Forecasting Mid-Term Electricity Market Clearing Price Using Support Vector Machines

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ABSTRACT

In a deregulated electricity market, offering the appropriate amount of electricity at the right time with the right bidding price is of paramount importance. The forecasting of electricity market clearing price (MCP) is a prediction of future electricity price based on given forecast of electricity demand, temperature, sunshine, fuel cost, precipitation and other related factors. Currently, there are many techniques available for short-term electricity MCP forecasting, but very little has been done in the area of mid-term electricity MCP forecasting. The mid-term electricity MCP forecasting focuses electricity MCP on a time frame from one month to six months. Developing mid-term electricity MCP forecasting is essential for mid-term planning and decision making, such as generation plant expansion and maintenance schedule, reallocation of resources, bilateral contracts and hedging strategies.

Six mid-term electricity MCP forecasting models are proposed and compared in this thesis: 1) a single support vector machine (SVM) forecasting model, 2) a single least squares support vector machine (LSSVM) forecasting model, 3) a hybrid SVM and auto-regression moving average with external input (ARMAX) forecasting model, 4) a hybrid LSSVM and ARMAX forecasting model, 5) a multiple SVM forecasting model and 6) a multiple LSSVM forecasting model. PJM interconnection data are used to test the proposed models. Cross-validation technique was used to optimize the control parameters and the selection of training data of the six proposed mid-term electricity MCP forecasting models. Three evaluation techniques, mean absolute error (MAE), mean absolute percentage error (MAPE) and mean square root error (MSRE), are used to analysis the system forecasting accuracy. According to the experimental results, the multiple SVM forecasting model worked the best among all six proposed forecasting models. The

proposed multiple SVM based mid-term electricity MCP forecasting model contains a data classification module and a price forecasting module. The data classification module will first pre-process the input data into corresponding price zones and then the forecasting module will forecast the electricity price in four parallel designed SVMs. This proposed model can best improve the forecasting accuracy on both peak prices and overall system compared with other 5 forecasting models proposed in this thesis.

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ANN	artificial neural network
KKT	Karush-Kuhn-Tucker
LMP	locational marginal pricing
LSSVM	least support vector machine
MAE	mean absolute error
MAPE	mean absolute percentage error
MCP	market clearing price
MSRE	mean square root error
PRIM	percentage improvement
PJM	Pennsylvania–New Jersey–Maryland
SVM	support vector machine

CHAPTER 1: INTRODUCTION

1.1 Electricity Systems

Electricity is one of the most important commodities in our everyday life. With the rapid growth of electricity demand in the last century, electricity systems evolved as complex web of networks connecting generation, transmission and distribution within geographical jurisdictions.

The generation of electricity is most often a process of transferring kinetic energy into electrical energy through electromechanical power plants. Thermal (coal) plants, natural gas plants, oil plants, hydro plants and nuclear plants are the most common power plants all over the world. Other power plants based on alternate source of energy such as solar plants, wind plants and geothermal power plants are getting more attention due to their relatively low impact on environment. Electrical energy is transmitted to load centres via elaborate networks of transmission lines. At the load centres, electrical energy is then distributed by a complex web of distribution networks to end users.

A part of the electrical energy is lost during its transmission due to the physical properties of transmission lines. This puts a physical limit as to the distances of generation centres from the load centres. However, by employing DC transmission, it became feasible to transport electrical energy over longer distance. Throughout their evolution, electrical systems predominantly remained bound to their geographical jurisdictions. In modern societies, due to the high demand of electricity in urban areas and the frequently occurring sudden shortage and surplus of electricity from place to place, nearby electricity systems are integrated with each other to form a much bigger system in order to maintain the supply and demand stability, provide better service and improve the reliability of electricity supply.

1.2 Electricity Markets and Pricing

An electricity market is a system for buying and selling electricity within provincial or regional boundaries. All electricity markets can be classified into two major categories: regulated electricity market and deregulated electricity market. Under a regulated electricity market, the main aspects of generation, transmission and often distribution are governed by one entity. Under a deregulated electricity market, multiple entities are allowed to compete for supplying and distributing electricity. In Canada, Alberta and Ontario have deregulated electricity markets and the rest of the provinces have regulated electricity markets. Under a regulated electricity market, electricity price is set by the local utility company to cover its generation and transmission cost of electricity, make money for future network expansion and guarantee a decent return for the shareholders. On the other hand, electricity price under a deregulated electricity market is determined by the market based on the electricity supply and demand relationship. Details on regulated and deregulated electricity markets and pricing are provided in the following sections.

1.2.1 Regulated Electricity Markets and Pricing

Since the commercialization of electricity, generation, transmission and distribution of electrical energy required huge capital investment for operation, maintenance and expansion. This type of investment was achieved by awarding monopoly over the entire geographical jurisdiction. In some places, Crown corporations were established and given monopoly of generation, transmission and distribution of electrical energy within pre-specified geographical boundaries. A single entity is authorized by the government to operate and control all aspects of generation, transmission and distribution within a geographical jurisdiction. The single entity can set its own rate sometimes with the approval from a regulatory body. A natural monopoly guaranteed a decent return on the huge investment that a single entity or a crown corporation would typically make. However, regulation became part of the electricity industry all over the world. Its chief objective was to protect the consumer from the inevitable consequences of a monopoly industry.

As there is no competition within the same geographical jurisdiction, the regulated electric market is still a natural monopoly industry but carefully watched by the government. The vertically integrated structure of a regulated electric market is shown in Figure 1.1. In the 1970's in North America, there was usually a limited number of huge corporations owning and operating few vertically integrated electric systems. Each corporation was an independent system. Combined, they controlled more than 90 percent of the total electric market in their country. In a natural monopoly (regulated) electric market, local consumers have no other choice for electricity service but the local provider. Electricity price is high and services are usually limited.

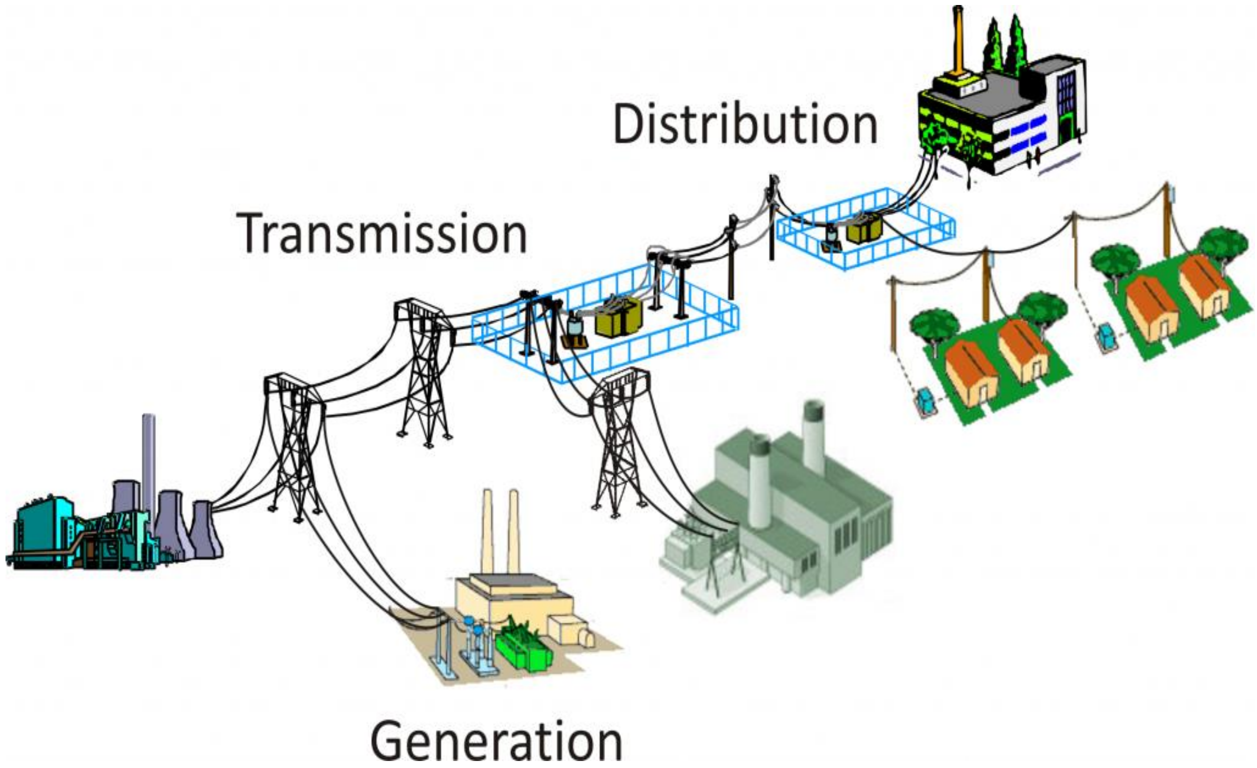
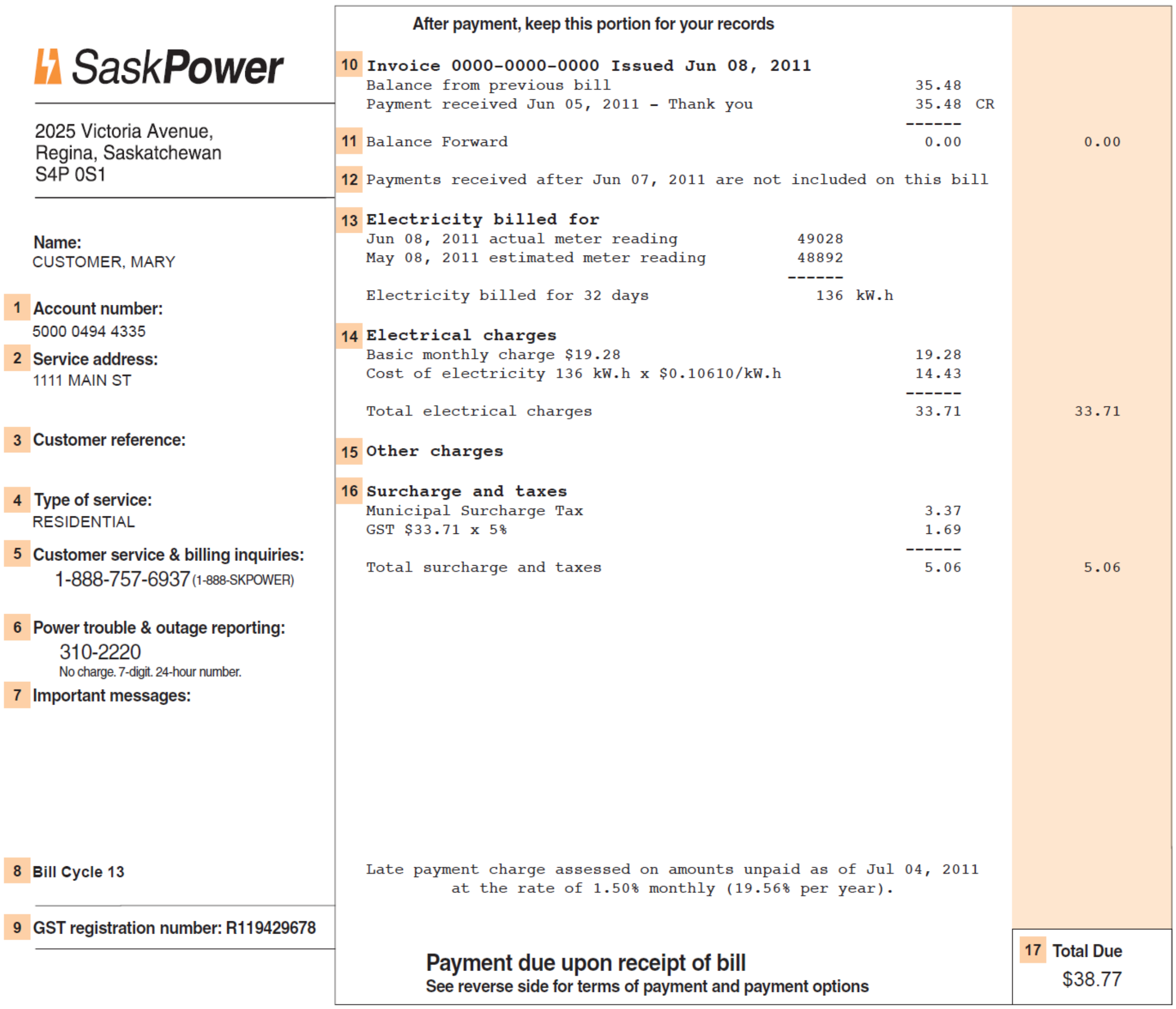


Figure 1.1: Regulated Electricity Market [1]

Taking province of Saskatchewan as an example, SaskPower is the only electricity provider in Saskatchewan. It owns and operates a $6.3 billion electricity market that includes generation, transmission and distribution assets. SaskPower operates three coal-fired power stations, seven hydroelectric stations, six natural gas stations and two wind facilities. Combined, it generates 3,513 megawatts (MW) of electricity. Meanwhile, SaskPower maintains nearly 152,000 kilometers of power lines, 55 high voltage switching stations and 186 distribution substations. SaskPower also has interconnections at the Manitoba, Alberta and North Dakota borders to buy and sell electricity from local and nearby facilities when needed. The performance of SaskPower including management and investment decisions are carefully watched by the Crown Investments Corporation of Saskatchewan and the provincial cabinet [2]. SaskPower sets its own electricity price based on the cost of service but carefully watched by the Saskatchewan Rate Review Panel who advises the Government of Saskatchewan on rate applications proposed by SaskPower and balances the interests of the customer, the crown corporation and the public [3]. An example of SaskPower residential electricity bill is shown in Figure 1.2.



SaskPower

2025 Victoria Avenue,
Regina, Saskatchewan
S4P 0S1

Name:
CUSTOMER, MARY

1 Account number:
5000 0494 4335

2 Service address:
1111 MAIN ST

3 Customer reference:

4 Type of service:
RESIDENTIAL

5 Customer service & billing inquiries:
1-888-757-6937 (1-888-SKPOWER)

6 Power trouble & outage reporting:
310-2220
No charge. 7-digit. 24-hour number.

7 Important messages:

8 Bill Cycle 13

9 GST registration number: R119429678

After payment, keep this portion for your records

```
10 Invoice 0000-0000-0000 Issued Jun 08, 2011
   Balance from previous bill                                35.48
   Payment received Jun 05, 2011 - Thank you                 35.48  CR
                                                            ------
11 Balance Forward                                            0.00        0.00
12 Payments received after Jun 07, 2011 are not included on this bill
13 Electricity billed for
   Jun 08, 2011 actual meter reading            49028
   May 08, 2011 estimated meter reading         48892
                                                ------
   Electricity billed for 32 days                 136  kW.h
14 Electrical charges
   Basic monthly charge $19.28                               19.28
   Cost of electricity 136 kW.h x $0.10610/kW.h              14.43
                                                            ------
   Total electrical charges                                  33.71       33.71
15 Other charges
16 Surcharge and taxes
   Municipal Surcharge Tax                                    3.37
   GST $33.71 x 5%                                            1.69
                                                            ------
   Total surcharge and taxes                                  5.06        5.06

   Late payment charge assessed on amounts unpaid as of Jul 04, 2011
        at the rate of 1.50% monthly (19.56% per year).
```

Payment due upon receipt of bill
See reverse side for terms of payment and payment options

17 Total Due
$38.77

Figure 1.2: SaskPower Residential Electricity Bill [4]

As SaskPower is the only electricity provider in Saskatchewan, there is no need to separate the electricity bill on each part of generation, transmission and distribution cost. It can be seen from

Figure 1.2 that the customer is charged on a fixed monthly charge plus the total amount of electricity consumed.

1.2.2 Deregulated Electricity Markets and Pricing

The meaning of deregulation is the reduction or elimination of government control in a particular industry. The purpose of deregulation is to promote more competition within the same industry and same geographical jurisdiction. It is generally believed that fewer and simpler regulations will lead to a raised level of competitiveness and would overall result in higher productivity, more efficiency and lower prices. After the huge success in airlines, trucking and telephone industries transformed from regulated market to deregulated market, electricity market started to deregulate in the early 1980s in Chile [5]. Electricity markets in North America started deregulation in the late 1990s and early 2000s. In Canada, deregulation of electricity market took effect in Alberta on January 1, 2001 and in Ontario on May 1, 2002. So far in Canada, only Alberta and Ontario electricity markets are deregulated. The rest of the provinces in Canada are still under regulated electricity market.

Deregulation in the electricity market transformed the old vertically integrated generation, transmission and distribution into horizontally separated businesses; 1) generation companies, 2) transmission and distribution utility and 3) retail electricity providers. Figure 1.3 shows a typical deregulated electricity market. Generation companies and retail electricity providers are under deregulated markets to encourage competition and innovation on technology. Several generation providers are operating in the same area instead of only one generation provider under a regulated electricity market. The local regulatory body can no longer set the electricity price. Consumers have more choices about their local electricity providers. They can choose different electricity providers depending on their requirement and demand. The transmission and distribution utilities are still under regulation in order to secure equal open access for all generation companies to the transmission and distribution network. The transmission and distribution network is operated by an independent non-profit entity called, independent system operator (ISO) or independent market operator (IMO).

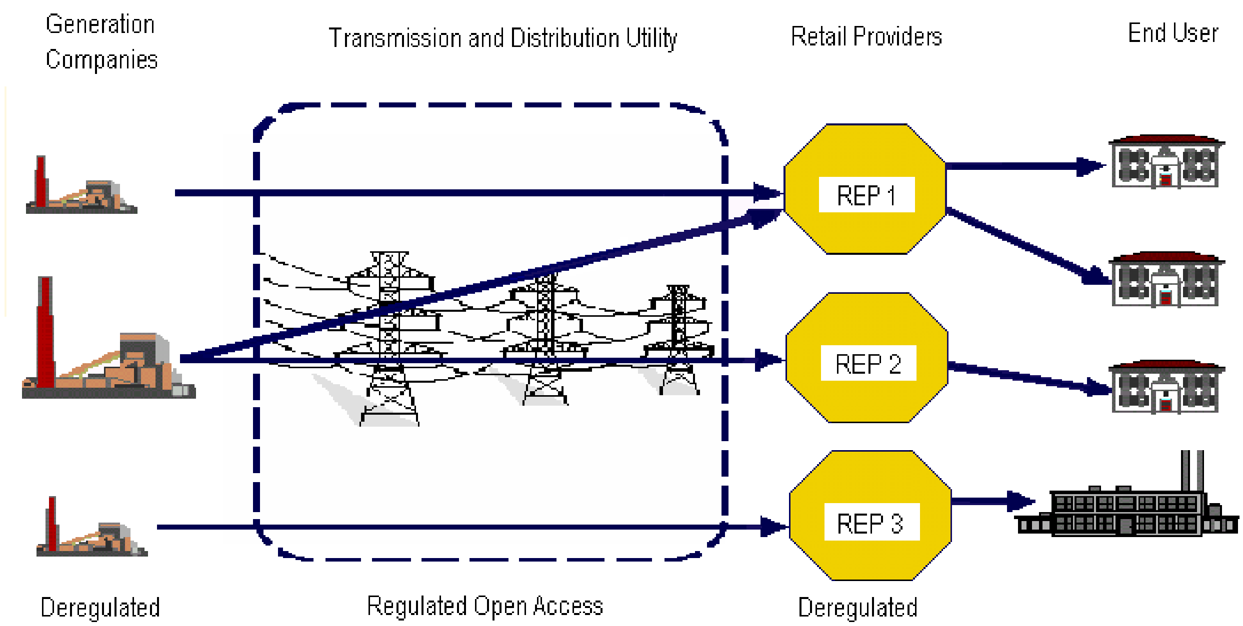


Figure 1.3: Deregulated Electricity Market Structure [6]

A deregulated electricity market bill from California is shown in Figure 1.4. Different from the bill from SaskPower, California electricity bill is charged separately on each part of generation, transmission and distribution because these parts are owned and operated by different companies. As a result, with the same amount of electricity usage, consumer's electricity bill would vary based on which electricity provider they choose. Transmission and distribution charge remain the same as those two parts are still under regulation where fixed price will be charged on every bill.

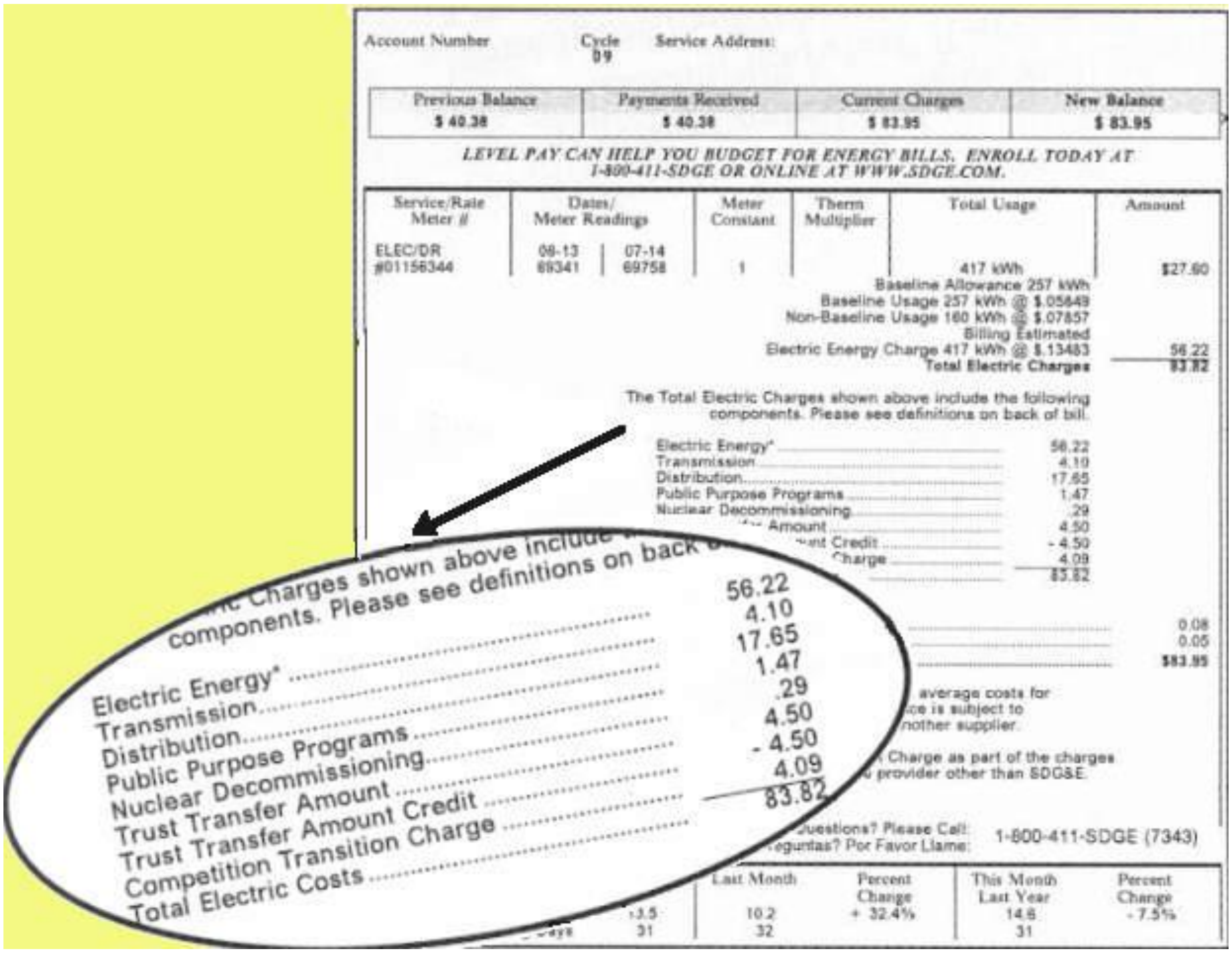


Figure 1.4: Sample Electricity Bill in California [7]

Taking Alberta electricity market as an example, as of June 2011, the Alberta electricity market contained 13,100 MW of capacity mixing with 45% coal, 41% natural gas, 7% hydro, 5% wind, and the remaining 2% is from other sources such as biomass. An average capacity of about 600 MW is imported from SaskPower and BC Hydro. The Alberta deregulated electricity market contains the generation market, the transmission and distribution market and the retail electricity market. The generation market is basically completely deregulated. The power transmission and distribution market is almost fully regulated and the retail power market is a mix between regulated and deregulated. Under generation market, by the end of 2011, ATCO, Balancing Pool, Capital Power, ENMAX, TransAlta and TransCanada are the six main suppliers who control total 76% of the electricity supply in Alberta [8]. The Alberta Electric System Operator (AESO) is responsible for the safe, reliable and economic planning and operation of the transmission and distribution market and ensures fair market rates and equal open access for all market participants. The regulated transmission and distribution service cost is approved by the Alberta Utilities Commission (AUC) to recover the cost of operating the system and the transmission companies' costs through the AESO's transmission tariff [9]. New transmission facilities construction, connection and operation in Alberta are also required to approve by the AUC. The retail electricity market is for buying and selling electricity services between end users and retail electricity providers. Albertans can choose their electricity provider and rate plan they preferred. Depending on consumers' need and budget, different electricity products with different rates, terms and services can be purchased under retail electricity market. Retail electricity providers purchase electricity through a combination of long-term contracts from the generation companies and short-term purchases through the power pool, a wholesale power market that sets price for electricity in each and every hour of the year [9] [10]. They then sell the electricity they have purchased to consumers, either at the Regulated Rate Option (RRO) rate or under deregulated contracted terms with variety of prices and service options [9]. The RRO rate is the default option for consumers and is regulated by the AUC [10]. The RRO rate varies month to month and is based on short and long-term market prices. Customers who consume less than 250,000 kWh per year are eligible for the RRO rate option. Moreover, there are four regulators, Utilities

Consumer Advocate (UCA), AESO, Balancing Pool and Market Surveillance Administrator (MSA), involved in Alberta deregulated electricity market to protect the interest of Albertans.

1.3 Electricity Market Clearing Price

Most mature deregulated electricity markets are arranged as a day-ahead electricity market and a real-time electricity market. The day-ahead electricity market is a forward market where hourly electricity price are calculated for the next operating day based on generation offers, demand bids and scheduled bilateral transactions. The real-time electricity market is a spot market where current electricity prices are calculated at five-minute intervals based on actual grid operating conditions [11]. Electricity market clearing price (MCP) usually refers to the day-ahead electricity market price.

Electricity MCP is the price that exists when an electric market is clear of shortage and surplus. In other words, the market is at equilibrium. It is the final outcome of market bidding price. When electricity MCP is determined, every supplier whose offering price is below or equal to the electricity MCP will be picked up to supply electricity at that hour. They will be paid at the same price, the electricity MCP, not the price they offered. The reason for this is to ensure fairness of the market and to avoid market manipulation. Figure 1.5 shows the determination of the electricity MCP.

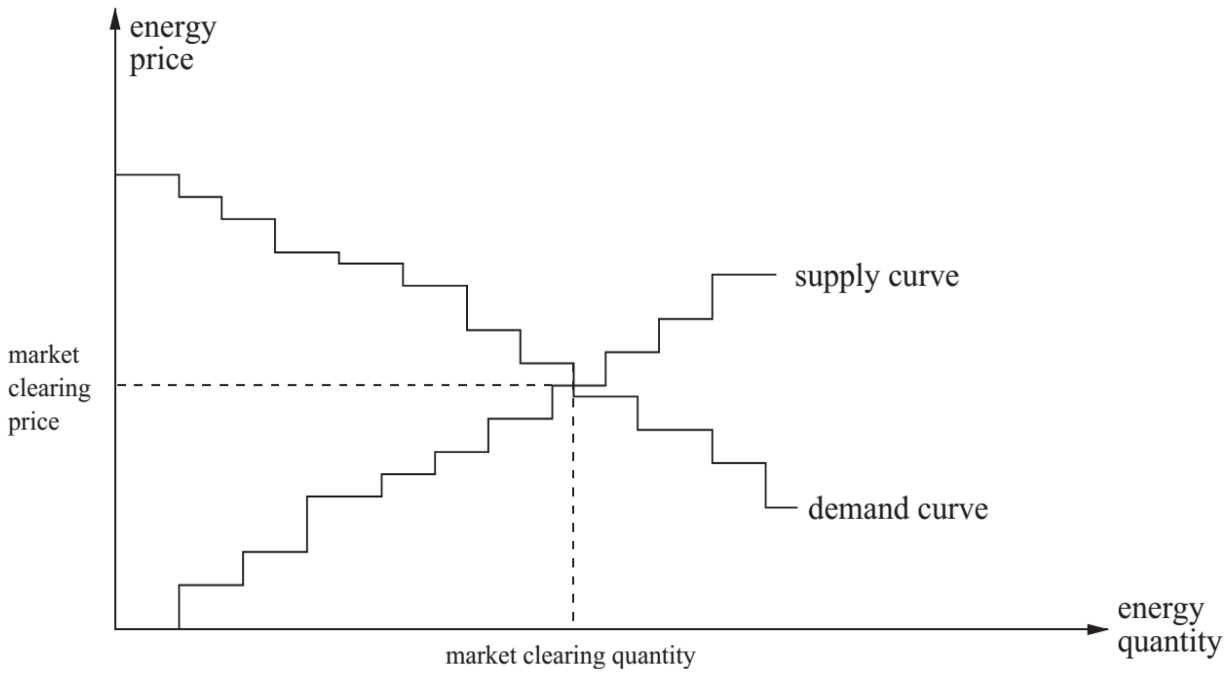


Figure 1.5: Electricity Market Clearing Price [12]

The process of determining the electricity MCP is basically the same in every deregulated electricity market. Every day, the ISO or IMO issues forecast of electricity demand for the next day and up to the month ahead including reserve energy on standby in case of an emergency. These forecasts are continually updated as new information comes in, such as changes in weather. Typically, the day-ahead forecasts are highly accurate, with less than a 2% variance from the actual demand figure [13]. Once the forecast information becomes public, the electricity providers will determine how much electricity they will supply and at what price. The electricity consumers (large volume consumers and retail electricity providers) will also determine how much electricity they will purchase and at what price. Both sides send their offers to the ISO or IMO. Meanwhile, they can also resubmit new offers till the deadline has been reached. The ISO or IMO then matches the offers in a merit order. It first accepts the lowest price offered and then “stacks” up the higher priced offers until enough energy have been accepted to meet consumers’ demands. Based on the last accepted offer, all accepted suppliers will get paid the same price, the market clearing price. This determination of the electricity MCP encourages electricity providers to keep their offered prices low in order to participate in selling all or most of their electricity at the market price. The market clearing price approach ensures the lowest possible price while maintaining reliability of the system [13].

1.4 Electricity Market Clearing Price Forecasting

The forecasting of electricity MCP is a prediction of future electricity price based on a given forecast of electricity demand, temperature, sunshine, fuel cost, precipitation and other related factors. Good electricity MCP forecasting can help consumers and suppliers to prepare their electricity usage and bidding strategy in order to maximize their profits. However, electricity MCP forecasting is a very complex task as there are many variables with various uncertainties that affect the electricity MCP. Some of these variables are straightforward and could be managed to forecast quite accurately such as temperature, sunshine, natural gas price and precipitation. Other variables, on the other hand, are more complex and less predictable such as bidding strategy, spot market price, spinning reserve market price, business competing strategy and unethical business behaviour. Based on the different time range, electricity MCP forecasting can be separated into short-term, mid-term and long-term forecasting.

Short-term electricity MCP forecasting, commonly known as the 24-hour day-ahead electricity price forecasting, is a widely used tool to predict the electricity market in the short-term. Currently, there are many techniques available for short-term forecasting of electricity MCP. The short-term MCP forecasting can help the generating companies to derive their bidding strategy in the pool and to optimally schedule its electric energy resources [14]. The electricity consumers (large volume consumers and retail electricity providers) also need short-term price forecasts for the same reasons.

The mid-term electricity MCP forecasting focuses electricity MCP on a time frame from one month to six months. It can be utilized in decision making and mid-term planning purposes. Some examples include adjustment of mid-term schedule and reallocation of resources. As the prediction horizon for mid-term forecasting is much longer and considering the volatile nature of electricity prices, forecasting electricity MCP for a longer horizon is more complicated than the short-term forecasting [5]. The mid-term electricity MCP forecasting is different from the short-term electricity MCP forecasting in the following ways. First of all, unlike the short-term electricity MCP forecasting, future segment for which we seek mid-term forecast is not contiguous to the immediate past history for which electricity MCP data are available. The short-term forecast, on the other hand, can utilize the trend from the immediate past. Mid-term forecast by its nature cannot utilize the trend from the immediate past. This requires that the mid-term forecasting model must possess very strong adaptability in handling out-of-sample and segmented data during training phase in order to accurately forecast the future electricity MCP with segmented input data. Moreover, because of the unavailability of immediate past data, forecasting technique such as time series cannot be utilized in mid-term forecasting. Every input data at hour t in mid-term electricity price forecasting has to be treated independently from its previous data $t-n$ or afterwards data $t+n$, for n equals 1, 2, 3… The third difference is the level of difficulty in locating and predicting peak prices. Because the short-term forecasting can utilize the trend from the immediate past, locating the peak prices in most cases is very accurate. The challenge is mainly how accurately the forecasting model can predict the values of the peak price. In the mid-term electricity MCP forecasting, due to the lack of availability of data from the immediate past, locating the peak prices becomes extremely difficult. This result accurately predicting the values of peak price becomes even more difficult. The fourth difference is the length of historical data to train the forecasting model. The short-term electricity price forecasting model usually only needs the last couple of days of data to train the forecasting model. The mid-term forecasting model, on the other hand, usually requires one year of historical data in order to train the forecasting model. Finally, only non-linear regression based forecasting model is capable of mid-term forecasting. Linear regression based forecasting model can only be considered as an add-on module in the mid-term forecasting. Currently, very little work has been done to forecast electricity MCP on a mid-term basis, but many techniques are available for short-term electricity MCP forecasting.

The long-term electricity MCP forecasting is developed annually for the purposes of generation expansion plans and long-term contractual decisions. The electricity consumers (large volume consumers and retail electricity providers) also need long-term price forecasts for portfolio establishment process [15].

1.5 Review of Current Studies

Currently, there are many techniques available for short-term forecasting of electricity MCP. Among these existing methods, regression methods such as auto-regressive integrated moving average (ARIMA) [16], wavelet transform [17], [18], Monte Carlo simulation [19], time series [20], [21], bid-based stochastic model [19] and dynamic regression [16] were the first generation of techniques utilized to forecast electricity MCP. Later on, artificial neural network (ANN), due to its flexibility in handling highly non-linear relationships and relatively easy implementation

[22]-[24], was applied to forecast short-term electricity MCP [25], [26]-[28]. Deregulated electric markets that utilize ANN method to forecast electricity MCP include PJM interconnection, Australian electric market, England-Wales pool and New England ISO [25].

Recently, support vector machine (SVM), a new learning method based on structural risk minimization, has gained increased attention in electricity MCP forecasting [29]-[32]. SVM optimizes itself based on the selection of training input data. A traditional SVM could achieve around 3% [33] better performance compared to a traditional ANN on the short-term electricity MCP forecasting. Several algorithms are used to improve the training of SVM that in turn improves the price forecasting accuracy. These algorithms include genetic algorithm (GA) [33]-[36], artificial fish swarm algorithm [37], independent component analysis (ICA) algorithm [38], [39] and rough sets algorithm [40], [41]. An upgraded SVM, called the least squares support vector machine (LSSVM) was also developed to improve the accuracy of the original SVM [36], [42]-[44]. Although each method has shown some improvements, the overall system accuracy was still quite low.

Electricity MCP forecasting using hybrid models combining several prediction methods is the new trend in recent electricity price prediction studies. Hybrid models can compensate the weaknesses of utilizing any individual established method and achieve better overall system results. Xu et al [28] proposed a short-term electricity price and load-forecasting model with the combination of non-decimated wavelet transform, ANN, and support vector machine (SVM) techniques. Xu's model had taken the weather factor into account. A set of feed-forward NN had been utilized as one of the several modules inside the whole forecasting system to predict the load data. The scaled conjugate gradient algorithm is used in training the ANN. Results from numerical examples indicate the capability of handling extremely chaotic market.

Zhou et al [30] proposed an accurate online support vector regression (SVR) method to upgrade the price forecasting model. It upgrades the existing parameter of the SVMs when the electricity price parameters are changed from time to time. This makes the SVM training always current. The real time electricity prices are continuously entered into the SVM to upgrade the existing SVM parameters.

Hu et al [31] presented a review of short-term electricity price forecasting techniques in deregulated electricity markets. The author mentioned that from his review of previous papers [45], including more factors in such models (HMM, ARIMA and ANN) does not necessarily mean that the predictive results will be better. The reason is because some additional factors are also unavailable and may need forecasting as well. Therefore, he concluded that the selection of a suitable forecasting technique with proper input factors is vitally important for forecasting accuracy.

Swief et al [32] proposed a SVM based combined load and price dynamic forecasting model utilizing time series load and price data. In this study, the number of previous points, which is related to the forecasted point, is selected from the set of data with the same spike indices. It first utilized the principle component analysis (PCA) and K nearest neighbor (KNN) points techniques to reduce the amount of data required by the model. SVM is applied to simulate and finally forecast the electricity MCP.

Saini et al [33] proposed a hybrid electricity price forecasting model utilizing SVM and GA data mining technique. Instead of single time series, separate time series of data for each trading interval have been employed to model each day's price profile. Results were compared with a heuristic technique, a linear regression model and the other reported works in the literature.

Testing results show that proposed GA-SVM model has better forecasting ability than the other forecasting models. The proposed work utilized complete 1-year data from two different power systems.

Sun et al [34] proposed a hybrid electricity price forecasting model that includes both genetic algorithm and SVM. It only utilized the historical price data. The time series data were included in the updated model [29]. The same hybrid method has also been proposed by Chen [35].

Mahjoob et al [36] proposed a hybrid forecasting model utilizing the LSSVM approach in combination with the GA optimization to forecast electricity market clearing price in Spain and California electric markets. The forecasting results are compared to those obtained using a select variety of previously proposed methods such as most likely position (MLP), ARIMA, WAVELET-ARMA, Fuzzy NN and Time Series based models. The performed comprehensive comparison demonstrates the remarkable accuracy and effectiveness of the proposed method.

Gone et al [37] also proposed a hybrid electricity price forecasting model utilizing both artificial fish swarm algorithm (AFSA) and SVM. In AFSA tuning, the SVM model is trained for various parameter settings, roughly from a large range with a large fixed step to a smaller range with a smaller fixed step. The validation-sample error is calculated for each parameter setting. Parameters with the smallest validation-sample errors are finally selected.

Zheng et al [38] proposed a hybrid electricity forecasting model utilizing both independent component analysis (ICA) and SVM algorithm. ICA has the special effect on extracting the latent source feature. The paper adopts Fast ICA algorithm proposed by Hyvärinen and Oja [46] in considering convergence speed and usability. ICA is a statistical model utilizing linear transformation in expressing observed data of the latent variables ("independent components") that are non-Gaussian and mutually independent.

Wang et al [40] proposed a combined algorithm including rough sets and particle swarm optimization SVM. Historical data are firstly normalized into scale from 0 to 1 before utilizing rough sets data mining technique.

Xie et al [42] proposed a hybrid electricity price forecasting model that integrates clustering algorithm with least square support vector machine (LSSVM). Clustering of the data samples are performed, which aims at mining the latent patterns in the data. LSSVM is then utilized for the electricity price modeling. The hybrid architecture resulted in more efficient training and forecasting. The results are compared with the standard LSSVM.

Fan et al [43] proposed a novel model for short-term electricity price forecasting based on hybrid forecasting model including the Bayesian Clustering by Dynamics (BCD) and SVM. The BCD classifier is applied to cluster the input data set into several subsets in an unsupervised manner. 24 SVMs are then utilized for forecasting the next day's electricity price. BCD is based on unsupervised learning, which has the ability to partition the space of input training data set into many subsets without prior knowledge about the classifying criteria. Compared to other clustering methods such as hierarchical clustering or Self Organizing Maps (SOM), BCD identifies the set of clusters with maximum posterior probability without requiring any prior input about the number of clusters, thereby avoiding the risk of over fitting.

Fan et al [44] proposed a two-stage architecture hybrid network of self-organized map (SOM) and SVM electricity price forecasting model for the next-day hourly electricity price. The SOM is applied to cluster the input data set into several subsets in an unsupervised manner. SVM is utilized to fit the training data of each subset in the second stage in a supervised learning. SOM has the ability to partition the space of input training data set into many subsets without prior knowledge about the classifying criteria (or unsupervised learning), where each subset is considered as a stationary time-series data set. During training, in order to improve the accuracy, statistical analysis of “studentised” residuals via dummy regression in applied to remove the noise data (high price peak). Data correlation analysis has also been applied in this proposed work.

Nogales et al [47] proposed two short-term electricity price forecasting models using both dynamic regression and transfer function based on time series analysis. These two techniques were used to check against each other. A hypothetical probability model was set up to represent the price and demand data which are recorded in time series. The time series method is also utilized by Obradovic [20] in forecasting day-ahead electricity market price and by Crespo [21] in forecasting electricity spot prices.

Li et al [48] proposed a “4+1” SVM where the first ‘4’ are four SVMs on four different input factors: days, price, load and weather. The ‘1’ is the last forecasting SVM. Fuzzy classification is utilized as data mining technique where each kind of data is classified and clustered into lowest, middle, highest and other (no data). Day type data are separated as work day and holiday.

Areekul et al [49] proposed a hybrid short-term electricity price forecasting model combining both ARIMA and ANN methods. The ARIMA was first applied to forecast the electricity price and then the ANN was added to forecast the adjustment for each predicted price done by the ARIMA. Australian national electricity market data was examined by the proposed hybrid model.

Zhao et al [50] proposed a novel data mining based approach that forecast the prediction interval of the electricity price utilizing SVM. Forecasting the prediction interval is essential for estimating the uncertainty involved in the price and thus is highly useful for making generation bidding strategies and investment decisions. It used a heteroscedatic variance equation for SVM to capture the non-linear patterns of the electricity price. Maximum likelihood estimation is used for model parameters. It first performed the Lagrange Multiplier test and verified that the electricity price is heteroscedastic, and the Non-linear conditional heteroscedastic forecasting (NCHF) model is therefore a suitable tool for forecasting such a time series. After that, the NCHF was compared with the ARIMA and GARCH (generalized autoregressive conditional heteroscedastic) model to demonstrate that the NCHF model has a better performance in forecasting the price interval. Results show that the proposed NCHF model could effectively forecast the price interval of the electricity price.

Zhao et al [51] [52] proposed a data mining approach to give a reliable forecast of the occurrence of price spikes. Zhao's upgraded model [52] is the advanced work based on [51]. Feature selection techniques are first described to identify the attributes relevant to the occurrence of spikes. Both SVM and probability classifier are used to predict the spike occurrence. Both normal prices forecasting model and spike value forecasting model are included in the proposed forecasting model.

Xie et al [53] proposed a sensitivity analysis of electricity price utilizing SVM and regression model where several price-load elasticity equations are built based on the price pattern data sets classified by SVM classification. A similar work focused on price-load elasticity analysis is done by Wang in [54].

Pousinho et al [55] proposed a hybrid short-term electricity prices forecasting model combined with particle swarm optimization (PSO) and adaptive-network based fuzzy inference system (ANFIS).

1.6 Research Objective and Scope

The objective of this research work is to develop forecasting models that can be utilized to predict the electricity MCP on a mid-term basis. The mid-term forecasting focuses electricity MCP on a time frame from one month to six months. Electricity market clearing price varies due to the changes in various variables such as load, temperature, fuel cost, precipitation, market clearing price bidding strategy and business competing strategy. However, mid-term electricity MCP forecasting by its nature cannot utilize the trend from the immediate past. Thus, the proposed models should be developed to meet the following criteria:

- Provide hourly forecasted electricity market clearing price on a mid-term basis.
- Possess very strong adaptability in handling out-of-sample and segmented data.
- Be flexible enough to accommodate changes on demand, fuel cost and precipitation.
- Be flexible enough to utilize alternative training data to avoid man-made effects such as business competing strategy and unethical business behaviors.

The main contribution of the proposed work includes: (1) developing techniques for mid-term electricity MCP forecasting, (2) developing techniques addressing and resolving the problems associated with utilizing to improve the forecasting performance of single non-linear regression based models such as single SVM and single LSSVM and (3) developing multiple SVM and multiple LSSVM based forecasting models containing both SVM/LSSVM classification and SVM/LSSVM regression modules.

1.7 Thesis Outline

This thesis is organized in seven chapters. Chapter 1 introduces the basic concepts of deregulated electric market, electricity MCP and electricity MCP forecasting methods. It also summarizes the present problems involved in electricity MCP forecasting and the methods utilized in forecasting the electricity MCP under deregulated electric market.

An introductory level of description of a typical support vector machine (SVM), least squares support vector machine (LSSVM) and auto-regressive moving average with external input (ARMAX) are presented in Chapter 2. The basic configuration and working principles of a SVM, LSSVM and ARMAX are also described. Historical information of SVM, LSSVM and ARMAX development are also discussed in this Chapter.

In Chapter 3, data collection and pre-process are described. It explains the PJM interconnected electric market data used in this work. Data selection and input data pre-processing are also discussed in this Chapter.

Chapter 4 introduces a comparison between two mid-term electricity MCP forecasting models: 1) a SVM forecasting model and 2) a LSSVM forecasting model. Forecasting model architecture and the selection of training data for classification and prediction modules are explained in detail. Testing process and forecasting results are evaluated using three different regression evaluation criteria.

Chapter 5 introduces two hybrid mid-term electricity MCP forecasting models: 1) a hybrid SVM and ARMAX forecasting model and 2) a hybrid LSSVM and ARMAX forecasting model. Architecture and the selection of training data of the two hybrid electricity MCP forecasting models are explained in detail. Testing process and forecasting results compared with utilizing a single SVM and a single LSSVM are also included in this Chapter.

Chapter 6 introduces mid-term electricity MCP forecasting utilizing a multiple SVM forecasting model and a multiple LSSVM forecasting model. Forecasting model architecture and the selection of training data for classification and prediction modules are explained in detail. Additional evaluation criteria for classification computation and forecasting results compared with utilizing a single SVM and a single LSSVM are also included in this Chapter.

The conclusions and the scope of future work are presented in Chapter 7.

CHAPTER 2: SUPPORT VECTOR MACHINE AND RELATED METHODOLOGIES

2.1 Introduction

Support vector machine (SVM), least squares support vector machine (LSSVM) and auto-regressive moving average with external input (ARMAX) are the three methodologies utilized in the proposed mid-term electricity MCP forecasting. Unlike the short-term electricity MCP forecasting, the mid-term electricity MCP forecasting is different in data selection and the use of underlying assumptions. Therefore, only non-linear regression based forecasting model is capable of mid-term forecasting. Linear regression based forecasting model can only be considered as an add-on module in the mid-term forecasting [57].

SVM is a new learning method based on structural risk minimization. Recently, SVM is gaining popularity in classification and regression computations over other self learning algorithms such as artificial neural network (ANN). The major advantages of SVM over ANN or any other forecasting algorithms are that SVM can avoid problems such as data over fitting, local minimum and unpredictably large out-of-sample data error while at the same time achieving better results. SVM is also a very robust forecasting model. Regardless of the initial value, SVM will always end up with the same result. Moreover, SVM has less adjustable parameters compared to ANN and therefore is less complicated in parameter selection. SVM optimizes itself based on the selection of training input data. A traditional SVM could achieve around 3% [33] better performance compared to a traditional ANN on the short-term electricity MCP forecasting.

In order to improve the accuracy of SVM, new algorithms such as genetic algorithm (GA), artificial fish swarm algorithm, independent component analysis (ICA) algorithm and rough sets algorithm are widely used to upgrade the training of SVM. Later on, a structural level upgraded SVM, the least squares support vector machine (LSSVM), was developed to improve the accuracy of the original SVM. LSSVM is the least squares formulation of a standard SVM. There are two major differences between SVM and LSSVM. The first difference is that in the training process, SVM uses a quadratic formulation while LSSVM uses a set of linear equations. The second difference is on the selection of support vectors where in SVM only the ones with non-vanishing coefficients are selected as support vectors while in LSSVM all training data are considered as support vectors [58].

ARMAX is the only linear regression methodology utilized in this work while SVM and LSSVM are the non-linear regression methodologies. It is an estimation method generally used in statistics and signal processing. Like wavelet transform, Monte Carlo simulation, time series, bid-based stochastic model and dynamic regression, ARMAX was among the first generation of techniques utilized to forecast electricity MCP. ARMAX is proposed as an add-on module in the proposed mid-term electricity MCP forecasting.

2.2 Support Vector Machine

SVM was first introduced by Vladimir Vapnik in 1979 based on statistical learnings and then developed by Vladimir Vapnik and his co-workers at AT&T Bell Laboratories in 1995. After the book “An Introduction of Support Vector Machines and other kernel-based learning methods” by

Nello Cristianini and John Shawe-Taylor published in 2000, it started getting more popularity and application in many fields. At the early stage, SVM was only used for classification purposes. Later on, the regression computation of nonlinear function was added by solving a convex quadratic optimization problem [59].

A brief SVM architecture is shown in Figure 2.1. It is very similar to a 3-layer feedforward ANN. It has the input layer and the output layer containing either single or multiple input/output data. The only difference is inside the hidden layer where kernels replace the hidden neurons. The working principle of a SVM is also different from that of an ANN. A 3-layer feedforward ANN contains two transfer functions connecting the input layer to the hidden layer and the hidden layer to the output layer. SVM, on the other hand, only has kernels acting like transfer functions inside the hidden layer connecting the input layer and the output layer. Kernels transfer low dimensional input data vector into a much higher dimensional vector (sometimes infinite) and eventually transfer the highly non-linear problem inside the input space into a linear problem inside the feature space. This procedure of utilizing a transfer function is shown in Figure 2.2. After the transformation is completed, optimization algorithms are then applied in order to perform the regression or classification computation. SVM uses a quadratic formulation as optimization algorithm.

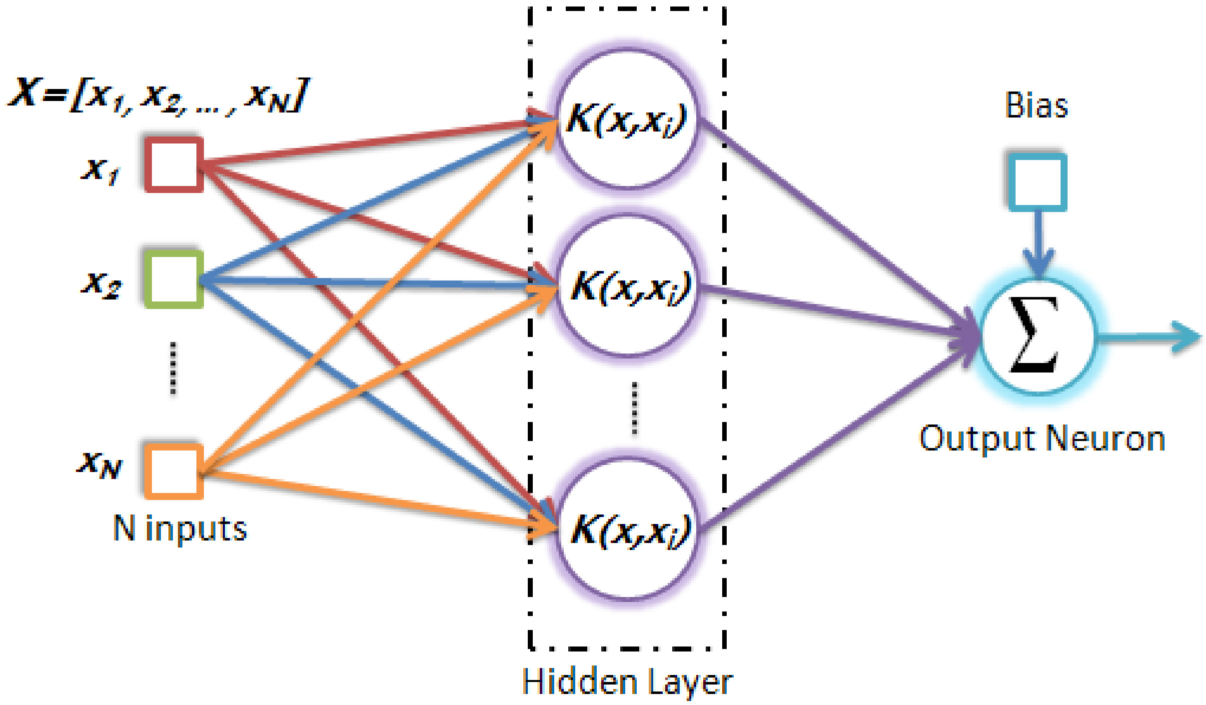


Figure 2.1: SVM Architecture [36]

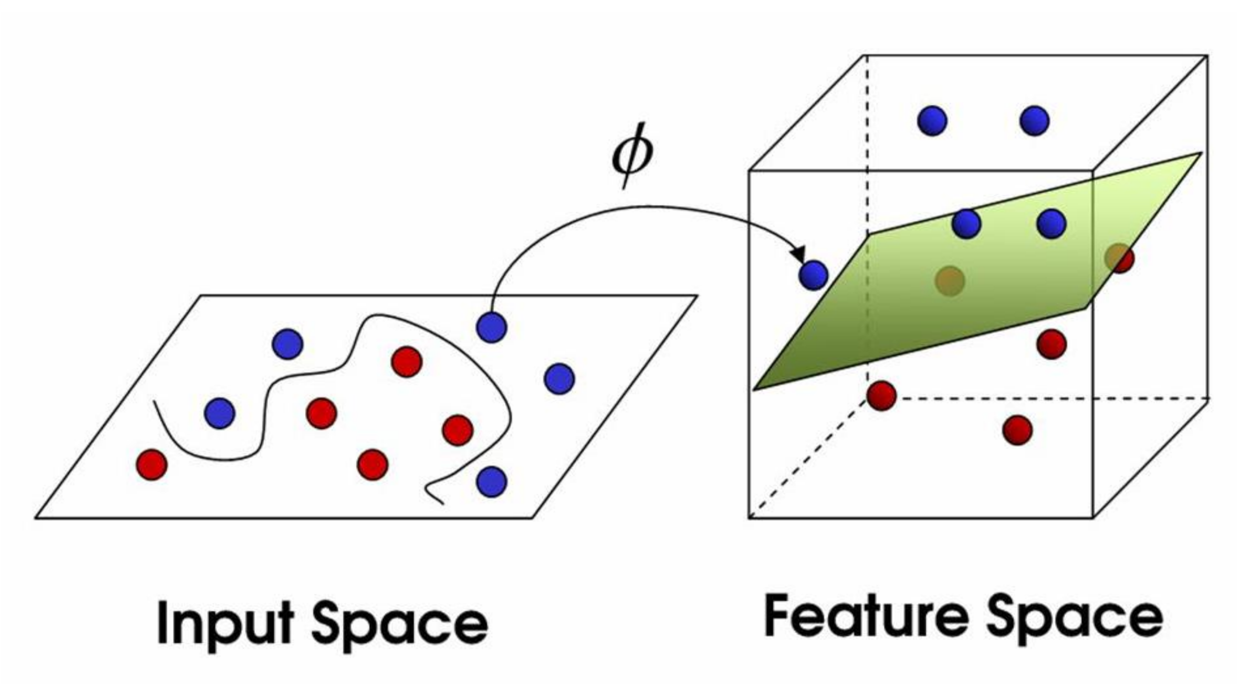


Figure 2.2: Transferring Vectors from Input Space into Feature Space [60]

SVM only selects the vectors with non-vanishing coefficients as support vectors. A two dimensional space linear separation by a SVM is shown in Figure 2.3 in order to show the difference between vectors and support vectors. It can be seen in Figure 2.3 that two groups of vectors (circles and crosses) are successfully separated by an optimal hyperplane that obtained the maximum (optimal) margin between the two groups. The vectors which are highlighted by the gray box are considered as support vectors for SVM.

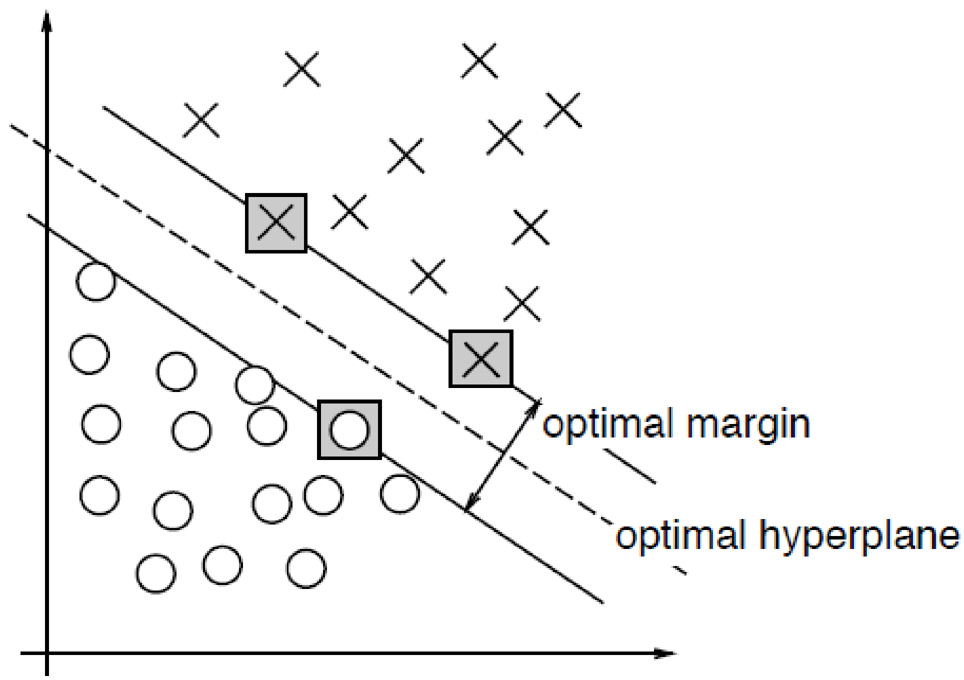


Figure 2.3: Two Dimensional Space Linear Separation by a SVM [58]

Suppose $\{(X_t, y_t)\}$ for t = 1 to N is a given set of data where $X_t = (x_{t1}, x_{t2,\ldots,} x_{tk})$ is the input vector with k multiple variables and y_t is the corresponding price data at time t which could be defined as

$$y_t = f(X_t, W) = \langle W, \varphi(X_t) \rangle + b \tag{1}$$

where $\langle , \rangle$ denotes the dot product, W is the weight vector, b is the bias, and $\varphi()$ is the mapping function that transfers input vector X_t into a much higher dimensional feature space (could be infinite). The corresponding optimization problem is then

$$
\begin{aligned}
&\text{minimize} \quad \frac{1}{2}\|W\|^2 + C\sum_{t=1}^{N}(\xi_t + \xi_t^*) \\
&\text{subject to} \quad \begin{cases} y_t - \langle W, \varphi(X_t)\rangle - b \le \varepsilon + \xi_t \\ \langle W, \varphi(X_t)\rangle + b - y_t \le \varepsilon + \xi_t^* \\ \xi_t, \xi_t^* \ge 0 \end{cases}
\end{aligned} \tag{2}
$$

where C is the regularization constant with regard to the unit cost of errors. ξ_t and ξ_t^* are the slack variables that measure the cost of the errors both above and below the target value on the training points shown in Figure 2.4. The ε-insensitive loss function with bandwidth 2ε is defined as

$$
|y_t - f(X_t, W)|_\varepsilon = \begin{cases} 0, & \text{if } |y_t - f(X_t, W)| \le \varepsilon \\ |y_t - f(X_t, W)| - \varepsilon, & \text{otherwise} \end{cases} \tag{3}
$$

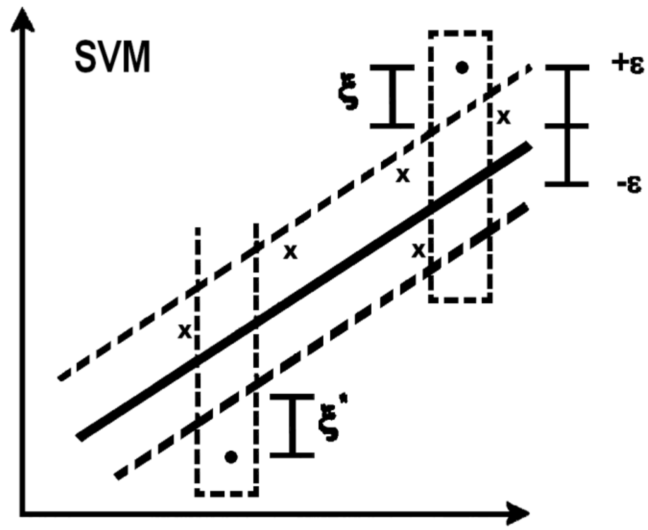


Figure 2.4: The ε-insensitive Loss Function and Slack Variables [58]

When adding the Lagrange multipliers to Eq. (2), the problem can be rewritten as

$$\begin{aligned} L(W,\xi,\xi^*,\alpha,\alpha^*,\eta,\eta^*) = \frac{1}{2}\|W\|^2 + C\sum_{t=1}^{N}(\xi_t+\xi_t^*) - \\ \sum_{t=1}^{N}\alpha_t(\varepsilon+\xi_t-y_t+\langle W,\varphi(X_t)\rangle+b) - \\ \sum_{t=1}^{N}\alpha_t^*(\varepsilon+\xi_t^*+y_t-\langle W,\varphi(X_t)\rangle-b) - \\ \sum_{t=1}^{N}(\eta_t\xi_t+\eta_t^*\xi_t^*) \end{aligned} \tag{4}$$

where $\alpha_t, \alpha_t^*, \eta_t$ and η_t^* are the Lagrange multipliers. The partial derivates of the Lagrange function with the primal variables (W, b, ξ_t, and ξ_t^*) are then

$$
\begin{cases}
\dfrac{\partial L_{SVM}}{\partial W} = 0 & \rightarrow \quad W = \sum_{t=1}^{N} (\alpha_t - \alpha_t^*) \varphi(X_t) \\
\dfrac{\partial L_{SVM}}{\partial b} = 0 & \rightarrow \quad \sum_{t=1}^{N} (\alpha_t - \alpha_t^*) = 0 \\
\dfrac{\partial L_{SVM}}{\partial \xi_t} = 0 & \rightarrow \quad C - \alpha_t - \eta_t = 0 \\
\dfrac{\partial L_{SVM}}{\partial \xi_t^*} = 0 & \rightarrow \quad C - \alpha_t^* - \eta_t^* = 0
\end{cases}
\tag{5}
$$

The dual problem can be obtained by substituting the relations from Eq. (5).

$$
\begin{aligned}
\text{maximize} \quad & -\frac{1}{2} \sum_{t,l=1}^{N} (\alpha_t - \alpha_t^*)(\alpha_l - \alpha_l^*) \langle \varphi(X_t), \varphi(X_l) \rangle - \\
& \varepsilon \sum_{t=1}^{N} (\alpha_t + \alpha_t^*) + \sum_{t=1}^{N} y_t (\alpha_t - \alpha_t^*) \\
\text{subject to} \quad & \begin{cases} \sum_{t=1}^{N} (\alpha_t - \alpha_t^*) = 0 \\ \alpha_t, \alpha_t^* \in [0, C] \end{cases}
\end{aligned}
\tag{6}
$$

According to the Karush-Kuhn-Tucker (KKT) conditions, the terms inside the equation containing the Lagrange multipliers will be vanished at the optimal solution. This means the following equations

$$
\begin{cases}
\alpha_t (\varepsilon + \xi_t - y_t + \langle W, \varphi(X_t) \rangle + b) = 0 \\
\alpha_t^* (\varepsilon + \xi_t^* + y_t - \langle W, \varphi(X_t) \rangle - b) = 0 \\
\eta_t \xi_t = (C - \alpha_t) \xi_t = 0 \\
\eta_t^* \xi_t^* = (C - \alpha_t^*) \xi_t^* = 0
\end{cases}
\tag{7}
$$

Eq. (7) indicates that for all samples whose Lagrange multipliers equal to zero are considered as non-support vectors. Samples with non-zero coefficients are considered as support vectors. Meanwhile, b can be calculated when the slack variables ξ_t and ξ_t^* equal to zero.

$$b = y_t - \langle W, \varphi(X_t) \rangle \pm \varepsilon \quad \text{for } \alpha_t, \alpha_t^* \in [0, C] \tag{8}$$

The final SVM for non-linear functions can be written as

$$y_t = f(X_t) = \sum_{t=1}^{N} (\alpha_t - \alpha_t^*) \langle \varphi(X), \varphi(X_t) \rangle + b \tag{9}$$

A modified version of Eq. (9) can be expressed as

$$y_t = f(X_t) = \sum_{t=1}^{N} (\alpha_t - \alpha_t^*) K(X, X_t) + b \tag{10}$$

where $K(X, X_t) = \langle \varphi(X), \varphi(X_t) \rangle$ is called the kernel function. Some commonly used kernel functions are defined below through Eq. (11)-(14).

1) Linear kernel:

$$K(X, X_t) = \langle X, X_t \rangle \tag{11}$$

2) Polynomial kernel:

$$K(X, X_t) = (\langle X, X_t \rangle + p)^d,\ d \in N, p > 0 \tag{12}$$

3) Gaussian Radial basis kernel:

$$K(X, X_t) = \exp(-\frac{\|X - X_t\|^2}{2\sigma^2}) \tag{13}$$

4) Hyperbolic tangent kernel:

$$K(X, X_t) = \tanh(c\langle X, X_t \rangle + d),\ c > 0, d > 0 \tag{14}$$

Gaussian Radial basis kernel is the most powerful one in non-linear function estimation. For SVM classification computation, the decision function, Eq. (10), will output classification results instead of regression results. Multi-class classification can be considered as regression computation with multiple predefined threshold values. SVM also has some disadvantages during classification and regression computation caused by its fundamental optimization algorithm. SVM intends to lose the top and the bottom peak values during training process because those values are considered as non-support vectors when utilizing the ε-insensitive loss function with 2ε bandwidth. Only the support vectors are used to create the 2ε tube and considered during simulation.

2.3 Least Squares Support Vector Machine

LSSVM was first proposed by J.A.K. Suykens and J. Vandewalle as a classifier in 1999. Recall Figure 2.1, the architecture of a LSSVM is the same as a SVM. It has the input layer and the output layer containing either single or multiple input/output data. The hidden layer contains kernels that transfer low dimensional input data vector into a much higher dimensional vector (sometime can be infinite shown in Figure 2.2) and eventually transfer the highly non-linear problem inside the input space into a linear problem inside the feature space. The working principle of a LSSVM is different from a SVM after the input vectors transfer into the feature space. Unlike the inequality constraints introduced in the standard SVM, LSSVM proposes equality constraints in the formulation. This results in the solution being transformed from one of solving a quadratic program to a set of linear equations known as the linear KKT systems. The regression computation using LSSVM was later proposed in 2002. LSSVM considers all training data as support vectors.

Recall Eq. (1), the corresponding optimization problem for LSSVM is formulated as

$$\begin{aligned} &\text{minimize} \quad \frac{1}{2}\|W\|^2 + \frac{1}{2}\gamma\sum_{t=1}^{N} e_t^2 \\ &\text{subject to} \quad y_t = \langle W, \varphi(X_t)\rangle + b + e_t \end{aligned} \tag{15}$$

where e_t is the error variable at time t, shown in Figure 2.5. γ is a regulation constant which is similar to C in SVM.

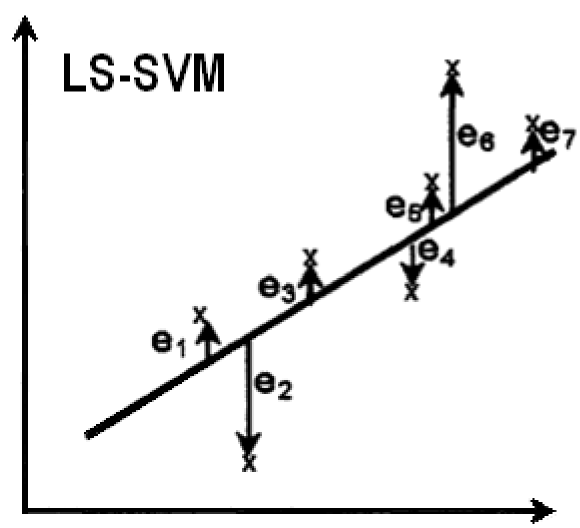


Figure 2.5: The Error Term Handling Principle by LSSVM [58]

The Lagrange function can be obtained as

$$L(W,e,\alpha)=\frac{1}{2}\|W\|^2+\frac{1}{2}\gamma\sum_{t=1}^{N}e_t^2-\sum_{t=1}^{N}\alpha_t(\langle W,\varphi(X_t)\rangle+b+e_t-y_t) \tag{16}$$

where α_t is the Lagrange multiplier. The partial derivates of the Lagrange function with the primal variables (W,b,e_t, and α_t) are obtained in Eq. (17).

$$\begin{cases}\dfrac{\partial L_{SVM}}{\partial W}=0 & \rightarrow \quad W=\sum_{t=1}^{N}\alpha_t\varphi(X_t)\\ \dfrac{\partial L_{SVM}}{\partial b}=0 & \rightarrow \quad \sum_{t=1}^{N}\alpha_t=0\\ \dfrac{\partial L_{SVM}}{\partial e_t}=0 & \rightarrow \quad \alpha_t=\gamma e_t\\ \dfrac{\partial L_{SVM}}{\partial \alpha_t}=0 & \rightarrow \quad \langle W,\varphi(X_t)\rangle+b+e_t-y_t=0\end{cases} \tag{17}$$

The dual equations can be obtained by substituting the relations from Eq. (17).

$$\begin{cases}y_t=\sum_{t,l=1}^{N}\alpha_t\varphi(X_t)\varphi(X_l)+b+\dfrac{\alpha_t}{\gamma}\\ \sum_{t=1}^{N}\alpha_t=0\end{cases} \tag{18}$$

An alternative formulation of Eq. (18) can be expressed as

$$\begin{bmatrix}0 & 1_N^T\\ 1_N & \Omega+I_N\gamma^{-1}\end{bmatrix}\begin{bmatrix}b\\ \boldsymbol{\alpha}\end{bmatrix}=\begin{bmatrix}0\\ Y\end{bmatrix} \tag{19}$$

where $Y=[y_1,\ldots,y_N]$, $1_N=[1,\ldots,1]$, $\boldsymbol{\alpha}=[\alpha_1,\ldots,\alpha_N]$, $\Omega=\langle\varphi(X_l),\varphi(X_t)\rangle=K(X_l,X_t)$ $t,l=1,\ldots,N$. The final LSSVM equation for function estimation is written as following with solution of $\boldsymbol{\alpha}$ and b from Eq. (19).

$$y_t = f(X_t) = \sum_{t=1}^{N} \alpha_t K(X, X_t) + b \tag{20}$$

Powerful Gaussian Radial basis kernel is the most commonly used kernel for LSSVM. For LSSVM classification computation, the decision function, Eq. (20), will output classification results instead of regression results. Multi-class classification can be considered as regression computation with multiple predefined threshold values.

The differences between SVM and LSSVM can be graphically viewed from Figure 2.6. These differences are caused by the different optimization algorithms Eq. (2) and Eq. (15). LSSVM is a structurally upgraded SVM using equality constraints instead of inequality constraints used in SVM. This results in SVM using selected support vectors whose value meet the criteria from the loss function while LSSVM considers all samples as support vectors. Moreover, SVM involves ε-insensitive loss function while LSSVM uses the least squares loss function. As a result, the solutions from SVM form a quadratic problem while the solutions from LSSVM form a linear KKT system. The advantages of LSSVM over SVM were recognized under a small data set [57]. However, in forecasting electricity MCP utilizing a huge historical data set, it is hard to say which methodology is the better option [57].

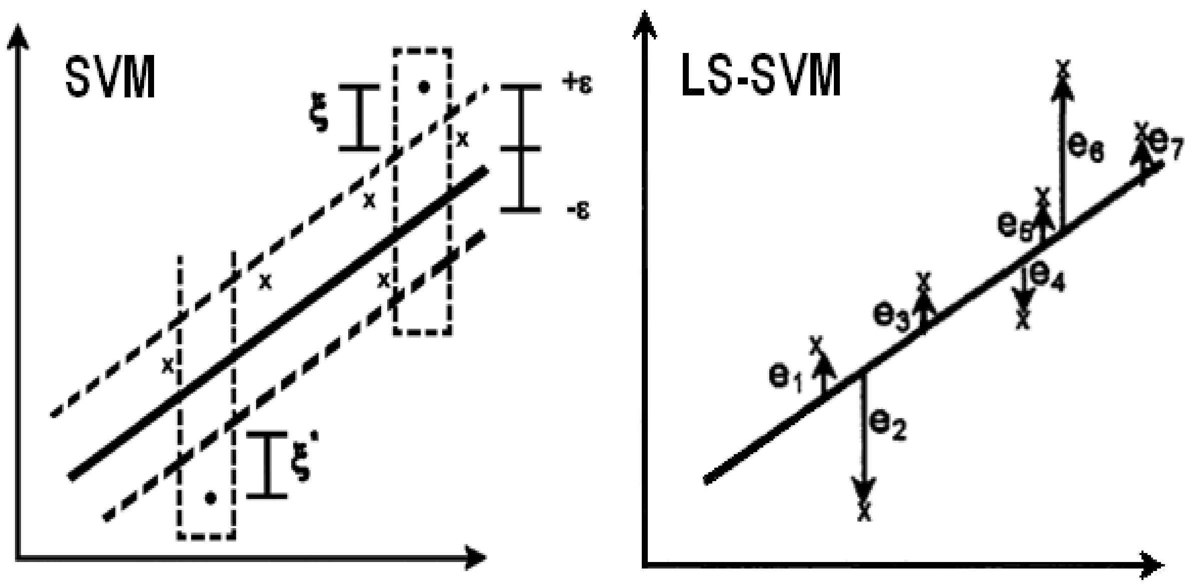


Figure 2.6: SVM vs. LSSVM [58]

2.4 Auto-Regressive Moving Average with External Input

ARMAX is an estimation method generally used in statistics and signal processing. Suppose $\{(X_t, y_t)\}$ for t = 1 to N is a given set of data where $X_t = (x_{t1}, x_{t2,...,} x_{tk})$ is the input vector at time t with k elements and y_t is the corresponding price data at time t, the corresponding ARMAX polynomial equation can be written as

$$A(q)y_t = \sum_{i=1}^{k} B_i(q)x_{ti} + C(q)e(t) \tag{21}$$

where $A(q)$, $B(q)$ and $C(q)$ are the polynomials expressed with a time shift term q^{-1} shown in (22). $e(t)$ is the white noise which is assumed to be λ. Control parameters n_a, n_b1, n_b2, ..., n_bk and n_c are determined during training phase using cross validation technique.

$$\left.\begin{aligned} A(q) &= 1 + a_1 q^{-1} + \cdots + a_{n_a} q^{-n_a} \\ B_i(q) &= b_{1i} + b_{2i} q^{-1} + \cdots + b_{n_b i} q^{-n_b i+1} \\ C(q) &= 1 + c_1 q^{-1} + \cdots + c_{n_c} q^{-n_c} \end{aligned}\right\} \tag{22}$$

The control parameter n_a is an integer that specifies the order of the auto-regressive part of the ARMAX. The control parameters n_b1, n_b2, ..., n_bk are integers that specify the order of the external input vector with k elements. The control parameter n_c is an integer that specifies the order of the moving average part of the ARMAX. a_i, b_{ik} and c_i are the polynomial coefficients determined by using polynomial curve fitting strategy supervised by least squares method in MATLAB after the control parameters are given.

2.5 Performance Evaluation

For regression computation evaluation, some widely used criteria include mean absolute error (MAE), mean absolute percentage error (MAPE), and mean square root error (MSRE). Under MAE evaluation, all individual differences are weighted equally. As percentage errors are not scale-independent, MAPE evaluation is often utilized to compare forecast performance [61]. Finally, the MSRE evaluations give a relatively high weight to large errors which make it useful when large errors are involved [62]. Given N historical electricity MCP data y_t and the corresponding forecasted price data $\hat{y}_t$ for t = 1 to N, MAE, MAPE and MSRE are defined as

$$\mathrm{MAE} = \frac{1}{N}\sum_{t=1}^{N}\left|y_t - \hat{y}_t\right| \tag{23}$$

$$\mathrm{MAPE} = \frac{1}{N}\sum_{t=1}^{N}\left|\frac{y_t - \hat{y}_t}{y_t}\right| \tag{24}$$

$$\text{MSRE} = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(y_t - \hat{y}_t)^2} \tag{25}$$

CHAPTER 3: DATA COLLECTION AND PRE-PROCESS

3.1 Introduction

Data collection is a very important process in machine learning. The proposed work focuses on utilizing single and multiple SVM and LSSVM to forecast mid-term electricity MCP. The accuracy of forecasting models is heavily depended on the selection of input data. Each element inside the input data will create an additional dimension for the forecasting model and in turn helps the forecasting model to better capture the characteristics of the problem. When there are few input elements inside the input data, a utilized methodology has to make compromise between the majority and the minority data and accept low accuracy as a consequence. More sophisticated models have to be designed to achieve better accuracy based on limited input data. On the other hand, when there are plenty of related and useful elements inside the input data, the forecasting model can be quite simple and still achieve high forecasting accuracy. A data collection process using cross-validation technique has been designed as a part of is work to help the forecasting model achieve the highest forecasting accuracy.

Data pre-process is a standard and straight forward technique that is used in machine learning to achieve optimal results. It converts all the elements into a common scale (usually between +1 and -1) before sending them into a forecasting model. By doing so, data pre-process can prevent a few elements with extreme large values from dominating the forecasting results. PJM interconnected electric market is studied as an example for the proposed work.

3.2 PJM Interconnected Electric Market

The PJM interconnected electric market is shown in Figure 3.1. It is the largest interconnected system in the world including Delaware, Illinois, Indiana, Kentucky, Maryland, Michigan, New Jersey, North Carolina, Ohio, Pennsylvania, Tennessee, Virginia, West Virginia and the District of Columbia. The market serves more than 51 million people in the United States. As of December 31, 2009, it had an installed generating capacity of 167,326 megawatts and over 500 market buyers, sellers and traders of electricity. Coal (74%) and natural gas (22%) are the two major types of fuel in the market. Locational marginal pricing (LMP) is used to reflect the value of the energy at the specific location and time it is delivered. The market consists of day-ahead and real-time markets. The day-ahead market is a forward market in which hourly LMP are calculated for the next operating day based on generation offers, demand bids and scheduled bilateral transactions. The real-time market is a spot market in which current LMP is calculated at five-minute intervals based on actual grid operating conditions. PJM settles transactions hourly and issues invoices to market participants monthly [63]. The LMP inside the PJM interconnected electric market is used as electricity MCP in this work. Historical data from the day-ahead market of 2008 and 2009 are used in this work to forecast the hourly electricity MCP in June 2010 [11].

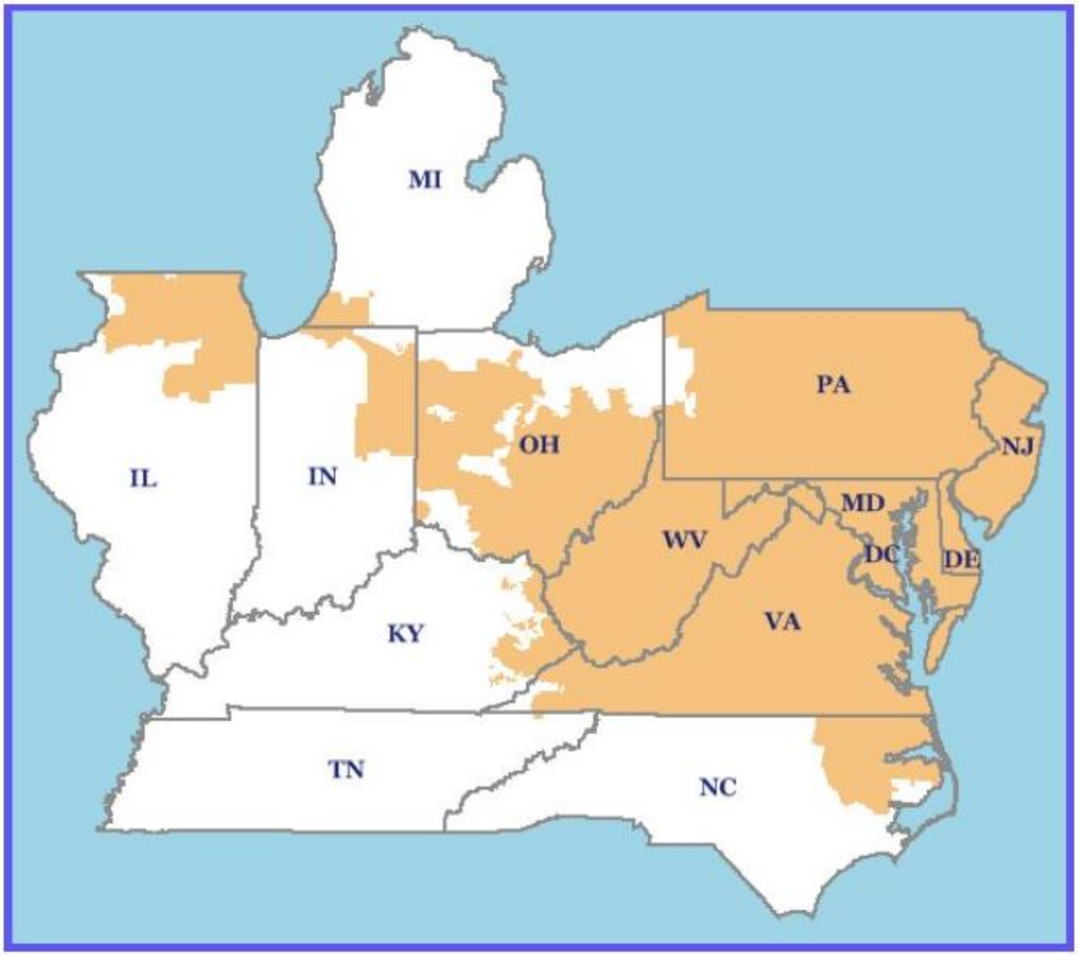


Figure 3.1: PJM Electricity Market [64]

3.3 Data Collection

Electricity MCP can be forecasted by evaluating a variety of elements [26] such as electricity demand, supply, natural gas price, coal price, hydro capacity, weather and temperature. An ideal forecasting model for electricity MCP should include all the possible elements which affect the final electricity MCP. However, in reality, it is impossible and unnecessary to include all those elements when forecasting electricity MCP. Since weather conditions including daily temperature are already considered in load forecasting, they don't have to be included in MCP forecasting process. Other elements such as business strategy and unethical competition behaviours cannot be easily represented mathematically. Finally, elements like generator status, representing the current failure or operating mode of a generator, in many deregulated electric market is confidential information. Based on the factors mentioned above, a data selection process, shown in Figure 3.2, is presented using a cross-validation technique to finalize the elements inside the input data that were taken into account for the proposed work.

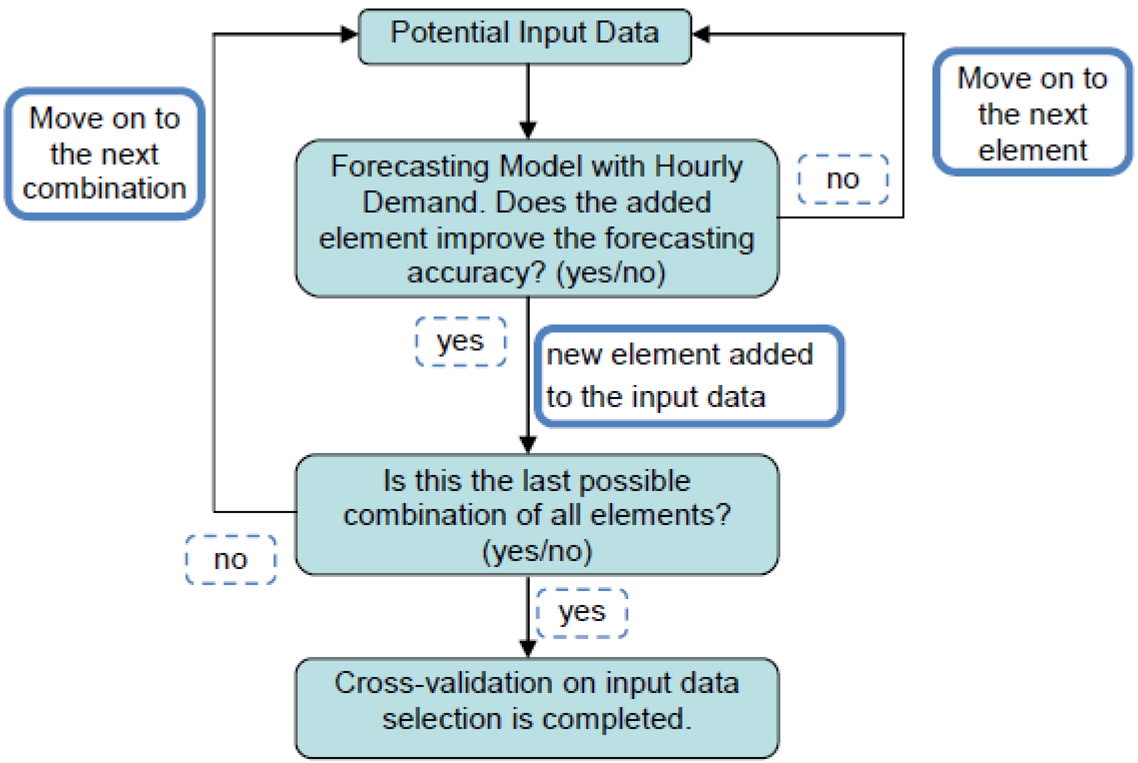


Figure 3.2: Data Selection Process

The data selection process starts with only the default input data (hourly electricity demand) for the forecasting model. Then, the next element inside the potential input data is added to the initial forecasting model to test whether the added element improve the MAE or not. A tested element will be added to the forecasting model if it improves the MAE. Otherwise, the forecasting model maintains its current input data and the next element inside the potential input data will be tested. Once all elements have been tested one at a time, different combinations of elements will also be tested using MAE evaluation because sometimes adding more than one element at the same time will achieve better forecasting results. By doing so, the data selection process shown in Figure 3.2 will guarantee to test not only every single element but also every possible combination of elements that would lead to the optimized forecasting results.

The final selected input data for the proposed forecasting models at each hour t are limited to electricity hourly demand at hour t, electricity daily peak demand, electricity monthly average demand, daily price of natural gas, previous year's monthly average electricity MCP, month (1 to 12), and hour of the day (1 to 24). Electricity hourly demand directly influences the electricity price, and therefore should be a part of the training input data. Electricity daily peak demand is also an important factor that influences the electricity price in a significant manner. When electricity daily peak demand is high, expensive units are run to meet the demand which in turn boosts the electricity price. Electricity monthly average demand contains information of monthly and seasonal demand pattern and is very useful when the forecasting model trying to determine the price zones for each corresponding future electricity price. Moreover, electricity monthly average demand also helps the forecasting model to generate the direct connection with the monthly average electricity MCP and therefore, should be included as a part of the training input data. During peak load, most generating units would be running under high and even full capacity, usually away from their most economic operating point. Unlike coal price, natural gas price fluctuates every hour just like electricity MCP. Thermal generating plants that use natural gas are widely used for peak shaving and load following due to their relatively short starting time. As electricity cannot be stored and has to be used as produced, a sudden increase in electricity demand is met by these type of fast starting generating units and usually cost 10 to 100 times more than the regular electricity MCP. Therefore, the daily price of natural gas also influences the electricity MCP and should be included as a part of the training input data. Although electricity MCP is very volatile, it is still normally distributed along its average value [50-52]. Therefore, previous year's monthly average electricity MCP is included in the input data to help the price forecasting model to set the initial forecasting point. Month (1 to 12) is a straightforward element that can represent the impact of season change on average electricity demand and price. For instance, the electricity MCP is high during summer and winter due to the higher consumption of electricity for heating and cooling. Hour of the day (1 to 24) is paired up with electricity daily peak demand so the forecasting model could better locate the time of daily peak demand during forecasting. The target datum at hour *t* is the electricity MCP at hour *t*. Moreover, based on the previous published works [22-24] regarding the selection of training data for mid-term electricity price forecasting, one year is the most optimized length of historical data to train the forecasting model.

Part of the training data are separated from the rest of training data and served as so called testing data. Testing data are treated unseen from the rest of training data and are used to optimize the control parameters of the proposed forecasting model. The rest of the training data are called the actual training data in this thesis. In the proposed work, data from January 1, 2009 to December 31, 2009 excluding June 2009 are selected as the actual training data. It can be viewed as a matrix with 8040 (24×335) rows and 8 columns. The 8040 rows are the number of hours from hour 1 (1:00 a.m.) on January 1, 2009 to hour 24 (12:00 a.m.) on December 31, 2009 excluding June 2009. The first 7 columns are the 7 input elements mentioned before. The last column is the training target data, electricity MCP from hour 1 (1:00 a.m.) on January 1, 2009 to hour 24

(12:00 a.m.) on December 31, 2009, excluding June 2009. Because the proposed mid-term electricity MCP forecasting models are designed to predict the 720 hourly electricity MCPs in June 2010, selecting data from hour 1 (1:00 a.m.) on June 1, 2009 to hour 24 (12:00 a.m.) on June 30, 2009 as the testing data could create the best scenarios on daily demand pattern, daily price pattern, weather, sunshine and precipitation during training process to optimize the control parameters. For the same reason, if the proposed models are utilized to forecast the 744 hourly electricity MCPs in May 2010, data from hour 1 (1:00 a.m.) on May 1, 2009 to hour 24 (12:00 a.m.) on May 31, 2009 will be selected as the testing data during training process. The testing data contains a matrix with 720 rows (24×30) and 8 columns. The first 7 columns are the testing input data and the last column is the testing target data.

Once the training procedure is done, the proposed forecasting models are used to forecast the mid-term electricity MCP of every hour in June 2010 using historical data from January 2009 to December 2009. The proposed work is based on the assumption that all forecasting input data have already been accurately predicted. The forecast output contains 720 (24×30) hourly electricity MCP which will insure the comprehensiveness of the test sample. The forecasting input data could be viewed as a matrix with 720 (24×30) rows and 8 columns. The 720 rows are the number of hours from hour 1 (1:00 a.m.) on June 1, 2010 to hour 24 (12:00 a.m.) on June 30, 2010. The first 7 columns are the forecasting input data and the last column is the electricity MCP from hour 1 (1:00 a.m.) on June 1, 2010 to hour 24 (12:00 a.m.) on June 30, 2010.

3.4 Input Data Pre-Processing

In order to improve the regression accuracy and avoid the dominance of some extremely large values inside the data set, data pre-processing is needed in machine learning. For electricity MCP forecasting, the most common and recommended data pre-processing techniques are normalization and denormalization. Normalization converts each datum inside its corresponding element into a value between –1 and +1 (sometime 0 to +1) with respect to each element's maximum and minimum values. Depending on the calculation, the maximum and minimum values can be either global or local. The denormalization usually applied at the end of electricity MCP forecasting. It transforms the forecast ratio values (between –1 and +1) to their real values (\$/kWh). Suppose $X_t = (x_{t1,} x_{t2,...,} x_{tk})$ is a given set of vector at time t with k multiple elements for t = 1 to N. The normalization and denormalization for datum x_{tk} could be defined as

$$\hat{x}_{tk} = \frac{x_{tk} - x_{MINk}}{x_{MAXk} - x_{MINk}} \tag{26}$$

$$x_{tk} = \hat{x}_{tk} \times (x_{MAXk} - x_{MINk}) + x_{MINk} \tag{27}$$

where $x_{\text{MAX}k}$ and $x_{\text{MIN}k}$ are either the global or local maximum and minimum values inside the k^{th} element. In the proposed work, only the normalization technique is utilized. All input data are pre-processed to optimize the computation. The target data (the forecast electricity MCP) will remain unchanged as it is the only element inside the output layer in the proposed work.

CHAPTER 4: SINGLE SVM AND SINGLE LSSVM BASED MID-TERM ELECTRICITY MCP FORECASTING APPROACHES

4.1 Introduction

Currently, there are many techniques available for short-term electricity MCP forecasting. SVM is a new learning method based on structural risk minimization. It has gained increased attention in electricity MCP forecasting [29]-[32]. The major advantages of SVM over any other forecasting models, for instance artificial neural network (ANN), are that SVM can avoid problems such as data over fitting, local minimum and unpredictably large out-of-sample data error while at the same time achieving better results. SVM is also a very robust forecasting model. Regardless of the initial value, SVM will always settle to the same result. Moreover, SVM has less adjustable parameters compared to an ANN and therefore, is less complicated in parameter selection. A traditional SVM could achieve around 3% [33] better performance compared to a traditional ANN on the short-term electricity MCP forecasting. Later, LSSVM was developed to improve the accuracy of the original SVM [36], [42]-[44]. LSSVM is the least squares formulation of a standard SVM. However, the forecasting accuracy of a SVM and a LSSVM was never compared for very large scale problem, such as mid-term electricity MCP forecasting.

In this Chapter, a comparison between a single SVM and a single LSSVM based mid-term electricity MCP forecasting model is presented. Both forecasting models are designed to predict hourly electricity MCP for an entire month, six months ahead. It is considered in this work that the forecasting input data are given so that the performance of the two presented forecasting models will not be affected by the inaccurate input variables. Historical data from the PJM interconnection system are used to evaluate the performance of the two proposed forecasting models. Computational results indicate that each forecasting model has some advantages and disadvantages when utilized in mid-term electricity MCP forecasting.

4.2 Single SVM and Single LSSVM Forecasting Models Architecture

The common architecture of a single SVM and a single LSSVM based mid-term electricity MCP forecasting model is shown in Figure 4.1.

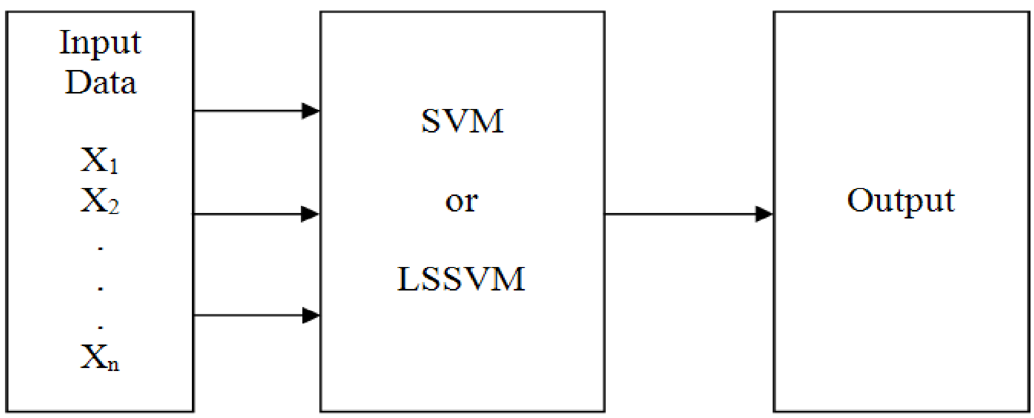


Figure 4.1: Single SVM and Single LSSVM Based Mid-Term Electricity MCP Forecasting Models Architecture.

As shown in Figure 4.1, the forecasting model utilizing single SVM or single LSSVM contains three layers. The first layer is the input layer, the second layer is the SVM or LSSVM layer and the final layer is the output layer. The input layer consists of input data such as electricity hourly demand, electricity daily peak demand and daily natural gas price described in Chapter 3.3. All input data are pre-processed before sending them to the SVM or LSSVM layer. Predicted mid-term electricity MCP values are sent to the output layer. Cross validation technique is applied to optimize the control parameters of SVM and LSSVM.

Part of the training data are separated from the rest of the training data and served as so called testing data. Testing data are treated unseen from the rest of the training data and are used to optimize the control parameters of the forecasting model. The rest of the training data are called actual training data in this thesis. In the proposed work, data from January 1, 2009 to December 31, 2009 excluding June 2009 are selected as the actual training data. Data from June 1, 2009 to June 30, 2009 are selected as the testing data to optimize the control parameters of both the SVM and LSSVM. Detailed explanation on data selection was included in Chapter 3.3. Once the training procedure is done, the proposed single SVM and single LSSVM forecasting models are used to forecast the mid-term electricity MCP for every hour in June 2010 using historical data from January 2009 to December 2009. The proposed work is based on the assumption that all forecasting input data have already been accurately predicted. All input data are pre-processed to optimize the computation. The target data remain the same. This will guarantee that all input elements remain at the same domain and thus avoid the dominance of extremely large value in the data.

4.3 Input Data Selection

The final input elements that have been taken into account for the proposed single SVM and single LSSVM based mid-term electricity MCP forecasting models at each hour *t* are electricity hourly demand at hour *t*, electricity daily peak demand, electricity monthly average demand, daily price of natural gas, previous year's monthly average electricity MCP, month (number 1-12) and hour of the day (number 1-24) as explained in Chapter 3.3. The target data at hour *t* is the electricity MCP at hour *t*. By utilizing the cross validation technique for the optimization of input elements selection and using MAE for the performance evaluation, the LSSVM model only utilizes 6 input elements while the SVM model utilizes all 7 input elements to forecast the mid-term electricity MCP. Moreover, based on the previous published works [22-24] regarding the selection of training data for mid-term electricity price forecasting, one year is the most optimized length of historical data to train the forecasting model.

4.4 Numerical Results

Using January 2009 to December 2009 excluding June 2009 as the actual training data and June 2009 as the testing data, the mid-term electricity MCP forecasting results are obtained. Figure 4.2 shows the forecast electricity hourly MCP for June 2009 using a single SVM and a single LSSVM forecasting models. MAE, MAPE and MSRE are selected for regression computation performance evaluation. The performance numbers are shown in Table 4.1.

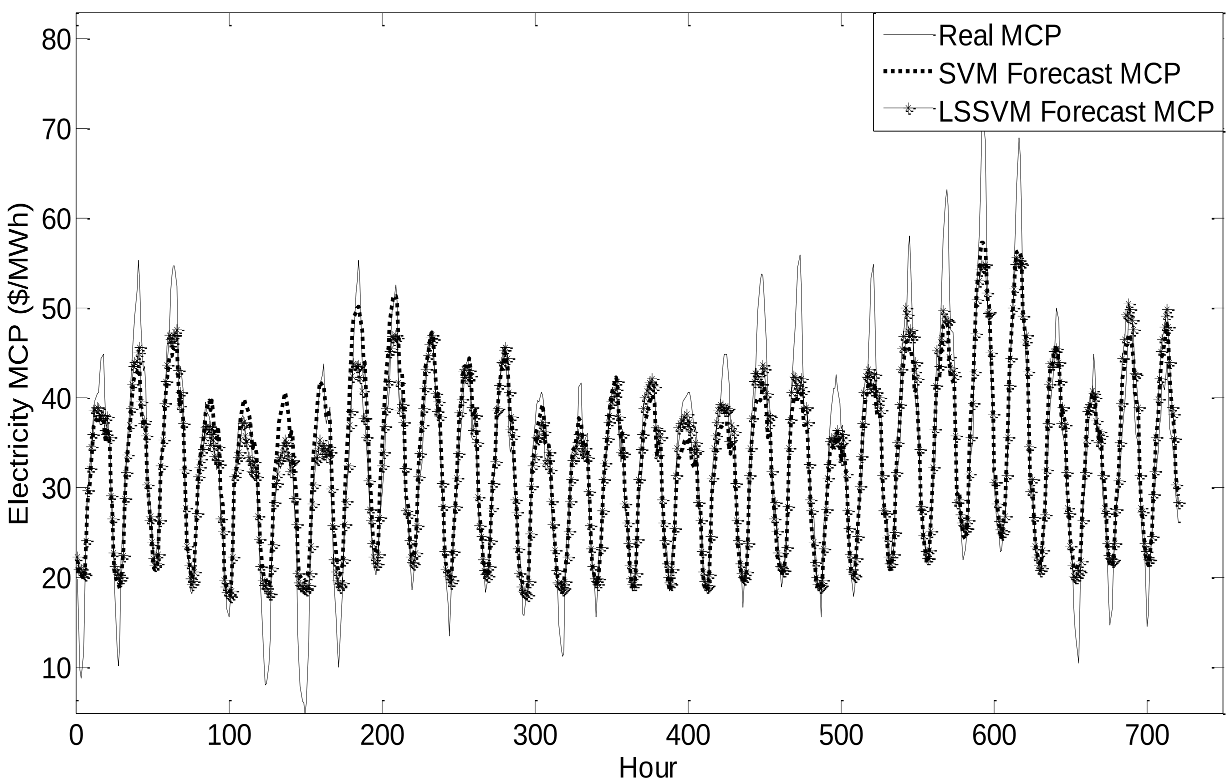


Figure 4.2: Forecasted Electricity MCP in June 2009 Using a Single SVM and a Single LSSVM Forecasting Models.

Table 4.1: Performance Evaluation Results of MAE, MAPE and MSRE between a Single SVM and a Single LSSVM Based Mid-term Electricity MCP Forecasting Models in June 2009

	MAE ($/MWh)	MAPE (%)	MSRE
Single SVM	2.9743	11.7491	0.1564
Single LSSVM	2.8152	10.9722	0.1513

According to Table 4.1, MAE, MAPE and MSRE results show that the LSSVM forecasting model is better than the SVM forecasting model during the training process. After the training process is done, both the single SVM and single LSSVM forecasting models are used to forecast the mid-term electricity MCP in June 2010 using historical data from January 2009 to December 2009. Figure 4.3 shows the forecasted electricity MCP in June 2010 using both the single SVM and the single LSSVM forecasting models. The performance numbers are shown in Table 4.2. The MAE, MAPE and MSRE indices show that the single SVM model is better than the single LSSVM model during the forecasting process.

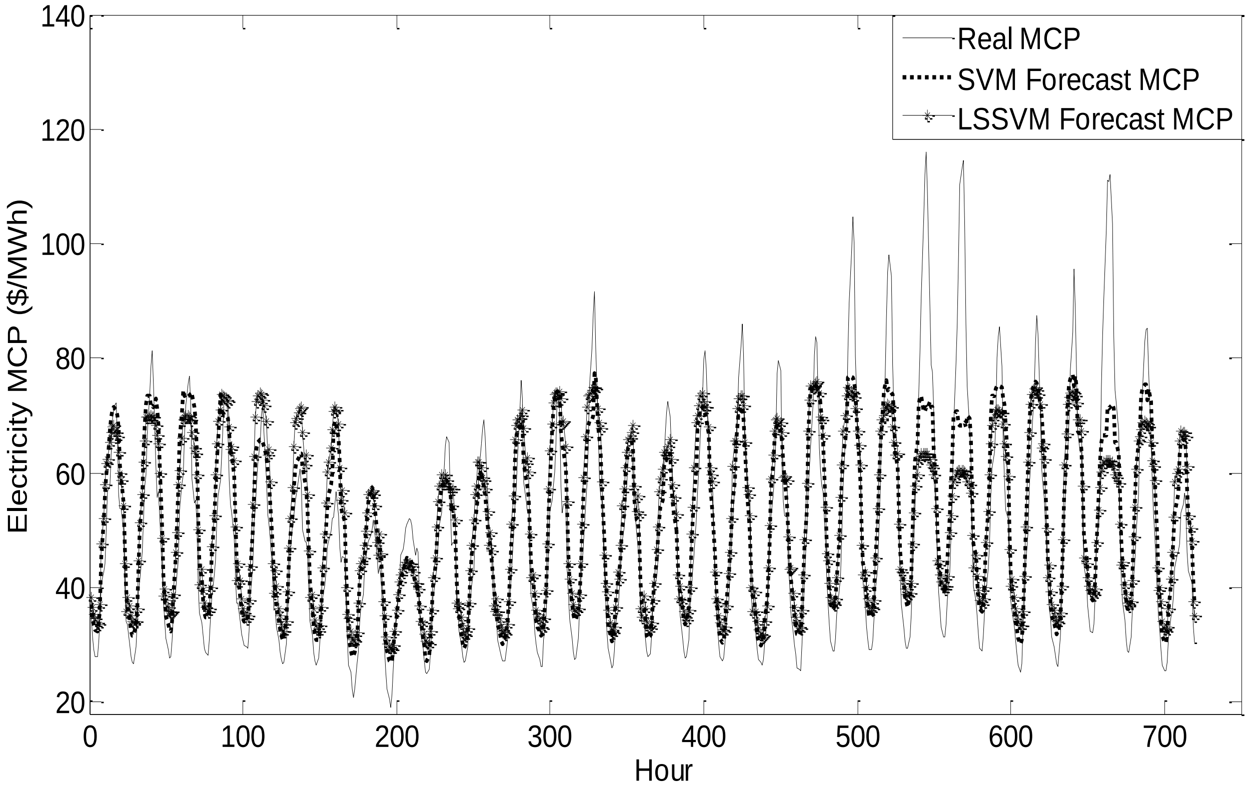


Figure 4.3: Forecasted Electricity MCP in June 2010 Using a Single SVM and a Single LSSVM Forecasting Models.

Table 4.2: Performance Evaluation Results of MAE, MAPE and MSRE between a Single SVM and a Single LSSVM Based Mid-term Electricity MCP Forecasting Models in June 2010

	MAE ($/MWh)	MAPE (%)	MSRE
Single SVM	7.2523	15.6454	0.3316
Single LSSVM	7.9003	16.2610	0.3964

4.5 Discussions

There are two major differences between SVM and LSSVM. The first difference is that during the training process, SVM uses a quadratic formulation while LSSVM uses a set of linear equations. The second difference is the selection of support vectors. SVM only selects the ones with non-vanishing coefficients as support vectors while LSSVM, on the other hand, considers all training data as support vectors [58]. In other words, LSSVM is more like an ANN but with fixed output.

SVM intends to lose the top and the bottom peak values during training process because those values are considered as non-support vectors when utilizing the ε-insensitive loss function with 2ε bandwidth. Only the support vectors are used to create the 2ε tube and only the values outside the 2ε tube are considered during simulation. Therefore, the forecast electricity MCP will lose most of its top and bottom peak values during forecasting process using the SVM forecasting model.

LSSVM considers all training data as support vectors and its forecasting accuracy highly depends on the selection of input data. The majority of the MCPs are dominated by the relationship between supply and demand and fuel cost under normal deregulated market. Meanwhile, few MCPs (price spikes) are dominated by bidding strategy, spot market price, spinning reserve market price, business competing strategy and unethical business behaviour. These variables are very complex and hard to quantize mathematically. Therefore, with only two control parameters, LSSVM has to make a compromise on the forecasting accuracy between the majority and the minority MCPs.

4.6 Summary

A comparison between a single SVM and a single LSSVM based mid-term electricity MCP forecasting models is presented in this Chapter. PJM interconnected electric market data have been used. The proposed work has shown that during the training process, the LSSVM forecasting model is better than the SVM forecasting model. However, during the forecasting process, the SVM forecasting model is better than the LSSVM forecasting model. Unless additional input data can be provided to create more dimensions for training, electricity MCP forecasting accuracy in the peak price area will remain low when utilizing either the single SVM or the single LSSVM forecasting model.

CHAPTER 5: HYBRID SVM AND ARMAX AND HYBRID LSSVM AND ARMAX BASED MID-TERM ELECTRICITY MCP FORECASTING APPROACHES

5.1 Introduction

According to the results presented in Chapter 4, the overall system accuracy was still quite low. Electricity MCP forecasting using hybrid models is a new trend in recent electricity price prediction studies. Hybrid models can compensate for the weaknesses of any single individual established methods and achieve better overall system results. In this Chapter, two hybrid mid-term electricity MCP forecasting models are presented to predict hourly electricity MCP for an entire month, six months ahead. It is considered in this work that the forecasting input data are given so that the performance of the presented hybrid forecasting model will not be affected by the inaccurate input variables. One proposed hybrid forecasting model contains a SVM module and an ARMAX module and the other proposed hybrid forecasting model contains a LSSVM module and an ARMAX module. The SVM and LSSVM methods are used as the major forecasting modules to predict the initial electricity MCP values. Next, the ARMAX method is used as an add-on module to improve the forecasting results obtained by either the SVM or the LSSVM module. The performance of the proposed hybrid forecasting models is evaluated by the historical data from the PJM interconnection system. Computational results indicate that the proposed hybrid forecasting models can improve the prediction accuracy of price values compared to using a single SVM or a single LSSVM in mid-term electricity MCP forecasting.

5.2 Problems Associated with Utilizing a Single SVM or a Single LSSVM Based Mid-term Electricity MCP Forecasting Models

Single SVMs and single LSSVMs have already been used in short-term electricity price forecasting. An advantage of utilizing a SVM or a LSSVM in function approximation is that it has less adjustable parameters, making it computationally less complicated compared to other estimation methods. However, this makes a SVM or a LSSVM output less accurate in situations where it is required to handle large amount of data containing very wide range target data and limited input data, such as electricity MCP in PJM electric market. Using PJM electric market historical data for the entire year of 2009 excluding the month of June as training data and historical data in June 2009 as testing data, mid-term electricity MCP forecasting results using a single SVM and a single LSSVM forecasting models are shown in Figure 5.1.

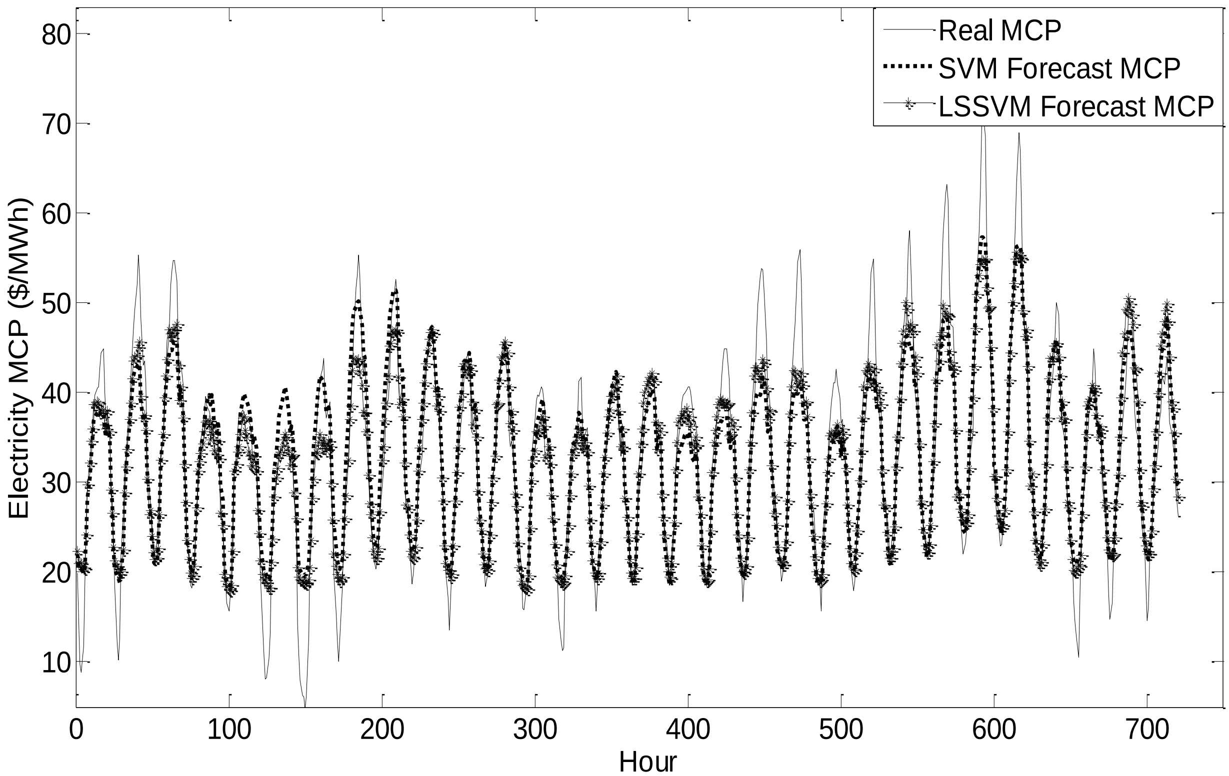


Figure 5.1: Forecasted Electricity MCP in June 2009 Using a Single SVM and a Single LSSVM Forecasting Models.

It can be observed from Figure 5.1 that the predicted electricity MCP are very close to the real electricity MCP in the middle section, but deviated significantly from the real electricity MCP in the top and the bottom sections. The system MAE, MAPE and MSRE are high as well that are shown in Table 5.1.

Table 5.1: MAE, MAPE and MSRE of a Single SVM and a Single LSSVM Based Mid-term Electricity MCP Forecasting Models

	MAE ($/MWh)	MAPE (%)	MSRE
Single SVM	2.9743	11.7491	0.1564
Single LSSVM	2.8152	10.9722	0.1513

Although both single SVM and single LSSVM forecasting models delivered low forecasting accuracy in the top and bottom sections, the reasons are different. A single SVM intends to lose the top and the bottom peak values during training process because those values are considered as non-support vectors when utilizing the ε-insensitive loss function with 2ε bandwidth. Only the support vectors are used to create the 2ε tube and only the values outside the 2ε tube are considered during simulation. Therefore, the forecast electricity MCP will lose most of its top and bottom peak values during forecasting process using the SVM forecasting model [65].

A single LSSVM considers all training data as support vectors and its forecasting accuracy highly depends on the selection of input data. The majority of the MCPs are dominated by the relationship between supply and demand and fuel cost in a deregulated market. Meanwhile, the peak and low MCPs are dominated by bidding strategy, spot market price, spinning reserve market price, business competing strategy and unethical business behaviour. These variables are very complex and hard to quantize mathematically. Therefore, with only two control parameters, LSSVM has to make a compromise between the majority and the minority MCPs [66].

Unless additional input data can be provided to create more dimensions for training, adjusting the only two control parameters inside the SVM or LSSVM will not make any significant effect. The system MAE, MAPE and MSRE will remain high [67].

5.3 Hybrid Forecasting Model Architectures

Hybrid forecasting models can compensate the weakness of utilizing single regression methodology in electricity price forecasting. A hybrid SVM and ARMAX based forecasting model can compensate the weakness of a single SVM and achieve better overall results. By combining an ARMAX module with a SVM module, some of the top and the bottom peak values which were considered as non-support vectors can be included inside the ARMAX simulation to estimate updates for SVM predicted price values. Figure 5.2 shows the architecture of a hybrid SVM and ARMAX based mid-term electricity MCP forecasting model.

Same as a SVM, a LSSVM has only two adjustable parameters. In handling large amount of data containing very wide range target data and limited input data, as LSSVM does not provide better results unless additional input data can be provided to create more dimensions for training. The system MAE, MAPE and MSRE will remain high. Due to the problems associated with utilizing a single LSSVM when forecasting mid-term electricity MCP, a hybrid forecasting model that combines an LSSVM with an ARMAX model is proposed. A hybrid LSSVM and ARMAX based forecasting model can compensate the weakness of a LSSVM and achieve better overall results. The architecture of a hybrid LSSVM and ARMAX based mid-term electricity MCP forecasting model is also shown in Figure 5.2.

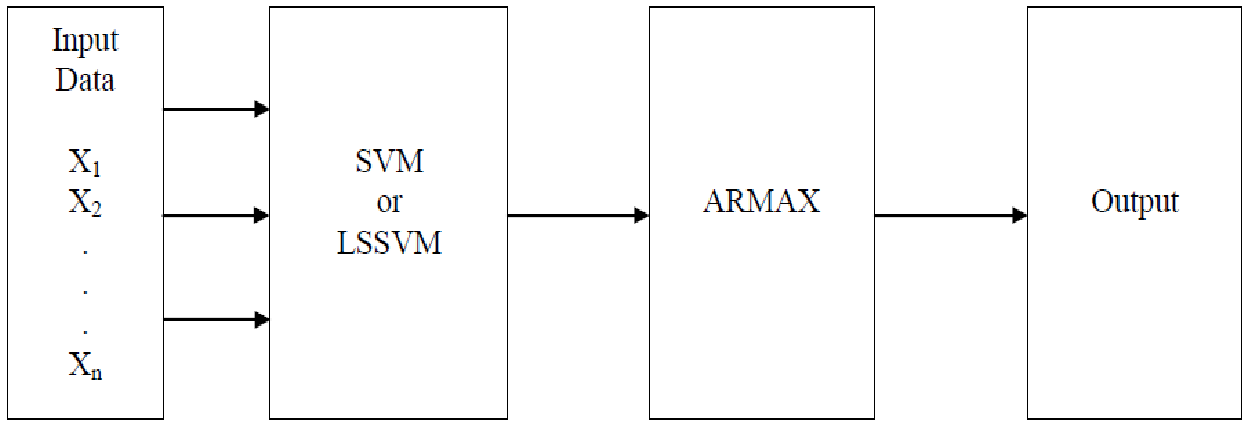


Figure 5.2: Hybrid SVM and ARMAX and Hybrid LSSVM and ARMAX Forecasting Model Architecture.

Both hybrid SVM and ARMAX and hybrid LSSVM and ARMAX based mid-term electricity MCP forecasting models shown in Figure 5.2 contain four layers. The first layer is the input layer, the second layer is the SVM/LSSVM layer and the third layer is the ARMAX layer and the final layer is the output layer. Inside the input layer, there will be input data such as electricity hourly demand, electricity daily peak demand and daily natural gas price explained in detail in Chapter 3.3. After all the data are pre-processed inside the input layer, the SVM/LSSVM module is first utilized to predict the initial electricity MCP values.

During the training process, SVM intends to lose the peak and the low values because these values are considered as non-support vectors when utilizing the ε-insensitive loss function with 2ε bandwidth. Only the support vectors are used to create the 2ε tube and only the values outside the 2ε tube are considered during simulation. Therefore, the forecast initial electricity MCP will lose most of its peak and low values during forecasting process through the SVM module. With only two control parameters to adjust and limited input data to apply, the forecasting accuracy will remain low. In order to improve the accuracy, after the initial electricity MCP forecasting is completed by the SVM module, the ARMAX module is utilized to predict the adjustments for each predicted initial electricity price. By adding an ARMAX module on a SVM module, some of the peaks and the lows which were considered as non-support vectors by the SVM can be included inside the ARMAX simulation to estimate updates for SVM predicted initial price values. After the electricity price adjustments are completed, the SVM predicted initial electricity price values and the ARMAX predicted electricity price adjustments are combined to form the final forecast electricity MCP inside the output layer.

As mentioned earlier, LSSVM has to make a compromise on the forecasting accuracy between the majority and the minority MCPs. This results low forecast accuracy. In order to improve the system accuracy, after the initial electricity MCP forecasting is completed by the LSSVM module, an ARMAX module is utilized to predict the adjustments for each predicted initial electricity price. By adding an ARMAX module on a LSSVM module, the peaks and the lows which were considered as minority MCPs and whose forecasting accuracy were compromised during training by the LSSVM can be included inside the ARMAX simulation to estimate updates for LSSVM predicted initial price values. Inside the output layer, LSSVM predicted electricity price values and the ARMAX predicted electricity price adjustments are combined to form the final forecast electricity MCP.

The training input data for the SVM, LSSVM and ARMAX modules are the same. The training target data for the SVM/LSSVM module is the historical electricity MCP and the training target data for the ARMAX module is the difference between the historical electricity MCP and the predicted electricity MCP obtained by the SVM/LSSVM module. Cross validation technique is applied during the training for the SVM, LSSVM and ARMAX modules to optimize the control parameters. Once the control parameters are determined using the testing data, both hybrid SVM and ARMAX and hybrid LSSVM and ARMAX based mid-term electricity MCP forecasting models are ready to forecast the future electricity MCP.

5.4 Input Data Selection

Although the proposed hybrid SVM and ARMAX and hybrid LSSVM and ARMAX forecasting models have the same architecture, the individual module inside each hybrid forecasting model is capable of utilizing different numbers of input elements to achieve the optimal results.

5.4.1 Hybrid SVM and ARMAX

There are total 7 input elements that have been taken into account for the proposed hybrid SVM and ARMAX model at each hour *t* that include electricity hourly demand at hour *t*, electricity daily peak demand, electricity monthly average demand, daily price of natural gas, previous year's monthly average electricity MCP, month (number 1-12) and hour of the day (number 1-24). The target data at hour *t* is the electricity MCP at hour *t*. Both SVM and ARMAX modules utilized all 7 input elements. Moreover, based on the previous published works [22-24] regarding the selection of training data for mid-term electricity price forecasting, one year is considered the most optimized length of historical data to train the forecasting model.

5.4.2 Hybrid LSSVM and ARMAX

There are total 7 input elements that have been taken into account for the proposed hybrid LSSVM and ARMAX model at each hour *t* including electricity hourly demand at hour *t*, electricity daily peak demand, electricity monthly average demand, daily price of natural gas, previous year's monthly average electricity MCP, month (number 1-12) and hour of the day (number 1-24). The target data at hour *t* is the electricity MCP at hour *t*. By utilizing the cross validation technique for the optimization of input elements selection and using MAE for the performance evaluation, the LSSVM module only utilizes 6 input elements while the ARMAX module utilizes all 7 input elements to forecast the mid-term electricity MCP. Moreover, based on the previous published works [22-24] regarding the selection of training data for mid-term electricity price forecasting, one year is the most optimized length of historical data to train the forecasting model.

5.5 Numerical Results

Using January 2009 to December 2009 excluding June 2009 as the actual training data and June 2009 as the testing data, the testing results are obtained. Figure 5.3 shows the forecast electricity MCP for June 2009 using a hybrid SVM and ARMAX and a hybrid LSSVM and ARMAX forecasting models. Compared to a single SVM, it can be seen from Figure 5.3 that the major benefit of using hybrid forecasting models is the improved forecasting results in the low and peak price areas. MAE, MAPE and MSRE are selected for regression computation performance evaluation. The performance numbers are shown in Table 5.2.

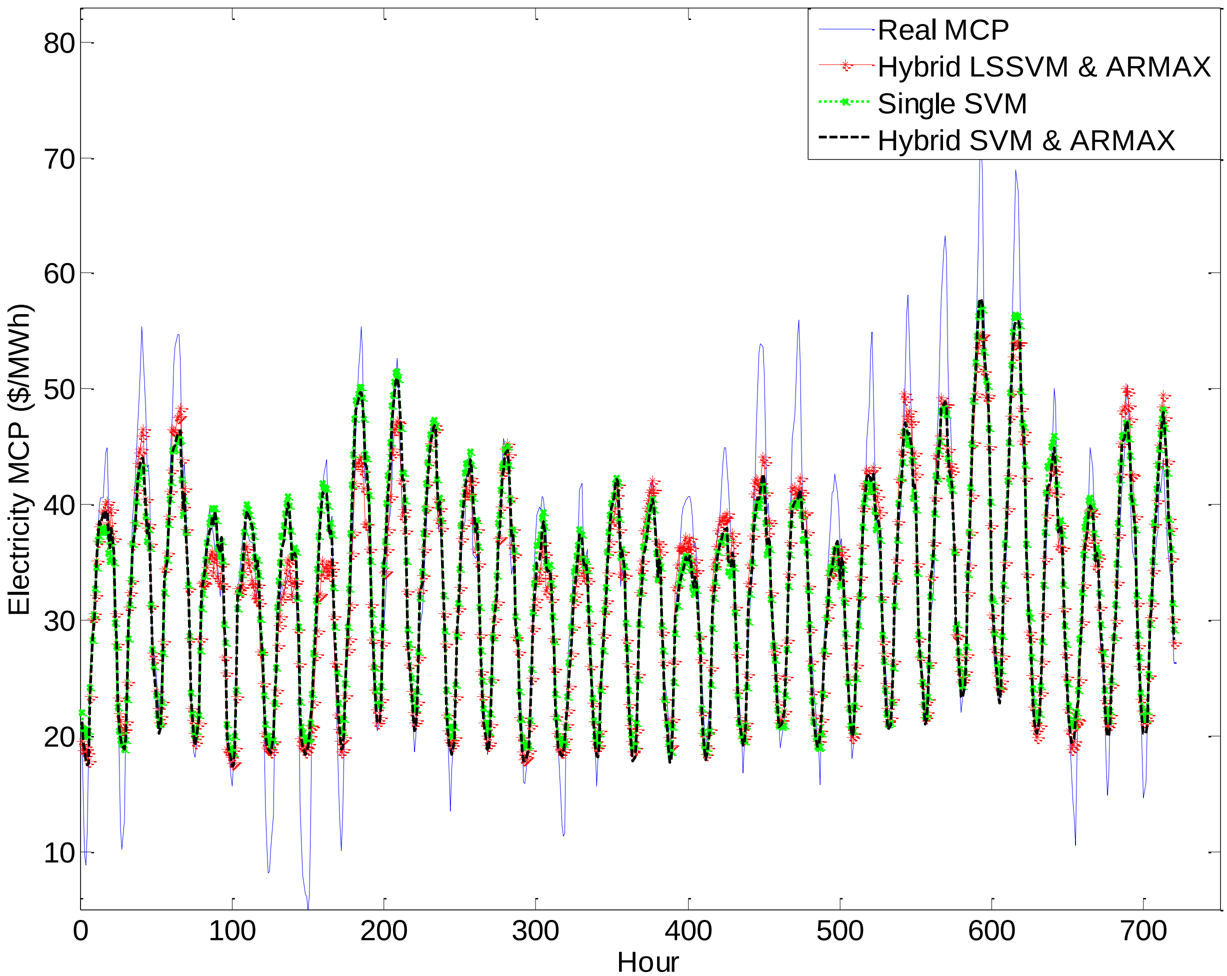


Figure 5.3: Forecasted Electricity MCP in June 2009 Using a Hybrid SVM and ARMAX Forecasting Model and a Hybrid LSSVM and ARMAX Forecasting Model.

Percentage improvement (PRIM) is used to compare the regression computation performance among the single SVM, the single LSSVM, the hybrid SVM and ARMAX and the hybrid LSSVM and ARMAX models with respect to the single SVM forecasting model results. The PRIM is calculated as

$$\mathrm{PRIM} = \frac{\text{single SVM\_MAE/MSRE - selected model\_MAE/MSRE}}{\text{single SVM\_MAE/MSRE}} \times 100\% \tag{28}$$

Positive PRIM values indicate that selected model is better than the single SVM model. Negative PRIM values indicate the opposite. The performance numbers in PRIM with respect to the single SVM forecasting model results are shown in Table 5.3.

Table 5.2: MAE, MAPE and MSRE of Single and Hybrid Models

	MAE ($/MWh)	MAPE (%)	MSRE
Single SVM	2.9743	11.7491	0.1564
Single LSSVM	2.8152	10.9722	0.1513
Hybrid SVM and ARMAX	2.6923	10.5256	0.1441
Hybrid LSSVM and ARMAX	2.7630	10.6706	0.1495

Table 5.3: Percentage Improvement of MAE, MAPE and MSRE of Single and Hybrid Models

	MAE (%)	MAPE (%)	MSRE (%)
Single SVM	---	---	---
Single LSSVM	5.35	6.61	3.26
Hybrid SVM and ARMAX	9.48	10.41	7.86
Hybrid LSSVM and ARMAX	7.10	9.18	4.41

MAE, MAPE and MSRE results show that the hybrid SVM and ARMAX and hybrid LSSVM and ARMAX models are better than the single SVM model or the single LSSVM model. As the testing results indicated that both hybrid models are better than the single SVM model or the single LSSVM model, the proposed hybrid SVM and ARMAX model and hybrid LSSVM and ARMAX model are used to forecast the mid-term electricity MCP in June 2010 using historical data from January 2009 to December 2009. Figure 5.4 shows the forecasted electricity MCP in June 2010 using a hybrid SVM and ARMAX forecasting model and a hybrid LSSVM and ARMAX forecasting model.

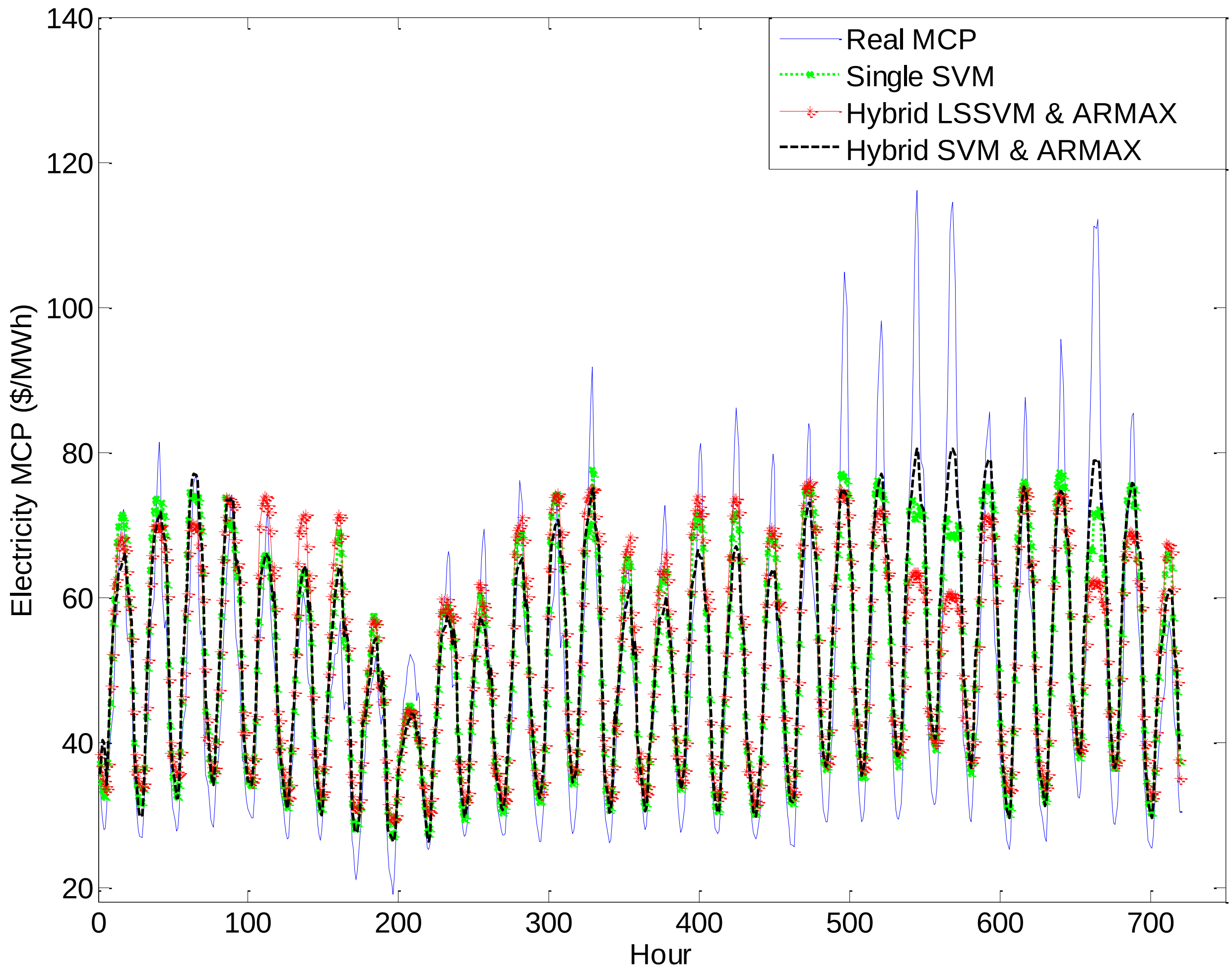


Figure 5.4: Forecasted Electricity MCP in June 2010 Using a Hybrid SVM and ARMAX Forecasting Model and a Hybrid LSSVM and ARMAX Forecasting Model.

The MAE, MAPE and MSRE are shown in Table 5.4. The performance numbers in PRIM with respect to the single SVM forecasting model results are shown in Table 5.5. According to the results in Table 5.5, the MAE, MAPE and MSRE indices show a corresponding improvement of 6.85%, 8.42% and 5.34% in forecasting results utilizing the hybrid SVM and ARMAX model and a corresponding improvement of 2.12%, 10.70% and −16.38% in forecasting results utilizing the hybrid LSSVM and ARMAX model. Although the PRIM values in MAPE and MSRE are negative indicating that the single SVM model is better than the hybrid LSSVM and ARMAX model, the performance of a hybrid LSSVM and ARMAX model is still better than a single LSSVM model as the PRIM values in MAE, MAPE and MSRE of a single LSSVM are -8.94%, −3.93% and −19.54%. These results indicate that by adding an ARMAX module to a SVM or a LSSVM module, the forecast electricity MCP by a single SVM or a single LSSVM can be improved.

Table 5.4: MAE, MAPE and MSRE of Single and Hybrid Models

	MAE ($/MWh)	MAPE (%)	MSRE
Single SVM	7.2523	15.6454	0.3316
Single LSSVM	7.9003	16.2610	0.3964
Hybrid SVM and ARMAX	6.7557	14.3275	0.3139
Hybrid LSSVM and ARMAX	7.0989	13.9709	0.3859

Table 5.5: Percentage Improvement of MAE, MAPE and MSRE of Single and Hybrid Models

	MAE (%)	MAPE (%)	MSRE (%)
Single SVM	---	---	---
Single LSSVM	-8.94	-3.93	-19.54
Hybrid SVM and ARMAX	6.85	8.42	5.34
Hybrid LSSVM and ARMAX	2.12	10.70	-16.38

5.6 Discussions

There are two major differences between SVM and LSSVM. The first difference is that during the training process, SVM uses a quadratic formulation while LSSVM uses a set of linear equations. The second difference is the selection of support vectors. SVM only selects the ones with non-vanishing coefficients as support vectors while LSSVM considers all training data as support vectors [58]. In other words, LSSVM is more like an ANN but with fixed output. Both hybrid SVM and ARMAX and hybrid LSSVM and ARMAX based mid-term electricity MCP forecasting models have showed improved forecasting accuracy compared to a single SVM and a single LSSVM based forecasting models. However, the reason for adding an ARMAX module to a single SVM forecasting model is different from adding it to a single LSSVM forecasting model.

5.7 Summary

A hybrid SVM and ARMAX and a hybrid LSSVM and ARMAX based mid-term electricity MCP forecasting models are proposed in this Chapter. The SVM or LSSVM module is first utilized to predict the initial electricity MCP values. After that, an ARMAX module is utilized to predict the adjustments for each predicted electricity price values resulting from the SVM or LSSVM module. The proposed hybrid SVM and ARMAX forecasting model and hybrid LSSVM and ARMAX forecasting model have shown improved forecasting accuracy compared to the forecasting model utilizing a single SVM or a single LSSVM. The proposed hybrid models also have the flexibility of using different numbers of input elements to achieve the optimal results. However, electricity MCP forecasting accuracy in the peak price area is still low when utilizing either the hybrid SVM and ARMAX forecasting model or the hybrid LSSVM and ARMAX forecasting model.

CHAPTER 6: MULTIPLE SVM AND MULTIPLE LSSVM BASED MID-TERM ELECTRICITY MCP FORECASTING APPROACHES

6.1 Introduction

In this Chapter, two mid-term electricity MCP forecasting models using multiple SVM and multiple LSSVM are proposed to predict hourly electricity MCP for an entire month, six months ahead. It is considered in this work that the forecasting input data are given. The proposed models have been utilized to predict both the price patterns and the values of electricity MCP.

The multiple SVM based mid-term electricity MCP forecasting model contains a SVM classification module and a SVM regression module. The SVM classification module is used to identify price patterns. There are four separated price patterns: low, medium, high and peak. After the classification computation is completed, the SVM regression module containing four parallel SVMs is utilized to forecast the price values within each price pattern.

The proposed multiple LSSVM based mid-term electricity MCP forecasting model has the same architecture as the proposed multiple SVM based forecasting model. It contains a LSSVM classification module and a LSSVM regression module. The LSSVM classification module is used to identify price patterns. The LSSVM regression module contains four parallel LSSVMs and is utilized to forecast the price values within each price pattern.

Experimental results using historical data from the PJM interconnection system demonstrated that the proposed multiple SVM and multiple LSSVM forecasting models can improve the prediction accuracy of price values especially in the low and peak price zones and eventually improve the overall system prediction accuracy [67].

6.2 Price Zones Analysis

Electricity is a very unique commodity. It cannot be economically stored in large quantity. In other words, electricity has to be produced as used. Because of its special characteristics, electricity price under deregulated electric market is volatile from time to time. Taking PJM interconnected electric market as an example, electricity price can be from as low as –$10/MWh to as high as $748/MWh [63]. The relationship between supply and demand under normal deregulated market is no longer the only dominant principle that determines the electricity price. Other factors such as business competing strategy and unethical business behavior are heavily involved and cannot be efficiently modeled. Therefore, the accuracy of the forecasted electricity MCP in the peak price zone is always very low.

Although electricity price is very volatile, it is still normally distributed along its average MCP value [50]-[52]. This special property could help researchers to study the relationship between electricity MCP and related variables when separating the electricity MCP into different price zones. The most straightforward and easiest way is to separate the electricity MCP into peak and non-peak price zones. If needed, they can be further divided into smaller zones. Using PJM electric hourly market historical data for the entire year of 2009 excluding month of June as training data and historical data in June 2009 as testing data, electricity MCP forecasting results using different numbers of price zones are shown in Table 6.1. According to the simulation results, separating the electricity MCP into four price zones has achieved the highest system forecasting accuracy compared to separating the electricity MCP into 2 (peak and non-peak), 3 (low, medium and high), or 5 (low, medium, high, low peak and high peak) price zones. It is not worth to separate electricity MCP into more than 5 price zones as the characteristics of some of the price zones becomes close to each other. In the proposed work, the electricity MCP is separated into four price zones: low, medium, high and peak price zones.

Table 6.1: The Tradeoff between SCA and MAE as Price Zones Increase Using Multiple SVM in June 2009

No. of Price Zones	SCA	MAE
1	100.00%	2.9743
2	93.89%	2.8736
3	80.56%	2.8539
4	74.31%	2.7940
5	72.92%	2.8615

In the medium price zone, most generating companies are participating in supplying electricity. Every participating generating unit is running at its optimal output. There is plenty of reserved energy available in the market which can be supplied immediately. Congestion is low in most areas and congestion cost is limited. At this moment, the market is at the stable state. Sudden shortage and surplus can be easily recovered and offset by other generating companies in the same and nearby jurisdiction. Supply and demand elasticity plays a major role and electricity MCP is mainly determined by the demand and fuel cost.

In the low price zone the profit margin is small, and therefore, only companies with low production cost and mandatory all-time running power units such as nuclear power plants are participating. Sudden shortage and surplus could cause price spikes because they cannot be recovered and offset as easily as in the medium price zone.

In the peak price zone, most power plants are running at their peak capacity. Transmission lines are under extreme load resulting extremely high congestion cost in some areas. System reserved energy is very low and generating companies expect to take advantage of it and make huge profits. Electricity MCP is mainly determined by business competing strategy and even unethical business behavior in the peak price zone. The high price zone is between the medium and the peak price zones, and therefore, shows characteristics from both price zones. The supply and demand relationship and business competing strategy both dominate the final electricity MCP in the high price zone.

The proposed work focuses on the mid-term electricity market clearing price forecasting utilizing PJM interconnected electric market data as an example. Let μ be the mean and σ be the standard deviation of the monthly historical electricity MCP. The four price zones for each month are determined based on the criterion listed below:

Low: $\text{MCP} < \mu - \sigma$

Medium: $\mu - \sigma \leq \text{MCP} < \mu + 0.5\sigma$

High: $\mu + 0.5\sigma \leq \text{MCP} < \mu + 1.5\sigma$

Peak: $\mu + 1.5\sigma \leq \text{MCP}$

About 15%-25% of the price will be in the low price zone (less than $\mu-\sigma$). 50%-60% of the price will be in the medium price zone (between $\mu-\sigma$ and $\mu+0.5\sigma$). 15% -20% of the price will be in the high price zone (between $\mu+0.5\sigma$ and $\mu+1.5\sigma$). Finally, the last 5%-10% of the price will be in the peak price zone (higher than $\mu+1.5\sigma$). The standard deviation multipliers are chosen based on the price characteristics of the PJM interconnected electric market and forecasting model parameter optimization. They can be modified when applying in a different electric market.

6.3 Problems Associated with Utilizing Single SVM or Single LSSVM Based Mid-term Electricity MCP Forecasting Models

Using PJM electric market historical data for the entire year of 2009 excluding month of June as the training data and the historical data in June 2009 as the testing data, mid-term electricity MCP forecasting results using single SVM and single LSSVM forecasting models are shown in Figure 6.1.

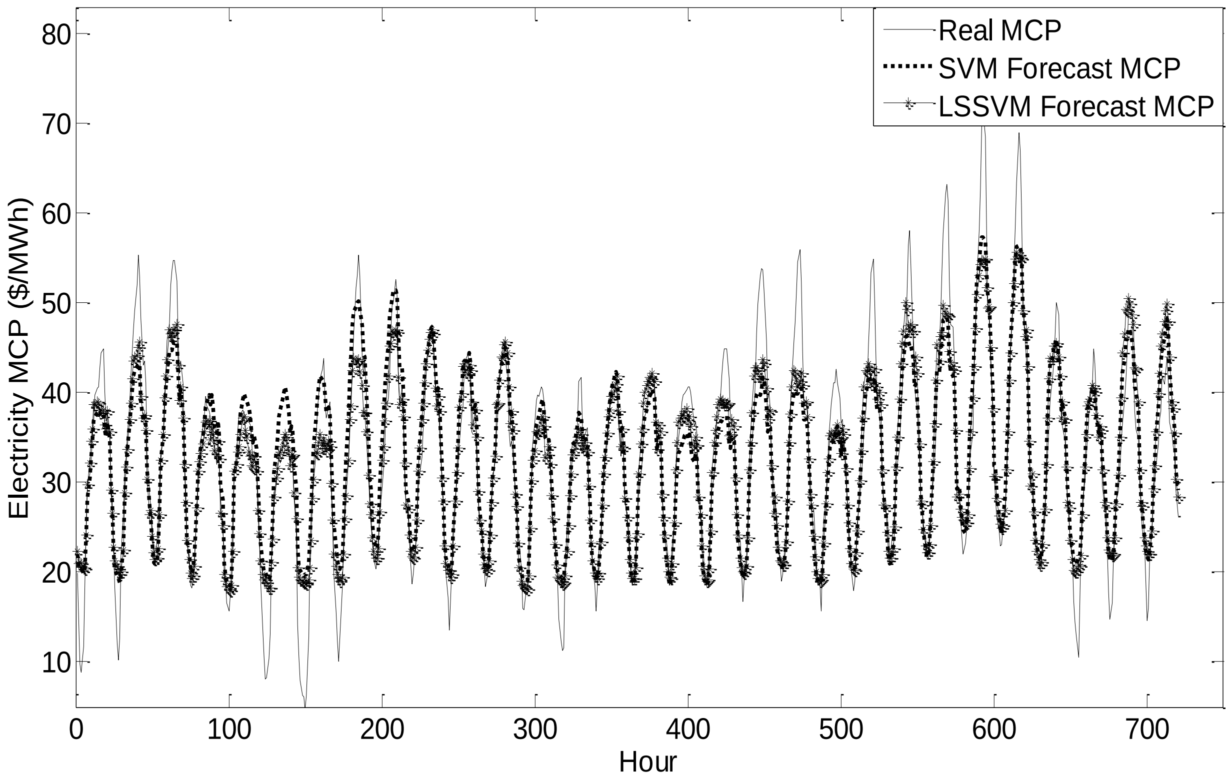


Figure 6.1: Forecasted Electricity MCP in June 2009 Using a Single SVM and a Single LSSVM Forecasting Models.

It can be seen from Figure 6.1 that the predicted electricity MCP by a single SVM or a single LSSVM forecasting models are very close to the real electricity MCP in the middle section, but deviated significantly from the real electricity MCP in the top and bottom sections. In order to take a closer look using multiple price zone analyses, MAE, MAPE and MSRE results have been calculated for four price zones and are shown in Table 6.2 and 6.3.

Table 6.2: MAE, MAPE and MSRE for Different Price Zones in June 2009 Using a Single SVM

Name	Price Zones				System
	Low	Medium	High	Peak	
Units	114	389	163	54	720
MAE ($/MWh)	4.0094	1.8941	3.0837	8.2403	2.9743
MAPE (%)	35.9821	6.1526	7.2207	14.5750	11.7491
MSRE	0.5200	0.1911	0.2933	1.2738	0.1564

Table 6.3: MAE, MAPE and MSRE for Different Price Zones in June 2009 Using a single LSSVM

Name	Price Zones				System
	Low	Medium	High	Peak	
Units	114	389	163	54	720
MAE ($/MWh)	3.6372	1.7443	2.9308	8.4446	2.8152
MAPE (%)	33.1702	5.6344	6.8900	14.8841	10.9722
MSRE	0.4846	0.1135	0.2866	1.2679	0.1513

It can be seen from Table 6.2 and 6.3 that the medium price zone has the lowest MAE, MAPE and MSRE values. The MAE, MAPE and MSRE values in the low and the peak price zones are all higher than the system MAE, MAPE and MSRE. The peak price zone has the highest MAE and MSRE and the low price zone has the highest MAPE. According to Table 6.2 and 6.3, a single SVM or a single LSSVM would result low forecast accuracy, especially in the low and peak price zones. Unless additional input data can be provided to create more dimensions for training, adjusting the only two control parameters inside the SVM will not make any significant affect. The system MAE, MAPE and MSRE will remain high.

6.4 Multiple SVM and Multiple LSSVM Forecasting Models Architecture

A multiple SVM or a multiple LSSVM based forecasting models are a combination of several SVMs or LSSVMs which could offset the weakness of utilizing a single SVM or a single LSSVM and achieve better overall system results. The proposed multiple SVM and multiple LSSVM based forecasting model has the advantage of grouping the input data into different categories based on a pre-designed data classification algorithm before regression computation to reduce the complexity of input data and making it possible to utilize more than one SVM or LSSVM simultaneously when forecasting the mid-term electricity MCP. The input data are grouped into four categories based on four previously defined price zones. As a result, instead of a single SVM forecasting the mid-term electricity MCP for the whole price range, there will be four SVMs or four LSSVMs to forecast the mid-term electricity MCP in four different price categories. The reduced forecasting price range of each SVM or LSSVM would result in improved accuracy in low, high and peak price zones and will finally improve the overall system accuracy of the multiple SVM and multiple LSSVM forecasting models. The architecture of a multiple SVM and a multiple LSSVM based mid-term electricity MCP forecasting models are shown in Figure 6.2 and 6.3.

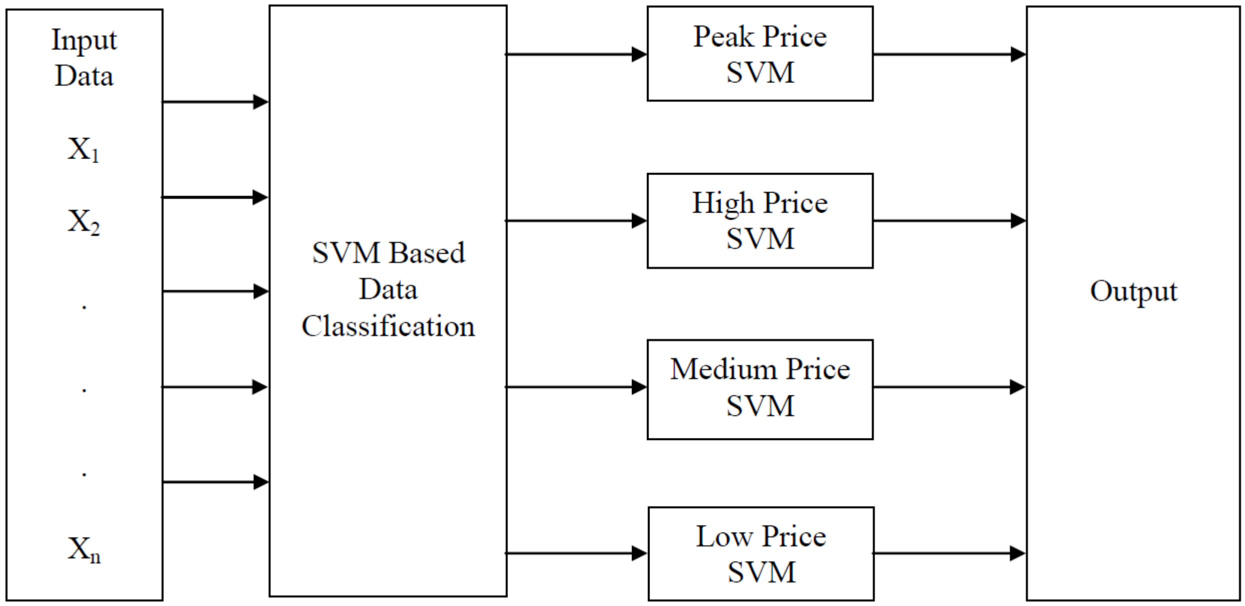


Figure 6.2: Multiple SVM Based Electricity Forecasting Model Architecture [68]

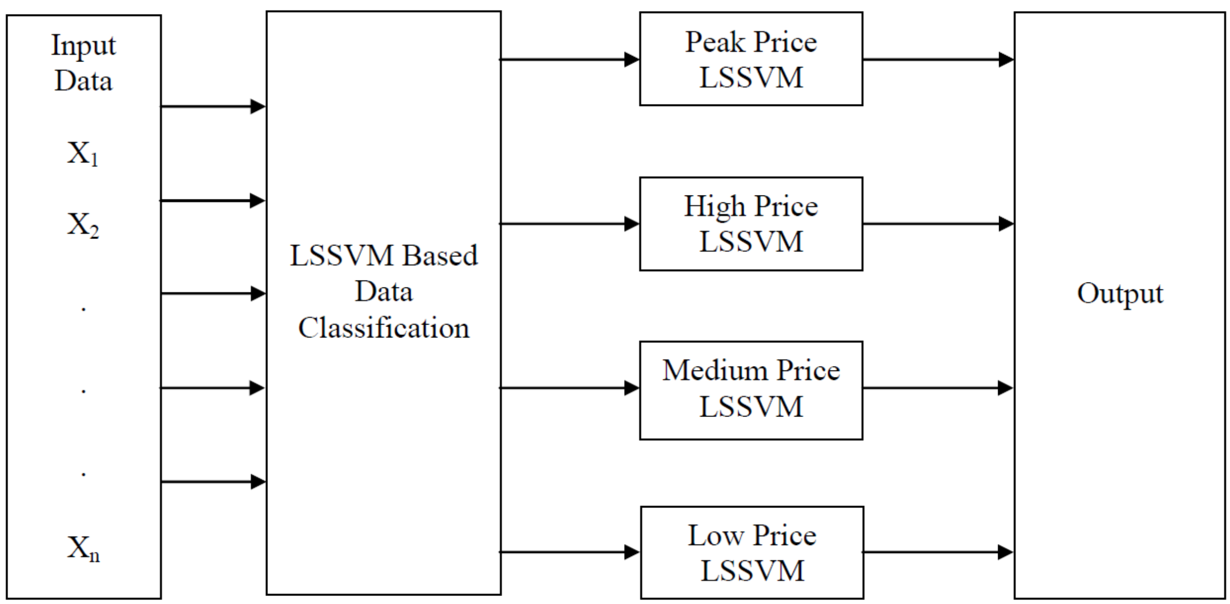


Figure 6.3: Multiple LSSVM Based Electricity Forecasting Model Architecture

As shown in Figures 6.2 and 6.3, a multiple SVM and a multiple LSSVM contain four layers. The first layer is the input layer. The second layer is the SVM or LSSVM data classification layer. Following that is the third layer, the SVM or LSSVM price prediction layer. The final layer is the output layer. The input layer contains input data such as electricity hourly demand, electricity daily peak demand and daily natural gas price. Data selection and pre-process are explained in detail in Chapter 3.3. After all the data are pre-processed in the input layer, the SVM or LSSVM classification module is utilized to group the input data into four sub data sets based on the four predefined electricity price zones: low, medium, high and peak. When forecasting the mid-term electricity MCP, the data classification module can significantly reduce the range each price prediction SVM or LSSVM shall cover and therefore improve the overall system accuracy. After the grouping is completed by the SVM or LSSVM classification module, the SVM or LSSVM prediction module is utilized to forecast the mid-term electricity MCP. The four parallel connected SVMs or LSSVMs in the price prediction module will forecast the electricity MCP in four different price zones. Based on the different ranges of input data, each price prediction SVM or LSSVM optimizes its own control parameters and the dimension of input data during the training process. This will make the SVM or LSSVM in each price zone capable to capture the characteristics between input and output data within that price zone. In the output layer, electricity price values by the predicted four SVMs or LSSVMs are combined to form the final forecast electricity MCP. The data classification module will assign the input data with serial numbers before sending them to the price prediction module. These serial numbers will be used when all four output data sets from the four price prediction SVMs or LSSVMs are regrouped in the output layer. The training input data for both modules is from the input layer. The target data for the SVM or LSSVM classification module is the converted historical electricity MCP data labelled number 1 to 4 representing the low, medium, high and peak price zones. The target data for the SVM or LSSVM prediction module is the historical electricity

MCP. Cross validation technique is applied in data classification and price prediction modules for the optimization of the control parameters.

6.5 Input Data Selection

Although the proposed multiple SVM and multiple LSSVM forecasting models have the same architecture, each module inside each forecasting model is capable of utilizing different numbers of input elements to achieve the optimal results.

6.5.1 Multiple SVM

A total of 8 input elements have been taken into account for the proposed multiple SVM forecasting model at each hour t including electricity hourly demand at hour t. They are: electricity daily peak demand, electricity monthly average demand, daily price of natural gas, previous year's monthly average electricity MCP, previous year's electricity MCP group number (1 to 4 representing the price zones: low, medium, high and peak) at t, month (number 1-12) and hour of the day (number 1-24). The target data at hour t is the electricity MCP at hour t.

All input data are pre-processed to optimize the computation. Utilizing the cross validation technique for the optimization of input data selection and using MAE for the performance evaluation, the final dimension of the input data for the proposed multiple SVM has been obtained as: 6 for the data classification SVM, 5 for the low price SVM, 8 for the medium price SVM, 7 for the high price SVM and 7 for the peak price SVM. Due to the fact that the price zone analysis is determined on a monthly basis, the input data for the data classification module are therefore normalized on a monthly basis. Meanwhile, the input data for the price prediction module are normalized on a yearly basis. Moreover, based on the previous published works [22-

24] regarding the selection of training data for mid-term electricity price forecasting, one year is the most optimized length of historical data to train the forecasting model.

6.5.2 Multiple LSSVM

A total of 8 input elements have been taken into account for the proposed multiple LSSVM forecasting model at each hour *t* including electricity hourly demand at hour *t* They are: electricity daily peak demand, electricity monthly average demand, daily price of natural gas, previous year's monthly average electricity MCP, previous year's electricity MCP group number (1 to 4 representing the price zones: low, medium, high and peak) at *t*, month (number 1-12) and hour of the day (number 1-24). The target data at hour *t* is the electricity MCP at hour *t*.

All input data are pre-processed to optimize the computation. Utilizing the cross validation technique for the optimization of input data selection and using MAE for the performance evaluation, the optimized dimension of the input data for the proposed multiple LSSVM are: 6 for the data classification LSSVM, 5 for the low price LSSVM, 7 for the medium price LSSVM, 7 for the high price LSSVM and 6 for the peak price LSSVM. Due to the fact that the price zone analysis is determined on a monthly basis, the input data for the data classification module are therefore normalized on a monthly basis. Meanwhile the input data for the price prediction module are normalized on a yearly basis. Moreover, based on the previous published works [22-24] regarding the selection of training data for mid-term electricity price forecasting, one year is the most optimized length of historical data to train the forecasting model.

6.6 Classification Performance Evaluation

In order to evaluate the performance of the proposed electricity MCP forecasting model, several evaluation criteria are introduced. For classification evaluation, the most common one is the system classification accuracy (SCA) which is defined as

$$\mathrm{SCA} = \frac{\text{no.of correctly predicted vectors}}{\text{no.of vectors}} \tag{29}$$

SCA gives straightforward results of classification performance, but it is not a very useful measurement for multi-class classification as the size of the data in each class is seriously imbalanced. For instance, the peak price class contains less than 10% of the total data. Even if the peak price class is totally misclassified and assuming other classes are 100% classified, the SCA is still more than 90%. Therefore, in order to properly evaluate the performance of a multi-class classification SVM or LSSVM, some modified criteria are introduced based on the study from [50]-[52]. The first criterion is called the individual class prediction measurement (ICPM) which is defined as

$$\mathrm{ICPM} = \frac{\text{no.of predicted vectors in class A}}{\text{no.of vectors in class A}} \tag{30}$$

ICPM will provide performance information of the multi-class classification SVM in each class. The ideal value of ICPM in each class is expected to be 100% when all predicted vectors are accurately classified. When ICPM is less than 100% in a class, this price class is under predicted. When ICPM is more than 100% in a class, this price class is over predicted. Classifying peak price class vectors is the most difficult classification due to the fact that in this class the prices are influenced by unethical business practice. ICPM can provide very important information in SVM classification accuracy in peak price class.

The second added criterion is called the individual class prediction accuracy (ICPA) which is defined as

$$\mathrm{ICPA} = \frac{\text{no.of correctly predicted vectors in class A}}{\text{no.of vectors in class A}} \tag{31}$$

ICPA will provide accuracy measurements of the SVM or LSSVM multi-class classifier performance in each class. It is very useful for optimizing SVM or LSSVM control parameter during training.

The last classification criterion introduced in this paper is called the individual class prediction excellence which is defined as

$$\mathrm{ICPE} = \frac{\text{no.of correctly predicted vectors in class A}}{\text{no.of predicted vectors in class A}} \tag{32}$$

ICPE will provide the percentage of correctly predicted vectors in each predicted class. It can be used to analyze the confidence of the SVM or LSSVM multi-class classification in each class.

6.7 Numerical Results

Using January 2009 to December 2009 excluding June 2009 as the actual training data and June 2009 as the testing data, the identification results of the SVM and LSSVM classification modules are shown in Figure 6.4 and 6.5. For both classification modules, it can be seen that the classification results are very accurate at the low and the medium price zones but less accurate at the high price zone. The peak price zone has the least accurate results. Many of the peak price zone numbers dropped into the high price zone and many of the high price zone numbers dropped into the medium price zone. Detailed evaluation results can be seen in Table 6.4 and 6.5. In both Tables, the actual and forecast number of units in each price zone are shown in the first and the second row. The accurately predicted units (APU) in each price zone are shown in the third row. It can be seen that the ICPM values decrease as price zones move from low to peak. This reflects the nature of electricity MCP forecasting where the peak prices are the most difficult ones to forecast. ICPA values imply that the low price zone can be classified with 100% accuracy. Medium zone classification achieved 83.55% accuracy by the SVM classification module and 85.35% accuracy by the LSSVM classification module. However, the classification accuracy in the high and the peak price zones are very low. Although ICPM and ICPA indicate that the high and the peak price zones are the most difficult ones to predict, the ICPE results are very encouraging. The peak price zone has the highest ICPE value which indicates that the proposed classification module can capture the points in the peak price zone with a better accuracy.

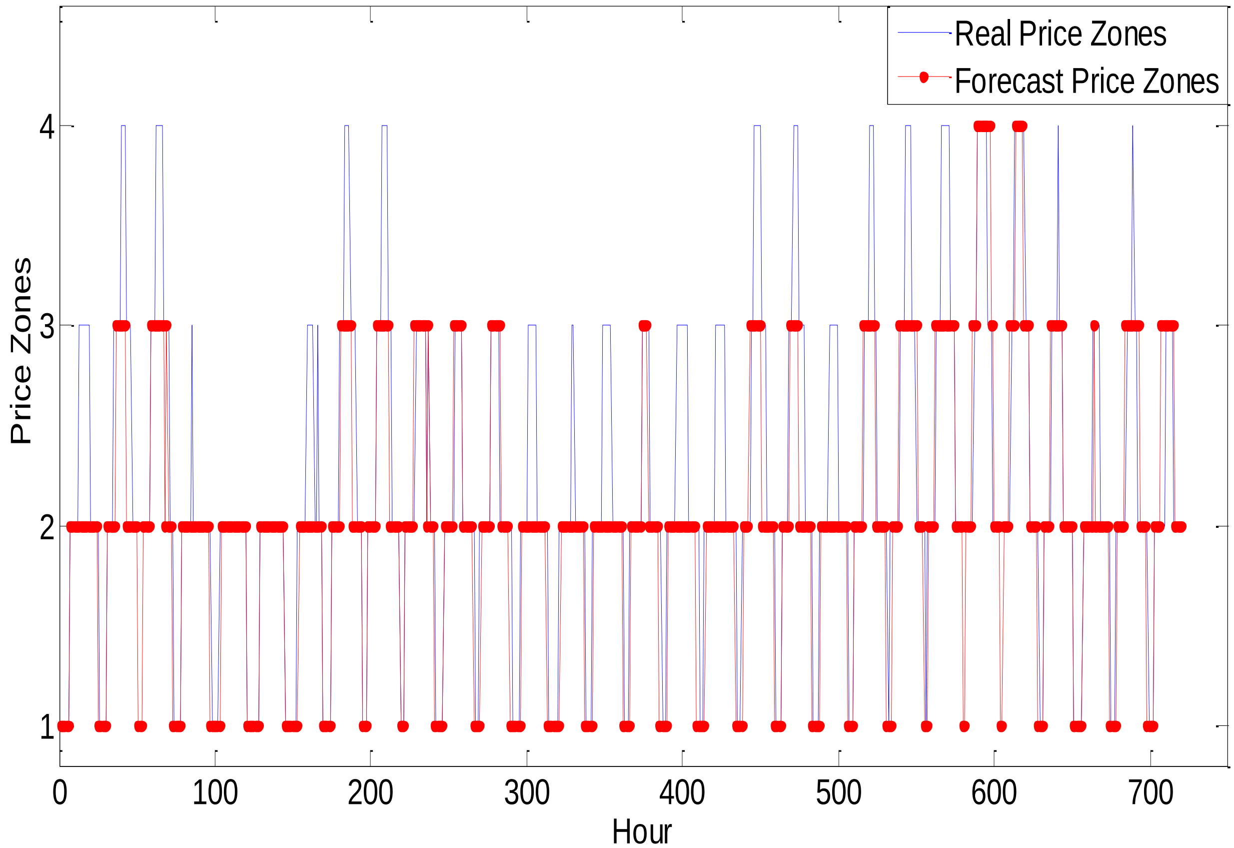


Figure 6.4: Forecasted Electricity Price Zones in June 2009 by the SVM Classification Module.

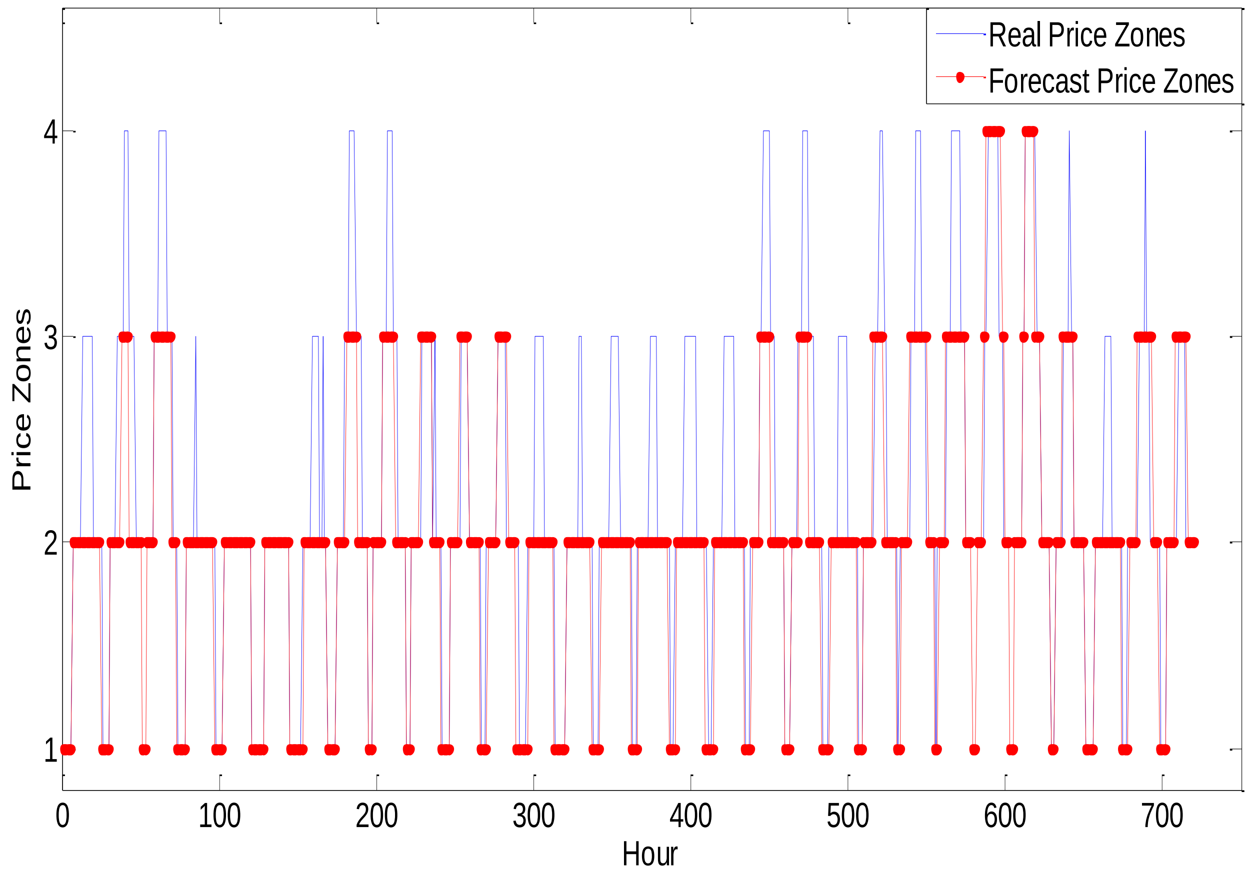


Figure 6.5: Forecasted Electricity Price Zones in June 2009 by the LSSVM Classification Module.

Table 6.4: Performance Evaluation Results of the SVM Classification Module in June 2009

Name	Low	Medium	High	Peak	System
Units	114	389	163	54	720
Multiple SVM	159	402	145	14	720
APU	114	325	84	12	535
ICPM (%)	139.47	103.34	88.96	25.93	100.00
ICPA (%)	100.00	83.55	51.53	22.22	74.31
ICPE (%)	71.70	80.85	57.93	85.71	74.31

Table 6.5: Performance Evaluation Results of the LSSVM Classification Module in June 2009

Name	Low	Medium	High	Peak	System
Units	114	389	163	54	720
Multiple SVM	155	416	133	16	720
APU	114	332	76	13	535
ICPM (%)	135.96	106.94	81.60	29.63	100.00
ICPA (%)	100.00	85.35	46.63	24.07	74.31
ICPE (%)	73.55	79.81	57.14	81.25	74.31

The final mid-term electricity MCP forecasting results are obtained by combining the forecasted price from four price prediction SVMs for the multiple SVM forecasting model or four price prediction LSSVMs for the multiple LSSVM forecasting model. Figure 6.6 shows the forecast electricity MCP in June 2009 using multiple SVM and multiple LSSVM forecasting models. Compared to the single SVM forecasting model, it can be seen that the major contribution of utilizing a multiple SVM or a multiple LSSVM based forecasting models are the improved forecasting results in the low and peak price zones. MAE, MAPE and MSRE are selected for regression computation performance evaluation. The performance numbers are shown in Table 6.6 and 6.7. PRIM is used to compare the regression computation performance of the multiple SVM forecasting model and the multiple LSSVM forecasting model with respect to the single SVM forecasting model results shown in Table 6.7. Positive PRIM values indicate that the multiple SVM model or the LSSVM model is better than the single SVM model in this price zone. Negative PRIM values indicate the opposite. The performance numbers in PRIM are shown in Table 6.8 and 6.9.

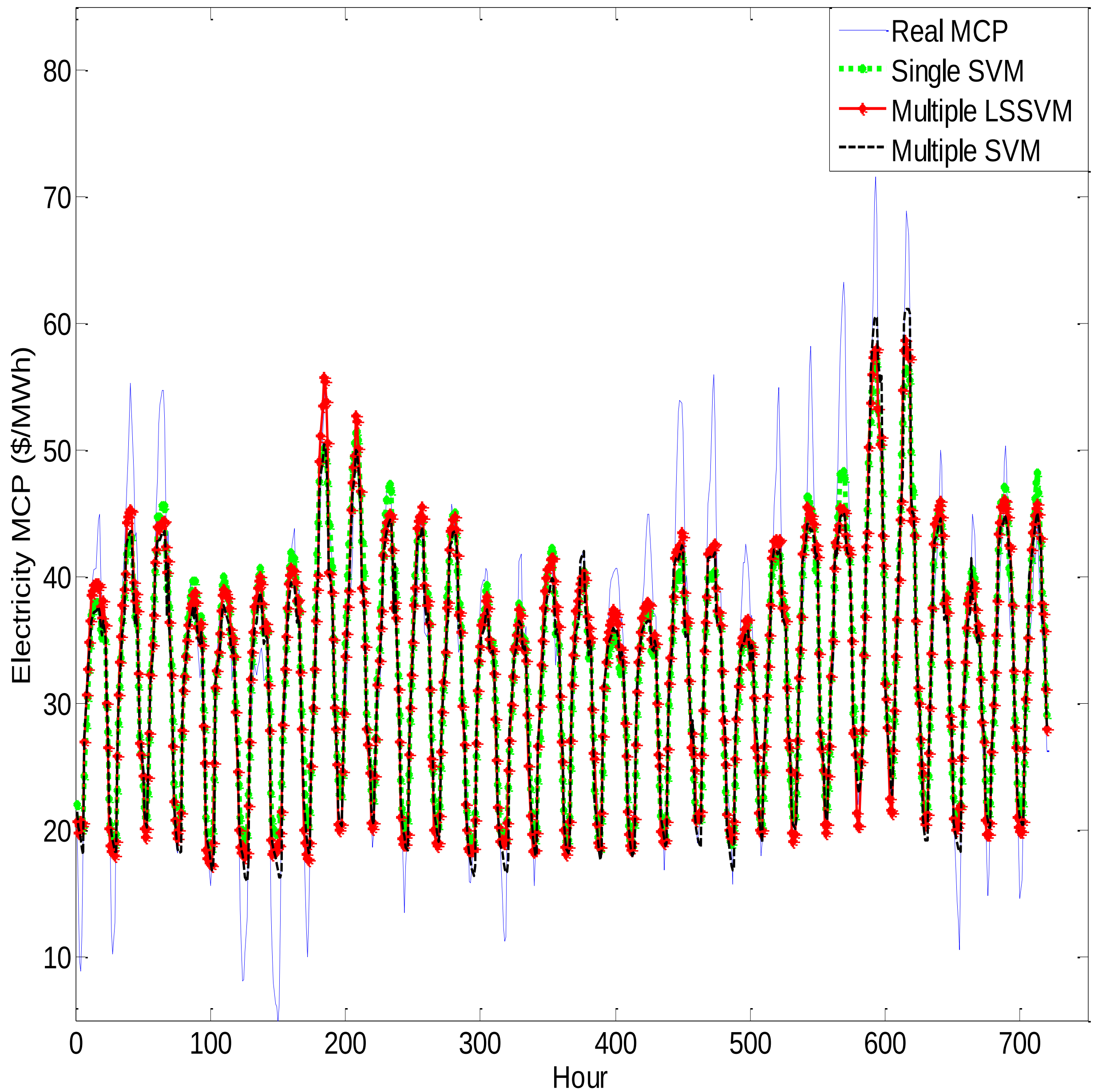


Figure 6.6: Forecasted Electricity MCP in June 2009 by a Multiple SVM and a Multiple LSSVM Based Mid-term Electricity MCP Forecasting Models.

Table 6.6: Performance Evaluation Results of MAE, MAPE and MSRE Using a Multiple SVM Model in Different Price Zones in June 2009

Name	Low	Medium	High	Peak	System
Units	114	389	163	54	720
MAE ($/MWh)	3.0808	1.9519	4.6215	4.7900	2.7940
MAPE (%)	23.9300	5.6497	9.5545	7.7140	10.5131
MSRE	0.3330	0.1289	0.5104	1.5882	0.1487

Table 6.7: Performance Evaluation Results of MAE, MAPE and MSRE Using a Multiple LSSVM Model in Different Price Zones in June 2009

Name	Low	Medium	High	Peak	System
Units	114	389	163	54	720
MAE ($/MWh)	3.0239	1.9757	4.7074	5.3577	2.7811
MAPE (%)	25.0042	5.8216	9.8296	8.2982	10.7466
MSRE	0.3452	0.1214	0.5271	1.7228	0.1463

Table 6.8: Performance Evaluation Results of MAE, MAPE and MSRE in PRIM Using a Multiple SVM Model in Different Price Zones in June 2009 with Respect to the Single SVM

Name	Low	Medium	High	Peak	System
Units	114	389	163	54	720
MAE (%)	23.16	-3.05	-49.87	41.87	6.06
MAPE (%)	33.49	8.17	-32.32	47.07	10.52
MSRE (%)	35.96	-8.23	-74.02	-24.68	4.92

Table 6.9: Performance Evaluation Results of MAE, MAPE and MSRE in PRIM Using a Multiple LSSVM Model in Different Price Zones in June 2009 with Respect to the Single SVM

Name	Low	Medium	High	Peak	System
Units	114	389	163	54	720
MAE (%)	24.58	-4.31	-52.65	34.98	6.50
MAPE (%)	30.51	5.38	-36.13	43.07	8.53
MSRE (%)	33.62	-1.93	-79.71	-35.25	6.46

In the low price zone, MAE, MAPE and MSRE values show that the multiple SVM and multiple LSSVM models are more accurate than the single SVM model by more than 23%. However, the MAE and MSRE results are opposite in the medium and high price zones. This is due to the misclassification in the data classification module. In the forecasted medium price zone, about 80% of the data are the medium price zone data. The remaining 20% of the misclassified data are from the high price zone. In the forecasted high price zone, only about 57% of data are the high price zone data. The remaining 43% of the misclassified data are from the medium zone and the peak price zone. These are the major drawbacks of the proposed multiple SVM and multiple LSSVM forecasting models. However, designing a classification module that can separate the input data into corresponding price zones so the price prediction SVM and LSSVM can work on smaller data range and achieve better overall system forecasting accuracy is also the major contribution of the proposed multiple SVM and multiple LSSVM mid-term electricity MCP forecasting models.

It can be noticed that the MAE value in the peak price zone resulting from the multiple SVM and multiple LSSVM is better than that of the single SVM while it is the reverse with MSRE value. Usually, the conclusions obtained from the performance numbers of MAE and MSRE should be identical. If the conclusions obtained from the system MAE and MSRE values are different, because all the control parameters are determined based on the global minimal MAE values, we will use the MAE values to determine which forecasting model is better. Figure 6.6 can also graphically support this conclusion as the multiple SVM and multiple LSSVM forecasted electricity MCPs are closer to the real electricity MCPs in the peak price zone.

As the testing results supported the fact that the multiple SVM and multiple LSSVM are better than the single SVM in mid-term electricity MCP forecasting, the proposed multiple SVM and multiple LSSVM models are used to forecast the mid-term hourly electricity MCP in June 2010 using historical data from January 2009 to December 2009. The hourly classification results in June 2010 are shown in Figure 6.7 and 6.8. Detailed classification evaluation results in each price zone are shown in Table 6.10 and 6.11. The system classification accuracy is 60.56% for the SVM classification module and 57.22% for the LSSVM classification module. According to the ICPM numbers, both the low and high price zones were over predicted. This time, the captured peak price zone data has 100% confidence in SVM classification module and 64.29% confidence in LSSVM classification module.

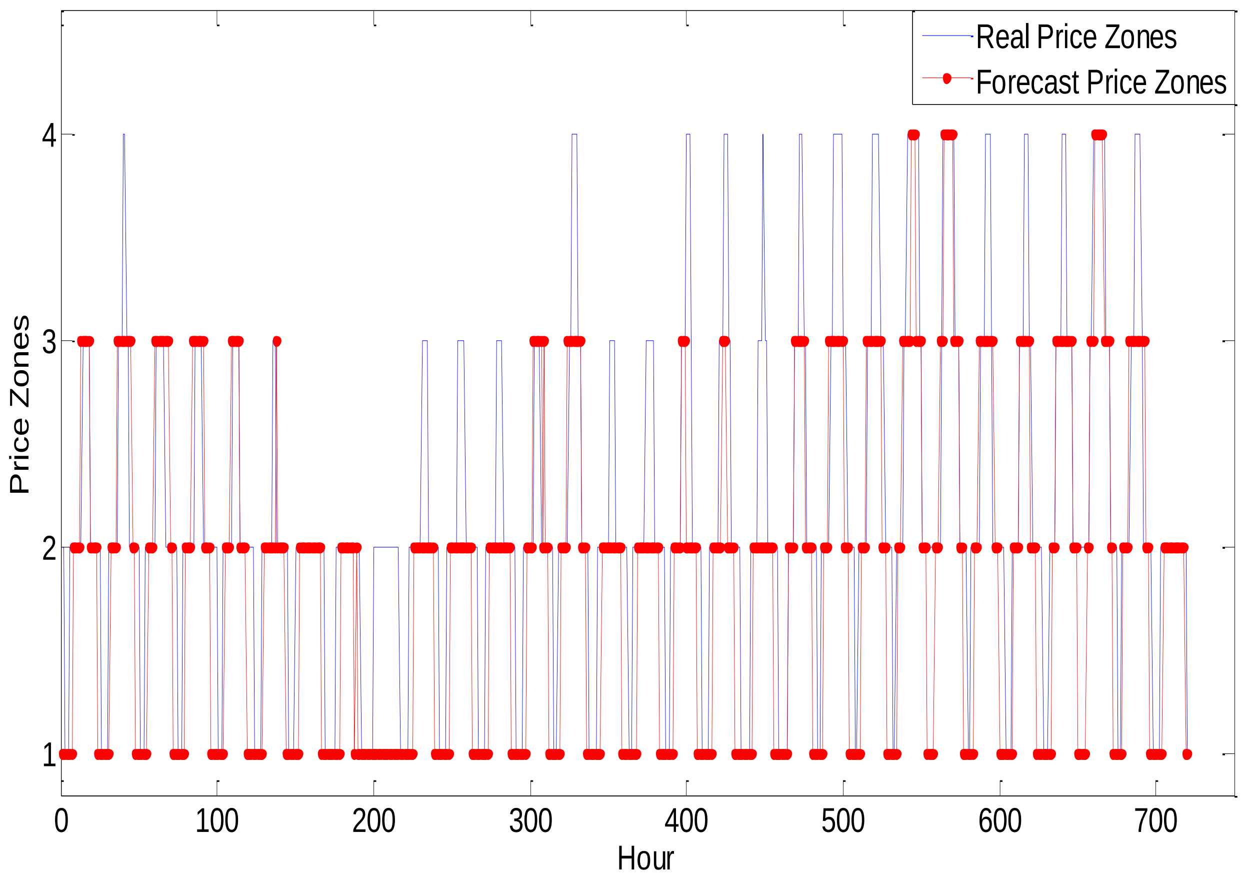


Figure 6.7: Forecasted Electricity Price Zones in June 2010 by the SVM Classification Module.

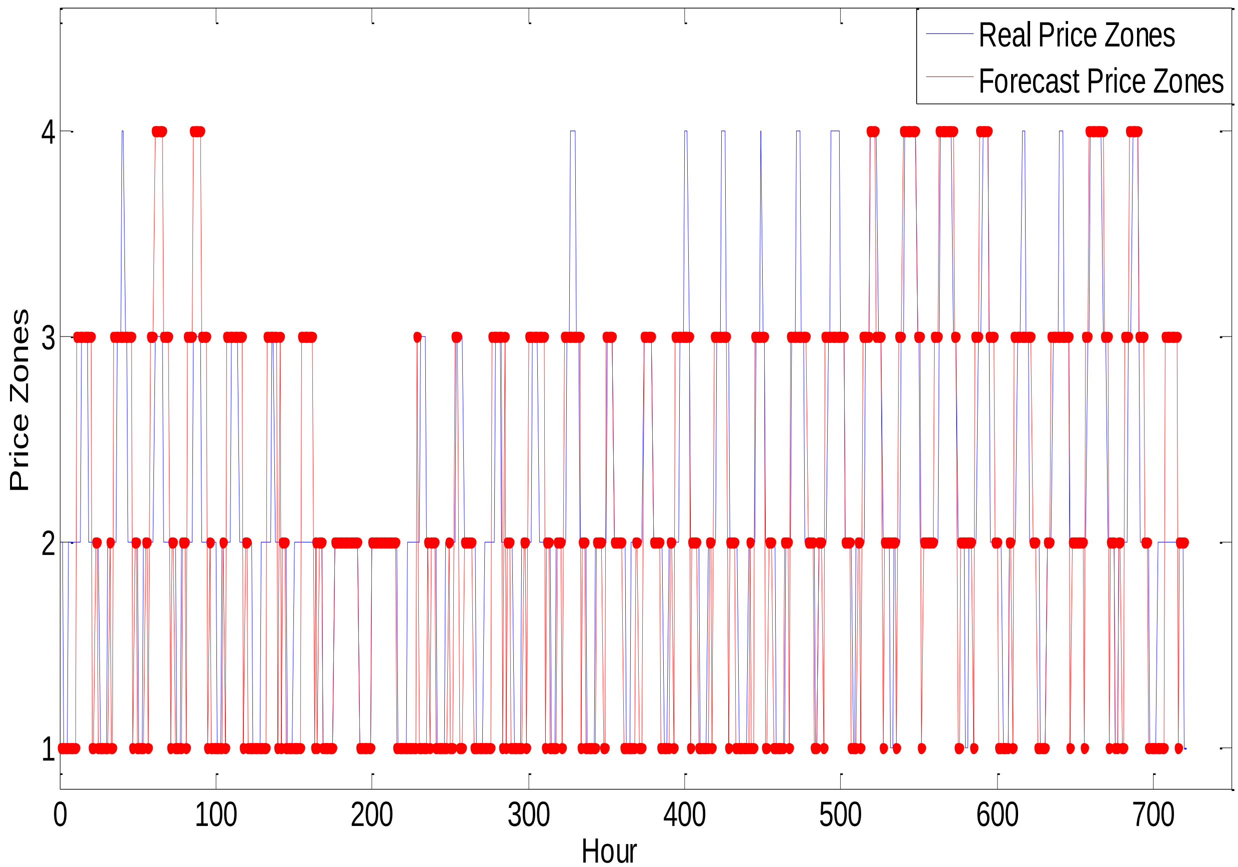


Figure 6.8: Forecasted Electricity Price Zones in June 2010 by the LSSVM Classification Module.

Table 6.10: Performance Evaluation Results of the SVM Classification Module for June 2010

Name	Low	Medium	High	Peak	System
Units	117	415	123	65	720
Multiple SVM	284	268	153	15	720
APU	117	222	82	15	436
ICPM (%)	242.74	64.58	124.39	23.08	100.00
ICPA (%)	100.00	53.49	66.67	23.08	60.56
ICPE (%)	41.20	82.84	53.59	100.00	60.56

Table 6.11: Performance Evaluation Results of the LSSVM Classification Module for June 2010

Name	Low	Medium	High	Peak	System
Units	117	415	123	65	720
Multiple SVM	258	176	230	56	720
APU	111	170	95	36	412
ICPM (%)	220.51	42.41	186.99	86.15	100.00
ICPA (%)	94.87	40.96	77.24	55.38	57.22
ICPE (%)	43.02	96.59	41.30	64.29	57.22

Figure 6.9 shows the forecasted electricity hourly MCPs in June 2010 using both multiple SVM and multiple LSSVM based mid-term electricity MCP forecasting models. The final mid-term electricity hourly MCP forecasting results are obtained from the combination of predicted price from four price prediction SVMs for the multiple SVM forecasting model or price prediction LSSVMs for the multiple LSSCVM forecasting model. Detailed evaluation results of MAE, MAPE and MSRE are shown in Table 6.12 and 6.13. The performance numbers in PRIM with respect to single SVM forecasting model results (shown in Table 6.14) are shown in Table 6.15 and 6.16. The multiple SVM forecasting model show an impressive 21.46 % improvement on MAE evaluation, 27.22% improvement on MAPE evaluation and 14.48% improvement on MSRE evaluation. The multiple LSSVM forecasting model only shows 2.17% improvement on MAE evaluation, 15.09% improvement on MAPE evaluation and -12.58% improvement on MSRE evaluation. As the MAE value in PRIM is positive and all the control parameters are determined based on the global minimal MAE values, we can still conclude that the multiple LSSVM forecasting model has higher forecasting accuracy than the single SVM forecasting model in mid-term electricity MCP forecasting. MCP forecasting results for the month of April 2010 are shown in Figure 6.10.

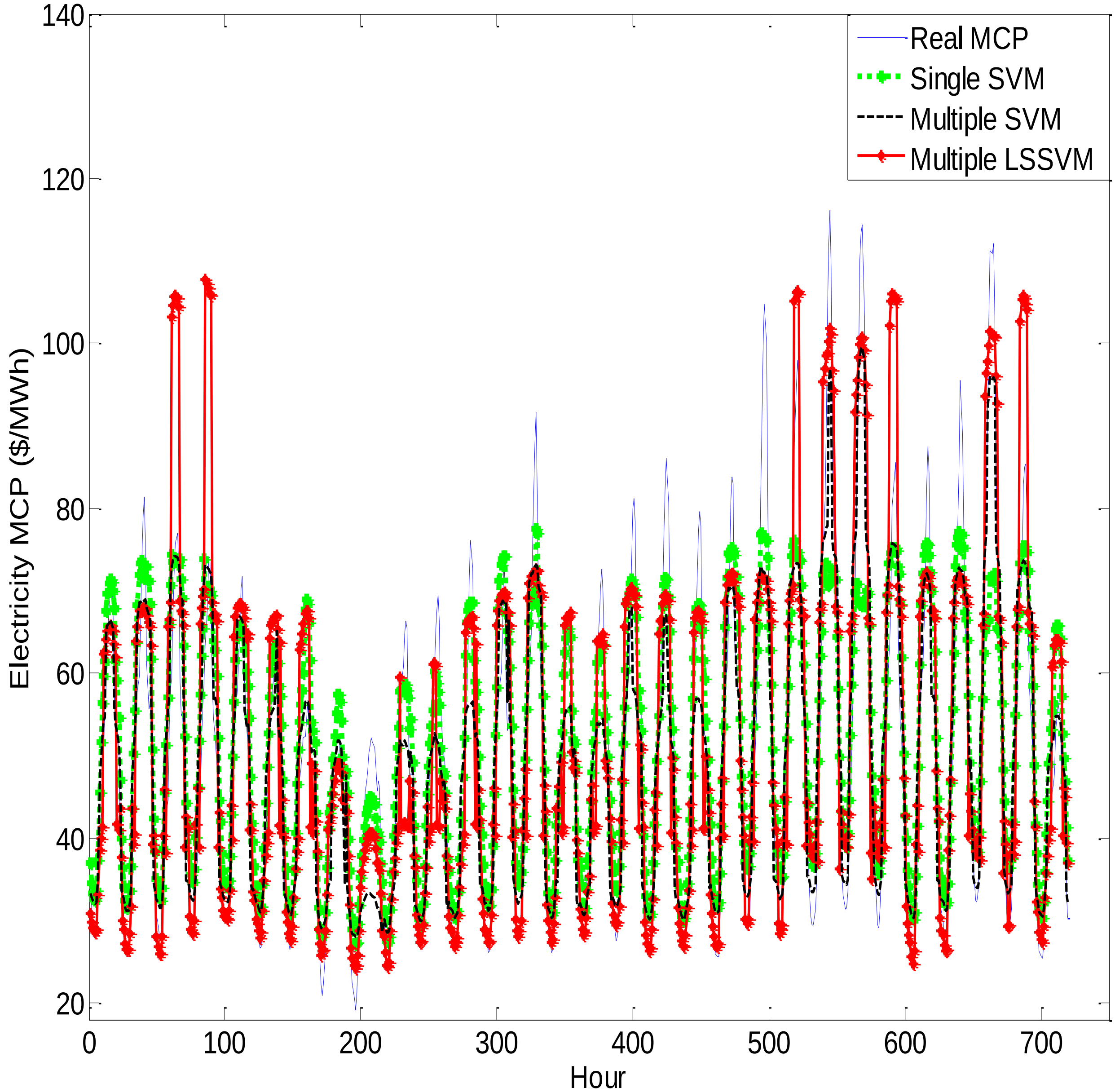


Figure 6.9: Forecasted Electricity MCP in June 2010 by a Multiple SVM and a Multiple LSSVM Based Mid-term Electricity MCP Forecasting Models.

Table 6.12: Performance Evaluation Results of MAE, MAPE and MSRE Using a Multiple SVM Model in Different Price Zones in June 2010

Name	Low	Medium	High	Peak	System
Units	117	415	123	65	720
MAE ($/MWh)	3.5448	6.0861	8.4676	11.1776	5.6958
MAPE (%)	10.7136	11.9350	11.7938	10.2199	11.3875
MSRE	0.2898	0.4704	0.8442	3.2214	0.2836

Table 6.13: Performance Evaluation Results of MAE, MAPE and MSRE Using a Multiple LSSVM Model in Different Price Zones in June 2010

Name	Low	Medium	High	Peak	System
Units	117	415	123	65	720
MAE ($/MWh)	3.6979	4.9565	9.5114	19.5440	7.0950
MAPE (%)	8.5126	12.8573	15.9831	25.5351	13.2850
MSRE	0.3875	0.4224	0.7262	3.0311	0.3733

Table 6.14: Performance Evaluation Results of MAE, MAPE and MSRE Using a Single SVM Model in Different Price Zones in June 2009

Name	Low	Medium	High	Peak	System
Units	117	415	123	65	720
MAE ($/MWh)	5.7523	6.9711	5.0316	15.9496	7.2523
MAPE (%)	21.0094	16.3663	7.5146	16.7736	15.6454
MSRE	0.4572	0.3350	0.5299	2.6890	0.3316

Table 6.15: Performance Evaluation Results of MAE, MAPE and MSRE in PRIM Using a Multiple SVM Model in Different Price Zones in June 2010 with Respect to the Single SVM

Name	Low	Medium	High	Peak	System
Units	117	415	123	65	720
MAE (%)	38.38	12.70	-68.29	29.92	21.46
MAPE (%)	49.01	27.08	-56.95	39.07	27.22
MSRE (%)	36.61	-40.42	-59.31	-19.80	14.48

Table 6.16: Performance Evaluation Results of MAE, MAPE and MSRE in PRIM Using a Multiple LSSVM Model in Different Price Zones in June 2010 with Respect to the Single SVM

Name	Low	Medium	High	Peak	System
Units	117	415	123	65	720
MAE (%)	35.71	28.90	-89.03	-22.54	2.17
MAPE (%)	59.48	21.44	-112.69	-52.23	15.09
MSRE (%)	15.24	-26.09	-37.04	-12.72	-12.58

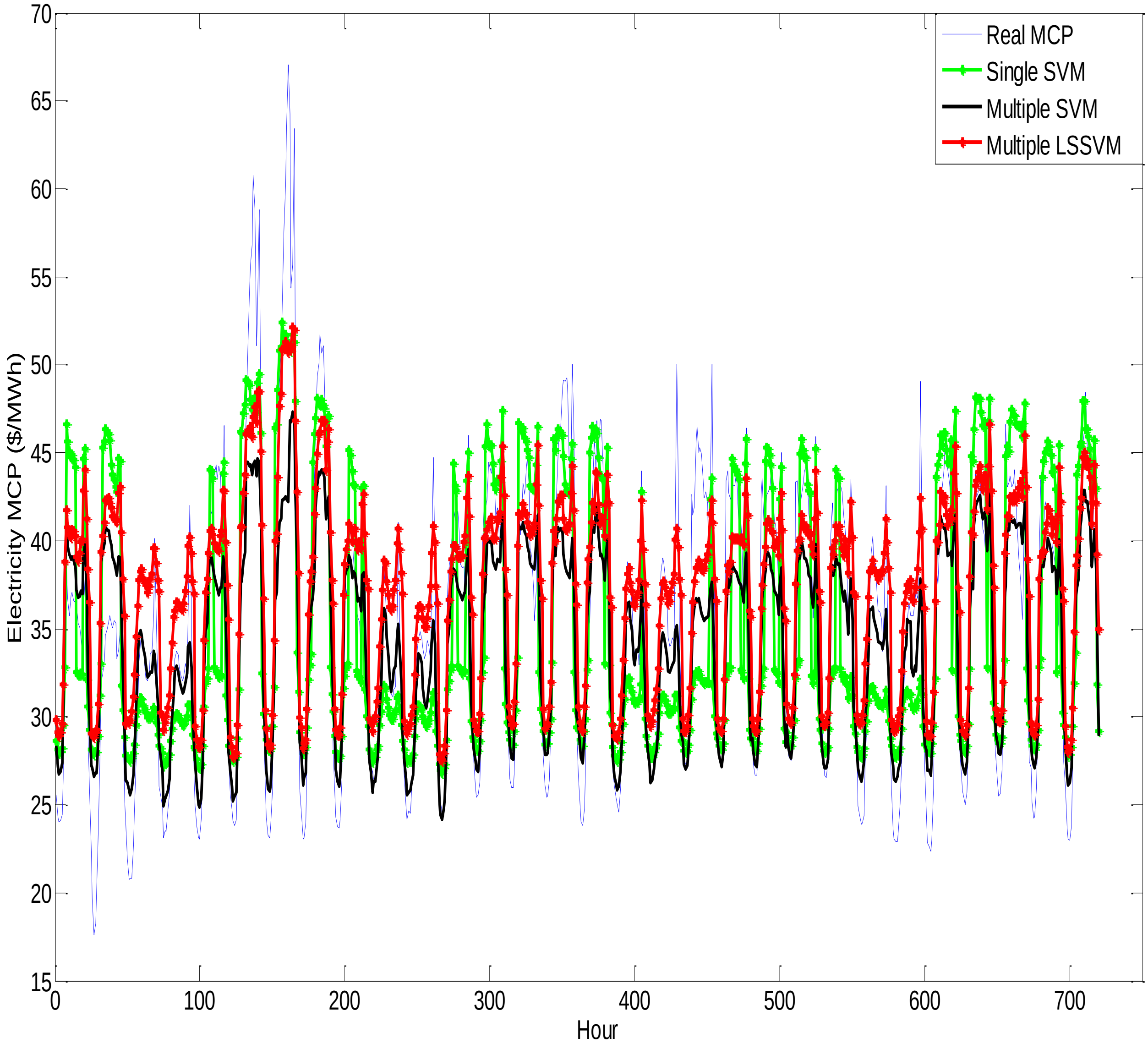


Figure 6.10: Forecasted Electricity MCP in April 2010 by a Multiple SVM and a Multiple LSSVM Based Mid-term Electricity MCP Forecasting Models.

6.8 Discussions

The fundamental reasons that affect the accuracy of the SVM and LSSVM classification modules are different from each other. SVM intends to lose the top and the bottom peak values during training process because those values are considered as non-support vectors when utilizing the ε-insensitive loss function with 2ε bandwidth. Only the support vectors are used to create the 2ε tube and only the values outside the 2ε tube are considered during simulation. Therefore, the least minority group (the peak price zone) will be misclassified the most. This characteristic of SVM will create the domino effect for the most data during the classification computation from the peak price zone all the way to the low price zone. Due to the domino effect, the peak price zone data are misclassified into the high price zone; the high price zone data are misclassified into the medium price zone and the medium price zone data are misclassified into the low price zone.

LSSVM considers all training data as support vectors. It does not have the ability to filter out those non-support vectors (mostly peak values) but accepting the fact that they will heavily affect the training process. The majority of the MCPs are dominated by the relationship between supply and demand and fuel cost under normal deregulated market. However, the electricity MCP in the peak price zone is mainly determined by business competing strategy and even unethical business behavior and those elements cannot be easily represented mathematically. When all peak price zone data are considered during the training process, they heavily affect the classification accuracy. This characteristic of LSSVM will also create the domino effect for the most data just like the SVM during the classification computation and end up with the similar misclassified results.

6.9 Summary

A multiple SVM and a multiple LSSVM based mid-term electricity MCP forecasting models are proposed in this chapter. A data classification module and a price forecasting module are designed to first pre-process the input data into corresponding price zones and then forecast the electricity price in four parallel designed SVMs for the multiple SVM forecasting model or four parallel designed LSSVMs for the multiple LSSVM forecasting model. The proposed multiple SVM and multiple LSSVM models showed improved forecasting accuracy in the low and the peak price zones and thus improving the overall forecasting accuracy compared to the forecasting model utilizing single SVM. The case studies also show that the performance of either a multiple SVM or a multiple LSSVM forecasting models is highly depended on the selection of the input data. Carefully selected training input data and correctly predicted sub data sets would significantly improve the accuracy of the forecasting model. The proposed multiple SVM and multiple LSSVM forecasting models each has ten adjustable control parameters compared to only two adjustable control parameters in a single SVM forecasting model. The four parallel SVMs or LSSVMs in the price forecasting module also have the flexibility of using different dimensions of input data to achieve optimal results.

CHAPTER 7: CONCLUSIONS

7.1 Conclusions

Six mid-term electricity MCP forecasting models are proposed and compared in this thesis: 1) a single SVM forecasting model, 2) a single LSSVM forecasting model, 3) a hybrid SVM and ARMAX forecasting model, 4) a hybrid LSSVM and ARMAX forecasting model, 5) a multiple SVM forecasting model and 6) a multiple LSSVM forecasting model. All six forecasting models were utilized to predict hourly electricity MCP for an entire month, six months ahead. It is considered in this work that the forecasting input data are given so that the performance of the proposed hybrid forecasting models will not be affected by the inaccurate input variables. The performance of the proposed six forecasting models is evaluated by the historical data from the PJM interconnection system. By using cross-validation technique, each forecasting model has the ability to choose the different dimensions of input data to optimize the forecasting results. Comprehensive evaluation results in MAE, MAPE and MSRE of all six proposed mid-term electricity MCP forecasting models are shown in Table 7.1 for the training results and Table 7.3 and 7.5 for the forecasting results. PRIM values of all the proposed forecasting models with respect to the single SVM forecasting model results are shown in Table 7.2 for the training results and Table 7.4 and 7.6 for the forecasting results.

Table 7.1: Performance Evaluation Results of MAE, MAPE and MSRE Using a Single SVM, a Single LSSVM, a Hybrid SVM and ARMAX, a Hybrid LSSVM and ARMAX, a Multiple SVM and a Multiple LSSVM Models in June 2009

	MAE ($/MWh)	MAPE (%)	MSRE
Single SVM	2.9743	11.7491	0.1564
Single LSSVM	2.8152	10.9722	0.1513
Hybrid SVM and ARMAX	2.6923	10.5256	0.1441
Hybrid LSSVM and ARMAX	2.7630	10.6706	0.1495
Multiple SVM	2.7940	10.5131	0.1487
Multiple LSSVM	2.7811	10.7466	0.1463

Table 7.2: Performance Evaluation Results of MAE, MAPE and MSRE in PRIM Using a Single LSSVM, a Hybrid SVM and ARMAX, a Hybrid LSSVM and ARMAX, a Multiple SVM and a Multiple LSSVM Models in June 2009 with Respect to the Single SVM

	MAE (%)	MAPE (%)	MSRE (%)
Single SVM	---	---	---
Single LSSVM	5.35	6.61	3.26
Hybrid SVM and ARMAX	9.48	10.41	7.86
Hybrid LSSVM and ARMAX	7.10	9.18	4.41
Multiple SVM	6.06	10.52	4.92
Multiple LSSVM	6.50	8.53	6.46

Table 7.3: Performance Evaluation Results of MAE, MAPE and MSRE Using a Single SVM, a Single LSSVM, a Hybrid SVM and ARMAX, a Hybrid LSSVM and ARMAX, a Multiple SVM and a Multiple LSSVM Models in June 2010

	MAE ($/MWh)	MAPE (%)	MSRE
Single SVM	7.2523	15.6454	0.3316
Single LSSVM	7.9003	16.2610	0.3964
Hybrid SVM and ARMAX	6.7557	14.3275	0.3139
Hybrid LSSVM and ARMAX	7.0989	13.9709	0.3859
Multiple SVM	5.6958	11.3875	0.2836
Multiple LSSVM	7.0950	13.2850	0.3733

Table 7.4: Performance Evaluation Results of MAE, MAPE and MSRE in PRIM Using a Single LSSVM, a Hybrid SVM and ARMAX, a Hybrid LSSVM and ARMAX, a Multiple SVM and a Multiple LSSVM Models in June 2010 with Respect to the Single SVM

	MAE (%)	MAPE (%)	MSRE (%)
Single SVM	---	---	---
Single LSSVM	-8.94	-3.93	-19.54
Hybrid SVM and ARMAX	6.85	8.42	5.34
Hybrid LSSVM and ARMAX	2.12	10.70	-16.38
Multiple SVM	21.46	27.22	14.48
Multiple LSSVM	2.17	15.09	-12.58

Table 7.5: Performance Evaluation Results of MAE, MAPE and MSRE Using a Single SVM, a Single LSSVM, a Hybrid SVM and ARMAX, a Hybrid LSSVM and ARMAX, a Multiple SVM and a Multiple LSSVM Models in April 2010

	MAE ($/MWh)	MAPE (%)	MSRE
Single SVM	4.1857	11.7545	0.1929
Single LSSVM	4.3553	14.2178	0.1956
Hybrid SVM and ARMAX	3.6163	11.3539	0.1631
Hybrid LSSVM and ARMAX	4.1914	14.6771	0.1993
Multiple SVM	3.0095	8.0477	0.1553
Multiple LSSVM	3.5718	11.0159	0.1627

Table 7.6: Performance Evaluation Results of MAE, MAPE and MSRE in PRIM Using a Single LSSVM, a Hybrid SVM and ARMAX, a Hybrid LSSVM and ARMAX, a Multiple SVM and a Multiple LSSVM Models in April 2010 with Respect to the Single SVM

	MAE (%)	MAPE (%)	MSRE (%)
Single SVM	---	---	---
Single LSSVM	-4.05	-20.96	-1.40
Hybrid SVM and ARMAX	13.60	3.41	15.45
Hybrid LSSVM and ARMAX	-0.14	-24.86	-3.32
Multiple SVM	28.10	31.54	19.49
Multiple LSSVM	14.67	6.28	15.66

The comparison between the forecasting results of a single SVM and a single LSSVM forecasting models has shown that during the training process, the single LSSVM forecasting model performed better than the single SVM forecasting model. However, during the forecasting process, the single SVM forecasting model performed better than the single LSSVM forecasting model. Mid-term electricity MCP forecasting utilizing a hybrid SVM and ARMAX forecasting model and a hybrid LSSVM and ARMAX forecasting model were then introduced in order to improve the forecasting accuracy obtained by either the single SVM or the single LSSVM forecasting model. The results have shown that the hybrid SVM and ARMAX forecasting model is better than the hybrid LSSVM and ARMAX forecasting model during both training process and forecasting process. Finally, multiple SVM and multiple LSSVM based mid-term electricity

MCP forecasting models were proposed to further improve the forecasting accuracy obtained by the four previous presented forecasting models. The results show that with the same input data, the multiple SVM forecasting model achieved the highest forecasting accuracy among all six proposed forecasting models.

7.2 Scope of Future Work

Both SVM and LSSVM are highly relying on the selection of training data. Although the proposed work have included up to 8 elements inside the input data, the forecasting accuracy at the peak prices are still low. Future work can focus on two parts to further improve the forecasting accuracy in mid-term electricity MCP forecasting. The first part is finding additional input data to create more dimensions for training and in turn improve the mid-term forecasting accuracy. This additional input data can be either original data with open access or artificial data created by game theory simulating the bidding strategy. The other part is designing more sophisticated forecasting model that can utilize the limited input data more efficiently and productively and in turn improve the mid-term forecasting accuracy.

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