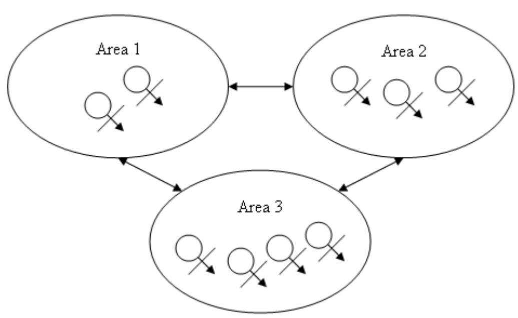


Figure 20: 3-area system connected via tie lines

In the proposed method there is no ACE since CE is calculated for each supplier and close to the aggregated value of bilateral and regulation load. Figure 22 and Figure 23 demonstrates that the maximum values of CE and ACE are, in fact, comparable. Hence, such a scheme, if implemented, can be configured to perform within the NERC specified control performance criteria.

Table 12: Summary of three balancing areas

	Area 1		Area 2			Area 3			
Generators	G1	G2	G3	G4	G5	G6	G7	G8	G9
AGC	✓	✓	✓	×	✓		✓	✓	✓
Bilateral Load	0	0.2	0.1	0	0.2		0	0.1	0.1
Reg. load	0.5		0.2			0			
Reg. pf	0.5	0.5	0.5	0	0.5		0.33	0.33	0.33

Another advantage of AGC with third party load following is that a generator which takes part in bilateral contract can participate in regulation too. In area 1 two generators are on AGC and one of them has bilateral load. In Figure 24, it shows that with third party control the regulation load is supplied solely by G1 since G2 has a bilateral load. But with load following AGC the regulation load is shared by both G1 and G2 depending on their regulation participation factor (Figure 25). The bilateral load is served by G2 alone. Hence, load following AGC helps more generators to take part in regulation making the frequency response faster.

Figure 26 and Figure 27 show the area 2 generations under the two different control schemes. The regulation load is supplied only by G3 in Figure 26 but in Figure 27, the regulation is shared by G3 and G5 since G4 is not on AGC. In both cases G3 serves a bilateral load in area 3. Figure 28 and Figure 29 show the generation response in area 3. In all instances the generators which are not on AGC reduce their output to zero at the steady state.

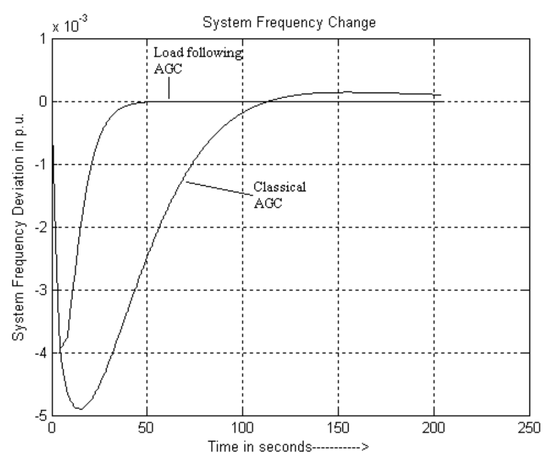


Figure 21: Frequency response a) classical AGC and third party control b) load following AGC

It is imperative for implementation of such control that all the generators entering in a bilateral contract should be on AGC even if they are not taking part in regulation. That implies almost all the generators in the network should have the communication facility to receive command from AGC.

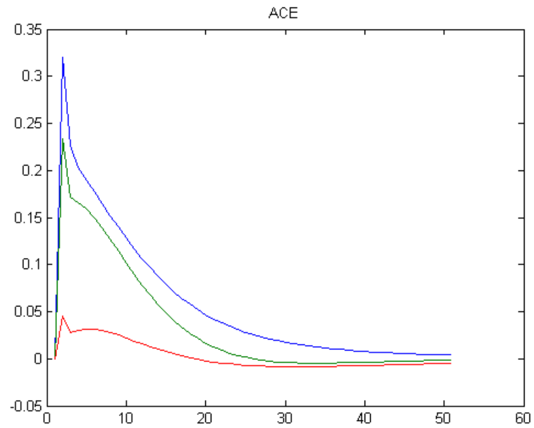


Figure 22: ACE for three areas with classical AGC and third party control

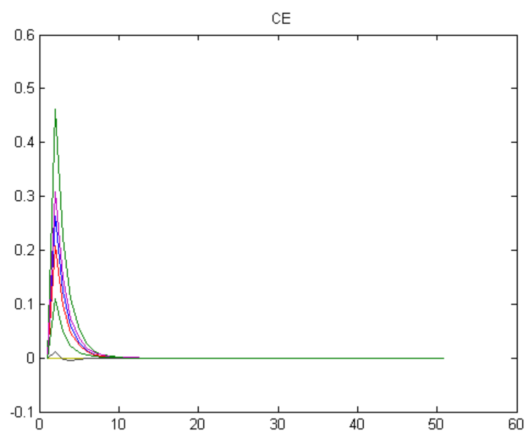


Figure 23: CE for 10 generators with load following AGC

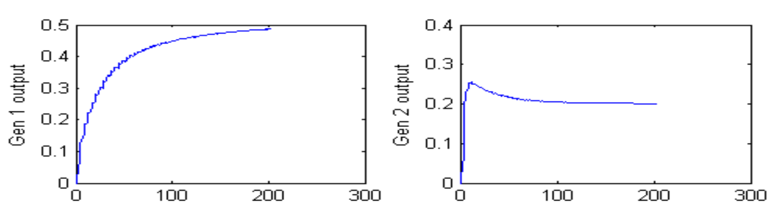


Figure 24: Area 1 generation – third party control

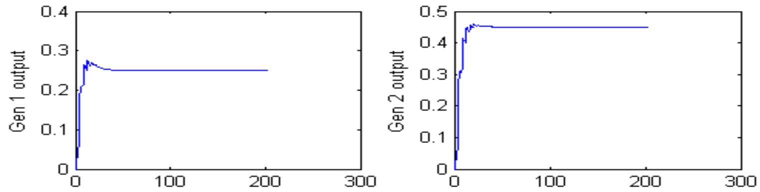


Figure 25: Area 1 generation – load following AGC

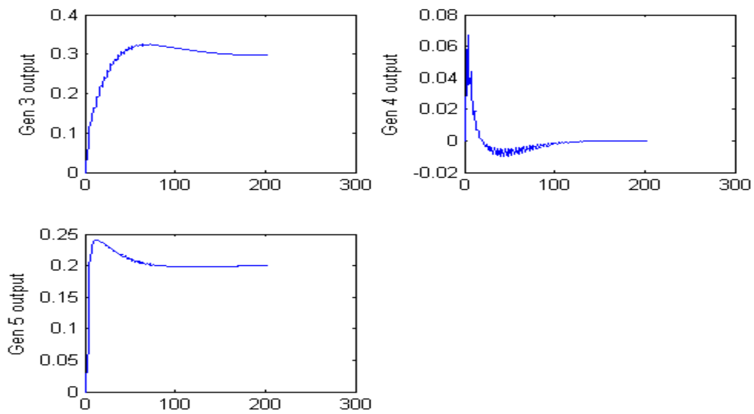


Figure 26: Area 2 generation – third party control

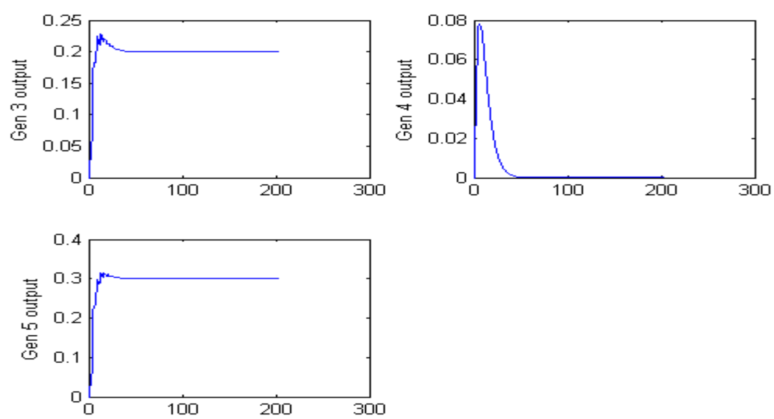


Figure 27: Area 2 generation – load following AGC

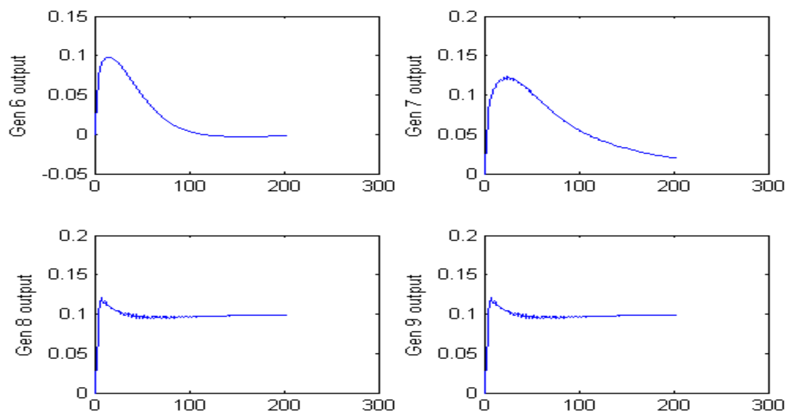


Figure 28: Area 3 generation – third party control

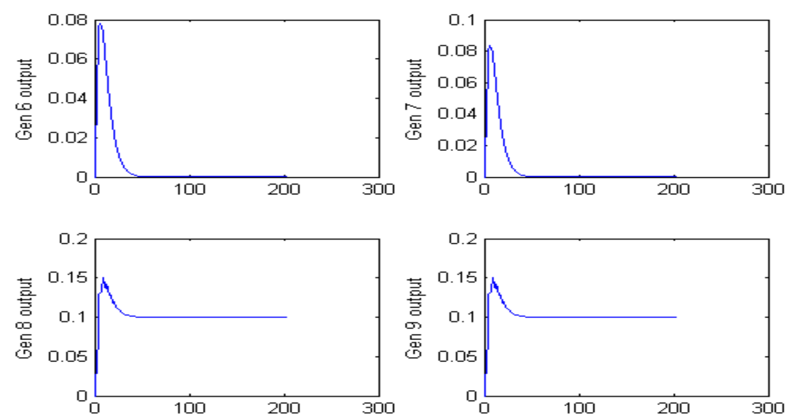


Figure 29: Area 3 generation – load following AGC

2.2.6.3 Remarks

The results of the experiment described above show that proposed load following AGC scheme can be used for frequency control. With bilateral load following integrated with the AGC, frequency can be brought back to desired value faster than separate third party control and with reasonable smoothness. Both regulation and bilateral loads can be served with such a control without the need of additional control hardware. Since every transaction is cleared by the System Operator, such scheme does not bring any additional burden, rather it becomes convenient to monitor the performance of individual service providers and maintain the power quality.

It is to be noted that by fixing the participation factor at a proper value the regulation participation of a generator in the system can still be controlled. The local control loop for third party control would force the output of a generator at its contracted value. Consequently the generators entering into bilateral contracts would not be able to participate significantly in regulation. Such restrictions are not present when bilateral load following is integrated with the AGC. As a result a supplier can take part in both markets if it wishes to do so. The ways in which the regulation participation can be determined is discussed in detail in the previous section.

In case a generator enters into a bilateral contract with a load outside the territory of the control area it has to be under control of the AGC of the area where the load is situated. In that case it would be expected that the generator would not take part in regulation in the home control area, because that would create conflict among two AGC signals.

The necessity to recognize load following as an ancillary service has already been discussed and addressed in the literature. The current deregulated market does not recognize load following. As a result the operation and maintenance cost for dispatching the units to follow the ramping loads accrue on the price on energy. Hence it is necessary to define and quantify load following service in the new market system and that will help to procure this service in a competitive manner and reduce overall price of energy. With the proposed scheme a load following market can be formed where the service would be procured as bilateral contracts between the supplier and load, yet the ultimate responsibility for performance would be on the hand of ISO or the equivalent authority. Alternatively a short term load following market may also be developed in this framework. Generators can competitively bid for a certain amount of load following service in such a market and ISO can procure the service for a given market goal.

2.3 Feasibility of VAR Markets for Secondary Voltage Control

2.3.1 Preface

From the system perspective, the task of voltage control can be organized into a three level hierarchy, primary, secondary and tertiary. The primary voltage control is essentially a local control whose objective is to keep the voltage at the local bus at specified value using the automatic voltage regulator (AVR) of the generating unit. The secondary voltage control, often automatic centralized control, coordinates the actions of the voltage regulators of the generating units in a region of the network, and targets to keep the voltages at multiple buses in that region at the proper level. The tertiary control is manual control used to coordinate and optimize the reactive power flow across networks. The overall task of all three controls is to maintain a proper voltage level over the network, to reduce congestion and to minimize transmission losses.

The provision of primary voltage control is compulsory in most power systems all over the world as it is necessary as part of the connection requirement to the grid (just as the primary frequency control by generator governor is mandatory). In some regions (Europe, China) secondary voltage control is being used sometimes even with a tertiary control that coordinates the secondary [50-51]. This service is sometimes paid a regulated price or via bilateral contract, but there has never been a competitive market for it. Secondary voltage control, on the other hand, is not a compulsory service and has been implemented in only a handful of European countries [52]-[54]. The system operator or ISO determines the reserve requirement and procures the reactive power resources through bilateral contracts or pay as bid contracts.

In recent works to investigate the feasibility of voltage control ancillary service markets it has been shown that area voltage control is especially suitable to form competitive markets for secondary voltage control due to its relatively local nature [55]. To implement such control, the network has been divided into a number of independent and uncoupled regions, called Voltage Control Areas (VCA) [56]. The voltage profile inside the VCA is then maintained by controlling the voltage reference set point of the generators in that region.

Here through experiments, it is shown that formation of a VAr market is possible with a similar method of voltage control by adjusting the reactive power generation at the units. The difference of this method from the earlier scheme is that a direct VAr set point is sent to the unit instead of voltage reference. In a case study of the same power system mentioned earlier, the feasibility of VAr markets with both types of control methods has been investigated side by side.

Apart from the voltage control methods described earlier, which are devoted means of secondary control, voltage at the load buses in a radial network can also be controlled by using automatic tap changing transformers. In modern power systems transformers on the load buses are under the direct control of the ISO and when voltage variation at the load buses are relatively small these are corrected by coordinated adjustment of tap changers. Due to limited capability transformer tap control may be used only as the preliminary tool of voltage control after a substantial disturbance occurs. The responsibility then can be taken over by the other specialized secondary voltage control. Before turning our attention to area wise voltage control, application of a centralized tap changer control has been explained and demonstrated in the next section. In section 2.3.3, voltage support by area voltage control methods have been elucidated in detail.

2.3.2 Voltage Support by Transformer Tap Control

2.3.2.1 Problem Formulation

The centralized control of tap changers in a network is shown in Figure 30. With controllable transformer buses present in the system, all the buses in the system can be categorized into three basic types, viz. PV or generator buses, PQ or load buses and TC or transformer controlled buses. Table 13 shows the known and unknown variables for each type of bus. TC buses are similar to PQ buses except the voltage is fixed at upper or lower limit and the tap ratio is varied to keep the voltage constant at that value. Consequently the tap ratio is unknown at a TC bus.

Table 13: Known and unknown variable at different buses

Bus type	PV	PQ	TC
Known	P, V	P, Q	P, Q, V
Unknown	δ, Q	δ, V	δ, t

The desired tap ratio can be calculated by solving the power flow. For each bus the power flow equations are given by:

$$P_i = P_{gi} - P_{Li} + \sum_{j=1}^{N} V_i Y_{ij} V_j \cos\left(\delta_i - \delta_j - \theta_{ij}\right)$$

$$Q_i = Q_{gi} - Q_{Li} - \sum_{j=1}^{N} V_i Y_{ij} V_j \sin\left(\delta_i - \delta_j - \theta_{ij}\right)$$

The Jacobean is calculated as:

$$J = \begin{bmatrix} \dfrac{\partial P}{\partial \delta} & \dfrac{\partial P}{\partial V} & \dfrac{\partial P}{\partial t} \\ \dfrac{\partial Q}{\partial \delta} & \dfrac{\partial Q}{\partial V} & \dfrac{\partial Q}{\partial t} \end{bmatrix}$$

The system operator has to monitor all the transformer buses for violation. When a violation occurs the controller will determine desired tap ratio and send it as a control signal to the respective bus.

It is important to note here that this type of control can have cascaded effects on the network. Change in tap ratio at one transformer can trigger voltage events at some neighboring buses. Consequently a number of complete control cycles may be needed before the all buses are at proper voltage level.

There are also upper and lower limits on tap ratios of a transformer. Naturally, voltage control capability of this scheme is limited by the range of the tap changer. Hence such scheme cannot be expected to take up the absolute responsibility of voltage control in a network, rather it can work as a preliminary control which would come into effect before other secondary voltage control are deployed. For example, once the system is perturbed and the voltages at the load buses fall outside the reliability limits, tap changer control may be deployed to correct the voltages at the buses which are equipped with tap changing transformers, and then the reactive injection at the generator buses can be controlled to correct the remaining violations.

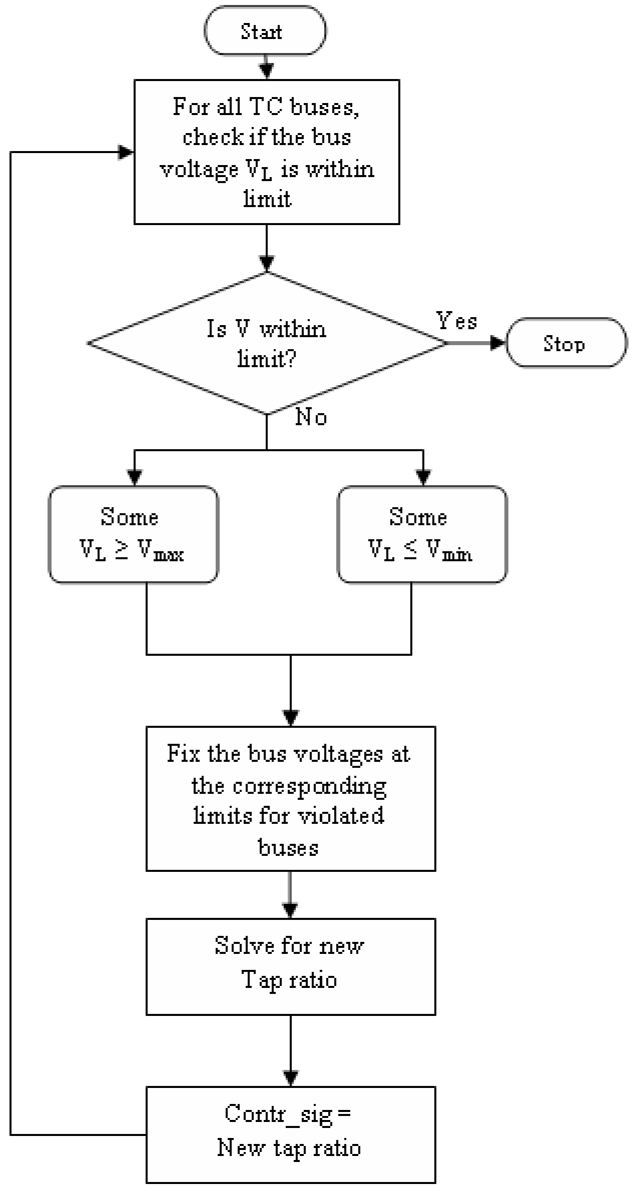


Figure 30: Automatic adjustment of tap changers

2.3.2.2 Case Study

The control method has been tested on the same WECC 225-bus model that has been mentioned in the frequency control sections. For the sake of convenience the admissible limits are assumed to be $V_{\max} = 1.06$ and $V_{\min} = 0.94$.

Table 14 shows the load buses which are outside the admissible range at the steady state condition and the voltage after the tap changers have been modified. The initial and final values of the tap ratios at the transformer are shown in Table 15.

Table 14: Buses voltages before and after tap changer control

Bus No	Initial	Final
55	0.935	0.94
61	0.93	0.94
67	1.076	1.047
68	1.073	1.06
71	1.069	1.059
143	0.932	0.942
146	0.923	0.94
184	0.935	0.942
187	0.917	0.94

The limited voltage control capability of tap changers makes it suitable for small voltage variation at the load buses. If the voltage variation is large more dedicated voltage control methods like the ones described in the subsequent sections are necessary to take over the control. Hence it can act as the preliminary tool to condition the network for reactive injection control or voltage reference control.

2.3.2.3 Remarks

The purpose of the above example is to demonstrate that small voltage disturbances in a network load buses can be eliminated by systematic control of transformer tap changers. The control of these transformers is under direct supervision of ISO. However, no market formation is feasible since transformers in a network are owned by the transmission companies.

Table 15: Tap ratios before and after control action

From bus	To bus	Tap ratio	
		Initial	Final
52	51	1.0017	1.001
53	51	1.0017	1.001
54	51	1	1.001
54	51	1	1.001
56	55	1.0106	0.934
56	55	1.0106	0.934
60	61	1.0133	1
68	67	0.9873	1.002
69	68	1.0238	1.07
69	68	1.0238	1.07
72	71	1.0234	1.022
140	143	1	0.993
145	146	1	0.942
151	187	1	0.929
151	187	1	0.929
151	187	1	0.929
183	184	1	0.983
183	184	1	0.983

2.3.3 Voltage Support by Area Voltage Control

Unlike AGC in previous sections, voltage control is almost always done locally (i.e. primary control) and only a few regions, mainly in Europe and China, have implemented secondary control. It is unlikely that an auction market can be set up with only primary control (although bilateral contracts are common), so we assume secondary control in our control schemes here. In this section, it is shown that voltage control performance will be affected by two factors:

- Methods of control implementation
- Methods of setting up the market

A. *Methods of control*

Method of control may typically be either manual or automatic. In the scope of this discussion, the focus our attention is on the automatic control of reactive power dispatch level of the generators on the network. The automatic area voltage control can be implemented by:

- Adjusting the voltage reference set point of the controlling units
- Adjusting the VAr injection at the point of dispatch of the generator

Scheme 1:

The control method and logic of voltage reference adjustment is well discussed in [55]. For the sake of simplicity it is assumed that voltage control areas (VCA) can be formed in a network that are largely uncoupled and have little effect on the voltage at the buses in the neighboring VCA s. To make sure that an acceptable voltage profile is maintained throughout the network all the load (PQ) buses are continuously monitored and if the voltage at a monitored bus falls outside the permissible limits the controller would automatically generate an appropriate error signal proportional to the violation. When there are violations at multiple buses the largest violation would set the error signal.

$$\varepsilon = \max(V_i - V_{limit}), \quad i = 1 \ldots N_{PV}$$

The error signal is then converted to appropriate control signal with the help of a set of weighting factors and used to adjust the voltage references of the generators.

Scheme 2:

This control scheme (shown in Figure 31) determines the error in the same way. The control signal is generated from the error signal by using the sensitivity of the controlling units towards the error signal. Assuming there are N_G number of controlling units in the VCA and violation ΔV at bus i to be the maximum magnitude amongst all the violations in the area, the control signal for each generator can be formed as:

$$cs_j = \Delta V \Big/ \left(\frac{\partial V_i}{\partial Q_j} \right), \quad j = 1 \ldots N_G$$

The value of the reactive sensitivity can be used from the ones derived for separation of VCA s [56]. The new level of reactive power generation at controlling unit j can be expressed as:

$$Q_{g_{j\,new}} = Q_{g_{j\,old}} + K_j * \frac{\Delta V}{\left(\partial V_i \big/ \partial Q_j \right)}$$

The participation of each controlling unit can further be controlled by another set of weighting / participation factors K_j, which can be determined based on the individual characteristics of each generators inside the area. As the quantity cs_j may not be essentially zero, the K factors for units outside a VCA can be made zero to prevent them from participating in the control action. It is also possible to distribute the responsibility of control over a multiple VCA s by setting nonzero values to the participation factors.

Though the end results of both control schemes are maneuvering of reactive reserve, scheme 2 has some transparency in term of VAr, since the operating target of the controlling unit would always be explicitly defined. The reactive generation level of the unit is not known beforehand when the controlling quantity is the voltage reference.

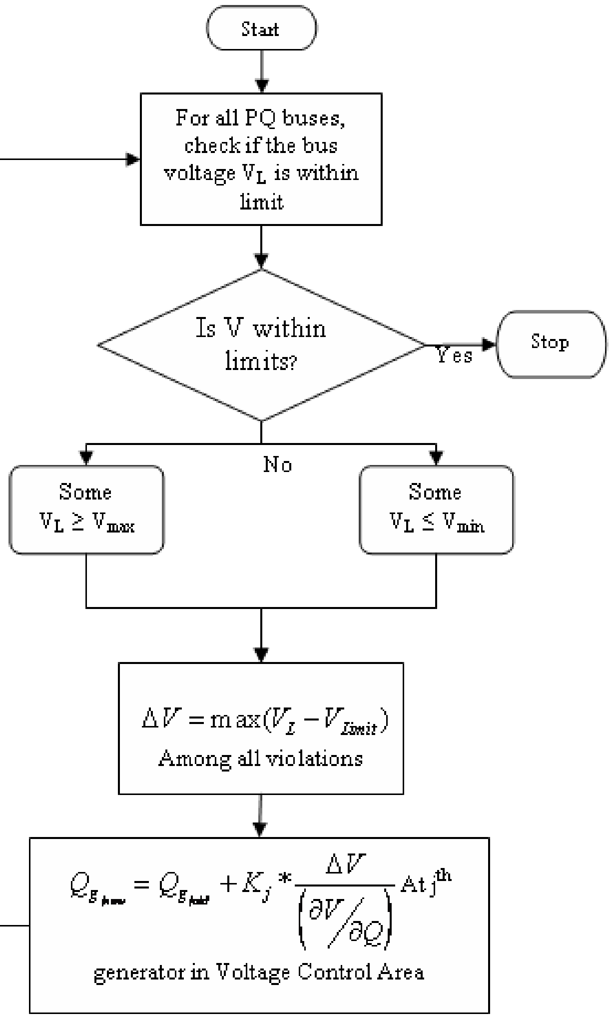


Figure 31: Automatic adjustments of reactive injection

B. Ancillary Market

The payment expectation of a generator in an ancillary VAr market comprises of two components (Figure 32).

- A cost component proportional to capacity made available
- A second order cost component to account for the lost opportunity

As a requirement for connection to the grid generators are required to be able to operate within a specified power factor limits while serving the load. This usually is not considered as an ancillary service, and no payment is associated with it.

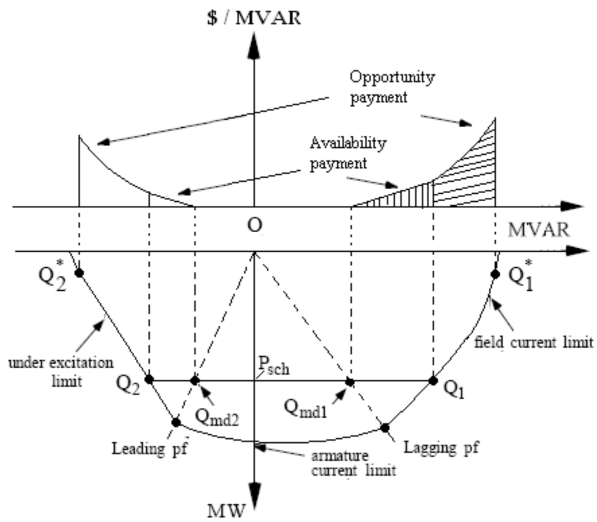


Figure 32: Ancillary service zone and payment

Following this payment method a VAr market can be set up on top of the above mentioned control scheme as follows.

Voltage control market – For the control scheme 1 the reactive power level of the generator is not known beforehand. Hence voltage levels can be determined from the generator capability curve and payment would be for the VAr needed to maintain the reference voltage so that the reactive power in within the ancillary service range.

VAr control market – For the control scheme 2, the reactive power output is explicitly specified. Hence a direct VAr market can be formed with payment for maintaining the VAr output of the generator in the ancillary service range.

Procurement from these markets can be decided by a regular auction method within each VCA. It may be desirable to coordinate the voltages across the VCAs through a modified Optimal Power Flow [57], sometimes called tertiary control. However, it is not consider this in our experiments here.

2.3.4 Case Study

Proposed control schemes were tested on the reduced WECC model described earlier. Among 225 buses represented in the system 40 are generators. As an initial condition all the load buses except the boundary buses are held between the permissible values of $V_{\max} = 1.08\,p.u.$ and $V_{\min} = 0.985\,p.u.$ respectively. To implement area voltage control the network has been divided in 24 VCAs. The simulations are focused on the central California region, VCA#16 consisting of 37 buses, 8 of which are controlling units. The names and types of the buses are shown in Table 16. Using summer 2004 loading data as the base case the load profile of the entire network was increased by 10%. The voltage reference V_{ref} at the controlling units and the reactive power injection MVAr values at the steady state are shown in the Table 17. The voltage at load buses #121, #133, #195, #199 and #204 are found to be 0.978, 0.962, 0.936, 0.925 and 0.949 respectively. Initially 0.925 drives the control. Starting from this condition control has been implemented to bring the voltage back within admissible range. First automatic voltage reference correction of controlling units (A) has been used, and then area voltage control with automatic reactive injection adjustment (B) has been implemented.

A. Voltage reference adjustment

The voltage sensitivity to reactive injection at the 8 controlling units for the 5 load buses are shown in the Table 18. It can be seen that Gen #110, #198 and #218 are most influential. Hence natural participation factors of these units are higher than the others in a perturbation.

Table 16: VCA#16 bus type and location

Bus #	Type	Bus #	Type	Bus #	Type	Bus #	Type
110	Gen. Bus	133	Load Bus	204	Load Bus	218	Gen. Bus
111	Load Bus	134	Load Bus	210	Gen. Bus	219	Gen. Bus
116	Gen. Bus	173	Load Bus	211	Load Bus	220	Load Bus
117	Load Bus	192	Load Bus	212	Load Bus	221	Load Bus
118	Gen. Bus	193	Load Bus	213	Load Bus	222	Load Bus
119	Load Bus	195	Load Bus	214	Load Bus	223	Load Bus
121	Load Bus	198	Gen. Bus	215	Load Bus	224	Load Bus
122	Load Bus	199	Load Bus	216	Load Bus	225	Load Bus
132	Load Bus	202	Load Bus	217	Load Bus	226	Gen. Bus

Table 17: Steady state condition after perturbation

Bus No	V_{ref}	MVAr
110	1.013	36.52
116	1.05	948.64
118	1.035	1504.01
198	1.035	366.87
210	1.035	290.76
218	1	613.35
219	1.007	835.99
226	1.035	129.17

Table 18: Voltage to reactive injection sensitivity

	Bus #121	Bus #133	Bus #195	Bus #199	Bus #204
Gen #110	0.021	0.017	0.036	0.029	0.028
Gen #116	0.005	0.001	0.024	0.021	0.022
Gen #118	0.005	0.001	0.024	0.021	0.022
Gen #198	0.017	0.012	0.048	0.038	0.037
Gen #210	0.006	0.001	0.04	0.035	0.039
Gen #218	0.014	0.012	0.023	0.018	0.017
Gen #219	0.008	0.003	0.028	0.025	0.026
Gen #226	0.009	0.005	0.027	0.023	0.024

From a control point of view there are three cases that can be considered.

Case A.1. All units are used for control together

The new steady state condition is shown in Table 19 when all of the 8 generators are used for control by adjusting voltage set point. The voltages at all the 5 load buses are now within the admissible range. The weighting factor used for all 8 units is 1. Total reactive power generated is 20102.71 MVAr and the reactive power generated by the controlling units is 4828.78 MVAr. It can be seen that the reactive power produced by the controlled units have increased from 2531.81 MVAr while total reactive power is less than 22703.35 MVAr without voltage control.

Table 19: Case A.1. Voltage reference adjustment at all 7 units

Bus No	Vref	MVAr
110	1.073	193.99
116	1.1	831.37
118	1.095	1458.68
198	1.095	489.15
210	1.095	299.42
218	1.06	600.45
219	1.067	826.73
226	1.095	128.99

Case A.2. Most influential units are used first

Now, initially three most influential units #110, #198, #218 are used to control the voltage. When these units reach maximum voltage limit other less influential units are used. The participation factors for all units are 1. The steady state values of and reactive power MVAr are shown in Table 20. The total reactive injection is 20229.98 MVAr. Total reactive power generated by the controlled units is 5024.42 MVAr.

Case A.3. Less influential units are used first

Units #116, #210, #219 and #226 are used for control initially, all with weighting factor 1. After these units reach their maximum voltage limit other units are called upon for control. The steady state values of voltage reference and reactive power injection at the generators are shown in Table 21. Total reactive injection in this case is 20039.68 MVAr. Reactive power generated by the controlling units is 4980.99 MVAr.

Table 20: Case A.2. Voltage reference adjustment of most influential units

Bus No	Vref	MVAr
110	1.1	212.4
116	1.1	736.03
118	1.065	810.57
198	1.095	457.11
210	1.1	287.85
218	1.1	1056.69
219	1.1	1343.78
226	1.1	76.56

Table 21: Case A.3. Voltage reference adjustment of less influential units

Bus No	Vref	MVAr
110	1.1	205.41
116	1.06	688.36
118	1.084	1310.21
198	1.1	463.68
210	1.084	316.43
218	1.1	1321.98
219	1.056	603.23
226	1.084	115.12

These three cases above show that as more reactive power is generated inside an area to counteract a voltage disturbance, total reactive power consumption of the system is reduced. For example, in absence of voltage control the generators inside VCA #16 supply 2531.81 MVAr. When voltage control is used total VAr consumption of the system for all three cases is less than this value. The reason is intuitive; higher availability of reactive power inside an area reduces the need to transport it from units far from the area, thus reducing absorption and loss over the network. Again, use of the most influential units first result in reduced reactive injection inside the VCA than using less influential units, which is justified, since more influential units would improve the voltage at the neighboring buses more effectively, i.e. at the cost of less reactive power.

B. Reactive injection adjustment

Now, control scheme 2 is used to manage the same disturbance. To implement the control the sensitivity of each unit towards the voltage variation, which drives the control, is determined. The sensitivities of the 8 controlling units inside VCA#16 towards a voltage variation at bus #195 are 0.036, 0.024, 0.024, 0.048, 0.04, 0.023, 0.028 and 0.027 respectively. Then K is chosen accordingly for three scenarios.

Case B.1. All units are used for voltage control

All units are used simultaneously for voltage control by adjusting reactive injection. Table 22 shows the new steady state voltage reference and reactive injection at the generators with K values of 1 for all 8 controlling units. The voltages at all the five load buses are within limits and the new reactive injection is 19971.47 MVAr compared to the reactive injection of 22703.35 MVAr before voltage control. Less amount of reactive injection indicates less congestion and lower loss. The reactive power generated by the controlled units is 4974.69 MVAr.

Case B.2. Most influential units are used

Units #110, #198 and #218 are used for voltage control. The K values for these three units are 2.5 and others are 0. Due to higher participation factors these units increase their reactive injection more than others. The steady state voltage and reactive injections at the generators are shown in Table 23. Total amount of reactive injection in this case is 20191.96 MVAr. The reactive power generated inside the VCA is 4460.75 MVAr. On contrary to A.2, voltage control is possible by adjusting the reactive injection of the most influential units only. Higher reactive injection inside the VCA result in an overall lower reactive power consumption in this case.

Table 22: Case B.1. Reactive injection adjustment at all units

Bus No	Vref	MVAr
110	1.1	204.91
116	1.1	723.99
118	1.075	914.43
198	1.1	452.46
210	1.1	290.76
218	1.1	1025.29
219	1.1	1286.3
226	1.1	76.55

Table 23: Case B.2. Reactive injection adjustment at most influential units

Bus No	Vref	MVAr
110	1.1	209.9
116	1.1	869.01
118	1.075	1146.08
198	1.1	465.07
210	1.072	251.34
218	1.1	765.46
219	1.062	618.82
226	1.1	135.07

Table 24: Case B.3. Reactive injection adjustment at less influential buses

Bus No	Vref	MVAr
110	1.085	10.28
116	1.1	724.59
118	1.075	931.71
198	1.075	348.36
210	1.1	277.28
218	1.1	1213.66
219	1.1	1289.53
226	1.1	76.54

Case B.3. Least influential units are used

In this case the less influential units at bus #116, #210, #219 and #226 have K value 2.5 and two of the most influential units #110 and #198 have K values 0.5 and 2.5 respectively. The steady state voltage and reactive power injection at the generating units are shown in Table 24. Noticeably most of the reactive power is produced by the less influential units. As in this case it is not possible to rectify all the voltage violations by adjusting the less influential units. Hence some of the most influential units have also been called upon to correct the violations. Total reactive injection in this case is 20085.04 MVAr. Reactive power generated inside the VCA is 4871.95 MVAr.

Comparing the total VAr consumption in B.1, 2 and 3 it can again be observed that overall power consumption of the system is reduced as the generators close to the perturbed buses increase reactive power injection. In B.1, generators in VCA #16 supply 4974.69 MVAr to achieve overall consumption of 19971.47 MVAr, whereas in B.2, supply in the VCA is 4460.75 MVAr for a total consumption of 20191.96 MVAr. When a system is divided into a number of areas and using types of voltage control methods described here, it may be particularly helpful for system operator to utilize the above mentioned knowledge for reserve requirement planning.

2.3.5 Impact Analysis

Controllability

The type of voltage control scheme dictates the way reactive resources can be controlled and to the extent they can be controlled. In case A.2 all of three most influential units are used first to correct the low voltages at the load buses. But as these generators reached their maximum reference voltage level, it was necessary to call upon the other less influential units for control. In case B.2, direct reactive set points were sent and these three units turned out to be sufficient to provide the VAr needed for the situation. Comparing the examples A.2 and B.2, in both of the cases most influential units are used to control the voltage, but clearly the later is advantageous because the reactive power to be produced by the units were predefined by the control. When controlling by the reference voltage, no control action can be taken on a generator once their voltage reaches maximum limit, but when units are controlled by direct VAr adjustment, the reactive output level of the generator is precisely known and it is the responsibility of the local primary control to produce it in whichever way is convenient. Hence there is certain amount of advantage in terms of control that can be gained from such a scheme. Also this gives the operator flexibility to use the resources which he thinks best from reliability or economic point of view.

The conventional way of allocating the reactive power to a unit is through OPF. But it is necessarily a manual control. In real-time the voltage incident may occur in dynamic range i.e. within a few seconds. The discussed methods of secondary voltage controls are automatic and can perform in real-time like automatic generation control (AGC). So the operator has some time to react and move the point of operation in safe zone.

Performance

It is evident from all the examples above that the more the number of controlling units in a VCA is used to control a voltage event the lower is the total consumption of reactive power and loss. In case B.1 all 8 generators have been used at once and the total reactive injection is 19971.47 MVAr. In B.2 and B.3, generators are used according to the sensitivity and the total reactive power injections are 20191.96 MVAr and 20085.04 MVAr respectively. In A.1, A.2 and A.3, all the eight units have been used. In A.3, practically all the units except two have reached the maximum voltage level. Naturally A.3 results in least system VAr consumption amongst those three cases. Hence involving more generators inside a VCA reduces the overall reactive injection because when generators close to the perturbed buses are able to supply the necessary reactive power, the need for transporting reactive power into the area is minimized and absorption and transmission loss is decreased.

While comparing the control performances of the methods described in this paper it should be mentioned that scheme 2, i.e. voltage control with direct VAr adjustment is better in terms of control, since reactive generation of each controlling unit is precisely known and hence total power consumption and VAr reserve can managed with relative ease. However, such control, being based on OPF, will behave conservatively and try to keep voltage levels close to lower limits. Scheme 1 i.e. generator voltage adjustment, on the other hand, may be more likely to maintain a better voltage profile by pushing the voltage at controlling units at higher value.

Economic consideration

The secondary voltage control methods discussed earlier are particularly suitable for creating competitive markets for VAr. For control scheme 1 a voltage control market can be formed where suppliers would bid reactive capacity and will be paid according to uniform clearing price calculated by OPF. The real time control of units will, however, be in voltage. Necessary measure has to be taken to operate the units within market awarded reactive limits. Similar VAr market can be formed for control scheme 2 as well.

While considering competitive markets for voltage control it is to be kept in mind that unlike frequency, voltage behavior of a network is locally influenced. Naturally, some of the generators may be absolutely necessary for voltage support due to their locational advantage. For example in almost all the cases described here, generator #110 has to be used to rectify all the bus voltages. In cases A.2 and A.3 it is necessary to involve both types of generators in control. In real market such units would be aware of their advantage and given the profit seeking nature of market participants, may try to influence the clearing price. If that be the case, market power may be unavoidable. One way to avoid that situation may be to split the market. Some amount of service can be made mandatory and the ISO can go into long term bilateral contracts with the generators and then create a short term market for the balance quantity.

It is also to be noted that the availability of the resources would not only be affected by its location in the network, but also by the market that it participates in. If a market fosters competition and involves more generators to procure the goal, it is better for the performance and thus minimizes congestion and loss. Importance has to be given on the performance considerations, not only the cost and a tradeoff have to be made to maintain a balance between to two.

2.3.6 Remarks

A comparative study of area voltage control schemes is presented in this section. Control of voltage is possible by adjusting the reactive power injection at the generators. Compared to controlling the voltage reference of a unit, this scheme provides the operator with better controllability over the reactive resources while being equally effective in reducing the congestion and loss. A competitive VAr market seems feasible in this control framework.

To achieve a better performance in terms of voltage profile, the market should make sure that sufficient amount of service is procured. For that purpose it may be necessary to involve more number of service providers. Consequently some resources may turn out to be crucial for control and stability of the system. In a spot market these resources may acquire market power.

2.4 Conclusions

In this work, it is demonstrated that the structure of ancillary service markets affect system performance. Those ancillary services that provide control, like the regulation market to control frequency and the VAr market to control voltage, are particularly important to design properly so that the desired control performance is obtained at the best price. This means that the structure of the ancillary markets should be such that those generators that can contribute more towards better control should be encouraged by the proper incentives. In the case of the regulation market this usually means the recognition that generating units with faster response (ramp) rates are more important to load balancing and frequency control. In the case of VAr markets, the speed of response is not as important as the location of the units and their VAr production capacities, i.e. voltage control is more sensitive to the electrical proximity of the VAr sources.

A simple experiment is chosen to show that the regulation market has a direct effect on the control performance of the system. Three different market structures were chosen to demonstrate the varying control performance on a reduced WECC model: the first is similar to what is used by the California ISO today but the other two were chosen somewhat arbitrarily to provide more incentives for generators with better response (ramp) rates. In the second structure, a second bid market for 5-mintue capacities is developed in addition to the existing 10-minute capacity market. The 5-minute market can be used for better control than the 10-min market and at the same time these faster generators can be rewarded with higher prices. In the third structure, separate markets for fast and slow units based on ramp rates are formed.

A comparative study of two different area voltage control schemes is presented to demonstrate feasibility of voltage control by adjusting the reactive power injection from the generators. A competitive VAr market seems feasible in either of these control frameworks. To achieve better performance in terms of the voltage profile, the market has to procure sufficient amount of reactive power reserve. A market for VArs for that purpose will provide the option to choose amongst resources. Unlike frequency control which is controlled very close to 60Hz, voltages are controlled within a band so that the robustness of the voltage profile maintained determines the VAr resources utilized. However, it is shown that just as in the regulation market certain generators provide better voltage control because of their location and VAr capacities and either scheme used in this paper will provide market incentives to the more effective generators.

This work shows that ancillary markets should be structured to reward those properties of the generator that better helps the ancillary service. It should however be made very clear that it may not always be possible to create such a market and there has to be enough generators in the market with similar capabilities to generate competition. For example, if there are only one or two generators with fast ramp rates in a balancing area of largely slow thermal units, these fast units will have too much market power in a spot market that incentivizes ramp rates. Similarly, if there are not enough generators near a load center to control the voltage, the few nearby generators will exercise too much market power to develop a viable VAr market.

Part 3. Power System Electricity Market Agent Model

3.1 Introduction

Active customer participation in electricity markets is expected to improve market performance and to improve profit for suppliers and lower expenditures for customers. In this project, the electricity market is modeled using three agents: the supplier, the customer and the market. The objective is to conclude on the possible improvements to the electricity markets if active customer participation was allowed.

The first part of our work consisted of an extensive research on the electricity markets to understand the need for customer participation. Thanks to this background knowledge, the design choices for our model were made. The main difficulty of the implementation of our model was to create an efficient learning algorithm for our agents and to program the market's mechanisms correctly to map the agents' interactions. Once the program code was done, data are gathered to create our agents' bid history. Another problem that we encountered was the small amount of accurate data for the load and the market prices we had access to. Therefore, most of the data used for the simulations was generated while trying to remain as close as possible to real data for more accurate and realistic simulation results.

Simulations were run to study the behavior of the agents responding to different market settings. Our results can provide insight to the policy makers as to what laws are needed for the market to allow customer participation. Indeed, the need of restrictive laws for the suppliers to protect the customers and the sanity of the market has been emphasized.

Our results are also interesting to the industry, as the electricity markets are being currently restructured; suppliers and customers need to learn how they can bid efficiently in the market. Our simulations showed that the suppliers and customers should learn as much as possible about the market environment and the bid history to maximize their profit and lower their expenditures, respectively. Customer participation is also important from an environmental point of view, as customers more aware of the market's mechanisms help improve the overall system efficiency and energy conservation. Since they are trying to minimize their expenditures, our simulations showed that they would lower their energy consumption to their exact needs.

3.2 Research Method

3.2.1 Intelligent Agents

Agents are able to view as perceiving its environment through sensors and acting upon that environment through effectors. By definition, software agents are programs which must measure up to several marks to be agents. Intelligent agents are software agents that exhibit some form of artificial intelligence that helps the user and will perform repetitive computer-related tasks. Intelligence implies the system has the ability to adapt and learn. In some literature, intelligent agents are also called autonomous agents. An autonomous agent is a system that it act independently and will learn and adapt to effect what it senses in the future.

The elements to compose an intelligent agent are the agent program and the architecture. The agent program is a function that implements the agent mapping from percepts to actions. The program chosen can accept and be run by some sort of computing device. The computing device is the architecture. The basic components for distinguishing different intelligent agents are environments, percepts, actions, and goals. Table 25 shows the PAGE (percepts, actions, goals, environments) description of the intelligent agent in our design system. In our system, the agent is based on the idea of goal-based agents which means the agent needs to find a way to achieve the goal. This kind of agent appears less efficient but is more flexible.

Table 25: Agent Types and PAGE descriptions

Agent Type	Percepts	Actions	Goals	Environment
Power System Market agent	Energy demands, supplier price and quantities	Determine market clearing price and quantity. Report the results to supplier and customer agents	All demand is met	Accessible, Deterministic, Episodic, and Dynamic, discrete

Properties of environments:

<u>Accessible</u>: The agent needs to maintain internal state to keep track of the world. There is interaction between suppliers, market agents; customers and market agents.

<u>Deterministic</u>: The next state of the environment is completely determined by the current state and the actions selected by the agents.

<u>Episodic</u>: The agent's experience is divided into "episodes" and each episode consists of the agent perceiving and then acting. The agent does not need to think ahead.

<u>Static</u>: The environment can change while an agent is deliberating, then the environment is considered to be dynamic for the agent. Otherwise, it is static.

<u>Discrete</u>: There are limited number of distinct, clearly defined percepts and actions that make the environment discrete. In our power market, a simple uniform price auction is assumed to determine market clearing price and quantity from the overlap of the curves for both suppliers and customers.

3.2.2 Electricity Market Agents

In our model, three classes are created to map the different agents involved in the simulation: Customer, Supplier and Market.

The main function of the program takes care of organizing the simulation, according to the following sequence:

- it reads the input files giving all the necessary data (demand and prices for customers and offer and prices for suppliers)
- then it creates as many instances of the Customer and Supplier classes as needed for the simulation, according to data from the input file
- and it creates one market, where the agents will interact together
- once all the agents necessary for the simulation have been created, the market's closing can start. A loop iterates the calculation every hour (day or month depending on the time parameter the simulation wants to study):
    - the market asks for the bids and offers of all the agents for the current hour
    - it computes the data collected to find the price clearance
    - finally, it returns the price and bids to the customers and suppliers
- each agent will then learn from the results of the market's closing implementing our algorithm, and adjust its bids for the next closing.

The format of the input file is simply two matrices used to group all the data about the customers on the one hand, and about the suppliers on the other hand. Both matrices are described in more details in the following parts, along with each agent's description.

As the learning algorithm is implemented, the history of the agents (storing the past bids and offers) will be used instead of the input file. From the memory, the agent will generate its bids for each hour (the details of the agents' logic is explained in the learning part of the report).

3.2.2.1 The customer Agent

Each customer wants to buy a specific amount of energy to satisfy his needs. So, for each market closing hour, he will bid the amount of energy he wants and the price he is willing to pay for this energy. The needs of each customer can be decomposed into a necessary part and a supplementary part: the necessary part is the minimum amount of energy that the customer absolutely needs even if the price is very high and the supplementary part groups all extra needs that the customer is willing to buy if the price is lower.

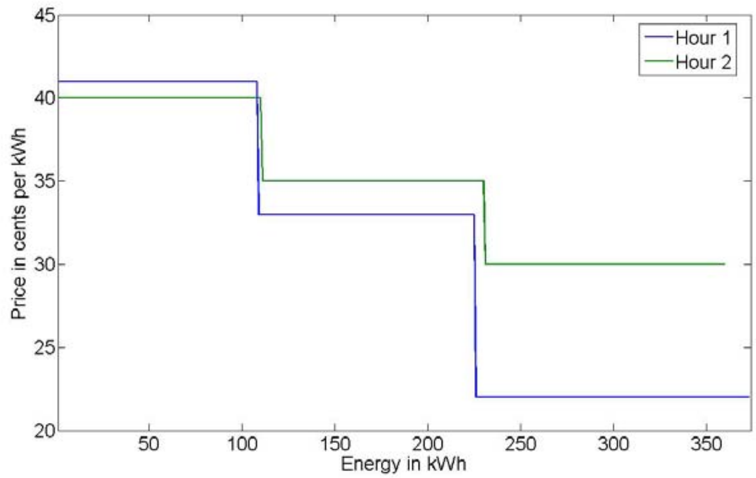


Figure 33: Model of Customer Demand Curve

Therefore, for each hour, the demand curve of the customer will be modeled as a downward-sloping step curve as shown in Figure 33. For this example, in the first hour, the minimum amount of energy needed by the customer is 108 kWh. He is willing to pay a high price for that, up to 41 cents/kWh. Then, if the price is between 33 and 41, the customer wants to buy more energy: 117 kWh. In our simulation, the curves are built in a cumulative way, so the amount of energy desired for each price is given by the length of the corresponding step.

At the beginning of the simulation, the demand and price bids of all the customers can be given in an input file. This data is stored in a 4 dimensional matrix, whose indices are the following: (hour, value, quantity or price, customer number). The number of step for each curve will be limited to three every hour: a low bid, a mid-bid and a high bid are considered.

Then, the quantity and price bids of the first customer, for our example, are given by:

```
CustDemandCurves(:,:,MW,1)=[  148 117 108 ;
                              130 120 110];
CustDemandCurves(:,:,Prc,1)=[ 22 33 41 ;
                        30 35 40];
```

The rows correspond to the different hours, and the columns to the different bids.

The customer agents' bids are calculated knowing the structure and organization of the market. The knowledge of the agents will grow with each market's closing: each agent stores in its database its past bids and how successful they were. This knowledge is used to predict the next bids, using the learning algorithm detailed in the following part.

As the learning algorithm is implemented, the memory attribute, storing the bid history, will be used instead of the input file. From the memory file, the agent will generate its bids for each hour. After each hourly market closes, the information about the quantity and price obtained is given back to the customers. Then, implementing the learning algorithm, they will adjust their bids to get the best deals possible. Their objective is to get the maximum amount of energy for the minimum price.

However, each agent knows only the results of its bids. In theory, the market cannot give more information about the other agents' bids, to prevent manipulation of the market and its prices. But in reality, each customer has a general idea of the competitive market's participants. Our simulation will study how the knowledge of the other customers' bids can help a customer improve its profit.

The data of each customer (attributes) and their range of actions (member functions) are summarized in the following class schema.

Customer Attributes:

- demand
- price
- intelligence level
- bidHistory
- name

Member functions:

- Customer()
- display()
- getDemand()
- getPrice()
- getIntelligence()
- getBidHistory()
- getName()
- sorter(customerAgents, order_flag)
- update(price, quantity)

The demand and price attributes of this class are matrices to store the demand and price of the current hour of the day. The intelligence level sets how much data the customer has access to, from the total memory of the market. The bidHistory is the private memory of the customer storing all its past bids and how successful they were.

The constructor of the class takes two matrices for parameters to initialize the demand and price attributes of the instance.

Then, getDemand(), getPrice(), getIntelligence(), getBidHistory() and getName() are simple functions to access the private attributes of the class. display() is used to show these attributes. sorter() can sort an array of customer according to their price, in decreasing order (more details about this function will be given with the market class' description, as it is used by this instance to build the supply and demand curves). This function will be used by the market to build the demand curve.

Finally, update(price, quantity) gathers the price and quantity given back after the market's closing to update the customer and implement the learning algorithm.

3.2.2.2 The supplier Agent

The supplier agent is built on the same framework as the customer agent. Even though they do not have the same objectives, they have similar characteristics and range of actions.

Each supplier wants to sell a specific amount of energy. So, for each market closing hour, he will bid the amount of energy he is offering and the price for this energy. As it has been explained in the first part of the report, the suppliers have:

- fixed costs, related to the activation of their generators or power plants
- and variable costs, which change in proportion to the amount of energy produced.

That is why, the supply curve indicating the price in cents per unit of energy can be modeled as an upward-sloping step curve.

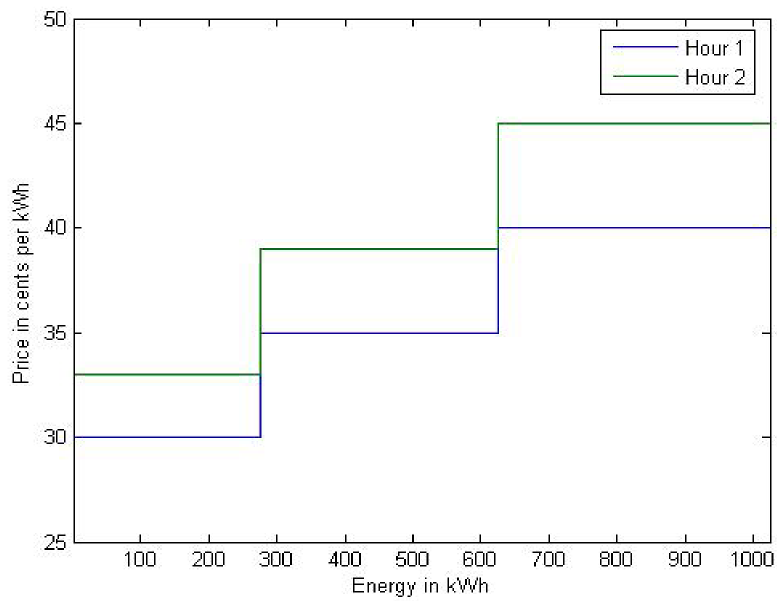


Figure 34: Model of Supply Curve

As shown in the example of figure 34, up to 275 kWh, the price is 30 cents per kWh for the first hour. If a higher demand has to be supplied, the supplier can respond in two ways:

- If the generators that are currently running are not at their maximum output, the supplier could increase the output from one of those generators.
- Otherwise, if all of his generators are already at their maximum, he has to turn on an additional one.

In order to determine their offers, the suppliers do not consider the fixed costs: they are assumed to be sunk costs, since the fixed costs cannot be changed whether or not a generator is on. Therefore only the incremental costs are taken into account to determine the price. The two previous possible responses of suppliers will affect the price:

- to increase the output of a generator, the supplier may need to run it at an output level with a lower efficiency than the previous output level, thus causing the operating costs to increase
- the suppliers turn on their generators in increasing order of costs. Therefore, if a new unit is required to be turned on, it will necessarily be a more expensive unit than those already running.

In our example, the price increases to 35 cents per kWh.

At the beginning of the simulation, the offers of all the suppliers can be given using the same format as the customers' bids in the input file. As a reminder, this data is stored in a 4 dimensional matrix, whose indices are the following: (hour, value, quantity or price, customer number). The number of step for each curve will be limited to three every hour: a low offer, a mid-offer and a high offer are considered.

Then, the offer and price bids of the last example are given by:

```
SupplyCurves(:,:,MW,1)=[ 275 350 400 ;
                         275 350 400];
SupplyCurves(:,:,Prc,1)=[ 30 35 40 ;
                          33 39 45];
```

After each market's closing, the information about the quantity and price obtained is given back to the suppliers. They will then adjust the first bids given as inputs of the simulation. Their objective is to maximize their profit, that is getting the highest price per unit of energy possible. Therefore, as the learning algorithm is implemented the memory attribute will be used instead of the input file.

Similarly as the customer agents, the supplier agents know about their bids and profit for past market closings. They use this database to adjust their bids, thanks to the learning algorithm. Market manipulation is prevented by disclosing to each supplier only the results of its bids.

Supplier Attributes:

- supply
- price
- intelligence level
- bidHistory
- name

Member functions:

- Supplier()
- display()
- getSupply()
- getPrice()
- getIntelligence()
- getBidHistory()
- getName()
- sorter(supplierAgents, order_flag)
- update(price, quantity)

The Supplier class is built on the same schema as the Customer class, but its attributes are the supply offers and the price asked for the energy.

3.2.2.3 The Market

The market's role is to gather the bids of all the agents and compute the clearing price for each hour (day or month depending on the time parameter the simulation wants to study). It will then give back the information about the final market price and the different quantities purchased or sold by the agents. In order to remain as fair as possible, the market only communicates to each agent the results of its own bids.

As explained in the previous part (cf. paragraph I 3 c.), different types of auction mechanisms can be used to determine the clearing price. To start our simulation, a uniform price auction was first considered. In the following will be explained the implementation structure of the Market class and the different algorithms used to calculate the price and report the information to the agents.

- Implementation structure

The market class has two attributes that are two arrays to store the customer and supplier agents currently involved in the market.

Then, the demand and supply step curves of the agents will be divided into blocks: each block represents the amount of energy asked for a price. Two additional arrays are used to store these blocks.

The constructor of this class takes four matrices for parameters to initialize the attributes of the instance initializes.

Market Attributes:

- customerAgents
- supplierAgents
- SortedCblocks
- SortedSblocks

Member functions:

- Market(allCustomers, allSuppliers)
- ask4bids(hour, allCustomers, allSuppliers)
- priceClearance(resultFile, hour, nbOfHour)
- report(hour, LMP, MktQ, allCustomers,
  allSuppliers, resultFile)

ask4bids(hour, allCustomers, allSuppliers) gets the demands and offers from the customers and suppliers for the current hour. The demand and supply curves of all the agents are divided into blocks. Then, the member function sorter() of the Customer and Supplier classes are called to sort the blocks respectively in decreasing and increasing order of price. The sorted blocks of all the agents are finally stored in the SortedCblocks and SortedSblocks attributes of the market.

The priceClearance(resultFile, hour, nbOfHour) function builds the supply and demand curves in a cumulative way (i.e. the amount of energy of all the blocks are added as the curves are built) from the two lists of sorted blocks. The function then calculates the price depending on where the curves intersect following the algorithm detailed in the following pseudo-code:

```
IF maximum price offer of the suppliers < minimum price bid of the
customers
      amount of energy supplied = sum of the maximum amounts of energy
demanded by the costumers
      clearing price = maximum price offered by the suppliers
      ELSE IF minimum price offer of the suppliers > maximum price bid of
the customers
      amount of energy supplied = 0
      clearing price = 0
      ELSE
            DETERMINE intersection of the curves
      amount of energy supplied = abscissa of the curve intersection
```

```
      IF both curves are at a step change
            clearing price = higher price of the two curves
      ELSEIF only the price of the supply curve is constant
            clearing price = price of the supply curve
      ELSE
            clearing price = price of the demand curve
      ENDIF
      ENDIF
```

The output of this function is the clearing price and the total amount of energy supplied for this hour.

Since a uniform price auction is considered, all agents in the market will get the same price. The report(hour, LMP, MktQ, allCustomers, allSuppliers, resultFile) function transmits the clearing price to the customer and supplier agents currently involved in the auction and how much energy each agent is getting depending respectively on their initial bids and offers. The algorithm used is detailed in the following pseudo-code:

```
      // Give the results back to the customers
      SET customer count to the block of the demand curve which closest to
the clearing price
      REPEAT
            IF the current customer is in the list of customers who
already received energy
                  DECREMENT customer count
            ELSE
                  amount of energy supplied to customer = demand of this
block
                  ADD customer to the list of customers who received
energy
                  ADD amount of energy supplied to the total amount of
energy
                  CALL update function of this customer with clearing
price and
                        energy amount parameters
            DECREMENT customer count
      ENDIF
      UNTIL customer count = 1
      FOR all the customers not in the list of customers who received
energy
            amount of energy supplied to customer = 0
            CALL update function of this customer with clearing price and
            energy amount parameters
      ENDFOR

      // Give the results back to the suppliers
      STORE all the supplier blocks whose offer is lower than the clearing
price in the list of possible winning suppliers in decreasing order of
price (keep only the closest block to the clearing price for each
supplier)
      STORE the rest of suppliers (who offered a higher price than the
clearing price) in the list of “losing” suppliers
      FOR all the supplier blocks of the winning list
```

```
            STORE the suppliers with the same price offers on the same row
in a 2-dimensional matrix
      ENDFOR
      SET number of suppliers paid to 0
      FOR each row of the matrix
            IF total amount of energy = 0
                  BREAK the for loop
            ENDIF
            FOR each column of this row
                  SUM the offers of the suppliers
            ENDFOR
            IF total amount of energy > sum of suppliers' offers
                  FOR each column of this row
                        amount of energy = offer of this block
                        DECREMENT the total amount of energy from the
offer of this block
                        INCREMENT number of suppliers paid
                        CALL update function of this supplier with
clearing price and energy amount parameters
                  ENDFOR
            ELSE
                  COMPUTE ratio = total amount of energy / sum of
suppliers' offers
                  FOR each column of this row
                        amount of energy = offer of this block * ratio
                        DECREMENT the total amount of energy from the
offer of this                       block
                        INCREMENT number of suppliers paid
                        CALL update function of this supplier with
clearing price and energy amount parameters
                  ENDFOR
            ENDIF
      SET supplier count in the winning list to number of suppliers paid +
1
      REPEAT
            amount of energy = 0
            CALL update function of this supplier with clearing price and
energy amount parameters
            INCREMENT supplier count
      UNTIL supplier count = size of winning list

      FOR each supplier of the "losing list"
            amount of energy = 0
            CALL update function of this supplier with clearing price and
energy amount parameters
      ENDFOR
```

A pro-rating solution has been implemented to break the tie between suppliers offering the same price. For example, if the total amount of energy demanded by the customer is 100 kWh. And there is two suppliers offering the same price for respectively 80 kWh and 70 kWh. The total amount of energy offered by the suppliers is higher than the 100 kWh demanded. Then, to choose how much energy each supplier should be awarded a pro-rating solution has been implemented. The first supplier will get (100/150) * 80 = 53 kWh and the second one will be awarded (100/150) * 70 = 47 kWh. Therefore the demand is distributed between the suppliers. It can be noted that the supplier who offered more energy for the same price will be favored by this method.

- Example of market clearance

Let's consider a simple example of market clearance. This auction will only run for two hours. There is two customer and two suppliers. The input data is the following:

```
CustDemandCurves(:,:,MW,1)=[148 117 108 ; 130 120 110];
CustDemandCurves(:,:,Prc,1)=[22 33 41 ; 30 35 40];

CustDemandCurves(:,:,MW,2)=[230 218 208 ; 200 180 170];
CustDemandCurves(:,:,Prc,2)=[25 28 32 ; 30 38 40];

SupplyCurves(:,:,MW,1)=[275 350 400 ; 275 350 400];
SupplyCurves(:,:,Prc,1)=[30 35 40 ; 35 40 45];

SupplyCurves(:,:,MW,2)=[65 125 185 ; 65 125 185];
SupplyCurves(:,:,Prc,2)=[25 26 28 ; 28 29 31];

SupplyCurves(:,:,MW,3)=[200 250 300 ; 200 250 300];
SupplyCurves(:,:,Prc,3)=[27 32 35 ; 29 35 39];
```

The market computes the supply and demand curves to calculate the clearing price. The figures 35 and 36 show the supply and demand curves for both hours, as well as the clearing price and quantity:

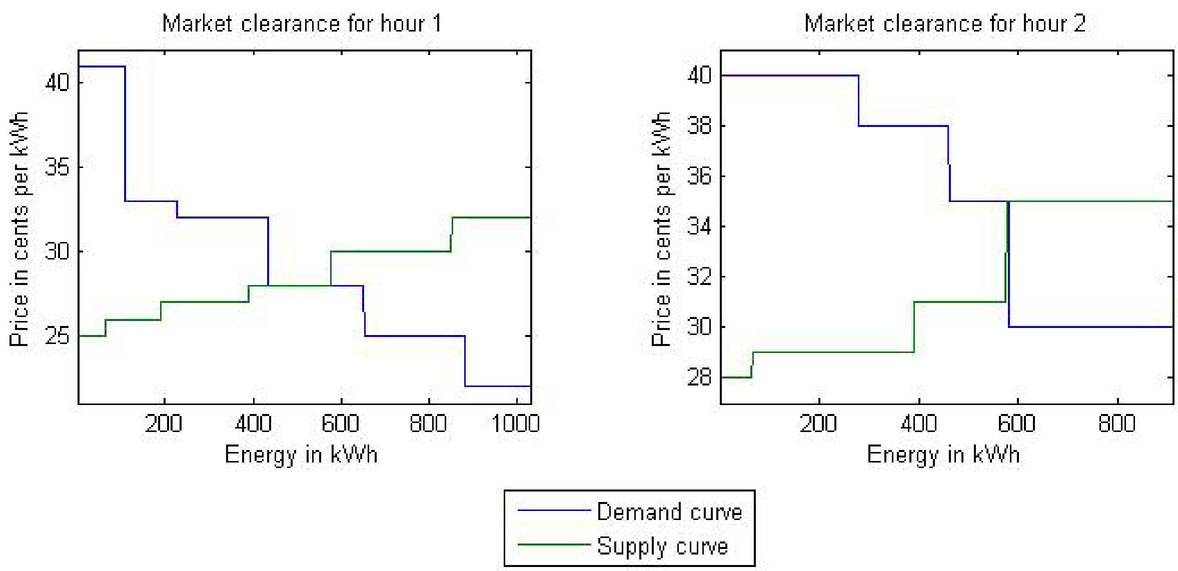


Figure 35: Cumulative supply and demand curves

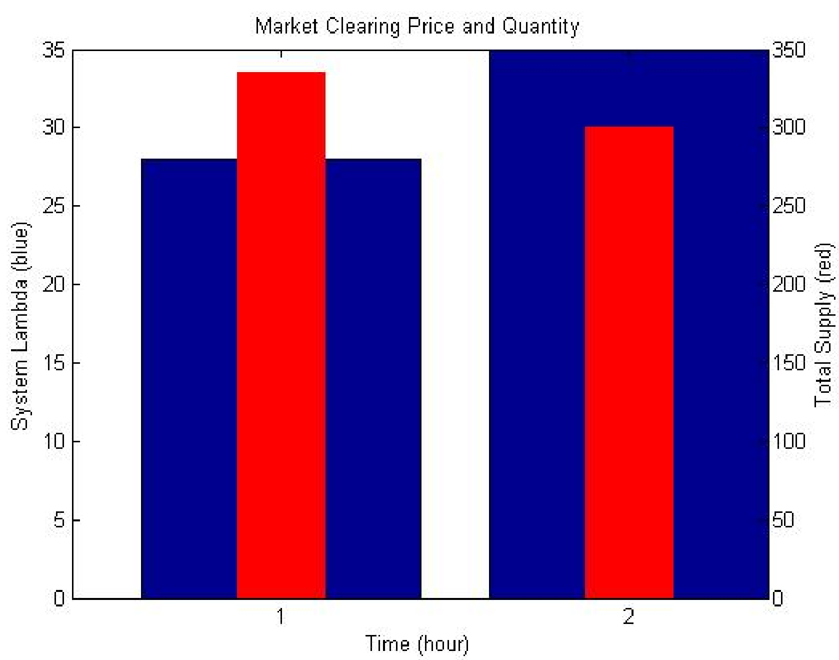


Figure 36: Market clearing price and quantity

The results given to the agents are:

```
Market clearance for hour 1
Price cleared: 28
Total energy supplied: 335

Report results to each customer
update customer 2 with price 28 and quantity 218
update customer 1 with price 28 and quantity 117

Report results to each supplier
update supplier 2 with price 28 and quantity 185
update supplier 3 with price 28 and quantity 150
update supplier 1 with price 28 and quantity 0


Market clearance for hour 2
Price cleared: 35
Total energy supplied: 300

Report results to each customer
update customer 1 with price 35 and quantity 120
update customer 2 with price 35 and quantity 180

Report results to each supplier
update supplier 3 with price 35 and quantity 143
update supplier 1 with price 35 and quantity 157
update supplier 2 with price 35 and quantity 0
```

3.2.3 Learning Algorithm

3.2.3.1 Algorithm Overview

- Customer agent

The customer agent learns based on two memories. One type of memory is the general memory in which the accumulated bids for each hour are added and one is the customer's private memory.

The general idea is to use the previous data to make new estimates. The notion of external factors is also included in the agents learning through the previous data. The way an agent analyzes previous data to find new estimates is what makes the agents thinking viable. It looks at the previous 2 months data and the previous 2 years data for the same month. This makes the estimates very relevant to how a human agent would think.

The following provides a walkthrough for the learning algorithm:

1. Customer agent looks at previous data to make the estimate for the customer curve.
    a. The previous data comes from a pool of data. This pool of data lists time, demand and price of a transaction.
    b. Previous data also comes from a history of the data of the current customer.
2. Customer makes an estimate of the price.
    a. The price is estimated by looking at the customer's market clearing price of the MWh for the past 3 months. Monte Carlo simulation is used to find the price range.
    b. The price is also estimated by looking at the price of the MWh for the next month for the past 3 years. We find the price interval using Monte Carlo simulation.
    c. Now two ranges of values are possible. The lower of the two values could be found and used for the prices.
3. Customer posts the price.
    a. The customer agent makes a quick check before posting the price to the market. The price for the previous bid (for the current customer) is checked. If the customer notes that the previous bid failed then there is a good chance the current bid will also fail. So, the customer increases its estimated bid by some dollar amount.
4. Customer waits for the market to close.
    a. The customer now adds this result from the market to its local memory.
    b. The shared memory pool of data is also updated by the market.

The customer agent also has an intelligence level. This level just tells the agent how many past bids it remembers, e.g. a customer with an intelligence level of 5 will have access to 50% of its historical data. Using less data will make the customer make estimates that are not close to what the simulations result in.

- Supplier agent

The supplier agent has a similar learning algorithm as the customer's agent except that the supplier tries for the maximum price in the range. Because the scope of the project is focusing on the customer side, a simpler agent model is used for the suppliers, in particular they do not have a private memory. They work on the global shared memory to make the estimates.

3.2.3.2 Agent Learning Details

A quick overview of the learning algorithm is given in the previous two sections. In this section, the details of the learning algorithm are studied. The following is the generic pseudo code for the different parts of an agent's learning.

- Finding the price

Getting the estimates using the past 'x' days

To find a price range using the past few days' data, the following procedure is carried out:

a. SET startDate equal to current date minus 'x' number of days.
b. SET endDate equal to current date
c. Gather the data that lies within startDate and endDate
d. Run Monte Carlo simulation using a confidence interval between 70-80%. This confidence interval percentage is a uniform distribution between 70 and 80.
e. Store the interval found in step 4, into a data buffer.

To find a price range using the past days' from last 'y' years

1. WHILE y >= 0
2. SET yearNumber equal to current year minus 'y'
3. SET startDate equal to current date minus 'x' number of days using yearNumber as the year.
4. SET endDate equal to current date using yearNumber as the year
5. Gather the data that lies within startDate and endDate. Store this data in a buffer.
6. SET y = y - 1
7. END WHILE
8. Run Monte Carlo simulation on the collected data using a confidence interval between 70-80%. This confidence interval percentage is a uniform distribution between 70 and 80.
9. Store the interval found in step 4, into a data buffer.

- Agents Intelligence Level

The intelligence level of each agent ranges from 1-10. 1 meaning 10% of the data and 10 means 100% of the data. This means that if the agent has an intelligence level of 1 then the agent will only view 10% of the data available for the time period. After this data acquisition the learning logic will find the price ranges based on the algorithm explained previously.

To get a normalized view of the data, we skip the data with equal interval. This means if an agent has access to 50% data then 5 data elements will be skipped within each block of 10 data elements. The following example shows how an intelligence level of 5 is executed:

1. index = 0
2. WHILE startDate <= endDate
    i. IF (index MODULUS 5 == 0)
        1. SKIP data element
    ii. ELSE
        1. STORE data element

iii. END IF

3. index = index + 1

4. END WHILE

- Finding the MWH per customer or per supplier

The agents find this range using the previous MWH (demand/supply) and adding a uniform random variable in ± x percentage of the previous MWH.

- Minimum price in Customer Agents

After calculating the ranges using the previous data the customer agents strive to pay the minimum price. This is done using the idea of reducing the calculated price by some very small percentage. This will not have a huge impact on the market in the short term. But on a longer timescale this brings the competition in the market. The price reduction be seen in the following pseudo-code:

1. Find estimates based on the history
2. Reduce the estimated price by some tiny percentage

The customer agents also have the logic that checks if the customer agent is losing bids. If the customer is losing the bid then the customer increases the price he is offering immediately. This makes sure that the customer is not always losing. After a few time periods of using this price increment the customer returns to his normal estimates and uses them. This is explained in the following pseudo-code:

a. IF one of the last 3 last bids lost
   i. Increase the price offerings
b. END IF

- Maximizing price in Supplier Agents

Similar to the customer agents the supplier agents get estimated price. After getting the estimated range the supplier agents add a small price percentage to the price to try and increase the price. Before giving the price range to the market the supplier agent does the following:

1. Find estimates based on the history
2. Increase the estimated price by some tiny percentage

The supplier agents will be wary of the fact that if the price is increased too much then they will end up losing the bid. So the supplier agents keep the track of the market and see if the suppliers are selling most of the offers they put into the market. If the supplier sees that he is not selling more than 80% of their offer in the market, they reduce the price. This can be seen in the following pseudo-code:

1. IF supplier agent sold less than 80% of the supplies in the last market closing
    i. decrease price than the estimated
2. END IF

The different simulations require us to change the code and the learning with tiny modifications.

3.2.4 Data Extraction

3.2.4.1 The Customer Agent

For our simulations, data needs to be collected in order to build the memory files of the customer agents. Our learning algorithm needs data about the successful bids of the past two years in order for each customer to make appropriate guess about the following bids. The demand data represent our approximation of the actual data from the California ISO. Unfortunately, the ISO does not disclose the price bids of its customers. Therefore, the prices were generated using a curve fit with other available data. We based our calculations for the price on real data to stay as close as possible to reality and thus obtain coherent and meaningful results from our simulations.

- Load data

The data contain the metered load for every hour of the year 2000 for different large customers from Southern California. To run our simulations, we chose four of these customers and extracted their data to build the load memory of our agents. Different sizes of customers were chosen in order to study how the variations in size can affect the agents' behavior during the simulation. The customer set chosen is detailed in Table 26.

Table 26: Customer set for simulations

NAME	SC_ID	CNGS_ZONE	Mean load (MWh)
City of Anaheim	ANHM	SP15	30.7
PGAE & COTP	COTP	NP15	119.9
Southern California Edison	PXC1 / SCE	SP15	871.9
San Diego Gas & Electric	PXC1 / SDGE	SP15	182.2

To extract the desired data, a VBA (Visual Basic for Applications) macro was used. The code is detailed in the following:

```
      Sub Data()
      '
      ' Data Macro
      ' Keyboard Shortcut: Ctrl+w
      '
          'Activate the .xls file from which the data should be extracted
(original
          'data file with all the customers
          Windows("Load_data.xls").Activate

          'Set the names of the customer to be extracted
          Name1 = Range("C2").Value
          Name2 = Range("C30").Value

          Dim NbRows As Double
          NbRows = ActiveSheet.UsedRange.Rows.Count
          Dim Cpt As Double

          'Go through the column of customers' names
          For Cpt = 1 To NbRows Step 1
              Windows("Load_data.xls").Activate
              Cells(Cpt, 3).Select

              'If the name corresponds to the wanted customer, the data is
copied to the corresponding file
              Select Case ActiveCell.Value
                  Case Name1
                      ActiveCell.EntireRow.Select
                      Selection.Copy
                      Windows("LoadData_name1.xls").Activate
                      'Go to the last cell of the spreadsheet
      ActiveSheet.UsedRange.SpecialCells(xlCellTypeLastCell).Offset(1, -
20).Select
                      ActiveSheet.Paste
                  Case Name2
```

```
                        ActiveCell.EntireRow.Select
                        Selection.Copy
                        Windows("LoadData_name2.xls").Activate

ActiveSheet.UsedRange.SpecialCells(xlCellTypeLastCell).Offset(1, -
20).Select
                        ActiveSheet.Paste
                End Select
            Next Cpt
        End Sub
```

- Price data

The total hourly load and price of New England is made available by the ISO of this region. We gathered data for a few days equally distributed throughout the year 2006 and plotted the price as a function of the normalized load. As shown on figure 37, the curve fit function obtained is: $price = 109.63 \times normalized\_load - 50.366$.

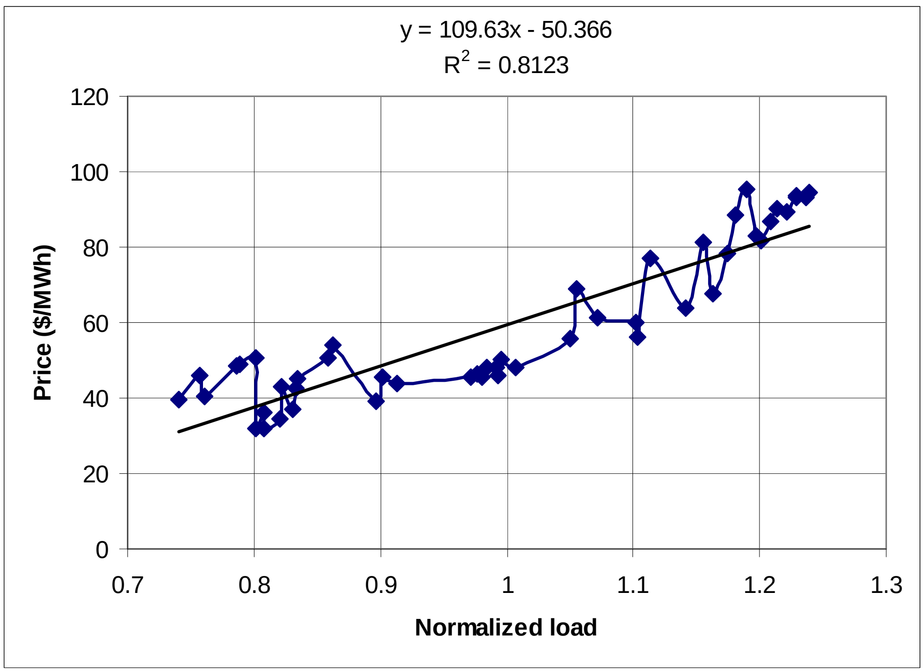


Figure 37: Price curve fitting for the customer agent

The load is normalized by the mean load of the data set so that the curve fit can be applied to different size of customers. If their load for one day is close to their mean load over the year, then the price will be about \$60/MWh. And the price will grow linearly if their load is below or above average.

From this partial data, the price history of our agents was then generated adding a random variation for every hour and a price inflation of 3% per year.

3.2.4.2 The Supplier Agent

Since our project is focusing on the influence of the customer participation on the market, simpler agents are used for the supplier side. Therefore, the history of the supplier agents was entirely generated. Even if the supply curves of the agents are not as realistic as possible, it is then easier to create the appropriate supplier agents for our simulations. Indeed, we want to study how the customer agents will react to different type of price evolution from the supplier side. More details about the types of simulations run is given in the next part.

Given the customer agents participating in the market, their total demand is summed up, to make sure that the suppliers will have enough energy to respond to their demand. Then, a weighed mean of the customers' price is used to calculate the global price of the suppliers.

This total amount of energy is then divided up between the suppliers participating in the simulation. We decided to create three suppliers, called simply SUP1, SUP2 and SUP3. As it was explained in the learning algorithm part, the private memory of the supplier agents is only used to store the bids of the current simulation. The agents base their bid calculations on the global memory of the market.

3.3 Simulations

3.3.1 Functioning of the Model

The model used to simulate the electricity market has been explained in extensive details in the Research Method's part. The functioning of the model is recapitulated using the flow chart shown on Figure 38.

Two types of input data are needed to run the simulation. The first is required to initiate the agents participating in the market. In order for them to implement the learning algorithm, they need enough data about their past bids, at least two years of hourly data is required. They are given as .csv files, stored in the "data" folder, each file name being the agent's name. Table 27 shows the history of one of the agent for one day, in order to highlight the format used for the data table.

Table 27: Sample data history of one agent

Date	Hour	Price ($/MWh)	Load (MWh)
1/1/2000	1	25.46	213.54
1/1/2000	2	20.85	200.34
1/1/2000	3	17.70	189.12
1/1/2000	4	13.01	179.64
1/1/2000	5	12.42	175.08
1/1/2000	6	13.71	176.88
1/1/2000	7	13.59	180.3
1/1/2000	8	13.55	178.86
1/1/2000	9	16.04	188.7
1/1/2000	10	21.67	201.06
1/1/2000	11	24.59	211.08
1/1/2000	12	26.12	213.54
1/1/2000	13	26.69	213.84
1/1/2000	14	24.19	211.08
1/1/2000	15	23.46	205.86
1/1/2000	16	21.48	203.7
1/1/2000	17	25.49	212.46
1/1/2000	18	38.35	248.94
1/1/2000	19	41.64	256.2
1/1/2000	20	40.59	252.72
1/1/2000	21	37.98	247.38
1/1/2000	22	35.13	238.08
1/1/2000	23	29.32	224.46
1/1/2000	24	24.58	207.66

The second type of input data is necessary to set the parameters of the simulation. Three files are stored in the "config" folder to set the values of these parameters. customer.csv and suppliers.csv set the intelligence level of the agents. And settings.csv can turn on and off the following options:

- controlVagueness: this configuration setting helps in running the simulation with data entered into the pool with some degree of vagueness. The vagueness is entered into the data to simulate the real world situation in which a supplier might not know the exact transactions the customers do. With this control variable turned on, the data entered in the common data pool is not exact.
- controlFallback: this control helps the customer react to losing bid. In this condition, if a customer loses a bid at a time unit then the customer agent will increase the price to much higher than the estimated for the next time unit. This copies the human reactive impulse into the software agent.
- constantSuppliers: this control variable helps us simulate the condition in which the suppliers do not react to the bid closing. In this simulation the suppliers put up a constant offer to the market no matter what. This variable helps us quickly start the simulation condition.
- linearPriceIncrease: the simulation in which the suppliers increase the price without regard to the market condition is linear price increase. We turn this simulation on using this control variable. So, if linearPriceIncrease is turned on, then the suppliers will increase the price with some constant factor after each time unit.

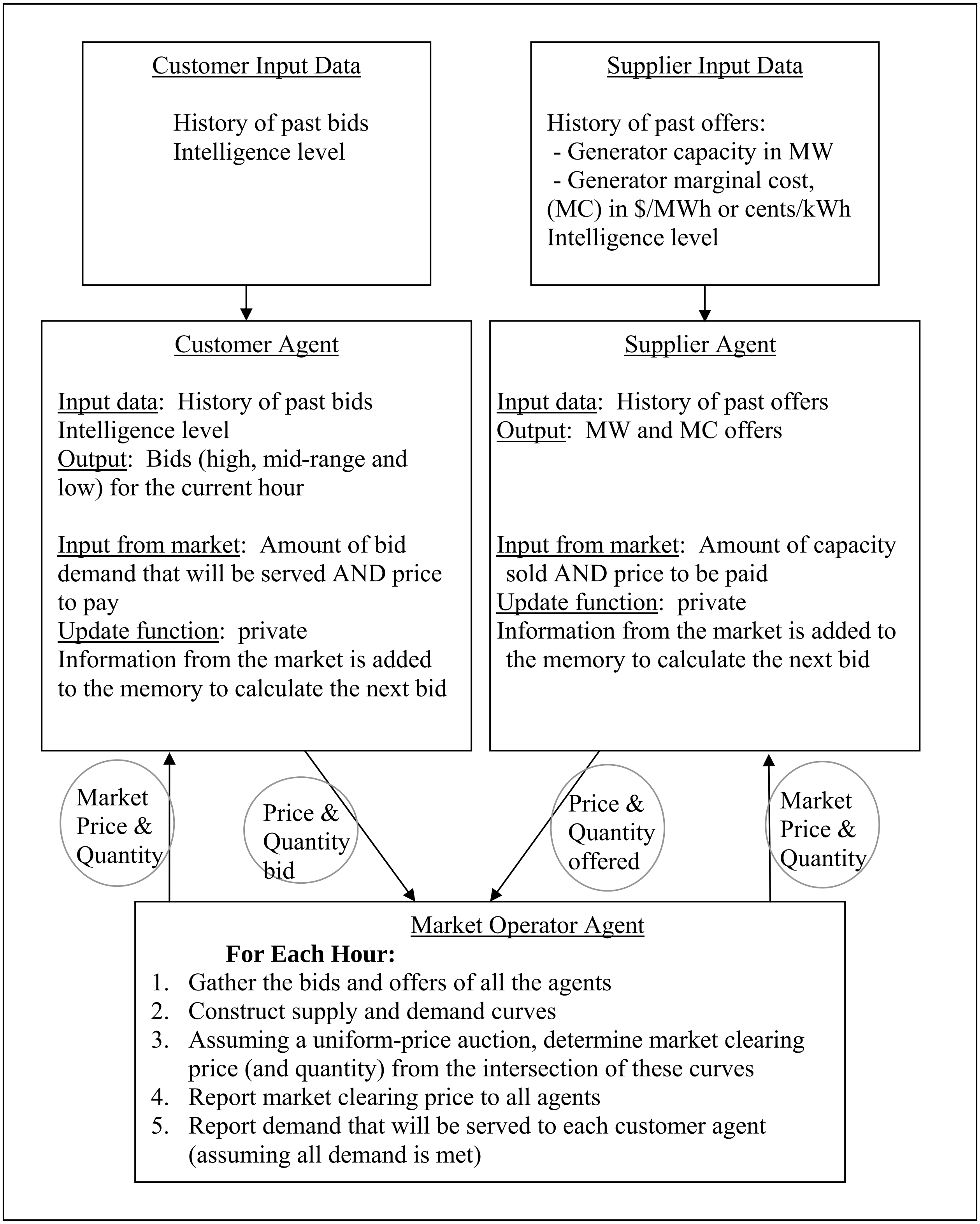


Figure 38: Flow chart of the model used in the simulations

After each market closing hour, the clearing price and how much energy the agents were able to buy or sell is calculated. The total amount of energy and the clearing price is stored in the global data file. The successful or unsuccessful bids are also stored in the individual memory of each customer. This output information can then be plotted to study the evolution of price depending on different parameters.

3.3.2 Simulation Descriptions

Thanks to the simulations, the customers' behavior in different market settings can be studied. Different parameters can be changed to modify the market settings: for example, the price evolution of the suppliers' bids, the intelligence level of the agents, etc. The different simulations run are described in the following. For each simulation, the four customers of the created set and the three suppliers are participating in the market for 3 months.

3.3.2.1 Base case: simulation of the current electricity markets

If there is no customer participation in the market, the suppliers only set the clearing price for energy. The passive customers simply state how much electricity they want to buy, at any price. It is then expected that, as the supplier agents are learning, the price should increase with time. In reality, if the price increases too much, the government will set limitations to the energy suppliers.

This base case is simulated by having the customer agents bid all their demand at a very high price showing willingness to buy everything at whatever the suppliers offer. The four customers of the set and the three suppliers are playing in this simulation running over 3 months.

3.3.2.2 Analysis of the customer agents' learning ability

In order to study only the customer agent's learning ability and conclude on the efficiency of the chosen learning algorithm, the suppliers' offers should be kept constant. Then the intelligence level of the customer agent can be studied to see how the knowledge of other customers' bids can help the agent maximize its profit.

3.3.2.3 Influence of the price evolution of suppliers

Thanks to their learning ability, the customer agents should be able to anticipate the offers of the suppliers to maximize their profit. We want to study how the customer agents react to changes in the price coming from suppliers. In this simulation, a linearly increasing price is modeled. This is controlled by setting the linearPriceIncrease option on. The supplier agents then calculate their offers using the learning algorithm, and then add an increasing value to the price.

The results from this simulation will then be compared to the previous simulation where the suppliers' offers were constant to see the differences in customers' behavior.

3.3.2.4 Vague data for suppliers

The intention of this simulation is to copy the real world scenario in which the suppliers don't know exactly what the customers are doing. But, the suppliers have an idea as to what the customers are paying and expecting. This notion is modeled into the simulations by adding vague data in to the data pool for the suppliers. So, this means that the market does not give out exact data to the suppliers and the suppliers have to make estimates using not so accurate data.

3.3.3 Results Analysis and Discussion

3.3.3.1 Base case: simulation of the current electricity markets

For this simulation, the demand of customers was kept constant and they had very high bids. As expected, with customers willing to buy energy at any price, only the suppliers control the evolution of the clearing price: as shown on figure 39, it increases continually with time. Starting from 53.76 $/MWh, it reaches 74.89417 $/MWh after three months.

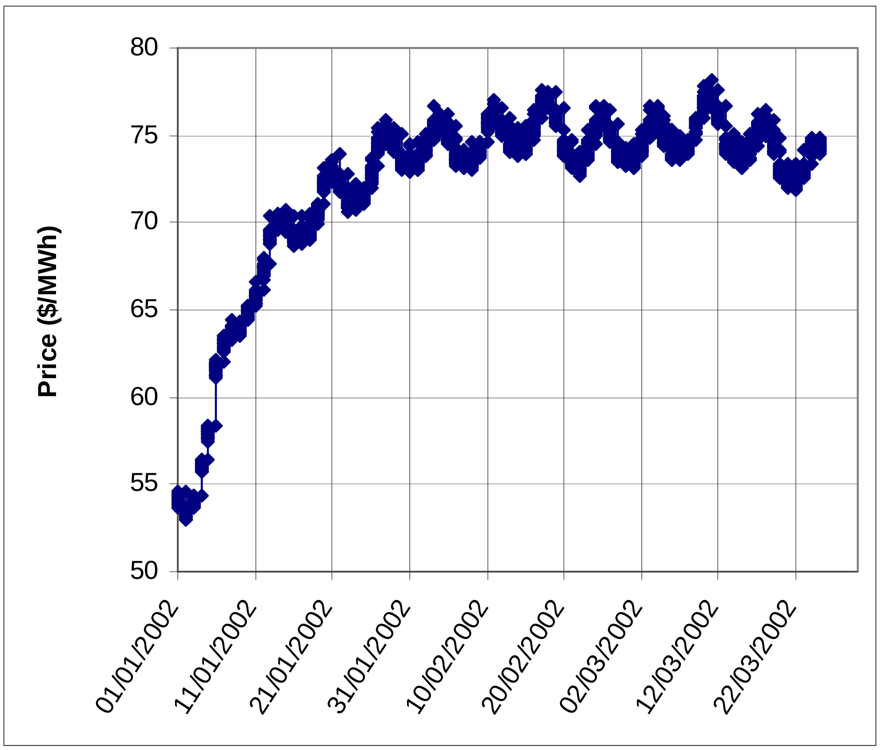


Figure 39: Price evolution of the base case simulation

However, it can be noticed that after 8 weeks, the price increases more slowly than at the beginning. This can be explained by the logics of our learning algorithm: to calculate their bids, the agents use the history of the past bids over at least two years and the data set that was used in the simulation does not show such an increase. Therefore, taking into account both the price evolution of the past years and of the more recent bids will make the supplier agents increase their price in a more reasonable way. If the simulation were to run over a longer period of time (one or two years), it is expected that the suppliers will then see the increasing trend more clearly and increase their price faster.

This simulation also shows that, in order to simulate the behavior of more aggressive agents, the learning algorithm can be modified to give more importance in the calculations to the recent bids than the history. Then if the price increases over the last market closings, the suppliers will keep increasing their price. In reality though, the suppliers are not allowed to increase their price indefinitely. The government will set limitations or require the suppliers to justify their prices.

3.3.3.2 Analysis of the customer agents' learning ability

In this simulation, we wanted to study how the intelligence level of the customer agent could affect his efficiency at making the right bids to maximize his profit. Two opposite cases were studied:

- in the first one, all the customers had the minimum level of intelligence, that is they do not have much access to the global memory of all the bids
- in the second one, all the customers had the maximum level of intelligence, which means they know everything about their environment. It is thus expected that the more intelligent agents will be more likely to win their bids.

The simulation results confirm these predictions. As shown in table 28, the percentage of successful bids is larger for the more intelligent agents. For example, with a higher intelligence level, ANHM improves its percentage of successful bids by 10 points: it reaches 94.6% with the maximum intelligence level.

Table 28: Percentage of successful bids for the customers with different intelligence level

NAME	SC_ID	Mean load (MWh)	Percentage of successful bids	
			Intelligence level: 1	Intelligence level: 10
City of Anaheim	ANHM	30.7	83.9%	94.6%
PGAE & COTP	COTP	119.9	95.8%	99.2%
Southern California Edison	PXC1 / SCE	871.9	89.0%	98.20%
San Diego Gas & Electric	PXC1 / SDGE	182.2	94.4%	99.10%

It is also interesting to analyze how the agents modified their bids in order to increase their probability of winning the bids. The results show that a higher intelligence level helps the agents avoid making unnecessarily high bids. As depicted on Figure 40, the agents with an intelligence level of 10 managed to always maintain the clearing price between 53 and 55 $/MWh, while still maximizing their percentage of successful bids. Whereas the less intelligent agents saw the clearing price increase up to 58 $/MWh.

Figure 41 shows that the bidding strategy of the two types of agents was different:

- the agents with an intelligence level of 1 tried to modify their demand as little as possible (the total demand remained around 900 MWh) and find the optimum price. This strategy leads to a higher clearing price: after 3 months, the average clearing price is 54.1 $/MWh.
- whereas the agents with an intelligence level of 10 reduced their total demand to around 750 MWh, which helped them reach a lower clearing price of 53 $/MWh.

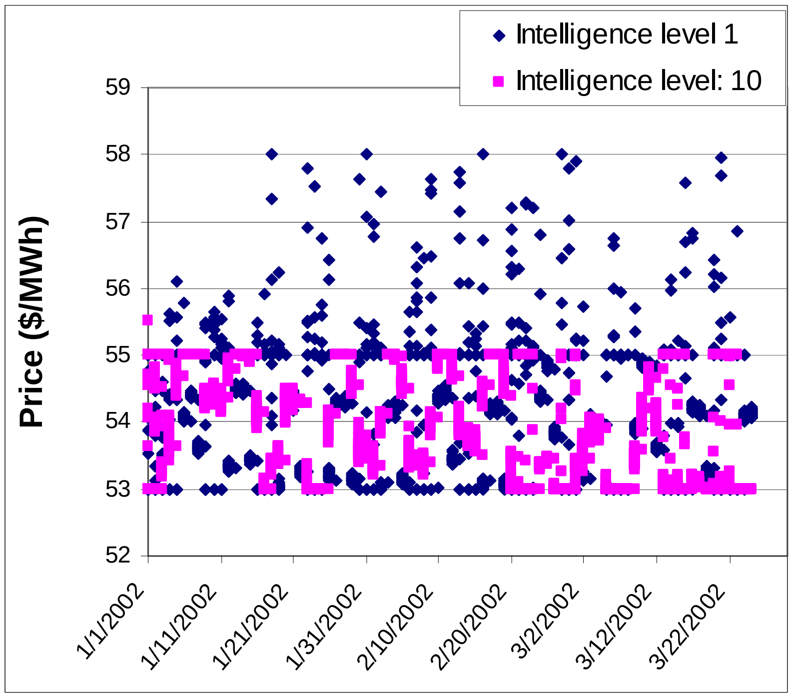


Figure 40: Price evolution over 3 months for different intelligence level

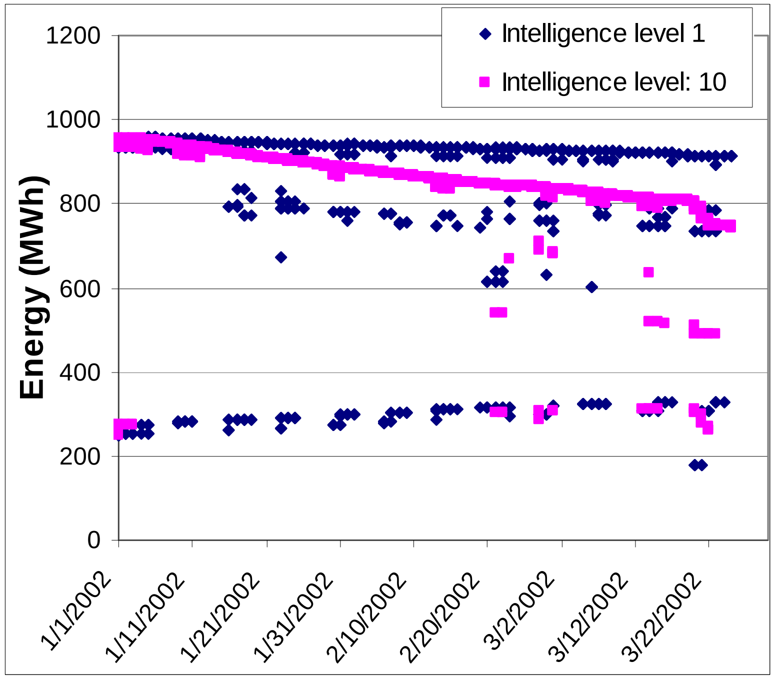


Figure 41: Energy evolution over 3 months for different intelligence level

These results show an important advantage in customer participation in the market: it can help improve the system efficiency and the energy conservation. Indeed, responding to the price, the intelligent agents reduce their demand of energy to optimize their profit. Instead of consuming all the energy that can be offered to them, they lowered their energy utilization to their exact needs.

In addition, these results also emphasize the importance of access to data on the customer side, as this simulation has shown that it is the agents with the highest intelligence level who optimized their energy consumption the most.

3.3.3.3 Vague data for suppliers

This simulation was intended to see the overall affect on the market by feeding vague data to the suppliers. The other parameters considered in this simulation are that the customer and the supplier agents are participating fully in the bidding. The participation of both the suppliers include increasing and decreasing the price based on the requirements, i.e. if the customers realize that they are not winning bids then they increase the price per MWh and similarly if the suppliers realize that they are not selling more than 70% of their offered capacity then they reduce the price per MWh.

The essence of this simulation is to study the affect of feeding vague data to the supplier agents. The supplier agents will then make their price estimates based on this slightly false data.

Overall market analysis

We look at the overall market analysis. The following graph shows the trend for the market clearing price over the 3 month period.

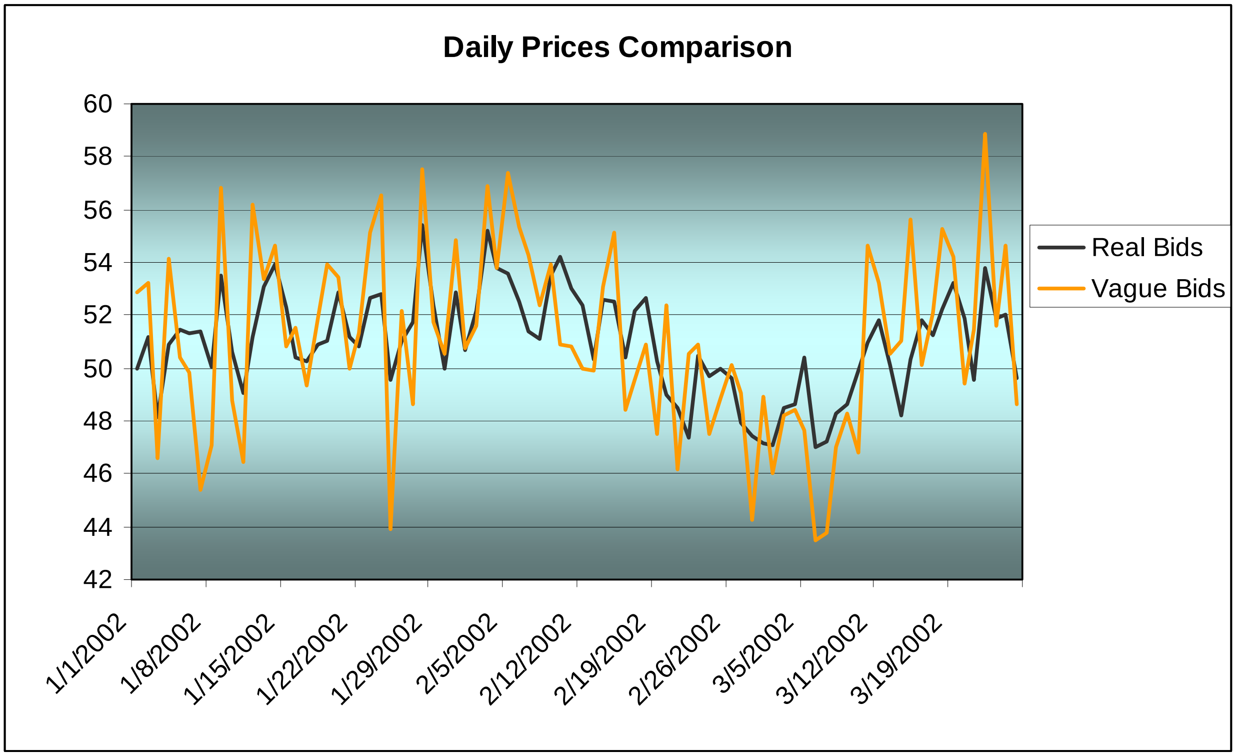


Figure 42: Comparison of prices between the actual market closing and vague data

In the above Figure 42, the bids are averaged over each day, i.e. the 24 hours prices in each day are averaged over a single day. This is done for readability. The graph is a comparison of the actual bids versus the vague data bids. The first thing that we gather from this data is that the vague data follows the same trend line as the real data. This conclusion is not very surprising because the vagueness data is based on the real bids with a fixed range of random increases or decreases.

The important result to extract from this simulation is that even with the vague data fed to the supplier agent, the market trend goes from prices going higher to prices going lower and then back higher up. So the trend follows a sine wave even though the data is vague. The reason for a sine wave is that initially the vague data does not have much impact on the agents' estimates but as the supplier agents start making bad estimates of the price, the customer agents benefit this and keep lowering the price. When the prices go too down too much the supplier agents estimate that they are selling their supply easily and start increasing the price. The price increases based on the past data and goes up very close to the original price. The vagueness factor does give benefits to some customers or suppliers in the short term, but the overall affect is the same as a price war between customers and suppliers.

Supplier's Behavior

The intent of this simulation is to see the reaction of the supplier using the vague data as input. We used three suppliers for this simulation but the parameters for each supplier were similar, so studying a single supplier should give us a good idea of the suppliers' behavior.

The summary for the supplier's bids are given below in table 29.

Table 29: Bids won/lost by supplier 1

	Supplier 1
Bids won	812
Bids lost	04

The above results are not so bad for the supplier, i.e. the supplier get's to sell 88.7% of the bids he makes in the market. What is more interesting is the time when the supplier starts losing bids. This can be seen below in Figure 43.

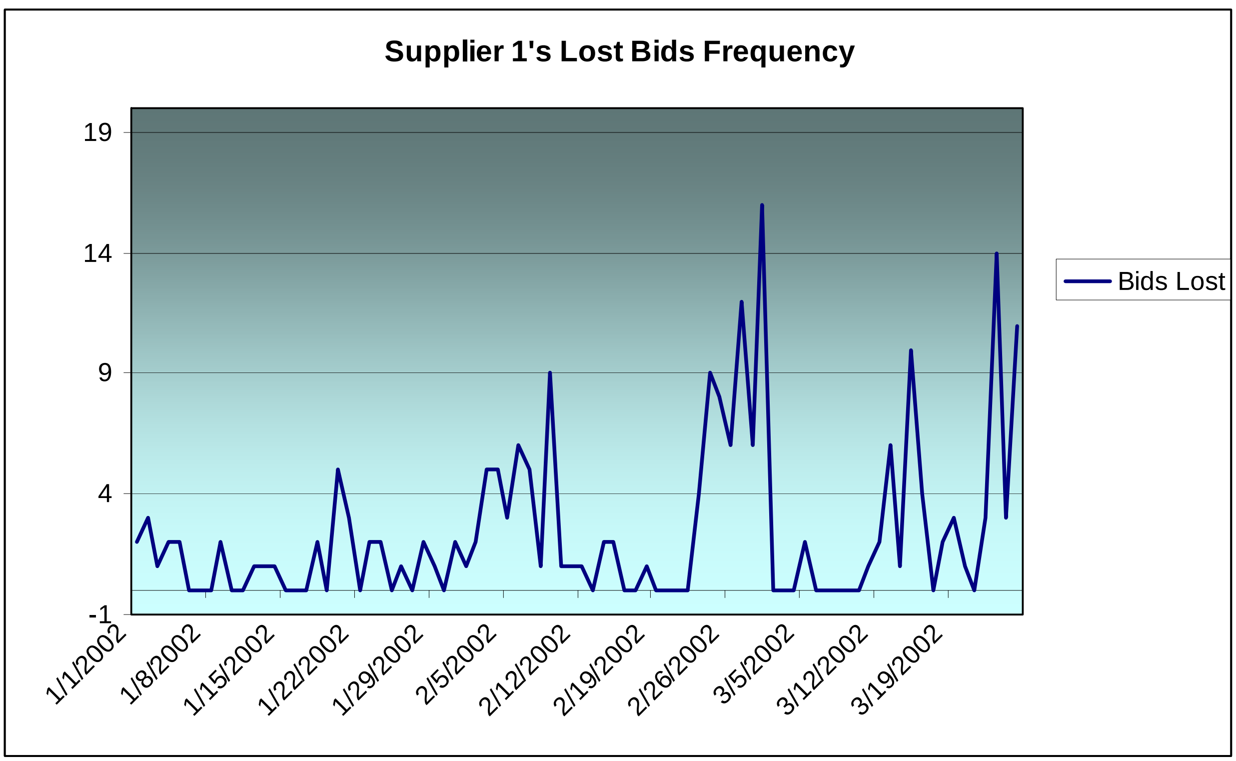


Figure 43: Supplier 1's lost bid frequency plot

We notice that the frequency of the lost bids increase after the second month. The plausible reason for this is that the suppliers' estimates are significantly different from acceptable prices during the last month. But the interesting questions is why this occurs in the third month and not so much in the first two months. The reason for that is that the supplier agents also look at the previous data and when the supplier gets in to the third month and looks back at the data, he sees a lot of vague data. The vagueness of the data comes into play more strongly in the third month and leads the supplier into making not so useful estimates. This makes the supplier's lost bids frequency increase towards the end of the period.

We note that the supplier agent is not so intelligent in reducing the price to keep up with the market. The following plot shows this:

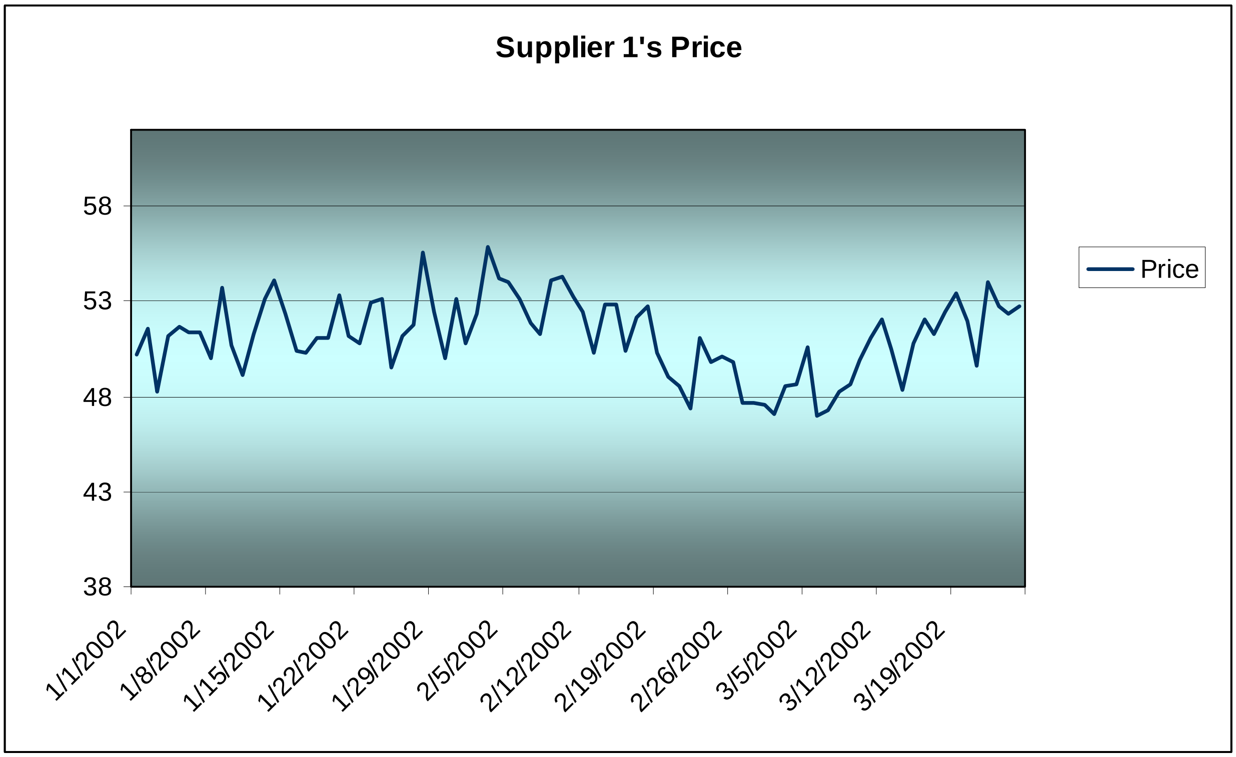


Figure 44: Price trend for Supplier 1

In the above Figure 44, we see that the agent is consistent in asking the price for the MWh. Normally with the accurate data, a supplier agent would reduce the price with the trend. But we note that the price trend remains the same throughout the period.

Customer's Behavior

We see a very odd behavior in the customer agents' behavior. The prices for the demand are consistent but the demands reduce abruptly. The demands reduce after some time passes by. The reason for this is that the customer agents are responding to the odd behavior of the suppliers at this time. It takes some time for the vague data to affect the supplier agents' prices estimates and when this happens the customer agents also feel the affect. The following bubble chart shows the intensity of demand decrease and the date at which each customer decreases its demand.

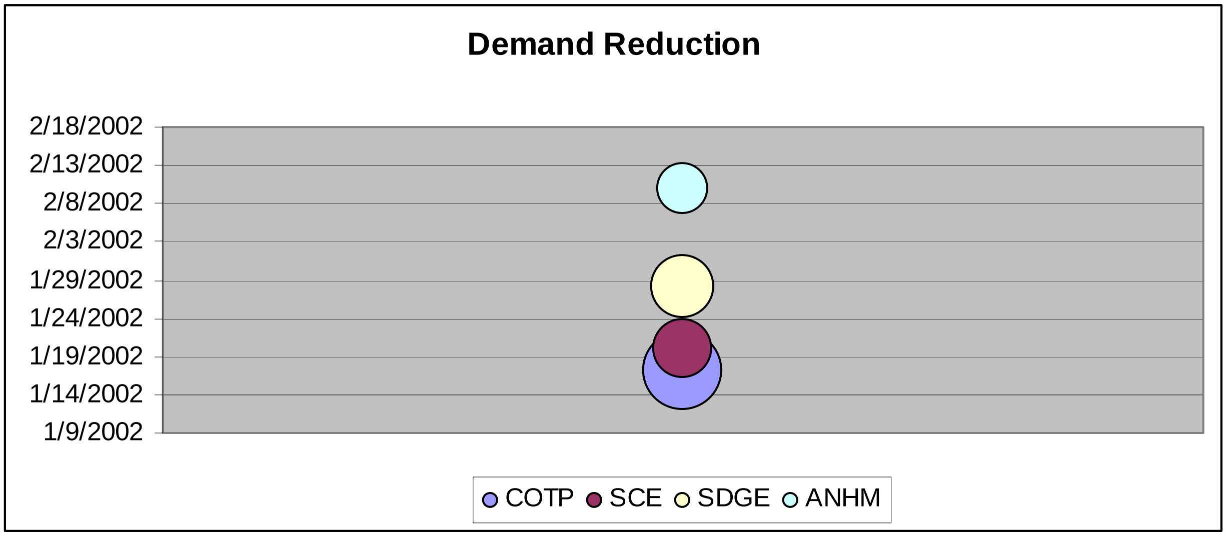


Figure 45: Demand reduction for each customer's bubble chart

In the above Figure 45, we see that the customers decrease their demand towards the end of the first month and into the middle of the second month. So, it takes the suppliers about a month to act oddly and this is when the customers start responding to the odd behavior.

In the previous figure the size of the bubble shows the degree of decrease of the demand by each customer.

3.4 Analysis

Using our agent models, we wanted to study how the electricity markets could be improved if the customers were more active in the market. The results of our simulations would be interesting to the industry as well as the policy makers. Indeed, as the electricity markets are being currently restructured, it is interesting for the electricity companies and the customers to learn how they can bid in the market in the most efficient way to maximize their profit. These simulations can also give insights to the policy makers as to what laws are needed for the market to allow customer participation.

Our base case simulation showed that if there is no customer participation (e.g. the customers are willing to buy the energy at any price), the suppliers will continually increase their prices to maximize their profit. In reality, government's limitations prevent the suppliers from raising their prices unreasonably. However, this simulation points out the importance of both customer participation and restrictive laws for the suppliers in order to have efficient electricity markets.

The learning ability of our agents has been studied as a function of the amount of information they had about their environment. The simulation results showed that for the customers to be efficient and competitive in the electricity markets, they need to learn as much as possible about the bid history. The more information they have, the better their prediction of the market's bids and clearing price will be. In reality, the market discloses to each customer only the information regarding his own bids. However, large customers often conduct studies to evaluate the market environment and have a general idea of their competitors.

This simulation also underlined the importance of customer participation in the market, as it can help improve the system efficiency and energy conservation. As the customers had more information about the market, they optimized their energy consumption the most, lowering their energy utilization to their exact needs.

The customer participation in the market is also noted in the case when the suppliers try to sell at prices that are not very realistic. The customers initially try to get the price down. If the erratic behavior of the suppliers continues, the customers cut down on their MWh demand. This automatic effect on the market relieves the regulatory bodies to completely control the suppliers.

The need for regulation laws in the market is emphasized by the simulation where suppliers increased their price linearly. In any case, this strategy is helpful neither to the suppliers nor the customers, not being able to anticipate and pay such a high price, will reduce their demand and eventually lose their bids. Therefore, to protect the customers and the sanity of the market, regulation laws have to set limitations to the suppliers' offers.

3.5 Future Work

3.5.1 Customer Agent

As the learning algorithm is a key feature of our simulations, future work should study how to improve it. In particular, different possibilities, such as Q-learning and game theory, should be implemented to develop different bidding strategies for the customer agents. The results of the simulations can then be compared to see which algorithm is the most efficient in maximizing the customers' profit.

Q – Learning is a reinforcement learning algorithm that learns by adjusting value for each action. In reinforcement learning, the algorithm uses the environment to learn and improve the reward over long term. Q-learning has the ability to learn without modeling the whole environment beforehand. This requires us go through an extensive training process.

Benefits of Q learning:

Looking at the advantages of Q learning we see a direct relation with this project. The idea of not modeling the while environment is favorable to us. We cannot have all the actions that an agent can perform right at the beginning of the simulations. The learning makes predictions based on the actions that come along as the agent learns. The other attractive feature of Q learning is that it is a reinforcement learning algorithm (increasing rewards over long-term). Normally, humans tend to have the reasoning to maximize rewards over long term. Using this algorithm can help us model the real life scenario very closely.

Drawbacks of Q learning:

Q – learning has the property of improving one parameter based on its learning but what we need in this project is to change that result depending upon other parameters. We have many variations for this project, e.g. the price cannot just increase as time passes over a year, the price has to vary in holidays or over the summers. The other modeling problem we see with Q-learning for this project is that the demand or supply also varies with time. There are not fixed rules that govern this but it can be just based on environmental factors e.g. a supplier might cut down supply because of natural disaster that might consume his generators. We couldn't come up with appropriate mapping between cost predictions for different supplies. These reasons led us in using our own learning mechanism (described in the next section).

Explanation of Q-learning:

The ideology of learning in this algorithm is based on the following formula.

$$\mathbf{Q}(state, action) = \mathbf{R}(state, action) + \gamma \cdot Max\left[\mathbf{Q}(next\ state, all\ actions)\right]$$

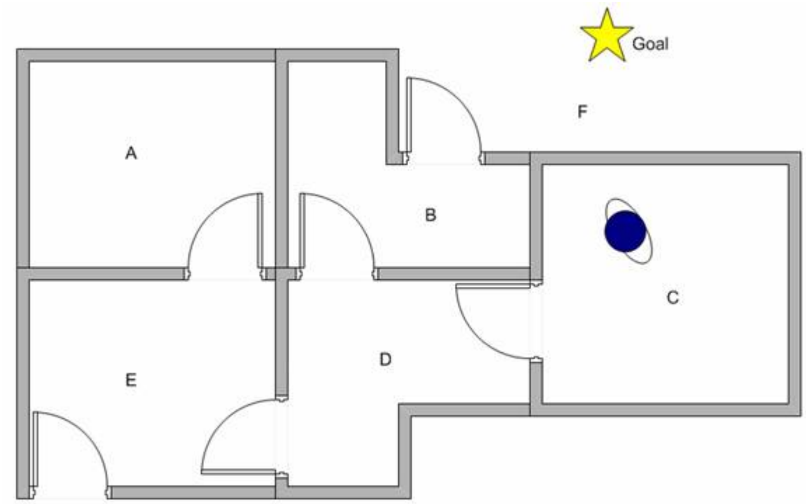
The three parameters in the above formula are Q, R and γ. Q and R are matrices. The R matrix is an initial state matrix that holds the state-transition and goal information for the system that is being modeled (this will be more clear after the example next). The Q matrix is the memory of the learning algorithm. So whatever the agent learns will be stored in matrix Q. Q also has a similar structure like R in that it models the different states in it.

Parameter γ is the learning parameter. The value for γ can be in between [0, 1]. The significance of this parameter is that with smaller value the algorithm will try to maximize short term rewards and vice versa.

So the formula provided previously gives a mechanism for the algorithm to learn. To make the algorithm actually learn we have go through episodes of runs. An episode is a complete run from the start state to the end state. After each episode the Q matrix is updated, which means that the agent has learned from the experience. We have to run a few episodes to make the agent capable of making useful decisions. After learning is done, the information in the Q matrix is used to make decisions.

The following example provides some insights into Q-Learning [58].

Suppose we want to design an agent that can move from any state in {A, B, C, D, E } to state F. So, state F is the final goal starting from any of the states. The following picture visualizes using doors and walls:



We now create the R matrix that contains the state-transition. R matrix looks like the following:

$$\mathbf{R} = \begin{array}{c} \textit{state} \setminus \textit{action} \\ A \\ B \\ C \\ D \\ E \\ F \end{array} \begin{array}{c} \begin{array}{cccccc} A & B & C & D & E & F \end{array} \\ \begin{bmatrix} - & - & - & - & 0 & - \\ - & - & - & 0 & - & 100 \\ - & - & - & 0 & - & - \\ - & 0 & 0 & - & 0 & - \\ 0 & - & - & 0 & - & 100 \\ - & 0 & - & - & 0 & 100 \end{bmatrix} \end{array}$$

The values of 100 are assigned to one step transitions to state F, which means that these are the most desirable transitions. A value of 0 is set to all the other connections but a '-' sign is assigned to all the other elements because there is no direct one step transition from the states to the others. Example: there is no door opening from C to B, so we see a '-' in the R matrix from row C to column B.

Now, using the formula:

$$\mathbf{Q}(\textit{state}, \textit{action}) = \mathbf{R}(\textit{state}, \textit{action}) + \gamma \cdot \textit{Max}\left[\mathbf{Q}(\textit{next state}, \textit{all actions})\right],$$

we can calculate the Q matrix.

Now, we have the Q matrix created appropriately with the environment. We can utilize this Q matrix by starting from state x and going to the next state that has the maximum weight. We keep on repeating this process until we reach our destination state.

3.5.2 Market

In order to improve the complexity of the market's algorithm, especially for the report function, the structures used to store the data about the bids of all the agents should be further investigated. We simply used matrix structures. If dynamic data structures, giving faster access to the stored elements (by indices or search), can be used with Matlab, they would help improving the algorithm.

Also, the demand and supply curves are stored using matrices. If the size of these matrices is proportional to the total amount of energy respectively demanded by the customers and offered by the suppliers. Therefore, our algorithm is slowed down by large customers and suppliers participating in the market. More efficient way of storing the demand and supply data for the market curves should be investigated.

3.5.3 Data

Lacking accurate and detailed data for the load and price of the customer agents, we generated part of the data in order to run our simulations. Further investigations can look for more sources of information and/or study how to create more realistic data. In particular, it could be interesting to see how the weather variations can influence the market. With the changes of climate, more or less energy is used in winter or summer. There are also variations during the day: more energy is used during the day time than the night time.

3.5.4 Simulations

3.5.4.1 Other types of simulations using our current model

More simulations can be run using our model.

The bidding strategy of the customer agents can be studied. When an agent loses a bid, it can either increase its price or lower its demand for the next iteration of the market. It would be interesting to study how fast each of these possibilities converges to the maximum profit for the customer agent. The control fallback option used in our simulations helped the customers win more bids, but may have reduced their overall profit.

The influence of the number of agents in the market can be simulated. If the customers are outnumbered by the suppliers, it is expected that they will have little influence on the suppliers offers and thus on the clearing price. Inversely, if there are many customers, they should be able to get the suppliers to lower their price more easily.

More simulations to study the influence of the price evolution of suppliers can also be run. In particular:

- a volatile price (e. g. a price that changes a lot all the time) should make it harder for the customer agents to predict the price and thus maximize their bids
- a spike in the price at instant in time can offset the customer agents bids calculations. In this situation, it is especially interesting to see how long it will take for the customers to get the right bids again.

3.5.4.2 Ancillary Services

To allow the customers to have more influence on the electricity market, the ancillary services available to the customers should also be modeled. We want to know how the customers can participate in the ancillary services market. In a first simple model, the customers' bids will be composed of two elements: the amount of energy they want and the amount to which they are willing to lower their demand if they participate in demand side programs.

3.5.4.3 Auction mechanisms

For our simulations, we only used a uniform-price auction. Other types, such as discriminatory, single-round or sequential auction, can be implemented to study how the type of auction can influence the behavior of the agents.

3.5.4.4 User interface

The parameters of our simulations are now being entered with the .csv files of the "config" folder, turning on and off the different options is done by changing the text in the files. A user input interface should be added to set the parameters more easily when starting a simulation.

Part 4. Conclusion

To evaluate the economical impact of market rules on market and system performance, this research results in a multi-agent based electricity market platform that incorporates energy and ancillary service markets and market power mitigation rules. Since the platform is built upon an agent oriented middleware and is fully programmed in JAVA, it facilitates the future extension of the models and techniques. The multi-agent platform built in this project includes three types of interaction agents: supplier agents, load serving entities, and market operator. The supplier agents are enabled with an anticipatory reinforcement learning algorithm called Q-learning.

To illustrate the usefulness of the proposed multi-agent platform in evaluating market rules, an important market design issue of market power mitigation is investigated here. The PJM-like local market power mitigation process is implemented in the simulation platform for the market evaluation. Three simulation scenarios are developed. The first scenario is the competitive benchmark where every supplier agent bids their marginal cost. The second scenario is the unmitigated scenario where every supplier agent bids strategically into the market according to the Q-learning rules in the absence of market power mitigation. The third scenario is the mitigated scenario where every supplier agent bid strategically into the market, however, the market adopts the PJM-like market power mitigation rules.

The simulation results indicate that, without market power mitigation rules, even in a rapid changing market environment, large generation owners who interact with one another in similar scenarios easily learn exercise their market power even without knowing others' historical bidding data. It is also shown that the PJM-like market power mitigation rules not only suppressed the market power exercise against strategic bidding supplier agents but also enhance the market efficiency by reducing the total generation cost comparing to the unmitigated scenario.

The effect of LSEs owning generation resources is examined in this report by assigning some generation units to certain LSEs. It is concluded from the simulation results that if a generator is owned by a LSE, it will tend to reveal its true marginal cost. However, if it is owned by a supplier agent, it will tend to bid at a much higher markup. Hence, the generation resources that are owned by LSEs would be a source of counteracting market power during peak hours to the suppliers group.

This report demonstrates that the structure of ancillary service markets affect the power system performance. The ancillary service markets should be designed to ensure that the desired control performance is achieved at the lowest price. This implies that the structure of the ancillary markets should be designed in such a way that those generators that can contribute more toward better control should be encouraged by the proper incentives. In the case of the regulation market this usually means the recognition that generating units with faster response (ramp) rates are more important to load balancing and frequency control. In the case of VAr markets, the speed of response is not as important as the location of the units and their VAr production capacities, i.e. voltage control is more sensitive to the electrical proximity of the VAr sources.

Three different market structures were chosen to demonstrate the varying frequency control performance on a reduced WECC model: the first is similar to what is used by the

California ISO but the other two are chosen somewhat arbitrarily to provide more incentives for generators with better response (ramp) rates. In the second structure a bid market is developed for 5-minute capacities in addition to the existing 10-minute capacity market. The 5-minute market can be used for better control than the 10-min market and at the same time these faster generators can be rewarded with higher prices. In the third structure separate markets are formed for fast and slow units based on ramp rates.

This report presented a comparative study of two different area voltage control schemes to demonstrate the feasibility of voltage control by adjusting the reactive power injection from the generators. A competitive VAr market seems feasible in either of these control frameworks. To achieve better performance in terms of the voltage profile, the market has to procure a sufficient amount of reactive power reserves. A market for VArs for that purpose will provide the option to choose amongst resources. However, it is shown that just as in the regulation market, certain generators provide better voltage control because of their location and VAr capacities and either scheme used in this report will provide market incentives to the more effective generators.

This report shows that ancillary markets should be structured to reward those properties of the generator that better achieve the desired performance of the ancillary service. It should, however, be made clear that it may not always be possible to create such a market and there has to be enough generators in the market with similar capabilities to generate competition.

Customer participation in the electricity market is modeled and analyzed in this project. The simulation results have shown the importance of having more active customer participation in order to deter the supplier market power, to lower electricity prices, to promote energy conservation and to improve the system reliability.

The electricity market was simulated using intelligent agents, whose behavior evolved depending on the market's environment and interactions. The agents learned from their historical bidding information and knowledge about the market's mechanisms.

In order to investigate how the market performance can be improved if the customers were more active, the behaviors of the learning agents are studied under different market structures. The simulation results show that restrictive laws for the suppliers are needed to protect the customers and the integrity of the market.

The simulation result illustrates that the market participants should learn as much as possible about the market environment and the bidding history to maximize their profit. The overall system efficiency and energy conservation could be enhanced if the customers are more familiar with the market's mechanisms. When the customers are trying to minimize their expenditures, they would lower their energy consumption to their exact needs. Therefore, customer participation is important from an environmental point of view.

Further research is needed on extensions of the proposed multi-agent platform to enable the negotiation of bilateral contracts between supplier agents and LSEs, so that the effects of forward contracts on day-ahead markets can be investigated in a comprehensive manner. In addition, it is desirable to incorporate marketers into the model to examine the impact of virtual bidding on the electricity market. Furthermore, the interaction between fuel market and electricity market could be studied by having the supplier agents trade in energy commodity markets. A limitation in this research is the use of only Q-learning to model the suppliers' learning behavior. This limitation arises from the curse of dimensionality. This weakness could be overcome in the future by designing other new algorithms that combine the strengths of both Q-learning and Artificial Neural Networks.

Appendix A. Quadratic Fuel Cost Curve Coefficients

Quadratic fuel cost curve coefficients of the 23 aggregated thermal units

GENCO NUMBER	a	b
0	0.00471795	55.189
1	0.0419865	53.793
2	0.029041	41.782
3	0.017112	55.645
4	0.022362	50.573
5	0.0	52.5
6	0.0032185	55.559
7	0.0022191	53.386
8	0.00287755	51.984
9	0.0055025	54.565
10	0.00359045	63.403
11	0.0087925	59.731
12	0.0434865	54.908
13	0.056835	54.64
14	0.0	66.72
15	0.0161175	34.674
16	0.0303945	53.881
17	0.0	78.0
18	0.0017795	56.601
19	0.12856	62.022
20	1.9517E-4	55.425
21	0.0123615	35.924
22	0.0106315	57.127

The marginal cost curve of an aggregated thermal unit can be expressed as following:

$$MC(P) = a + 2 \cdot b \cdot P .$$

Appendix B. WSCC 225-Bus Model

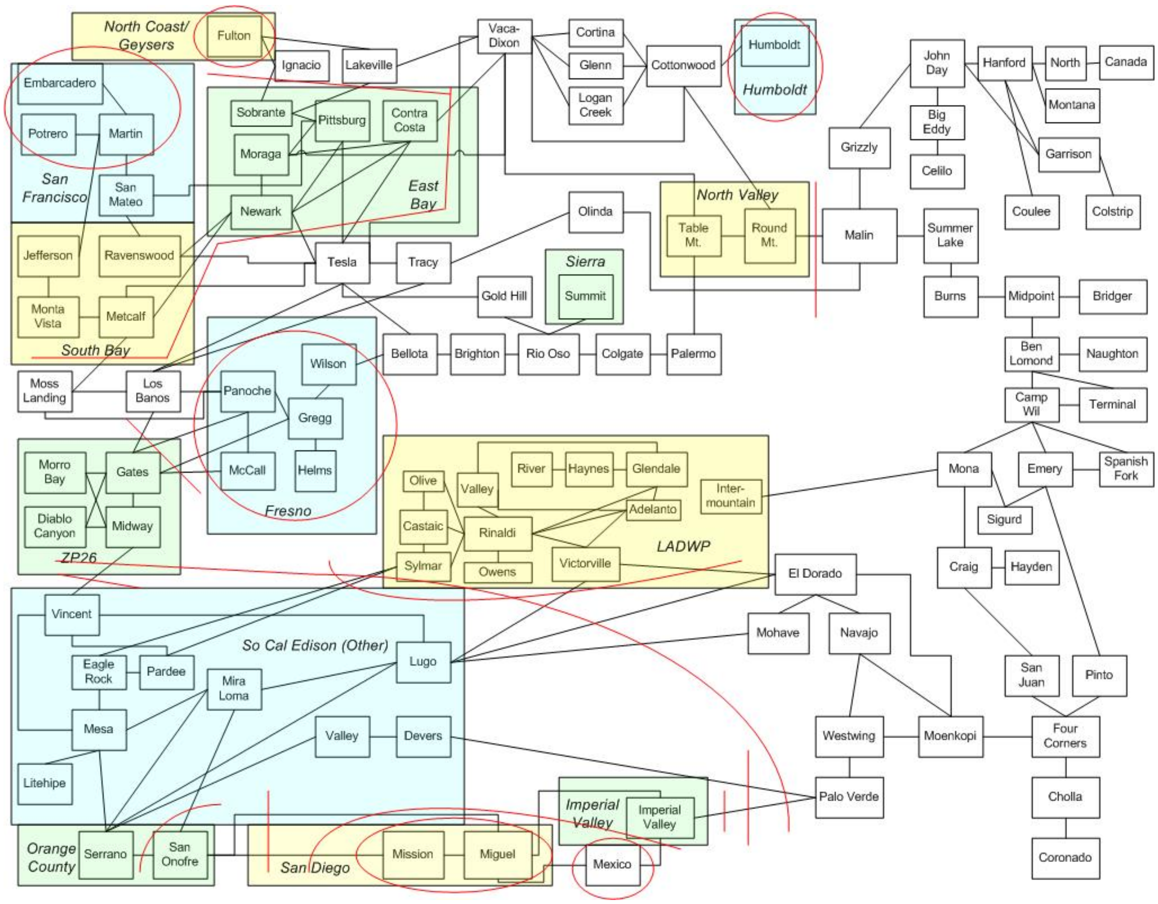


Figure 46: Major Substations of WSCC Reduced Model (courtesy CAISO)

Appendix C. Voltage Control Area

A power system can be divided into a number of voltage control areas consisting of coherent buses and reactive resources able to sustain the reactive requirement of the area. The systematic method to determine such VCA s has been described in [57]:

1. Calculation of electrical distance between all the nodes of a system
2. Identification each area using topological classification within the border of the network

The electrical distance between the buses in a network can be derived from $\left[\partial P/\partial \theta\right]$, which is a part of the Jacobean matrix J. Since we are interested in the reactive power sensitivity of the buses, it is necessary to obtain $\left[\partial Q/\partial V\right]$ and the $\left[\partial Q/\partial V\right]$ part of the Jacobean does not include generator buses, the complete matrix can be derived from $\left[\partial P/\partial \theta\right]$ as follows:

$$\frac{\partial Q_i}{\partial V_j} = \frac{\partial P_i}{\partial \theta_j}, \qquad \text{for} \qquad i \neq j$$

$$\frac{\partial Q_i}{\partial V_i} = Q_i - B_{ii} V_i^2, \qquad \text{for} \qquad i = j$$

Hence, the sensitivity $\left[\partial V/\partial Q\right] = \left[\partial Q/\partial V\right]^{-1}$ is the measure of propagation of voltage variation following a reactive power injection at the bus. The magnitude of voltage coupling between two buses can be quantified by the maximum attenuation of voltage variation between these two buses:

$$\Delta V_i = \alpha_{ij} \Delta V_j$$

The attenuation is given by:

$$\alpha_{ij} = \left(\frac{\partial V_i}{\partial Q_j} \right) \Bigg/ \left(\frac{\partial V_j}{\partial Q_j} \right)$$

The attenuation matrix thus obtained is non-symmetric. To ensure positivity and symmetry the electrical distance between any two nodes i and j is calculated as:

$$D_{ij} = D_{ji} = -\log_{10}\left(\alpha_{ij} \cdot \alpha_{ji}\right)$$

Once the electrical distance between any two nodes of the network has been defined VCA s can be formed by grouping the electrical distance into certain ranges. Starting from a generator bus, all the buses whose electrical distances from that bus is less than the range is included in one area. A number of areas can be formed like this until every bus belongs to at least one area. In case a bus belongs to more than one area some judgment is to be used to classify it in any one area.

Appendix D. Additional Material

Source: New England ISO (http://www.isone.org/markets/hst_rpts/hstRpts.do)
Type of data: Day-Ahead LMPs and Hourly Day-Ahead Cleared Demand

Load (MWh)	Normalized load	Price ($/MWh)	Load (MWh)	Normalized load	Price ($/MWh)
11014	0.740835407	39.7347368	14770	0.993475483	45.8412253
11257	0.757180332	45.7562947	14799	0.995426112	50.3134787
11307	0.760543486	40.3267263	14964	1.006524517	47.9076636
11688	0.786170714	48.3895684	15614	1.05024551	55.5433437
11721	0.788390395	48.7298316	15686	1.055088451	68.7326842
11915	0.80143943	50.6046	15930	1.071500639	61.1879789
11919	0.801708482	31.8204984	16378	1.101634493	59.9716615
12011	0.807896684	36.1393354	16412	1.103921437	56.054621
12011	0.807896684	31.7237072	16548	1.113069214	77.1209684
12195	0.820273088	34.6539564	16976	1.141857806	63.7465628
12208	0.821147508	42.7742783	17179	1.155512208	81.1833789
12355	0.831035179	37.1192939	17282	1.162440304	67.5497508
12380	0.832716755	42.5440291	17453	1.173942288	78.0907158
12405	0.834398332	44.9429907	17549	1.180399543	88.4682105
12768	0.858814825	50.6992316	17679	1.189143741	95.3946211
12817	0.862110715	54.0380947	17805	1.197618887	83.1271579
13335	0.896952983	39.2253583	17860	1.201318356	81.8139789
13403	0.901526872	45.723053	17976	1.209120872	86.6355895
13578	0.913297908	43.6457632	18046	1.213829286	90.2136
14439	0.971211408	45.6993977	18166	1.221900854	89.2688
14516	0.976390664	46.353676	18265	1.228559898	93.5804105
14570	0.980022869	45.652866	18276	1.229299791	93.0004737
14638	0.984596758	48.026812	18389	1.236900518	93.3438105
14753	0.99233201	47.9604881	18415	1.238649358	94.2875789

Mean load: 14867.08

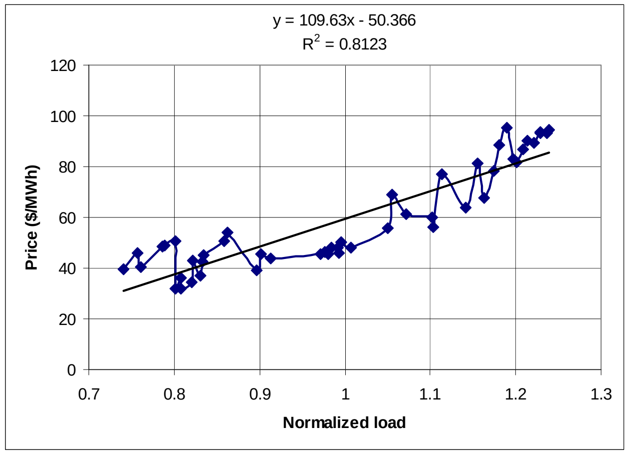


Figure 47: Price Curve Fitting for the customer agent

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