CONTROL SYSTEM MODEL FOR ANALYSIS OF ELECTRICITY MARKET BIDDING PROCESS

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This dissertation proposes a closed-loop control system model to facilitate mathematical analysis and promote operational efficiency of the dynamic bidding process. Electricity market deregulation has brought an innovation of the market structure and changed the electric power production from the old monopolistic way to a competitive market environment. Electricity is treated as a commodity and being traded among the market participants. The analysis of electricity market behavior becomes increasingly important and challenging. This dissertation develops a control-theoretic model to analyze and predict electricity market behavior. The model is based on the perspective of the power generation side (GENCOS) and ISO. The purpose is to achieve a rational profit maximizing behavior for GENCOS during the day-ahead bidding process and to improve the wholesale market efficiency. The control-theoretic model uses the game theory embedded with the learning ability as the major bidding strategy, which allows GENCOS to adjust their next-day bidding in the form of supply function equilibrium (SFE) through market observations. Recursive least square (RLS) method based on two ARMA models is introduced for demand and price forecasting in order to maximize the GENCOs profit. This method is implemented into the bidding strategy of SFE with learning process. In order to better capture the demand and price dynamics beforehand, this dissertation also introduces an adaptive multiresolution prediction algorithm. This algorithm establishes a systematic structure to hierarchically decompose the original demand and price data into subtasks with different time frames, within which the data are able to be trained separately and efficiently. The real market data from New

York Independent System Operator and PJM interconnection are used to demonstrate the effectiveness of the proposed model and training algorithm.

Keywords: Electricity market, supply function equilibrium, recursive least square, multiresolution prediction algorithm.

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1.0 OVERVIEW

1.1 MOTIVATION

In the late 1970s, [1] the earliest energy market concepts and privatization were introduced and started to take place in Chile. Since then, the electricity institutions worldwide have started to experience a deregulation process. In the United States, after the first Energy Policy Acts [2] was launched in 1992, Federal Energy Regulatory Commission (FERC) opened access to the electric transmission grid and economic forces were implemented into the electrical power industry. Along with this market restructuring, a traditional utility is separated into three genetic entities: generation companies (GENCOs), transmission companies (TRANCOs), and the distribution companies (DISCOS). During the operation of the newly established wholesale electricity market, electricity has been treated as a commodity which is capable of being bought, sold and traded through bidding and offering.

Given the competitive electricity market environment, GENCOs take the responsibilities of maintaining and operating the generation plants while Independent System Operators/Regional Transmission Organizations (ISO/RTOs) (Fig. 1)[3] are in charge of operating the electricity market securely and efficiently, both of which are considered as key players during market operation. As a result, the objectives of maximizing profit of GENCOs by employing appropriate bidding strategy and ensuring the fair competition during the bidding process were established. Therefore, the demands of research on this topic are growing in order to help increase the social welfare.

Due to its close relation to people's daily life, electricity is considered to be the largest commodity being traded in the United States, which values its market in total of 200 billion dollar per year [4]. Additionally, from the perspective of financial and commodity market,

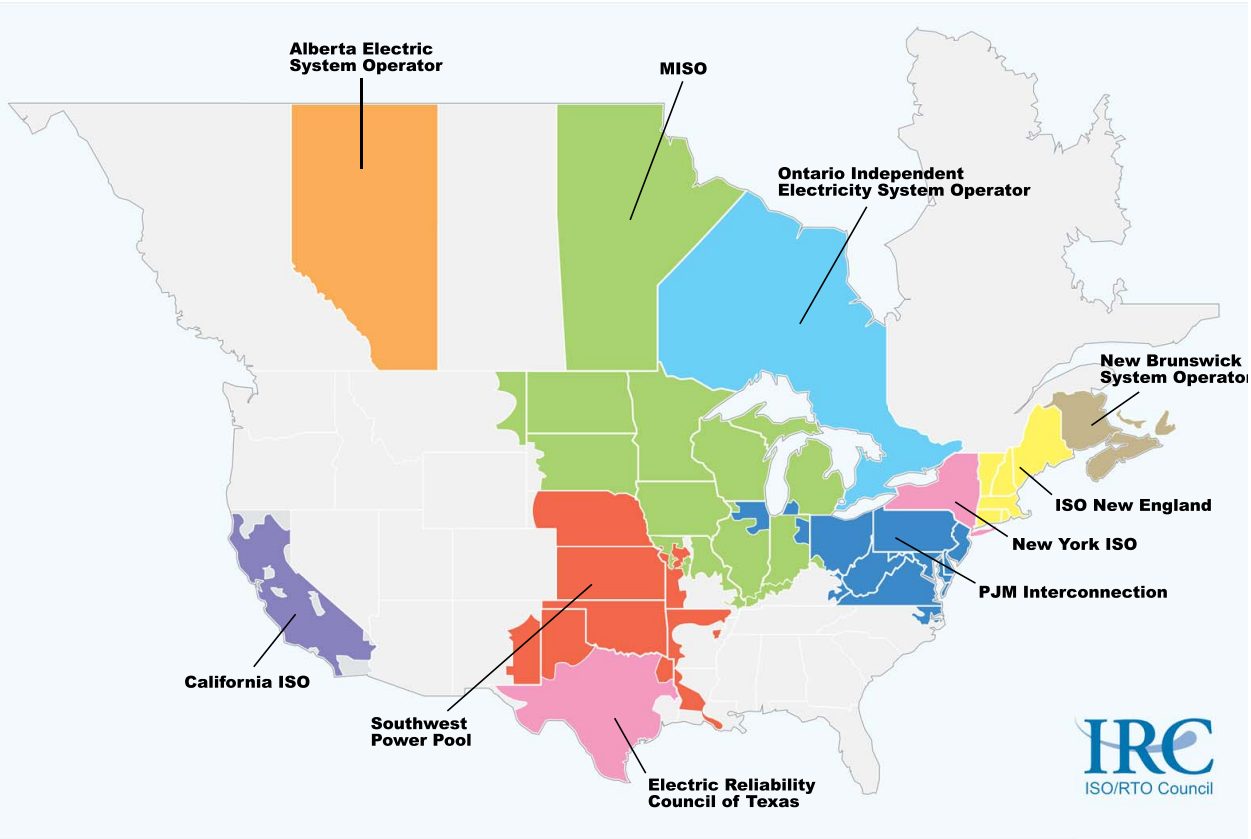

Figure 1: ISO/RTOs operating regions (Figure adapted from [3]).

electricity price is extremely volatile compared to prices in other commodity markets, which results in the existence of risk issues and arbitrage activities. Without the appropriate market regulation and analysis, these phenomenons could cause negative effects on the market participants' decision making and lead to huge economic losses. One example is the California electricity crisis of 2000 and 2001 [5], which was resulted from market manipulation. It led to 40 to 45 billion dollar loss and affected 1.5 million customers' electricity use.

Therefore, the application of the economic theory and financial models has become increasingly important for assisting market regulation on risk management and arbitrage activities. This fact, along with the previously mentioned current focus on searching for the most

efficient bidding method for GENCOs to obtain profit maximization, have drew researcher's attention on formulating the bidding process models in the search for more efficient and profitable ways when facing market instability.

1.2 OBJECTIVES

The main objective of this dissertation is to design a closed-loop control system model to facilitate mathematical analysis and promote operational efficiency of the dynamic bidding process. The model is based on the perspective of the power generation side (GENCOs) and ISO. The purpose is to achieve a rational profit maximizing behavior for GENCOs during the day-ahead bidding process and to improve the wholesale market efficiency. This goal is to be achieved by pursuing the following subtasks:

1.2.1 Design a dynamic bidding model using linear supply function equilibrium

Three oligopolistic equilibrium models (Bertrand equilibrium, Cournot equilibrium and supply function equilibrium) were introduced and compared in order for us to select the most appropriate one as the basic method for electricity bidding. Recent research [6] has proposed the idea of the combination of linear supply function equilibrium (SFE) and learning process. However, the main innovation of this task is to design a dynamic bidding model from the side of GENCOs to maximize its market net profit during the day-ahead electricity market bidding process. A coherent combination of tools from control theory and linear supply function equilibrium from game theory were used to formulate this adaptive closed-loop control system. This model simulates the dynamic bidding process of GENCOs and allows GENCOS to adjust their next-day bidding in the form of supply function equilibrium (SFE) through market observations. The analysis shows that it is unnecessary for GENCOs to know the generation costs and commitments of other competitors.

1.2.2 Demand and price forecasting using recursive least square method

Based on the data of day-ahead demand and market clearing price published by NYISO, this dissertation formulates two ARMA models and utilizes Recursive least square (RLS) method [7, 8] to solve the system identification problem. According to the results, the demand and price are able to be foretasted beforehand, which helps GENCOs better adjust their bidding strategies using the forecast data instead of the approached data. The predicted data was applied into the SFE bidding activities to formulate the adaptive control system. Moreover, the simulation results based on different bidding strategies were compared.

1.2.3 Demand and price forecasting using multiresolution prediction method

With the goal of maximizing the GENCOs market profit, we improved GENCOs bidding activities by adding the external inputs for the ARMA models and further reinforced the RLS prediction accuracy. We applied the multiresolution prediction method into RLS filter in order to establish a systematic structure to hierarchically decompose the original demand and price data into subtasks with different time frame, within which the decomposed data are able to be trained easily for better capture the electricity market movement.

1.2.4 Introduce the idea of an optimal portfolio strategy for GENCOs to participate into the electricity market operation

Due to the fluctuation of electricity price during market operation, the stabilization of price is the necessary condition for carrying out trading activities among market participants. Firstly, this dissertation conducted analysis on arbitrage behavior in electricity market operation. Secondly, we will introduce the idea of arbitrage pricing theory (APT) [9] based on the model, this was considered as GENCOs' another bidding strategy when facing price difference in different electricity markets and different time periods. The goal is to maximize the sharp ratio in order to obtain more profit. Based on these, we will fomulate the closed-loop control system model.

1.3 SIGNIFICANCE

This study created a closed-loop control system model to facilitate mathematical analysis and promote operational efficiency of the dynamic bidding process. This model successfully combined the application of control theory, game theory, system identification, multiresolution, microeconomic, and financial theory, which has been proved to be reliable, efficient, and corresponded to the characteristics of the electricity market.

Firstly, inside this model, supply function equilibrium was implemented with adaptive RLS prediction function and was treated as a controller for the dynamic bidding, which helps increase the speed of convergence to the Nash Equilibrium.Secondly, based on this design, all the competitors bidding strategies, generation costs are reflected in the price and demand, which can be captured beforehand. Thirdly, this research delivered important insights for the decision making of GENCOs when taking responsibilities of maintaining and operating the generation plants as well as participating into the electricity market bidding process. The principles, methods, and tools developed from this study provide a template for researchers to build other system from different perspectives in order to simulate the market operation process, the detailed implementation of the control idea is served as a guideline and be readily generalized to other process of electricity market, e.g. the decision making problem on supply chains [10] and the optimal dispatch problem of power generation [11]. Lastly, this research addresses a dynamic bidding framework which can be used to estimate the various situations such as arbitrage based on risk analysis and adjustment of the selection of the bidding portfolios.

2.0 LITERATURE REVIEW AND BACKGROUND INTRODUCTION

Over the past two decades, the electricity institutions worldwide have started to experience a deregulation process, which resulted in a substantial electricity market restructuring. The introduction of economics and policy decision as well as mathematics have created electricity market a combination of social science and natural science. This causes the traditional electrical operation models and methods to exhibit poor performance when facing the new circumstances including the market participants' behaviors. Therefore, in order to improve the market efficiency and profit, researches on electricity market structure, GENCOs' bidding strategies, and electricity market operation risk has become the major directions.

In this chapter, we introduced the research development and background of the regulated and deregelatued electricity market for better analysis on the market process. Moreover, the basic knowledge in economics was presented in order for us to know the behavior of market participants, market operation principles and the regularity of electricity markets. This helps to prepare for the implementation of the algorithm on the bidding process.

2.1 ELECTRICITY MARKET MODEL

The liberalized electricity market model design has been focused on reliability and economics [1], this is decided by the market operation mode. England started the restructuring procedure by adopting a mandatory pool in 1990s [12, 13], this so called England and Wales Power Pool was considered as an advanced electricity operation mode and had brought a huge effect for other countries. As a centralized marketplace, the power pool provided a platform for the market participants to submit bids and offers in the form of electronic auc-

tion, this was under the organization and regulation of the market operator. Two settlement mechanisms including uniform pricing [14] and pay-as-bid were proposed. However, along with more researches conducted on economic side, new problems [15, 16, 17] started to appear. For example, in order to earn excessive profits, the large generation companies might collide during the bidding process, this abuse of the market power would cause the electricity price seriously higher than its cost.

The introduction of bilateral contracts [18] and future options formulated the bilateral contracts model, in which the bilateral contracts are negotiable agreements on the power delivery and receipt among buyers, sellers, and traders. The function of ISO in this model is to ensure the sufficient completion of the contract and maintain the transmission capacity corresponds to the contract terms. Although this operation mode provides flexibility for trading parties in terms of the delivery time and the specification of their own contracts terms, the cost for negotiating and writing the contracts as well as the credit risk were still be considered as its drawbacks [19].

The hybrid model combines features of PoolCo model and bilateral contracts model. Inside this model, the PoolCo is no longer obligatory, which enables the demand customers ether accept the power price from PoolCo market or negotiate the power supply agreement directly with suppliers. Therefore, this operational mode offers more options for market participants to satisfy their benefits. For most of the electricity markets in US, hybrid model has been widely adopted.

2.2 GENCOS BIDDING STRATEGIES

From the perspective of microeconomics, in a perfect market condition, the marginal cost are supposed to be the optimal bid for market participants. However, the characteristic of the newly established electricity market determines its imperfect market environment along with the regulation and constraint of electric power system operation. Therefore, rational manipulation of market power, choosing the optimal bidding strategy have become the vital part for increasing the profit during market operation.

In 1988, Schweppe firstly discussed the implementation of management into the electricity market [20], it included the electricity marketplace itself, the regulatory commission and the market participants. Later, with the fast development of the electricity markets in England and Wales, the bidding strategic issues had been proposed by David in the form of an optimal bidding model and a dynamic programming method [21]. Since then, more research attentions have been attracted to model the competition activities among GENCOs, which were no longer be restricted in the form of generation cost but also were expand to the employment of bidding strategies. These could be classified into three different modeling approaches.

2.2.1 Optimization model based on single GENCO

These group of researches were focused on the specific GENCO while simplifying the rest of the market system, the objectives were to solve the optimization problem based on cost minimization under the market constraints [22]. Inside this group, the application of stochastic programming methods [23], Dynamic Programming method [24], Nonlinear Programming method [25, 26], Mixed Integer Programming method [27] were proposed from different perspectives of electricity market operation. Besides, a multi-stage SILP model for hedging and scheduling in electricity markets was introduced to capture the fluctuation of electricity demand and price [28]. Particle swarm optimization methods [29] were proposed to determine bid prices and quantities for application in PJM market. For the decision making of GENCOs, Markov decision process models were introduced for optimizing bidding decisions and maximizing long-term profit [30, 31, 32]. Moreover, bi-level optimization algorithm were applied for the strategic interactions among market participants as well as the hybrid model of Pool market and bilateral contracts market, where the electricity and the forward contracts are traded paralleled [33, 34, 35]. Also, some researches were focused on the minimization of the generation cost such as emission of pollutants [36] and the unit maintenance [37]. More optimization models based on single GENCO can be found in literature [38, 39, 40, 41, 42].

2.2.2 Agent based model

Agent based modeling algorithm was firstly developed as a relatively simple concept in the late 1940s and has became widespread since the 1990s [43]. This model is able to simulate the behaviors and interactions of multiple agents, which can be applied to predict and improve the complex system operation. Therefore, the complex trading issues in liberalized electricity market have adopted this algorithm by modeling the market participants as adaptive agents [44]. A genetic algorithm was proposed by Sheble in order to optimize GENCOs bidding strategies in a double-sided auction market, this method started to take consideration of the different behaviors of other market participants [45]. In energy and spinning reserve markets, Wen and David realized the fact of coordinated bidding strategies and developed research on Monte Carlo simulation and a refined genetic algorithm under the market constraints [46]. In addition, Bunn designed an agent-based model by adopting computational learning algorithm, this model was proved to be efficient on analysis of vertical integration and market power [47]. Some researchers focused on the comparison and coordination among different algorithms. Walter and Gomide started from a genetic algorithm based approach on the marginal cost and fuzzy theory by obtaining an evolutionary GENCO bidding strategy [48], they continued this application on a dynamic system and introduced a co-evolutionary algorithm to further improve the GENCOs' profits [49]. More studies on application of agent-based modeling in electricity market can be found in literature [50, 51, 52, 53]. This group of models are able to mimic market participants' behaviors and have been proved to be more flexible, robust and easily implemented [44]. However, the mathematical foundation is yet to be clearly verified.

2.2.3 Game theory model

As a branch of applied mathematics, game theory has a wide range of applications in economics, biology, political science, engineering and philosophy [1]. For the GENCOs' decision making of electricity market bidding, game theory helps to mathematically model the strategies which depend on the choice of its competitors. The objective of game theory models is to drive the market to a Nash equilibrium [54], which occurs when no player will change

its bidding strategy alone. The application of game theory in electric power markets started back in 1999, when Singh firstly proposed the application of game theory in electric power markets [55], the academic interests had been reflected by a large number of publications. Given the oligopolistic market environment and the different concentration of bidding strategies, the studies have been focused on three most popular oligopolistic equilibrium models: Bertrand equilibrium, Cournot equilibrium and Supply function equilibrium(SFE).

2.2.3.1 Bertrand equilibrium In Bertrand equilibrium model, GENCOs compete by setting their own price simultaneously without any cooperation [56], the unit costs are constant and there are no capacity constraints. Once the amount of electricity is determined by the demand customers, the GENCOs will supply the corresponding quantity. However, research [57] has proved that no capacity constraints would result in perfect competition model, which was not efficient for bidding in the oligopolistic electricity market. Relevant studies can also be found in [58, 59, 60].

2.2.3.2 Cournot equilibrium Compared with the price-setting strategies of Bertrand equilibrium, Cournot equilibrium [61] defines that GENCOs compete by setting their own supply quantities simultaneously while accepting the market price determined by demand customers. It assumes firms do not cooperate and each firm is trying to maximize its own profits based on the hypothesis that its competitors do not change their production output [62, 63]. This equilibrium model used to be considered the most appropriate model for application in electricity market, and is still be widely used in recent researches. However, the quantity competition of Cournot equilibrium model is incompatible with the price-quantity competition mode of electricity market. In addition, it can not be efficiently applied to inelastic demand. More studies can be found in [64, 65, 66, 67, 68, 69, 70, 71].

2.2.3.3 Supply function equilibrium Based on the assumptions of Cournot equilibrium and Bertrand equilibrium, researchers have identified the drawbacks and started to develop an alternative method to better analyze the electricity market bidding strategies. Klemperer and Meyer [72] firstly introduced Supply Function Equilibrium (SFE) for un-

certain demand, different from Cournot and Bertrand competition, SFE demonstrated its advances by giving GENCOs the possibility for competing in the form of supply functions rather than pure prices and pure quantities. Therefore, the SFE not only provides more accurate market price than Cournot model but also provides higher production output than Bertrand. Green and Newbery [73] presented the application of SFE model in the England and Wales pool market with considering of the capacity constraints. Later, this work was extended by adding the forward contracts [74]. Based on the general SFE model, Green [75] proposed the linear SFE model, in which the asymmetric firms behaviors in large-scale systems could be easily captured. Moreover, Rudkevich derived a closed-form solution by adding learning process into the bidding strategies [6], which contributed to the SFE theory. This dissertation will start from a control perspective, formulate the closed-loop control system based on SFE model with learning process, together with the forecasting function, are treated as a controller for GENCOs' daily bidding. More researches can be found in [76, 77, 78, 79, 80, 81, 82].

2.3 PRICE AND LOAD FORECASTING

In the restructured electricity market, the major objective for GENCOs is to maximize their profit in order to survive the fierce competition , especially with the high volatility of the electricity price movements as well as the uncertain demand quantities. Thus the development of different bidding strategies has attracted a large number of attentions for researchers, among which the studies on forecasting the electricity demand and price have become one of the major research fields [83]. So far, the most popular forecasting models includes Artificial Neural Network based Models [84], Data-mining Models [85], Regression or Causal Models [86] and Parsimonious Stochastic Models [83]. Moreover, the researches on adaptive filter [87] has been developed and applied with the previous mentioned models into the electricity price and demand forecasting. This method allow system to self adjust its transfer function according to an optimization algorithm driven by an error signal. By conducting investigation on the time series models as well as the adaptive filtering knowledge,

this dissertation designs an adaptive recursive filter using exponentially weighted Recursive Least Square algorithm [7] based on two ARMA models. Results show that the demand and price are able to be forecast beforehand, which helps GENCOs better adjust their bidding strategy with the forecast data instead of the approached data.

2.4 ELECTRICITY MARKET STRUCTURE

2.4.1 Regulated market structure

Since early 1882, Edison opened the world's first electricity generating station in London, UK [88], the electric power industry started to experience a rapid development. It had been dominated by regulated, investor owned, and vertically integrated utilities [89], as shown in Fig. 2. Within this domain, the generation process, transmission process and distribution process are carried out and guaranteed to the demand customers, the price and the entry regulation are set by a governmental regulatory agency, which also reflects the average cost of the different processes. Moreover, the vertically integrated utility company is the only electricity provider to the demand customers in a given location by holding the franchise [90]. These characteristics make the electric power industry a natural monopoly, which may cause a variety of operation problems such as excessive price, dead weight loss and market inefficiencies [91].

2.4.2 Deregulated market structure

Due to the problems brought by the monopolistic inefficiency, economic consideration of driving the price of electricity supply and the incentive of social welfare maximization, the motivation of building an open environment for electric power industry has been accumulated within different regions and contries [92]. Since the first Energy Policy Acts [2] was launched in 1992, Federal Energy Regulatory Commission (FERC) opened access to the electric transmission grid and economic forces were implemented into the electrical power industry. Moreover, government started to reduce its control and provided the electric power

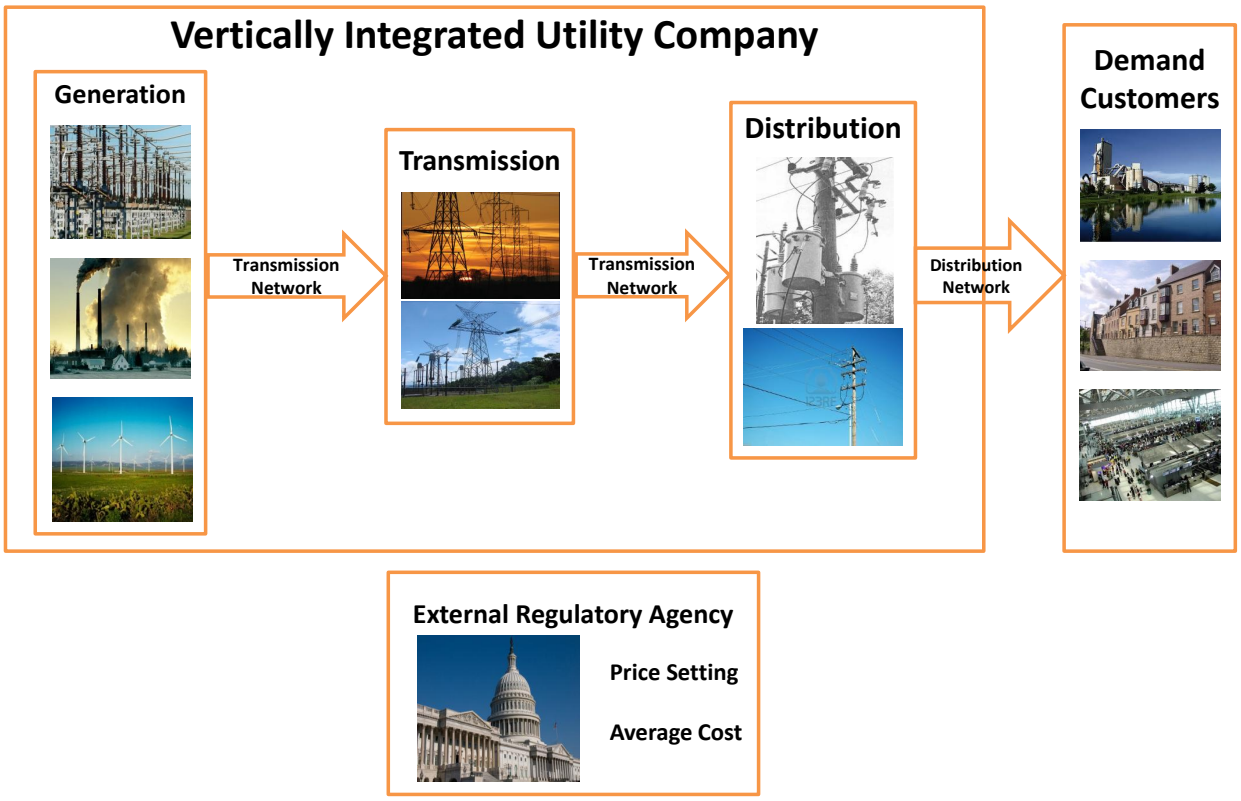

Figure 2: Regulated electricity market structure.

industry greater freedom for its market operation, which led the traditional electricity market structure go through a restructuring process from the natrual monoply to oligopoly. This to some extant has brougt more market efficiency and gave rise to a wide range of different outcomes.

This market restructuring process has caused a vertically integrated utility company separated into three genetic entities: generation companies (GENCOS), transmission companies (TRANCOS), and the distribution companies (DISCOS), together with energy service company (ESCO), energy management company (EMCO), energy brokers, aggregations, marketers and retailers (RETAILCOS), are known as the market participants. The deregulated market structure is illustrated in Fig. 3. Based on the figure, an independent system opera-

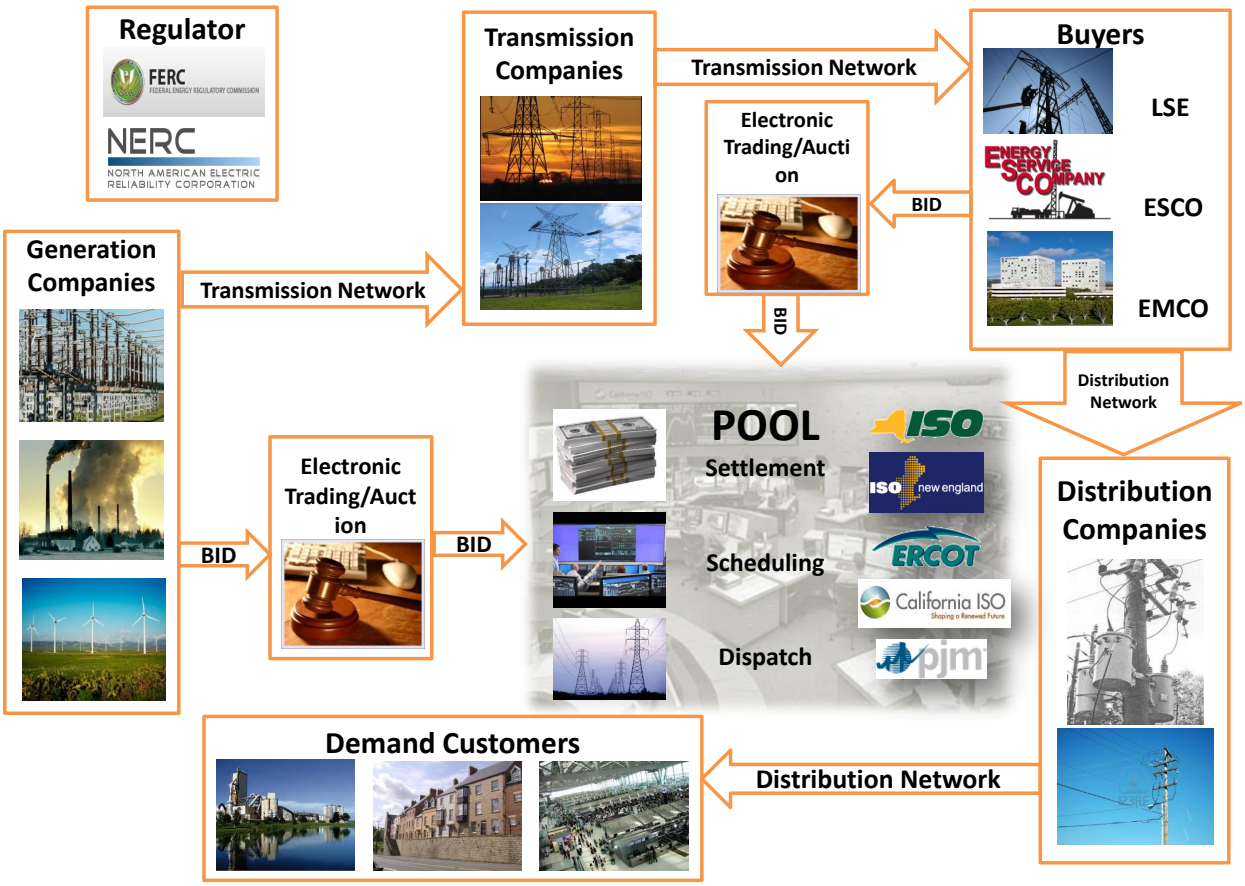

Figure 3: Deregulated electricity market structure.

tor (ISO) or a regional transmission organization (RTO), as a system and market operator, is responsible for operating the electricity market securely and efficiently on a regional basis. Different market participants play different role during the market operation process, GENCOs maintain and operate the generation plants while holding the opportunities to sell electricity through bilateral contracts as well as participating into the electronic trading and auction activities inside the market pool. Buyers such as load serving entities (LSE) , ESCOs, and EMCOs are also given the rights to submit their bids into the market pool. Inside the pool, ISOs will carry out the market clearing, market settling, market scheduling, and economic dispatch according to the bids and offers. In addition, TRANSCOs are in charge of building, operating and maintaining the transmission network in order to ensure the power

delivery under the ISO's schedule [1]. Once the power is delivered to the buyers, DISCOs will distribute the electricity through distribution grids into demand customers according to ISO's economic dispatch and schedule. Therefore, during the operation of the newly established wholesale electricity market, electricity is treated as a commodity which is capable of being bought, sold and traded through bidding and offering. The deregulated electricity market is regulated and ensured by Federal Energy Regulatory Commission (FERC) [93] and North American Electric Reliability Corporation (NERC) [94].

2.5 ELECTRICITY MARKET SETTLEMENT

The wholesale electricity market settlement is a multi-settlement system under FERC's Standard Market Design (SMD) [95]. It includes day-ahead market (forward market) and real-time market (Spot market), each of which has different market schedules and produces different types of financial settlement under the operation and regulation of ISOs [96].

2.5.1 Day-ahead market

Day-ahead market (DAM) occurs one day before the real time market (RTM), during which the generation side and demand side submit their supply offers and demand bids into the power pool for each hour and each relative location of the next operating day. All of the bidding process are in terms of electronic auction. After collecting and matching the aggregate bids and offers for each location, ISOs calculate the day ahead market clearing price and market clearing quantity by finding the intersection of the increment offers curve and decrement bids curve, as illustrated in Fig. 4.

In addition, ISOs which are in charge of different electricity market will perform a security constrained unit commitment (SCUC) and economic dispatch for day-ahead market in order to select the most economic generation and transmission allocation to minimize the total market operation cost. After the market is cleared, ISOs then carry out the market scheduling activities for the market participants, which includes the bilateral transactions, both electric

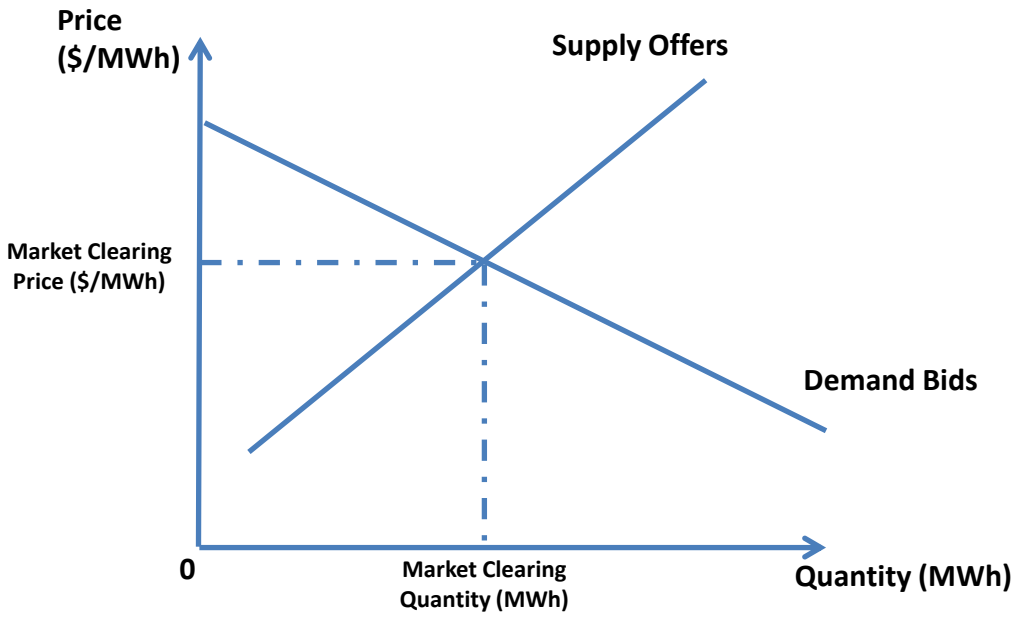

Figure 4: Market clearing.

power quantity purchase and sales, customer commitments and transmission and distribution charges. Moreover, all of the prices and quantities cleared in the day ahead market are financially, not physically [96].

2.5.2 Real-time market

Real-time market (RTM), also named as spot market, occurs on the real operation day. During the real time market settlement, ISOs perform a security Constrained Economic dispatch (SCD) according to the difference between the day-ahead market settlement and the real time operation. The market clearing prices are calculated every five minutes [97]. In real-time market settlement, the schedules that produced by ISOs one day ahead can be largely changed due to unexpected incidents such as generation outages, transmission constraint and unexpected weather change. Therefore, for the purpose of ensuring a stable electricity market operation environment, the generators which are not selected in day-ahead

market are given new opportunities to participate into the real time market by adjusting their bids based on the real time operation conditions. Moreover, market participants are also given the rights to offer or request electricity imports and exports from neighboring areas [96] under the reliability assessment of ISOs.

2.5.3 Electricity market time-line

As shown in Fig. 5, we used ISO-NEW ENGLAND market as an example to describe the market time line. Day-ahead market starts from midnight to 12 AM, inside which the day-ahead supply offers, demand bids are accumulated and settled by ISO. The day-ahead market clearing results are then published 90 minutes after the market is closed. Subsequently, a two hour re-offer period starts from 4:00 PM to 6:00 PM [96], this allows the generators which are not selected in day-ahead market to re-offer their bids into the power pool, demand bids are not qualified for this period. Real-time market starts from midnight and lasts the whole day, during which the electricity generation is dispatched and the market clearing demand and price are calculated every five minutes. ISO is taking the responsibilities of physically balancing and maintaining the market operation.

2.6 ECONOMIC MARKET STRUCTURE

We also took into account the electricity market structure from the perspective of economics, based on which we were able to better analyze the production decisions made by GENCOs corresponding to the market dynamics. We summarized three most common market forms including perfect competition, monopoly and oligopoly [98], shown in Table 1.

In perfectly competitive market, there are a certain amount of firms which are at the same level in terms of sales, all firms are price takers that no one has the market power to affect the market price by changing its sales. The barrier of this market is very low, which allows firms to enter or exit the market easily. Moreover, all of the market information regarding the price, production and cost are known by each market participants. On the

Figure 5: Electricity market timeline.

contrary, in a monopolistic market, there is only one specific firm, who is able to provide all the supply of a certain commodity and to operate the market. The barrier of this market is very high so that there are no substituting commodity in the market [99]. In the middle of the previously mentioned two market structures, the oligopolistic market is dominated by a few large companies instead of a single one, each of whom depends on its major competitors' decisions during the market operation. The market entry is also very high compared to perfectly competitive market. The deregulated electricity market is mostly like an oligopolistic market, inside which the generation companies develop strategic planning and bidding by taking into account others' behaviors.

Table 1: Economic Market Structure

Characteristics	**Market Structure**		
	Perfect Competition	Oligoply	Monopoly
Buyer Number	Many	Many	Many
Seller Number	Many	Few	One
Buyer Entry Barriers	No	No	No
Seller Entry Barriers	No	Yes	Yes
Pricing	Price Taker	Price Maker	Price Maker
Economic efficiency	High	Low	Low
Innovative behaviour	Weak	Very Strong	Potentially Strong

3.0 ELECTRICITY MARKET MODEL STRUCTURE DESIGN

3.1 CLOSED-LOOP CONTROL SYSTEM STRUCTURE DESIGN

Based on the perspective of the power generation side (GENCOs) and ISO power pool, we proposed a closed-loop control system model, illustrated in Fig. 6. This model provides a platform to facilitate mathematical analysis and to promote operational efficiency of the dynamic bidding process. The purpose is to achieve a rational profit maximizing behavior for GENCOS during the day-ahead bidding process and to improve the wholesale market efficiency.

The control-theoretic model uses the game theory embedded with the learning ability as the basic bidding strategy, which allows GENCOs to adjust their next-day bidding in the form of supply function equilibrium (SFE) through market observations of the historical data. The analysis shows that it is unnecessary for GENCO to know the generation costs and commitments of other competitors.

Recursive least square (RLS) method based on two ARMA models is introduced for demand and price forecasting so that GENCO are able to capture the market process beforehand, and make its next bidding decision accordingly. This method is implemented into the bidding strategy of supply function equilibrium with learning process in order to further maximize the GENCO's profit.

Based on the fact that the electricity price is extremely volatile compared to prices in other commodity markets [100], the risk inside the electricity market are inevitable. Therefore, the problems of risk management which includes asset valuation and risk analysis are also embedded inside the control system for helping the profit maximization. Moreover, this control model introduces an structure of providing bidding strategies for GENCOs when

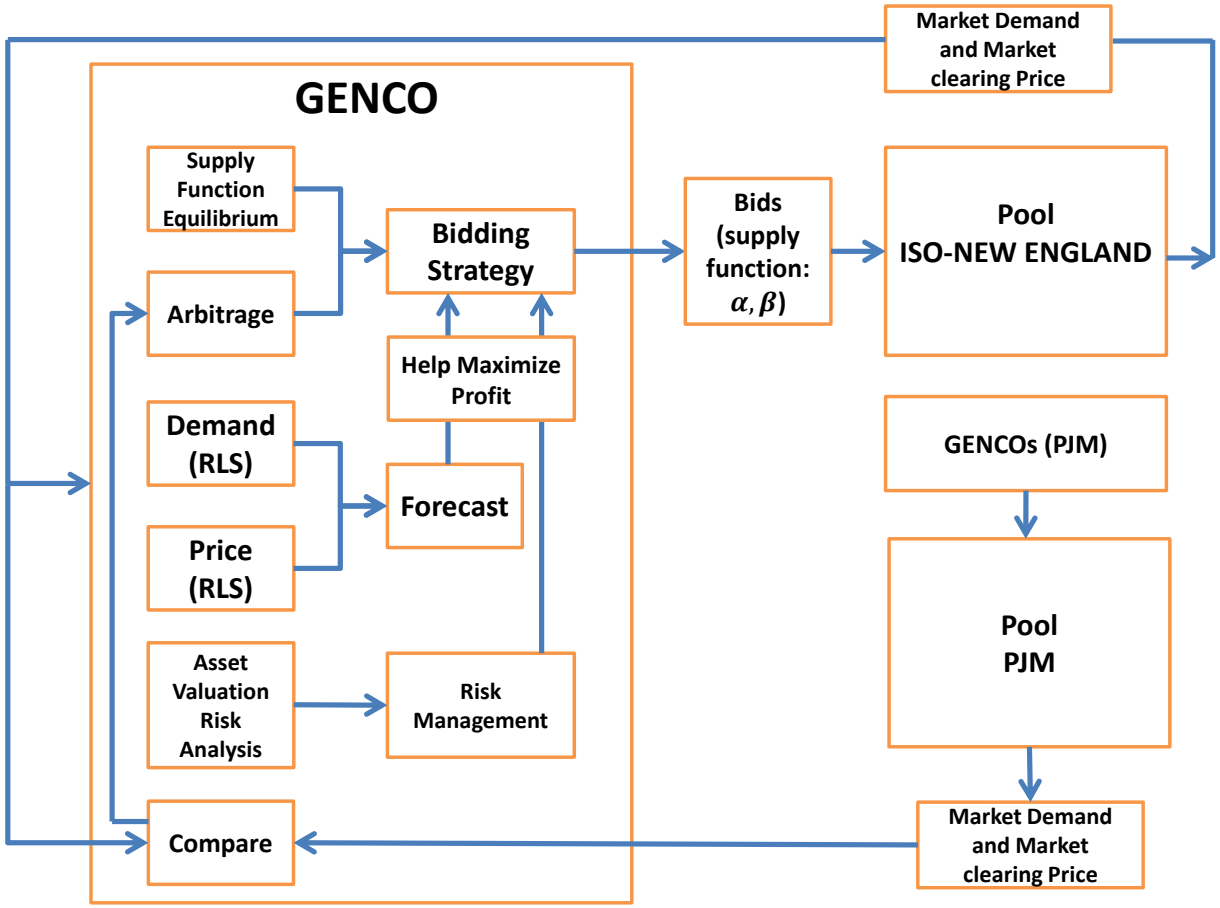

Figure 6: Closed-loop control system model for bidding process.

facing price difference in different electricity markets such as PJM and ISO-NEW ENGLAND as well as different time periods. The dissertation obtains real market data from PJM [101] and ISO-NEW ENGLAND [102] website and presents simulation results based on the closed-loop control system model.

3.2 DYNAMIC BIDDING PROCESS USING SUPPLY FUNCTION EQUILIBRIUM MODEL

3.2.1 Nash equilibrium

This section introduces the notation and definition of Nash Equilibrium which are considered as the major concepts throughout the study. The key for solving the game problem for GENCOs are to find the Nash Equilibrium [54], which is a set of strategies if no competitors can achieve more profit by unilaterally changing their strategies. Let G be a game with n players, all optional set of strategies of each player is called strategy space, denoted by $St_1, St_2..., St_n$; $s_{ij} \in St_j$ represents the jth strategy of the ith player; u_i describes the profit of the ith player. The game G of n players can be given as:

$$G = \{St_1, St_2..., St_n; u_1, u_2..., u_n\}. \tag{3.1}$$

Inside this game, if any player i has a strategy Si^* that no unilateral deviation in strategy by any single player is profitable for that player, then the strategy space $S_1^*, S_2^*...S_n^*$ is a nash equilibrium of game G.

3.2.2 Electricity market assumption

Based on the needs of building up the dynamic bidding process model, this dissertation has made some assumptions by considering the day-ahead bidding operation of n generation firms. Let q_i be the production quantity and C_i be the production cost of each firm, it is characterized by a quadratic function:

$$C_i(q_i) = \frac{1}{2}c_i q_i^2 + a_i q_i \tag{3.2}$$

where $C_i(q_i)$ is the total cost for firm i producing power at quantity q. Based on the cost funtion, the marginal cost function is equal to:

$$C_i'(q_i) = c_i q_i + a_i \tag{3.3}$$

which is linear monotonically increasing and is a function of its outputs. $S_i(p)$ is considered as the supply function of firm i and is represented as:

$$\begin{aligned} S_i(p) &= \beta_i p_i + \alpha_i \\ &= q_i \end{aligned} \tag{3.4}$$

where β and α are slope and intercept of the supply function individually. The supply function is the form of bidding strategy that each GENCO submits into the electricity market pool. It is monotonically increasing and a function of the market clearing price which implies the quantity that GENCO intends to sell at price p [6]. Therefore, selecting the optimal sets of β and α with different prices as variables are the objective of the GENCOs' bidding strategy.

$D(t, p)$ represents the total electricity system demand at time t and price p, it linearly depends on price and is updated hourly, denoted as:

$$D(t, p) = N - \theta p(t) \tag{3.5}$$

where N is the intercept of the demand function, θ is the slope and can also reflect demand price elasticity.

3.2.3 Supply function equilibrium model

Supply Function Equilibrium was firstly introduced by Klemperer and Meyer [72], then Green and Newbery [73] presented the application of SFE model in the England and Wales pool market. In supply function equilibrium, the decision makings of each GENCO are in terms of supply function, which reflects the relationship between price and quantity. In market operation, this represents the competition strategy. Due to the fact that the market demand is uncertain, SFE is able to describe the decision making according to different demand level more realistically.

In day-ahead market, after collecting the demand bids and supply offers, ISO will develop optimal dispatch and clear the market, as illustrated in Fig. 4. At time t, the market clearing condition (market equilibrium condition) can be represented as:

$$\sum_{i=1}^{n} S_i(t,p) \quad = \quad D(t,p). \tag{3.6}$$

Based on the market clearing condition, the aggregate supply function of GENCO's competitors is described as:

$$\sum_{j=1,j\neq i}^{n} S_j(t,p) \quad = \quad D(t,p) - S_i(t,p). \tag{3.7}$$

Conversely, the single GENCO's residual demand can be expressed as:

$$R_i(t,p) \quad = \quad D(t,p) - \sum_{j=1,j\neq i}^{n} S_j(t,p). \tag{3.8}$$

Let $\pi(t)$ denote the market net profit of firm i at time t, which can be expressed as:

$$\pi(t) \quad = \quad q_i(t)p(t) - C_i(q_i). \tag{3.9}$$

Each GENCO's objective is to maximize their market net profit, by substituting (3.7) into (3.9), it is given by following expression:

$$\begin{aligned} \max\ \pi(t) &= \max\left\{q_i(t)p(t) - C_i(q_i)\right\} \\ &= \max\left\{p(t)[D(t,p) - \sum_{j=1,j\neq i}^{n} S_j(t,p)] - C_i[D(t,p) - \sum_{j=1,j\neq i}^{n} S_j(t,p)]\right\} \end{aligned} \tag{3.10}$$

The first order condition for maximizing the profit is written as following:

$$\begin{aligned} \frac{d\pi_i(t)}{dp(t)} &= D(t,p) - \sum_{j=1,j\neq i}^{n} S_j(t,p) \\ &+ \left\{p - C_i'[D(t,p) - \sum_{j=1,j\neq i}^{n} S_j(t,p)]\right\}[D'(t,p) - \sum_{j=1,j\neq i}^{n} S_j'(t,p)]\ . \end{aligned} \tag{3.11}$$

In oligopolistic market, from the perspective of GENCOs, when marginal revenue is larger than its marginal cost, the total profit will be increasing, when marginal revenue is less than its marginal cost, the total profit will be decreasing, between these two conditions,

the profit reaches to a maximum point when marginal revenue equals marginal cost, which indicates that the marginal profit at time t is zero [103], described as following:

$$\frac{d\pi_i(t)}{dp(t)} = 0. \tag{3.12}$$

Substituing (3.12) into (3.11), the supply function equilibrium condition is solved as following:

$$S_i(t,p) = [p - C_i'(q_i)][\sum_{j=1,j\neq i}^{n} S_j'(t,p) - D'(t,p)] \tag{3.13}$$

toghter with (3.7), of which the solutions would represent a nash equilibrium in the market operation. (3.13) could also be rewritten in terms of aggregate supply:

$$\sum_{j=1,j\neq i}^{n} S_j'(t,p) = \frac{S_i(t,p)}{p - C_i'(q_i)} + D'(p). \tag{3.14}$$

Substituting (3.3), (3.4) and (3.5) into (3.13):

$$\beta_i(p - \alpha_i) = (p - c_i\beta_i(p - \alpha_i) - a_i)(\theta + \sum_{j=1,j\neq i}^{n} \beta_j) \tag{3.15}$$

where the coefficient of p and the constant on both sides of the equation should be equal, based on this and after some rearrangement, the optimal slope and intercept of the supply function are derived as:

$$\beta_i^* = \frac{\theta + \sum_{j=1,j\neq i}^{n} \beta_j}{1 + c_i(\theta + \sum_{j=1,j\neq i}^{n} \beta_j)} \tag{3.16}$$

$$\alpha_i^* = 1 - c_i\beta_i \tag{3.17}$$

where β_i^* of firm i depends on the slope of demand function, aggregate slope of other competitors and its marginal cost. Once β_i^* is known, α_i^* can be solved through (3.17). These two values formulate the optimal bidding supply function. Therefore, the process for GENCOs to find the optimal bidding strategy is to find an optimal set of β_i^* and α_i^* so that it satisfies the supply function equilibrium, based on which the profit will be maximized and no single player can increase profit by unilaterally changing its bidding supply function [75].

3.3 DYNAMIC SUPPLY FUNCTION EQUILIBRIUM ADJUSTING PROCESS

In order to apply SFE into the dynamic bidding process and to correspond with the closed-loop control dynamic model, this dissertation formulates a learning and adjusting process for GENCO. It starts at 12PM, the time that ISO clears the day-ahead market and publishes the market data, repeats over time so that the following bids are submitted. The whole process is illustrated in Fig. 7.

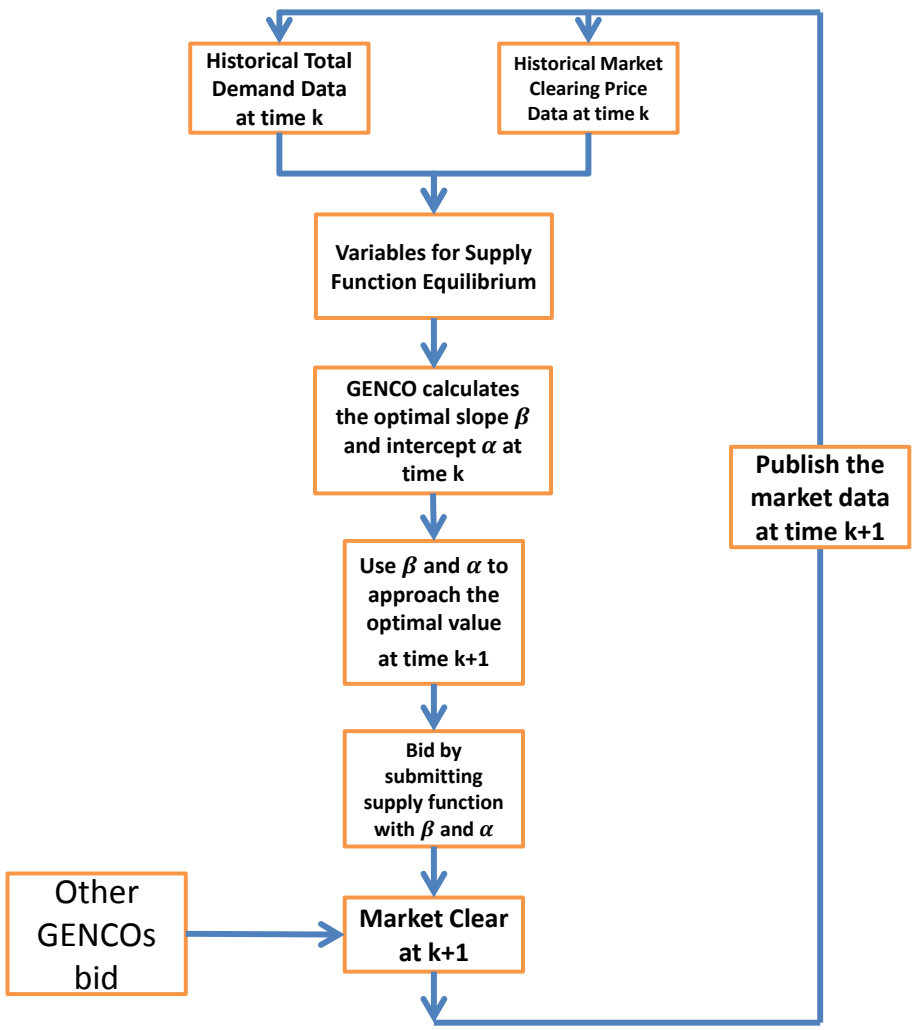

Figure 7: Dynamic SFE adjusting bidding process.

At the starting point, each GENCO obtains the hourly market clearing demand data and the hourly market clearing price data from day-ahead market publishing. Subsequently, GENCO collects the information including the market equilibrium condition, the market data and its previous supply function which has already been submitted into the day-ahead market. With all the variables, GENCO develops the analysis by calculating its competitors' aggregate supply functions using (3.7) and calculate the optimal supply function which satisfies (3.14), the market equilibrium condition of the previous day-ahead market. Subsequently, GENCO uses this newly calculated supply function including the optimal β_i^* and α_i^* as the next bidding data set and consider it the optimal bid for the next bidding day. When the next day-ahead market is cleared, the GENCO will obtain new market data for new analysis, then the whole process is repeated again. The mathematical procedure expression is described below.

From 0 AM to 12 PM of the first operating day k, all GENCOs submit bids into day-ahead market:

$$S_i(k,p) = \beta_i(k)p + \alpha_i(k) \tag{3.18}$$

which is supposed to be the optimal supply function of the day $k-1$. In order to simplify the calculation, this dissertation assumes that $\alpha_i(k) = 0$. After the market is cleared, the day-ahead market clearing price $p(k)$ and demand $D(k)$ are published, the aggregate supply function of the competitors and the aggregate slope of all GENCOs can be given as:

$$\sum_{j=1, j\neq i}^{n} S_j(k,p) = D(k,p(k)) - S_i(k,p(k)) \tag{3.19}$$

$$\begin{aligned} B(k) &= \sum_{i=1}^{n} \beta_i(k). \\ &= \frac{D(k,p(k))}{p(k)} \end{aligned} \tag{3.20}$$

The aggregate slopes of the competitors can be described as:

$$\sum_{j=1, j\neq i}^{n} \beta_j(k) = B(k) - \beta_i(k). \tag{3.21}$$

At time $k+1$, GENCO continues to form the new optimal supply function by approaching from the condition of supply function equilibrium of time k. Substituting (3.21) into (3.14) and after some rearrangement, the equation describing the relationship between the two biddings is given:

$$\sum_{j=1,j\neq i}^{n} \beta_j(k) = \frac{\hat{S}_i(k+1,\hat{p}(k+1))}{p(k) - c_i\hat{S}_i(k+1,\hat{p}(k+1))} - \theta \tag{3.22}$$

The slope can be solved as:

$$\hat{\beta}_i(k+1) = \frac{\sum_{j=1,j\neq i}^{n} \beta_j(k) + \theta}{1 + c_i[\sum_{j=1,j\neq i}^{n} \beta_j(k) + \theta]} \tag{3.23}$$

and the intercept is described as:

$$\hat{\alpha}_i(k+1) = 1 - c_i\hat{\beta}_i(k+1) \tag{3.24}$$

where $\hat{\beta}_i(k+1)$ and $\hat{\alpha}_i(k+1)$ formulate the supply function equilibrium for time k, and are used to approach the real supply function equilibrium for time $k+1$. When the necessary data for calculating the SFE of time $k+1$ are published, the whole bidding process will be repeated. The supply quantity and net profit of GENCO at time $k+1$ can be calculated as:

$$\hat{S}_i(k+1) = \hat{\beta}_i(k+1)\hat{p}(k+1) + \hat{\alpha}_i(k+1) \tag{3.25}$$

$$\hat{\pi}(k+1)) = q_i(k+1)\hat{p}(k+1) - C_i(k+1). \tag{3.26}$$

This dynamic SFE adjusting process is embedded in the closed-loop model as the basic bidding strategy in order to catch the market participants' behaviors. More algorithms will be introduced in the following chapters.

4.0 ELECTRICITY MARKET DEMAND AND PRICE PREDICTION ALGORITHMS

4.1 DYNAMIC BIDDING PROCESS BASED ON ADAPTIVE CONTROL SYSTEM

4.1.1 Short-term price and load forecasting

In the restructured electricity market, the major objective for GENCOs is to maximize their net profits in order to survive the fierce competition , especially under the high volatility of the electricity price movements as well as the uncertain demand quantities. Although the previously mentioned dynamic supply function equilibrium adjusting process can well describe the dynamic process of the electricity market bidding activities, it uses an certain limitations of using optimal supply function of the previous bidding step to approach the optimal strategy of the next time step, which does not satisfy the real situation. Therefore, this study designed an adaptive control system using exponentially weighted Recursive Least Square algorithm [7] based on two ARMA models. Results show that the demand and price are able to be forecast beforehand, which helps GENCOs better adjust their bidding strategy according to the forecast data instead of the approached data.

4.1.2 Recursive lest squares adaptive filter

Adaptive filter has been considered as an appropriate tool for predicting non stable signals. During the prediction process, the coefficients of the filter need to update over time in order to follow the non-stationarity of the signal. The most common approach for adaptive filter includes the Kalman filter, the least mean squares (LMS) filter and the recursive least squares

(RLS) filter. This study focuses on introducing and implementing the RLS filter in order to predict the electricity market clearing price and demand over time so that the GENCOs are able to adjust the bidding strategies beforehand [8].

The idea of RLS algorithm is defined in Fig. 8, $\hat{D}(t)$ and $\hat{P}(t)$ represent the predicted demand and price value, $\bar{\mathbf{X}}(t)$ and $\bar{\mathbf{Y}}(t)$ are the vectors that containing p historical demand and p price data individually:

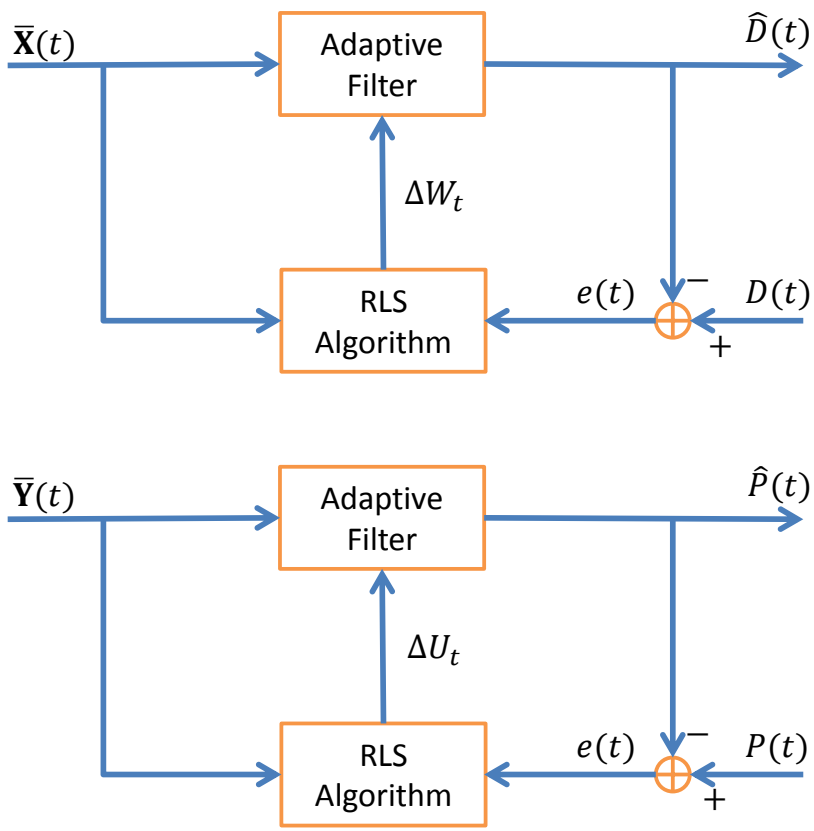

Figure 8: RLS prediction process.

$$\bar{\mathbf{X}}(t) = [D(t-1), ..., D(t-p)]^{\mathrm{T}} \tag{4.1}$$

$$\bar{\mathbf{Y}}(t) = [P(t-1), ..., P(t-p)]^{\mathrm{T}}. \tag{4.2}$$

The relation between the historical data and the predicted data can be formulated as following:

$$\begin{aligned} \hat{D}(t) &= \sum_{k=1}^{p} W_t(k) D(t-k) \\ &= \mathbf{W_t}^{\mathrm{T}} \ \bar{\mathbf{X}}(t) \end{aligned} \tag{4.3}$$

$$\hat{P}(t) = \sum_{k=1}^{p} U_t(k) P(t-k) \tag{4.4}$$

$$= \mathbf{U_t}^{\mathrm{T}} \ \bar{\mathbf{Y}}(t) \tag{4.5}$$

where p denotes the order of the filter, $\mathbf{W_t}$ and $\mathbf{U_t}$ are the vectors with the coefficients of the filter, which are given below:

$$\mathbf{W_t} = [W_t(1), ..., W_t(p)]^{\mathrm{T}} \tag{4.6}$$

$$\mathbf{U_t} = [U_t(1), ..., U_t(p)]^{\mathrm{T}}. \tag{4.7}$$

According to Fig. 8, at each time step t, the predicted value is compared with the real value, the two error functions are defined as:

$$\begin{aligned} e_1(t) &= D(t) - \hat{D}(t) \\ &= D(t) - \mathbf{W_t}^{\mathrm{T}} \ \bar{\mathbf{X}}(t) \end{aligned} \tag{4.8}$$

$$\begin{aligned} e_2(t) &= P(t) - \hat{P}(t) \\ &= P(t) - \mathbf{U_t}^{\mathrm{T}} \ \bar{\mathbf{Y}}(t). \end{aligned} \tag{4.9}$$

The errors are then injected into the RLS in order to update the coefficients so that the coefficients of the adaptive filter can minimize the weighed least square error cost function [7], which is formulated as:

$$\varepsilon = \sum_{k=1}^{t} \lambda^{t-k} e(k)^2 \tag{4.10}$$

where λ is the weighting (forgetting) factor, such that the recent samples become more relevant in the minimization. Once the new set of optimal coefficients are updated, it will be used to calculate the newly predicted data through (4.3) and (4.5). The whole mathematical derivation can be found in [7], taking demand prediction as an example, the RLS algorithm is summarized as follows:

$$
\begin{aligned}
Parameters: \; p &= Filter\ order \\
\lambda &= Exponential\ weighting\ factor \\
\delta &= Value\ used\ to\ initialize\ \mathbf{P}(0)
\end{aligned}
$$

$$
\begin{aligned}
Initialization: \; \mathbf{W}(0) &= \mathbf{0} \\
\mathbf{P}(0) &= \delta^{-1}\mathbf{I} \\
Computation: \; For\ t &= 1, 2, ..., \ compute \\
\mathbf{g}(t) &= \frac{1}{\lambda + \mathbf{x}^T(t)}\mathbf{z}(t) \qquad (4.11) \\
\alpha(t) &= d(n) - \mathbf{W}_{t-1}^T \bar{\mathbf{X}}(t+1) \\
\mathbf{W}_t &= \mathbf{W}_{t-1} + \alpha(t)\mathbf{g}(t) \\
\mathbf{P}(t) &= \frac{1}{\lambda}[\mathbf{P}(t-1) - \mathbf{g}(t)\mathbf{z}^H(t)]
\end{aligned}
$$

$$
\bar{\mathbf{X}}(t) = \begin{bmatrix} D(t-1) \\ D(t-2) \\ \vdots \\ D(t-p) \end{bmatrix}
$$

where $\mathbf{P}(t)$ denotes the inverse of a $(p+1) \times (p+1)$ exponentially weighted deterministic autocorrelation matrix, $\mathbf{g}(t)$ is the gain vector, $\mathbf{W}(t)$ represents the coefficients, $\alpha(t)$ is the difference between the desired value and the estimated value that is formed by applying the previous set of filter coefficients, $\mathbf{W}(t-1)$, to the new data vetor $\bar{\mathbf{X}}(t)$. By setting the order of the filter at 4, the linear predictors are given:

$$\hat{D}(t) = W_t(1)D(t-1) + W_t(2)D(t-2) + W_t(3)D(t-3) + W_t(4)D(t-4) \quad (4.12)$$

$$\hat{P}(t) = U_t(1)P(t-1) + U_t(2)P(t-2) + U_t(3)P(t-3) + U_t(4)P(t-4) \quad (4.13)$$

where the coefficients including $W_t(1)$, $W_t(2)$, $W_t(3)$, $W_t(4)$, $U_t(1)$, $U_t(2)$, $U_t(3)$ and $U_t(4)$ are obtained and updated over time according to RLS algorithm. Once the data and coefficients are trained with the adaptive RLS algorithm, they will be used to predict the next new data. Therefore, the predicted demand and price at the specific time points can be approximated by using the historical data.

4.1.3 Adaptive control system

With the application of RLS methods, the electricity demand and price are able to be captured beforehand, thus GENCOs are able to adjust their bidding strategy by calculating the supply function equilibrium and generate the more optimal α and β with the forecast data which are much closer to the real market data.

Taking the bidding strategy and forecasting part of the previously mentioned closed-loop control system (Fig. 6), this study also designed a control model for dynamic bidding process, inside which we formulate the recursive least squares adaptive filter and supply function equilibrium bidding strategy as an adaptive controller during electricity market operation, illustrated in Fig. 9.

Firstly, this adaptive control system uses the previous four sets of historical demand and price data as the input ($\bar{\mathbf{X}}(t)$ and $\bar{\mathbf{Y}}(t)$) of the controller, inside which the historical data go

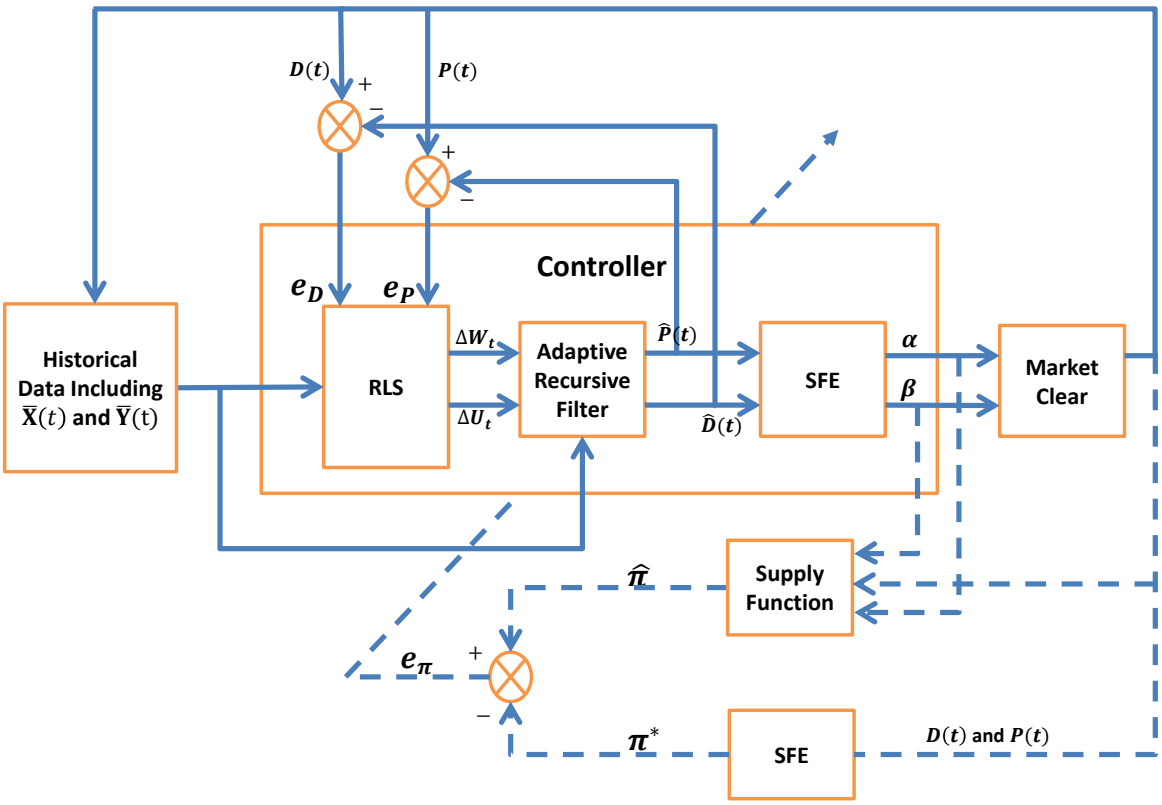

Figure 9: Bidding strategy using adaptive control system model.

through the adaptive filtering process in order to estimate the data of future demand and price ($\hat{D}(t)$ and $\hat{P}(t)$). Once the new sets of data are predicted, they are then compared with the real data ($D(t)$ and $P(t)$) which are published by ISO after market clears, the errors (e_D and e_P) are injected into the RLS in order to update the coefficients so that the coefficients of the adaptive filter can minimize the weighed least square error cost function.

Secondly, the newly predicted value are applied into the SFE bidding process as a replacement of the previously used approaching data. In addition, these predicted data are treated as the variables for calculating the optimal supply function that satisfies the equilibrium condition. The results, treated as the outputs of the controller, are in terms of slope

and intercept (α and β). GENCO will then use these outputs as the bidding data for participation of the electronic auction during day-ahead market operation. After all the bidding data are collected, ISO will start the market settlement procedure.

Thirdly, after the market is cleared, the real data of demand and market clearing price ($D(t)$ and $P(t)$) are published by ISOs. For the purpose of test the adaptive control system bidding algorithm, we inject the real data into SFE calculation again to derive the optimal profit at market equilibrium. This profit is the ideal profit for GENCO based on the calculation with real data, it is then compared with the profit which is derived from the predicted demand and price, the error will be used for adjusting the controller to such changing conditions. Moreover, the real market data also go back to RLS for the comparison with the predicted data, which update the adaptive filter coefficients for the next time step.

This adaptive control system applied control theory, game theory and signal processing idea into the dynamic bidding process. It establishes a self adjusting bidding structure for GENCOs to perform deeper analysis of the dynamic electricity market. In order to test the adaptive bidding results, we used market clearing demand and price data to perform the simulation.

4.2 ADAPTIVE MULTIRESOLUTION PREDICTION USING ARMA MODELS

4.2.1 Introduction

In previous sections, we have introduced an adaptive control system and used it as a platform for simulating the dynamic bidding process. Compared to supply function equilibrium bidding strategy, the adaptive control system is able to perform a prediction of electricity demand and price in order to give GENCOs an opportunity to make bidding adjustments promptly while facing sudden changes. However, the data we used for simulation based on previous methods are relatively short, which has a negative effect on the accurate prediction. In addition, the original whole data on an hourly basis are simplified as the daily

average data, the relationship between electricity price and demand was also ignored during the prediction progress, which was reflected by using AR models instead of ARMA models. These are all considered as the drawbacks of the adaptive control system, which may cause inaccurate prediction results and decrease the GENCOs net profits.

On the other side, based on the electricity market rule and real time operating situation, all of the market participants are not able to obtain the day-ahead market clearing data until ISOs release through its website by the end of the day. This makes the demand and price prediction activity conducted one day ahead and each prediction data set are composed of 24 hourly values corresponding to the real values generated on operating day.

Given these concerns, it is desirable now to improve our prediction methods in order to provide more accurate and more reasonable prediction of the electricity market varieties. Our objective is, once again, to further increase GENCO's profit during the electricity market operation through capturing the market movement in advance. Based on this, we introduced multiscale techniques and applied into recursive least square prediction process. In addition, we improved the ARMA models by adding the external inputs to better describe the internal dynamics of the electricity markets.

4.2.2 Multiresolution algorithm

In previous section, we used single resolution-based RLS prediction method, in which the original daily average signal is employed as the only scale for the entire training period. When facing complicated original data series that may include a large amount of uncertainties, such algorithm is not able to transform the original data into simpler components, this may limit the training effect and the applications of the recursive least square prediction method to a large extent. Moreover, the single resolution- based RLS prediction is a relative flat training process which may not be able to offer good scalability to electricity market movements [104]. Moreover, the electricity market operating rules does not allow the market participants to obtain the real market data until ISOs publishment by the end of each day, which increased the difficiculties of data collecting and processing.

Such limitations restrict the application of adaptive RLS prediction method for dynamic bidding process. Therefore, in order to maximize the superiority of the adaptive control system, we replaced the single resolution-based prediction algorithm with multiresolution technique and used it as a framework for the application of RLS methods and game theory. The basic idea of multiresolution analysis (MRA) approach is to decompose a given time series and to illustrate time dependence at multiple scales [105].

Compared to previous method, MRA establishes a systematic structure to hierarchically decompose the original demand and price data into subtasks with different time frame, within which the decomposed data are able to be trained easily. MRA is able to provide a more advanced platform for the adaptive filter, which helps to find more optimal weights for the historical electricity market data from each representation at corresponding resolution level. Moreover, different scale based on different time frame can be used to represent different dynamics and correlation structures in order to perform a deep analysis of the overall system dynamics.

In this chapter, we obtained two new sets of electricity demand and price data from PJM for our analysis, each data set lasts for a whole year and is on an hourly basis. Due to the characteristics of the electricity market, the data sets are both lengthy and largely unstable, which increased the difficulty of prediction. Therefore, by taking time frame as a reference, we applied the multiresolution analysis by decomposing the original demand and price data into different scales. Firstly, we calculated the daily average value of demand and price, as we have done in previous sections. Secondly, we calculated the residual value, which is the difference between the original data points on an hourly basis and the average value for the entire day. As a result, each of the original demand and price data set are split into two new sets, which are then implemented into RLS prediction method to generate new prediction results for different time frames. The data processing procedure is shown in Fig. 10.

From this figure, we are able to observe that once the prediction results are generated from the decomposed data using RLS prediction method, they will be integrated together to generate the final prediction results. In addition, the time frame from the subtasks are also transformed back to the original time frame. The prediction results are then compared with the original data in order to test the accuracy of the data prediction.

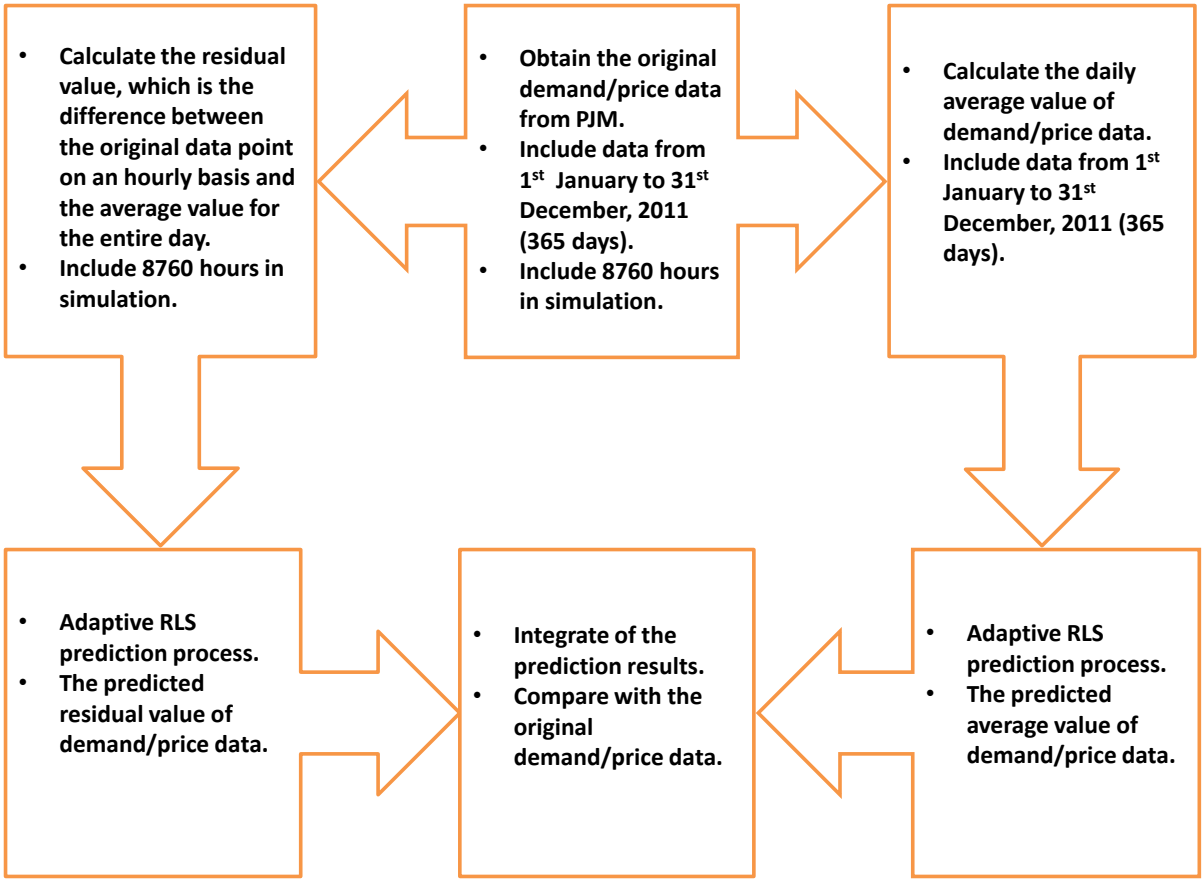

Figure 10: Multiresolution prediction data flow.

4.2.3 Multiresolution prediction structure

Starting from Fig. 8, we improved the prediction structure by applying the multiresolution prediction algorithm as well as the ARMA models with external inputs. The whole adaptive multiresolution prediction structure can been represented in Fig. 11.

The original sets of demand and price data are illustrated in equation (4.14) and (4.15), both of which represent the PJM market trend of year 2011 and are updated hourly. As shown in the figure, we decomposed the original data of price and demand into different scales according to different time frame, illustrated in equation (4.16), (4.17), (4.18), (4.19).

Therefore, we generated four sets of data from the original price and demand time series data. $\bar{\mathbf{D}}_{ave}(d)$ and $\bar{\mathbf{P}}_{ave}(d)$ represent the daily average value of market clearing demand and market clearing price while $\bar{\mathbf{D}}_{res}(h)$ and $\bar{\mathbf{P}}_{res}(h)$ denote the residual value between the original data value and the daily average value.

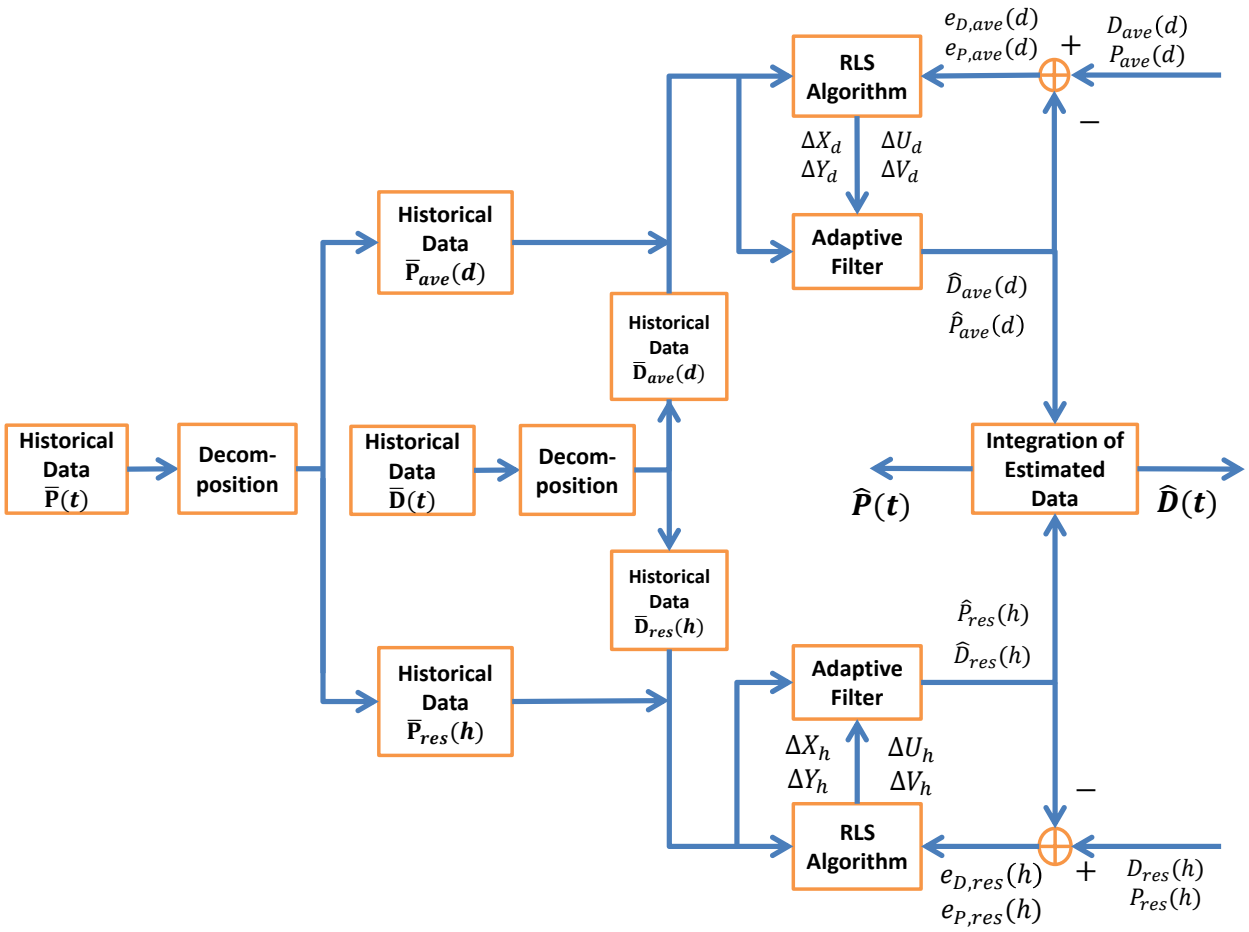

Figure 11: Multiresolution prediction structure.

$$\bar{\mathbf{D}}(t) = [D(1), D(2)..., D(8760)]^{\mathrm{T}} \tag{4.14}$$

$$\bar{\mathbf{P}}(t) = [P(1), P(2)..., P(8760)]^{\mathrm{T}} \tag{4.15}$$

$$\bar{\mathbf{D}}_{ave}(d) = [D_{ave}(1), D_{ave}(2)..., D_{ave}(365)]^{\mathrm{T}} \tag{4.16}$$

$$\begin{aligned}\bar{\mathbf{D}}_{res}(h) &= [D(1) - D_{ave}(1), ...D(24) - D_{ave}(1), ... \\ &... \quad D(25) - D_{ave}(2), ...D(48) - D_{ave}(2), ... \\ &... \quad D(8737) - D_{ave}(365), ...D(8760) - D_{ave}(365)]^{\mathrm{T}}\end{aligned} \tag{4.17}$$

$$\bar{\mathbf{P}}_{ave}(d) = [P_{ave}(1), P_{ave}(2)..., P_{ave}(365)]^{\mathrm{T}} \tag{4.18}$$

$$\begin{aligned}\bar{\mathbf{P}}_{res}(h) &= [P(1) - P_{ave}(1), ...P(24) - P_{ave}(1), ... \\ &... \quad P(25) - P_{ave}(2), ...P(48) - P_{ave}(2), ... \\ &... \quad P(8737) - P_{ave}(365), ...P(8760) - P_{ave}(365)]^{\mathrm{T}}.\end{aligned} \tag{4.19}$$

In real situation, flowing with the electricity market movements, the trend of market clearing price and demand always influence each other and the relationship between these two variables can not be ignored. Therefore, as illustrated in Fig. 11, we improved the ARMA models by adding the external inputs. The ARMA model used for predicting the daily average demand value is given an external input of daily price value $\bar{\mathbf{P}}_{ave}(d)$ while the ARMA model for predicting the residual demand value is given an external input of residual price value $\bar{\mathbf{P}}_{res}(h)$. On the same way, The ARMA model used for predicting the daily average price value is given an external input of daily demand value $\bar{\mathbf{D}}_{ave}(d)$ while the ARMA model for predicting the residual price value is given an external input of residual demand value $\bar{\mathbf{D}}_{res}(h)$.

For the daily average value prediction, the decomposed two sets of daily average demand and price data are trained in order to provide an approximation of the future daily average value, these prediction results holds the general trend of the original signal. As inside the filter, the predicted daily average value of demand or price is then compared with the original value to generate the error signal $e_{D,ave}(d)$ or $e_{P,ave}(d)$, which is then applied into the recursive least square algorithm to update the coefficient sets of the ARMA models. $\hat{D}_{ave}(d)$ and $\hat{P}_{ave}(d)$ are used to represent prediction results of the demand and price daily average value respectively.

Another prediction scale includes decomposed residual values of demand set $\bar{\mathbf{D}}_{res}(h)$ and price set $\bar{\mathbf{P}}_{res}(h)$, representing the difference between the original demand or price data

for each hour and the daily average demand or price data on the entire day. This part is considered as the high-frequency components of the original signal, which are also applied into the adaptive filter as historical values to generate the future predicted residual values $\hat{D}_{ave}(d)$ and $\hat{P}_{ave}(d)$.

Once $\hat{D}_{ave}(d)$, $\hat{P}_{ave}(d)$, $\hat{D}_{res}(h)$ and $\hat{D}_{res}(h)$ are generated, these sets of data will go through the integration process in order to formulate the predicted signal $\hat{D}(t)$ and $\hat{P}(t)$. Subsequently the final predicted results are the data for GENCOs to calculate the bidding terms inside the adaptive control systems.

4.2.4 Daily average value of market clearing demand and price prediction

In this section, we will mathematically discuss the daily average value prediction process. As shown in Fig. 12, we calculated the daily average value of demand and price ranging from day 1 to day 365 as the original comparing data, then we chose the calculated results from day 1 to day 14 as the historical data for training and comparing activities.

When ISO publishes the market clearing demand and price data corresponding to 24 hours by the end of day 14, GENCOs are able to calculate the daily average values of each variable from day 1 to day 14 and used these two sets of data as historical data for the ARMA models. Subsequently, starting from day 15, which is considered as the first predicting day, the historical values go through the adaptive filter in order to generate the prediction results for the very day. After that, the real value of market clearing demand and price are published by ISO again by the end of day 15. The newly published demand and price data values are then used for calculating the daily average values of day 15. Then we continue to use this newly calculated daily average demand and price data as historical value for the prediction of day 16. The old historical values on day 1 are then abandoned to keep the filter order as 14. The whole procedure is then repeated until the daily average values of day 365 are predicted. In this work, we used ARMA model with external inputs to describe the relationship between the predicted data and historical data, which is shown in following equations:

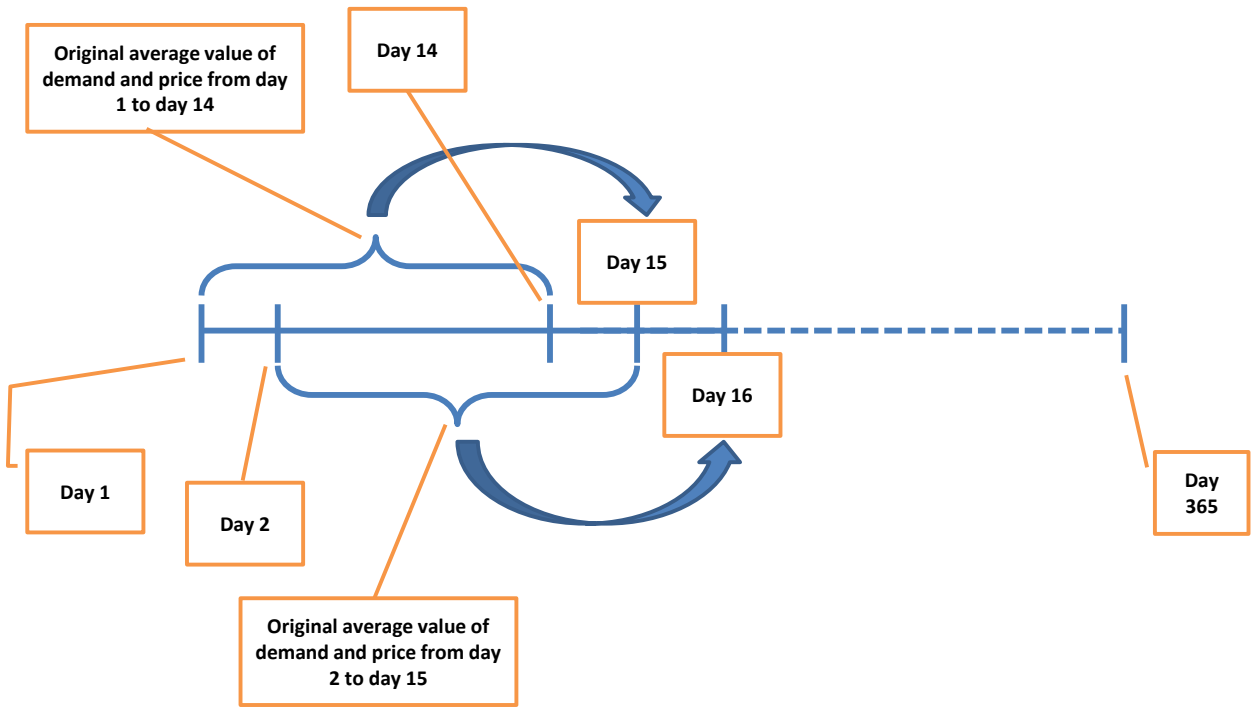

Figure 12: Daily average values prediction.

$$\begin{aligned}\hat{D}_{ave}(d) &= \sum_{k=1}^{p} U_d(k) D_{ave}(d-k) + \sum_{k=1}^{p} V_d(k) P_{ave}(d-k) \\ &= \mathbf{U_d}^{\mathrm{T}}\ \bar{\mathbf{D}}_{his}(d) + \mathbf{V_d}^{\mathrm{T}}\ \bar{\mathbf{P}}_{his}(d) \end{aligned} \tag{4.20}$$

$$\begin{aligned}\hat{P}_{ave}(d) &= \sum_{k=1}^{p} X_d(k) P_{ave}(d-k) + \sum_{k=1}^{p} Y_d(k) D_{ave}(d-k) \\ &= \mathbf{X_d}^{\mathrm{T}}\ \bar{\mathbf{P}}_{his}(d) + \mathbf{Y_d}^{\mathrm{T}}\ \bar{\mathbf{D}}_{his}(d) \end{aligned} \tag{4.21}$$

where p denotes the order of the filter, by setting p as 14, we used 14 days of daily average data as historical value for predicting. $\mathbf{U_d}$, $\mathbf{V_d}$, $\mathbf{X_d}$ and $\mathbf{Y_d}$ are the vectors of the filter coefficients, which are updated over time in oder to minimize the error cost function inside the RLS method, as illustrated below:

$$\mathbf{U_d} = [U_d(1), ..., U_d(p)]^{\mathrm{T}} \tag{4.22}$$

$$\mathbf{V_d} = [V_d(1), ..., V_d(p)]^{\mathrm{T}} \tag{4.23}$$

$$\mathbf{X_d} = [X_d(1), ..., X_d(p)]^{\mathrm{T}} \tag{4.24}$$

$$\mathbf{Y_d} = [Y_d(1), ..., Y_d(p)]^{\mathrm{T}}. \tag{4.25}$$

$\hat{D}_{ave}(d)$ and $\hat{P}_{ave}(d)$ are the predicted daily average value at day d, $\bar{\mathbf{D}}_{his}(d)$ and $\bar{\mathbf{P}}_{his}(d)$ represent the historical data sets, as given below:

$$\bar{\mathbf{D}}_{his}(d) = [D_{ave}(d-1), D_{ave}(d-2)..., D_{ave}(d-p)]^{\mathrm{T}} \tag{4.26}$$

$$\bar{\mathbf{P}}_{his}(d) = [P_{ave}(d-1), P_{ave}(d-2)..., P_{ave}(d-p)]^{\mathrm{T}}. \tag{4.27}$$

According to Fig. 11, during the RLS prediction process, the predicted daily average price and demand are compared with the real values at each time step d, the two error functions are defined as:

$$\begin{aligned} e_{D,ave}(d) &= D_{ave}(d) - \hat{D}_{ave}(d) \\ &= D_{ave}(d) - \mathbf{U_d}^{\mathrm{T}}\ \bar{\mathbf{D}}_{his}(d) + \mathbf{V_d}^{\mathrm{T}}\ \bar{\mathbf{P}}_{his}(d) \end{aligned} \tag{4.28}$$

$$\begin{aligned} e_{P,ave}(d) &= P_{ave}(d) - \hat{P}_{ave}(d) \\ &= P_{ave}(d) - \mathbf{X_d}^{\mathrm{T}}\ \bar{\mathbf{P}}_{his}(d) + \mathbf{Y_d}^{\mathrm{T}}\ \bar{\mathbf{D}}_{his}(d). \end{aligned} \tag{4.29}$$

The errors are then injected into the RLS in order to update the coefficients so that the coefficients of the adaptive filter can minimize the weighed least square error cost function [7], which is formulated as:

$$\varepsilon = \sum_{k=1}^{d} \lambda^{d-k} e(k)^2 \tag{4.30}$$

where λ is the weighting (forgetting) factor, such that the recent samples become more relevant in the minimization. In our case, we set the forgetting factor as 1, this is because we have already included 14 days of daily average demand and price data for prediction, which are long enough to provide the prediction, we do not need to let the system gradually forget the historical data during prediction process.

4.2.5 Hourly residual value of market clearing demand and price prediction

As we have discussed the first prediction trend of daily average demand and price value, we will introduce the mathematical calculation process of the residual values prediction, which are also based on ARMA models with external inputs. Fig. 13 describes the prediction procedure.

According to the prediction process described in this figure, we firstly obtained the real demand and price data from hour 1 to hour 48, then subtract the demand and price daily average value of day 1 and day 2, which corresponds to the hourly data. The residual value results are represented in (4.17) and (4.19). Secondly, we used the 48 hourly residual demand values and same number of price values as the first set of historical data for the first prediction, during which the historical data are applied into the adaptive filter for the purpose of training. Once the filter coefficients are updated, we are able to predict the demand and price value of hour 49, prior to the official data publishing time.

Same as previous predictions, we used different ARMA models with external inputs to describe the relationship between the predicted residual value and historical data, which is shown in following equations:

$$\hat{D}_{res}(49) = \sum_{k=1}^{p} U_{49}(k) D_{res}(49-k) + \sum_{k=1}^{p} V_{49}(k) P_{res}(49-k)$$

$$= \mathbf{U_{49}}^{\mathrm{T}}\ \bar{\mathbf{D}}_{his}(49) + \mathbf{V_{49}}^{\mathrm{T}}\ \bar{\mathbf{P}}_{his}(49) \tag{4.31}$$

$$\hat{P}_{res}(49) = \sum_{k=1}^{p} X_{49}(k) P_{res}(49-k) + \sum_{k=1}^{p} Y_{49}(k) D_{res}(49-k)$$

$$= \mathbf{X_{49}}^{\mathrm{T}}\ \bar{\mathbf{P}}_{his}(49) + \mathbf{Y_{49}}^{\mathrm{T}}\ \bar{\mathbf{D}}_{his}(49) \tag{4.32}$$

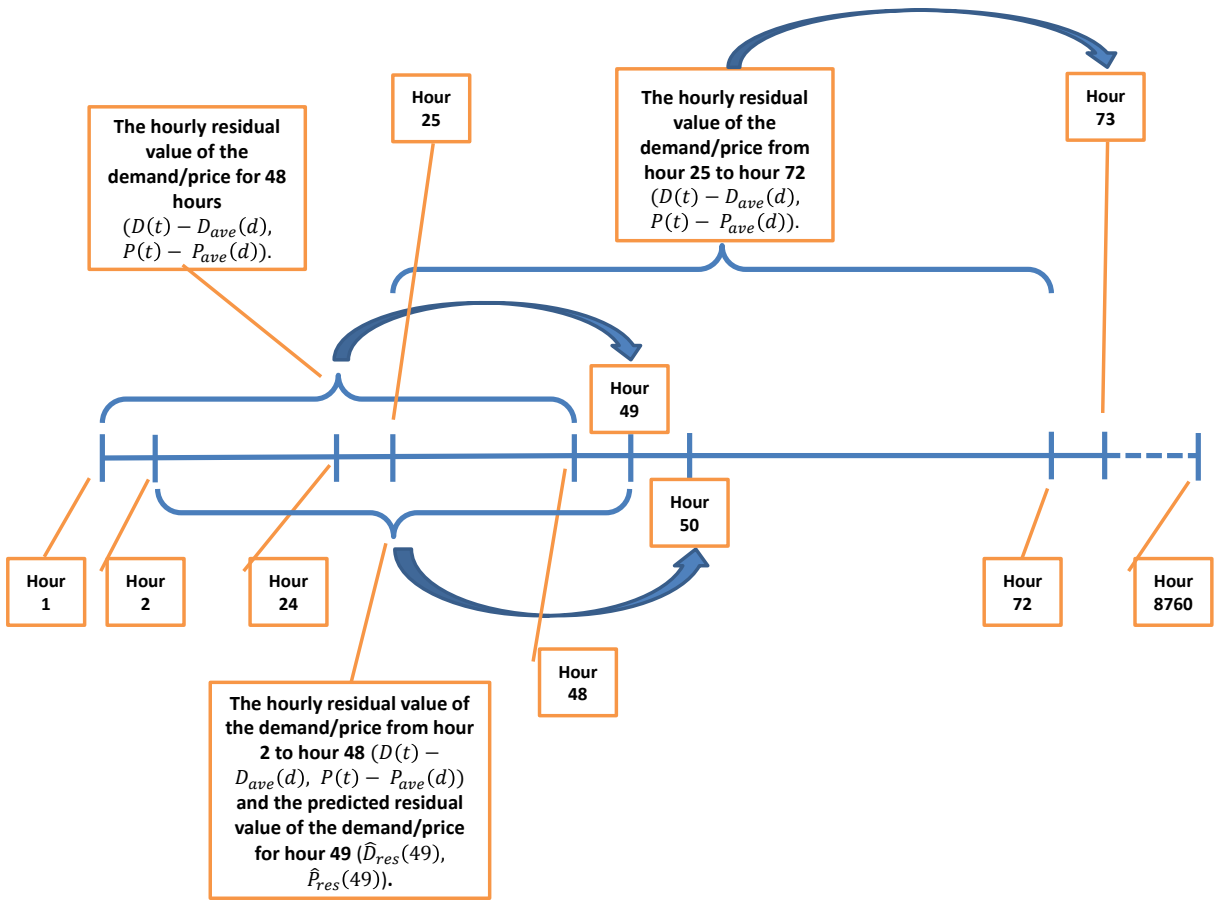

Figure 13: Residual values prediction.

where p denotes the order of the adaptive filter, by setting p as 48, we used 48 hours of residual value data as historical value for predicting. $\mathbf{U_{49}}$, $\mathbf{V_{49}}$, $\mathbf{X_{49}}$ and $\mathbf{Y_{49}}$ are the vectors of the filter coefficients at hour 49, which are given below:

$$\mathbf{U_{49}} = [U_{49}(1), ..., U_{49}(48)]^{\mathrm{T}} \tag{4.33}$$

$$\mathbf{V_{49}} = [V_{49}(1), ..., V_{49}(48)]^{\mathrm{T}} \tag{4.34}$$

$$\mathbf{X_{49}} = [X_{49}(1), ..., X_{49}(48)]^{\mathrm{T}} \tag{4.35}$$

$$\mathbf{Y_{49}} = [Y_{49}(1), ..., Y_{49}(48)]^{\mathrm{T}}. \tag{4.36}$$

$\hat{D}_{res}(49)$ and $\hat{P}_{res}(49)$ are the predicted residual value of market clearing demand and price at hour 49, $\bar{\mathbf{D}}_{his}(49)$ and $\bar{\mathbf{P}}_{his}(49)$ both represent the historical data of demand and price from hour 1 to hour 48, as given below:

$$\bar{\mathbf{D}}_{his}(49) = [D_{res}(1), D_{res}(2)..., D_{res}(48)]^{\mathrm{T}} \tag{4.37}$$

$$\bar{\mathbf{P}}_{his}(49) = [P_{res}(1), P_{res}(2)..., P_{res}(48)]^{\mathrm{T}}. \tag{4.38}$$

Thirdly, having the first predicted data at hour 49, we abandoned the old historical data at hour1 and include the newly predicted data in order to keep the number of historical values at 48 for each set. Therefore, the residual value at hour 50 will be predicted using the pre-calculated residual values ranging from hour 2 to hour 48 and the newly predicted value at hour 49. For both demand and price historical values sets, the whole procedure will then be repeated over time with the number of pre-calculated data decreasing and the newly predicted data increasing. This is described in following equations:

$$
\begin{aligned}
\hat{D}_{res}(50) &= \sum_{k=2}^{p} U_{50}(k) D_{res}(50-k) + \sum_{k=2}^{p} V_{50}(k) P_{res}(50-k) \\
&+ U_{50}(1)\hat{D}_{res}(49) + V_{50}(1)\hat{P}_{res}(49) \\
&= \mathbf{U_{50}}^{\mathrm{T}} \left[D_{res}(2), D_{res}(3)...D_{res}(48), \hat{D}(49)\right] \\
&+ \mathbf{V_{50}}^{\mathrm{T}} \left[P_{res}(2), P_{res}(3)...P_{res}(48), \hat{P}(49)\right] \qquad (4.39)
\end{aligned}
$$

$$
\begin{aligned}
\hat{P}_{res}(50) &= \sum_{k=2}^{p} X_{50}(k) P_{res}(50-k) + \sum_{k=2}^{p} Y_{50}(k) D_{res}(50-k) \\
&+ X_{50}(1)\hat{P}_{res}(49) + Y_{50}(1)\hat{D}_{res}(49) \\
&= \mathbf{X_{50}}^{\mathrm{T}} \left[P_{res}(2), P_{res}(3)...P_{res}(48), \hat{P}(49)\right] \\
&+ \mathbf{Y_{50}}^{\mathrm{T}} \left[D_{res}(2), D_{res}(3)...D_{res}(48), \hat{D}(49)\right]. \qquad (4.40)
\end{aligned}
$$

Lastly, after we obtained the predicted residual demand and price values of day 72 by training the predicted data from hour 49 to hour 71 and the pre-calculated data from hour 24 to hour 48, we started to reconstruct the historical data sets again. This is because by the end of day 3, ISO will release the sets of demand and price data from hour 49 to hour 72, based on which we are able to calculate the real residual value sets. These sets will be included together with the residual data sets from hour 24 to hour 48 in the new historical data sets which will be used for predicting the residual values at hour 73.

In summary, regarding the demand and price residual value prediction of the first hour on each day, we used the historical data of previous 48 hours and calculated the historical residual values based on the real published data. Then starting with the prediction of the second hour on that day, by setting the forgetting factor as 1, we used the newly predicted data instead of the least recent pre-calculated data, together with the rest 47 data to conduct the next prediction. Once the residual value of the third hour is predicted, the whole procedure is repeated.

Let d and h denote the number of the day and hour corresponding to the data point respectively, if we are about to predict the residual value of the first hour on a new day, we describe the mathematical process in following equations:

$$If \quad h \;=\; 24d + 1,$$

$$\begin{aligned}
\hat{D}_{1res}(h) &= \sum_{k=1}^{p} U_h(k) D_{res}(h-k) + \sum_{k=1}^{p} V_h(k) P_{res}(h-k) \\
&= \mathbf{U_h}^{\mathrm{T}}\ \bar{\mathbf{D}}_{his}(h) + \mathbf{V_h}^{\mathrm{T}}\ \bar{\mathbf{P}}_{his}(h) \qquad (4.41)
\end{aligned}$$

$$\begin{aligned}
\hat{P}_{1res}(h) &= \sum_{k=1}^{p} X_h(k) P_{res}(h-k) + \sum_{k=1}^{p} Y_h(k) D_{res}(h-k) \\
&= \mathbf{X_h}^{\mathrm{T}}\ \bar{\mathbf{P}}_{his}(h) + \mathbf{Y_h}^{\mathrm{T}}\ \bar{\mathbf{D}}_{his}(h) \qquad (4.42)
\end{aligned}$$

where we set p, the order of the filter, as 48. $\mathbf{U_h}$, $\mathbf{V_h}$, $\mathbf{X_h}$ and $\mathbf{Y_h}$ are the vectors including the filter coefficients, $\bar{\mathbf{D}}_{his}(h)$ and $\bar{\mathbf{P}}_{his}(h)$ are the historical residual value calculated based on the original data.

If we already have at least one predicted residual value and about to predict the residual values corresponding to the rest hours of the predicting day, we follow the next steps:

$$If \quad h \;=\; 24d + j,$$

$$1 < j < 24,$$

$$
\begin{aligned}
\hat{D}_{2res}(h) &= \sum_{k=j+1}^{p} U_h(k) D_{res}(h-k) + \sum_{k=j+1}^{p} V_h(k) P_{res}(h-k) \\
&+ \sum_{i=1}^{j} U_h(i) \hat{D}_{2res}(h-i) + \sum_{i=1}^{j} V_h(i) \hat{P}_{2res}(h-i) \\
&= \mathbf{U_h}^{\mathrm{T}} \, [\hat{\mathbf{D}}_{2his}(h), \bar{\mathbf{D}}_{his}(h)] + \mathbf{V_h}^{\mathrm{T}} \, [\hat{\mathbf{P}}_{2his}(h), \bar{\mathbf{P}}_{his}(h)] \\
&= \mathbf{U_h}^{\mathrm{T}} \, \overline{\mathbf{DD}}_{his}(h) + \mathbf{V_h}^{\mathrm{T}} \, \overline{\mathbf{PP}}_{his}(h)
\end{aligned} \tag{4.43}
$$

$$
\begin{aligned}
\hat{P}_{2res}(h) &= \sum_{k=j+1}^{p} X_h(k) P_{res}(h-k) + \sum_{k=j+1}^{p} Y_h(k) D_{res}(h-k) \\
&+ \sum_{i=1}^{j} X_h(i) \hat{P}_{2res}(h-i) + \sum_{i=1}^{j} Y_h(i) \hat{D}_{2res}(h-i) \\
&= \mathbf{X_h}^{\mathrm{T}} \, [\hat{\mathbf{P}}_{2his}(h), \bar{\mathbf{P}}_{his}(h)] + \mathbf{Y_h}^{\mathrm{T}} \, [\hat{\mathbf{D}}_{2his}(h), \bar{\mathbf{D}}_{his}(h)] \\
&= \mathbf{X_h}^{\mathrm{T}} \, \overline{\mathbf{PP}}_{his}(h) + \mathbf{Y_h}^{\mathrm{T}} \, \overline{\mathbf{DD}}_{his}(h)
\end{aligned} \tag{4.44}
$$

where $\overline{\mathbf{DD}}_{his}(h)$ and $\overline{\mathbf{PP}}_{his}(h)$ are the historical data sets used for training, both of which include the most recent predicted residual values and the less recent pre-calculated residual values. $\mathbf{U_h}$, $\mathbf{V_h}$, $\mathbf{X_h}$ and $\mathbf{Y_h}$ are the vectors of filter coefficients.

After the above two steps of residual values prediction, we combined the predicted value sets $\hat{\mathbf{D}}_{\mathbf{1res}}$, $\hat{\mathbf{D}}_{\mathbf{2res}}$, $\hat{\mathbf{P}}_{\mathbf{1res}}$, $\hat{\mathbf{P}}_{\mathbf{2res}}$ in order to formulate the final predicted residual demand and price data sets $\hat{\mathbf{D}}_{\mathbf{res}}$ and $\hat{\mathbf{P}}_{\mathbf{res}}$, as illustrated below:

$$
\hat{\mathbf{D}}_{\mathbf{res}} = [\hat{\mathbf{D}}_{\mathbf{1res}}, \hat{\mathbf{D}}_{\mathbf{2res}}] \tag{4.45}
$$

$$
\hat{\mathbf{P}}_{\mathbf{res}} = [\hat{\mathbf{P}}_{\mathbf{1res}}, \hat{\mathbf{P}}_{\mathbf{2res}}] \tag{4.46}
$$

4.2.6 Integration of daily average and residual demand/price prediction results

Following the previously discussed multiresolution prediction process, we are able to predict the future daily average values and hourly residual values of market clearing demand and price for different scales. In this section, we will integrate these predicted data sets based on different time frame to generate the final prediction results.

According to Fig. 14, the data reconstruction process is a summation process, during which we added the predicted residual demand and price value of each hour to the predicted daily average demand and price value of that entire day. The mathematical process is described below.

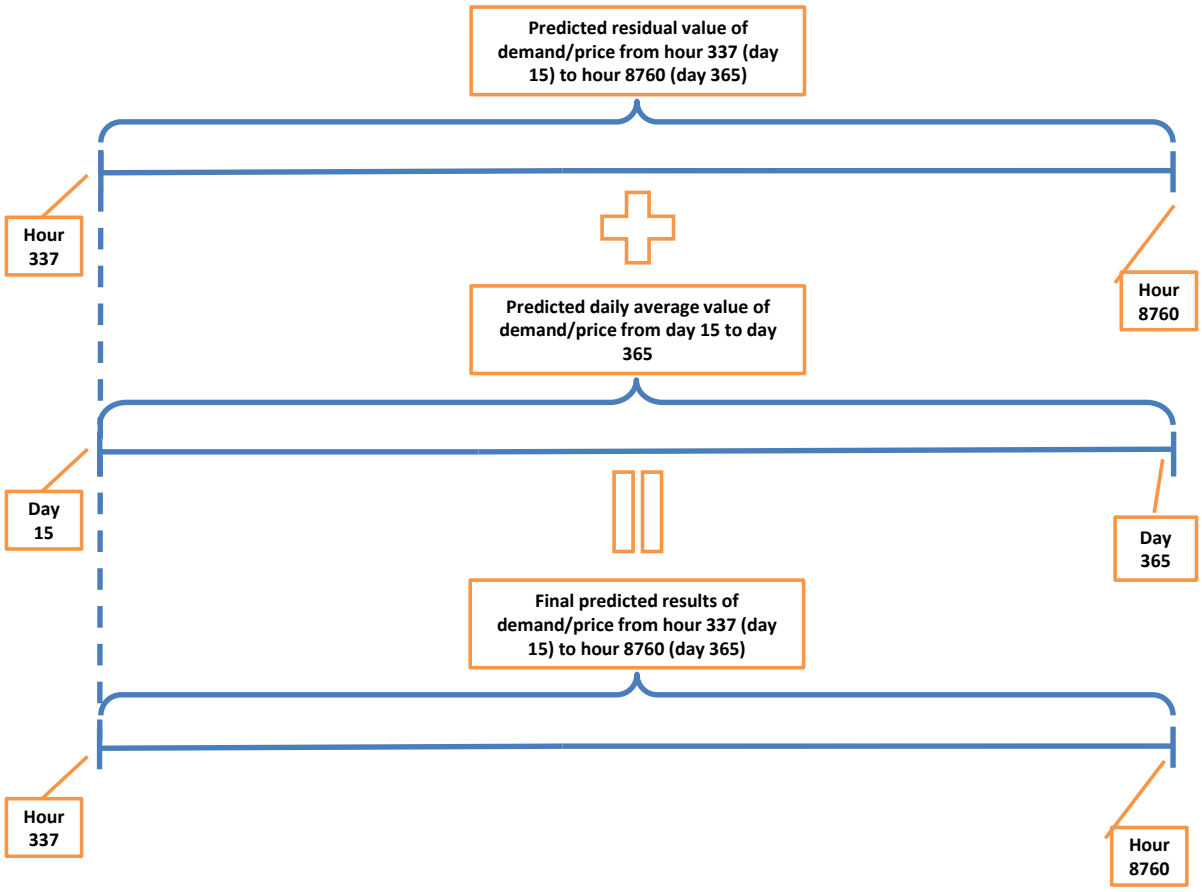

Figure 14: Integration of the predicted results.

Let d and h denote the time step corresponding to the day and hour respectively, then for the prediction of the market clearing demand and price value at h, we have:

$$h = 24d + j,$$

$$\hat{D}(h) = \hat{D}_{ave}(d) + \hat{D}_{res}(h) \tag{4.47}$$

$$\hat{P}(h) = \hat{P}_{ave}(d) + \hat{P}_{res}(h) \tag{4.48}$$

For the prediction of daily average values, we set the order of adaptive filter as 14, meaning that our first predicted average values starts from day 15. In addition, having the same starting point while on a different scale, the first prediction of residual values starts from hour 337, which is the first hour of day 15. By combining these two prediction results from different scales, we are able to generate the final prediction results of electricity market clearing demand and price.

5.0 RESULTS AND DISCUSSIONS

5.1 RLS PREDICTION DATA SELECTION

In this section, we will introduce the data selected for the simulation of supply function bidding strategy and RLS prediction.

This study obtained the day-ahead hourly clearing demand data and hourly market clearing price data from ISO-NEW ENGLAND website [102]. We selected the time frame from 1st January 2012 to 1st March 2012, as shown in Fig. 15 and Fig. 16. As described in these two figures, the day-ahead electricity demand of the area under ISO-NEW ENGLAND's operation ranges from 9771 MWh to 18656 MWh while the day-ahead electricity price ranges from \$1.49/MWh to \$22.02/MWh, both of which are updated hourly.

Although we formulate GENCOs bidding strategies corresponding to each hour of the day, for the simulation of the adaptive control system, we conducted our analysis on the simplified lengthy and tedious data by targeting on the daily average value of the day-ahead market clearing price and demand, as illustrated in Fig. 17 and Fig. 18. Therefore, the time frame of both data sets are changed from 1440 hours into 60 days, based on which we developed and simulated the closed-loop control system as well as the study on the bidding strategy simulation.

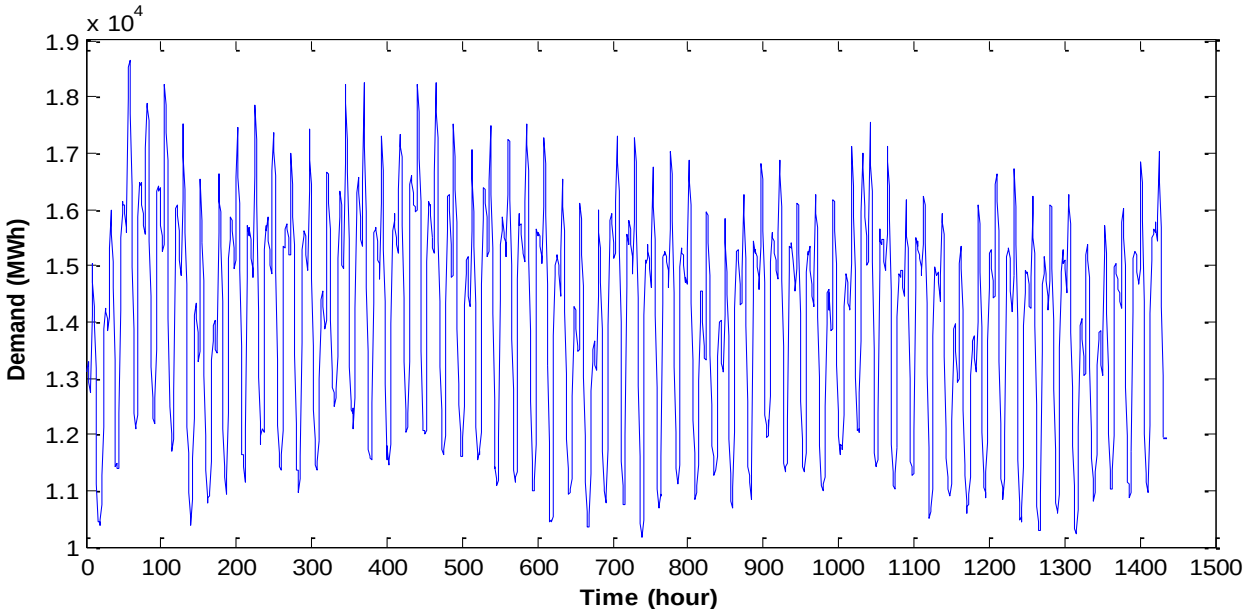

Figure 15: Day-ahead market clearing demand of ISO-NE (1st January 2012 - 1st March 2012).

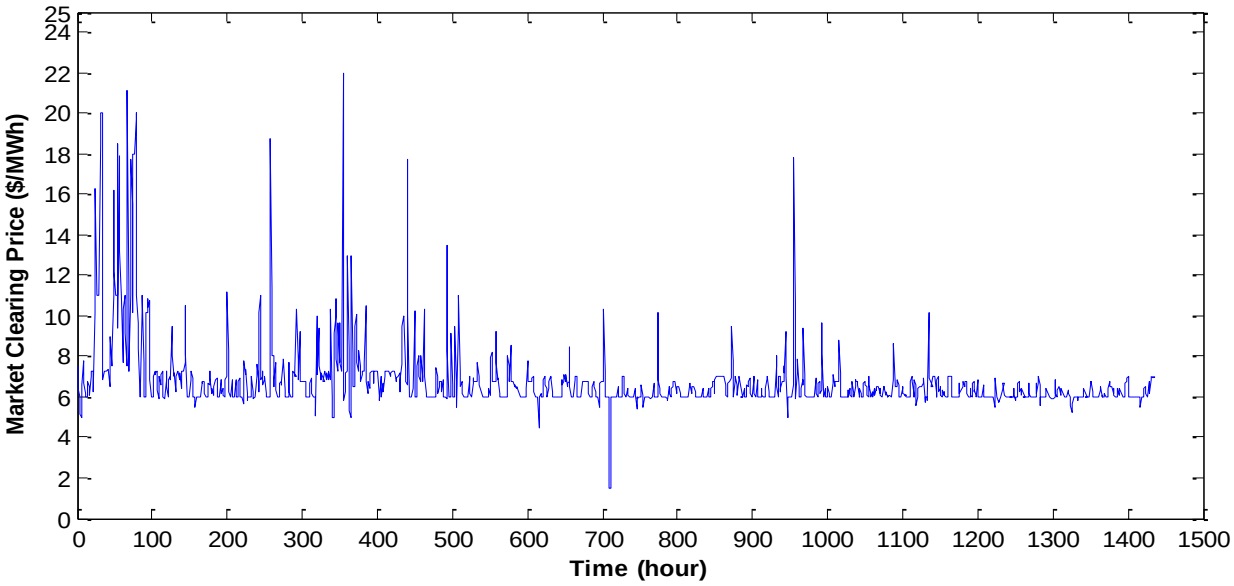

Figure 16: Day-ahead market clearing price of ISO-NE (1st January 2012 - 1st March 2012).

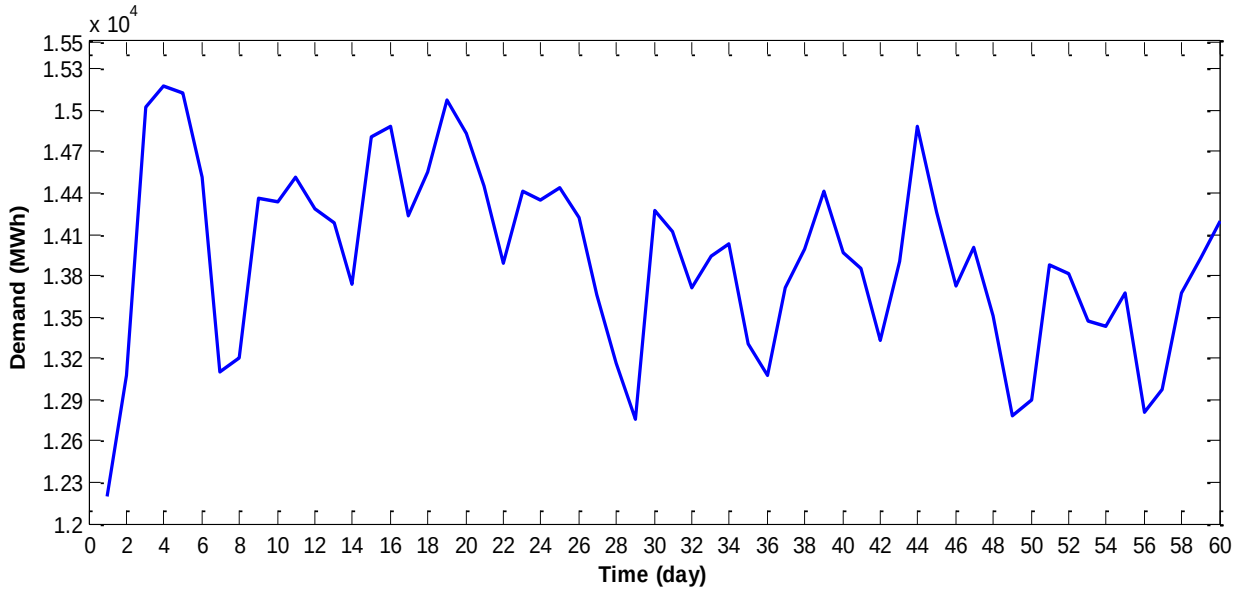

Figure 17: Daily average day-ahead clearing demand of ISO-NE market (1st January 2012 - 1st March 2012).

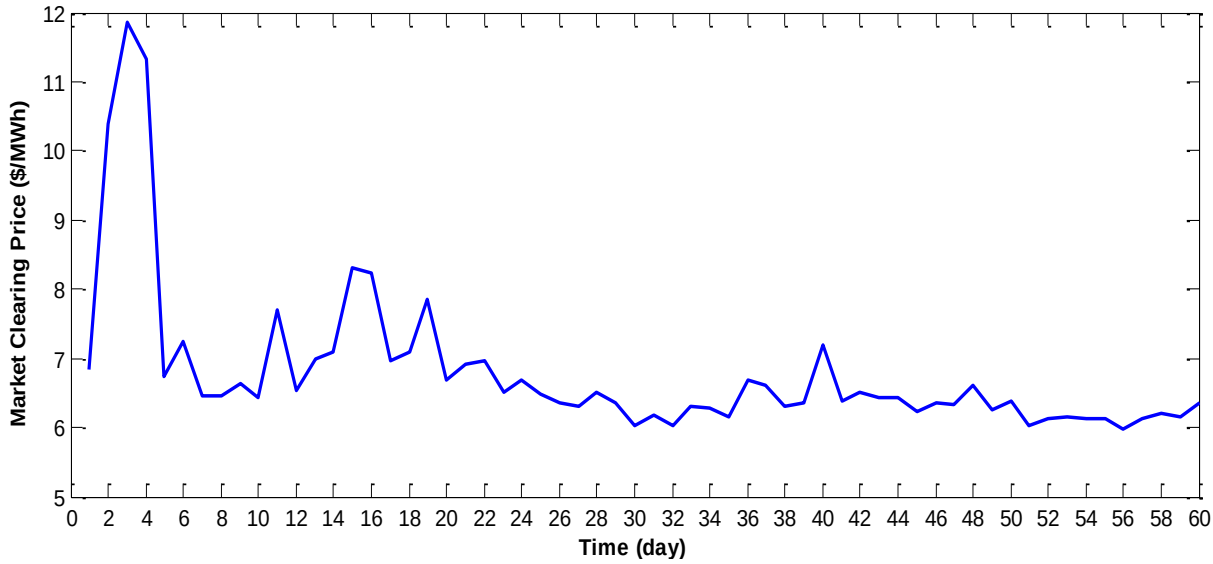

Figure 18: Daily average day-ahead market clearing price of ISO-NE market (1st January 2012 - 1st March 2012).

5.2 SUPPLY FUNCTION EQUILIBRIUM BASED BIDDING STRATEGY

In order to apply the idea of supply function equilibrium into the dynamic bidding process and to correspond with the dynamic closed-loop control model, this dissertation formulated a learning and adjusting process for GENCO. The whole process starts at 12 PM, the time that ISO clears the day-ahead market and publishes the market data, ends at the time that next bid is submitted.

In this study, we assumed that this specific GENCO win the electronic auction for each day during the time frame, this provides the necessary condition for GENCO to participate into the market by giving GENCO the right to generate the electricity for the demand sides. Then we set the GENCOs generation cost at around 30% of the total gross profit in order to obtain an average value of different type of energy used for the electricity generation process. Moreover, based on the result from the linear regression of market clearing price and market clearing demand, we concluded that the price-demand elasticity in ISO-NEW ENGLAND operation area is relatively low during the time frame.

For the calculation, we followed the whole SFE bidding process in Fig. 7 and calculated the slope and intercept of supply function equilibrium according to (3.23) and (3.24). Subsequently, with the necessary variables for formulating the supply function, we derived the quantity of the electricity that the GENCO will provide through bidding using (3.25), illustrated in Fig. 19. From which we can see that the bidding quantity ranges from 29.7992 MWh to 59.1346 MWh. The profit can therefore be calculated through (3.26), which are given in Fig. 20.

From Fig. 20, we are able to take an overview of the daily average profit of the GENCO. Compared with Fig. 17 and Fig. 18, the profit of GENCO is closely linked to the electricity demand and price, as the demand goes up, the possibility for GENCO to succeed in bidding will go up, which brings more opportunity for GENCO to make profit. However, by describing the dynamic bidding process, we calculated the supply function equilibrium of the previous bidding day and used this equilibrium condition to approach the condition of next bidding day. After that, we used this supply function including the optimal β_i^* and α_i^* as the next bidding data and considered it the optimal bidding term for the next bidding day.

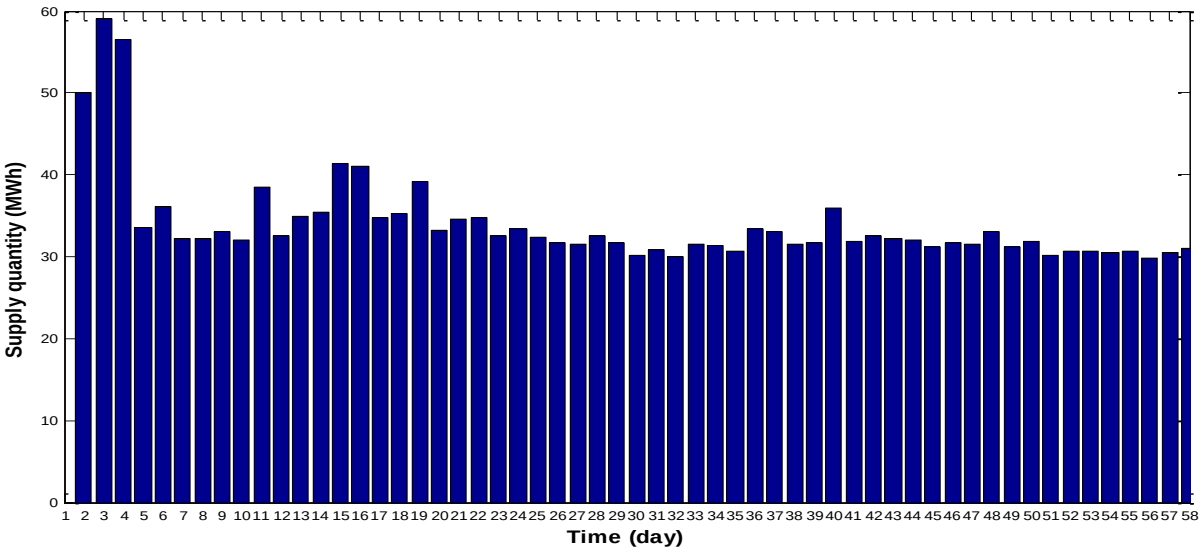

Figure 19: Daily average electricity supply quantity (supply function equilibrium bidding strategy).

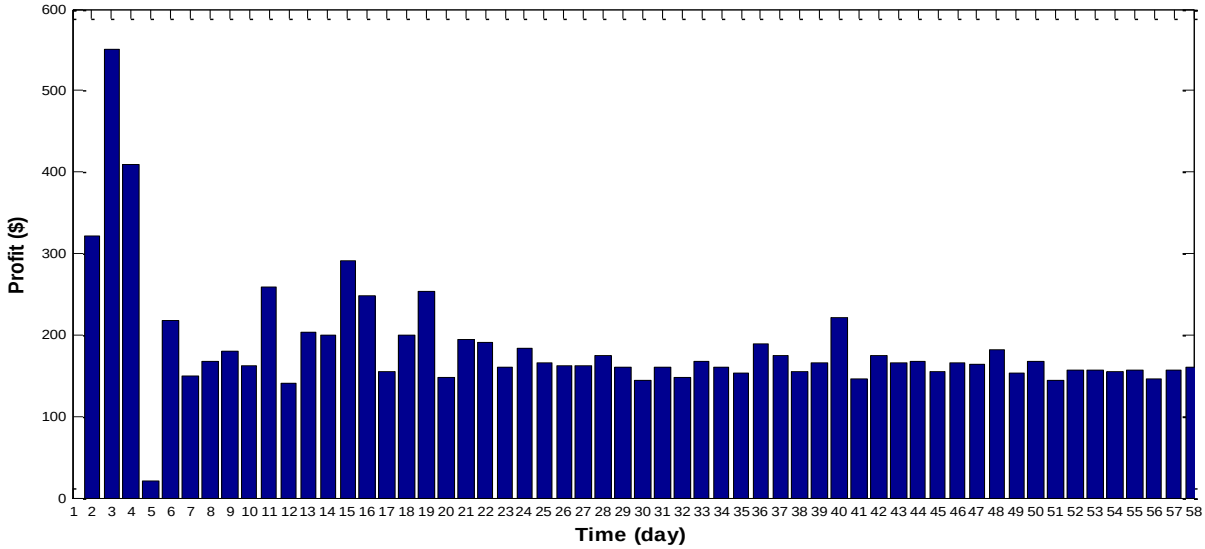

Figure 20: Daily average net profit (supply function equilibrium bidding strategy).

Results show that for some time steps, this approaching bidding method are able to present a good performance while the approaching value is not accurate enough for some extreme situations.

As shown in Fig. 18, at time of day 5, there is a sudden price drop, which causes the market equilibrium condition largely different from day 4. However, the bidding strategy for day 5 is approached by the calculation from market equilibrium of day 4, causing the profit for GENCO at day 5 decreases dramatically compared to the previous day. Thus in dealing with the situation of sudden incidents, the dynamic SFE adjusting algorithm exposes its drawbacks.

5.3 ESTIMATION OF MARKET CLEARING DEMAND AND PRICE USING RECURSIVE LEAST SQUARE METHOD

In this section, the main purpose is to use the historical data to estimate the day-ahead market clearing price and day-ahead market clearing demand by applying adaptive recursive filter, which was previously defined in Fig. 8. This method is formulated based on two ARMA models given in (4.12) and (4.13), the historical data are selected from four days before the estimating day. By keeping updating and forgetting the coefficients of the ARMA models, we are able to predict the future data, given in Fig. 21 and Fig. 22.

As shown in these two figures, the dotted line represents the historical data, solid line represents the desired data and the dash line is the predicted data. At a certain point of the time frame, our objective is to use the given historical data (dotted line) to find a set of data (dash line) which is as close to the desired data (solid line). Results show that the adaptive filter using RLS algorithm provides a very good prediction of the historical data, since the predicted data resembles in shape the original data and precedes in time the historical data over time.

In order to better test the prediction results with the desired data, we also calculated the absolute value of errors between the predicted data and the desired data, comparing with the absolute value of errors between the historical data and the desired data, as illustrated in

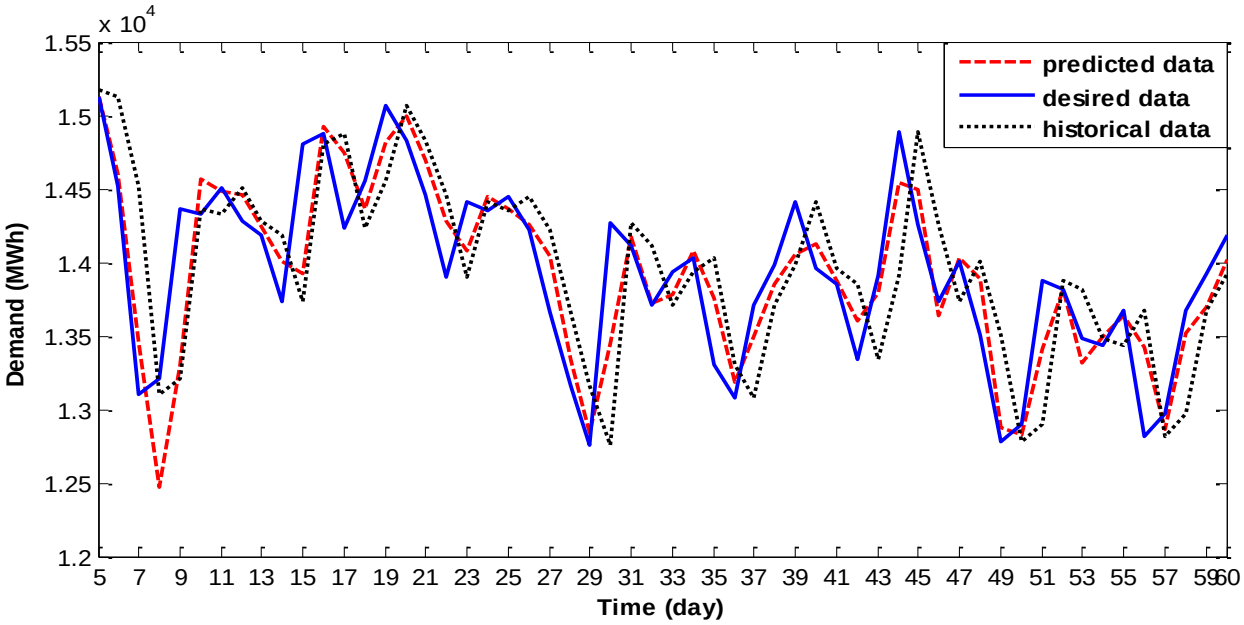

Figure 21: Comparison among historical, desired and prediction of daily average day-ahead market clearing demand of ISO-NE (1st January 2012 - 1st March 2012).

Fig. 23 and Fig. 24. In these two figures, we used dash line to represent the prediction errors and solid line to represent the approaching errors. Based on the observation, we calculated that the larges demand prediction error is 1062 MWh and the demand approaching error is 1507 MWh while the smallest demand prediction error is almost 0 MWh and the demand approaching error is 28.8 MWh. The largest price prediction error is $ 1.692 and the price approaching error is $ 4.596 while the smallest price prediction error is almost 0 and the price approaching error is $ 0.014.

In addition, we calculated the total error of the two methods in terms of demand and price, as shown in Fig. 25 and Fig. 26, based on which we also calculated that the value of total demand prediction error is 12644.7 MWh and of the total demand approaching error is 23946.68 MWh; The total price prediction error is $11.87 and the total price approaching error is $21.5. These values of errors further reinforced the accuracy of the RLS prediction results.

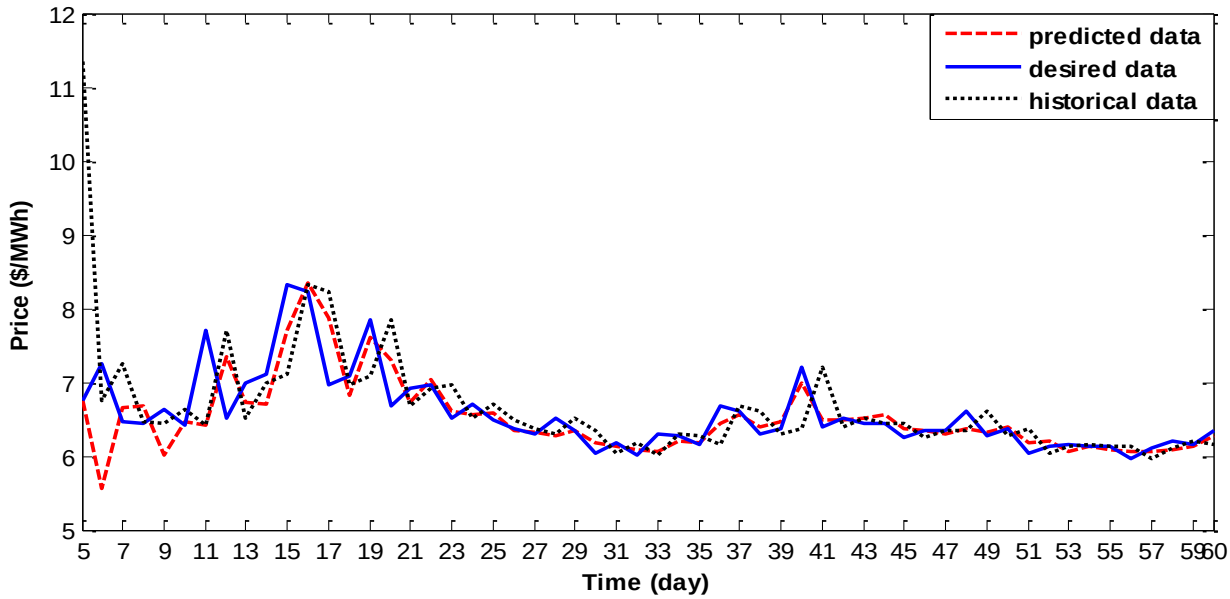

Figure 22: Comparison among historical, desired and prediction of daily average day-ahead market clearing price of ISO-NE (1st January 2012 - 1st March 2012).

Moreover, we concluded from the simulation process that for a given system the performance of the RLS algorithm is dictated by the forgetting factor. if we consider a stationary process, a larger forgetting factor will allow a smaller squared error. For the situation that forgetting factor $\lambda = 1$, the squared error will approach the squared error of a Wiener filter [106]. However, as demonstrated by the simulations, higher values of λ can be harmful when the system is non-stationary since the algorithm takes into account the data from all past times instead of forgetting the historical information. Lower values of λ decrease the importance of older data, which affect the prediction accuracy especially for the situation that the historical data is not enough. The problem with the Wiener filter is that the spectral characteristics of the signal must be known before hand and the inputs are stationary, which are generally impractical assumption. On the other hand, adaptive filtering algorithms, like RLS, require no knowledge of the spectral characteristics and can be well applied for non-stationary signals.

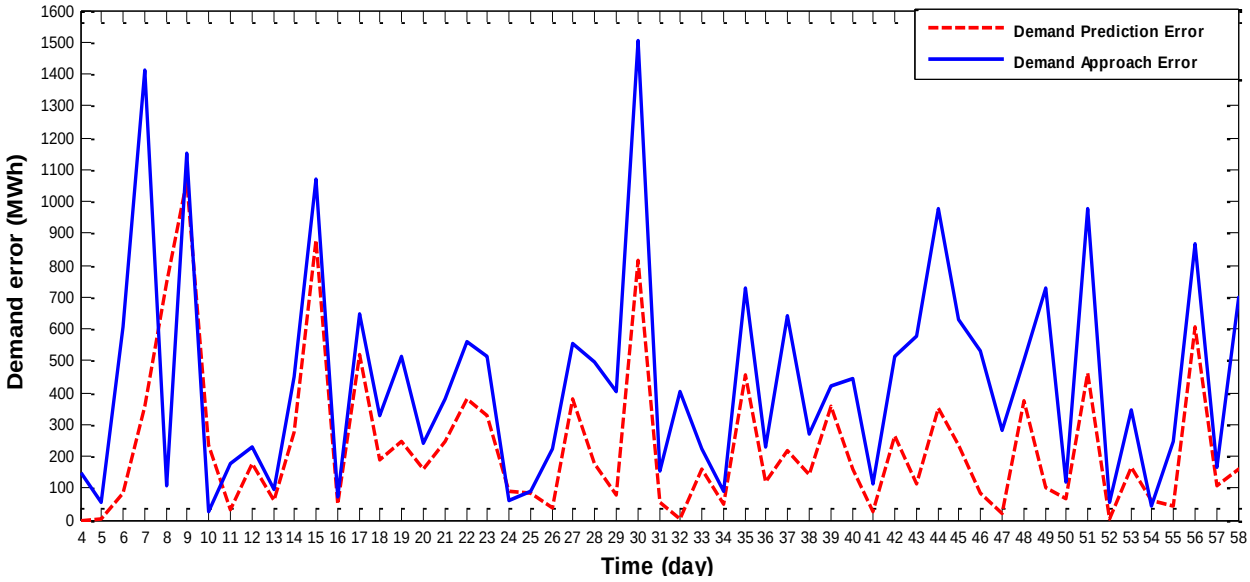

Figure 23: Demand prediction error and demand approaching error.

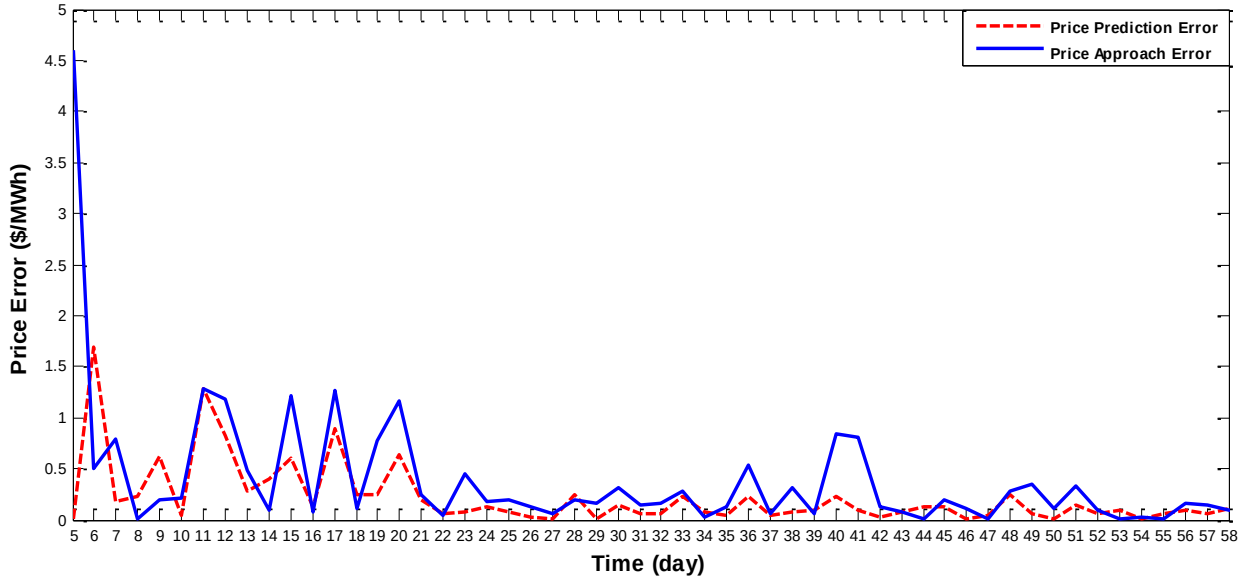

Figure 24: Price prediction error and price approaching error.

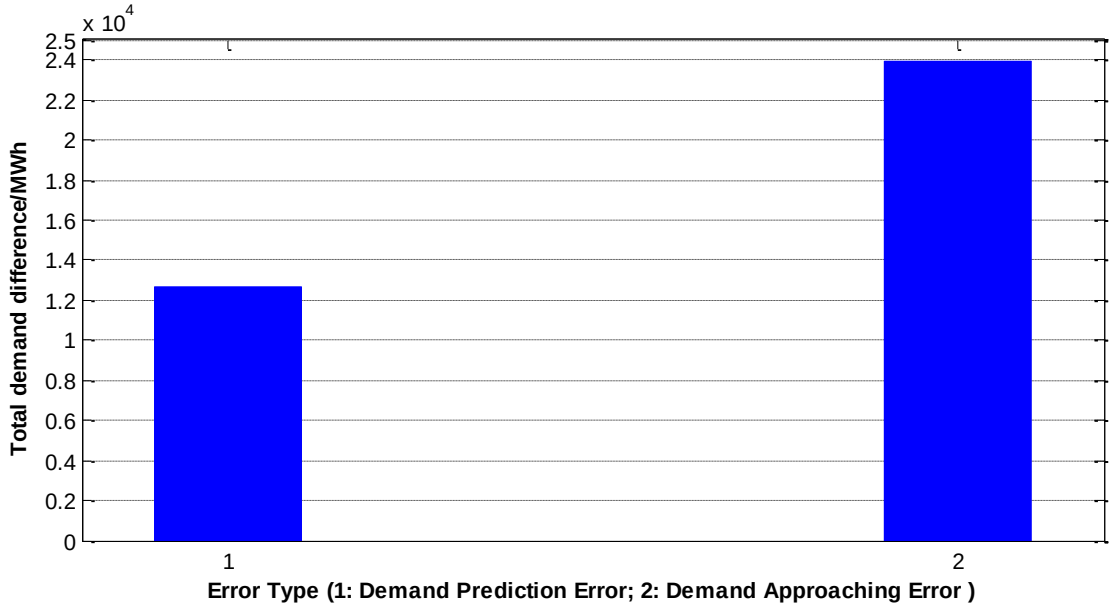

Figure 25: Total demand prediction error and total demand approaching error (day 5 to day 58).

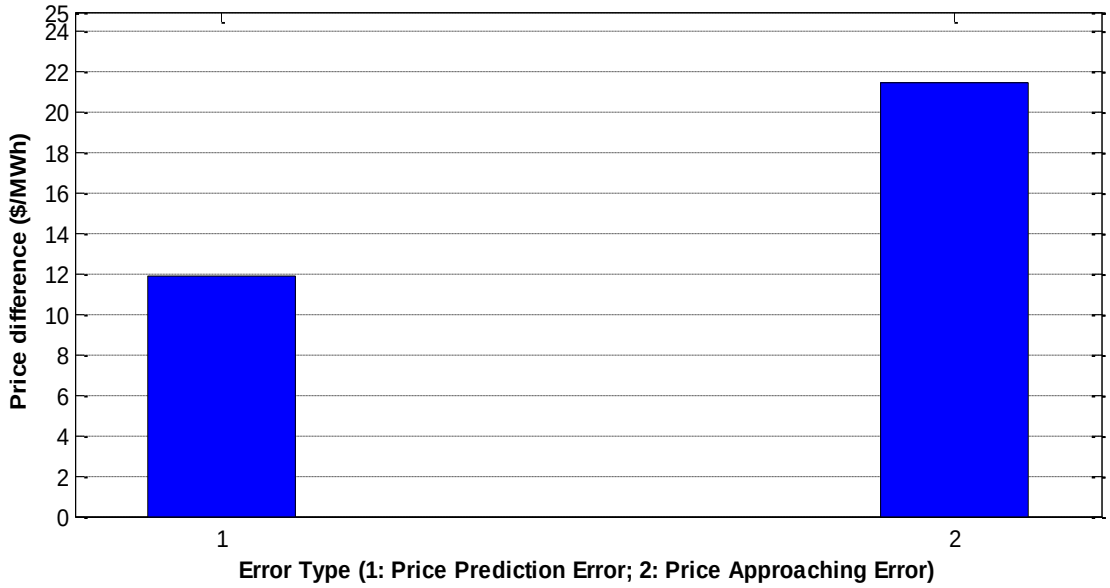

Figure 26: Total price prediction error and total price approaching error (day 5 to day 58).

5.4 GENCO BIDDING STRATEGY BASED ON ADAPTIVE CONTROL SYSTEM

The purpose of this task is to apply the RLS prediction process, which was previously discussed in Fig. 8, into the adaptive control system model (Fig. 9). According to the application of RLS methods, the market clearing demand and price are both able to be captured before published by ISO, thus with the forecast data which are much closer to the real market data, GENCOs are able to adjust their bidding strategies by calculating the estimated supply function equilibrium, then generate a different set of α and β compared to the previously mentioned SFE approaching methods.

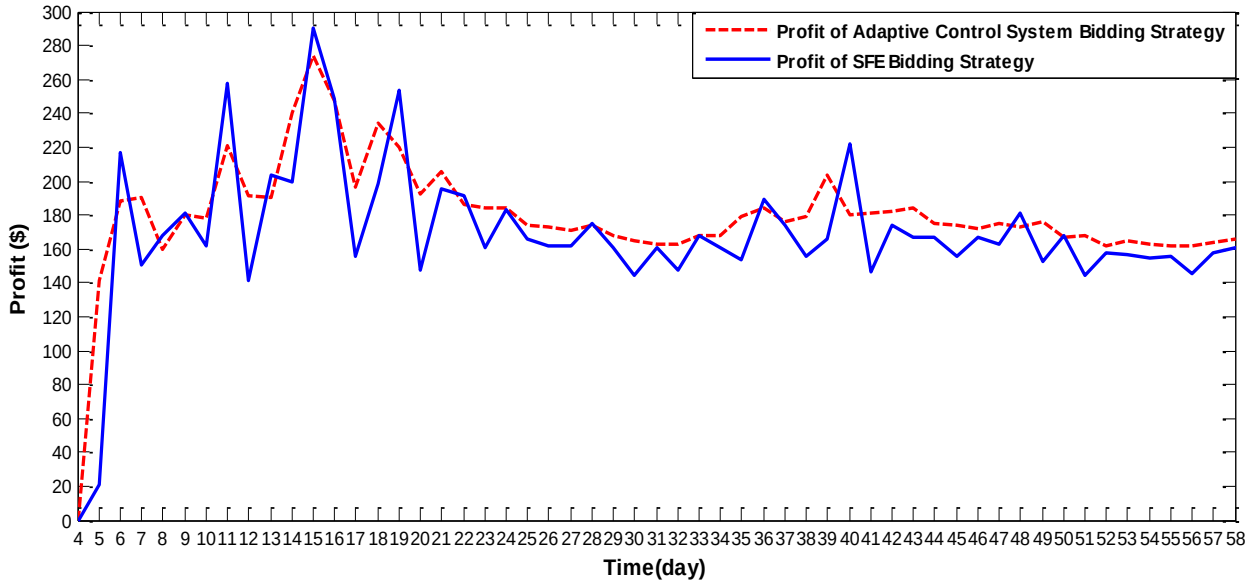

Figure 27: Daily average market profits by using SFE bidding strategy and adaptive control system bidding strategy (day 5 to day 58).

Fig. 27 shows the simulation results of GENCOs market net profits by using SFE bidding strategy and adaptive control system bidding strategy. In this figure, the solid line represents the profit gained by using SFE bidding strategy and the dash line represents the profit gained

by adopting adaptive control system bidding strategy. By setting the order of the adaptive filter as 4, we used the historical data starting from four days prior to the predicting day, therefore, the simulation time period ranges from day 5 to day 58.

As we mentioned in previous section, when there is a sudden price change, the dynamic SFE bidding strategy was not able to make a prompt adjustment with the approached calculation, which causes a big loss of profit, as shown at day 5. On the contrary, the adaptive control system utilized adaptive recursive filter, which is able to capture the future market trend beforehand so that the market profit gained by bidding strategy is not seriously affected by the sudden change of market clearing price. This compensates the huge profit difference between \$20.56 and \$141.3 at day 5.

In order to better compare the two different bidding strategies, we made a summation for the total market profits and compared them in Fig. 28. Calculation results show that the total daily average profit of adopting SFE adjusting algorithm is \$9417.6 while the total

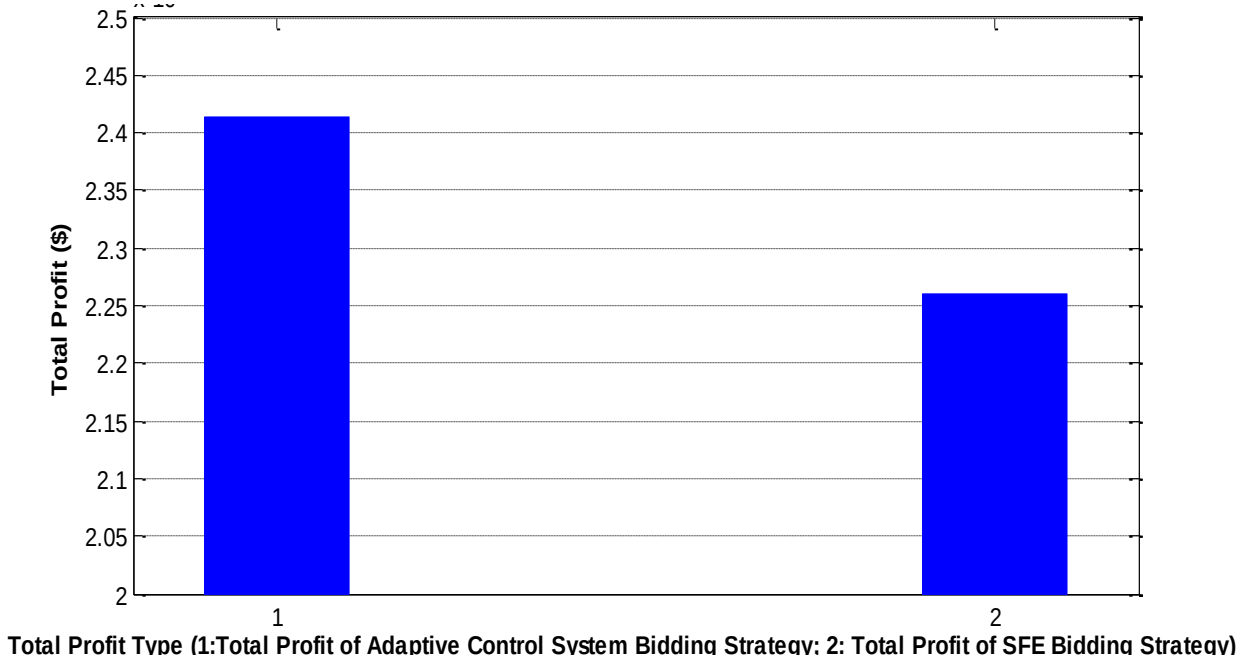

Figure 28: Total market profit by using adaptive control system bidding strategy and SFE bidding strategy (day 5 to day 58).

daily average profit of adopting adaptive control system algorithm is $10059.3. Moreover, since the total profit here is a daily average value, which is the average value of each hour of the day, by combining the whole values together, the total profit for all day during the time period by using the two bidding strategies should be $226020 and $241420. Therefore, we can conclude that the adaptive control system bidding strategy is superior to the SFE adjusting bidding strategy by increasing the GENCOs market net profit by 6.38% during the time frame.

5.5 ESTIMATION OF MARKET CLEARING DEMAND AND PRICE USING ADAPTIVE MULTIRESOLUTION PREDICTION METHOD

This section presents the simulation results of applying adaptive multiresolution algorithm into adaptive recursive least square prediction method and ARMA models with external inputs. Our objective is, once again, to further increase GENCO's profit during the electricity market operation through capturing the market movements in advance.

5.5.1 Data processing

Different from previous sections, we obtained the day-ahead hourly cleared demand data and hourly market clearing price data from PJM website [101], taking as two new data sets for our prediction training. In order to make the simulation condition more relative to the real situation, we selected the time frame from 1st January 2011 to 31st December 2011, as shown in Fig. 29 and Fig. 30.

As described in the two figures, the day-ahead electricity demand of the area under PJM's operation ranges from 17948 MWh to 57811 MWh while the day-ahead electricity price ranges from $0/MWh to $465.1/MWh, both of which are updated hourly.

According to the data sets which last for 8760 hours, we learned that it would be too long and tedious for training easily because of the unstable characteristics of demand and price, the simplification of using daily average value only can not represent the real situation

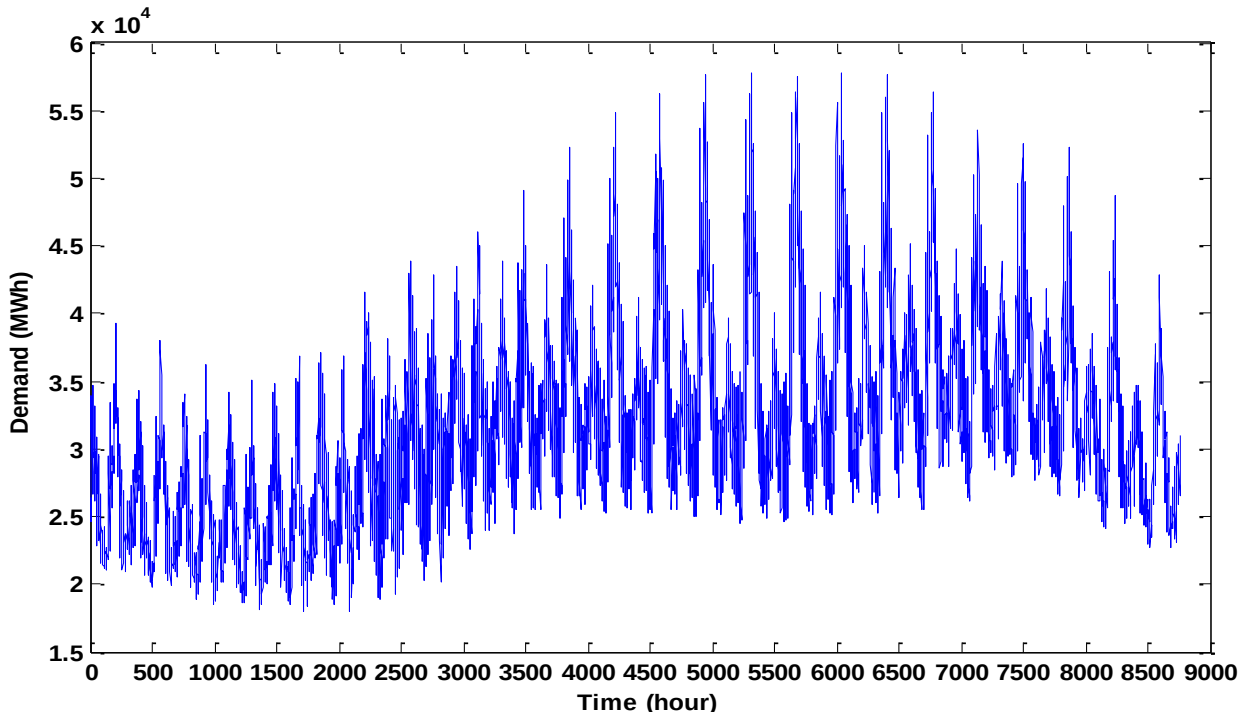

Figure 29: Day-ahead market clearing demand of PJM (1st January 2011- 31st December 2011).

accurately. Therefore, on the purpose of providing more accurate and reasonable prediction results as well as the electricity market dynamics, we followed the data flow described in Fig. 10, applied the multiresolution analysis by decomposing the original demand and price data into different scales. The daily average value of market clearing demand and price and the residual value of market clearing demand and price.

Fig. 31 and Fig. 32 showed the daily average value of PJM market demand and price, which are calculated the same as the process described in previous sections. As we can see from the two figures, the time frame of both data sets changed from 8760 hours into 365 days with demand average value ranging from 20510 MWh to 49680 MWh while price average value ranging from \$7.425 to \$54.85. The prediction results of the daily average value data

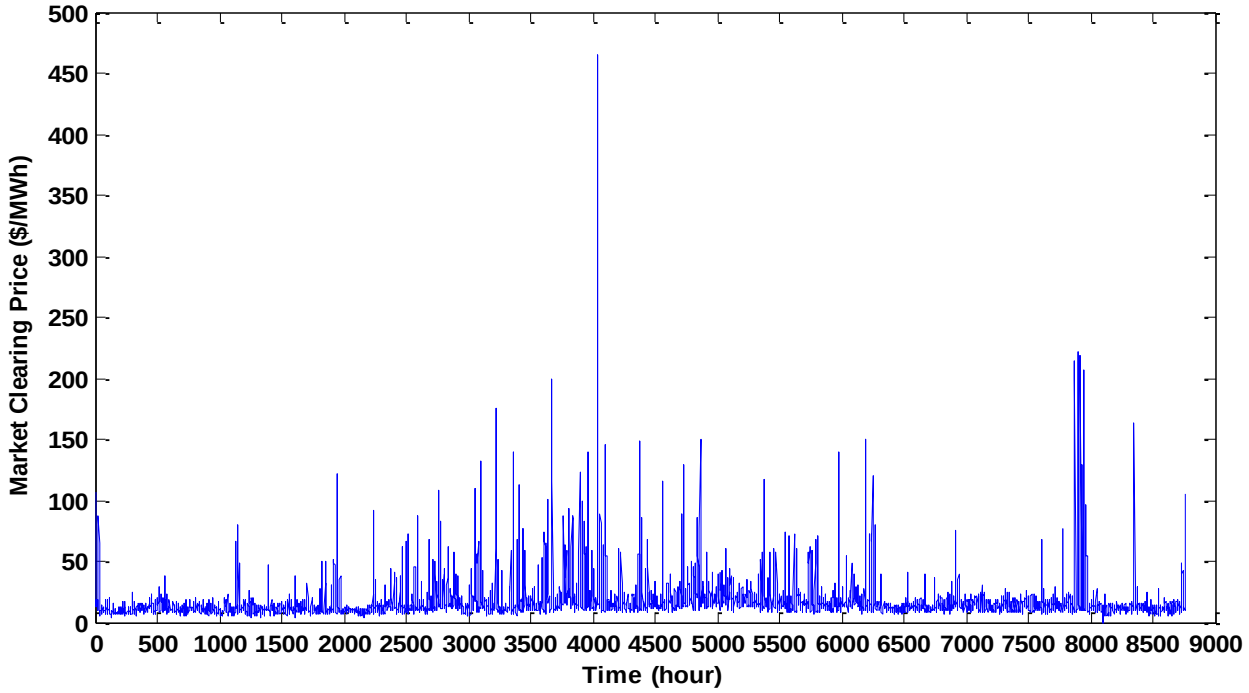

Figure 30: Day-ahead market clearing price of PJM (1st January 2011- 31st December 2011).

sets hold the general trend of the original signal sets, which is not used to simply represent the original signal as previous discussions. Moreover, based on the two figures, we can observe that the market clearing price has much more uncertainty than the market clearing demand even in terms of daily average value, this leads more difficulties when conducting the prediction activities.

After calculating the daily average data sets, we further split the data by calculating the residual values of PJM market clearing demand and price in order to provide more accurate and more reasonable prediction as well as the varieties of the electricity market. Fig. 33 and Fig. 34 represent the difference between the original hourly data value and the daily average data value respectively, both of which include 8760 hours for simulation.

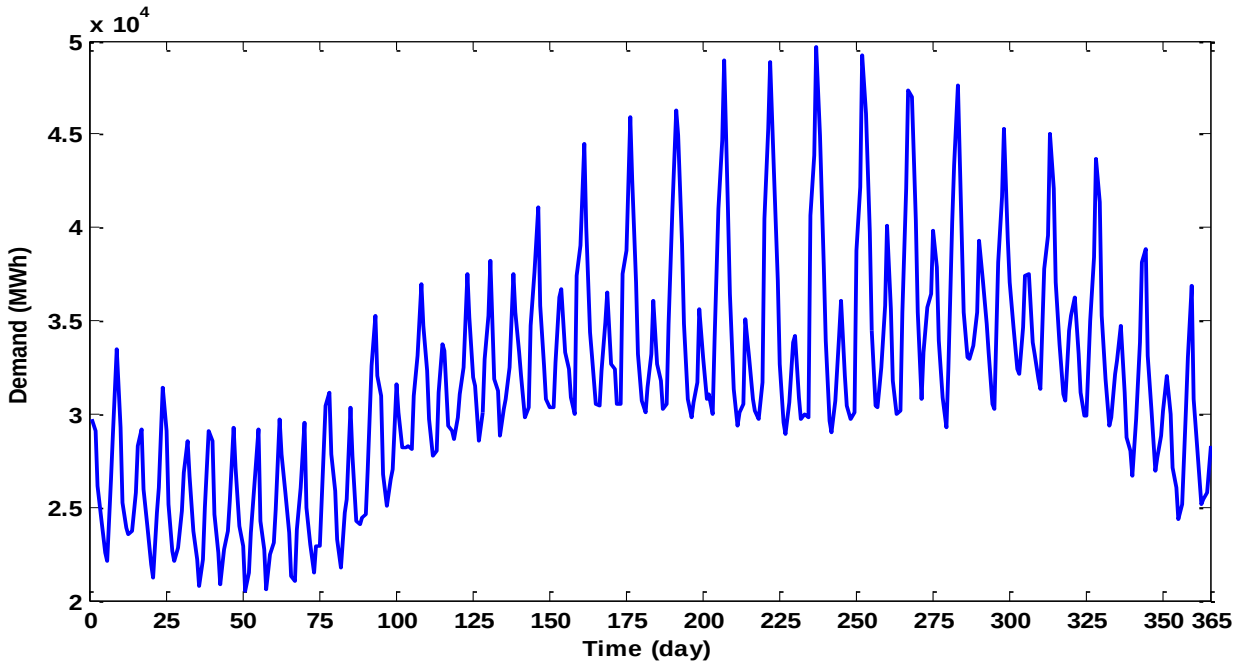

Figure 31: Daily average day-ahead clearing demand of PJM market (1st January 2011- 31st December 2011).

As shown in the figures, the demand difference between the original value and the daily average value fluctuate around 0 and ranges from -11770 MWh to 16770 MWh, which to some extent denotes that the demand curve changes regularly according to different time of the day and different seasons. On the other hand, the price difference between the original value and the daily average value can have very large fluctuations, which ranges from \$-43.4254 to \$410.2546. The uncertainty of the price residual value also increases the difficulties of training the data and providing accurate prediction.

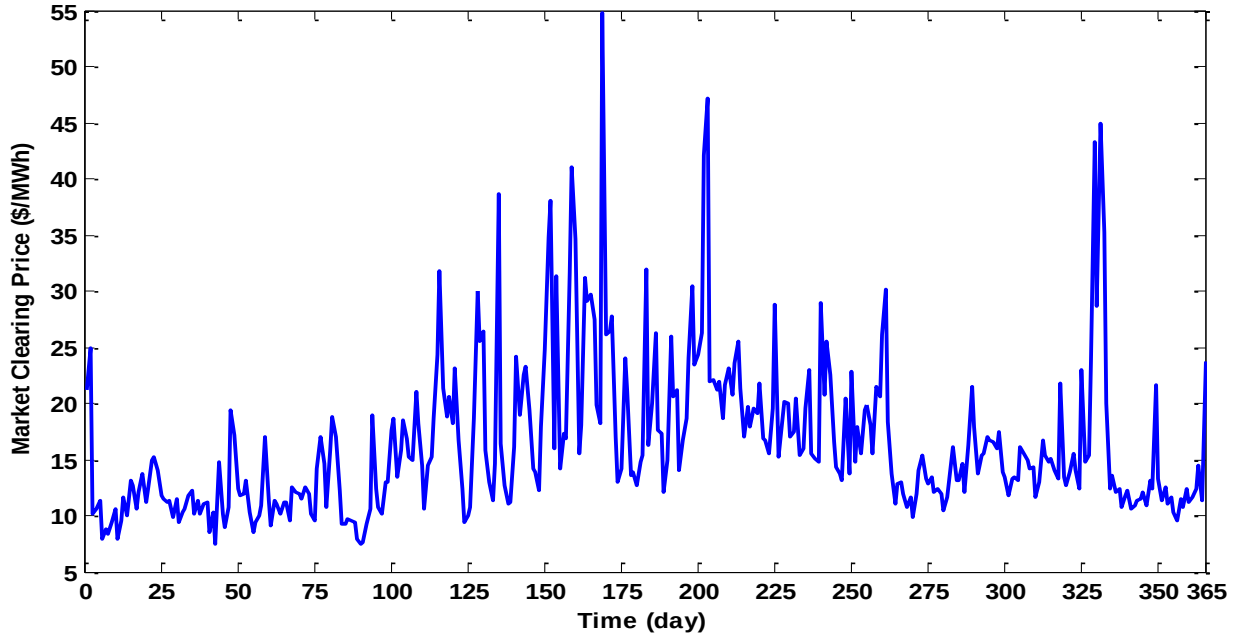

Figure 32: Daily average day-ahead clearing price of PJM market (1st January 2011- 31st December 2011).

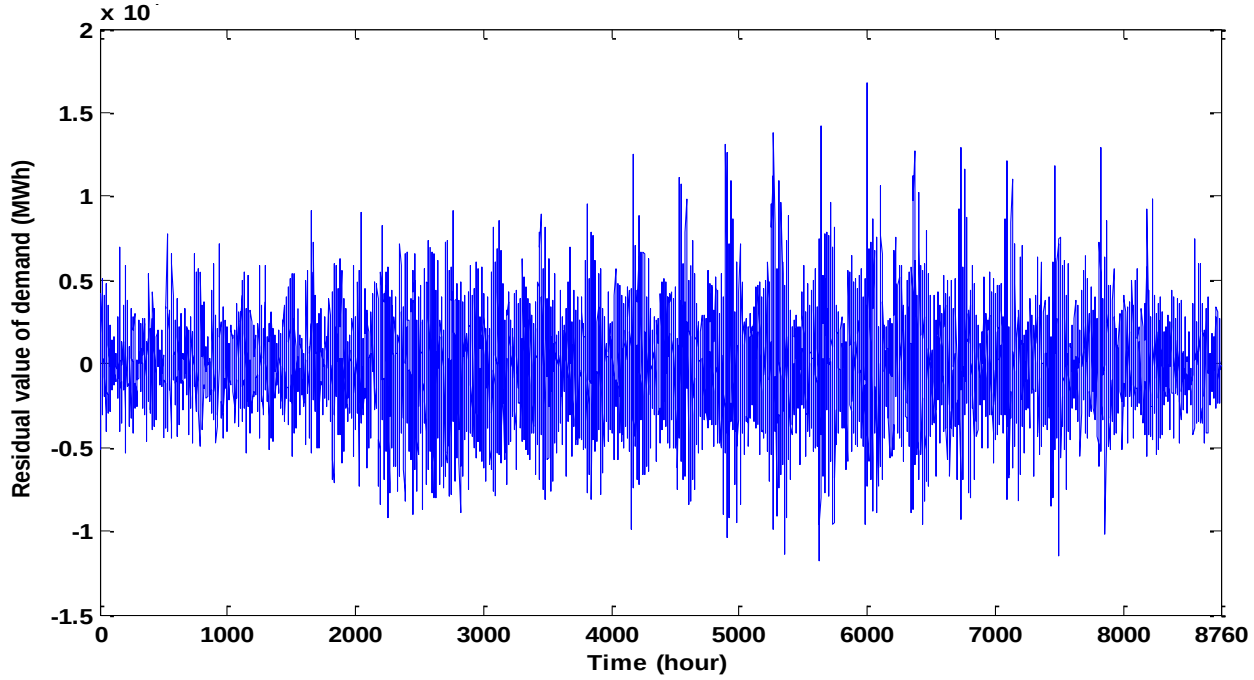

Figure 33: Residual day-ahead market clearing demand of PJM market (1st January 2011- 31st December 2011).

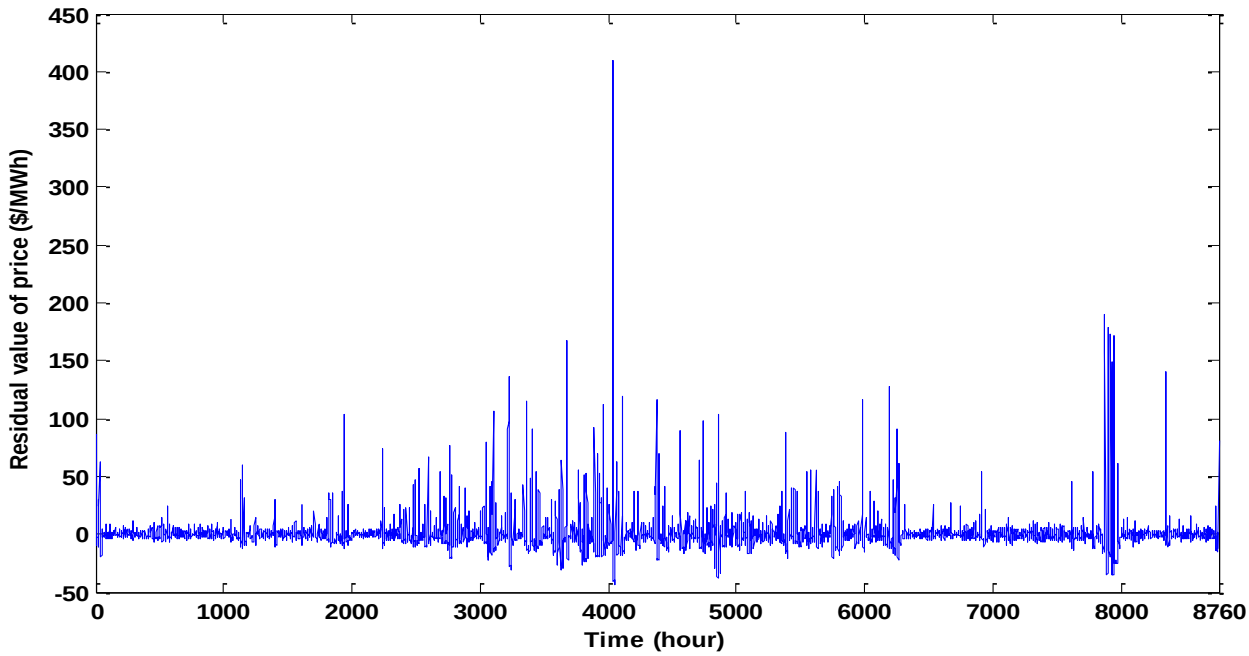

Figure 34: Residual day-ahead market clearing price of PJM market (1st January 2011- 31st December 2011).

5.5.2 Multiresolution prediction results

In this subsection, the main purpose is to use the historical demand and price data based on different scales to estimate the future values by applying adaptive recursive filter, which was previously defined in Fig. 11.

The daily average value of demand and price prediction method is formulated based on two ARMA models given in (4.20) and (4.21), different from the previous prediction process, the historical data are selected from 14 days before the estimating day, and the ARMA model requires the external inputs in order to specify the relationship between demand and price. By keeping updating and forgetting the coefficients of the ARMA models, we are able to predict the future data, given in Fig. 35 and Fig. 36.

As shown in these two figures, the dotted line represents the historical data, solid line represents the desired data and the dash line represents the predicted data. At a certain point of the time frame, our objective is to use the given historical data (dotted line) to find a set of data (dash line) which is as close to the desired data (solid line). Results show that the adaptive filter using RLS algorithm provides a very good prediction of the historical data based on daily average time frame, since the predicted data resembles in shape the original data and precedes in time the historical data. In order to better compare the prediction results with the desired data, we also calculated the absolute value of errors between the predicted data and the desired data, compared with the absolute value of errors between the historical data and the desired data, as illustrated in Fig. 37 and Fig. 38. Since both of the daily average data sets last for 365 days, we only exported the data sets ranging from day 50 to day 150 in order to get a clearer observation.

From these two error comparison figures, we are able to conclude that the daily average demand prediction error is 587000 MWh and the demand approaching error (difference between the historical value and the desired value) is 943000 MWh while the daily average price prediction error is 1170 \$/MWh and the price approaching error is 1310 \$/MWh. We set the forgetting factor λ as 1 so that we put equal weights on each historical data used for predicting. In addition, whenever we obtain a new predicted data, we will abandon the first historical data and include a most recent one in order to conduct the new prediction process,

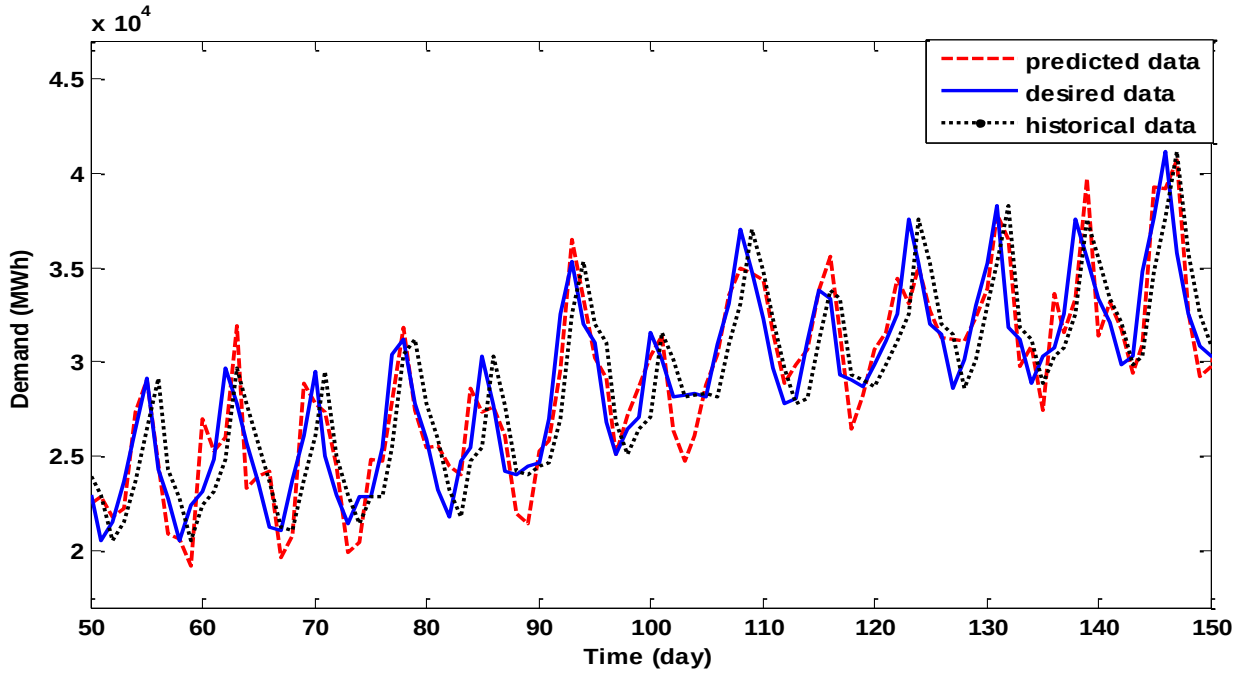

Figure 35: Comparison among historical, desired and prediction of daily average day-ahead market clearing demand of PJM (1st January 2011- 31st December 2011).

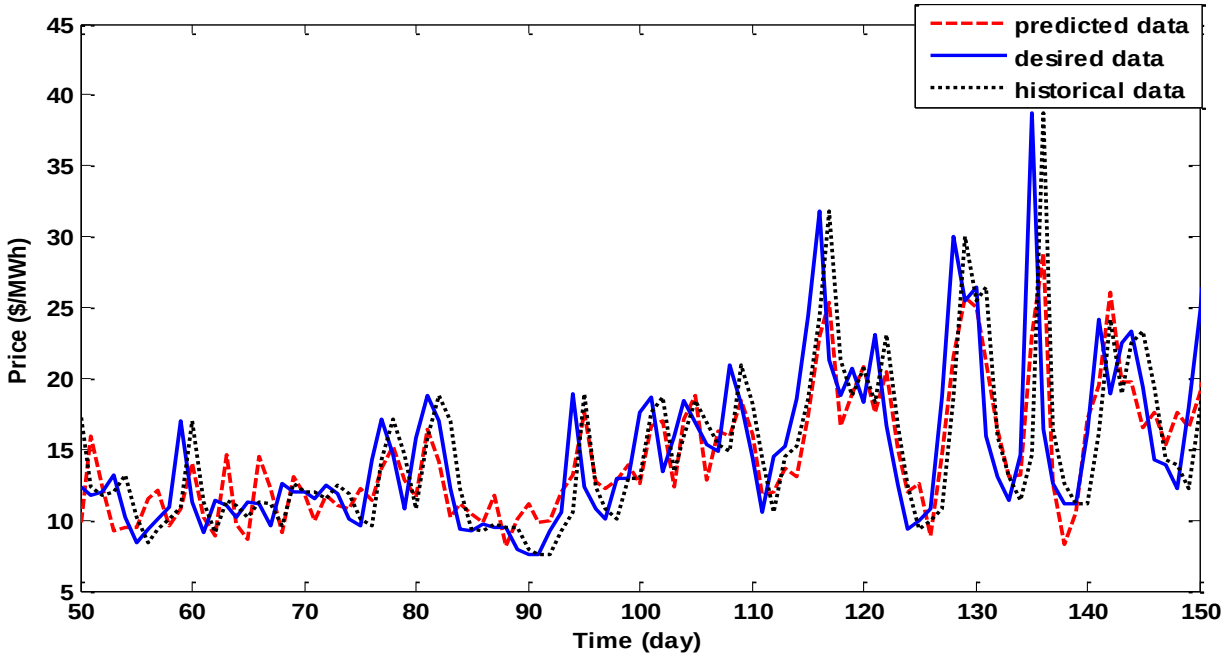

Figure 36: Comparison among historical, desired and prediction of daily average day-ahead market clearing price of PJM (1st January 2011- 31st December 2011).

based on which the number of historical data is kept unchanged. The simulation results further reinforce the accuracy of the prediction method and the advantage of the improved ARMA models.

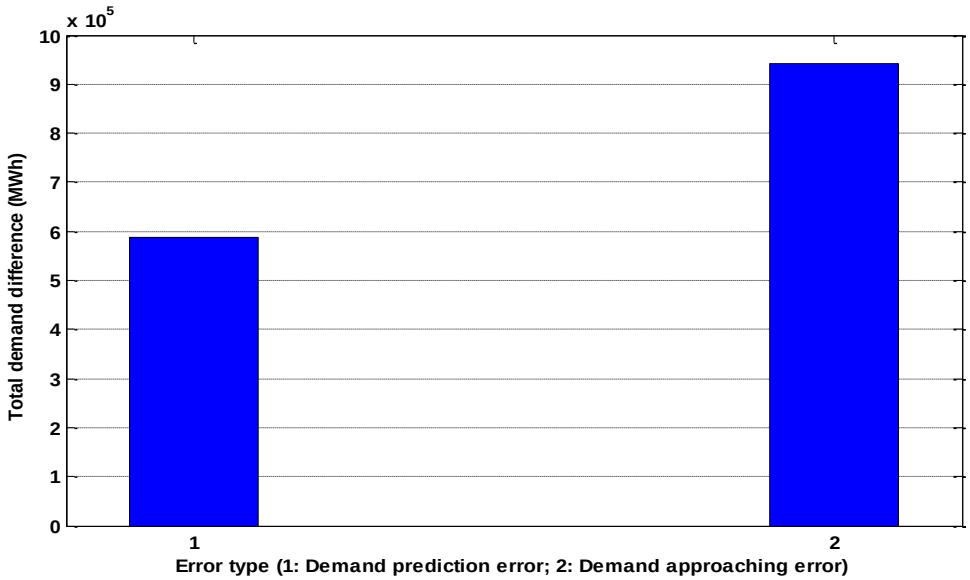

Figure 37: Total daily average demand prediction error and total demand approaching error.

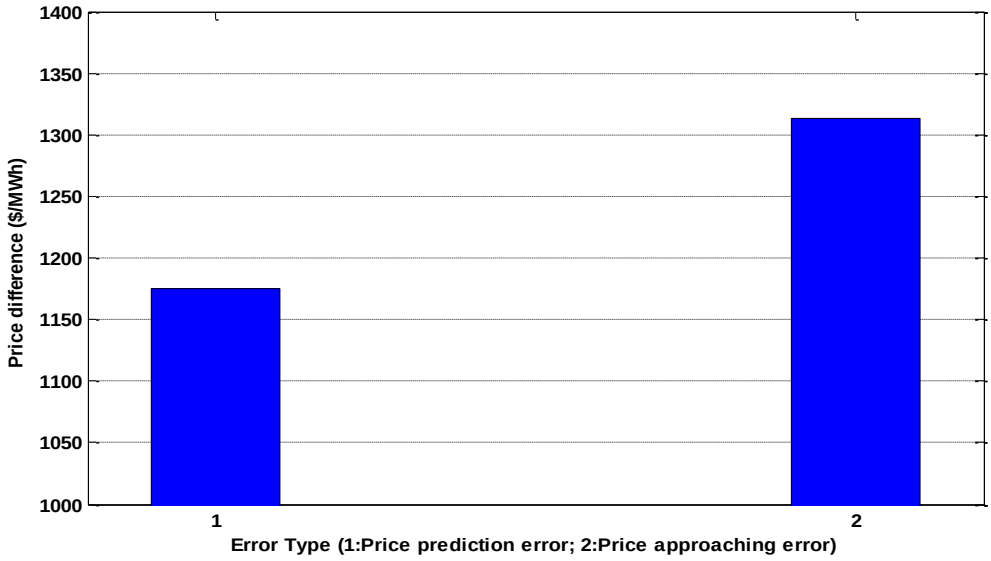

Figure 38: Total daily average price prediction error and total price approaching error.

Then we followed the multiresolution prediction procedure described in Fig. 10 and Fig. 11 to conduct the residual value of demand and price prediction. We set the forgetting factor λ as 1 and selected the historical data for 48 hours before the estimating day. Similarly, based on the mutual influence between demand and price, we set the historical demand residual value data as the input of the ARMA model which is used to predict the price residual value, and the same on the contrary. By keeping updating and forgetting the coefficients of the ARMA models, we are able to predict the future data, the simulation results are given in Fig. 39 and Fig. 40.

As shown in these two figures, the dotted line represents the historical data, solid line represents the desired data and the dash line represents the predicted data. Likewise, we took an interception of the demand data ranging from hour 3105 to hour 3200 and the price data ranging from hour 6384 to hour 6480 for analysis since the simulation results include 8760 values.

Based on our observation, although the data of residual values are in terms of hour, the difference between historical value and desired value are 24 hours. Moreover, during the real electricity market operation, the day-ahead demand and price data including 24 values are only published by the end of each day, if GENCOs are about to predict the market data of any values on next day, the most recent real data that can be used is the last hour of the day before the predicting day. In addition, any data after that hour is unknown until the end of the predicting day. Therefore, in order to predict the hourly data on the predicting day, we not only rely on the known historical data but also rely on the newly predicted data.

Moreover, we can also observe that in most situations, the forecast data corresponding to the first hour of predicting day is usually the most accurate while the one corresponding to the last hour is usually the least accurate. This is due to the reason that for the first data, we used the original 48 residual values as historical data for training, these data were calculated based on the published market data. After that, we started to include more and more predicted data into historical data sets for training, which brings more errors into prediction process, especially for the predicted data of the last hour, we were using 23 newly predicted data and 25 calculated data.

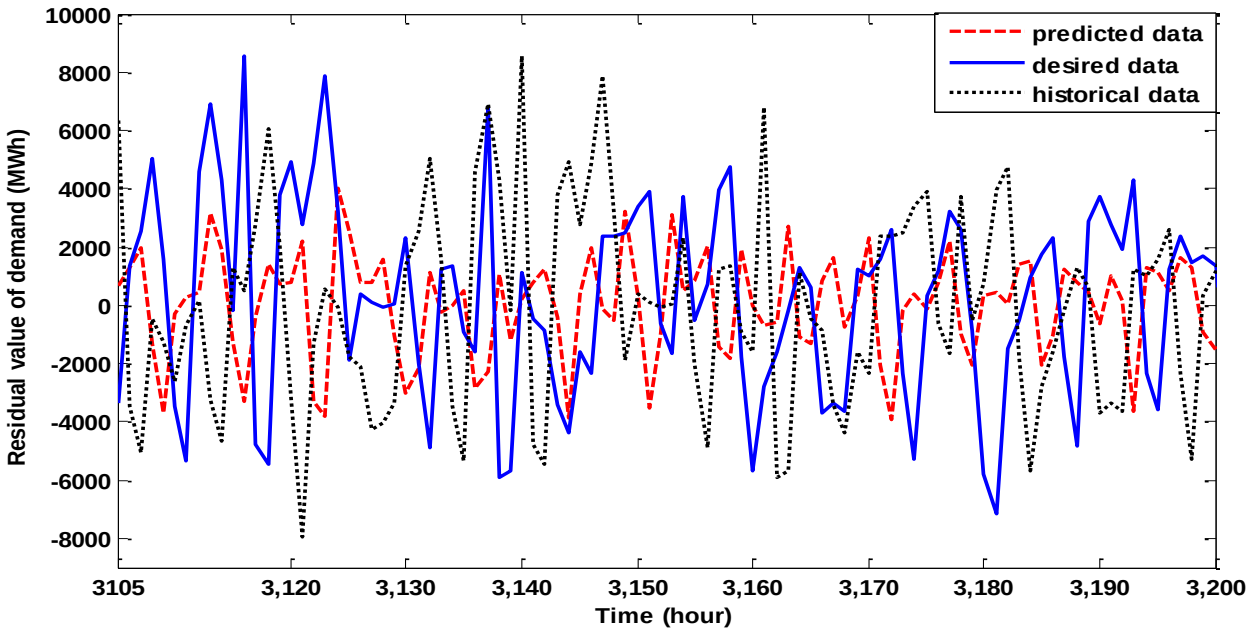

Figure 39: Comparison among historical, desired and prediction of residual value of PJM day-ahead market clearing demand.

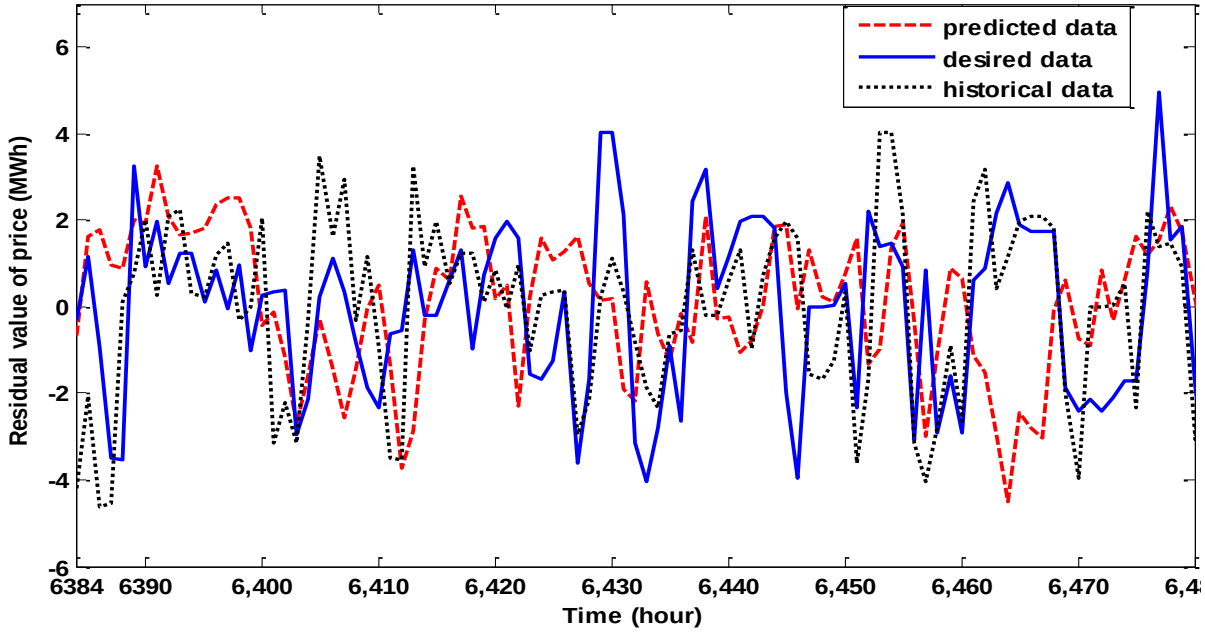

Figure 40: Comparison among historical, desired and prediction of residual value of PJM day-ahead market clearing price.

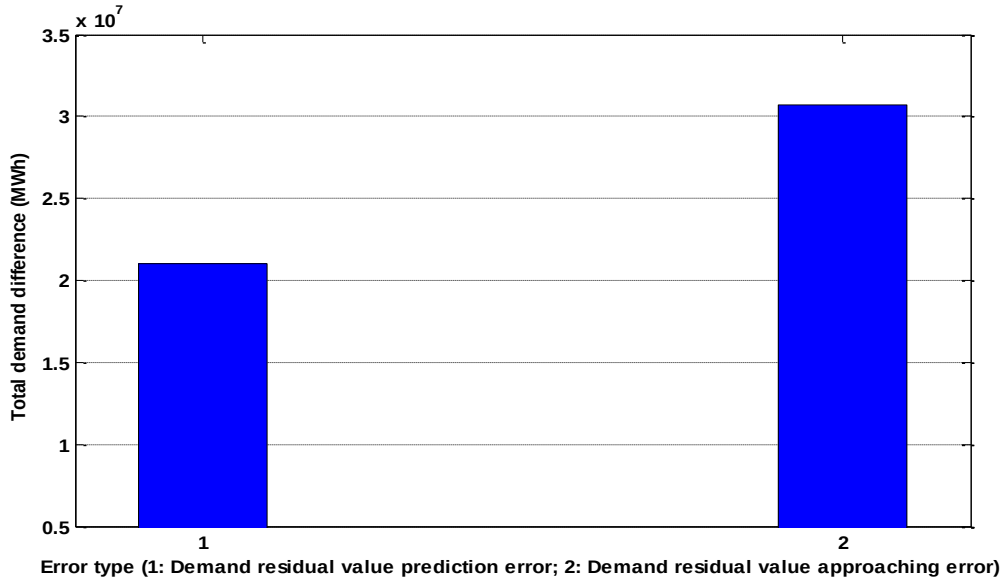

Figure 41: Total residual demand value prediction error and total residual demand approaching error (8760 hours).

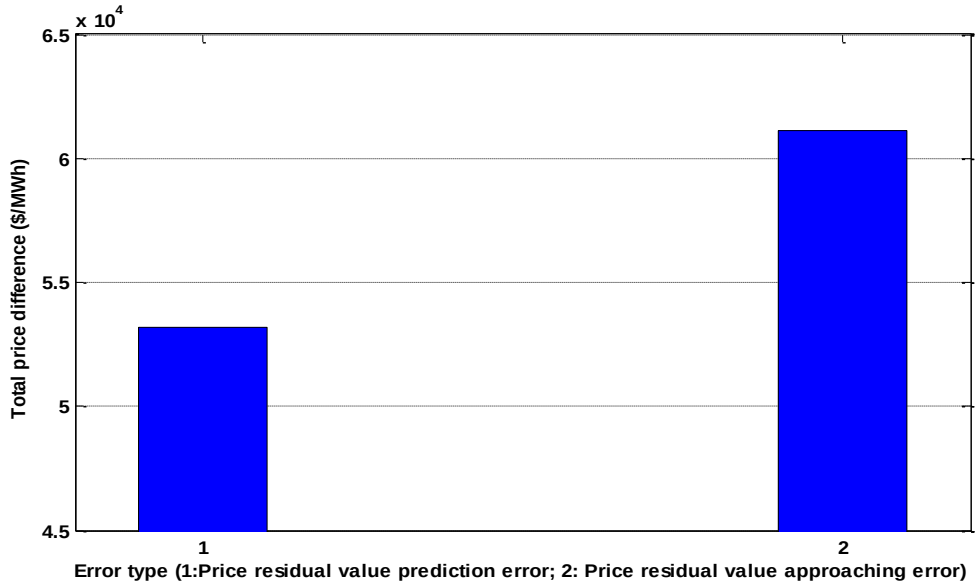

Figure 42: Total residual price value prediction error and total residual price approaching error (8760 hours).

In order to test the prediction results, we also calculated the absolute value of errors between the predicted residual data and the desired data, comparing with the absolute value of errors between the historical data and the desired data, as illustrated in Fig. 41 and Fig. 42.

From these two error comparison figures, we are able to conclude that during the 8760 hours of simulation, the residual demand prediction error is 21000000 MWh and the demand approaching error (difference between the historical value and the desired value) is 30700000 MWh while the daily average price prediction error is 53200 $/MWh and the price approaching error is 61100 $/MWh. The results shows that compared to the one-day ahead approaching residual value, the predicted demand and price residual value are closer to the original value.

5.5.3 Integration of multiresolution prediction results

After we obtained the multiresolution prediction results for different scales, we integrated the prediction results following (4.47) and (4.48). based on which we added the predicted hourly residual value of demand and price to the daily average value for the entire day. The summation results are the final multiresolution prediction results. The simulation results of the comparison among the predicted data, desired data and historical data are represented in Fig. 43 and Fig. 44.

As we can see from these two figures, the prediction starts from the first hour of day 15, which is also the first predicted data of daily average value scale and residual value scale. Similarly from the previous data processing, we took both simulation data curves for 96 hours in order to better observe the data trend. In these two figures, the dotted line line represents the historical data, solid line represents the desired data and the dash line represents the predicted data.

Results show that the adaptive multiresolution algorithm using RLS and improved ARMA models provides a good prediction of the historical data, the predicted demand and price data resembles in shape the original data and precedes in time the historical data. In order to better compare the prediction results with the desired data, we also calculated

the absolute value of errors between the predicted data and the desired data, comparing with the absolute value of errors between the historical data and the desired data, as illustrated in Fig. 45 and Fig. 46.

As shown in these two figures, the demand prediction error is 25300000 MWh while the demand approaching error is 37000000 MWh, the price prediction error is $ 56400 while the price approaching error is $ 56500. Moreover, in order to comprehensively test the multiresolution prediction method, we also compared the prediction results with the single scale RLS prediction method.

For the traditional single scale RLS prediction, we directly used the hourly demand and price data as historical data for training instead of calculating the daily average value and residual value. Similar as the residual value prediction, we set the forgetting factor as 1 and the filter order as 48. The real situation limitation is still considered, which is that before the end of each operating day, GENCOs are not able to obtain the real data for prediction. Therefore, we used the first 48 known hourly demand and price data to predict the first data of the prediction day and then include it as a new historical value for the next prediction while abandon the first historical value. The whole procedure will then be repeated until the data of the whole day is obtained.

As shown in Fig. 47 and Fig. 48, bar 1 represents the multiresolution prediction error, bar 2 represents the approaching error and bar 3 represents the single scale RLS prediction. Based on these two figures, we concluded that the single scale demand and price prediction are 41500000 MWh and $ 61100 respectively, which are both higher than the approaching error and the multiresolution prediction error. This indicates that the adaptive multiresolution RLS prediction method is superior to the single scale RLS prediction method.

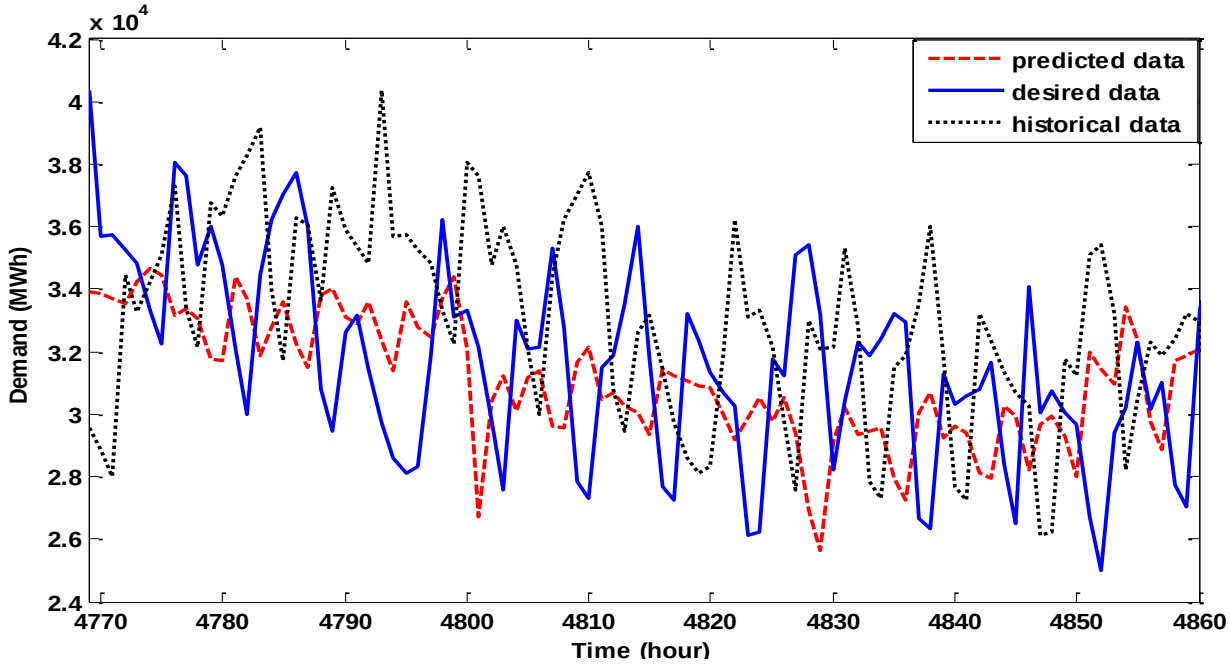

Figure 43: Comparison among historical, desired and multiresolution prediction of PJM day-ahead market clearing demand.

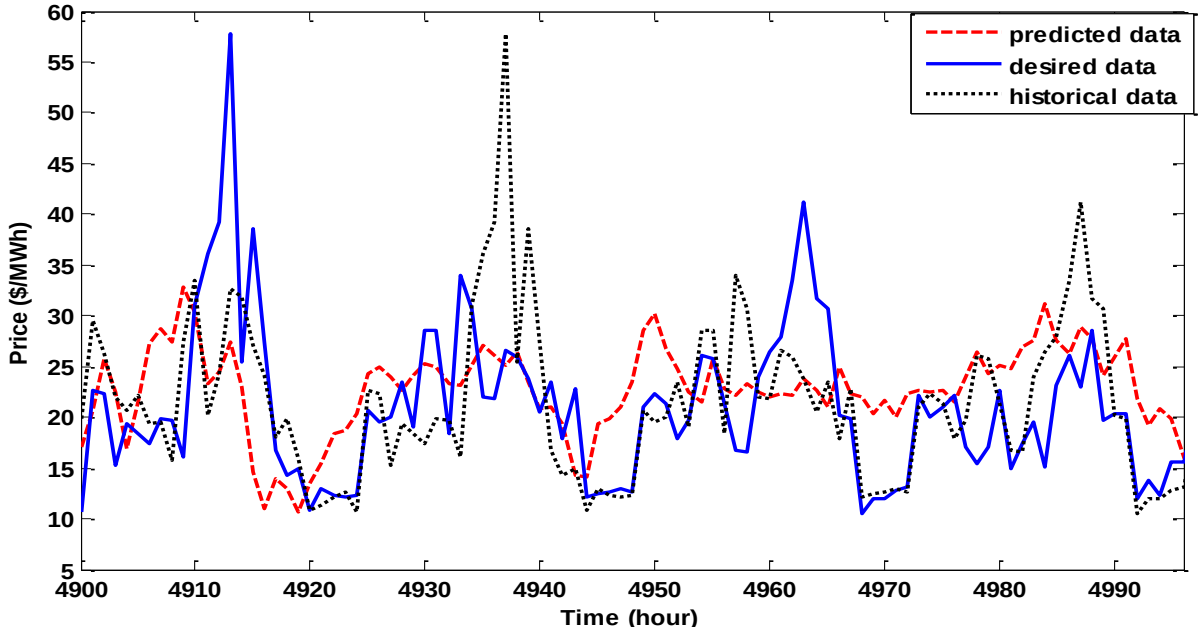

Figure 44: Comparison among historical, desired and multiresolution prediction of PJM day-ahead market clearing price.

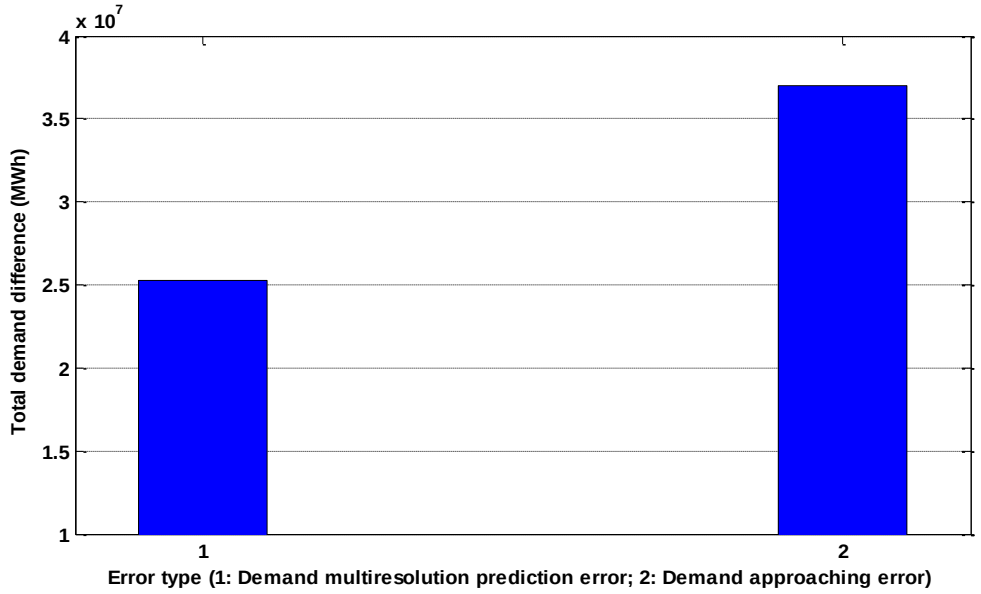

Figure 45: Total multiresolution demand prediction error and total demand approaching error (8760 hours).

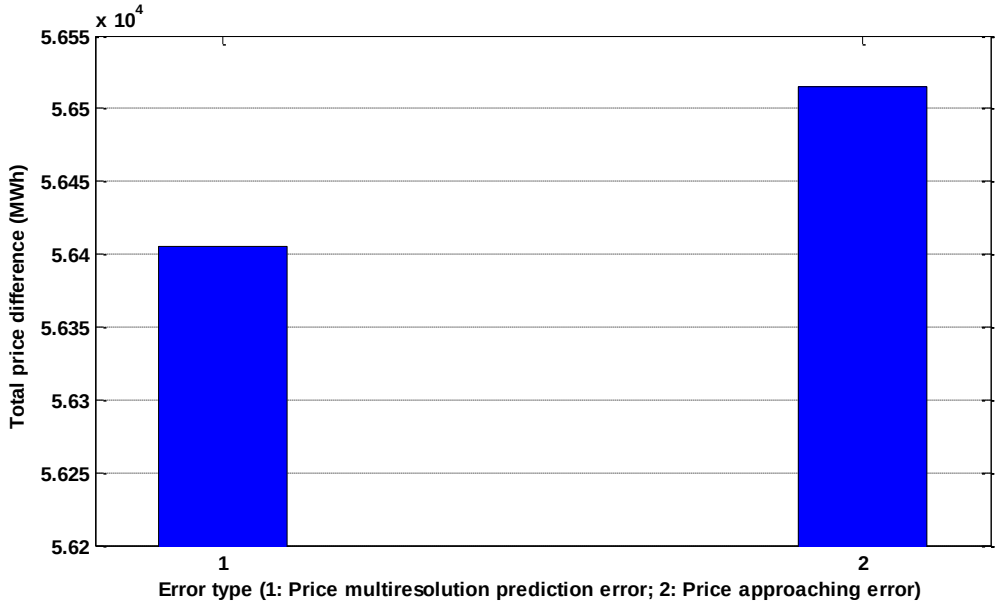

Figure 46: Total multiresolution price prediction error and total price approaching error (8760 hours).

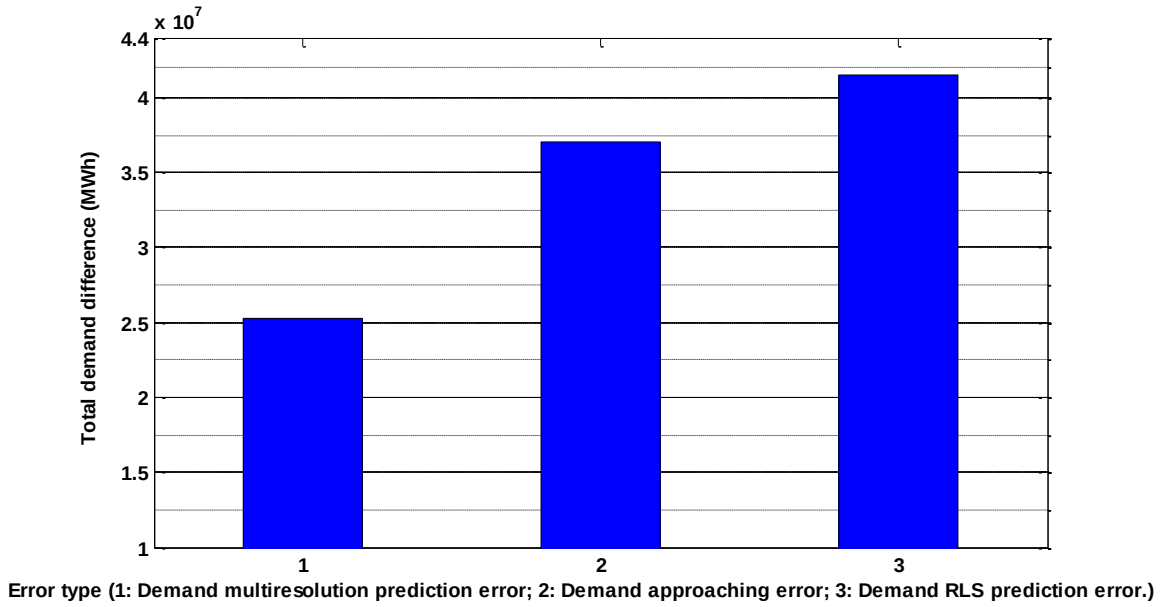

Figure 47: Comparison among total multiresolution demand prediction error, total demand approaching error and demand single scale RLS prediction error (365 days).

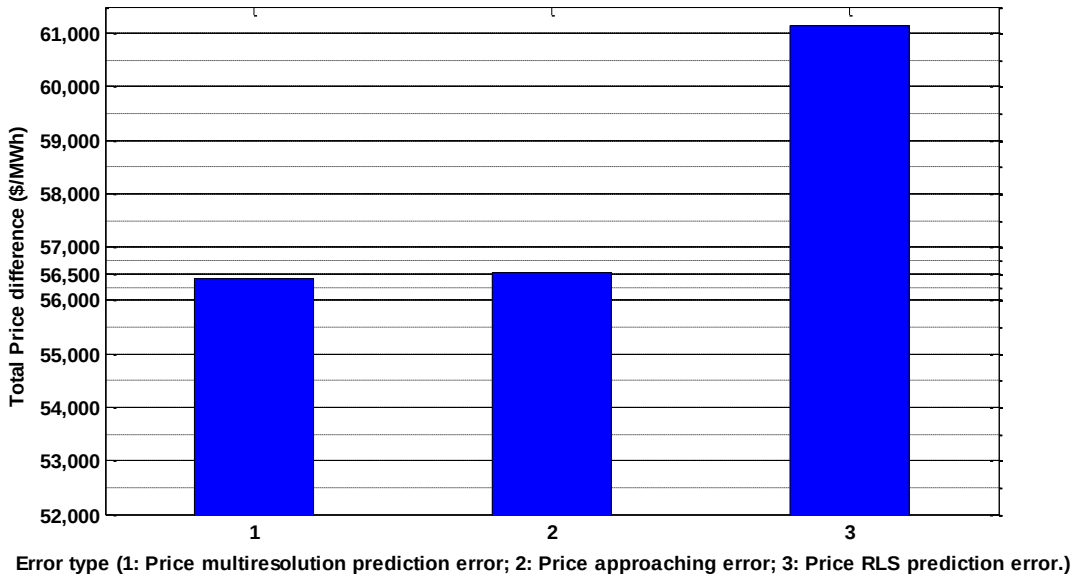

Figure 48: Comparison among total multiresolution price prediction error, total price approaching error and price single scale RLS prediction error (365 days).

6.0 CONCLUSION

6.1 SUMMARY

In this work, we introduced a closed-loop control system model to facilitate mathematical analysis and promote operational efficiency of the dynamic bidding process. The model is based on the perspective of the power generation side (GENCOS) and ISO. The purpose is to achieve a rational profit maximizing behavior for GENCOS during the day-ahead bidding process and to improve the wholesale market efficiency.

The control-theoretic model uses the game theory embedded with the learning ability as the major bidding strategy, which allows GENCOS to adjust their next-day bidding in the form of supply function equilibrium (SFE) through market observations. However, in dealing with the situation of sudden incidents, the dynamic SFE adjusting algorithm exposes its drawbacks. Therefore, We also designed an adaptive Recursive least square (RLS) control system based on two AR models and implement it into the bidding strategy of supply function equilibrium with learning process in order to help GENCO increase the market profit.

Multiresolution prediction algorithm is introduced in order to improve the electricity market demand and price prediction accuracy, the original data is decomposed into daily average value scale and hourly residual value scale, both of which are applied into the adaptive filter to generate the coefficients of ARMA models with external inputs.

Simulation results show that it was unnecessary for GENCO to know the competitors generation costs and commitments; The adaptive control system bidding strategy is able to catch the market behavior beforehand and generate more daily average profit than SFE adjusting bidding strategy. The multiresolution prediction method is able to provide even more accurate demand and price prediction effects than the single scale RLS prediction

method and the approximate historical value. This allows GENCOs to better catch the market behavior beforehand and brings GENCOs more real demand and price data used for bidding activities, which is also capable for GENCOs to obtain more profit during electricity market operation.

6.2 FUTURE EXTENSION

In the future, some possible research topics can be conducted based on this work. The author gives some aspects of possible extensions corresponding to the closed-loop control system model.

1. The multiresolution prediction results will be applied into the supply function equilibrium bidding strategy to formulate a more advanced adaptive control system in order to calculate the GENCOs market profit change.
2. GENCOs arbitrage and risk management parts will be considered inside the closed-loop control system. Study and implement the arbitrage pricing theory in the closed-loop control system. Implement the asset valuation and risk analysis in terms of multiple periods and combined with transmission constraint model in order to investigate the electricity market equilibrium.
3. Apply the closed-loop control system into real time electricity market so that the whole electricity market operation process can be studied and analyzed.

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