

**A Novel Hybrid Technique for Short-term  
Electricity Price Forecasting in Deregulated  
Electricity Markets**

Submitted for Doctor of Philosophy of Brunel University

March, 2010

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## ABSTRACT

Short-term electricity price forecasting is now crucial practice in deregulated electricity markets, as it forms the basis for maximizing the profits of the market participants. In this thesis, short-term electricity prices are forecast using three different predictor schemes, Artificial Neural Networks (ANNs), Support Vector Machine (SVM) and a hybrid scheme, respectively.

ANNs are the very popular and successful tools for practical forecasting. In this thesis, a hidden-layered feed-forward neural network with back-propagation has been adopted for detailed comparison with other forecasting models. SVM is a newly developed technique that has many attractive features and good performance in terms of prediction. In order to overcome the limitations of individual forecasting models, a hybrid technique that combines Fuzzy-C-Means (FCM) clustering and SVM regression algorithms is proposed to forecast the half-hour electricity prices in the UK electricity markets. According to the value of their power prices, thousands of the training data are classified by the unsupervised learning method of FCM clustering. SVM regression model is then applied to each cluster by taking advantage of the aggregated data information, which reduces the noise for each training program.

In order to demonstrate the predictive capability of the proposed model, ANNs and SVM models are presented and compared with the hybrid technique based on the same training and testing data sets in the case studies by using real electricity market data. The data was obtained upon request from *APX Power UK* for the year 2007.

Mean Absolute Percentage Error (MAPE) is used to analyze the forecasting errors of different models and the results presented clearly show that the proposed hybrid technique considerably improves the electricity price forecasting.

*Keywords:* Short-term price forecasting; Electricity markets; Fuzzy-C-Means; Support Vector Machine; Hybrid models; Artificial Neural Networks.

## **ACKNOWLEDGEMENTS**

The author of this work is greatly indebted to her supervisors, Dr. Gary Taylor and Professor Malcolm Irving, for their helpful advice and encouragement.

Many thanks are also due to the *APX Power UK* and *Centrica*. I would like to acknowledge them for providing the real market data as well as their technical support.

I would also like to thank my parents, along with my colleagues at the Institute of Power Systems of Brunel University, for all their support and kindness.

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# SYMBOLS

ANN: Artificial Neural Network

APE: Absolute Percentage Error

BETTA: British Electricity Trading and Transmission Arrangements

BM: Balancing Mechanism

EMR: Empirical Risk

FCM: Fuzzy-C-Means

GARCH: Generalized Autoregressive Conditional Heteroskedastic

HMM: Hidden Markov Model

LSSVM: Least Square Support Vector Machine

MAPE: Mean Absolute Percentage Error

MSE: Mean Squared Error

NETA: New Electricity Trading Arrangements

NGC: National Grid Company

PX: Power Exchange

SBP: System Buy Price

SMP: System Marginal Price

SRM: Structural Risk Minimization

SSE: Sum Squared Error

SSP: System Sell Price

SVM: Support Vector Machine

SVC: Support Vector Classification

SVR: Support Vector Regression

VC: Vapnik-Chervonenkis

# **1. Introduction**

## **1.1 BACKGROUND AND MOTIVATION**

The restructuring of power markets has been ongoing in various countries around the world, including the UK, over the last two decades [1]. The electricity supply industry has moved to privatised and deregulated practices in order to deliver a lower cost to the consumers. In such market environments, profitability as a result of privatisation has become the main objective for all the market participants, such as generators, power suppliers, investors and traders. In order to compete for the market share through spot and bilateral markets, price forecasting is now regarded as a very valuable tool by market participants for either bidding or hedging against price volatility in currently deregulated electricity markets. Due to the unique electrical characteristics, uncertainties in operation as well as the bidding strategies of the market participants, the electricity price forecasting is much more complex than the load forecasting. Hence, the issue of developing more accurate and effective price forecasting tools has become a very active area for researchers.

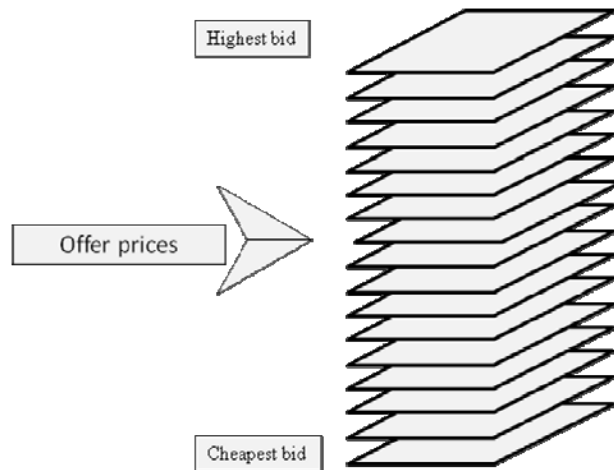
## **1.2 EVOLVING ELECTRICITY MARKETS**

Great effort has been made in recent decades with regard to the development of electricity markets. There have been three major evolutions of UK electricity markets since the 1990s. The first electricity market that was established in the UK was the power pool based market, and the other two evolutions brought about the bilateral contract based electricity market in the UK. [1-3]

### **1.2.1 Power Pool**

On March 31<sup>st</sup> 1990, the British Electricity Act came into effect and a power pool was introduced with the purpose of improving the economic efficiency for power industry [1].

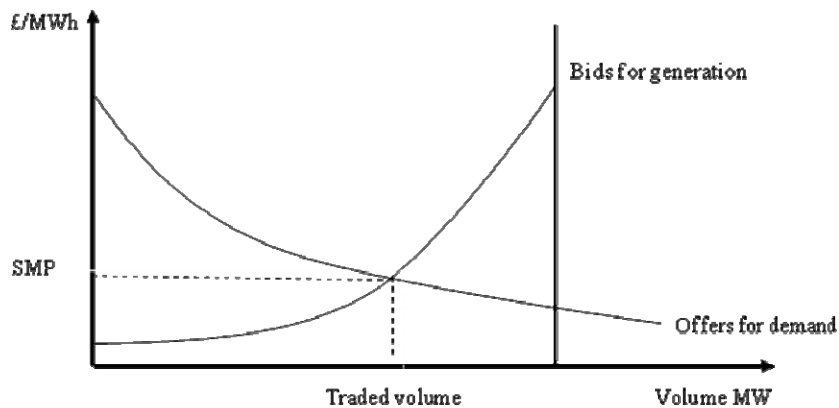
In the power pool, power suppliers and consumers had to submit their bids and offers to the National Grid Company (NGC), whose responsibility was to manage and dispatch generation as well as to keep a balance between power supply and demand.



**Fig. 1.1** Merit order in the Pool

Under the pool, each time segment was half-hour. Hence, twenty-four hours were divided into forty-eight time segments. One day in advance, the power suppliers and consumers submitted their bids and offers into the pool for the future trading periods. Then NGC as system operator ranked the bids in the increasing order of price and the offers in the decreasing order of price, respectively. A simple example of merit order for the ranking of bids can be seen in figure 1.1.

The market equilibrium is the intersection of the cumulative supply and demand curves as shown in figure 1.2. The corresponding price is the market clearing price, which is also called system marginal price (SMP). After the market clearing, the generators with bids less than the SMP will be instructed to generate electricity as agreed. At the same time, the consumers with offers greater than the SMP will be informed that they are allowed to draw the amount of energy as agreed.



**Fig. 1.2** Pool based market clearing

From 1990 to 2001, the UK power pool was partially successful. Over these 11 years, the energy supply and price were secure and stable to the consumers. However, there were also some justified criticisms of the pool system [1]:

- Complexity of bids
- Market competition favoured generation
- Pool capacity payments
- Slow progress in change and decision making
- Lack of transparency in contracts for differences

Due to some of the above shortcomings, the UK power pool was stopped in the early 2001. However, at present there are also many other countries, such as Norway, Sweden, Finland and Denmark, that appearing to be successful with a power pool market.

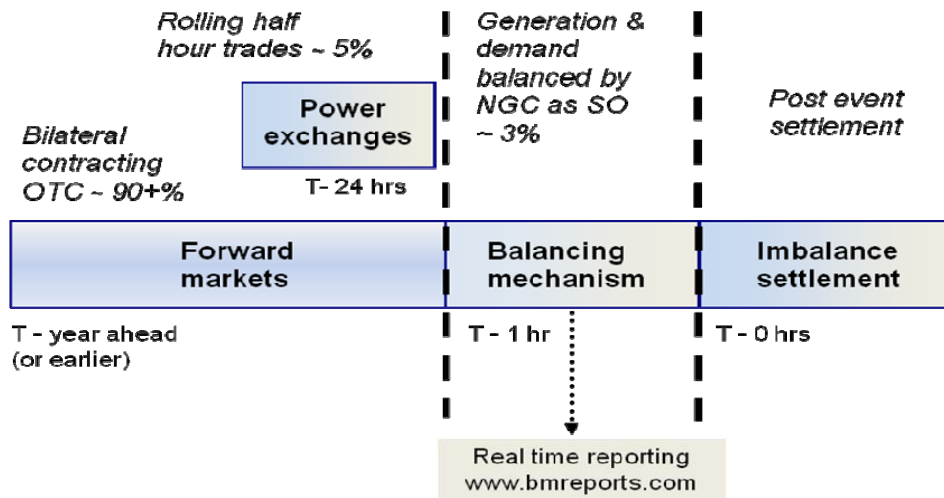
### **1.2.2 NETA**

In March 2001, NETA (New Electricity Trading Arrangements) replaced the Power Pool in the UK. According to ref. [2], the role of NETA was not to dictate how energy will be bought and sold on these exchanges or in bilateral contracts. Instead it was to provide

mechanisms for near real-time clearing and settlement of the imbalances between contractual and physical positions of those buying, selling, producing and consuming electrical energy.

The key features of NETA were as follows: [3]

- ◆ All generators “self-dispatch” for running their units
- ◆ Generators sell contracts either to the wholesale market, energy suppliers or directly to the consumers
- ◆ Suppliers buy contracts to meet their load forecasts either from the wholesale markets or directly from generators
- ◆ Electricity “Traders” are allowed
- ◆ Wholesale market prices are set by bilateral trading – no price regulation
- ◆ National Grid (as the England and Wales system operator) controls the physical balancing of the system after Gate Closure
- ◆ “Balancing Mechanism (BM)” is a key tool for the system balancing
- ◆ “Balancing Mechanism Unit (>50MW)” may choose to participate the BM
- ◆ Elexon administers the commercial notification of trades and settlements – deemed demands and imbalance charges



**Fig. 1.3** Electricity markets timescale

The electricity markets timescale is shown as Figure 1.3. The settlement period of NETA is half hour. The bilateral contracts can be made year ahead or even earlier. Twenty-four hours ahead of the settlement period, Power Exchange (PX) is open and all the participants can fine tune their forwards contracts based on this platform. Trading stops at “Gate Closure”, which is one hour before each half-hour settlement period. In the Balancing Mechanism, system operators take the action to balance the power supply and demand for the electrical systems. In the imbalance settlement, there are two key prices, such as System Buy Price (SBP) and System Sell Price (SSP), which are used to control the participants’ commercial behaviors. For instance, if a generator produces less energy than its agreement, then it must pay for the shortfall at the SBP. On the contrary, if a generator produces more energy than its agreement, then it will be paid for the excess at the SSP. Therefore, NETA is a system that bases on the self-dispatch rather than the central-dispatch.

### **1.2.3 BETTA**

British Electricity Trading and Transmission Arrangements (BETTA) went live in April 2005. It extended NETA and introduced effective competition to electrical power supply and generation throughout Great Britain, including Scotland. [4]

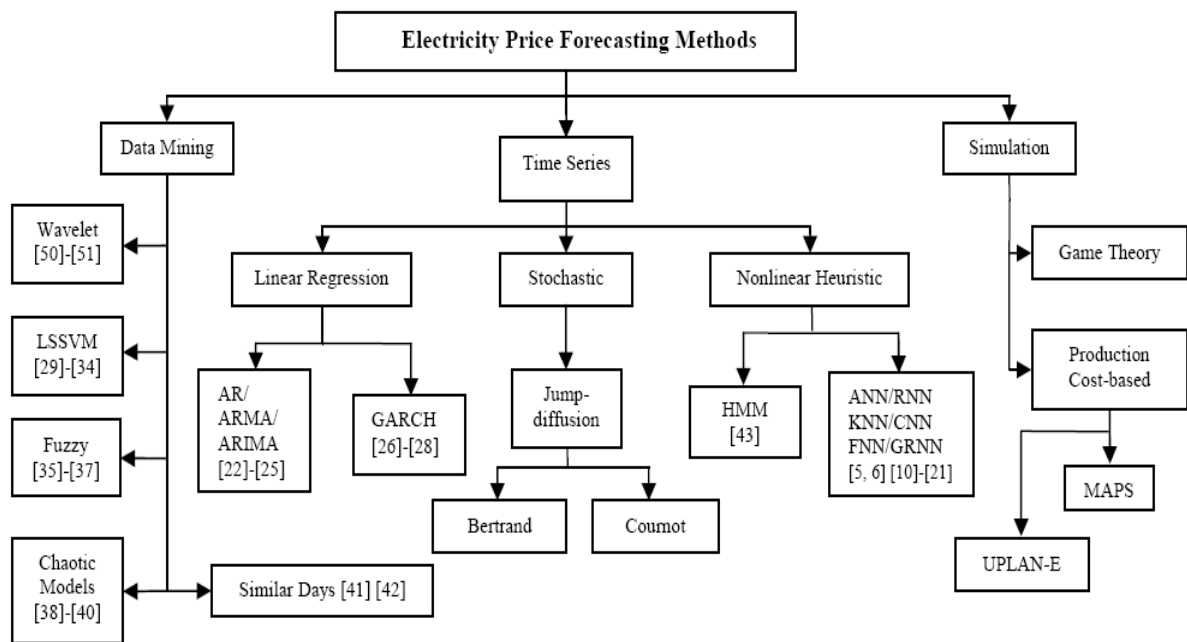
Under BETTA, generators have much more freedom to trade with other companies in England, Wales and Scotland. Meanwhile, they have to take much more responsibilities. In addition National Grid now operates the transmission system for the whole of Great Britain.

In conclusion, the reform of the UK electricity market introduced competition to both the power generation and supply sides in order to create a fair and transparent market environments for both energy buyers and sellers.

## **1.3 LITERATURE REVIEW**

In the last decade many methods have been applied to predict prices in electricity markets. Several papers have proposed taxonomies of the forecasting methods. According to reference [5], there are two categories of forecasting methods: parametric methods and artificial intelligence based methods. In [6], the forecasting models are divided into two groups: traditional models and modern techniques. Approaches can also be classified in two sets: time-series and simulations as proposed in reference [7]. Based on the original tree in reference [7], an extended classification of forecasting methods is presented in Figure 1.4 [8].

In Figure 1.4, a new branch of data mining methodologies has been added to the tree and more typical forecasting methods are included along with the survey papers. In this survey, many publications indicate ANNs have become a more popular approach for price forecasting. Meanwhile, hybrid models that combine two or more forecasting methods to overcome the individual limitations are becoming a novel direction for researchers. [8, 9]



**Fig. 1.4** Price forecasting methods classification

Due to the simplicity and flexibility, Artificial Neural Networks (ANNs) have typically received much attention recently. ANNs are highly interconnected simple processing units designed to model how the human brain performs a particular task. The ANN models could be different with regard to combinations of different numbers of hidden layers, different numbers of units in each layer and different types of transfer function. From the survey, it indicates that three-layered neural networks are commonly chosen for the models [10-13]. In [6], a four-layered network has been used for price forecasting.

In order to improve the accuracy of such methods for forecasting, different techniques have been combined with ANNs. An ANN model based on a similar day method to forecast day-ahead electricity price has been proposed in [12] and [14]. A feature selection technique, relief algorithm, has been combined with ANNs in [13] and particle swarm optimization has been used for ANN training in [15]. The clipping technique for simplifying the relationship between ANN input and output variables has been presented in [16]. In [17], K-Means clustering method has been used to find clusters for the number of neural networks. The wavelet and ANN models have been fitted together for greater



price forecasting accuracy in [18]. In order to improve the limitation of being “over-fitting”, a new Genetic algorithm has been introduced for ANN based forecaster in [21].

Much work has been done on electricity price forecasting with the Auto Regressive Integrated Moving Average (ARIMA) method [22-25]. In particular, the ARIMA method has been extended to include error correction for the worse market conditions with high price volatility in [22]. In [23], techniques that based on the wavelet transform and ARIMA model have been applied to Spanish power markets in order to improve the accuracy of price forecasting.

As a consequence of the success in solving nonlinear regression and time series problems, Support Vector Machine (SVM) has gained attention as a novel algorithm with regard to forecasting electricity prices. Genetic algorithms, in combination with LSSVM (Least Square Support Vector Machine), have been proposed in [29] and [31]. A probability classifier and statistical model have been employed in combination with SVM models in [33] and [34], respectively. In both cases, it has been proven that the forecasting is more accurate than the original SVM forecasting.

Moreover, different integrated techniques have also been proposed by many researchers [44-51]. In [44], an integration of two machine learning technologies: Bayesian Clustering by Dynamics (BCD) and SVM has been introduced. An efficient tool for one-step-ahead forecasting that combines several prediction methods has been checked and compared for a span of some years [45]. Multivariate models have been used to compare with that of single models in [46] and the outcomes showed that the forecasting accuracy has been improved. In addition, efficient data mining techniques, such as clustering [47-48] and wavelet analysis [50-51] have been applied in combination with ANNs. From the comparison of different forecasting approaches, the hybrid models have clearly indicated advantages and are now setting the trend with regard to short-term price forecasting methodologies.

## 1.4 AIM AND CONTRIBUTIONS

The aim of this thesis is to develop a more accurate and effective forecasting tool for the short-term electricity price forecasting in the UK electricity market. A hybrid forecasting model is proposed for the project and the step by step objectives are as follows:

1. Paper survey and current methodology research
2. Practical data collection – the data used for the experiments in this thesis are from APX Power UK
3. ANN modelling and forecasting with practical data
4. SVM modelling and forecasting with practical data
5. Hybrid model creation and testing with practical data
6. Forecasting error analysis for testifying the advanced model
7. Dissertation writing up

Based on the forecasting error comparisons, the developed forecasting model, which fits Fuzzy-C-Means (FCM) technique into SVM model, has been proved more efficiently. Therefore, the main contributions of this research work are:

- ❖ Simulation of the UK practical market price forecasting by using different forecasting models, such as ANNs, SVM and hybrid model;
- ❖ Development of a hybrid model, which shows the advantages of forecasting in two aspects:
  - ◆ Successful improvement of the forecasting model SVM by combining the clustering technique FCM

**Validation:** *Hybrid Model vs SVM Model*

- ◆ Successful generalization of the developed model

**Validation:** *Hybrid Model vs ANNs Model*

## **1.5 DISSERTATION ORGANIZATION**

The remainder of this thesis is organized as follows: Chapter 2 describes the research project with details of the background and preparation. The formulation of ANNs approach is presented in Chapter 3 along with case studies for testing the proposed ANN model. In Chapter 4, SVM methodology is explained and the experiments based on the same training data set are demonstrated with regard to the performance of SVM model. In Chapter 5, a hybrid forecasting model that combines FCM Clustering and SVM algorithm is introduced. The forecasting results of proposed hybrid model are presented and analyzed in detail as well. Based on the predicted results of the numerical experiments, different forecasting models are compared and analyzed in Chapter 6. This thesis ends with conclusions and further research in Chapter 7.

## 2. Project Research

### 2.1 THE IMPORTANCE OF FORECASTING

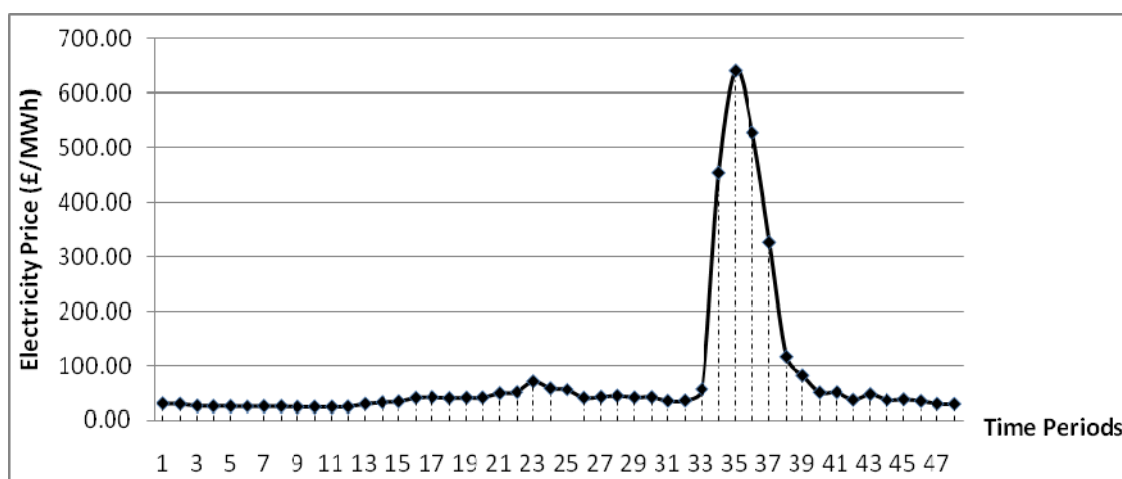
Generally speaking, price forecasting can be classified in terms of planning time horizon, such as short-term (from hours to days), medium-term (from days to weeks/months) and long-term (from months to years) price forecasting. Due to the severe competition in electricity markets, short-term price forecasting has become increasingly vital to all the market participants. With a prior knowledge of electricity price, the market players are able to manage the risk and take advantages when competing in the spot power markets. The beneficial parties and their advantages with regard to short-term electricity price forecasting are listed below [12]:

- To: generation companies  
Advantages: strategic bids into the markets, optimal management of its assets, and optimally self-schedule.
- To: large consumers  
Advantages: strategic bids into the markets, and utility planning.
- To: traders  
Advantages: strategic bids into the markets, negotiation skills, and trading speculation.
- To: transmission companies  
Advantages: schedule short-term generator outages, and design load response programs.
- To: power systems,  
Advantages: planning, operation, risk assessment, and decision making.

## 2.2 ANALYSIS OF ELECTRICITY PRICE SERIES

### 2.2.1 Characteristics of Price Series

Electricity can be viewed as a specific commodity. Unlike common products, such as rice, electricity has the unique characteristic of infeasible storing and needs the balance between supply and demand in every second of the day. Due to these inherent characteristics as well as the influential factors, electricity price series is therefore very specific. The main features of price series are the price spikes and the seasonal behaviors, which are shown in figure 2.1 and figure 2.2, respectively.



**Fig. 2.1** Half-hour electricity price in the UK spot markets on 15<sup>th</sup> Nov. 2007

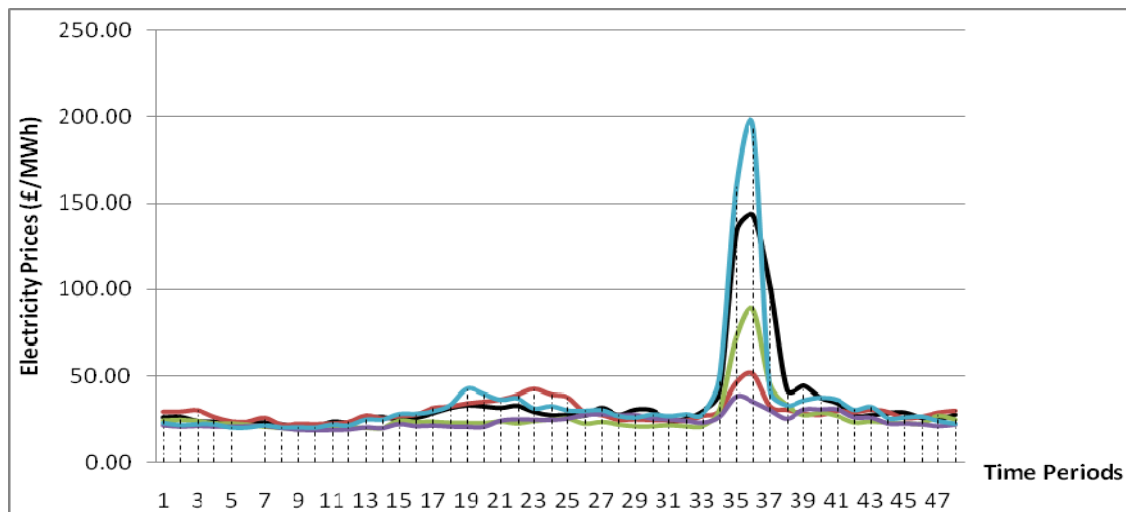
Price spikes are known as one of the most pronounced features of electricity markets. The spot price can change extremely within a very short period of time - see figure 2.1, where the system price increases substantially to the tens of times of its normal value and then drops back to the previous level soon after. Hence, the electricity price is far more volatile than that of the other commodities.

The intensity of price spikes is non-homogeneous with regard to the time scale. Usually, the price spikes occur during the high consumption periods and the peak hours, such as around 09:00 and 18:00 on weekdays as shown in figure 2.2. As mentioned before, the

phenomenon of price spikes is the effect of non-storability of electricity as well as the influential factors. Therefore, the extreme load fluctuations, which are often caused by severe weather conditions and big events, in combination with generation outages or transmission failures, can lead to the price spikes. [52]

Normally, the price spikes exist quite short. Prices fall back to the normal level soon after the weather or outage problem is over. For example, from figure 2.1 on November 15, 2007, the spot prices of the UK electricity markets at the 35<sup>th</sup> time period (between 17:00-17:30) was 639.54 £/MWh, which is more than 10 times of the normal value, such as 50.63 £/MWh at the 40<sup>th</sup> time period (between 19:30-20:00). During the 24 hours of that day, the spikes lasted around 2 hours from the time period of number 34 to number 38. The rest of prices on the day seemed to remain within the normal level.

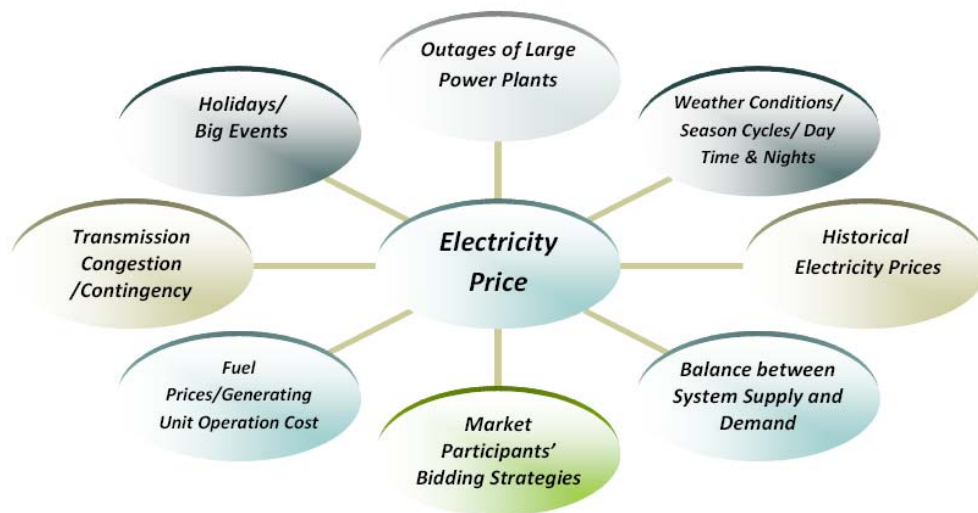
The seasonal behavior of electricity prices can be observed from figure 2.2. The shape of electricity price profile reveals its seasonality characteristic, which is the daily, weekly and seasonal cycle. Typically, the price profile of weekdays is different from that of weekend days, which means that the daily prices from Monday to Friday could be separated from those on Saturday and Sunday. Furthermore, the price profile on public holidays is particularly different from those on non-holidays.



**Fig. 2.2** Half-hour electricity price in the UK spot markets from 1<sup>st</sup> Nov. 2007 to 5<sup>th</sup> Nov. 2007

## 2.2.2 Influential Factors to the Price Patterns

Electricity prices, especially the short-term electricity prices, are influenced by many factors, such as load demand, market players' bidding strategies as well as weather conditions and so on. Most of the influential factors to electricity prices are illustrated in figure 2.3. One of the factors is transmission congestion, which is explained here for a further understanding. In power systems, there exists the problem of bottle-necks or the limitation of transportation capacity. Therefore, in some occasions, the electricity cannot be transported from one region to another, which may also affect the electricity prices.



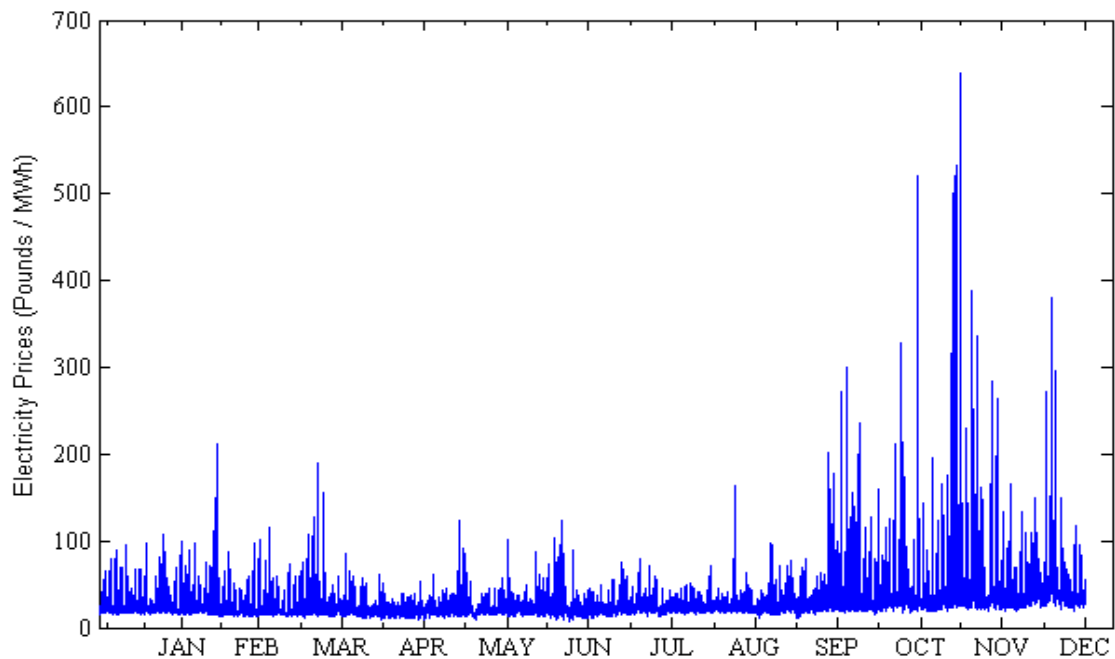
**Fig. 2.3** Influential factors to the electricity prices

## 2.3 ANALYSIS OF EXPERIMENTAL FACTORS AND DATA

In theory, the electricity price forecasting will be accurate when all the influential factors are considered. However, it is very difficult to apply this on the real-world case study. On one hand, it is impossible to collect the full information of every factor. On another hand, including more factors as inputs to the forecasting models does not necessarily mean that the predictive results will be better, as some additional factors are also unavailable and

may need forecasting as well. Therefore, the selection of a suitable forecasting technique with proper input factors is vitally important for accurately forecasting electricity prices.

In this thesis, the influential factors are not taken into account when forecasting the short-term electricity prices. The reasons for doing this are as follows. First of all, such influential factors, such as the amount of different types of reserve, power import and predicted power shortfall do not improve the forecast at all [53]. Secondly, the effect of temperature is incorporated with the load demand. According to ref. [54], considering the historical load demand as the input factor does not significantly improve the predictions of ANN and SVM models, which are adopted for our forecast. Finally, the extremely high prices are considered as the consequence of bidding strategies by the market players. Those speculative behaviors are unpredictable. Therefore, only the publicly historical price data are used to forecast the future prices in this thesis, as the natural correlation between the historical and future price data are believed.



**Fig. 2.4** HH system prices in the UK spot markets at the year 2007



The data adopted for prediction are half-hour system prices of the UK spot markets at the year 2007. The original data are attached in Appendix I and shown as figure 2.4. Considering the distribution of these data points, data of the first six months could be separated from that of the latter six months of the year. Therefore, those two groups of data will be used respectively in two case studies in order to forecast the short-term electricity prices.

## 2.4 PROJECT MANAGEMENT

Figure 2.5 illustrates the project management. In the project, three forecasting schemes are developed respectively. The forecasting models are tested one by one based on the same training data, which are half-hour reference price data requested from the *APX Power UK* at the year 2007. In order to testify the advantages of those forecasters, the forecasting accuracy is analyzed according to the criterion of Mean Absolute Percentage Error (MAPE). The details of each forecasting scheme are as follows:

➤ ***Forecaster 1: ANN model***

- *Case Study A:*

Training data set: 01/01/2007 - 31/05/2007; Testing data set: 15/06/2007 - 30/06/2007;

- *Case Study B:*

Training data set: 01/07/2007 - 30/11/2007; Testing data set: 01/12/2007 - 15/12/2007;

➤ ***Forecaster 2: SVM model***

- *Case Study A:*

Training data set: 01/01/2007 - 31/05/2007; Testing data set: 15/06/2007 - 30/06/2007;

- *Case Study B:*

Training data set: 01/07/2007 - 30/11/2007; Testing data set: 01/12/2007 - 15/12/2007;

➤ ***Forecaster 3: Hybrid model***

- *Case Study A:*

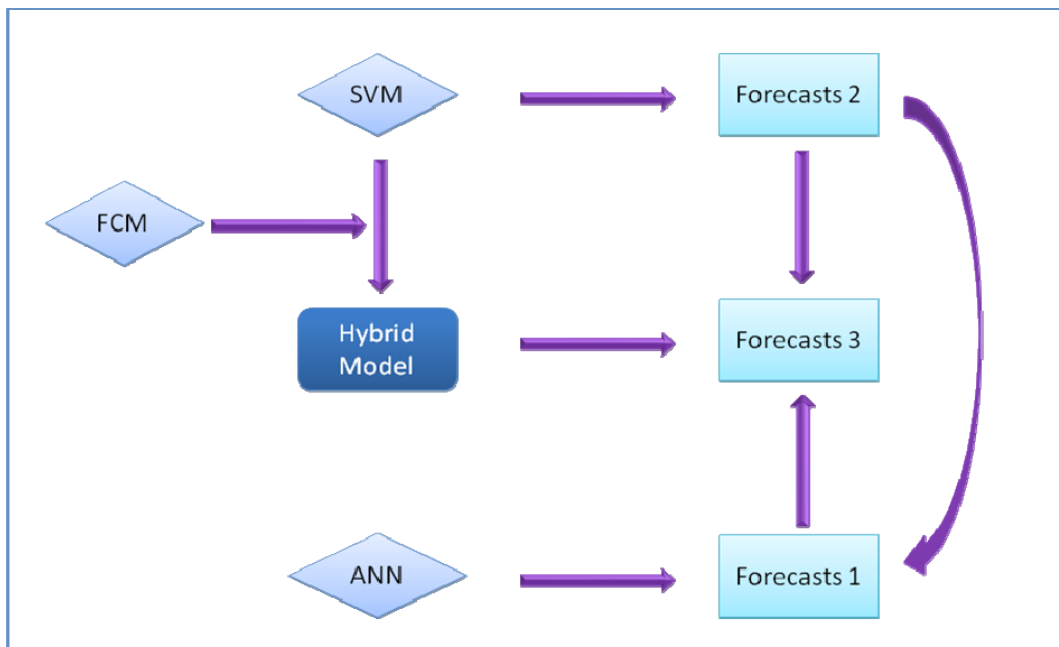
Training data set: 01/01/2007 - 31/05/2007; Testing data set: 15/06/2007 - 30/06/2007;

- *Case Study B:*

Training data set: 01/07/2007 - 30/11/2007; Testing data set: 01/12/2007 - 15/12/2007;

- ❖ *Forecasting error comparisons: MAPE*

- a) *ANN model* vs *SVM model*
- b) *ANN model* vs *Hybrid model*
- c) *SVM model* vs *Hybrid model*



**Fig. 2.5** Structure of the project management

## **3. ANNs Modeling and Forecasting Electricity Prices**

### **3.1 INTRODUCTION**

In recent years, Artificial Neural Networks (ANNs) have been successfully used as practical tools with many applications in power systems, such as load forecasting, component and system fault diagnosis, security assessment and unit commitment. [12] ANN models are capable of learning nonlinear functional mapping and are able to implement multiple training algorithms. The computing aim of neural network is to generate the desired output by optimizing a set of parameters with respect to the training data set. The network model is composed of one input layer, one or more hidden layers and one output layer. In particular, the most popular and practical ANN architecture for forecasting is feed-forward back-propagation neural networks. In this chapter, a three-layered feed-forward neural network with back-propagation is proposed for the application of forecasting short-term electricity prices in the UK spot power markets. In order to evaluate the forecasting accuracy of proposed model, case studies are presented along with the training data requested from the *APX Power UK* at the year 2007.

This chapter is structured as follows: Section 3.2 introduces the approach of artificial neural networks. In Section 3.3, based on the UK electricity markets, experimental results of the proposed ANN model are reported. Section 3.4 concludes this chapter.

### **3.2 ARTIFICIAL NEURAL NETWORK APPROACH**

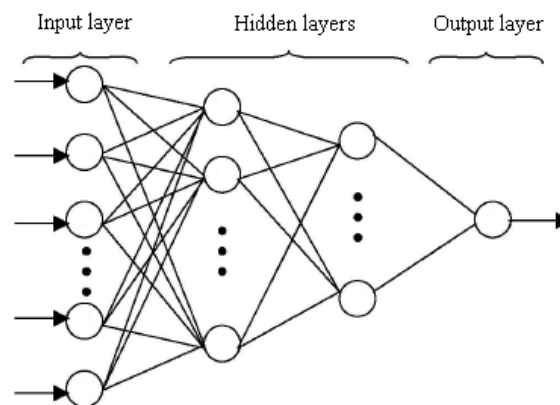
Neural Networks are information-processing systems designed to simulate how the human brain performs a particular task. ANN models have been developed as generalization of mathematical models, based on the following assumptions [55]:

- Information processing happens at many simple elements called neurons;
- Signals are passed between neurons over the networks;
- An associated weight between neurons will multiply the signal transmitted;
- Transfer functions applied on neurons' inputs will determine the output signals.

### 3.2.1 Architectures

#### ◆ Feed-forward networks

Neural networks are composed of many processing elements called neurons, units or cells. Those neurons are arranged in different layers, for instance one input layer, one or more hidden layers and one output layer. An example of neural networks is shown in figure 3.1.



**Fig. 3.1** Example of ANN model

In the networks, neurons are connected to each other with associated weights, which represent information being used to solve a problem. Each input is weighted with an appropriate  $w$ . The sum of the weighted inputs and the bias forms the inputs to neurons, which can employ different transfer functions to generate their outputs. The output as a kind of signal is broadcasted from a neuron to several other neurons. For example, a neuron with a single  $R$ -element input vector is shown in figure 3.2 [58].

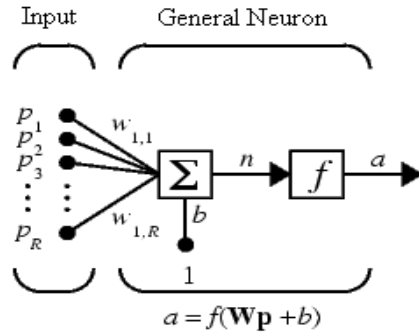


Fig. 3.2 Neuron with R-element input vector

Where R is the number of elements in input vector.  $Wp$  is the sum of dot product of (single row) matrix  $W$  and vector  $p$ . The neuron has a bias  $b$ , which is summed with the weighted inputs to form the network input  $n$ .

$$n = w_{1,1}p_1 + w_{1,2}p_2 + \dots + w_{1,R}p_R + b \quad (1)$$

$f$  is transfer function and  $a$  is the output, which is transmitted to the other neurons in the networks. A network could have several layers. A structure of three-layer network is shown in figure 3.3 [59].

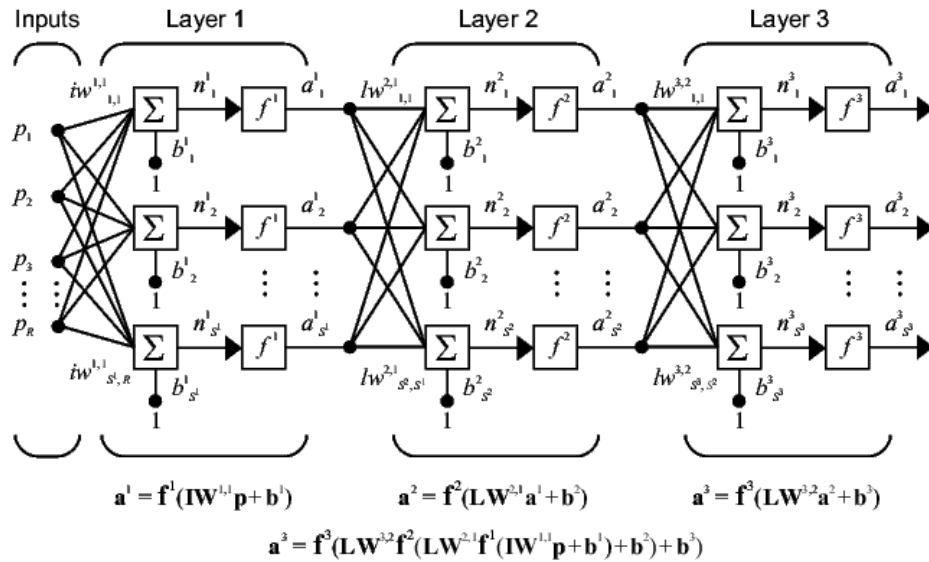


Fig. 3.3 Multiple layers of neural networks

◆ Neuron Models

As mentioned before, neurons can use different transfer functions  $f$  to generate their outputs. In multilayer feed-forward networks, the often used transfer functions are log-sigmoid (*logsig*) transfer function, tan-sigmoid (*tansig*) transfer function and the linear transfer function *purelin*. [58]

I. Log-sigmoid Transfer Function

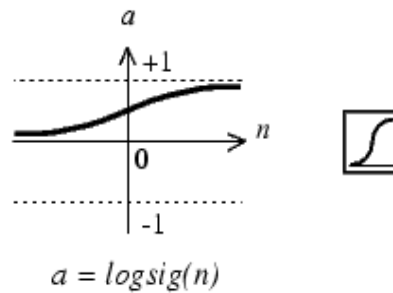


Fig. 3.4 Log-sigmoid Transfer Function

Figure 3.4 shows that the output generated by function *logsig* is between 0 and 1, while the neuron's input goes from negative to positive infinity.

II. Tan-sigmoid Transfer Function

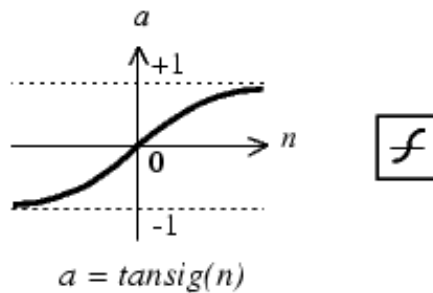
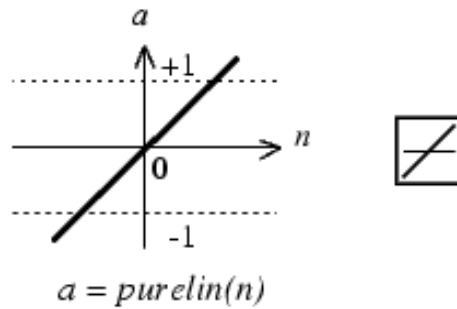


Fig. 3.5 Tan-sigmoid Transfer Function

Alternatively, tan-sigmoid transfer function, which is shown in figure 3.5, can be applied on the neurons and generate output between -1 and +1.

### III. Linear Transfer Function



**Fig. 3.6** Linear Transfer Function

It is obvious that the output value will be limited within a certain range when the *logsig* and *tansig* transfer functions are applied on the last layer neurons of networks. With the linear transfer function *purelin* shown in figure 3.6, the network outputs can take on any value.

The above three transfer functions are the most commonly used transfer functions for back-propagation networks. However, the other different transfer functions can also be used with back-propagation networks.

#### 3.2.2 Back-propagation Training Algorithm

Back-propagation training algorithm is a gradient descent method to minimize the total squared error of the outputs computed by neuron networks. For a training data set, the objective function is given by

$$E = \frac{1}{2} \sum (\Delta O - \Delta O^*)^2 \quad (2)$$

where  $\Delta O$  is the network output and  $\Delta O^*$  is the network desired output.

There are three stages involved in the training process with back-propagation. [55-57]

- Feed-forward of the input training pattern

During feed-forward process, neurons in the input layer broadcast the input information to the neurons of the hidden layers, without any processing. Each hidden neuron receives the signal and computes its activation, which is then passed onto the neurons of output layer. Finally, each output neuron computes its activation as the actual response of the network. During this forward pass, the associated weights are all fixed.

- Back-propagation of the associated error

The network output is compared with the network desired output to determine an associated error. Based on this error, the factor  $\delta_k$  is produced and used to propagate the error signal backward through the networks, layer by layer. The weights between different layers are therefore updated according to the factor  $\delta_k$ .

- Adjustment of the weights

After all the factors are determined, the weights for all layers are adjusted simultaneously. The weight adjustment is based on the factor  $\delta_k$  and the activation of each neuron. Based on the measures of minimal error between the produced output and the desired output, the training process is repeated until an acceptable error is reached. After the model acquires the knowledge, new data set can be tested for forecasting.

In back-propagation networks, it is important that the transfer functions are able to calculate their own derivatives. Each of the transfer functions described above, such as *logsig*, *tansig* and *purelin*, can satisfy this condition.

### **3.3 CASE STUDY: FORECASTING HALF-HOUR UK SPOT POWER MARKETS' PRICES WITH ANN MODELS**

The prediction focuses on short-term electricity price decisions associated to the UK electricity markets. Therefore, only the forecasts of each half-hour electricity prices are



considered. In this section, two case studies are presented and the historical price data used for training are from the *APX Power UK* at the year 2007. Those original price data are attached in appendix I.

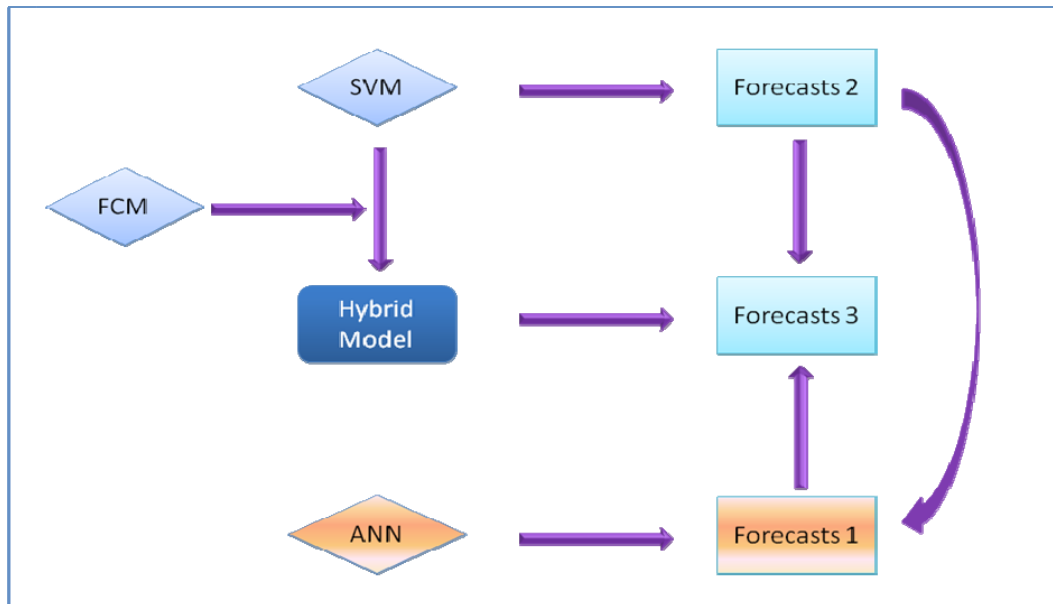
In the first case study A, the data used for ANNs training are from January 1<sup>st</sup>, 2007 to May 31<sup>st</sup>, 2007. In order to evaluate the accuracy of the proposed ANN model, data from June 16<sup>th</sup>, 2007 to June 30<sup>th</sup>, 2007 are selected for testing. In the second case study B, the training data are from July 1<sup>st</sup>, 2007 to November 30<sup>th</sup>, 2007 and the testing data are from December 1<sup>st</sup>, 2007 to December 15<sup>th</sup>, 2007. Those settings are based on two reasons:

1. In the training data set, there should have enough information to be learned by models for prediction;
2. During the Christmas holidays, the accuracy of forecasting models cannot be shown correctly, due to the unusually volatile prices affected by traders' speculation.

ANN models could be different with regard to the combinations of different numbers of hidden layers, different numbers of units in each layer and different types of transfer functions. It is well known that a multilayer network with one or more hidden layers can learn better than a single-layer network, which has limitations in the mappings. The network with more than one hidden layer may be beneficial for some applications, but one hidden-layered network is sufficient. [55]

For the application, one hidden-layered feed-forward neural network with back-propagation has been proposed. The transfer function is '*tansig*' for the hidden layer and '*purelin*' for the output layer. '*Traingdm*' is the network training function used to update the weights and bias values according to gradient descent momentum. Due to flexibility and simplicity, neural network toolbox of MatLab is selected as the forecasting tool.

In figure 3.7, the orange color shows the forecasting objective in this chapter and the current procedure against the whole project structure.



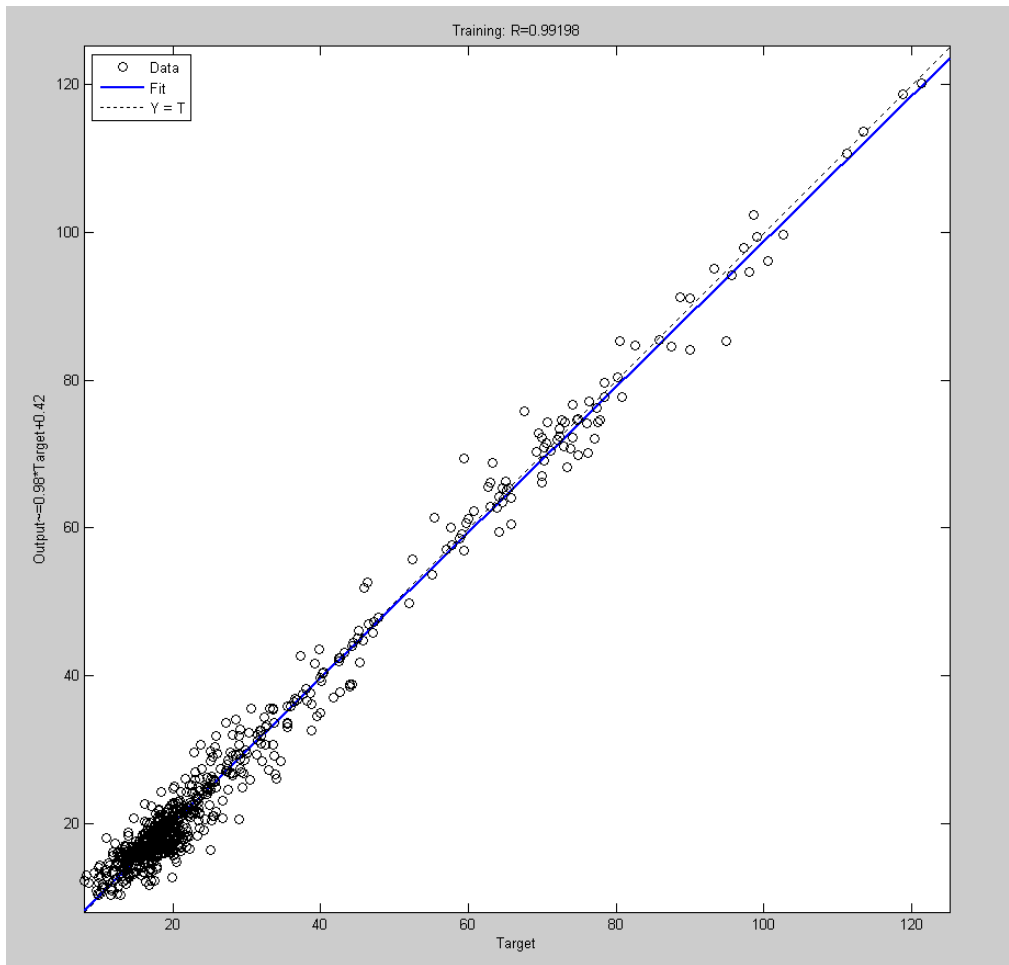
**Fig. 3.7** Objective I and current procedure

### 3.3.1 Forecasts of Case A

In the UK spot power markets, electricity prices are updated in each half-hour. Hence, one day is composed of forty-eight time periods, where one time period can be viewed as one datum point for the training. In this case study A, the number of training points is 7248, which covers the days from January 1<sup>st</sup>, 2007 to May 31<sup>st</sup>, 2007. There are 720 testing points in total, which are selected from June 16<sup>th</sup>, 2007 to June 30<sup>th</sup>, 2007.

MatLab neural network toolbox is used for the training and it is completed in 1 minute and 53 seconds. Figure 3.8 shows the correlation between outputs and targets trained by the proposed one hidden-layered ANN model.

Both original price data and forecasting results are listed in table A (a) (b) and (c) in appendix, respectively. Corresponding to the original price curves, the curves of forecasting prices to the days (16/06/2007-30/06/2007) are illustrated in each of the figures (3.9 - 3.23).



**Fig. 3.8** Correlation between outputs and targets by one hidden-layered ANN model  
(June 16<sup>th</sup>, 2007- June 30<sup>th</sup>, 2007)

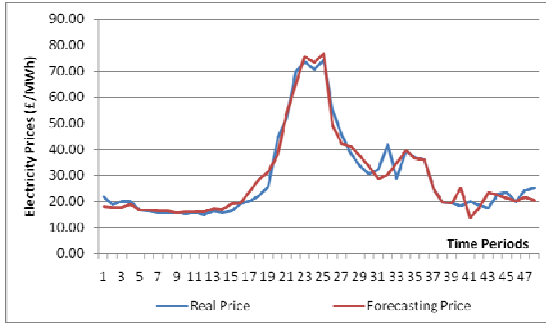


Fig. 3.9 ANNs forecasting results on Jun 16<sup>th</sup>, 2007

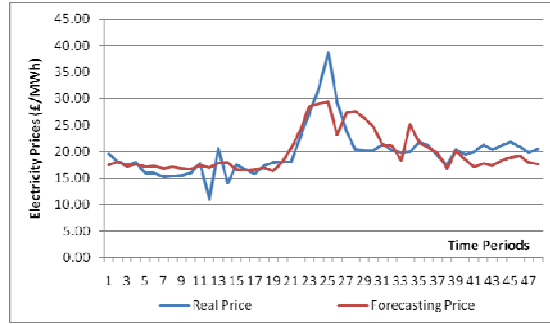


Fig. 3.10 ANNs forecasting results on Jun 17<sup>th</sup>, 2007

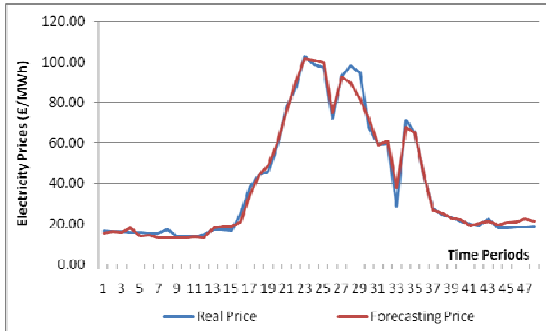


Fig. 3.11 ANNs forecasting results on Jun 18<sup>th</sup>, 2007

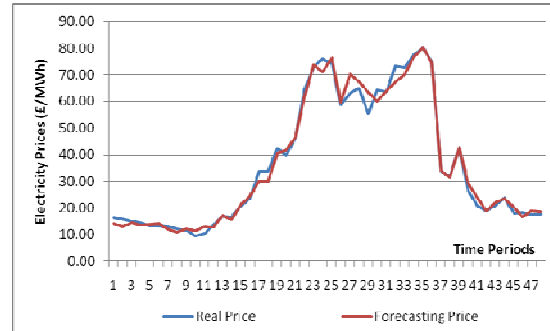


Fig. 3.12 ANNs forecasting results on Jun 19<sup>th</sup>, 2007

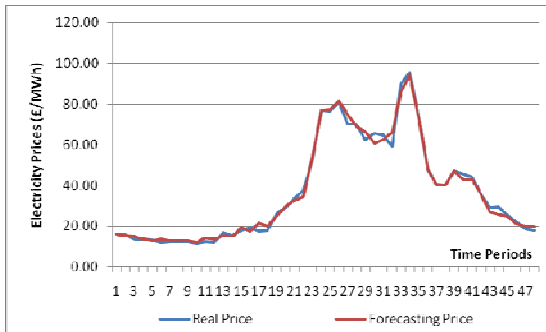


Fig. 3.13 ANNs forecasting results on Jun 20<sup>th</sup>, 2007

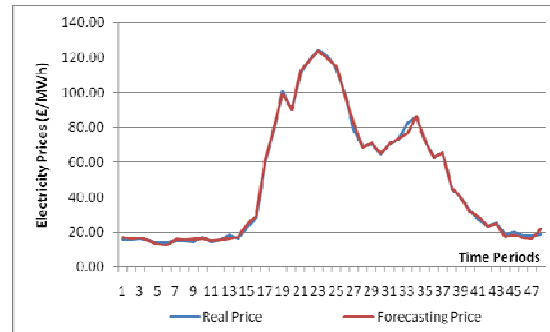


Fig. 3.14 ANNs forecasting results on Jun 21<sup>st</sup>, 2007

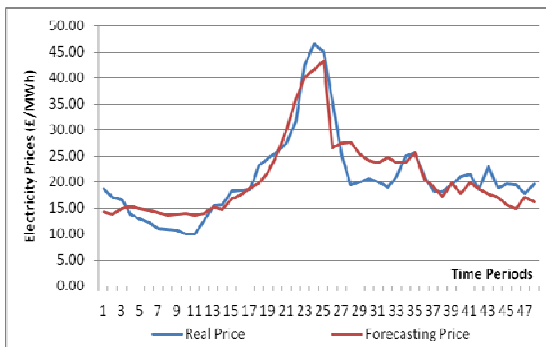


Fig. 3.15 ANNs forecasting results on Jun 22<sup>nd</sup>, 2007

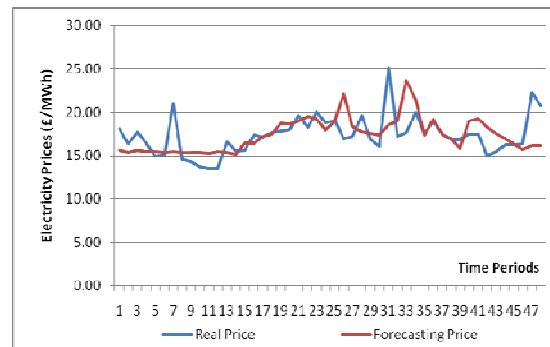


Fig. 3.16 ANNs forecasting results on Jun 23<sup>rd</sup>, 2007

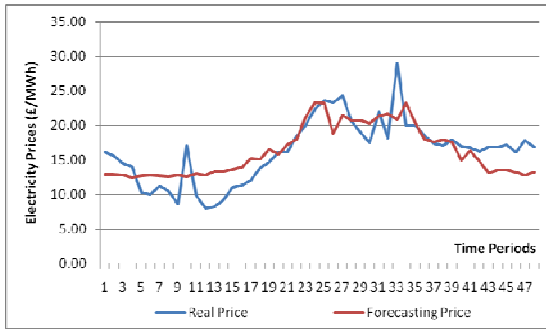


Fig. 3.17 ANNs forecasting results on Jun 24<sup>th</sup>, 2007

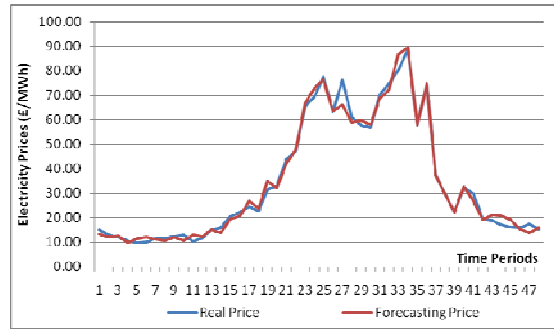


Fig. 3.18 ANNs forecasting results on Jun 25<sup>th</sup>, 2007

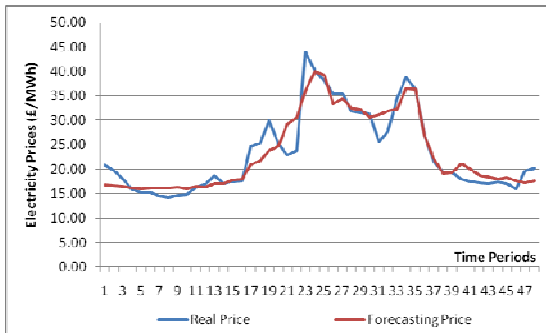


Fig. 3.19 ANNs forecasting results on Jun 26<sup>th</sup>, 2007

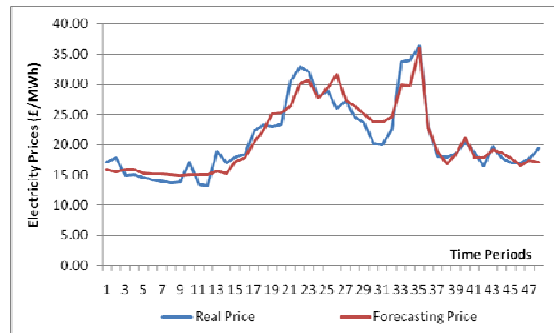


Fig. 3.20 ANNs forecasting results on Jun 27<sup>th</sup>, 2007

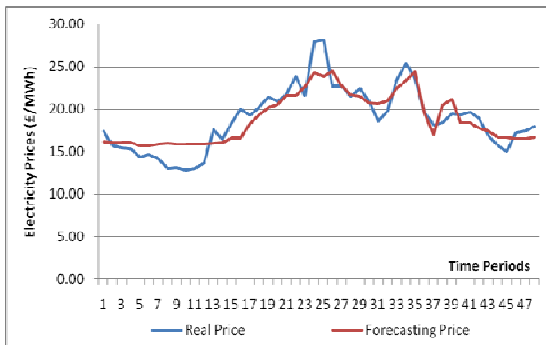


Fig. 3.21 ANNs forecasting results on Jun 28<sup>th</sup>, 2007

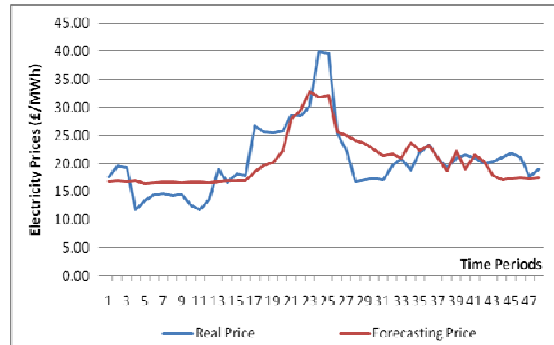


Fig. 3.22 ANNs forecasting results on Jun 29<sup>th</sup>, 2007

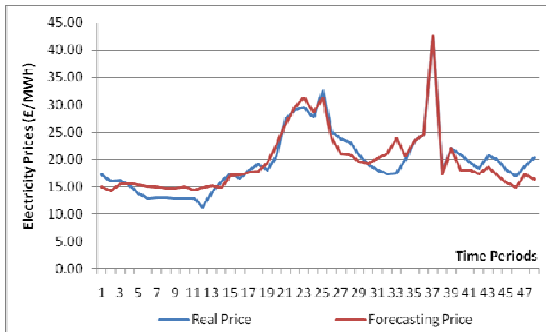


Fig. 3.23 ANNs forecasting results on Jun 30<sup>th</sup>, 2007

The most commonly used algorithm for the calculation of prediction errors is defined as MAPE, the mean absolute percent error, which is given by,

$$MAPE = \frac{1}{N} \sum_{i=1}^N \frac{|P_i - P_i'|}{P_i} \times 100\% \quad (3)$$

where  $N$  is time period,  $P_i$  is real price and  $P_i'$  is forecast price.

Therefore, the MAPE of 48 time periods from June 16<sup>th</sup>, 2007 to June 30<sup>th</sup>, 2007 are calculated according to equation (3). The forecasting errors of each time period are listed in table 3.1 and illustrated in figure 3.24.

<b>Time Periods</b>	1	2	3	4	5	6
<b>MAPE</b>	11.605	8.888	6.734	7.898	9.779	10.987
<b>Time Periods</b>	7	8	9	10	11	12
<b>MAPE</b>	11.930	12.833	12.909	15.197	15.952	17.827
<b>Time Periods</b>	13	14	15	16	17	18
<b>MAPE</b>	11.336	9.999	7.734	7.111	11.053	9.186
<b>Time Periods</b>	19	20	21	22	23	24
<b>MAPE</b>	10.253	4.473	6.323	6.784	4.566	5.744
<b>Time Periods</b>	25	26	27	28	29	30
<b>MAPE</b>	5.716	10.363	7.541	11.605	11.826	9.858
<b>Time Periods</b>	31	32	33	34	35	36
<b>MAPE</b>	10.244	12.018	14.445	7.900	0.687	0.727
<b>Time Periods</b>	37	38	39	40	41	42
<b>MAPE</b>	1.798	2.814	1.889	10.173	9.111	5.997
<b>Time Periods</b>	43	44	45	46	47	48
<b>MAPE</b>	11.645	9.855	11.618	9.405	11.524	13.397

**Table 3.1** MAPE\_ANNs of 48 time periods (16th -30th June 2007)

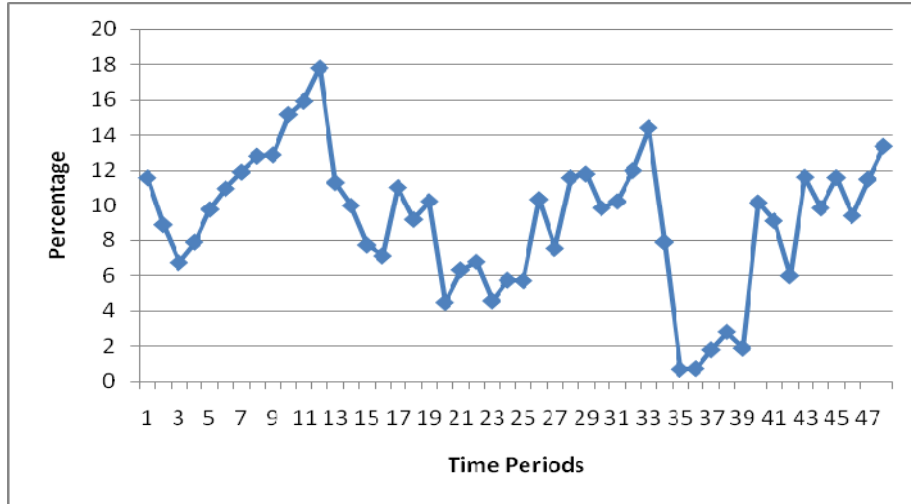
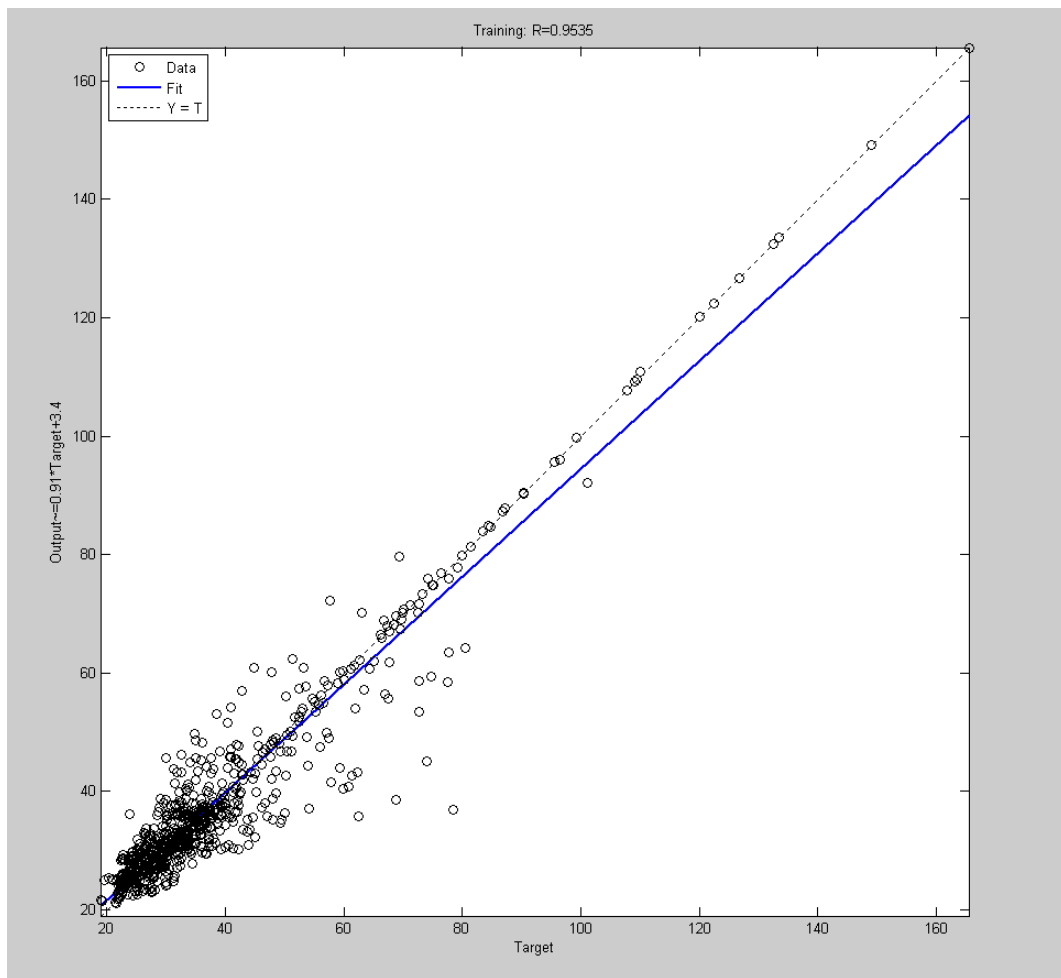


Fig. 3.24 MAPE\_ANNs of 48 time periods (16th -30th June 2007)

### 3.3.2 Forecasts of Case B

In case study B, the number of training points is 7344, which is the number of half-hour time segments from July 1<sup>st</sup>, 2007 to November 30<sup>th</sup>, 2007. The information learned from those data is used to forecast the half-hour electricity prices from December 1<sup>st</sup>, 2007 to December 15<sup>th</sup>, 2007. Therefore, there are 720 testing points in case study B as well.

The forecasting ANN model and transfer functions are the same as that used in case study A. The training program ends within 2 minutes and the correlation between outputs and targets is shown in figure 3.25. Both reference data and forecasting results are listed in table B (a) (b) and (c) in appendix, respectively. Figure 3.26 - 3.40 illustrates the comparisons between original price curves and the curves of forecasting prices to the fifteen days, from December 1<sup>st</sup>, 2007 to December 15<sup>th</sup>, 2007.



**Fig. 3.25** Correlation between outputs and targets by one hidden-layered ANN model  
(December 1<sup>st</sup>, 2007-December 15<sup>th</sup>, 2007)



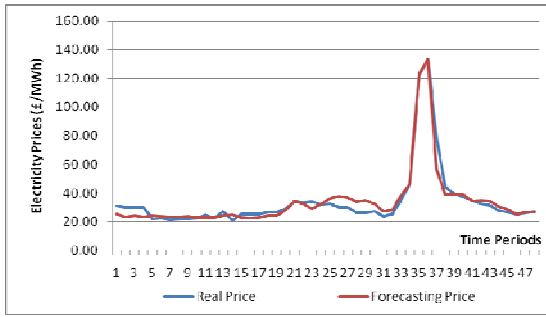


Fig. 3.26 ANNs forecasting results on Dec 1<sup>st</sup>, 2007

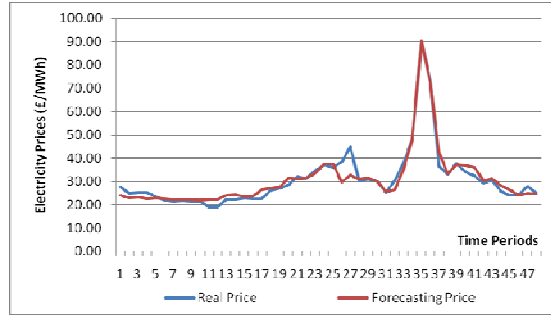


Fig. 3.27 ANNs forecasting results on Dec 2<sup>nd</sup>, 2007

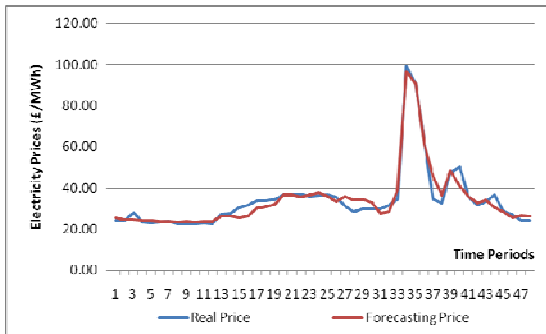


Fig. 3.28 ANNs forecasting results on Dec 3<sup>rd</sup>, 2007

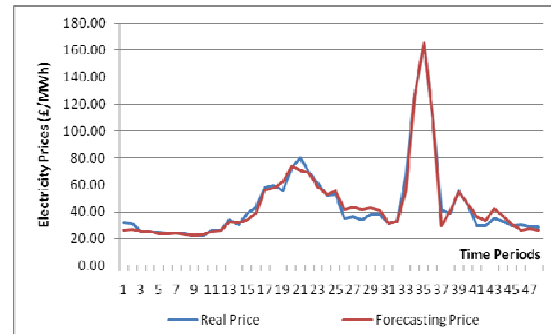


Fig. 3.29 ANNs forecasting results on Dec 4<sup>th</sup>, 2007

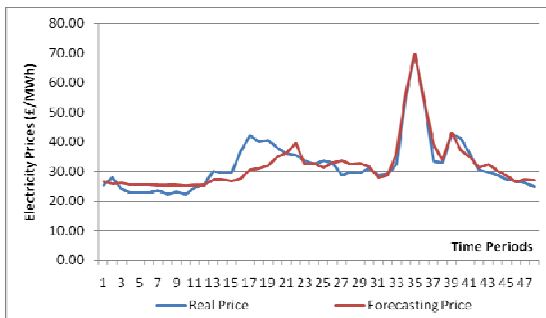


Fig. 3.30 ANNs forecasting results on Dec 5<sup>th</sup>, 2007

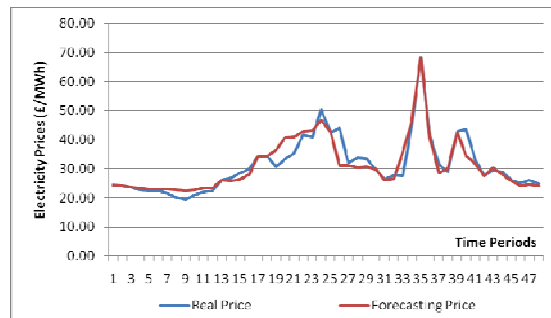


Fig. 3.31 ANNs forecasting results on Dec 6<sup>th</sup>, 2007

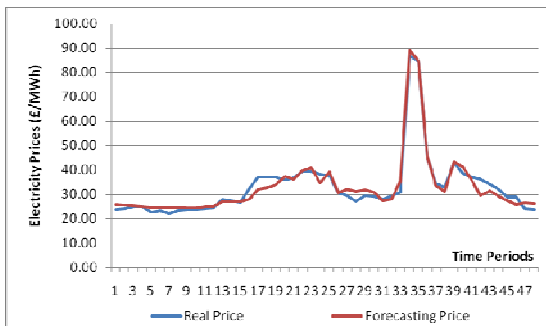


Fig. 3.32 ANNs forecasting results on Dec 7<sup>th</sup>, 2007

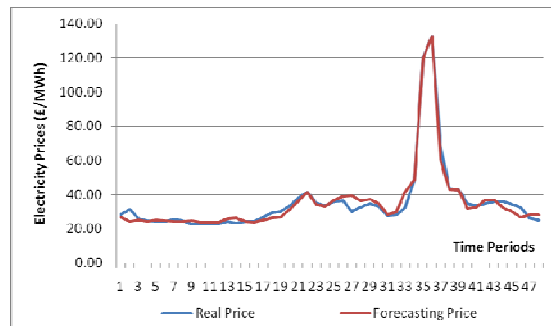


Fig. 3.33 ANNs forecasting results on Dec 8<sup>th</sup>, 2007

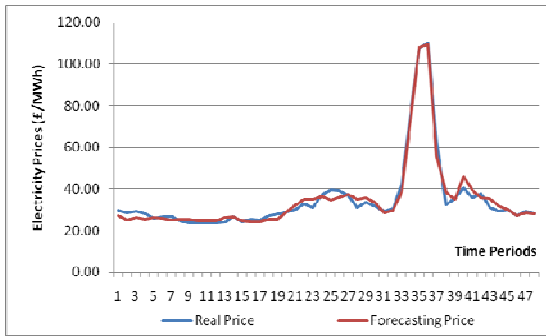


Fig. 3.34 ANNs forecasting results on Dec 9<sup>th</sup>, 2007

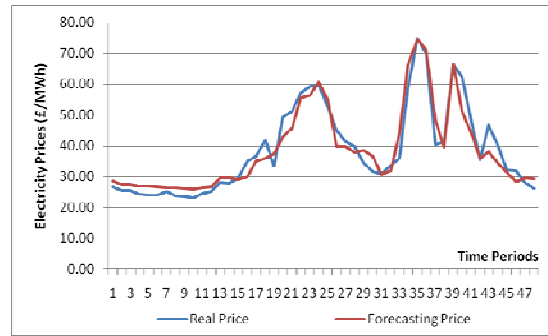


Fig. 3.35 ANNs forecasting results on Dec 10<sup>th</sup>, 2007

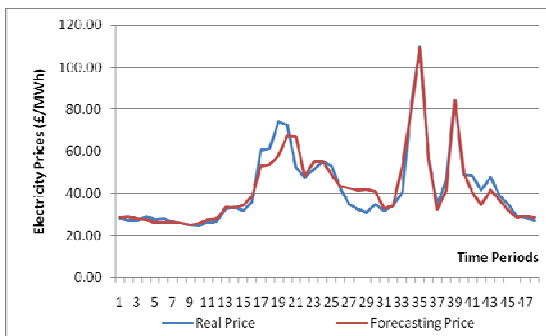


Fig. 3.36 ANNs forecasting results on Dec 11<sup>th</sup>, 2007

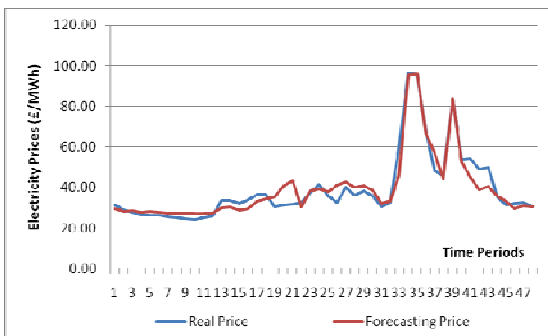


Fig. 3.37 ANNs forecasting results on Dec 12<sup>th</sup>, 2007

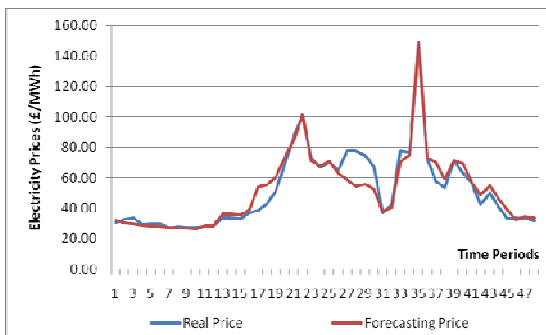


Fig. 3.38 ANNs forecasting results on Dec 13<sup>th</sup>, 2007

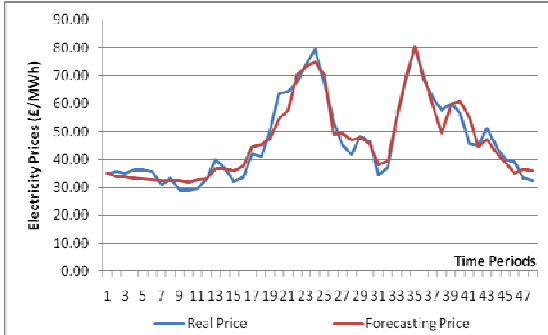


Fig. 3.39 ANNs forecasting results on Dec 14<sup>th</sup>, 2007

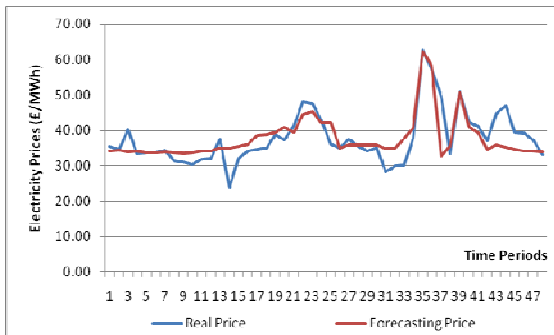
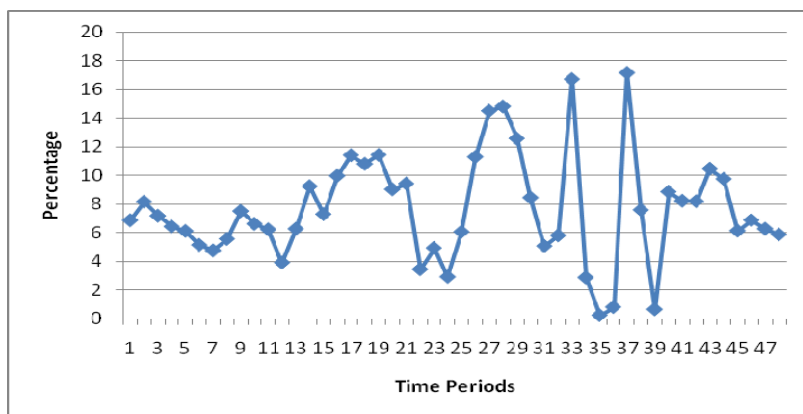


Fig. 3.40 ANNs forecasting results on Dec 15<sup>th</sup>, 2007

In case study B, the same algorithm, MAPE, is used to calculate forecasting errors of each time period from December 1<sup>st</sup>, 2007 to December 15<sup>th</sup>, 2007. The MAPE results are shown in table 3.2 and illustrated in figure 3.41.

<b>Time Periods</b>	1	2	3	4	5	6
<b>MAPE</b>	6.850	8.148	7.158	6.415	6.098	5.126
<b>Time Periods</b>	7	8	9	10	11	12
<b>MAPE</b>	4.742	5.546	7.488	6.600	6.213	3.894
<b>Time Periods</b>	13	14	15	16	17	18
<b>MAPE</b>	6.256	9.222	7.275	9.948	11.390	10.787
<b>Time Periods</b>	19	20	21	22	23	24
<b>MAPE</b>	11.414	9.012	9.408	3.431	4.919	2.903
<b>Time Periods</b>	25	26	27	28	29	30
<b>MAPE</b>	6.046	11.271	14.493	14.799	12.562	8.437
<b>Time Periods</b>	31	32	33	34	35	36
<b>MAPE</b>	5.056	5.786	16.703	2.857	0.220	0.790
<b>Time Periods</b>	37	38	39	40	41	42
<b>MAPE</b>	17.146	7.564	0.626	8.843	8.208	8.178
<b>Time Periods</b>	43	44	45	46	47	48
<b>MAPE</b>	10.449	9.734	6.119	6.860	6.255	5.853

**Table 3.2** MAPE\_ANNs of 48 time periods (1st -15th December 2007)



**Fig. 3.41** MAPE\_ANNs of 48 time periods (1st -15th December 2007)

### **3.4 SUMMARY**

As a simple, powerful and flexible tool for forecasting, ANNs have received much attention recently.

Neural networks have well-known advantages of being able to solve undefined relationships between input and output variables, approximate complex nonlinear functions and implement multiple training algorithms. However, neural networks are also recognized to have the following disadvantages: the network will not be flexible enough to model data well with too few neurons, and on the contrary, over-fitting can occur with too many neurons.

In order to compare the accuracy of ANNs with that of the other forecasting models, one hidden-layered neural network model is proposed and used to forecast the UK half-hour electricity prices in this chapter. Through the two case studies, the result has been shown that the proposed ANN model is feasible and efficient. In addition, more results' comparisons with regard to the different forecasting models, such as ANNs, support vector machines and hybrid models, will be analyzed and discussed in chapter 6.

## 4. SVM Modeling and Forecasting Electricity Prices

### 4.1 INTRODUCTION

Support Vector Machine (SVM) is a supervised learning technique used for classification and regression. The foundations of SVM were developed by Vladimir Vapnik and his co-workers in 1992, and it was not until 1995 that the soft margin version was introduced. Due to many attractive features and good performance, SVM is recently gaining popularity. SVM is based on the concept of hyperplanes that define decision boundaries in high dimensional space. A hyperplane is one that separates between a set of objects having different class memberships. In general, a good separation is achieved by the hyperplane that has the largest distance to the closest training data points of any classes. In classification problems, the maximum margin between a hyperplane and training data points is corresponding to the minimal weight vector, which is used for the generalization control. In regression problems, the minimization of the weight vector can also be used as a criterion along with a modified loss function.

Because the price data in spot power markets often have enormous noise and complex dimensionality, ANN models have some limitations with regard to forecasting. Recently, SVM has been successfully applied in the field of prediction. Therefore, in this chapter, it proposes SVM for the prediction of short-term electricity prices based on the same training data in order to compare with the previous study of ANNs.

The rest of this chapter is organized as follows: The statistical learning theory is explained in section 4.2. Support vector classification and regression are introduced in section 4.3 and section 4.4 respectively. In section 4.5, two case studies are used to demonstrate the price forecasting. Section 4.6 summarizes the modeling and experimental results.

## 4.2 STATISTICAL LEARNING THEORY

### 4.2.1 VC Dimension

The VC (Vapnik-Chervonenkis) dimension is used to measure the capacity of machines' learning convergence and generalization. "The VC dimension of a set of functions is  $p$  if and only if there exists a set of points  $\{x^i\}_{i=1}^p$  such that these points can be separated in all  $2^p$  possible configurations, and that no set  $\{x^i\}_{i=1}^q$  exists where  $q > p$  satisfying this property." [61]

The VC dimension is a scalar value that shows the capacity of a set of functions. With a higher VC dimension, the learning machine becomes more complex. So far there is no universal theory for the calculation of VC dimension. However, only some of the specific functions of VC dimension are known. For example, the function  $f(x, a) = \sin(ax)$  has an infinite VC dimension, and the VC dimension of linear indicator function in  $n$  dimensional space is  $n+1$ . It is much more difficult to decide the VC dimension for a complex learning machine, such as neural networks, because the VC dimension is not only related to the network structures, but also affected by the algorithm. Currently, the calculation of VC dimension is still a researching issue in the area of statistical learning theory.

### 4.2.2 Structural Risk Minimization (SRM)

The empirical risk (EMR) minimization principle was usually used to estimate the expected risk in the traditional statistical learning theory. However, it does not turn out to be optimal. EMR does not guarantee a small actual risk when the number of training samples is limited. The neural network is an unsuccessful example. A small error on the training set does not imply a small error on an independent testing set. The system complexity is increased by a small error, which at the same time will decrease the ability of system generalization. Thus, the smallest EMR does not mean the smallest actual risk. This situation is commonly called "overfitting" from neural network theory.

In order to overcome this limitation, the principle of structural risk minimization (SRM) is introduced for learning from finite training data sets. The relationship between actual risk  $R(w)$  and empirical risk  $R_{emp}(w)$  is given by (4),

$$R(w) \leq R_{emp}(w) + \sqrt{\frac{h(\ln(2n/h) + 1) - \ln(\eta/4)}{n}} \quad (4)$$

Where  $h$  is VC dimension,  $n$  is the number of observations.

It can also be defined simply by (5),

$$R(w) \leq R_{emp}(w) + \Phi(h/n) \quad (5)$$

Where  $\Phi(h/n)$  is called confidence interval.

Therefore, SRM inductive principle is intended to minimize the risk function with respect to both empirical risk and confidence interval. Notice that the confidence interval depends on the chosen class of functions, which are converted into a set of nested subsets  $(S_1, S_2, S_3)$ . For each subset, it is necessary to find a hypothesis  $h$  from a hypothesis space  $S$ , or to choose  $h$  that gives the lowest risk bound. The empirical risk and actual risk depend on one particular function chosen by the training procedure. SRM then is finding that model which gives the lowest upper bound on the actual risk. A structure of SRM is shown in figure 4.1.

The design of SVM senses the spirit of SRM principle to achieve the goal of minimizing confidence interval and training errors concurrently, by a completely automatic optimization procedure.

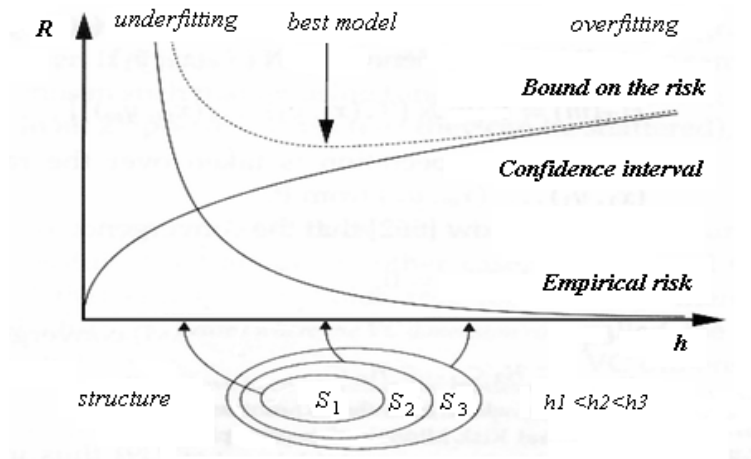


Fig. 4.1 Structural risk minimization

## 4.3 SUPPORT VECTOR CLASSIFICATION (SVC)

### 4.3.1 Optimal Separating Hyperplanes

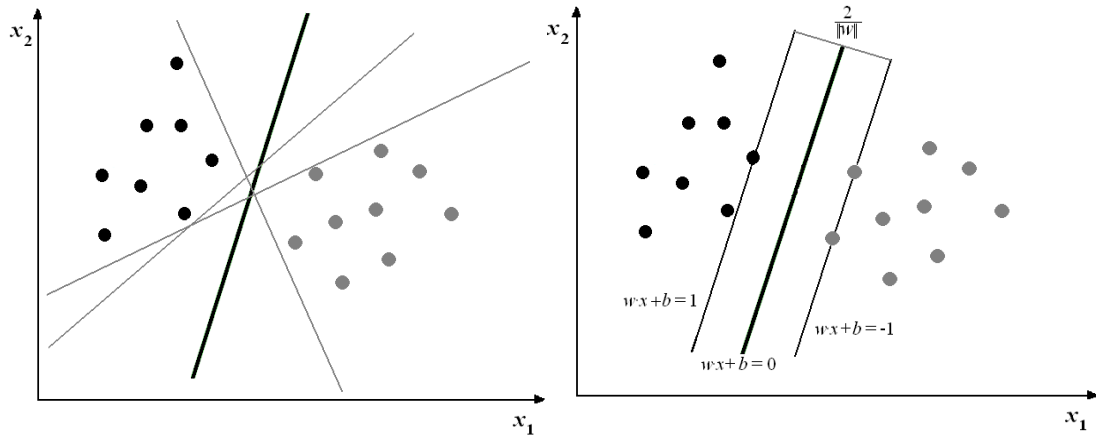
SVM was originally developed to solve the classification problems. Considering the example in figure 4.2, suppose some given data points in a two-dimension space. Each datum point belongs to one of two classes. The goal is to separate the two classes by a function, which is called a hyperplane. Apparently, the data points can be classified by many hyperplanes as shown on the left hand side of figure 4.2. However, there is only one maximum-margin hyperplane that maximizes the distance between it and the nearest data point of each class. It can be seen on the right hand side of figure 4.2.

Label the training data,

$$\{x_i, y_i\}, i = 1, \dots, m, y_i \in \{-1, 1\}, x_i \in R^d$$

Where  $y_i$  is either 1 or -1, indicating the two separate classes to which data point  $x_i$  belongs.





**Fig. 4.2** Hyperplanes and maximum-margin hyperplane for two classes' samples

Assume that the data points as defined by the coordinates  $x_i$  and  $y_i$  that lie on the hyperplane satisfy

$$w \cdot x_i + b = 0 \quad (6)$$

where  $w$  is normal to the hyperplane,  $\cdot$  denotes the dot product. Suppose that all the data points satisfy the constraints:

$$x_i \cdot w + b \geq +1 \quad \text{for } y_i = +1 \quad (7)$$

$$x_i \cdot w + b \leq -1 \quad \text{for } y_i = -1 \quad (8)$$

Then (7) and (8) can be combined into the inequalities (9):

$$y_i(x_i \cdot w + b) - 1 \geq 0 \forall_i \quad (9)$$

The perpendicular distance between a point  $x_i$  and the hyperplane is  $\frac{|1-b|}{\|w\|}$  or  $\frac{|-1-b|}{\|w\|}$ .

Therefore, the margin is the sum of these distances and given by  $\frac{2}{\|w\|}$ . In order to

maximize the margin, the optimal hyperplane that separates the data can be found by minimizing the equation (10).

$$\varphi(w) = \frac{1}{2} \|w\|^2 \quad (10)$$

where the factor of 1/2 is used for mathematical convenience.

Now the Lagrangian function is used to formulate the problem. The main reasons for doing this are [62]:

- Constraints (9) will be replaced by the much easier constraints on Lagrange multipliers themselves;
- Training data will only appear in the form of dot products between vectors, which is the key property to generalize the procedure to nonlinear cases.

Thus, non-negative Lagrange multipliers  $\alpha_i$ ,  $i = 1, \dots, m$ , are introduced to combine the objective and constraints into (11):

$$\varphi(w, b, \alpha) = \frac{1}{2} \|w\|^2 - \sum_{i=1}^m \alpha_i y_i (x_i \cdot w + b) + \sum_{i=1}^m \alpha_i \quad (11)$$

The Lagrangian has to be minimized with respect to  $w$ ,  $b$  and maximized with respect to  $\alpha \geq 0$ . Then the dual problem becomes:

$$\max_{\alpha} W(\alpha) = \max_{\alpha} (\min_{w, b} \varphi(w, b, \alpha)) \quad (12)$$

Now minimize  $\varphi(w, b, \alpha)$  with respect to  $w$  and  $b$ ,

$$\frac{\partial \varphi}{\partial b} = 0 \Rightarrow \sum_{i=1}^m \alpha_i y_i = 0 \quad (13)$$

$$\frac{\partial \varphi}{\partial w} = 0 \Rightarrow w = \sum_{i=1}^m \alpha_i y_i x_i \quad (14)$$

Substitute (13) and (14) into equation (11), then the optimization problem is:

$$\underset{\alpha \in \mathbb{R}^m}{\text{maximize}} W(\alpha) = \sum_{i=1}^m \alpha_i - \frac{1}{2} \sum_{i,j=1}^m \alpha_i \alpha_j y_i y_j x_i \cdot x_j \quad (15)$$

Therefore, the optimal hyperplane for separable linear case is objective to maximize  $W(\alpha)$  with respect to  $\alpha_i$ , subject to the constraints  $\sum_{i=1}^m \alpha_i y_i = 0$  and  $\alpha_i \geq 0, i = 1, \dots, m$ . The solution to this problem is (14). Note that the “support vectors” are those points for which  $\alpha_i > 0$  in the solution, as those points with  $\alpha_i = 0$  do not support the hyperplane separation. An expression that can be evaluated in terms of dot products is obtained,

$$f(x) = \text{sgn}\left(\sum_{i=1}^m \alpha_i^* y_i K(x_i, x) + b^*\right) \quad (16)$$

Where  $K(x_i, x)$  is the kernel function,

$$K(x_i, x) = \varphi(x_i) \cdot \varphi(x) \quad (17)$$

The training data are mapped into a high dimensional space by  $\varphi$ . If the kernel function  $K$  is known, then there is no need to explicitly even know what  $\varphi$  is. Therefore, the idea of the kernel function is to enable the computation to be performed in the input space instead of a high dimensional space, where the inner product does. The commonly used kernel functions will be introduced in section 4.3.3.

### 4.3.2 Generalized Optimal Separating Hyperplanes

The above algorithm is for separable data case. By introducing non-negative slack variables  $\xi_i, i = 1, \dots, m$  in the constraints (7) and (8), the algorithm can be extended to the application of non-separable data case.

$$x_i \cdot w + b \geq +1 - \xi_i \quad \text{for } y_i = +1 \quad (18)$$

$$x_i \cdot w + b \leq -1 + \xi_i \quad \text{for } y_i = -1 \quad (19)$$

$$\xi_i \geq 0 \forall_i \quad (20)$$

Thus, the objective function is to minimize,

$$\varphi(w, \xi) = \frac{1}{2} \|w\|^2 + C \sum_{i=1}^m \xi_i \quad (21)$$

Where  $C$  is a parameter corresponding to the errors penalty, and  $\sum_{i=1}^m \xi_i$  is an upper bound on the number of training errors.

The solution to optimization problem of equation (21) under constraints (18) and (19) is given by the Lagrangian,

$$\varphi(w, b, \alpha, \xi, \mu) = \frac{1}{2} \|w\|^2 + C \sum_{i=1}^m \xi_i - \sum_{i=1}^m \alpha_i \{y_i(x_i \cdot w + b) + \xi_i\} + \sum_{i=1}^m \alpha_i - \sum_{i=1}^m \mu_i \xi_i \quad (22)$$

where  $\alpha, \mu$  are Lagrange multipliers. The Lagrangian has to be minimized with respect to  $w, b, \xi$  and maximized with respect to  $\alpha, \mu$ . Then the dual problem becomes:

$$\max_{\alpha, \mu} W(\alpha, \mu) = \max_{\alpha, \mu} (\min_{w, b, \xi} \varphi(w, b, \alpha, \xi, \mu)) \quad (23)$$

Now minimize  $\varphi(w, b, \alpha, \xi, \mu)$  with respect to  $w, b$  and  $\xi$

$$\frac{\partial \varphi}{\partial b} = 0 \Rightarrow \sum_{i=1}^m \alpha_i y_i = 0 \quad (24)$$

$$\frac{\partial \varphi}{\partial w} = 0 \Rightarrow w = \sum_{i=1}^m \alpha_i y_i x_i \quad (25)$$

$$\frac{\partial \varphi}{\partial \xi} = 0 \Rightarrow \alpha_i + \mu_i = C \quad (26)$$

Through the substitution, neither  $\xi_i$  nor Lagrange multipliers appear in the dual problem anymore. So the optimization problem is:

$$\underset{\alpha \in \mathbb{R}^m}{\text{maximize}} W(\alpha) = \sum_{i=1}^m \alpha_i - \frac{1}{2} \sum_{i,j=1}^m \alpha_i \alpha_j y_i y_j x_i \cdot x_j \quad (27)$$

Subject to,

$$0 \leq \alpha_i \leq C, i = 1, \dots, m \quad (28)$$

$$\sum_{i=1}^m \alpha_i y_i = 0 \quad (29)$$

The solution to the problem is (25). Therefore, the only difference from the previous optimal hyperplane, which has been discussed in section 4.3.1, is that  $\alpha_i$  has an upper bound  $C$  now.

### 4.3.3 Kernel Functions

The kernel functions  $K(x_i, x_j) = \varphi(x_i) \cdot \varphi(x_j)$  are used to construct a mapping from the input space into a high dimensional feature space. The mostly popular used kernel functions are listed below:

- Polynomial

$$\text{Homogeneous:} \quad K(x_i, x_j) = (x_i \cdot x_j)^d \quad d \in \mathbb{N} \quad (30)$$

$$\text{Inhomogeneous:} \quad K(x_i, x_j) = (x_i \cdot x_j + c)^d \quad d \in \mathbb{N}, c \geq 0 \quad (31)$$

- Gaussian Radial Basis Function (RBF)

$$K(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right) \quad \sigma > 0 \quad (32)$$

- Exponential Radial Basis Function

$$K(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|}{2\sigma^2}\right) \quad \sigma > 0 \quad (33)$$

- Sigmoid

$$K(x_i, x_j) = \tanh(\kappa x_i \cdot x_j + c) \quad \kappa > 0, c < 0 \quad (34)$$

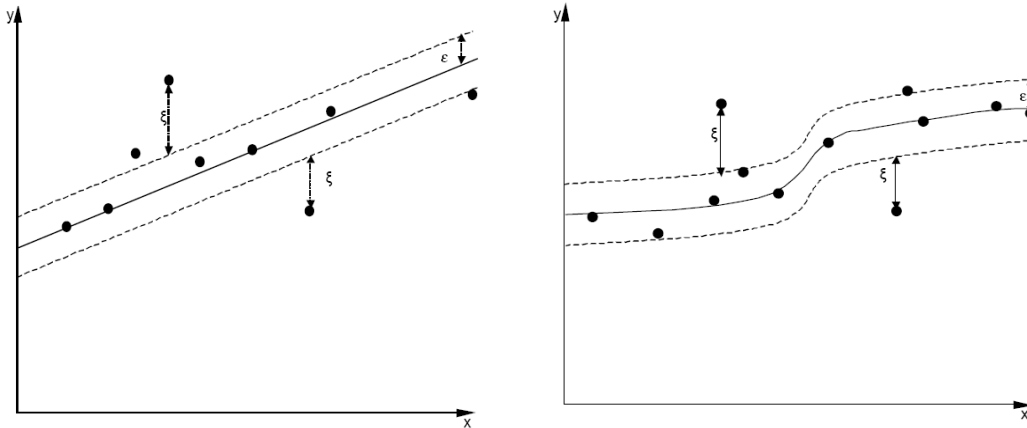
- Fourier Series

$$K(x_i, x_j) = \frac{\sin(N + \frac{1}{2})(x_i - x_j)}{\sin(\frac{1}{2}(x_i - x_j))} \quad \text{on the interval } [-\frac{\pi}{2}, \frac{\pi}{2}] \quad (35)$$

#### 4.4 SUPPORT VECTOR REGRESSION (SVR)

SVM can be applied not only to classification problems but also to the cases of regression by introducing an alternative loss function. SVR retains all the main features of SVC that characterize the maximal margin. The function that ignores errors within a certain distance of the true value is defined as an  $\varepsilon$ -insensitive loss function.

Figure 4.3 illustrates one dimensional linear regression (on the left hand side) and non-linear regression (on the right hand side) with  $\varepsilon$ -insensitive band [63]. The variables  $\xi$  are used for measuring the cost of errors on the training points. These are zero for all points inside the band. The advantages of using this type of loss functions are that can ensure the existence of a global minimum, and meanwhile optimize a reliable generalization bound.



**Fig. 4.3** One-dimensional linear regression and non-linear regression with  $\varepsilon$ -insensitive band

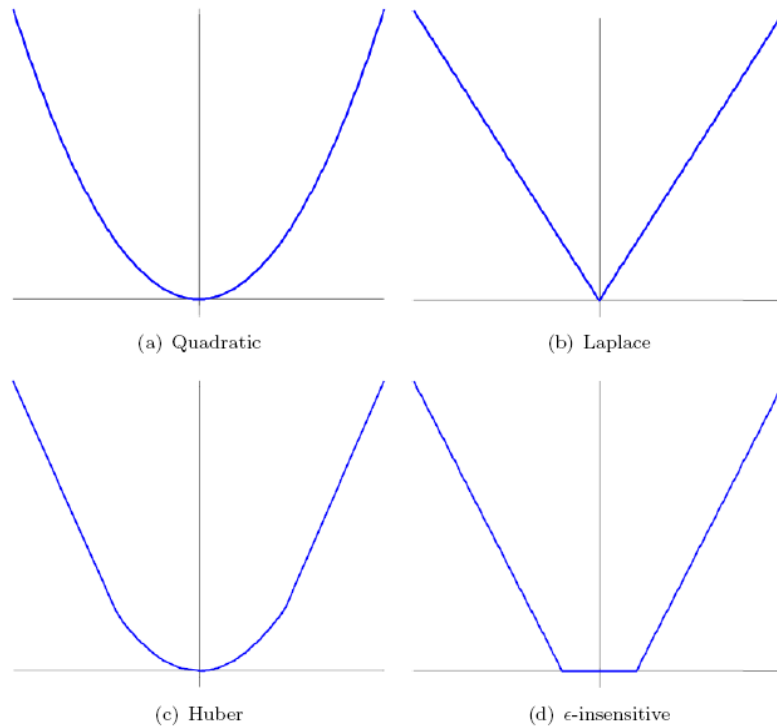
The  $\varepsilon$ -insensitive loss function is given by [64],

$$L(y, f(x, \alpha)) = L(|y - f(x, \alpha)|_\varepsilon) \quad (36)$$

where it is set

$$|y - f(x, \alpha)|_\varepsilon = \begin{cases} 0, & \text{if } |y - f(x, \alpha)| \leq \varepsilon, \\ |y - f(x, \alpha)| - \varepsilon, & \text{otherwise} \end{cases} \quad (37)$$

The four possible loss functions are presented and explained below, corresponding to each loss function as illustrated in figures 4.4 (a) – (d) [61].



**Fig. 4.4** Loss functions

- The linear  $\epsilon$ -insensitive loss function:

$$L(y - f(x, \alpha)) = |y - f(x, \alpha)|_{\epsilon} \quad (38)$$

- The quadratic  $\epsilon$ -insensitive loss function:

$$L(y - f(x, \alpha)) = |y - f(x, \alpha)|_{\epsilon}^2 \quad (39)$$

- The Huber loss function:

$$L(|y - f(x, \alpha)|) = \begin{cases} c|y - f(x, \alpha)| - \frac{c^2}{2} & \text{for } |y - f(x, \alpha)| > c \\ \frac{1}{2}|y - f(x, \alpha)|^2 & \text{for } |y - f(x, \alpha)| \leq c \end{cases} \quad (40)$$



Now the solution to the optimal regression problem is to minimize function (41),

$$\varphi(w, \xi^*, \xi) = \frac{1}{2} \|w\|^2 + C \sum_{i=1}^m (\xi_i^* + \xi_i), \quad (41)$$

Subject to,

$$y_i - (w \cdot x_i) - b \leq \varepsilon + \xi_i^*, \quad i = 1, \dots, m, \quad (42)$$

$$(w \cdot x_i) + b - y_i \leq \varepsilon + \xi_i, \quad i = 1, \dots, m, \quad (43)$$

$$\xi_i^* \geq 0, \quad \xi_i \geq 0, \quad i = 1, \dots, m. \quad (44)$$

Where  $C$  is a pre-specified value, and  $\xi_i^*, \xi_i$  are slack variables representing upper and lower constraints on the outputs of system.

The parameter  $\varepsilon$  will be useful, if the accuracy of approximation can be specified beforehand. However, in some cases, the researchers just want to seek the estimation as accurate as possible, without specifying it by them. Therefore, another algorithm that can compute the  $\varepsilon$  automatically is introduced. By using a non-negative constant  $\nu$ , the size of  $\varepsilon$  can be traded off against model complexity and slack variables. This model is called  $\nu$ -SVR, which objective is to minimize the functional,

$$\varphi(w, \xi^*, \xi, \varepsilon) = \frac{1}{2} \|w\|^2 + C \cdot (\nu \varepsilon + \frac{1}{m} \sum_{i=1}^m (\xi_i^* + \xi_i)), \quad (45)$$

Subject to,

$$y_i - (w \cdot x_i) - b \leq \varepsilon + \xi_i^*, \quad i = 1, \dots, m, \quad (46)$$

$$(w \cdot x_i) + b - y_i \leq \varepsilon + \xi_i, \quad i = 1, \dots, m, \quad (47)$$

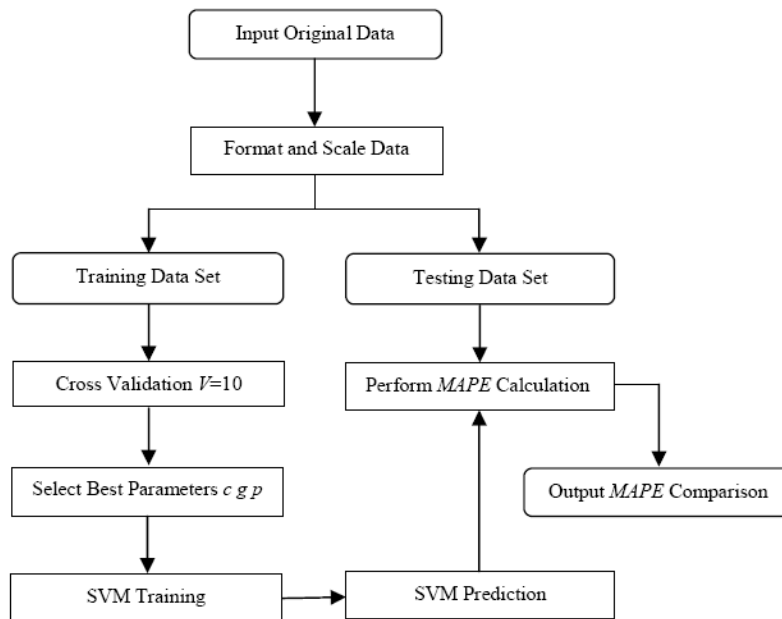
$$\xi_i^* \geq 0, \quad \xi_i \geq 0, \quad \varepsilon \geq 0, \quad i = 1, \dots, m. \quad (48)$$

Therefore, both parameters  $C$  and  $\varepsilon$  affect model complexity in different ways. For example, on one hand, if  $C$  is too big, the objective is to minimize the empirical risk only, without considering the model's generalization abilities. On another hand, with a bigger  $\varepsilon$ , a wider  $\varepsilon$ -insensitive zone is used for fitting the training data. The fewer selected support vectors will result in a "flat" regression construction. Thus, both parameters  $C$  and  $\varepsilon$  are very important for SVR. Two case studies will demonstrate the forecasts of short-term electricity prices by using SVR algorithm in next section.

#### **4.5 CASE STUDY: FORECASTING HALF-HOUR UK SPOT POWER MARKETS' PRICES WITH SVM MODELS**

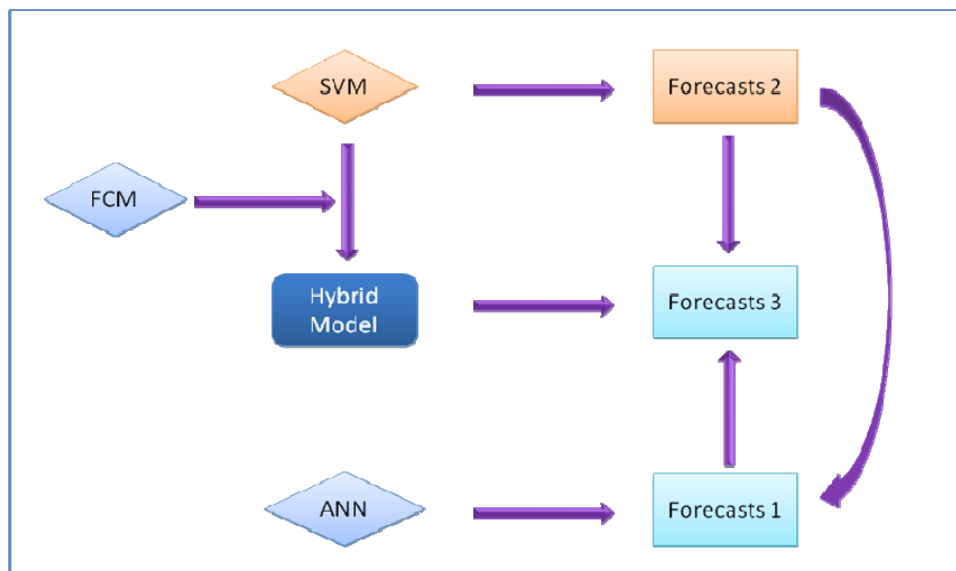
Two case studies are used to demonstrate the price forecasts by SVM models in this section. The price data are the same as that used for ANN model's forecasts and listed in appendix I. These data of the year 2007 are divided into two groups. One is from date January 1<sup>st</sup>, 2007 to June 30<sup>th</sup>, 2007 and another is from July 1<sup>st</sup>, 2007 to December 31<sup>st</sup>, 2007. In each group, the data are again divided into training data set and testing data set. Hence, as ANNs forecasting procedures, the training data are selected from date January 1<sup>st</sup>, 2007 to May 31<sup>st</sup>, 2007 and used to predict the half-hour UK spot prices on the days from June 16<sup>th</sup>, 2007 to June 30<sup>th</sup>, 2007 in case study A. Similarly, in case study B, the training data set is from date July 1<sup>st</sup>, 2007 to November 30<sup>th</sup>, 2007 and used to predict the prices on the days from December 1<sup>st</sup>, 2007 to December 15<sup>th</sup>, 2007. The reason for doing this is that it is possible to compare the forecasting results of ANNs and SVM, based on the same training data, which is more convictive to show the forecasting accuracy of different models.

LIBSVM is a useful tool for both SVM classification and regression. On April 1<sup>st</sup> 2009, a new version 2.89 of LIBSVM is released in order to reduce the loading time of SVM training and prediction. The practical prediction steps by LIBSVM are illustrated in the flow chart of figure 4.5.



**Fig. 4.5** LIBSVM prediction steps

The orange color in figure 4.6 shows the forecasting objective in this section and the current procedure against our whole project structure.



**Fig. 4.6** Objective II and current procedure

### 4.5.1 Forecasts of Case A

The number of training points in case study A is 7248, which covers the date from January 1<sup>st</sup>, 2007 to May 31<sup>st</sup>, 2007. It is half-hour electricity price data from the UK spot power markets. Therefore, a day (24 hours) is divided into forty-eight time segments (half-hour) in total. There are 720 testing points in case study A correspondingly, which are selected from the date June 16<sup>th</sup>, 2007 to June 30<sup>th</sup>, 2007.

The algorithm for prediction is epsilon-SVR and the kernel function is RBF shown as formula (49).

$$K(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right) \quad \sigma > 0 \quad (49)$$

During the cross-validation, users need to set an optimal number of folders  $V$  in order to compute the best parameters for training program. In both case studies A and B, the folders are set for 10. Therefore, in case study A, the best parameters for training program are determined by  $c=64.0$ ,  $p=0.03125$ ,  $g=0.015625$ . The calculation for best parameters is attached in appendix II. The electricity prices of different time periods are forecasted one by one. Reference data and the forecasting results are listed in table C (a) (b) and (c) in appendix, respectively. Corresponding to real price curves, the curves of forecasting prices to the fifteen days, from June 16<sup>th</sup>, 2007 to June 30<sup>th</sup>, 2007, are illustrated in each of the figures (4.7 - 4.21).

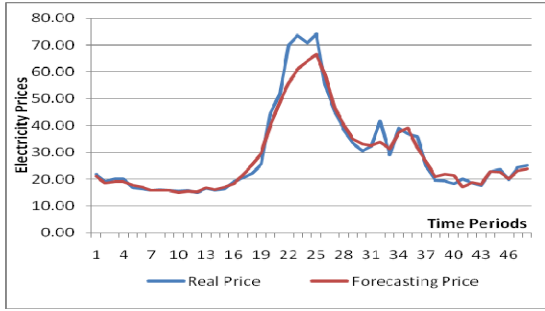


Fig. 4.7 SVM forecasting results on Jun 16th, 2007

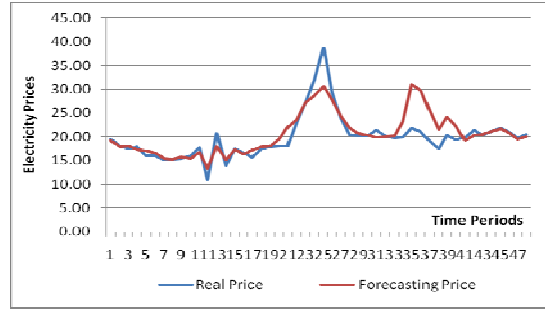


Fig. 4.8 SVM forecasting results on Jun 17th, 2007

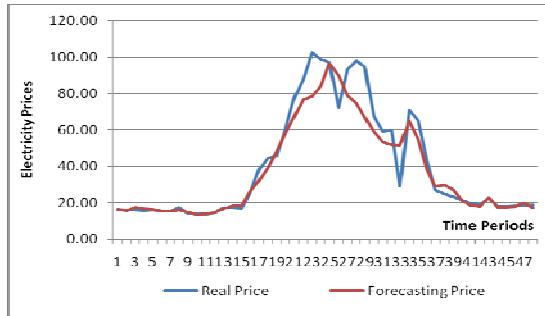


Fig. 4.9 SVM forecasting results on Jun 18th, 2007

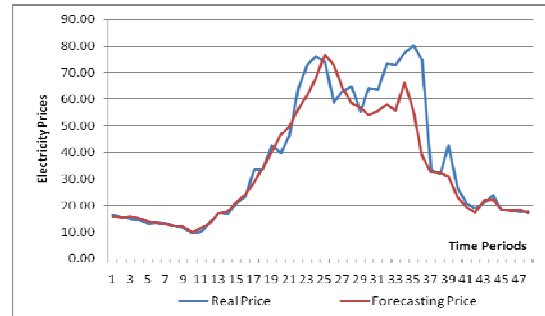


Fig. 4.10 SVM forecasting results on Jun 19th, 2007

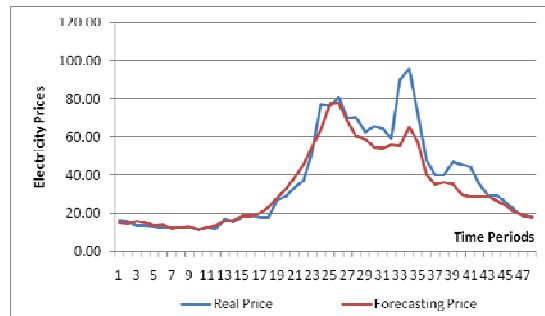


Fig. 4.11 SVM forecasting results on Jun 20th, 2007

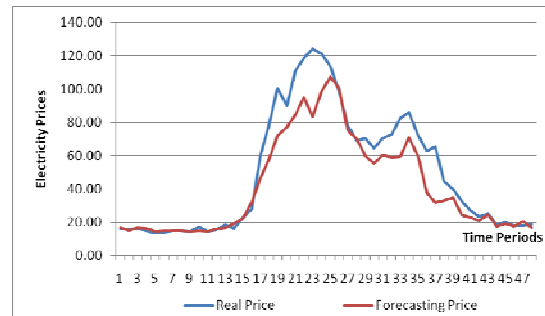


Fig. 4.12 SVM forecasting results on Jun 21st, 2007

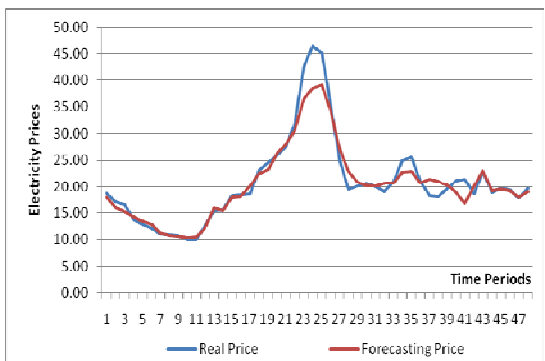


Fig. 4.13 SVM forecasting results on Jun 22nd, 2007

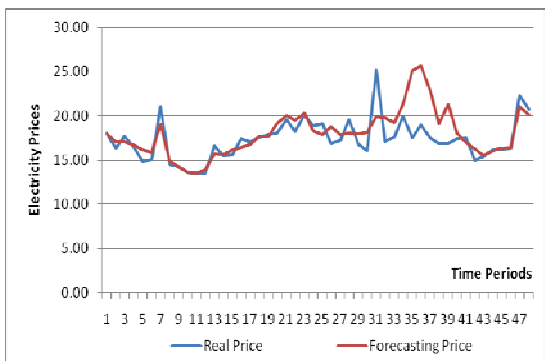


Fig. 4.14 SVM forecasting results on Jun 23rd, 2007

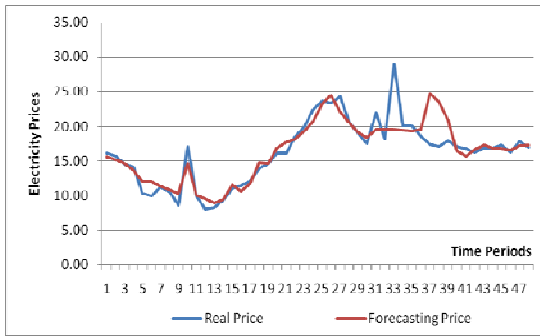


Fig. 4.15 SVM forecasting results on Jun 24th, 2007

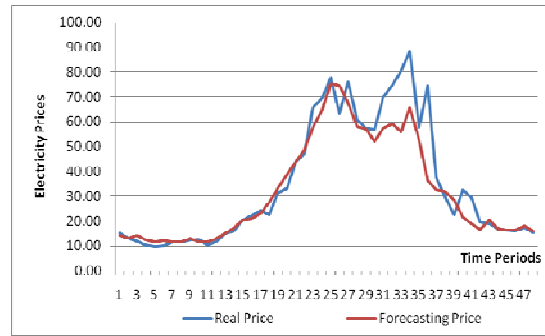


Fig. 4.16 SVM forecasting results on Jun 25th, 2007

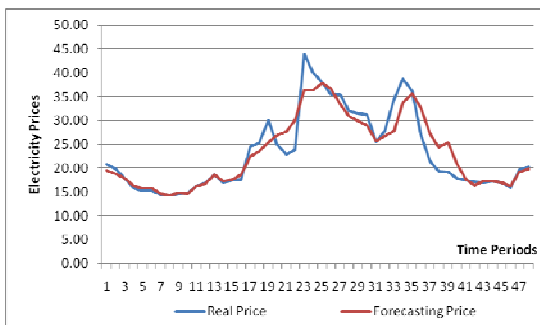


Fig. 4.17 SVM forecasting results on Jun 26th, 2007

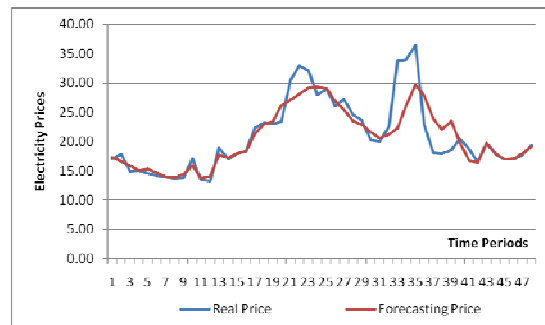


Fig. 4.18 SVM forecasting results on Jun 27th, 2007

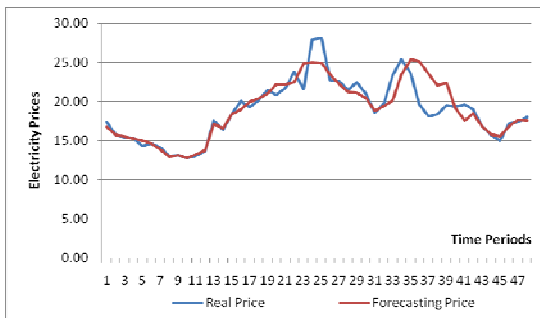


Fig. 4.19 SVM forecasting results on Jun 28th, 2007

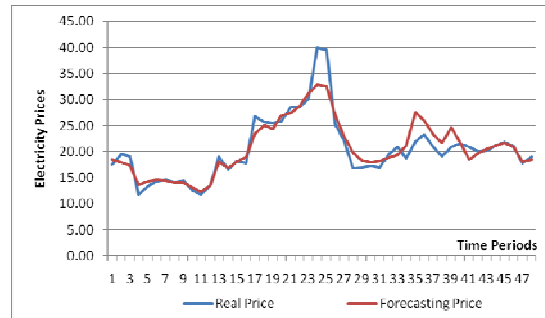


Fig. 4.20 SVM forecasting results on Jun 29th, 2007

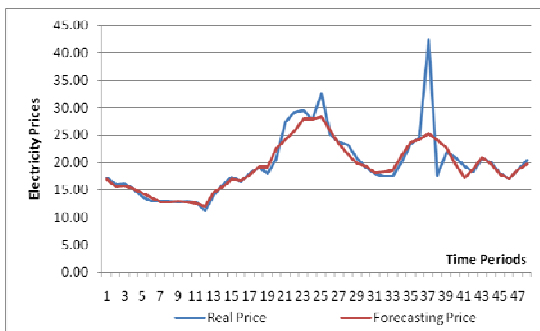


Fig. 4.21 SVM forecasting results on Jun 30th, 2007

The algorithm used for calculating prediction errors is defined as MAPE, which is given by,

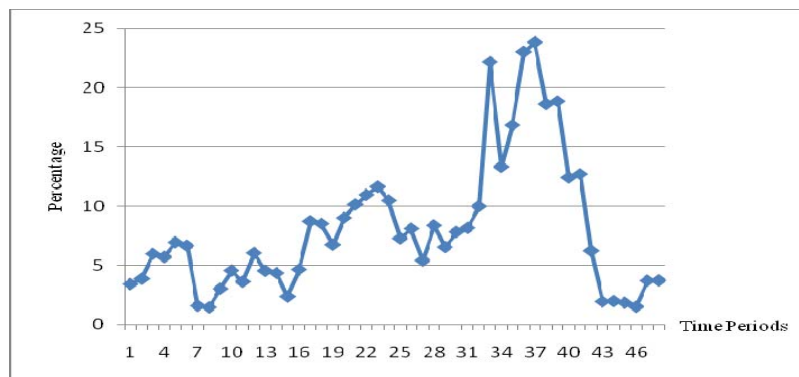
$$MAPE = \frac{1}{N} \sum_{i=1}^N \frac{|P_i - P'_i|}{P_i} \times 100\% \quad (50)$$

Where  $N$  is time periods,  $P_i$  is real price and  $P'_i$  is forecasting price.

From June 16<sup>th</sup>, 2007 to June 30<sup>th</sup>, 2007, the MAPE of 48 time periods are calculated vertically. The forecasting errors are listed in table 4.1 and shown in figure 4.22.

<b>Time Periods</b>	1	2	3	4	5	6
<b>MAPE</b>	3.412	3.866	5.963	5.698	6.938	6.652
<b>Time Periods</b>	7	8	9	10	11	12
<b>MAPE</b>	1.590	1.452	3.021	4.564	3.617	6.037
<b>Time Periods</b>	13	14	15	16	17	18
<b>MAPE</b>	4.536	4.345	2.360	4.647	8.716	8.516
<b>Time Periods</b>	19	20	21	22	23	24
<b>MAPE</b>	6.742	9.004	10.129	10.946	11.623	10.466
<b>Time Periods</b>	25	26	27	28	29	30
<b>MAPE</b>	7.274	8.093	5.406	8.367	6.535	7.811
<b>Time Periods</b>	31	32	33	34	35	36
<b>MAPE</b>	8.153	9.968	22.130	13.315	16.83	23.002
<b>Time Periods</b>	37	38	39	40	41	42
<b>MAPE</b>	23.807	18.600	18.834	12.399	12.696	6.224
<b>Time Periods</b>	43	44	45	46	47	48
<b>MAPE</b>	1.935	1.976	1.836	1.506	3.699	3.721

**Table 4.1** MAPE\_SVM of 48 time periods (16th -30th June 2007)



**Fig. 4.22** MAPE\_SVM of 48 time periods (16th -30th June 2007)

### 4.5.2 Forecasts of Case B

In case study B, the number of training data points is 7344, which equals the number of half-hour time segments from July 1<sup>st</sup>, 2007 to November 30<sup>th</sup>, 2007. The information obtained from those training data is used to forecast half-hour electricity prices on the days from December 1<sup>st</sup>, 2007 to December 15<sup>th</sup>, 2007. Therefore, there are 720 testing data points in case study B as well.

The prediction algorithm and kernel function are the same as that used in case study A. Folder V is set for 10 in the cross-validation, and the best parameters for training program are  $c=64.0$ ,  $p=0.25$ ,  $g=0.0078125$ , which are shown in appendix III. Both reference data and forecasting results are listed in table D (a) (b) and (c) in appendix, respectively. Figure 4.23 - 4.37 illustrates the comparisons between real price curves and the curves of forecasting prices to the fifteen days, December 1<sup>st</sup>, 2007 to December 15<sup>th</sup>, 2007.



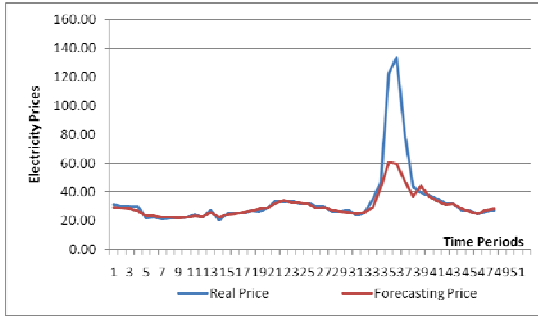


Fig. 4.23 SVM forecasting results on Dec 1st, 2007

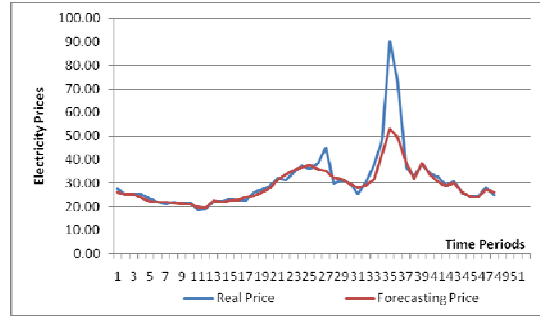


Fig. 4.24 SVM forecasting results on Dec 2nd, 2007

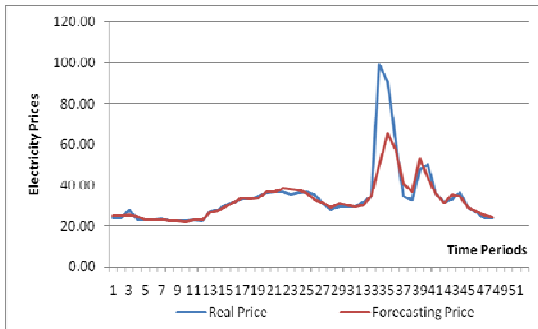


Fig. 4.25 SVM forecasting results on Dec 3rd, 2007

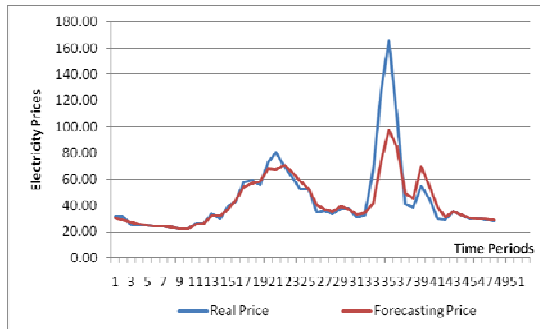


Fig. 4.26 SVM forecasting results on Dec 4th, 2007

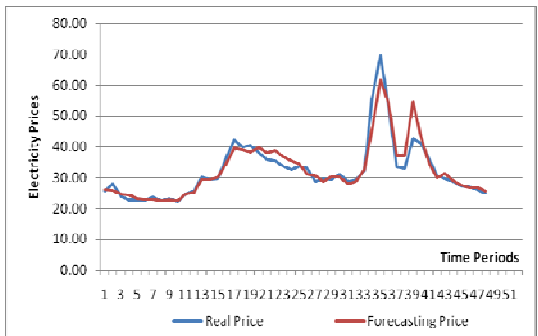


Fig. 4.27 SVM forecasting results on Dec 5th, 2007

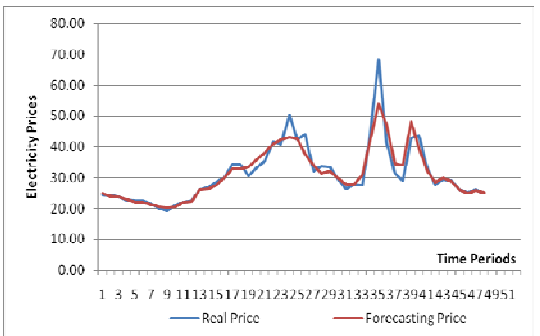


Fig. 4.28 SVM forecasting results on Dec 6th, 2007

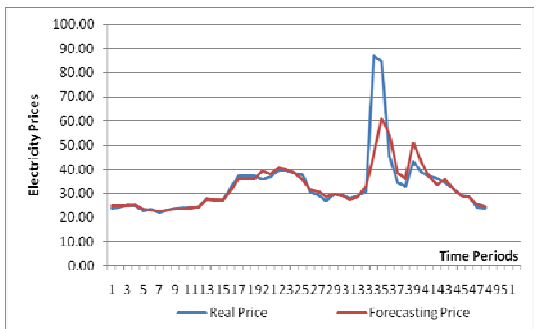


Fig. 4.29 SVM forecasting results on Dec 7th, 2007

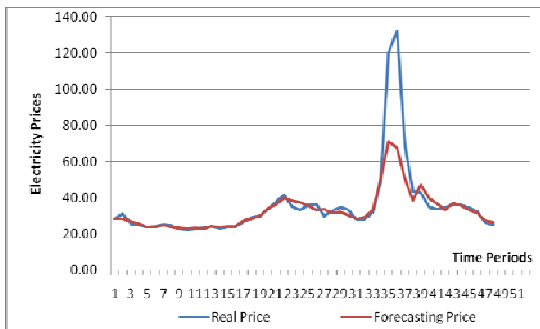


Fig. 4.30 SVM forecasting results on Dec 8th, 2007

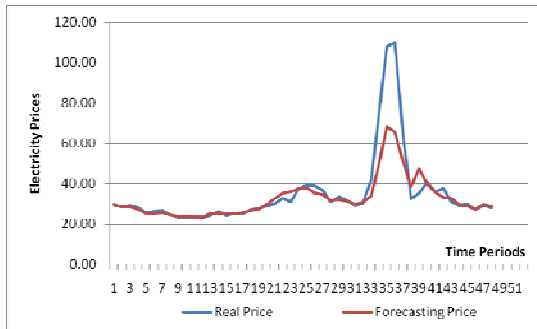


Fig. 4.31 SVM forecasting results on Dec 9th, 2007

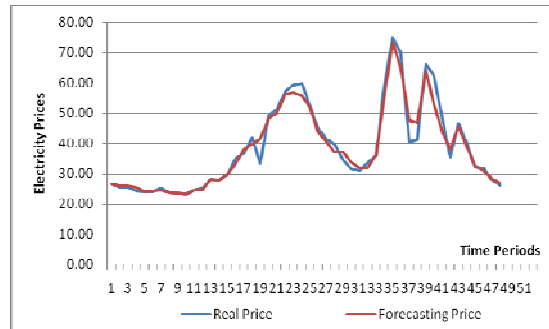


Fig. 4.32 SVM forecasting results on Dec 10th, 2007

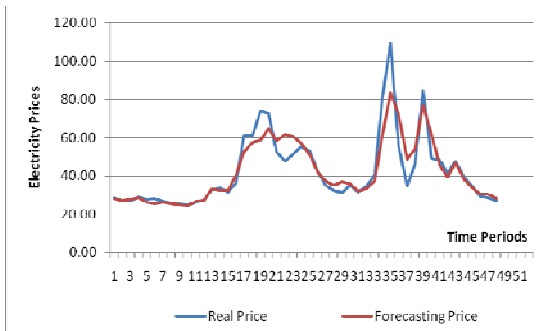


Fig. 4.33 SVM forecasting results on Dec 11th, 2007

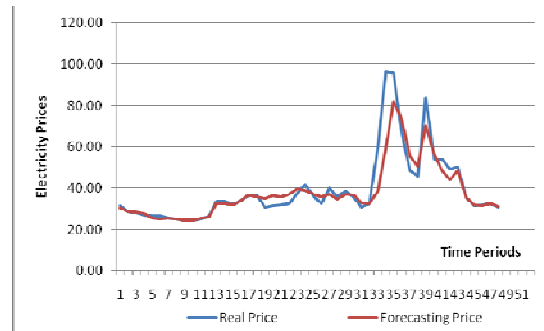


Fig. 4.34 SVM forecasting results on Dec 12th, 2007

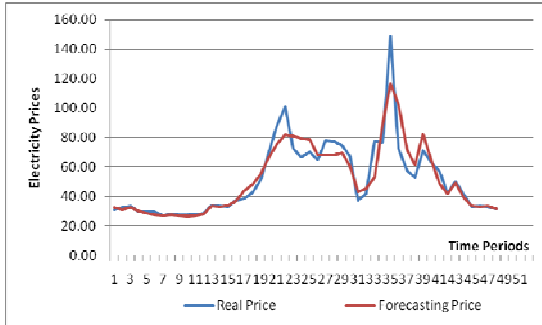


Fig. 4.35 SVM forecasting results on Dec 13th, 2007

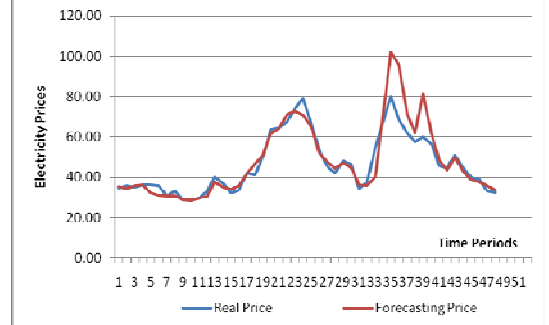


Fig. 4.36 SVM forecasting results on Dec 14th, 2007

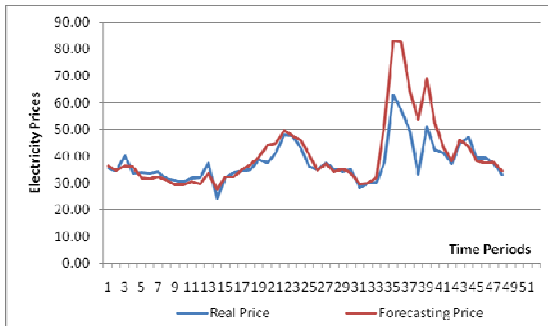
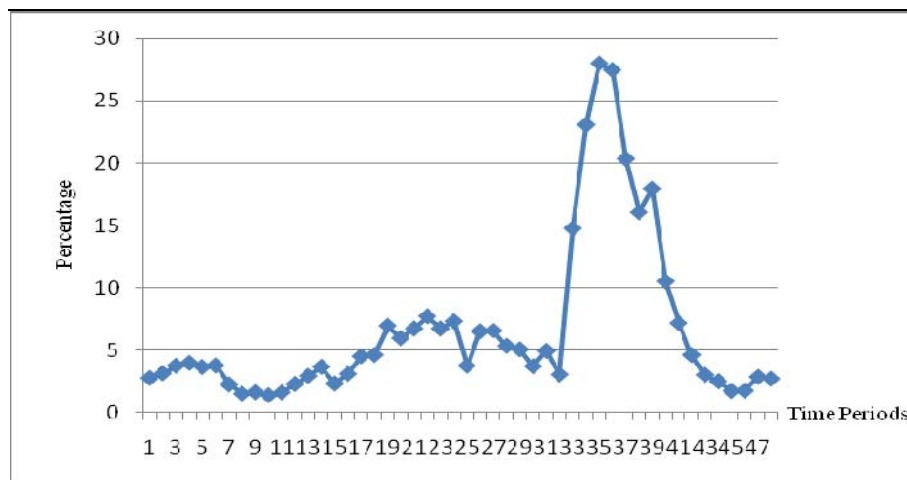


Fig. 4.37 SVM forecasting results on Dec 15th, 2007

The same method MAPE is used to calculate the forecasting errors in case study B. The results are listed in table 4.2 and illustrated in figure 4.38.

<b>Time Periods</b>	1	2	3	4	5	6
<b>MAPE</b>	2.761	3.131	3.736	3.96	3.639	3.758
<b>Time Periods</b>	7	8	9	10	11	12
<b>MAPE</b>	2.245	1.500	1.620	1.379	1.607	2.278
<b>Time Periods</b>	13	14	15	16	17	18
<b>MAPE</b>	2.926	3.655	2.316	3.091	4.499	4.613
<b>Time Periods</b>	19	20	21	22	23	24
<b>MAPE</b>	6.945	5.961	6.721	7.703	6.717	7.304
<b>Time Periods</b>	25	26	27	28	29	30
<b>MAPE</b>	3.745	6.499	6.552	5.336	5.057	3.7
<b>Time Periods</b>	31	32	33	34	35	36
<b>MAPE</b>	4.935	3.037	14.757	23.053	27.975	27.449
<b>Time Periods</b>	37	38	39	40	41	42
<b>MAPE</b>	20.324	16.030	17.921	10.508	7.154	4.602
<b>Time Periods</b>	43	44	45	46	47	48
<b>MAPE</b>	3.003	2.496	1.727	1.744	2.844	2.69

**Table 4.2** MAPE\_SVM of 48 time periods (1<sup>st</sup> -15<sup>th</sup> December 2007)



**Fig. 4.38** MAPE\_SVM of 48 time periods (1<sup>st</sup> -15<sup>th</sup> December 2007)

## **4.6 SUMMARY**

SVM is a useful tool to solve both classification and regression problems. It overcomes the limitation of traditional forecasting models by introducing the structural risk minimization principle. Through above two case studies, it can be found obviously that the prediction during off-peak time performs much better than during peak-time. This is because of the conflict between empirical risk and generalization ability. If the empirical risk is decreased in order to forecast more accurately, the ability of models' generalization will become weak accordingly. Therefore, in order to improve the forecasting accuracy during peak-time without affecting the generalization ability, a data clustering method called Fuzzy-C-Means (FCM) will be introduced in chapter 5. It is a data preprocessing algorithm that clusters thousands of data into different groups according to the price value rather than the time scale.

# 5. Hybrid Forecasting Models Based on Fuzzy C-Means Clustering and Support Vector Machines

## 5.1 INTRODUCTION

Clustering of numerical data can be considered the most important unsupervised learning problem. It forms the basis of many classification and modeling algorithms. The purpose of clustering is to determine the intrinsic structure in a large set of unlabeled data, producing groups whose members are similar in some way. The limitation of SVM forecasting model is revealed and analyzed through case studies in chapter 4. In order to improve the model, Fuzzy C-Means (FCM) clustering is introduced to preprocess data by clustering those into different groups according to their natural memberships, which is the value of electricity prices rather than the time scale. The advantages of doing this is that the noise can be reduced for each of training data sets after the data aggregation; meanwhile, SVM could maintain its characteristics of empirical risk and generalization ability. Therefore, in this chapter, the FCM model is fitted into SVM model in order to develop a hybrid forecasting model, which can be used to forecast the UK electricity spot prices based on the same training data for the purpose of comparing with single SVM and ANN forecasting models.

The structure of this chapter is as follows: After this introduction, the proposed hybrid forecasting algorithm is described in details in section 5.2. Section 5.3 gives the method to specify the number of data clustering groups. In section 5.4, experimental results are presented in case studies. Finally, section 5.5 concludes this chapter.

## 5.2 FUZZY C-MEANS CLUSTERING ALGORITHM

Clustering is a useful tool to obtain the partitioning of data. Generally speaking, a cluster is a group of objects with more similar memberships to one another than to the objects of other clusters. The most popular types of clustering are listed as follows [65]:

- Exclusive Clustering
- Overlapping Clustering
- Hierarchical Clustering
- Probabilistic Clustering

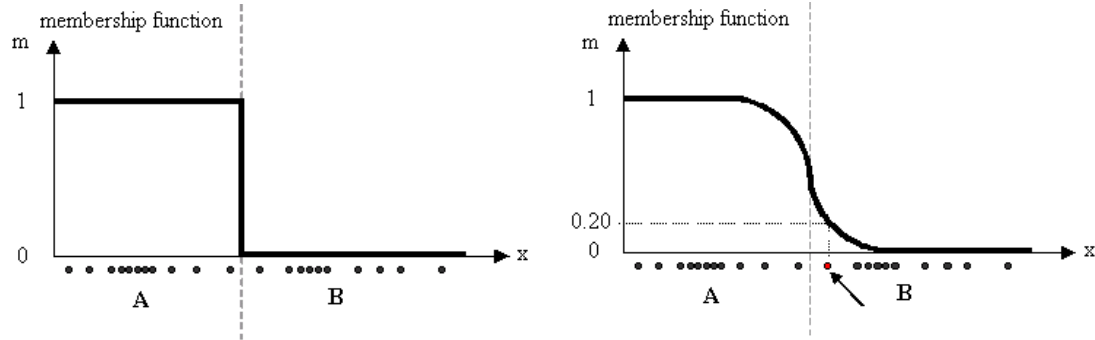
Corresponding to each of the clustering types, four of the most used clustering algorithms are as follows:

- K-Means
- Fuzzy C-Means
- Hierarchical Clustering
- Mixture of Gaussians

FCM Clustering was developed by Dunn in 1973 and improved by Bezdek in 1981 [65], since then it became very popular and frequently used for data classification problems. Thus, the FCM clustering algorithm is proposed in this work.

The basic idea of FCM is that each datum point belongs to a cluster by a membership grade. Therefore, one piece of datum could belong to two or more clusters. The cluster center, which is used to mark the mean location of each cluster, keeps updating along with the membership grade for each datum point until it moves to a proper location. This iterative adjustment is based on the evaluation of an objective function that represents the distance between any given data and the cluster center weighted by the membership grade.

For a better understanding, figure 5.1 shows that a given data set is classified into cluster ‘A’ and ‘B’ by two different approaches [65].



**Fig. 5.1** (a) K-Means Clustering; (b) Fuzzy C-Means Clustering

In the first approach shown on the left hand side of figure 5.1, the coefficient of each datum is unitary, which indicates that one datum belongs only to one cluster. On the contrary, in FCM approach, every datum may be classified into several clusters with different coefficient that represents the membership grad between the datum and cluster center. The matrix is introduced to show the coefficient from above figure (a) and (b).

$$U_{KM} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 1 & 0 \\ \dots & \dots \\ 0 & 1 \end{bmatrix}$$

(a)

$$U_{FCM} = \begin{bmatrix} 0.8 & 0.2 \\ 0.3 & 0.7 \\ 0.6 & 0.4 \\ \dots & \dots \\ 0.9 & 0.1 \end{bmatrix}$$

(b)

Suppose  $x_i$  is the  $i$ th of  $d$ -dimensional measured datum and the membership degree of  $x_i$  in the cluster  $j$  is  $u_{ij}$ , then

$$\sum_{j=1}^c u_{ij} = 1, \forall i = 1, 2, \dots, n \quad (51)$$

The objective function is to minimize the functional (52) given by,

$$J_m = \sum_{i=1}^n \sum_{j=1}^c u_{ij}^m \|x_i - c_j\|^2, \quad 1 \leq m < \infty \quad (52)$$

Where  $m$  is the weighted coefficient greater than 1,  $c_j$  is the  $d$ -dimension center of the cluster.

The membership  $u_{ij}$  and the cluster centers  $c_j$  are defined by,

$$u_{ij} = \frac{1}{\sum_{k=1}^c \left( \frac{\|x_i - c_j\|}{\|x_i - c_k\|} \right)^{\frac{2}{m-1}}} \quad (53)$$

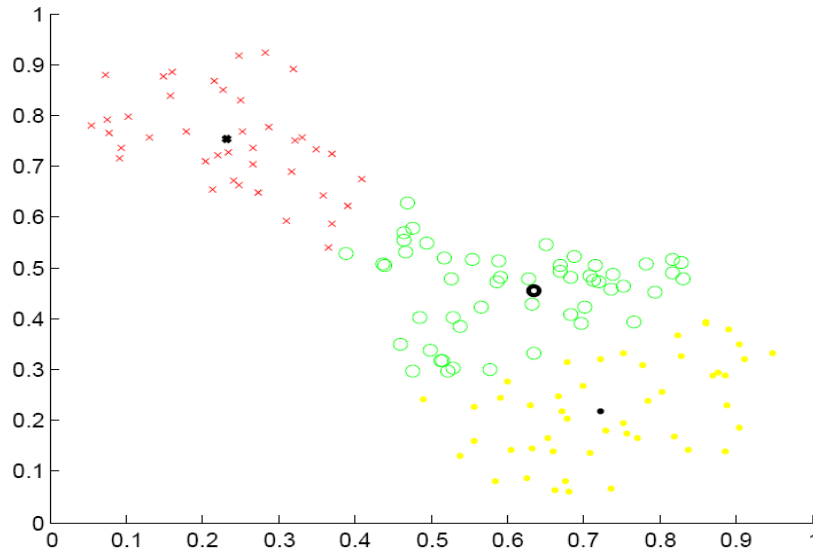
$$c_j = \frac{\sum_{i=1}^n u_{ij}^m \cdot x_i}{\sum_{i=1}^n u_{ij}^m} \quad (54)$$

Fuzzy partitioning is processed through the iterative optimization of objective function along with the update of membership  $u_{ij}$  and cluster centers  $c_j$ . The program will stop until it reaches a termination criterion  $\varepsilon$  in the  $k$  iteration step. The steps of FCM algorithm are as follows [65]:

- 1) Initialize  $U = [u_{ij}]$  matrix,  $U^{(0)}$ ;
- 2) At  $k$ -step: calculate the centers vectors  $C^{(k)} = [c_j]$  with  $U^{(k)}$  by equation (54);
- 3) Update  $U^{(k)}$ ,  $U^{(k+1)}$  by equation (53);
- 4) If  $\|U^{(k+1)} - U^{(k)}\| < \varepsilon$ , then stop; otherwise return to step 2.



A demonstrating example of FCM algorithm is shown in figure 5.2. The data are 2-dimensional and classified into three clusters with colors of red, green and yellow. The centers of clusters are marked by a bigger size point with black color.



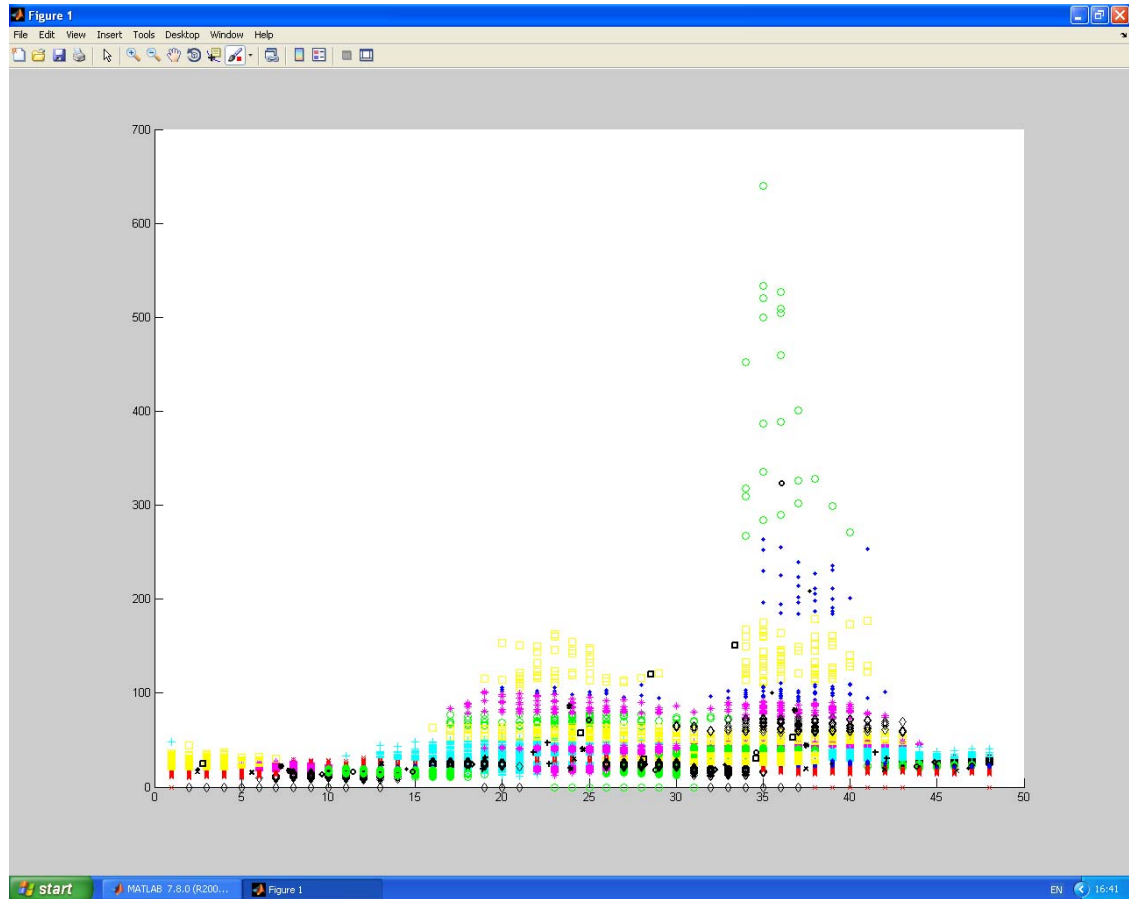
**Fig. 5.2** Illustration of FCM clustering

### 5.3 OPTIMUM NUMBER OF CLUSTERS

In the course of FCM partitioning, the number of clusters must be specified by the users before calculation. However, usually there is no clear idea regarding to how many clusters there should be for a given set of data. Therefore, the optimum number of clusters to our case studies will be discussed in this section.

As mentioned before, the data in our case studies are half-hour electricity spot prices. A trading day is therefore divided into 48 time segments in the cases. Hence, in theory, the number of clusters should be 48, because the prices are considered similar in one time period. Nevertheless, the practical prices are not aggregated according to the time periods when the value of price is affected by many factors in the real world. Those factors, such as balance demand, load constraints, weather conditions, and bidding strategies etc., have

been discussed in chapter 2. The data from *APX-Power UK 2007* are used for the demonstration shown in figure 5.3, which indicates that it is not proper to classify the data into 48 clusters.



**Fig. 5.3** 48 clusters by FCM algorithm

Through the observation and experiments, optimum number of clusters for case study *A* is 4 and for case study *B* is 5. The principle of the number selection is as follows:

- ◆ The more number of clusters, the fewer number of training data in each cluster, which has not enough information for the models to catch during training process;
- ◆ The fewer number of clusters, the much more noise in each training data set, which will influence the accuracy of forecasting models.

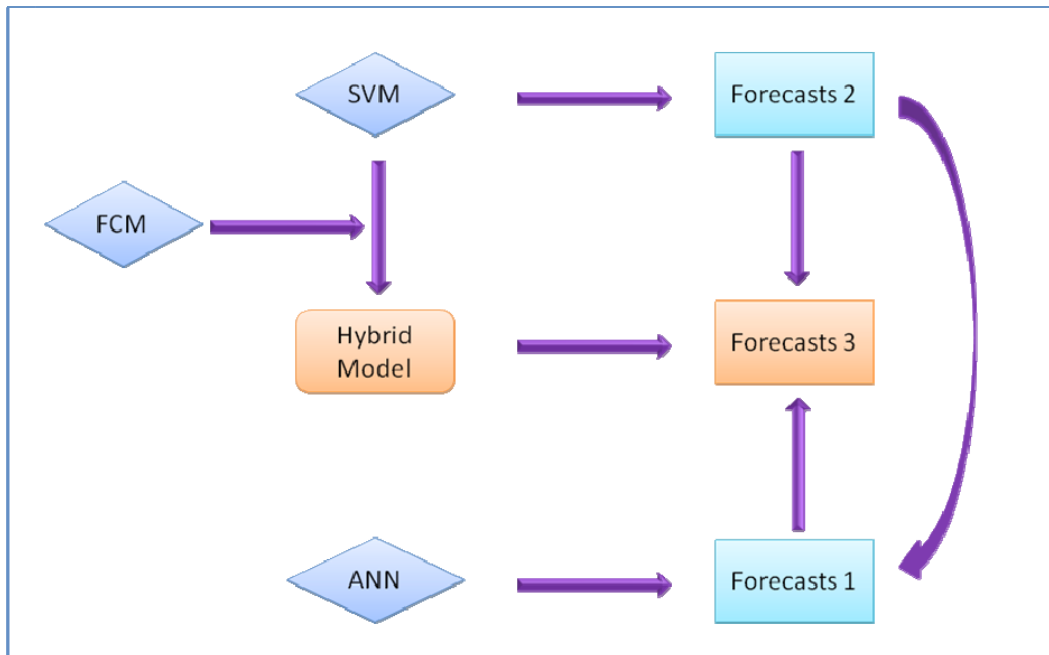
The experiments that employ SVM and FCM with different number of clusters are carried out in next section.

#### **5.4 CASE STUDY: FORECASTING HALF-HOUR UK SPOT POWER MARKETS' PRICES WITH HYBRID MODELS**

In order to test the proposed hybrid models, two simulation experiments are carried out based on the same original data as that used for ANN and SVM models' forecasts. In the first experiment, data are selected from date January 1<sup>st</sup>, 2007 to June 30<sup>th</sup>, 2007 and classified into four partitions by FCM model. Data from date July 1<sup>st</sup>, 2007 to December 31<sup>st</sup>, 2007 are divided into five partitions by FCM model in the second experiment. In each of the partitions, SVM model is applied respectively to forecast half-hour electricity prices by taking the advantages of aggregated data information. Therefore, in this chapter, a hybrid forecasting model is developed by conjunctive use of FCM clustering algorithm and SVM algorithm in order to overcome the limitations of individual model and get a high degree of prediction accuracy.

MatLab is both a powerful numerical computing environment and programming language. For the experiment of data fuzzy partitioning, the software MatLab has been used to solve the problem.

The orange color in figure 5.4 shows the forecasting objective III of this section and the current procedure against the whole project structure.

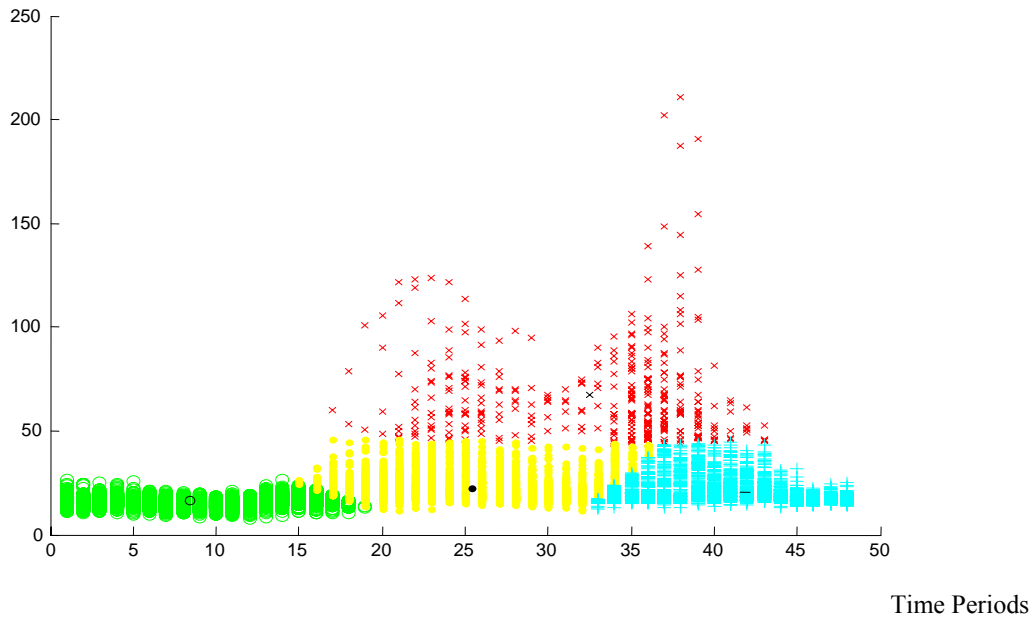


**Fig. 5.4** Objective III and current procedure

### 5.4.1 Forecasts of Case A

As mentioned before, data of case study A are half-hour UK spot power market prices in the first half year 2007. The total number of data is 7968. Those data are classified into four clusters, which are shown in different colors, such as green, red, yellow and blue in figure 5.5. The center of each cluster is marked in black color with a bigger size.

Electricity Prices ( £/MWh)



**Fig. 5.5** FCM\_4 clusters of case *A*

In each of the clusters, training data set is separated from testing data set, which is composed of points belonged to the forecasting time periods from June 16<sup>th</sup>, 2007 to June 30<sup>th</sup>, 2007.

Forecasting model SVM is applied on data clusters one by one and the algorithm for prediction is epsilon-SVR with kernel function RBF. During the cross-validation, folder *V* is set for 10. The best parameters of each training program are listed in table 5.1.

Clusters Number	Clusters Color	Points Number	Best Parameters		
			C	P	Q
Cluster 1	Red	366	64.0	0.00390625	0.03125
Cluster 2	Yellow	2677	64.0	0.00390625	0.00390625
Cluster 3	Light blue	2205	64.0	0.00390625	0.00390625
Cluster 4	Light green	2720	32.0	0.00390625	0.00390625

**Table 5.1** Best Parameters for each training program in case *A*

Reference prices and the forecast prices are listed in table E (a) (b) and (c) in appendix, respectively. Corresponding to the real price curves, the curves of forecast prices to the fifteen days (16<sup>th</sup> – 30<sup>th</sup> June 2007) are illustrated in figures 5.6 - 5.20.

Criterion *MAPE* is used to calculate the forecasting errors of proposed hybrid models. The calculation results are listed in table 5.2 and illustrated in figure 5.21.

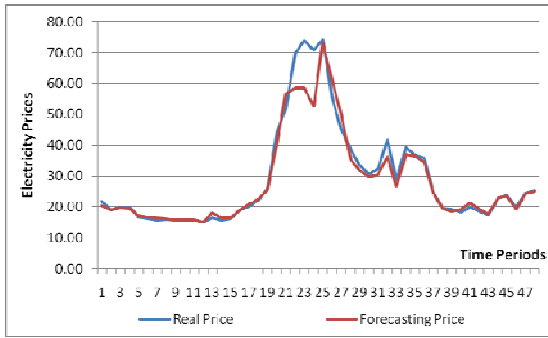


Fig. 5.6 Hybrid model forecasting results on Jun 16th, 2007

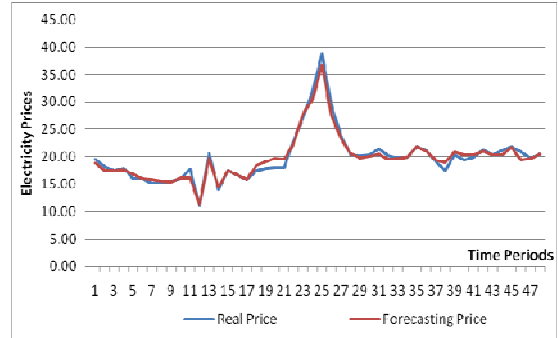


Fig. 5.7 Hybrid model forecasting results on Jun 17th, 2007

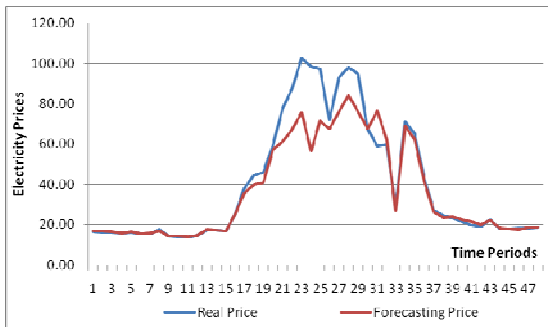


Fig. 5.8 Hybrid model forecasting results on Jun 18th, 2007

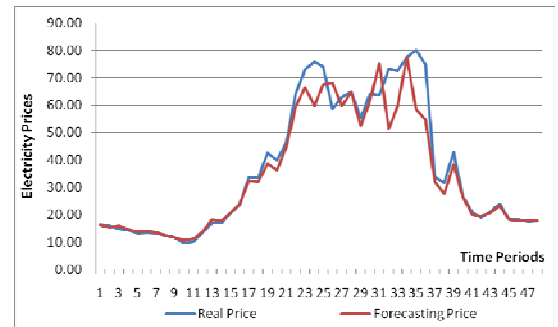


Fig. 5.9 Hybrid model forecasting results on Jun 19th, 2007

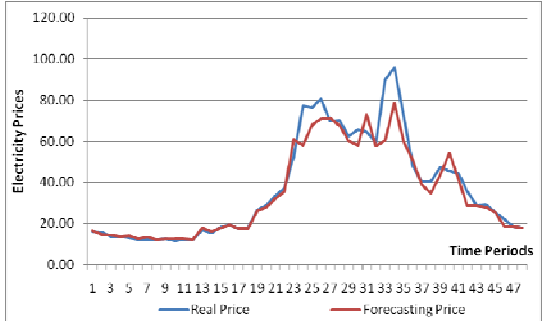


Fig. 5.10 Hybrid model forecasting results on Jun 20th, 2007

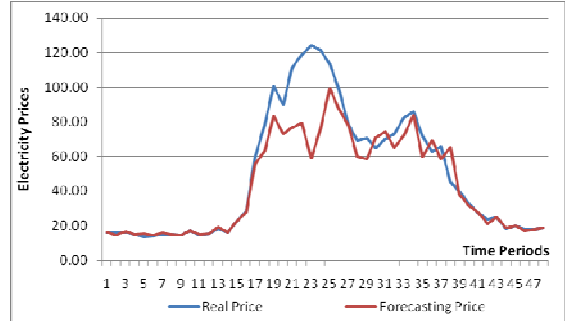


Fig. 5.11 Hybrid model forecasting results on Jun 21st, 2007

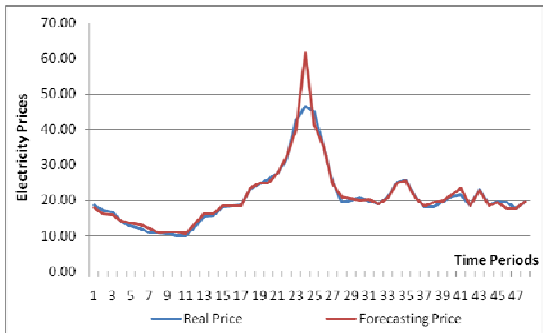


Fig. 5.12 Hybrid model forecasting results on Jun 22nd, 2007

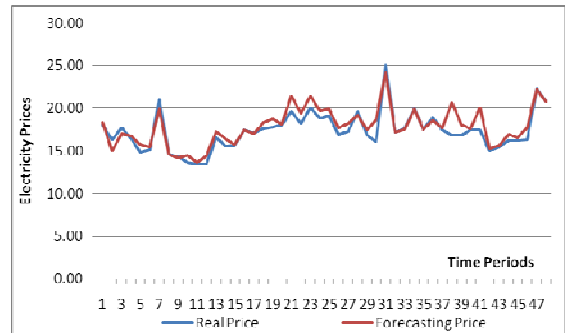


Fig. 5.13 Hybrid model forecasting results on Jun 23rd, 2007

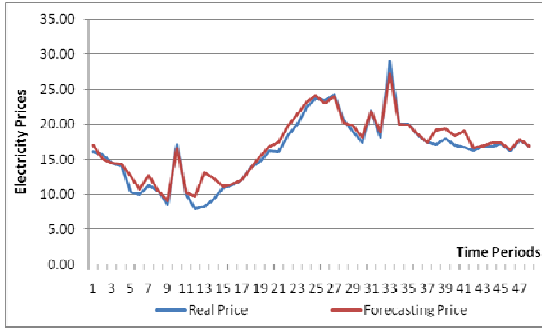


Fig. 5.14 Hybrid model forecasting results on Jun 24th, 2007

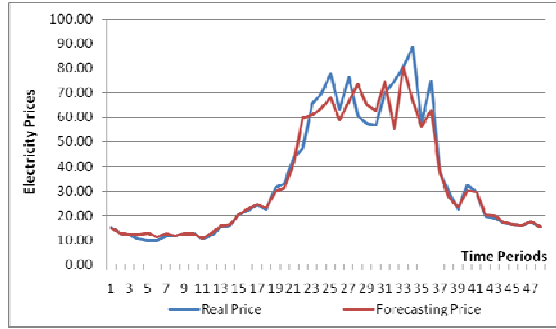


Fig. 5.15 Hybrid model forecasting results on Jun 25th, 2007

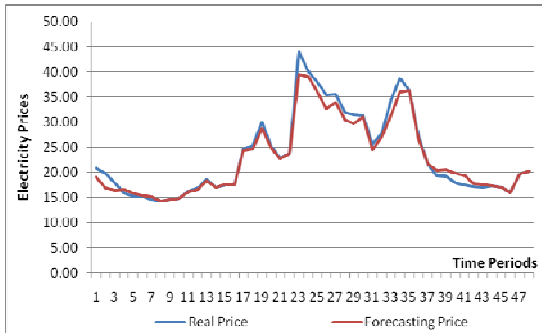


Fig. 5.16 Hybrid model forecasting results on Jun 26th, 2007

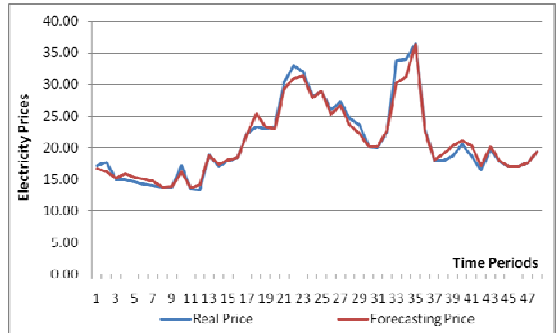


Fig. 5.17 Hybrid model forecasting results on Jun 27th, 2007

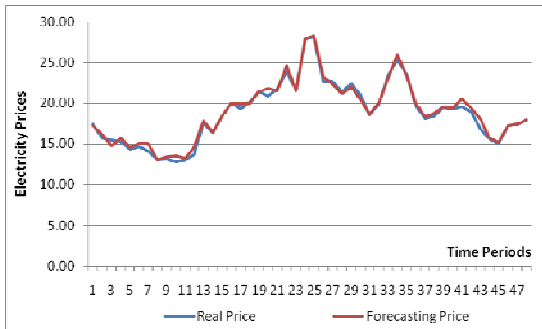


Fig. 5.18 Hybrid model forecasting results on Jun 28th, 2007

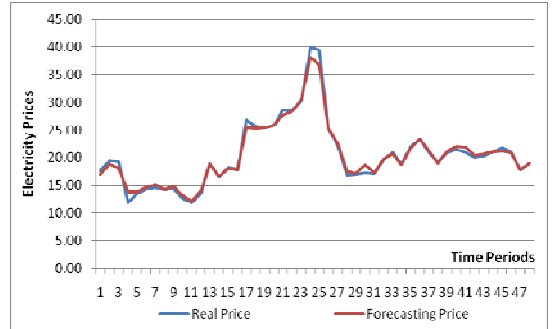


Fig. 5.19 Hybrid model forecasting results on Jun 29th, 2007

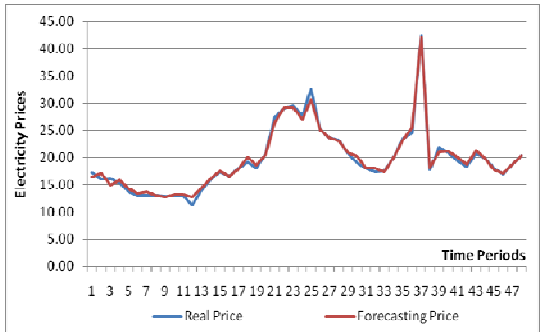
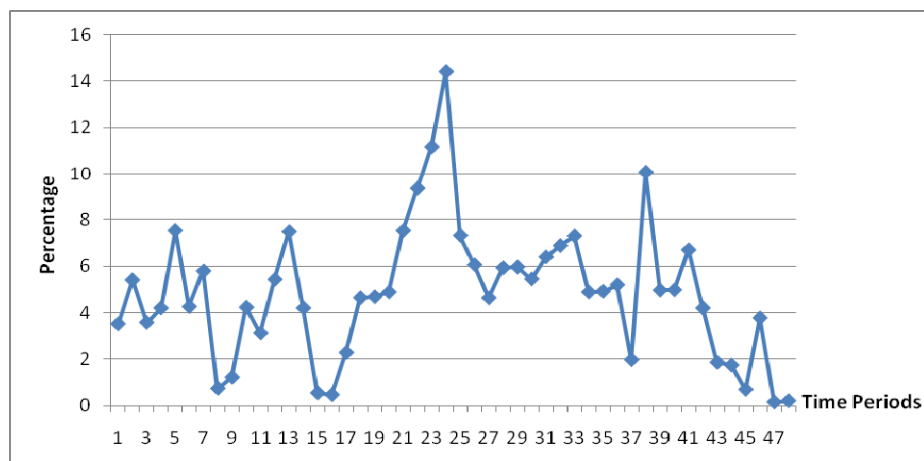


Fig. 5.20 Hybrid model forecasting results on Jun 30th, 2007



<b>Time Periods</b>	1	2	3	4	5	6
<b>MAPE</b>	3.513	5.4	3.573	4.193	7.527	4.256
<b>Time Periods</b>	7	8	9	10	11	12
<b>MAPE</b>	5.785	0.734	1.215	4.226	3.118	5.425
<b>Time Periods</b>	13	14	15	16	17	18
<b>MAPE</b>	7.48	4.196	0.542	0.468	2.279	4.635
<b>Time Periods</b>	19	20	21	22	23	24
<b>MAPE</b>	4.677	4.88	7.523	9.345	11.159	14.401
<b>Time Periods</b>	25	26	27	28	29	30
<b>MAPE</b>	7.309	6.056	4.629	5.924	5.957	5.443
<b>Time Periods</b>	31	32	33	34	35	36
<b>MAPE</b>	6.394	6.876	7.293	4.877	4.911	5.192
<b>Time Periods</b>	37	38	39	40	41	42
<b>MAPE</b>	1.972	10.066	4.958	4.972	6.692	4.195
<b>Time Periods</b>	43	44	45	46	47	48
<b>MAPE</b>	1.858	1.739	0.689	3.768	0.155	0.209

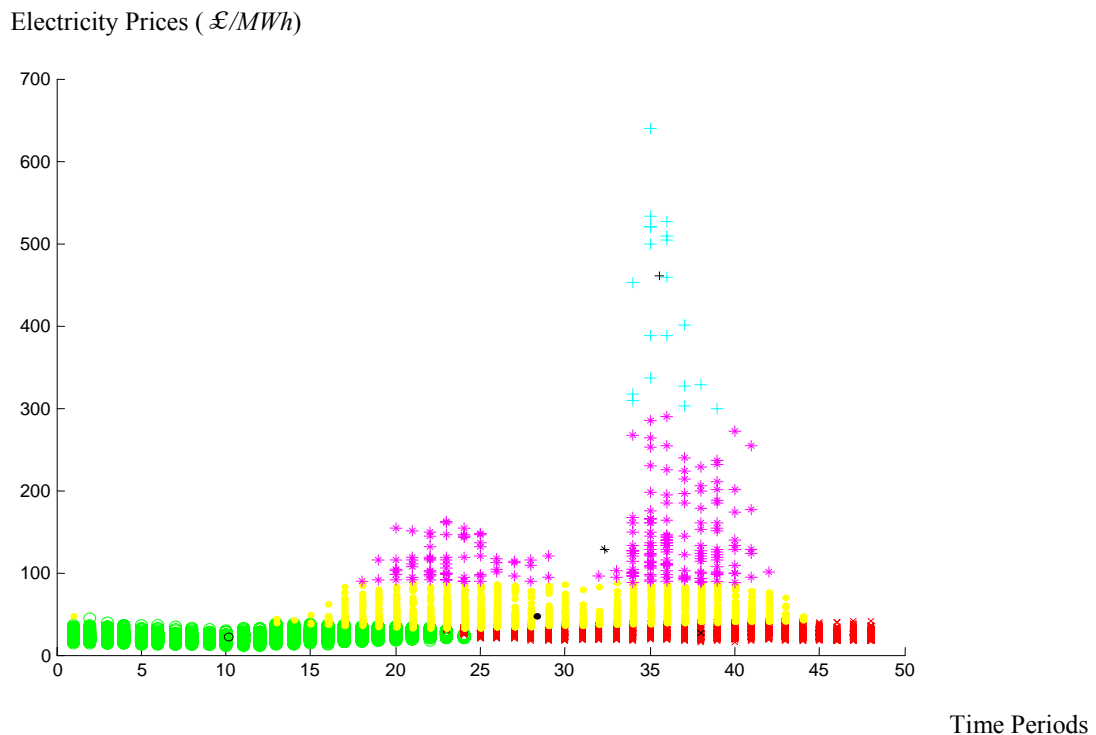
**Table 5.2** Hybrid models' MAPE of 48 time periods (16<sup>th</sup> - 30<sup>th</sup> June 2007)



**Fig. 5.21** Hybrid models' MAPE of 48 time periods (16<sup>th</sup> - 30<sup>th</sup> June 2007)

## 5.4.2 Forecasts of Case B

Data of case study B are half-hour UK spot power market prices in the second half year 2007. The total number of data is 8064. From figure 5.22, it can be seen that the data are classified into five clusters shown in different colors, such as green, red, blue, purple and yellow. The bigger sizes of points in black color are the centers of clusters.



**Fig. 5.22** FCM\_5 clusters of case B

In each of the clusters, training data set is separated from testing data set whose points are belonged to the forecasting time periods, December 1<sup>st</sup> 2007 to December 15<sup>th</sup> 2007.

As the same forecasting procedure in case study A, model SVM is applied on data clusters one by one in case study B. The algorithm for prediction is epsilon-SVR and the kernel function is RBF. The folder V in cross-validation is set for 10. The best parameters of each training program are listed in table 5.3.

Clusters Number	Clusters Color	Points Number	Best Parameters		
			C	P	Q
Cluster 1	Light green	3378	64.0	0.00390625	0.00390625
Cluster 2	Purple	209	64.0	0.5	0.0625
Cluster 3	Yellow	1362	64.0	0.00390625	0.00390625
Cluster 4	Light blue	20	NA	NA	NA
Cluster 5	Red	3095	64.0	0.00390625	0.00390625

**Table 5.3** Best Parameters for each training program in case *B*

In case study B, the data of cluster 4 are the extremely volatile price spikes. Therefore, the twenty data points, as shown above in table 5.3, are computed automatically independent of the other data groups and are not used for the training programs, consequently the data noise is reduced with regard to the forecasting.

The forecasting results of case study B and reference data are listed in table F (a) (b) and (c) in appendix, respectively. Corresponding to real price curves, the curves of forecasting prices to the fifteen days, December 1<sup>st</sup> 2007 to December 15<sup>th</sup> 2007, are illustrated in figures 5.23 - 5.37.

The forecasting errors of proposed hybrid models are calculated by the same method *MAPE*. The calculation results are listed in table 5.4 and illustrated in figure 5.38.

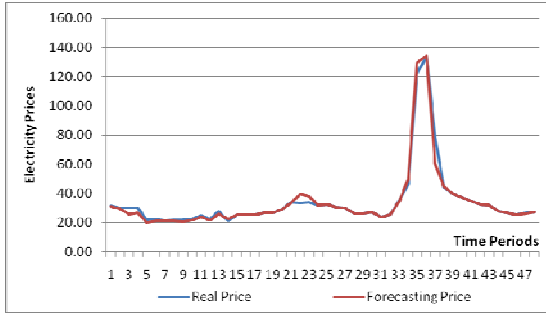


Fig. 5.23 Hybrid model forecasting results on Dec 1st, 2007

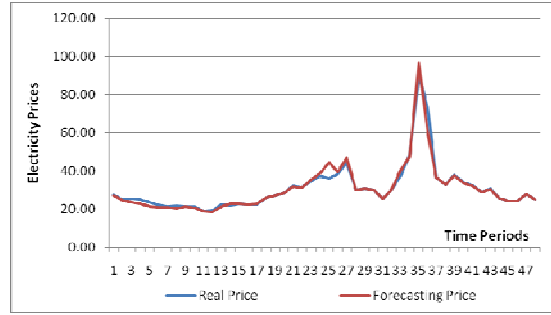


Fig. 5.24 Hybrid model forecasting results on Dec 2nd, 2007

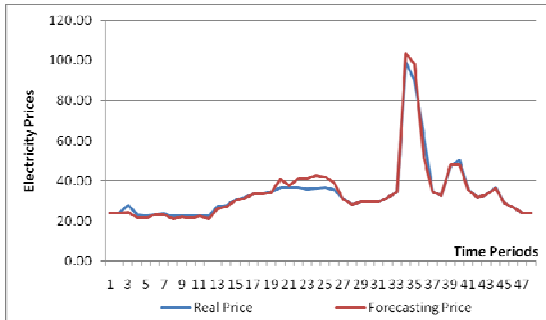


Fig. 5.25 Hybrid model forecasting results on Dec 3rd, 2007

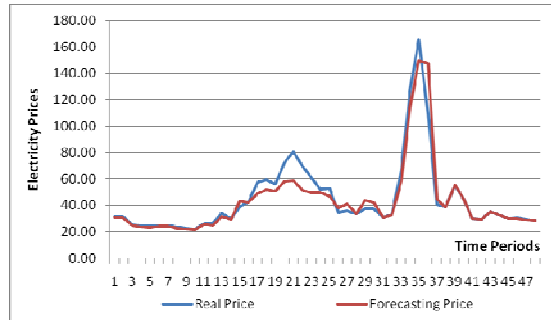


Fig. 5.26 Hybrid model forecasting results on Dec 4th, 2007

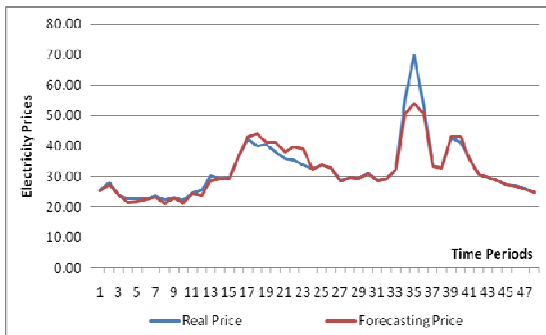


Fig. 5.27 Hybrid model forecasting results on Dec 5th, 2007

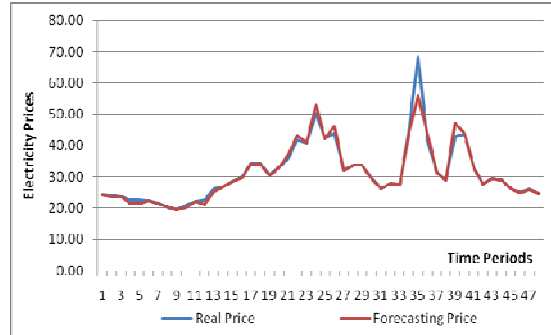


Fig. 5.28 Hybrid model forecasting results on Dec 6th, 2007

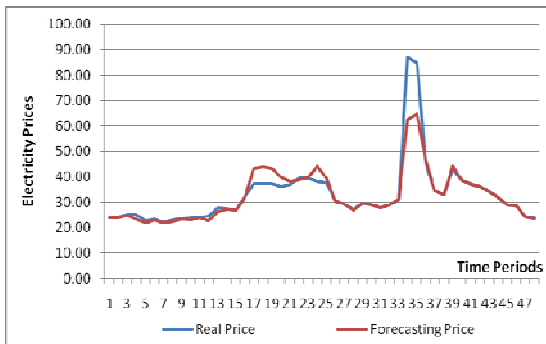


Fig. 5.29 Hybrid model forecasting results on Dec 7th, 2007

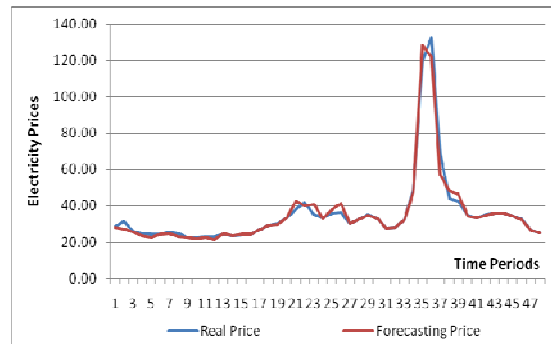


Fig. 5.30 Hybrid model forecasting results on Dec 8th, 2007

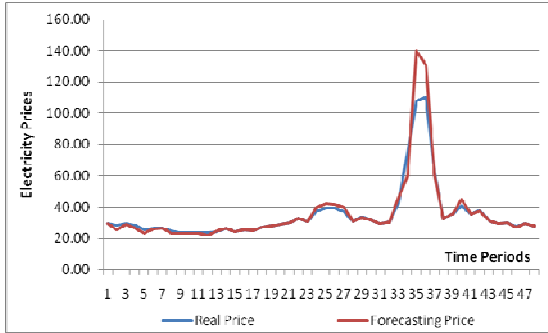


Fig. 5.31 Hybrid model forecasting results on Dec 9th, 2007

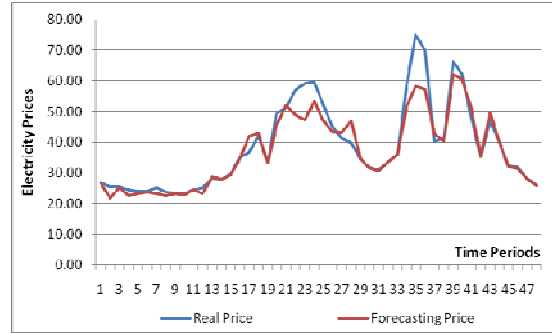


Fig. 5.32 Hybrid model forecasting results on Dec 10th, 2007

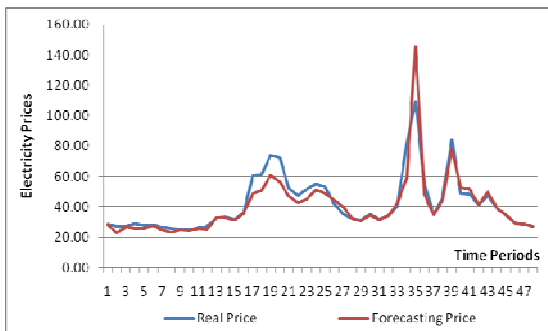


Fig. 5.33 Hybrid model forecasting results on Dec 11th, 2007

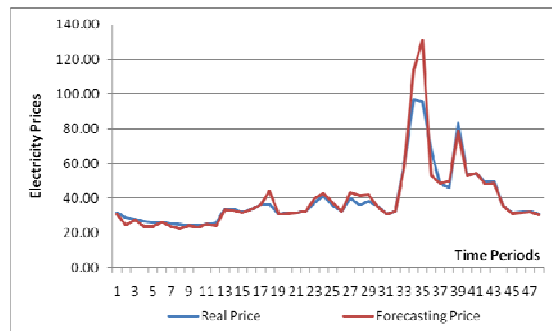


Fig. 5.34 Hybrid model forecasting results on Dec 12th, 2007

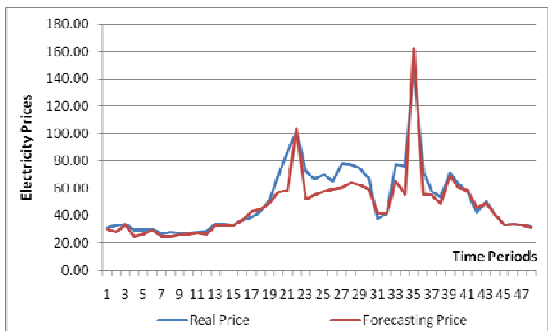


Fig. 5.35 Hybrid model forecasting results on Dec 13th, 2007

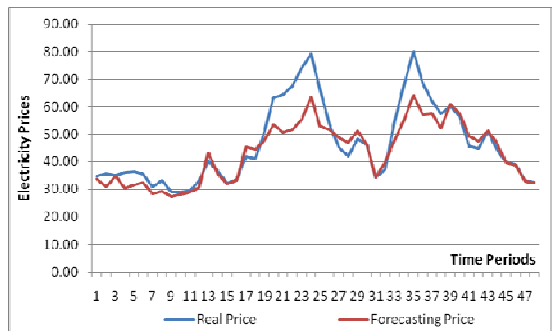


Fig. 5.36 Hybrid model forecasting results on Dec 14th, 2007

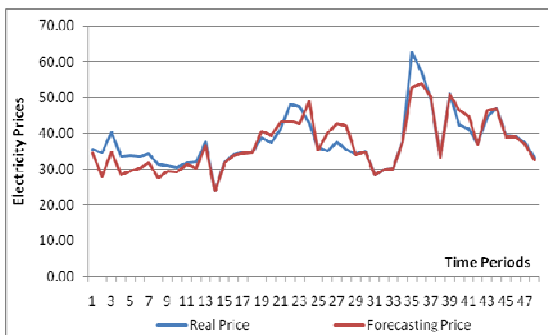
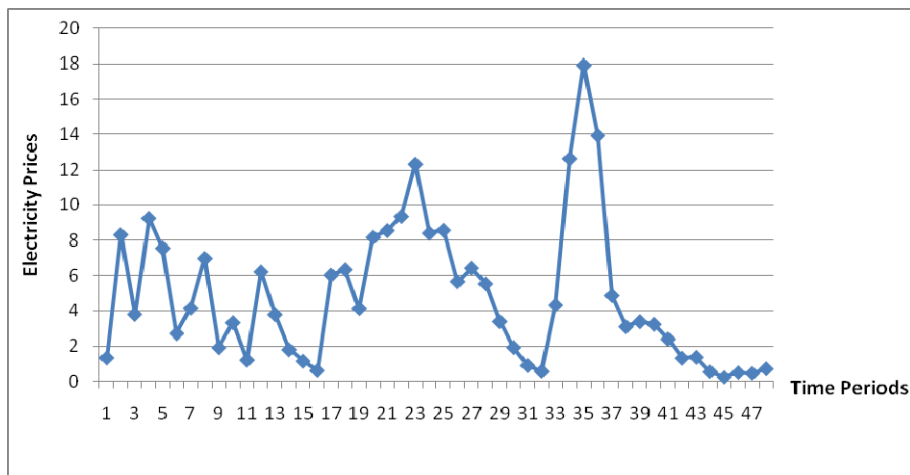


Fig. 5.37 Hybrid model forecasting results on Dec 15th, 2007

<b>Time Periods</b>	1	2	3	4	5	6
<b>MAPE</b>	1.375	8.315	3.803	9.24	7.57	2.733
<b>Time Periods</b>	7	8	9	10	11	12
<b>MAPE</b>	4.16	7.000	1.946	3.332	1.245	6.24
<b>Time Periods</b>	13	14	15	16	17	18
<b>MAPE</b>	3.791	1.832	1.19	0.658	6.056	6.367
<b>Time Periods</b>	19	20	21	22	23	24
<b>MAPE</b>	4.138	8.168	8.549	9.346	12.335	8.4
<b>Time Periods</b>	25	26	27	28	29	30
<b>MAPE</b>	8.564	5.679	6.453	5.549	3.402	1.958
<b>Time Periods</b>	31	32	33	34	35	36
<b>MAPE</b>	0.941	0.604	4.338	12.645	17.916	13.925
<b>Time Periods</b>	37	38	39	40	41	42
<b>MAPE</b>	4.884	3.11	3.392	3.245	2.425	1.357
<b>Time Periods</b>	43	44	45	46	47	48
<b>MAPE</b>	1.409	0.587	0.266	0.538	0.497	0.758

**Table 5.4** Hybrid models' MAPE of 48 time periods (1<sup>st</sup> -15<sup>th</sup> December 2007)



**Fig. 5.38** Hybrid models' MAPE of 48 time periods (1<sup>st</sup> -15<sup>th</sup> December 2007)

## **5.5 SUMMARY**

In order to overcome the limitations of individual forecasting model, a hybrid model combining FCM clustering algorithm and SVM regression is proposed in this chapter. According to the value of power prices, thousands of price data are classified by the unsupervised learning algorithm of FCM clustering. SVM regression model is applied onto each cluster by taking the advantages of aggregated data information, which has less noise for the training programs. Based on the same experimental data as that used for ANN and SVM forecasting, two case studies are carried out to test the proposed hybrid model and the results show its feasibility. In order to demonstrate the advances of the improved forecasting model, a further comparison among ANN model, single SVM model and the hybrid model will be analyzed and shown in next chapter 6.

# 6. Comparative Analysis of Different Modeling and Forecasting

## 6.1 INTRODUCTION

The short-term electricity prices are forecasted by three different predictors, ANNs, SVM and the hybrid models, respectively. ANNs are the most popular and successfully practical tools for forecasting. SVM is a newly developed technique that has many attractive features and good performance in terms of prediction. A hybrid model, which combines SVM and FCM algorithm, has been developed in order to overcome the limitations of single forecaster. In order to evaluate the accuracy and advantages of different models, forecasts are based on the same training data set. Those data are real power price data requested from *APX Power UK* at the year 2007. The data from January 1<sup>st</sup>, 2007 to May 31<sup>st</sup>, 2007 are trained and applied on the models to forecast the prices with regard to each half-hour from June 16<sup>th</sup>, 2007 to June 30<sup>th</sup>, 2007. Similarly, the data from July 1<sup>st</sup>, 2007 to November 30<sup>th</sup>, 2007 are trained to forecast the prices on the date from December 1<sup>st</sup>, 2007 to December 15<sup>th</sup>, 2007. Therefore, based on the UK spot power markets, the prediction focuses on each half-hour electricity prices, fifteen days ahead.

In this chapter, the criterion of forecasting errors, MAPE, is used to evaluate the accuracy of forecasting models.

The rest of this chapter is structured as follows: The criteria of forecasting errors are introduced in Section 6.2. Section 6.3 compares and analyzes the different forecasters, such as ANNs, SVM and the hybrid models. Section 6.4 summarizes this chapter.



## 6.2 CRITERIONS

There are many criterions to assess the forecasting accuracy. Four different criterions are introduced one by one in this section. The most widely used standard for price forecasting error is the Mean Absolute Percentage Error – MAPE.

- Absolute Percentage Error – APE

$$APE = \frac{|p_i - p'_i|}{p_i} \times 100\% \quad (55)$$

- Mean Absolute Percentage Error – MAPE

$$MAPE = \frac{1}{N} \sum_{i=1}^N \frac{|p_i - p'_i|}{p_i} \times 100\% \quad (56)$$

- Sum Squared Error – SSE

$$SSE = \sum_{i=1}^N (p_i - p'_i)^2 \quad (57)$$

- Mean Squared Error – MSE

$$MSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (p_i - p'_i)^2} \quad (58)$$

Where  $N$  is time periods,  $p_i$  and  $p'_i$  is the actual and the forecast electricity prices, respectively.

## 6.3 FORECASTERS COMPARISON AND ANALYSIS

### 6.3.1 Numerical Results Based on Case A (16<sup>th</sup> - 30<sup>th</sup> June 2007)

In order to demonstrate the advantages of proposed hybrid model, comparisons of forecast price curves among ANN model, single SVM model and the hybrid model are shown in figure 6.1 - 6.15.

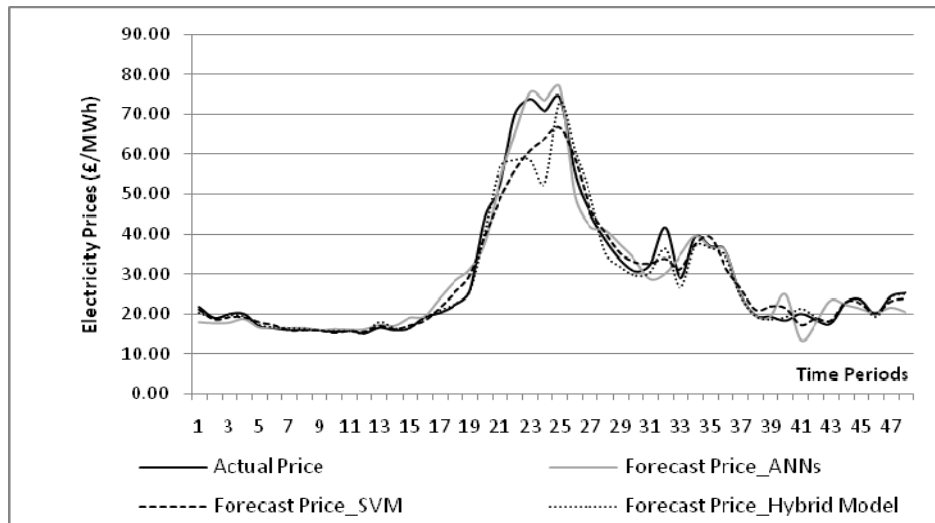


Fig. 6.1 Forecasting results comparison on June 16<sup>th</sup>, 2007

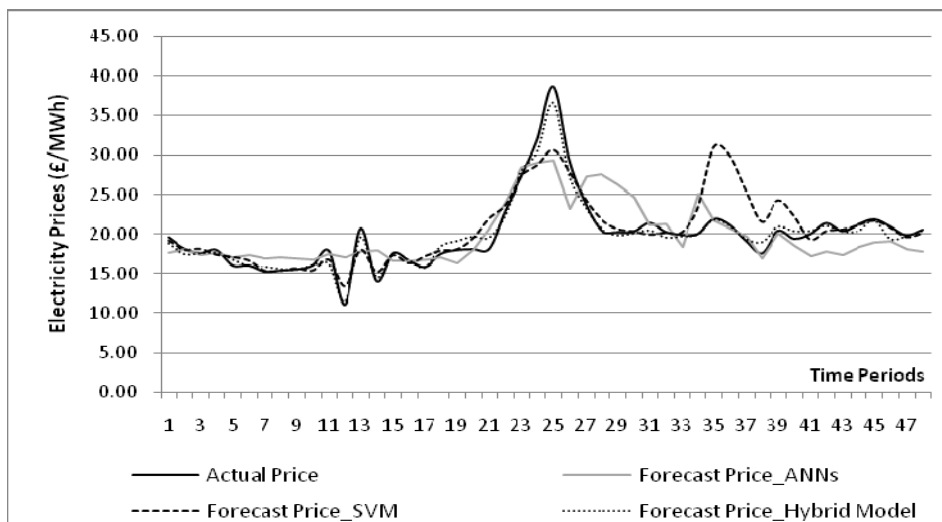
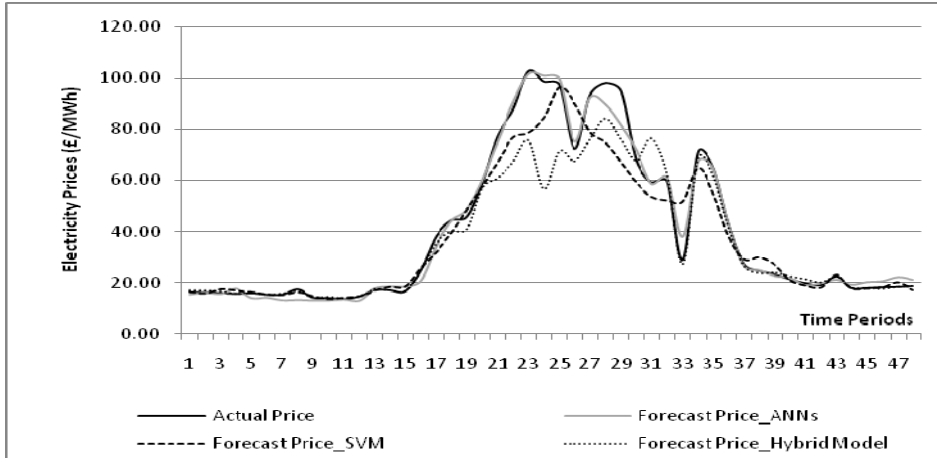
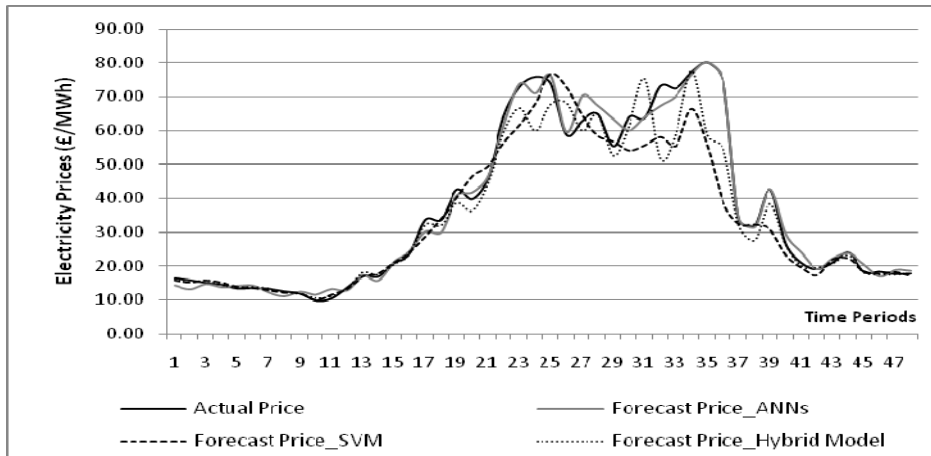


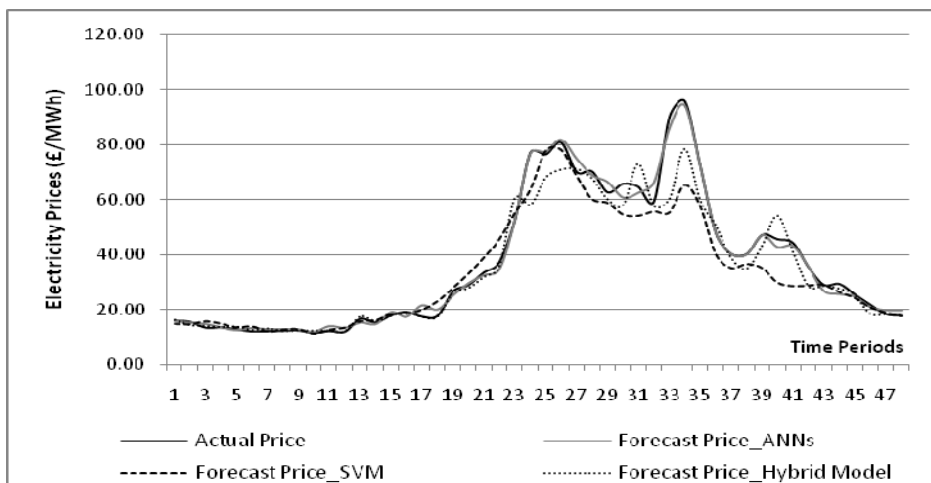
Fig. 6.2 Forecasting results comparison on June 17<sup>th</sup>, 2007



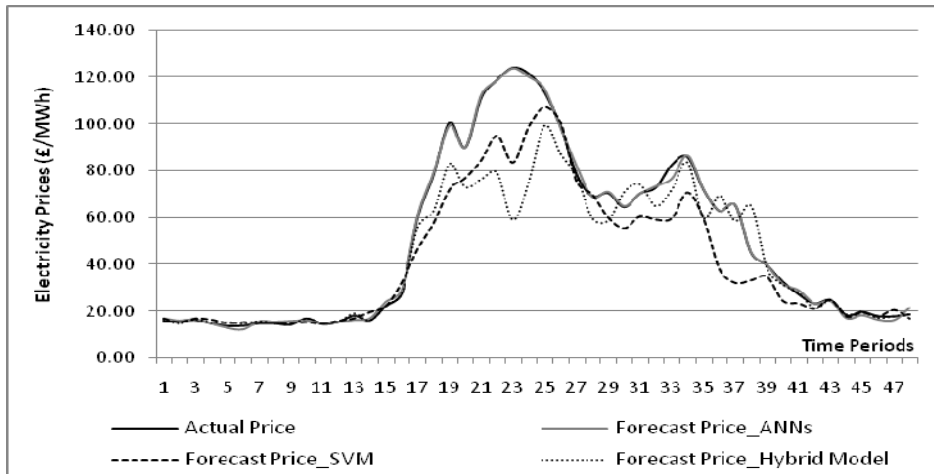
**Fig. 6.3** Forecasting results comparison on June 18<sup>th</sup>, 2007



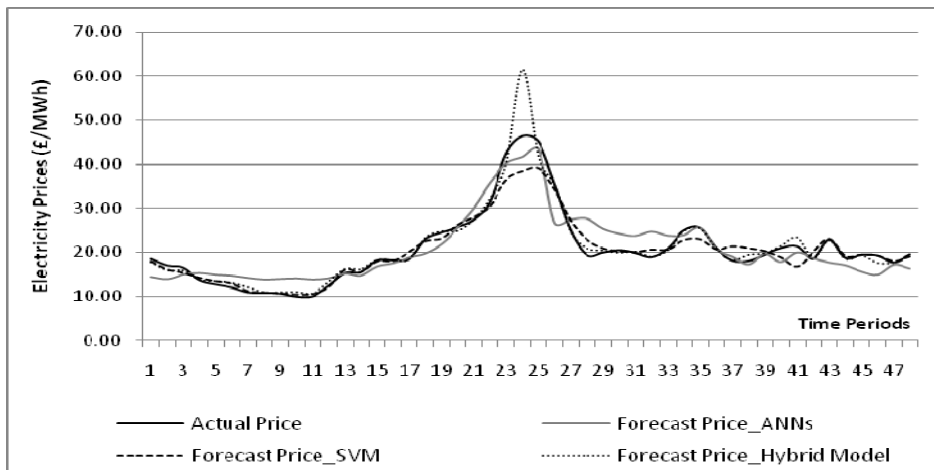
**Fig. 6.4** Forecasting results comparison on June 19<sup>th</sup>, 2007



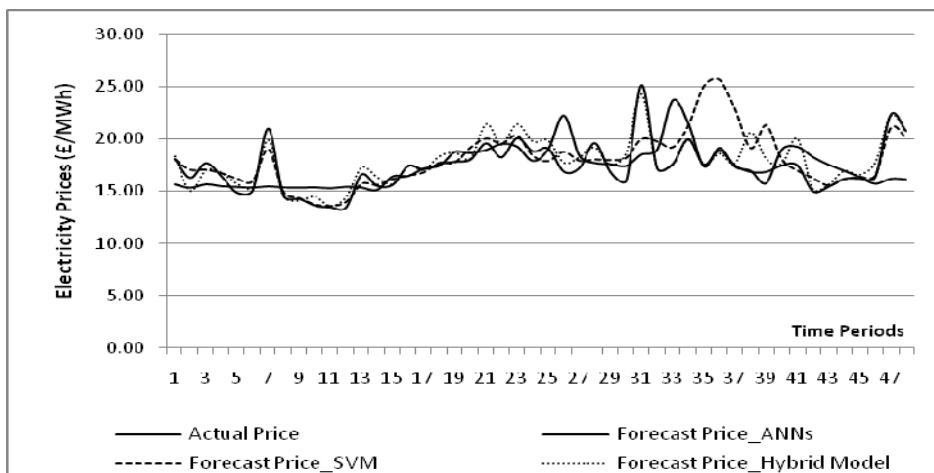
**Fig. 6.5** Forecasting results comparison on June 20<sup>th</sup>, 2007



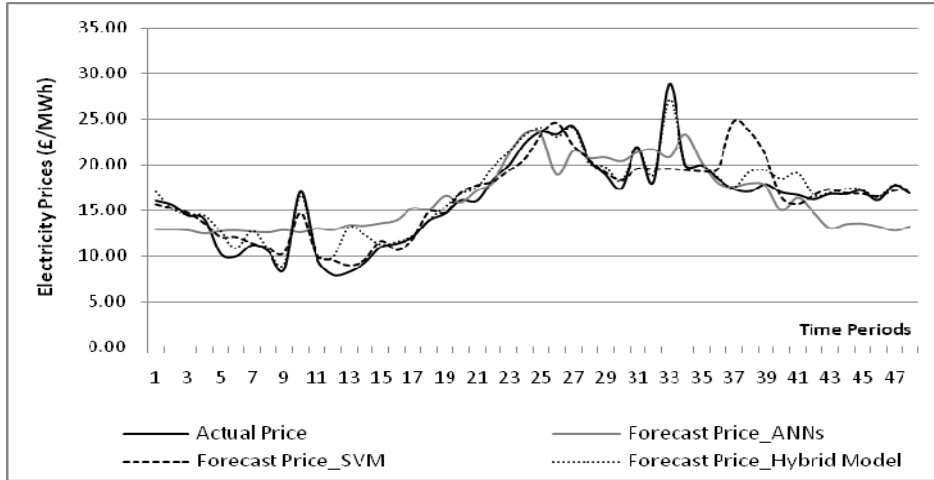
**Fig. 6.6** Forecasting results comparison on June 21<sup>st</sup>, 2007



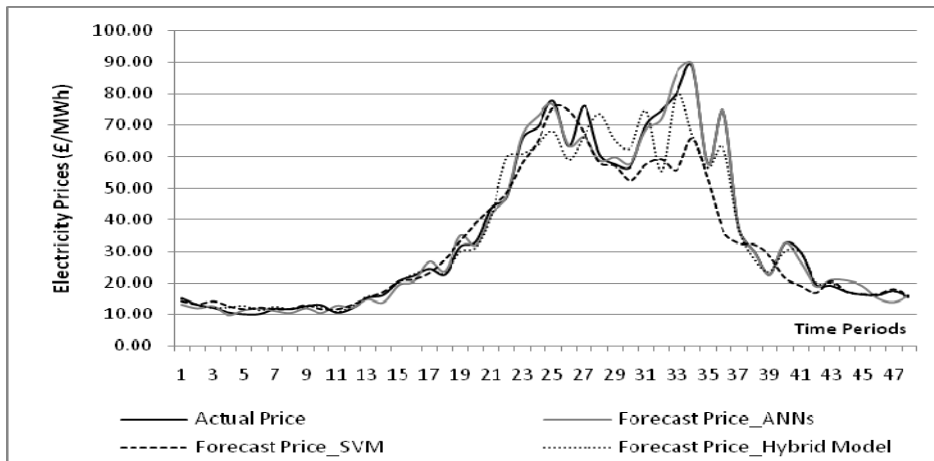
**Fig. 6.7** Forecasting results comparison on June 22<sup>nd</sup>, 2007



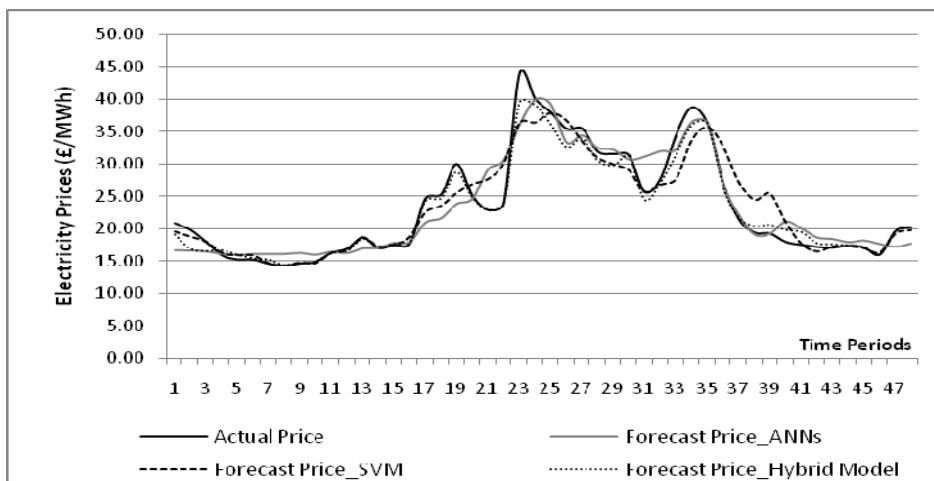
**Fig. 6.8** Forecasting results comparison on June 23<sup>rd</sup>, 2007



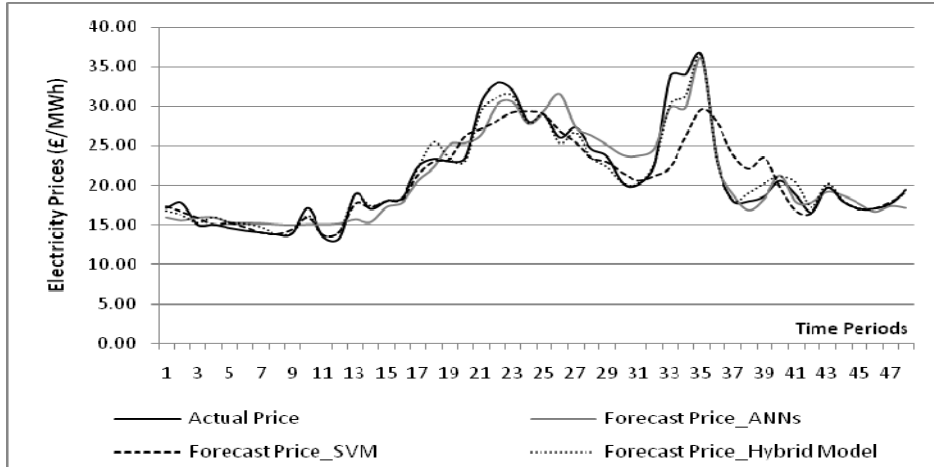
**Fig. 6.9** Forecasting results comparison on June 24<sup>th</sup>, 2007



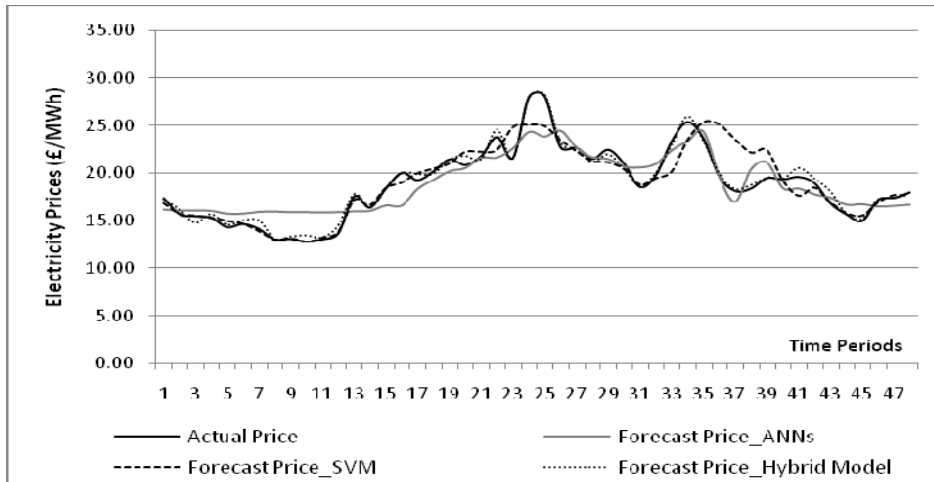
**Fig. 6.10** Forecasting results comparison on June 25<sup>th</sup>, 2007



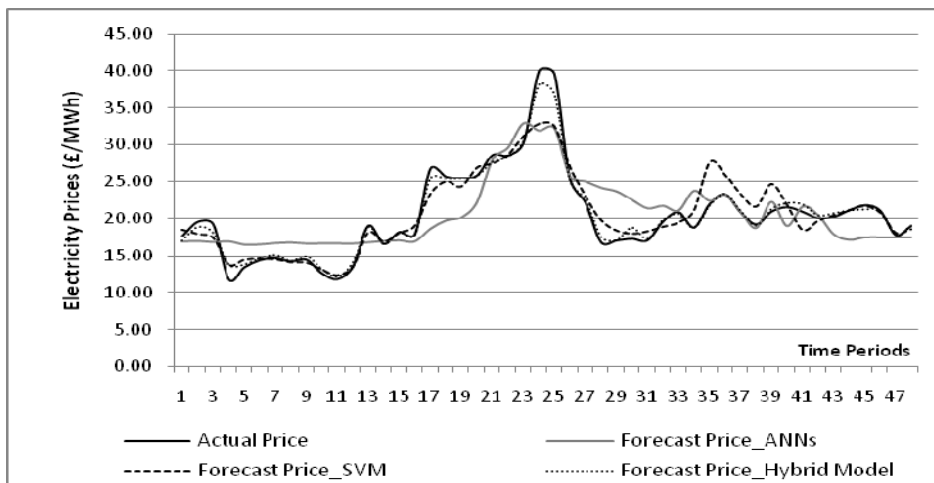
**Fig. 6.11** Forecasting results comparison on June 26<sup>th</sup>, 2007



**Fig. 6.12** Forecasting results comparison on June 27<sup>th</sup>, 2007



**Fig. 6.13** Forecasting results comparison on June 28<sup>th</sup>, 2007



**Fig. 6.14** Forecasting results comparison on June 29<sup>th</sup>, 2007

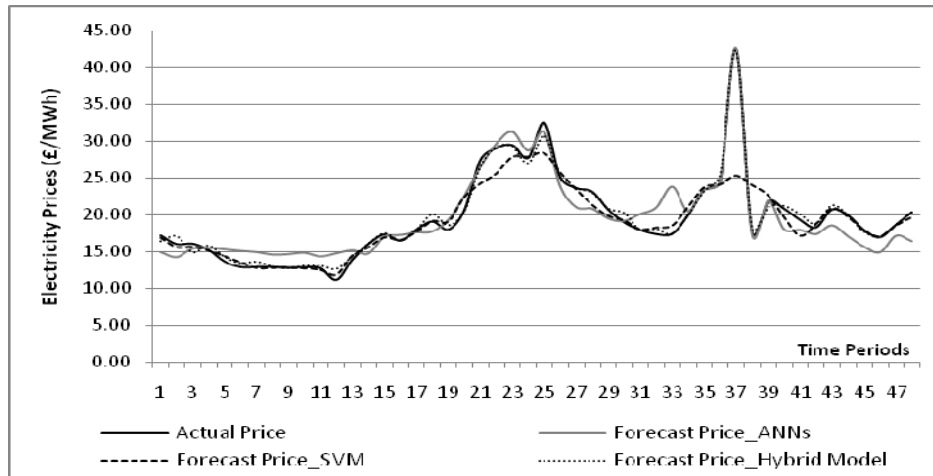


Fig. 6.15 Forecasting results comparison on June 30<sup>th</sup>, 2007

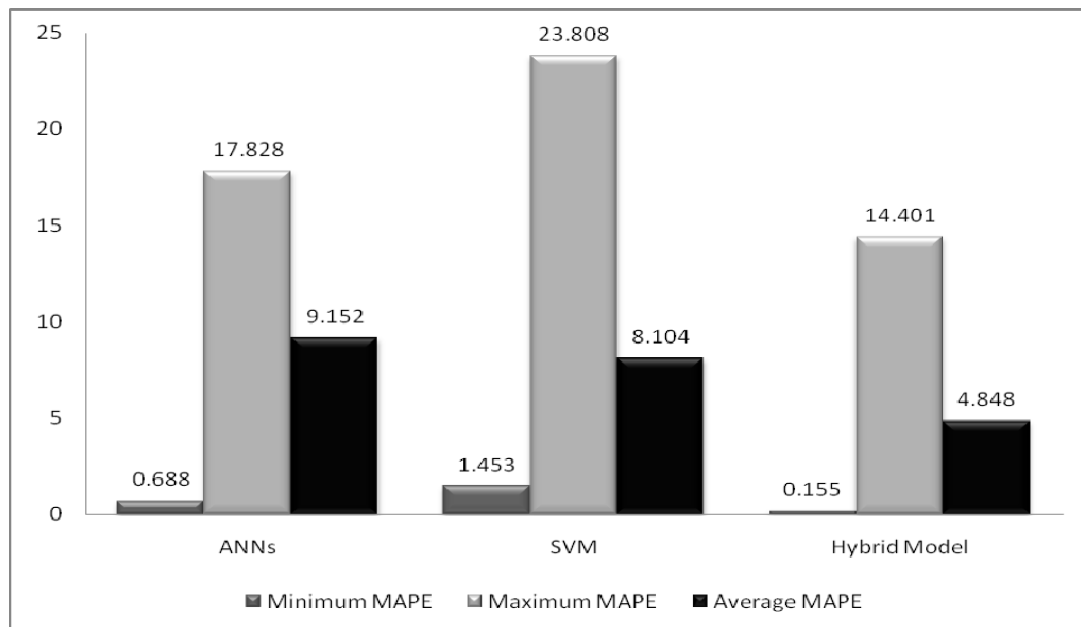
Time Periods	ANNs	SVM	Hybrid Model	Time Periods	ANNs	SVM	Hybrid Model
1	11.605	3.413	3.513	25	5.716	7.275	7.309
2	8.889	3.867	5.400	26	10.363	8.094	6.057
3	6.735	5.963	3.574	27	7.541	5.406	4.629
4	7.899	5.698	4.194	28	11.606	8.367	5.925
5	9.779	6.939	7.527	29	11.827	6.536	5.958
6	10.987	6.653	4.256	30	9.858	7.812	5.443
7	11.931	1.590	5.785	31	10.244	8.153	6.394
8	12.834	1.453	0.735	32	12.019	9.968	6.877
9	12.909	3.021	1.215	33	14.446	22.131	7.293
10	15.197	4.565	4.226	34	7.900	13.315	4.878
11	15.952	3.618	3.119	35	0.688	16.830	4.912
12	17.828	6.037	5.426	36	0.727	23.005	5.193
13	11.337	4.536	7.480	37	1.798	23.808	1.972
14	10.000	4.345	4.197	38	2.815	18.600	10.066
15	7.735	2.361	0.542	39	1.890	18.834	4.959
16	7.111	4.648	0.468	40	10.173	12.399	4.973
17	11.054	8.717	2.280	41	9.111	12.697	6.693
18	9.187	8.516	4.636	42	5.997	6.224	4.195
19	10.253	6.743	4.678	43	11.645	1.936	1.858
20	4.474	9.004	4.880	44	9.856	1.976	1.740
21	6.324	10.130	7.524	45	11.618	1.836	0.690
22	6.784	10.946	9.346	46	9.405	1.507	3.769
23	4.566	11.623	11.159	47	11.525	3.699	0.155
24	5.744	10.467	14.401	48	13.398	3.722	0.209

Table 6.1 Comparative MAPE results for 48 time periods (% , 16<sup>th</sup> - 30<sup>th</sup> June, 2007)

According to the forecasting results in case study A, forecasting errors of the three forecasters, such as ANNs, SVM and hybrid models, are calculated in terms of MAPE for each time period and listed in table 6.1. Results analysis of MAPE to the 48 time periods, during the second half month of June 2007, are shown in table 6.2 and illustrated in figure 6.16.

MAPE	ANNs	SVM	Hybrid Model
<b>Minimum MAPE</b>	0.688	1.453	0.155
<b>Maximum MAPE</b>	17.828	23.808	14.401
<b>Average MAPE</b>	9.152	8.104	4.848

**Table 6.2** Statistical analysis of MAPE for 48 time periods (% , 16<sup>th</sup> - 30<sup>th</sup> June, 2007)



**Fig. 6.16** Statistical analysis of MAPE for 48 time periods (% , 16<sup>th</sup> - 30<sup>th</sup> June, 2007)



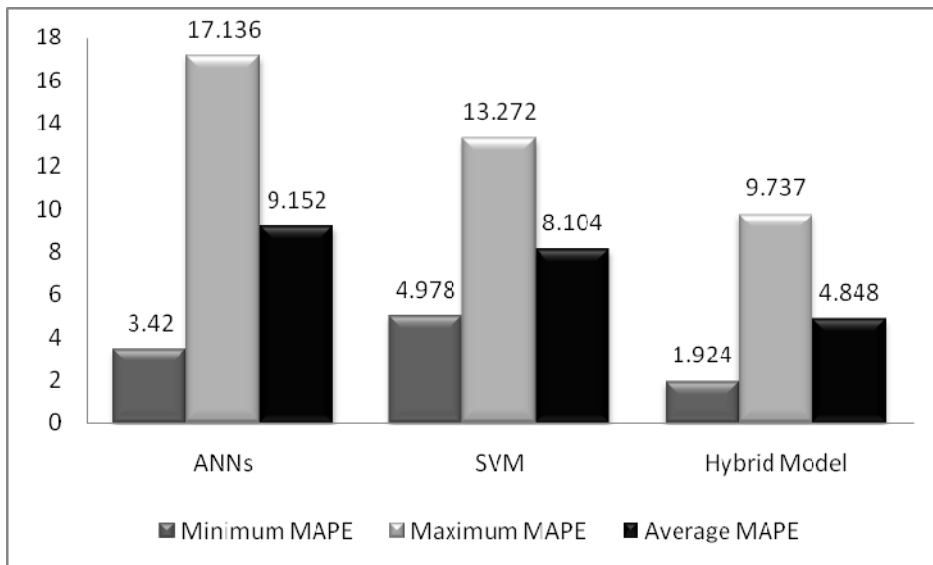
Table 6.3 lists the forecasting errors calculated for each day in case study A. The results analysis of daily MAPE from June 16<sup>th</sup>, 2007 to June 30<sup>th</sup>, 2007 is shown in table 6.4. Through the comparisons illustrated in figure 6.16 and figure 6.17, it can be seen that the hybrid model is capable of improving the forecasting ability of established single SVM model and producing lower MAPE than ANN predictors.

Date	ANNs	SVM	Hybrid Model
16-Jun-07	9.490	6.494	4.698
17-Jun-07	10.869	7.978	2.980
18-Jun-07	6.959	10.176	7.164
19-Jun-07	6.281	9.049	6.749
20-Jun-07	5.094	11.539	7.024
21-Jun-07	3.420	13.272	9.737
22-Jun-07	14.212	5.662	3.910
23-Jun-07	9.012	7.277	4.144
24-Jun-07	17.136	7.724	6.123
25-Jun-07	6.921	11.593	6.935
26-Jun-07	8.521	7.205	3.487
27-Jun-07	7.517	7.070	3.088
28-Jun-07	7.867	5.040	1.924
29-Jun-07	14.883	6.500	2.344
30-Jun-07	9.093	4.978	2.413

**Table 6.3** Daily MAPE results (% , 16<sup>th</sup> - 30<sup>th</sup> June, 2007)

MAPE	ANNs	SVM	Hybrid Model
<b>Minimum MAPE</b>	3.420	4.978	1.924
<b>Maximum MAPE</b>	17.136	13.272	9.737
<b>Average MAPE</b>	9.152	8.104	4.848

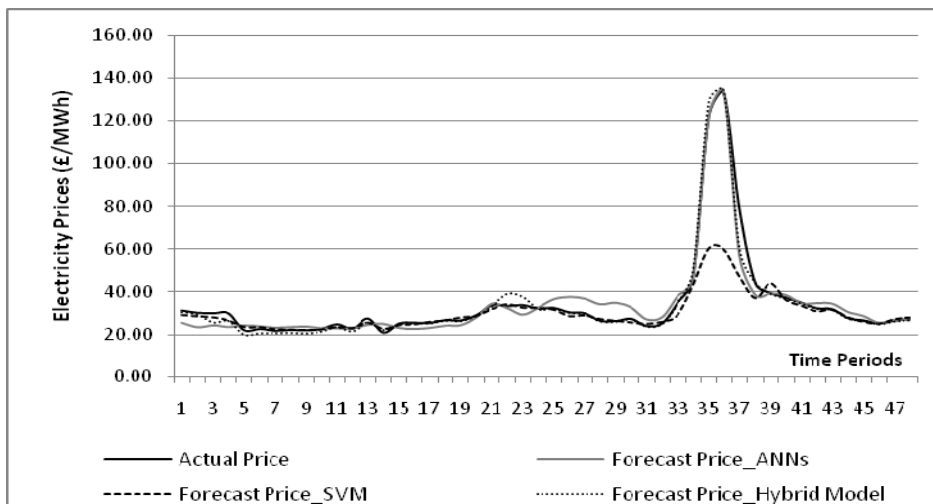
**Table 6.4** Statistical analysis of daily MAPE (% , 16<sup>th</sup> - 30<sup>th</sup> June, 2007)



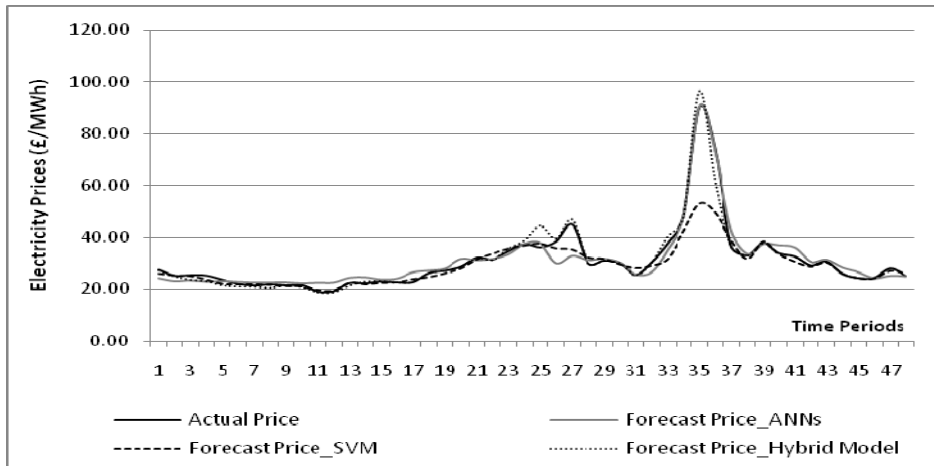
**Fig. 6.17** Statistical analysis of daily MAPE (% , 16<sup>th</sup> - 30<sup>th</sup> June, 2007)

### 6.3.2 Numerical Results Based on Case B (1<sup>st</sup> - 15<sup>th</sup> December 2007)

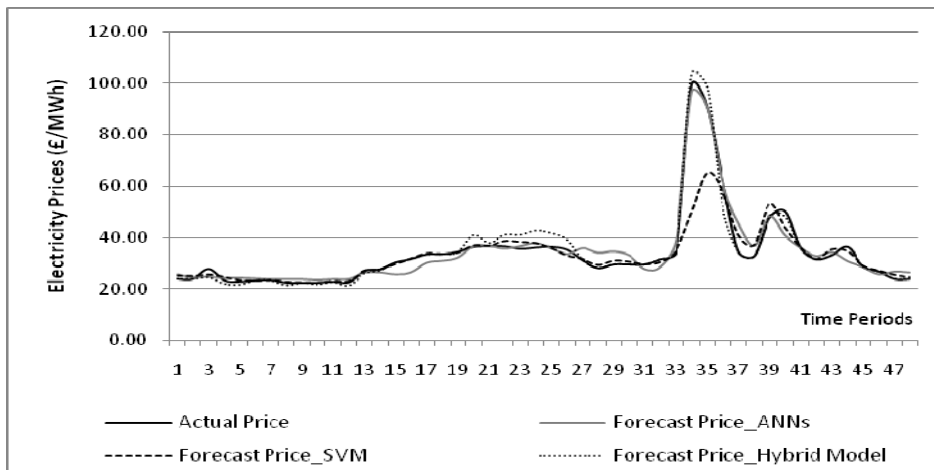
The forecast prices of hybrid model are compared with that of ANN model and SVM model, during days from December 1<sup>st</sup>, 2007 to December 15<sup>th</sup>, 2007. The forecast price curves with regard to the three forecasters are shown in figure 6.18 – 6.32.



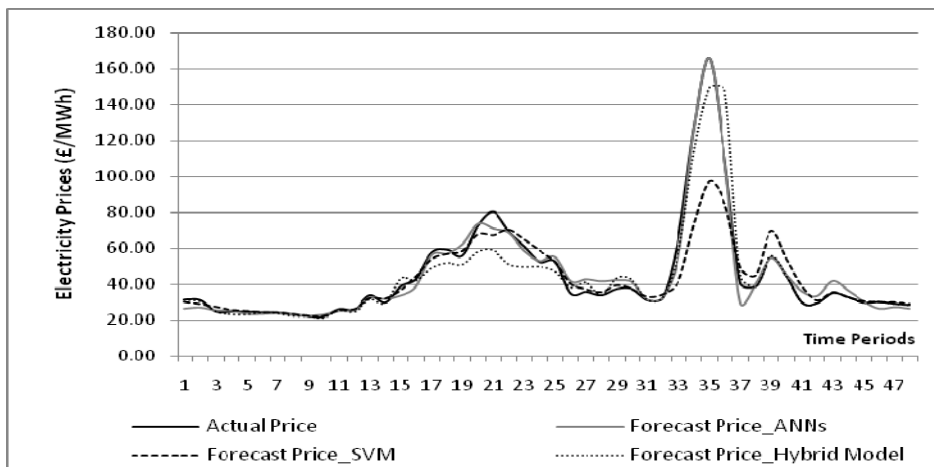
**Fig. 6.18** Forecasting results comparison on December 1<sup>st</sup>, 2007



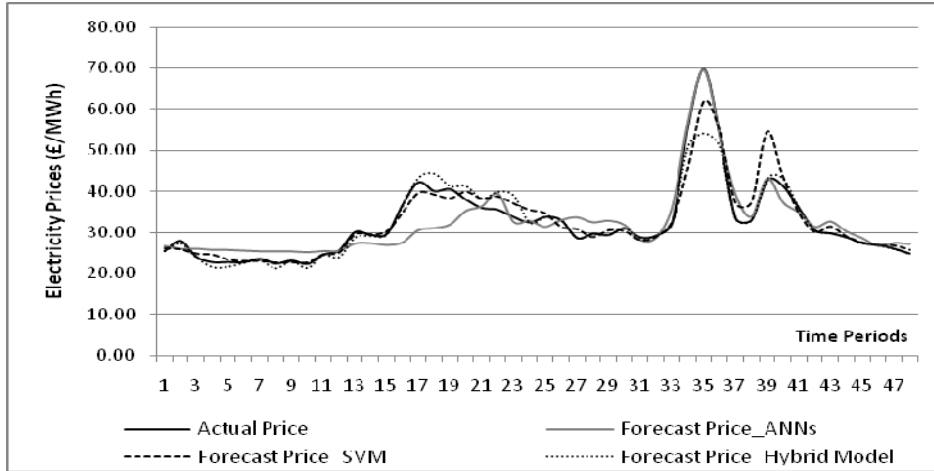
**Fig. 6.19** Forecasting results comparison on December 2<sup>nd</sup>, 2007



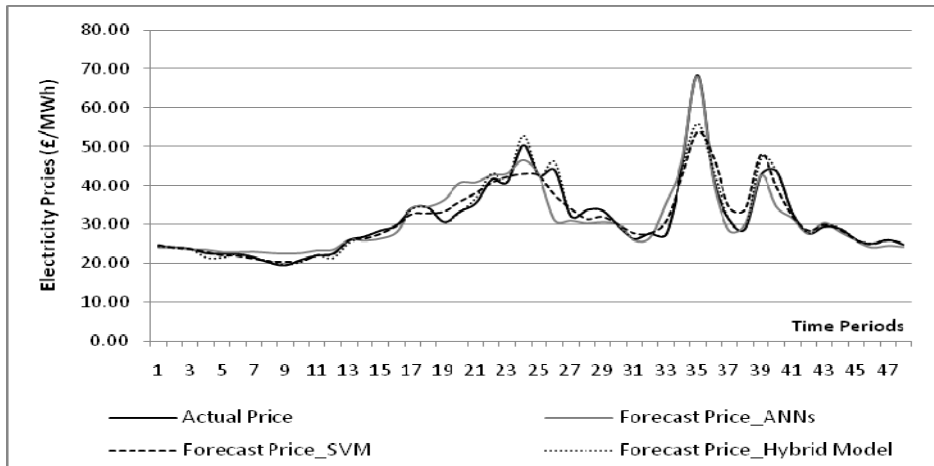
**Fig. 6.20** Forecasting results comparison on December 3<sup>rd</sup>, 2007



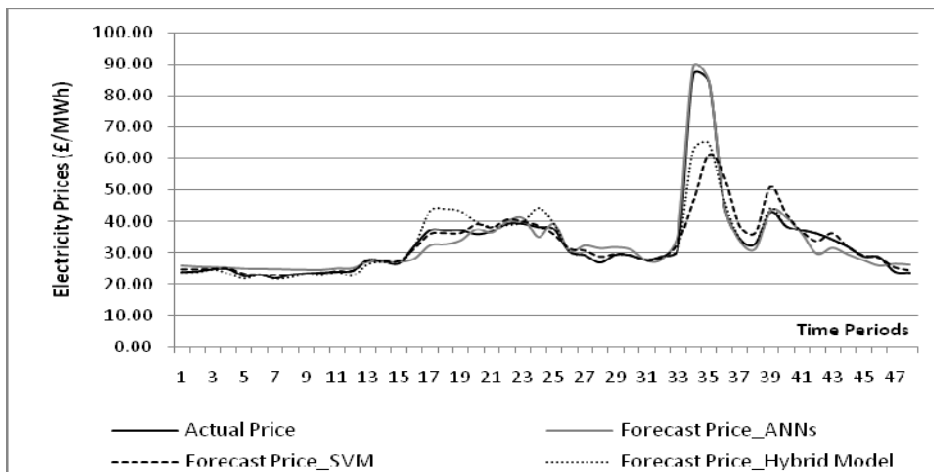
**Fig. 6.21** Forecasting results comparison on December 4<sup>th</sup>, 2007



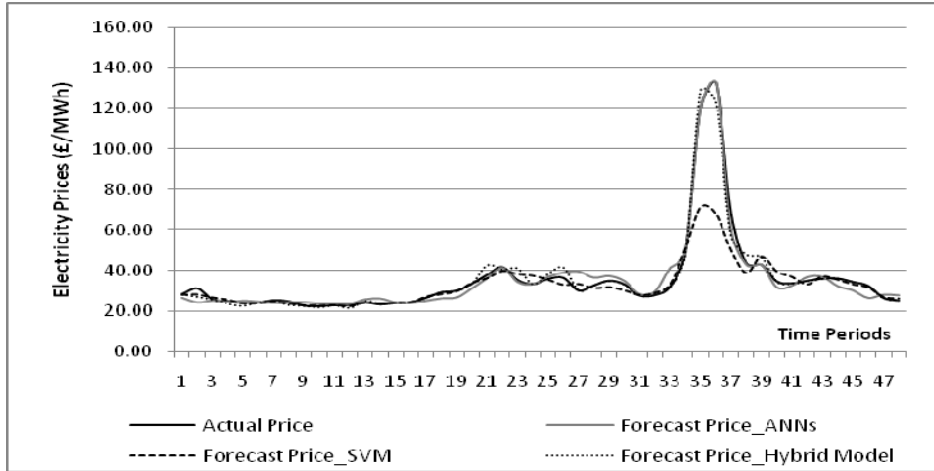
**Fig. 6.22** Forecasting results comparison on December 5<sup>th</sup>, 2007



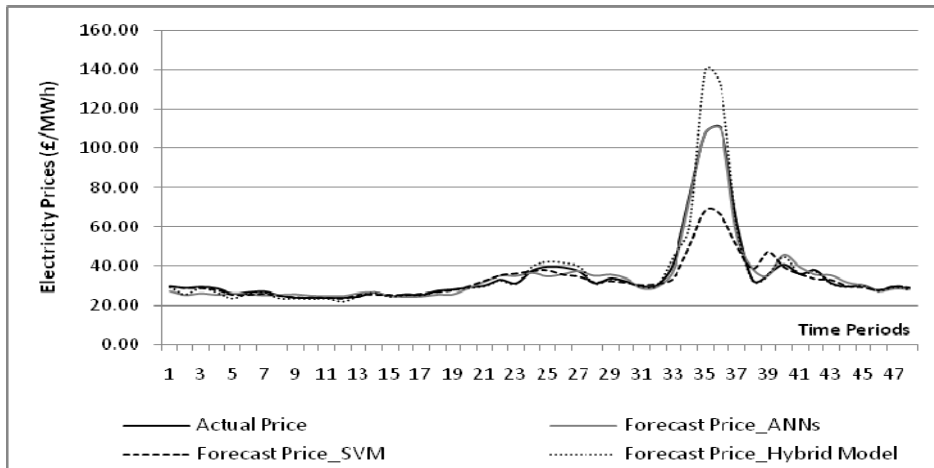
**Fig. 6.23** Forecasting results comparison on December 6<sup>th</sup>, 2007



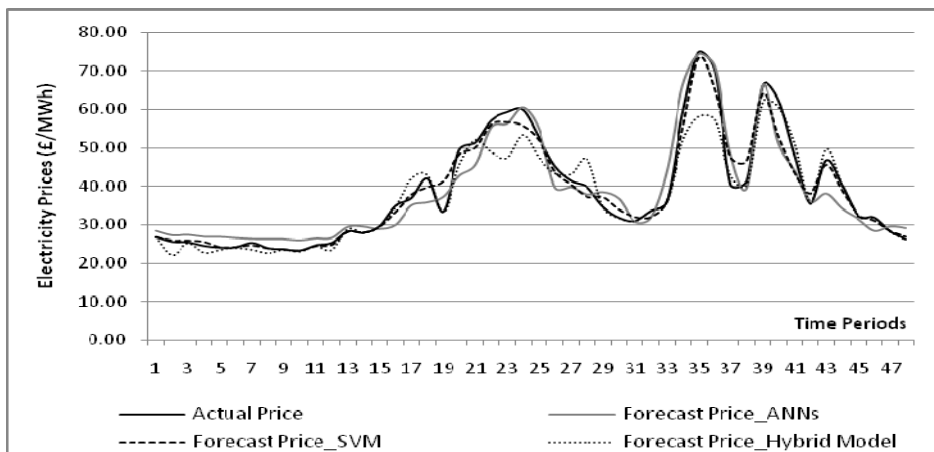
**Fig. 6.24** Forecasting results comparison on December 7<sup>th</sup>, 2007



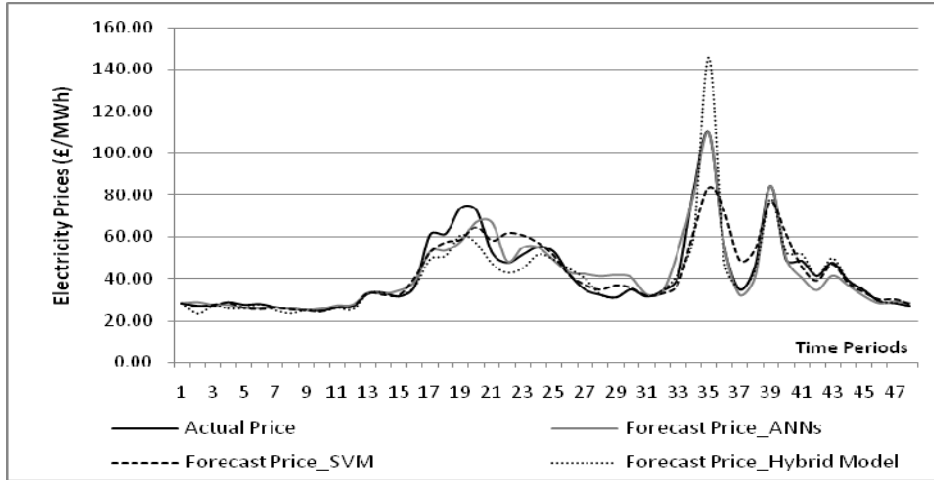
**Fig. 6.25** Forecasting results comparison on December 8<sup>th</sup>, 2007



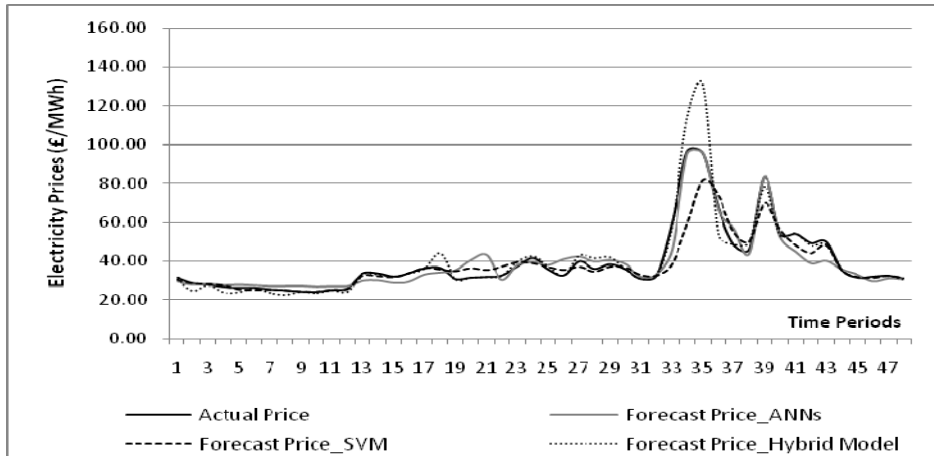
**Fig. 6.26** Forecasting results comparison on December 9<sup>th</sup>, 2007



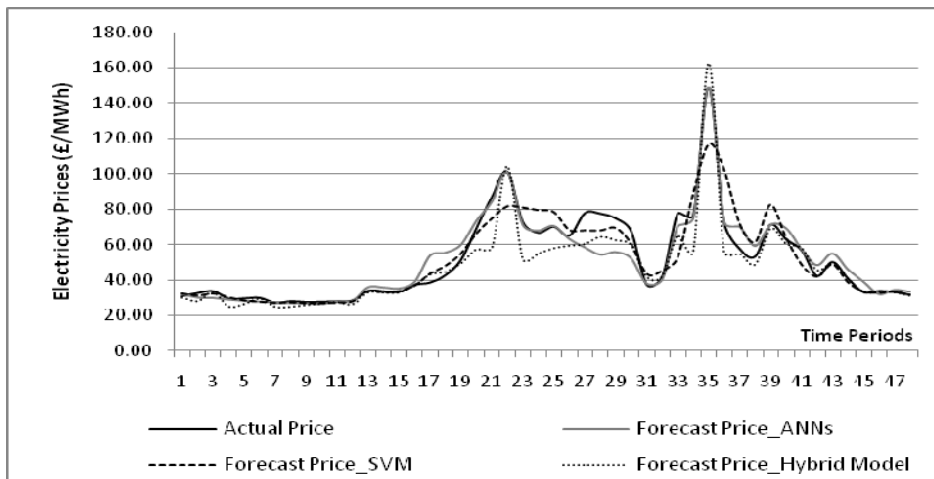
**Fig. 6.27** Forecasting results comparison on December 10<sup>th</sup>, 2007



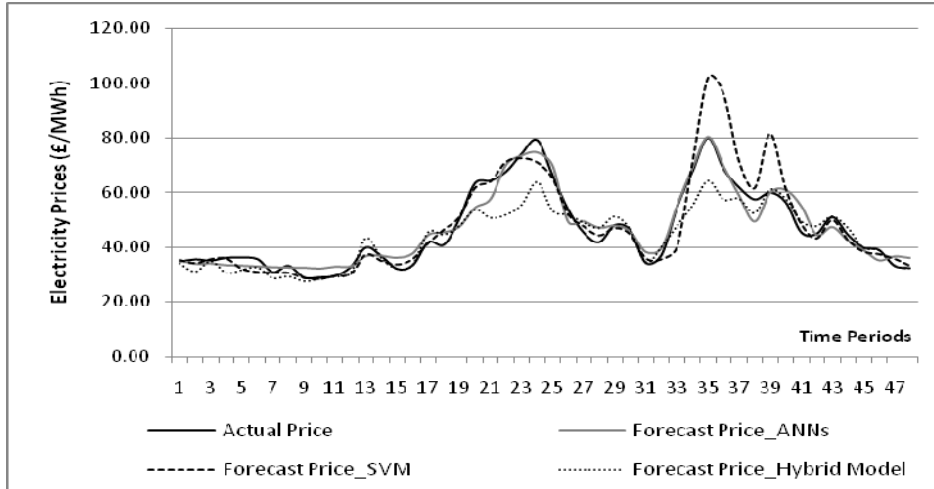
**Fig. 6.28** Forecasting results comparison on December 11<sup>th</sup>, 2007



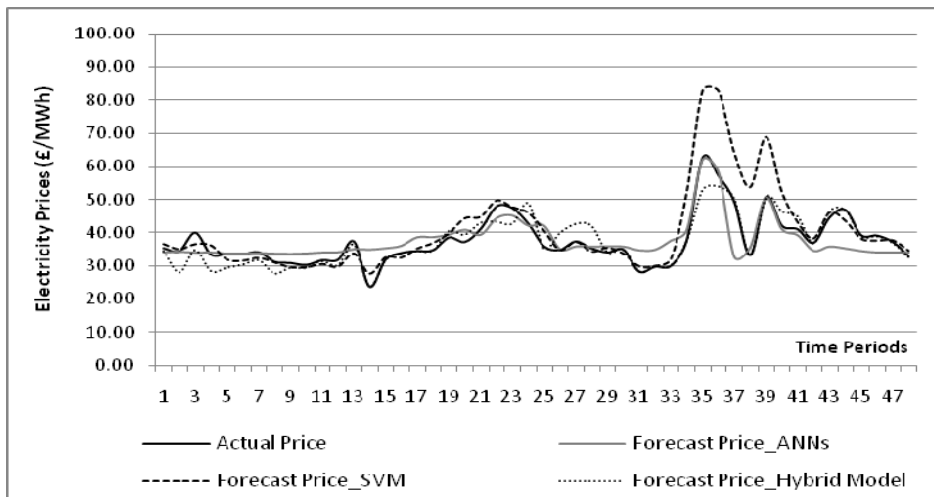
**Fig. 6.29** Forecasting results comparison on December 12<sup>th</sup>, 2007



**Fig. 6.30** Forecasting results comparison on December 13<sup>th</sup>, 2007



**Fig. 6.31.** Forecasting results comparison on December 14<sup>th</sup>, 2007



**Fig. 6.32** Forecasting results comparison on December 15<sup>th</sup>, 2007

From forecasting results of case study B, MAPE with regard to the three forecasters is calculated for the forty-eight time periods and listed in table 6.5. The statistical analysis of MAPE based on the forty-eight time periods from December 1<sup>st</sup>, 2007 to December 15<sup>th</sup>, 2007 is shown in table 6.6 and illustrated in figure 6.33.

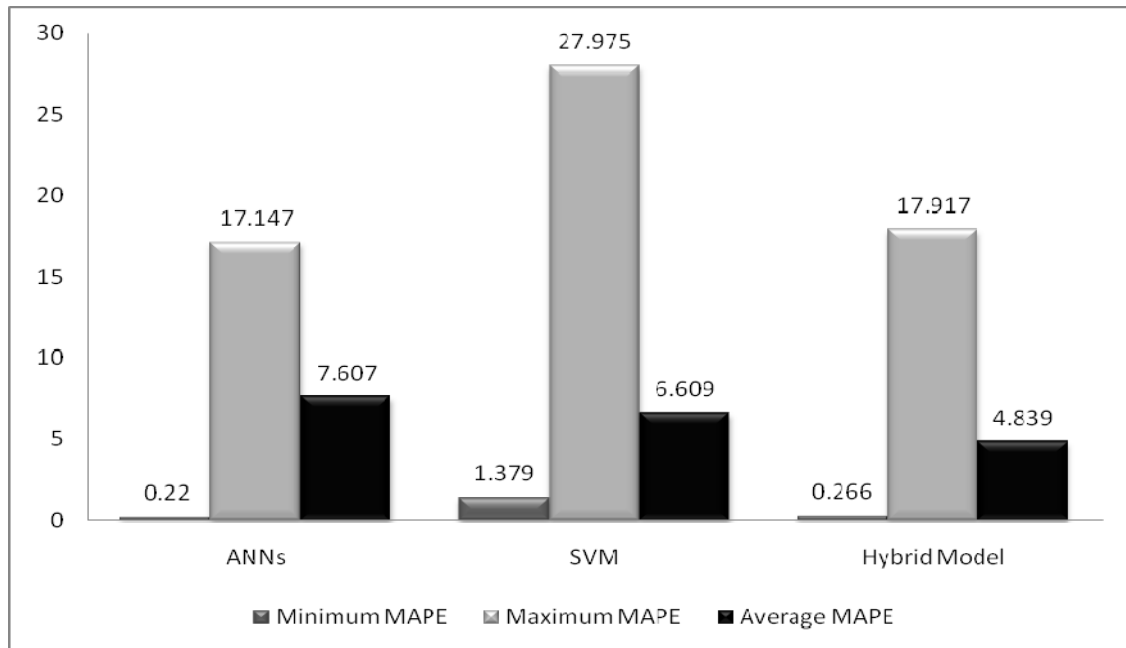
<b>Time Periods</b>	<b>ANNs</b>	<b>SVM</b>	<b>Hybrid Model</b>	<b>Time Periods</b>	<b>ANNs</b>	<b>SVM</b>	<b>Hybrid Model</b>
<b>1</b>	6.850	2.762	1.375	<b>25</b>	6.046	3.745	8.564
<b>2</b>	8.149	3.132	8.316	<b>26</b>	11.272	6.499	5.679
<b>3</b>	7.159	3.736	3.804	<b>27</b>	14.494	6.552	6.453
<b>4</b>	6.416	3.961	9.240	<b>28</b>	14.800	5.336	5.550
<b>5</b>	6.099	3.640	7.570	<b>29</b>	12.562	5.058	3.403
<b>6</b>	5.127	3.759	2.733	<b>30</b>	8.437	3.701	1.959
<b>7</b>	4.742	2.245	4.160	<b>31</b>	5.057	4.936	0.942
<b>8</b>	5.546	1.500	7.001	<b>32</b>	5.787	3.037	0.605
<b>9</b>	7.488	1.620	1.947	<b>33</b>	16.703	14.758	4.338
<b>10</b>	6.601	1.379	3.332	<b>34</b>	2.858	23.054	12.646
<b>11</b>	6.214	1.608	1.245	<b>35</b>	0.220	27.975	17.917
<b>12</b>	3.895	2.278	6.240	<b>36</b>	0.791	27.449	13.925
<b>13</b>	6.256	2.927	3.791	<b>37</b>	17.147	20.325	4.884
<b>14</b>	9.223	3.656	1.832	<b>38</b>	7.564	16.031	3.111
<b>15</b>	7.275	2.317	1.190	<b>39</b>	0.627	17.921	3.392
<b>16</b>	9.948	3.091	0.658	<b>40</b>	8.844	10.508	3.245
<b>17</b>	11.390	4.499	6.057	<b>41</b>	8.208	7.154	2.425
<b>18</b>	10.788	4.613	6.367	<b>42</b>	8.179	4.603	1.358
<b>19</b>	11.414	6.945	4.139	<b>43</b>	10.450	3.004	1.409
<b>20</b>	9.012	5.962	8.168	<b>44</b>	9.735	2.496	0.587
<b>21</b>	9.408	6.721	8.550	<b>45</b>	6.119	1.728	0.266
<b>22</b>	3.431	7.703	9.346	<b>46</b>	6.861	1.744	0.538
<b>23</b>	4.919	6.717	12.335	<b>47</b>	6.255	2.844	0.497
<b>24</b>	2.903	7.304	8.401	<b>48</b>	5.854	2.691	0.759

**Table 6.5** Comparative MAPE results for 48 time periods (% , 1<sup>st</sup> - 15<sup>th</sup> December, 2007)

<b>MAPE</b>	<b>ANNs</b>	<b>SVM</b>	<b>Hybrid Model</b>
<b>Minimum MAPE</b>	0.220	1.379	0.266
<b>Maximum MAPE</b>	17.147	27.975	17.917
<b>Average MAPE</b>	7.607	6.609	4.839

**Table 6.6** Statistical analysis of MAPE for 48 time periods (% , 1<sup>st</sup> - 15<sup>th</sup> December, 2007)





**Fig. 6.33** Statistical analysis of MAPE for 48 time periods (% , 1<sup>st</sup> - 15<sup>th</sup> December, 2007)

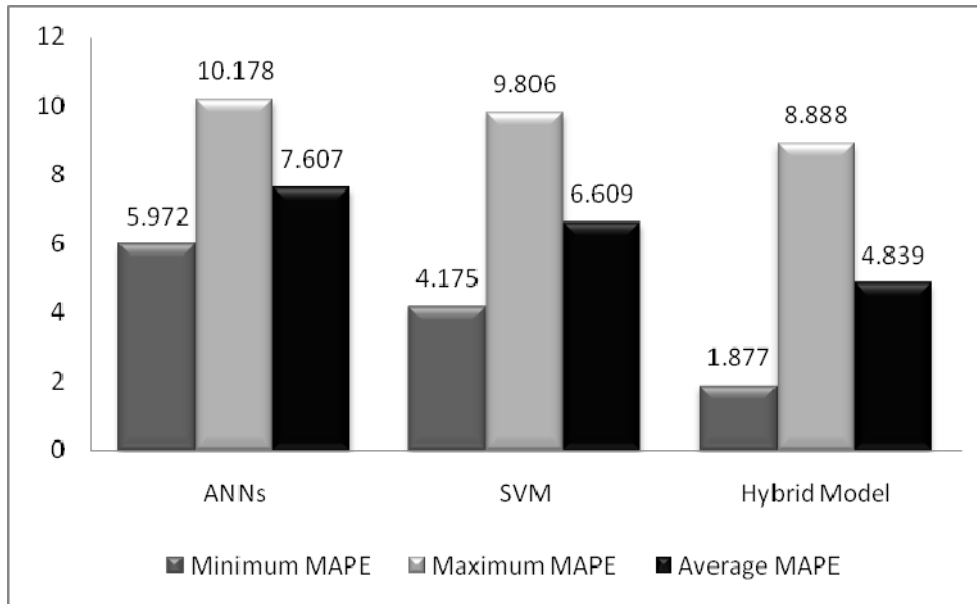
Table 6.7 lists the daily forecasting errors of three forecasters, such as ANNs, SVM and the hybrid models in case study B. The results analysis of daily MAPE from December 1<sup>st</sup>, 2007 to December 15<sup>th</sup>, 2007 is shown in table 6.8. The illustration in figure 6.33 and figure 6.34 shows that the hybrid model can produce lower prediction errors than the other two models. Therefore, the comparisons among predictors, ANNs, SVM and the hybrid model, in terms of MAPE indicate that the developed hybrid model is capable of forecasting the short-term electricity prices effectively and accurately.

Date	ANNs	SVM	Hybrid Model
01-Dec-07	10.178	7.095	3.283
02-Dec-07	6.610	5.376	2.762
03-Dec-07	7.196	4.995	3.763
04-Dec-07	7.536	8.837	7.074
05-Dec-07	8.074	4.775	2.965
06-Dec-07	6.359	4.779	1.877
07-Dec-07	6.019	5.187	3.867
08-Dec-07	6.669	6.494	3.423
09-Dec-07	5.972	6.944	3.653
10-Dec-07	8.521	4.175	5.185
11-Dec-07	8.047	8.461	6.822
12-Dec-07	8.868	6.364	5.140
13-Dec-07	8.526	8.780	8.888
14-Dec-07	6.634	7.064	8.360
15-Dec-07	8.894	9.806	5.517

**Table 6.7** Daily MAPE results (% , 1<sup>st</sup> - 15<sup>th</sup> December, 2007)

MAPE	ANNs	SVM	Hybrid Model
<b>Minimum MAPE</b>	5.972	4.175	1.877
<b>Maximum MAPE</b>	10.178	9.806	8.888
<b>Average MAPE</b>	7.607	6.609	4.839

**Table 6.8** Statistical analysis of daily MAPE (% , 1<sup>st</sup> - 15<sup>th</sup> December, 2007)



**Fig. 6.34** Statistical analysis of daily MAPE (%), 1<sup>st</sup> - 15<sup>th</sup> December, 2007)

## 6.4 SUMMARY

Three forecasting schemes are proposed to predict the half-hour electricity prices in the UK spot power markets. In order to verify the predictive ability of the proposed models, the simulations are performed for two case studies by using the information from real markets. The training data are divided into two groups for the case studies. A comparison was made among these predictors, ANNs, SVM and the hybrid model, in terms of MAPE, which is the standard of forecasting errors. The forecasting results showed that the developed forecaster, which is the combination of FCM and SVM models, can provide a considerable improvement of forecasting accuracy. Especially, the MAPE results confirmed that the hybrid model could produce lower prediction errors than the other two models, ANNs and SVM. Therefore, the proposed hybrid forecasting model could effectively benefit the conventional short-term price forecasting systems.

## 7. Conclusions and Further Research

### Conclusions

The restructuring of power markets has changed the electricity supply into a private and deregulated product. In such market environment, profitability as a result of privatisation has become the main objective for all the market participants. In order to compete for the market share through spot and bilateral markets, the price forecasting has now regarded as a very valuable tool by the participants for either bidding or hedging against volatility in the current upheaval of deregulated electricity markets [60]. Therefore, the task of developing more accurate and effective price forecasting tools has become very active and important.

As a simple, powerful and flexible tool of forecasting, Artificial Neural Networks (ANNs) have typically received much attention in recent years [8]. In this thesis, a three-layered feed-forward neural network with back-propagation has been proposed for application of forecasting the short-term electricity prices in the UK spot power markets. In order to verify the accuracy of such algorithm, case studies have been presented and the result shows the proposed ANN model is feasible and efficient. However, because the price data of spot power markets often have enormous noise and complex dimensionality, the effectiveness of ANN models are limited.

Support Vector Machine (SVM) is a supervised learning technique used for classification and regression. Due to many attractive features and good performance, SVM has been successfully applied in the field of prediction [8]. It is well known that SVM model has overcome the limitation of many traditional forecasting models by introducing the structural risk minimization principle. Hence, the SVM model is proposed to predict the short-term electricity prices based on the same training data as that used for ANNs training, in order to compare the forecasting accuracy of different models. Two case studies have been used to demonstrate the price forecasting of SVM model. Through the case studies, it obviously showed that the prediction during off-peak time performs much

better than that during peak-time. This is because of the conflict between empirical risk and generalization ability. If the empirical risk is decreased in order to forecast more accurately, the generalization ability of models will become weak accordingly. Therefore, in order to improve the SVM model's forecasting accuracy during peak-time without affecting its generalization ability, a data clustering method Fuzzy-C-Means (FCM) has been introduced to combine with it.

Clustering of numerical data can be considered as the most important unsupervised learning problem. It forms the basis of many classification and modeling algorithms. The purpose of clustering is to determine the intrinsic structure in a large set of unlabeled data, producing groups whose members are similar in some way. In order to improve the forecasting accuracy of SVM model, FCM clustering technique has been introduced to preprocess the thousands of training data by clustering them into different groups according to their natural memberships, which are the value of electricity prices rather than the time scale. The advantages of doing this are the noise can be reduced for each of training data sets after the data aggregation; meanwhile, SVM model could maintain its characteristics of empirical risk and generalization ability. Therefore, in this thesis, a hybrid forecasting model has been developed by conjunctive use of FCM clustering algorithm and SVM algorithm in order to overcome the limitations of individual models and get a high degree of prediction accuracy.

In order to evaluate the accuracy and effectiveness of different forecasting models, such as ANNs, SVM and the hybrid model, forecasts are based on the same training data sets. Those data are real power price data requested from *APX Power UK* at the year 2007. The data from January 1<sup>st</sup>, 2007 to May 31<sup>st</sup>, 2007 have been trained and applied on the models to forecast the prices with regard to each half-hour from June 16<sup>th</sup>, 2007 to June 30<sup>th</sup>, 2007. Similarly, the programs are trained by using data from July 1<sup>st</sup>, 2007 to November 30<sup>th</sup>, 2007 in order to forecast the prices on the days from December 1<sup>st</sup>, 2007 to December 15<sup>th</sup>, 2007. Therefore, based on the UK spot power markets, the prediction focuses on each half-hour electricity prices, fifteen days ahead.

In this thesis, the criterion of forecasting errors, MAPE, has been used to evaluate the accuracy of different forecasting models. Comparison of forecasting errors MAPE has been made from the forecasting results and it showed that the developed forecaster, which is the combination of FCM and SVM models, can provide a considerable improvement of the forecasting accuracy. Especially, the MAPE results confirmed that the hybrid model could produce lower prediction errors than the other two models, ANNs and SVM. Therefore, the proposed hybrid forecasting model could effectively benefit the conventional short-term price forecasting systems.

### **Further Research**

Further research may include selection of more appropriate data classification methods, for instance, the input training data can be separated according to the working days, weekend days and the public holidays [12]. In theory, based on those similar days, the forecasting accuracy of the proposed hybrid model could be considerably improved.

In order to further test the effectiveness of the proposed hybrid model, more forecasting techniques could be taken into the comparisons. Especially, compare with the other existing hybrid models, such as the integrated model of Bayesian Clustering by Dynamics (BCD) and SVM [44], the combination of Relief algorithm and ANNs [13] and the hybrid model of K-Means Clustering and ANNs [17], and so on.

In addition, due to the different format of input data required by the software programming, it will be necessary to create the interface between each piece of FCM and SVM software packages, which could make the hybrid forecasting model more easily and practically used by the researchers as well as the software users.

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# Appendix

## I. Reference Price Data H-H 2007

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
01-Jan-07	23.86	24.61	25.22	24.77	22.18	20.28	18.43	18.83	17.99	18.16	17.94	17.35	16.96	17.22	16.70	15.83	14.18	14.32	15.78	15.04	14.69	14.91	15.75	16.58
02-Jan-07	24.73	23.56	19.79	19.11	19.00	19.34	18.15	17.87	17.81	18.03	18.29	18.21	21.23	19.68	21.04	20.54	24.09	26.81	29.59	28.00	27.98	27.97	27.47	27.02
03-Jan-07	18.53	19.03	19.14	18.64	18.64	18.03	17.70	16.96	16.77	16.72	16.41	16.37	19.84	19.94	21.89	21.73	24.78	25.73	23.70	23.78	23.23	23.11	22.08	21.34
04-Jan-07	19.30	19.36	19.06	19.74	18.52	19.20	19.26	18.29	18.47	18.07	18.79	18.56	20.63	20.64	20.98	21.93	27.29	26.51	28.48	29.92	31.77	31.15	29.92	30.02
05-Jan-07	19.52	18.11	18.88	17.78	18.00	18.20	17.71	17.11	16.91	16.61	18.31	18.48	21.71	20.55	22.72	23.54	26.72	26.80	28.33	29.27	32.74	32.86	35.87	31.41
06-Jan-07	19.30	17.70	17.59	17.38	17.01	16.95	17.31	16.07	16.49	16.29	16.27	16.02	17.26	17.07	17.65	17.41	17.78	17.70	18.49	19.68	20.78	20.33	20.14	19.83
07-Jan-07	19.30	18.46	18.18	17.75	16.92	17.51	17.99	16.18	16.64	16.80	16.00	16.08	16.40	17.16	15.96	15.86	17.48	18.14	18.14	18.23	17.83	20.04	18.36	20.48
08-Jan-07	19.00	19.99	18.23	19.50	17.52	17.22	16.72	16.05	16.02	15.98	16.06	16.02	17.82	19.18	20.51	21.66	21.83	20.96	23.92	32.26	39.83	39.59	43.94	37.82
09-Jan-07	19.57	17.62	17.42	17.27	18.45	18.18	16.34	16.98	17.10	17.30	17.18	17.20	17.98	18.50	19.31	18.76	19.13	17.91	18.00	30.95	30.00	21.94	19.62	19.00
10-Jan-07	19.54	16.78	18.30	17.89	17.75	17.93	17.22	16.88	17.08	16.85	17.58	17.11	18.72	18.70	18.91	22.02	23.62	21.60	21.93	21.97	20.72	21.98	23.80	25.13
11-Jan-07	18.37	18.30	18.89	18.06	18.00	17.93	17.00	16.97	16.89	16.61	16.91	16.89	19.20	18.83	18.56	19.88	20.08	19.83	20.00	20.27	24.67	24.20	27.14	31.76
12-Jan-07	18.66	18.99	19.01	18.34	18.20	18.18	18.25	17.94	17.91	18.04	17.88	17.64	18.55	19.29	18.43	19.41	28.02	24.06	23.10	25.03	27.03	27.70	26.16	26.13
13-Jan-07	18.10	18.11	17.55	18.19	17.25	18.14	17.39	16.96	17.00	16.99	17.01	16.93	17.01	16.58	17.67	17.93	17.43	17.26	19.89	17.97	17.16	17.18	17.06	17.12
14-Jan-07	18.06	17.87	17.98	17.28	16.79	17.53	17.44	16.88	16.73	16.65	16.73	16.80	16.85	16.73	16.77	16.46	16.54	17.15	17.13	17.99	18.19	18.16	18.25	21.71
15-Jan-07	18.79	18.12	19.20	18.03	17.91	17.52	17.58	17.37	17.84	17.51	17.53	17.31	18.84	20.24	23.92	26.48	28.72	28.05	27.62	30.26	30.07	29.41	32.47	34.33
16-Jan-07	17.75	17.07	18.25	17.07	17.48	17.42	17.38	16.00	16.05	16.00	17.32	16.93	19.83	20.43	21.89	24.32	27.83	25.06	21.67	23.37	23.08	22.21	24.70	25.18
17-Jan-07	19.52	19.34	18.18	17.70	17.77	17.77	17.51	17.04	17.00	17.01	17.10	17.47	20.11	20.75	21.02	27.39	33.41	34.09	32.64	34.56	30.17	27.61	30.05	29.62
18-Jan-07	18.65	18.31	18.54	17.11	17.03	17.33	16.26	16.02	16.01	16.01	17.19	17.13	20.88	19.93	23.24	25.35	26.00	24.91	29.27	30.40	34.01	34.09	38.54	39.27
19-Jan-07	18.03	18.55	18.60	17.37	17.17	17.35	17.19	16.94	16.49	16.72	16.30	17.85	19.41	19.77	18.33	21.38	24.68	22.00	25.38	24.11	23.63	22.80	24.78	21.64
20-Jan-07	18.28	18.00	18.00	16.75	16.28	16.36	16.67	16.00	16.13	16.12	16.04	16.06	17.15	16.67	17.59	17.11	17.60	18.91	20.00	20.86	20.17	20.30	20.49	19.84
21-Jan-07	18.32	18.69	17.03	17.71	16.79	17.05	17.19	17.08	16.87	16.34	16.53	16.23	16.35	17.16	16.30	16.30	16.67	16.88	18.15	17.74	19.95	20.12	20.84	22.31
22-Jan-07	18.75	19.42	19.95	19.91	19.71	19.80	19.23	19.47	17.70	17.73	20.96	19.20	22.20	21.76	22.21	28.10	30.07	29.84	31.47	28.76	30.90	30.75	25.00	22.99
23-Jan-07	19.48	18.90	18.83	19.04	17.35	17.95	17.99	17.27	17.46	17.44	17.91	18.04	21.14	22.29	25.19	27.10	27.31	28.89	26.26	25.42	26.83	26.28	25.00	27.77
24-Jan-07	19.46	20.05	20.63	20.48	18.16	18.65	18.02	17.45	16.93	17.01	17.81	18.15	21.82	22.11	25.87	27.69	27.30	24.13	26.39	30.56	26.94	22.87	24.68	24.63
25-Jan-07	22.67	19.66	20.25	19.81	20.29	20.00	19.44	18.04	17.30	17.85	18.44	18.33	23.86	22.88	24.50	27.34	30.35	27.79	29.99	29.20	28.00	27.60	27.36	27.17
26-Jan-07	19.53	18.87	19.08	18.27	18.14	18.56	18.05	17.77	17.68	17.55	17.60	17.84	21.30	21.67	21.67	21.43	23.30	23.05	22.98	23.28	24.07	24.46	29.90	27.88
27-Jan-07	21.61	19.48	22.00	21.96	20.44	21.00	19.20	20.23	19.50	18.56	17.96	17.81	19.79	16.84	18.81	18.99	19.12	19.27	20.48	23.25	23.30	23.21	28.49	27.83
28-Jan-07	18.35	17.20	17.19	17.19	17.05	17.02	16.60	16.00	15.79	16.00	15.77	15.70	16.04	16.04	15.89	16.02	16.07	16.39	17.05	17.18	17.28	18.74	21.03	24.13
29-Jan-07	17.59	18.26	17.35	17.15	17.20	17.92	17.61	16.90	16.62	16.36	16.98	16.68	19.54	19.46	19.95	20.98	20.47	20.83	25.02	22.40	20.96	20.23	21.54	22.25
30-Jan-07	17.18	17.62	17.48	17.88	17.03	17.01	17.10	17.02	16.02	15.68	17.23	17.55	17.17	18.22	17.75	18.26	18.05	18.43	17.51	20.73	19.60	20.32	19.56	19.18
31-Jan-07	16.48	16.34	16.06	16.04	16.30	16.53	16.00	15.92	15.93	16.37	16.37	15.65	17.78	17.55	16.83	18.00	19.57	19.11	20.19	21.77	21.48	22.46	29.43	30.15

	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48
01-Jan-07	17.51	17.69	18.10	18.11	17.97	18.50	18.43	17.26	17.89	28.66	38.41	41.25	29.87	26.04	31.19	32.24	24.99	23.27	18.75	20.58	19.63	20.08	20.23	19.89
02-Jan-07	25.66	25.88	26.00	26.87	25.76	24.94	23.23	23.27	25.57	42.54	54.20	50.91	33.41	29.19	36.56	29.07	28.77	21.21	27.27	20.15	19.72	19.03	20.01	17.89
03-Jan-07	21.13	23.05	20.00	21.74	21.88	24.37	20.87	20.93	24.91	36.34	64.75	44.09	29.47	30.45	33.42	29.53	23.92	21.74	22.01	21.41	20.82	20.17	19.13	18.34
04-Jan-07	28.65	27.50	29.40	26.53	25.37	24.98	21.07	21.94	27.21	58.11	65.00	46.49	41.22	29.42	33.76	29.66	28.14	23.14	21.11	20.79	19.95	18.84	19.81	19.83
05-Jan-07	30.21	26.74	28.00	24.61	21.12	20.98	21.67	23.09	26.54	43.95	79.08	42.60	31.05	28.20	28.37	24.77	21.56	20.50	20.21	19.64	19.30	18.79	19.13	18.69
06-Jan-07	19.84	19.50	19.96	20.00	20.16	22.50	20.07	23.05	23.26	35.60	80.00	47.40	27.35	24.25	24.99	23.60	19.10	18.13	18.51	18.00	17.91	17.95	18.99	19.18
07-Jan-07	18.83	22.89	18.54	19.96	19.85	19.09	18.61	18.46	19.80	28.55	90.00	36.97	23.23	23.19	29.13	21.23	19.41	18.59	18.52	17.87	17.63	17.57	18.80	18.72
08-Jan-07	38.74	25.92	25.42	25.66	26.13	28.49	26.76	27.14	21.48	45.06	69.06	54.78	38.29	26.98	28.74	23.44	20.26	19.95	21.99	18.54	17.93	19.25	18.88	18.84
09-Jan-07	18.84	18.90	19.00	18.48	18.67	19.01	17.57	18.47	22.40	44.03	69.84	43.54	32.40	24.99	28.18	25.30	22.31	21.17	20.59	19.37	18.57	18.57	19.39	19.13
10-Jan-07	24.67	20.57	22.00	20.83	20.87	18.97	17.55	18.06	23.58	44.70	95.97	58.11	40.74	37.06	32.53	22.81	22.02	20.57	18.41	20.57	18.22	18.60	18.85	18.36
11-Jan-07	32.09	30.99	29.65	29.03	25.53	23.92	18.98	19.72	21.45	48.06	58.20	49.30	30.52	30.52	34.24	31.47	24.69	20.46	21.09	20.40	19.65	18.41	17.54	17.81
12-Jan-07	25.37	33.05	27.81	20.86	17.50	18.59	19.37	18.99	24.49	36.42	45.64	34.65	24.18	24.29	23.36	21.15	21.32	20.56	21.95	19.23	18.93	17.64	18.26	18.99
13-Jan-07	17.09	17.00	17.01	17.35	17.77	17.10	17.10	17.04	18.08	25.00	36.76	33.23	24.38	20.27	24.07	21.05	22.38	17.98	18.09	18.00	17.00	17.16	18.11	17.45
14-Jan-07	26.84	25.93	20.69	19.64	20.74	19.28	18.31	18.23	24.40	40.00	57.74	67.69	32.96	24.55	28.32	23.71	22.43	19.72	19.44	17.57	17.34	17.89	17.48	17.06
15-Jan-07	31.17	27.07	24.00	25.60	23.49	20.15	19.44	21.21	24.39	36.29	67.70	42.26	24.11	24.39	32.17	28.49	23.88	20.06	19.99	19.38	17.79	17.52	18.25	18.46
16-Jan-07	24.26	22.19	21.12	20.36	20.39	19.30	17.97	19.60	23.15	38.35	67.72	48.72	23.16	23.29	29.71	22.50	20.40	19.74	18.54	18.52	17.37	16.98	18.51	17.61
17-Jan-07	29.49	25.35	22.86	23.33	19.75	23.02	19.81	22.18	23.68	33.14	58.41	36.94	25.37	25.35	35.43	34.71	27.02	19.51	25.86	19.75	18.30	16.88	19.79	18.84
18-Jan-07	38.36	35.62	31.80	24.23	21.99	22.78	20.13	21.84	23.60	34.37	96.67	53.46	42.93	33.55	34.89	32.98	33.98	21.46	23.23	23.19	22.37	18.81	18.04	17.97
19-Jan-07	21.98	20.10	18.94	18.65	18.72	17.76	17.94	17.84	16.91	18.59	34.05	25.75	20.22	19.77	21.46	19.61	19.12	19.55	19.14	18.76	17.83	17.30	18.08	18.10
20-Jan-07	19.53	19.48	18.25	17.82	17.43	18.66	18.74	18.50	18.43	20.13	31.00	30.70	30.18	23.81	22.51	20.54	19.99	19.36	19.81	18.13	18.00	17.98	17.97	17.74
21-Jan-07	26.32	25.90	20.29	19.34	18.26	18.00	18.73	18.92	19.24	29.43	55.00	58.52	50.48	33.25	38.72	32.66	30.97	27.54	23.21	20.12	22.18	19.75	18.12	17.93
22-Jan-07	22.20	21.64	22.40	24.42	26.22	24.53	23.32	22.69	26.37	36.95	45.47	38.81	23.84	23.72	33.80	26.56	22.79	22.53	22.38	19.92	19.14	18.22	20.37	19.08
23-Jan-07	27.55	28.45	29.55	29.58	28.65	26.47	26.84	31.59	21.59	35.35	81.75	69.82	38.25	30.91	47.22	41.78	30.39	28.77	25.90	26.03	24.06	22.42	19.70	18.51
24-Jan-07	26.63	22.54	24.13	22.41	23.17	21.66	22.68	22.42	27.54	48.98	106.44	104.13	51.45	36.69	59.21	33.61	29.56	29.45	30.08	31.16	19.12	18.25	19.22	19.92
25-Jan-07	29.45	29.53	29.00	25.59	27.69	25.81	22.21	22.17	26.62	40.03	87.47	84.19	54.61	43.89	75.00	43.41	38.08	28.82	32.37	21.77	20.74	20.03	22.24	19.51
26-Jan-07	27.95	24.63	22.00	18.69	21.80	19.33	18.74	19.72	19.32	20.53	47.79	36.79	26.88	24.40	31.45	24.80	22.29	20.54	21.30	22.23	21.33	21.05	19.83	19.73
27-Jan-07	23.29	22.11	19.99	17.92	17.06	16.95	21.75	20.14	17.14	25.06	31.07	38.02	35.04	27.06	38.10	28.26	23.02	17.86	23.42	18.71	17.45	17.78	19.23	19.41
28-Jan-07	27.92	29.40	23.56	22.47	17.59	17.23	17.74	18.91	17.98	18.04	37.74	45.71	40.05	35.90	52.65	34.34	27.28	17.47	19.32	19.26	18.24	17.48	18.17	16.84
29-Jan-07	22.49	20.56	18.73	18.30	19.61	18.46	22.92	22.83	20.01	28.16	65.75	68.41	32.55	24.19	26.29	20.36	18.65	17.96	17.65	17.63	16.55	16.22	17.47	16.64
30-Jan-07	18.91	18.64	18.00	18.01	18.03	18.33	18.08	19.34	18.06	28.38	67.69	82.55	44.50	34.72	26.06	23.31	19.33	19.34	19.46	18.97	17.63	16.32	17.07	16.79
31-Jan-07	29.98	29.49	29.45	25.74	27.53	25.43	20.42	20.24	22.63	41.48	83.64	99.42	67.47	43.29	35.31	23.77	21.21	17.09	18.71	17.51	16.54	16.73	16.89	17.79



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
01-Dec-07	31.26	30.15	29.97	29.95	22.00	22.62	21.72	22.15	21.92	22.55	24.73	22.66	27.50	20.84	25.20	25.49	25.46	26.76	26.56	29.06	33.78	33.31	33.78	32.13
02-Dec-07	27.55	25.14	25.36	25.19	23.50	22.02	21.33	21.87	21.47	21.53	19.00	19.13	22.35	22.18	22.96	22.59	22.63	26.19	27.19	28.61	32.11	31.40	34.67	37.36
03-Dec-07	24.13	24.07	28.00	23.52	23.00	23.50	23.71	22.60	22.56	22.60	23.02	22.79	27.28	27.83	30.54	31.77	33.61	33.70	34.58	36.56	36.83	36.79	35.82	36.33
04-Dec-07	31.73	31.43	25.01	25.00	25.00	24.56	24.47	23.51	22.42	22.15	26.37	26.07	34.12	30.05	39.23	43.05	57.86	59.33	56.00	72.76	80.45	69.52	61.12	52.39
05-Dec-07	25.55	27.94	24.05	22.77	22.80	22.75	23.62	22.45	23.17	22.37	24.58	25.66	30.09	29.40	29.65	36.76	42.18	40.07	40.55	37.98	35.93	35.51	33.74	32.46
06-Dec-07	24.44	24.20	23.82	22.65	22.47	22.44	21.61	20.21	19.50	21.04	22.03	22.53	26.01	26.89	28.49	29.83	34.22	34.34	30.59	33.28	35.48	41.66	40.86	50.32
07-Dec-07	23.96	24.26	25.00	24.98	22.68	23.20	22.05	23.16	23.56	23.83	24.07	24.49	27.85	27.36	26.84	32.26	37.20	37.17	37.23	35.97	36.89	39.40	39.37	38.29
08-Dec-07	28.50	31.22	25.78	24.87	24.15	24.36	25.41	24.88	22.71	22.58	22.93	23.16	24.29	23.35	24.09	24.23	26.68	29.33	30.07	33.59	37.96	41.69	35.28	33.33
09-Dec-07	29.54	28.70	29.23	28.38	25.69	26.41	26.82	24.81	23.67	23.67	23.55	23.69	24.17	26.36	24.43	25.48	25.04	27.18	27.85	28.89	29.91	32.91	31.00	37.48
10-Dec-07	26.78	25.50	25.37	24.41	23.95	24.04	25.21	23.78	23.53	23.19	24.60	25.19	28.18	27.81	29.51	34.93	36.76	41.95	33.37	49.34	51.28	57.12	59.27	59.80
11-Dec-07	28.50	27.23	27.24	28.98	27.76	28.11	26.65	25.79	25.17	24.93	26.35	26.96	32.95	33.48	31.79	36.23	60.89	61.31	73.91	72.68	52.44	47.74	51.64	55.24
12-Dec-07	31.56	28.70	27.94	26.78	26.37	26.38	25.50	25.10	24.38	24.24	25.18	26.04	33.64	33.67	32.04	33.82	36.34	36.54	30.79	31.48	31.81	32.50	37.30	41.67
13-Dec-07	30.89	32.59	33.65	29.47	29.62	29.87	27.11	27.98	27.51	27.62	27.85	28.41	33.79	33.64	33.20	37.23	38.50	42.73	51.27	69.37	87.10	101.16	72.59	66.77
14-Dec-07	34.80	35.60	35.18	36.23	36.26	35.70	30.86	33.27	28.94	29.05	29.57	32.86	39.96	36.68	32.13	33.48	41.89	41.00	50.35	63.44	64.38	67.62	74.17	79.21
15-Dec-07	35.48	34.61	40.17	33.55	33.82	33.67	34.29	31.39	31.00	30.42	31.85	31.98	37.53	23.88	32.03	34.06	34.62	34.91	38.72	37.38	41.29	48.06	47.57	42.85
16-Dec-07	35.36	34.17	35.34	35.05	34.93	34.69	32.03	26.61	30.00	27.89	26.41	25.55	25.98	27.18	31.27	30.43	29.89	29.77	28.65	28.65	30.05	31.90	44.84	49.00
17-Dec-07	31.42	32.01	30.01	28.00	26.65	26.13	28.98	25.99	25.17	25.01	25.42	29.90	34.67	34.63	38.01	46.06	73.46	81.73	85.64	87.48	89.67	92.85	89.32	79.76
18-Dec-07	39.68	38.35	39.80	42.00	40.00	39.00	35.03	33.85	28.66	28.99	29.80	32.91	39.47	42.95	39.78	39.22	43.17	42.82	39.42	40.31	40.50	36.33	38.21	44.00
19-Dec-07	36.95	35.23	33.93	32.58	33.61	31.64	35.22	33.85	33.97	34.11	33.93	33.90	41.24	40.67	39.64	45.46	51.52	53.94	58.53	69.38	87.03	98.20	105.19	113.88
20-Dec-07	43.20	43.50	44.59	44.09	43.44	42.37	40.02	37.37	31.04	29.75	31.73	35.28	46.59	43.87	36.36	44.59	58.64	60.04	77.09	105.67	110.26	119.73	120.05	123.11
21-Dec-07	32.21	31.40	32.03	30.46	29.21	30.28	29.02	30.00	25.26	28.25	25.69	28.89	34.96	33.25	34.37	35.98	38.19	37.98	52.15	45.90	45.77	47.95	49.64	47.89
22-Dec-07	33.08	31.36	34.33	33.97	31.79	33.09	30.44	29.28	27.49	27.35	26.40	26.26	27.12	26.81	28.22	28.37	31.45	39.47	36.66	33.91	37.45	37.04	42.54	43.53
23-Dec-07	34.76	31.69	33.36	31.09	28.13	28.08	30.44	29.65	28.37	28.06	28.98	22.00	28.58	29.23	27.04	27.23	27.85	29.11	31.92	35.74	40.15	39.77	40.00	47.81
24-Dec-07	39.89	34.01	32.83	32.98	30.25	30.33	31.43	28.43	26.73	26.10	26.88	26.21	27.68	24.27	29.12	29.54	28.25	30.37	45.18	41.99	51.27	58.46	60.88	53.63
25-Dec-07	31.08	31.31	31.48	29.00	24.97	25.34	26.91	25.10	25.14	25.26	25.00	25.00	24.97	25.47	24.74	24.64	25.79	29.45	28.05	28.15	33.15	33.34	29.68	36.43
26-Dec-07	26.02	25.00	25.77	24.97	24.29	24.11	24.67	23.64	22.96	23.57	23.17	23.69	24.47	24.22	25.24	25.00	25.23	26.22	26.04	27.13	28.09	34.47	27.83	35.19
27-Dec-07	31.11	28.56	28.74	26.09	26.02	25.35	25.35	24.55	23.66	24.37	24.14	24.42	25.88	24.96	24.96	24.66	27.27	27.77	31.41	35.75	38.42	39.31	42.05	39.75
28-Dec-07	30.62	30.28	30.32	26.53	18.25	26.69	25.30	25.08	25.29	25.04	24.27	24.19	25.88	25.43	26.94	26.92	28.26	29.20	32.11	42.32	42.82	46.54	54.92	49.12
29-Dec-07	29.43	29.56	29.49	27.30	26.01	26.11	26.12	24.78	24.95	24.86	24.63	24.74	24.82	24.75	26.52	26.75	26.53	26.56	30.74	28.94	29.53	29.50	32.06	30.20
30-Dec-07	28.49	27.91	27.11	26.70	25.15	25.64	27.15	24.00	25.00	24.97	25.02	24.64	25.39	25.65	25.23	24.58	24.85	26.67	28.14	26.08	27.14	29.28	35.08	36.72
31-Dec-07	26.07	27.23	25.22	24.54	25.00	25.66	25.02	25.33	23.95	24.08	24.01	24.02	24.80	24.30	23.98	24.17	24.94	26.24	27.93	29.16	31.77	39.49	40.00	42.24

	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48
01-Dec-07	32.45	30.39	29.95	26.45	26.32	27.38	23.98	25.30	35.01	46.65	122.46	133.40	78.48	44.03	39.55	37.33	34.89	32.32	31.83	27.61	26.69	25.17	26.52	27.17
02-Dec-07	36.13	38.36	45.00	30.00	30.97	30.00	25.42	30.25	37.79	48.02	90.30	73.23	36.70	32.99	37.89	33.93	32.58	29.03	30.69	25.77	24.18	24.32	28.03	24.96
03-Dec-07	36.59	35.46	31.25	28.31	29.73	29.69	29.72	31.74	34.55	99.20	90.43	61.72	34.61	32.87	47.69	50.27	35.90	31.68	33.32	36.58	28.86	26.96	24.05	24.04
04-Dec-07	52.83	35.00	36.03	34.03	37.67	37.65	31.27	33.05	66.85	126.72	165.54	109.13	40.88	39.00	55.00	44.80	29.88	29.62	35.33	32.98	29.93	30.40	29.35	28.65
05-Dec-07	33.76	33.00	28.63	29.64	29.37	31.02	28.78	29.22	32.41	55.71	69.75	53.54	33.46	32.96	42.59	41.28	35.89	30.57	29.76	28.81	27.38	26.96	26.05	24.87
06-Dec-07	42.46	43.96	32.16	33.72	33.65	29.60	26.29	27.70	27.45	44.33	68.40	41.49	31.30	28.96	42.88	43.68	32.77	27.67	29.47	28.94	26.03	25.09	26.06	24.80
07-Dec-07	37.66	30.54	29.34	27.05	29.49	29.21	27.87	29.03	30.97	86.87	84.78	45.46	34.54	32.93	43.01	38.62	37.22	36.17	34.29	32.00	28.97	28.77	24.18	23.83
08-Dec-07	35.88	36.43	30.18	32.70	34.96	33.18	27.84	28.05	32.16	48.62	120.15	132.47	68.82	43.71	42.83	34.63	33.67	34.97	36.00	36.08	34.35	32.47	26.57	25.27
09-Dec-07	39.45	39.11	36.90	31.05	33.55	31.92	29.47	30.43	41.96	75.07	107.80	110.07	62.39	32.63	35.51	40.62	35.74	37.78	31.11	29.32	30.08	27.32	29.41	28.18
10-Dec-07	52.48	45.13	41.37	39.75	34.57	31.71	30.85	33.50	35.97	58.91	74.90	69.96	40.41	41.31	66.22	62.37	47.91	35.37	46.73	40.08	32.23	31.80	28.12	26.14
11-Dec-07	52.98	42.20	35.00	32.51	31.23	35.04	31.69	34.38	40.43	81.46	109.52	56.21	34.88	46.15	84.44	49.07	48.61	41.43	47.71	39.24	34.84	29.44	28.54	27.25
12-Dec-07	35.88	32.61	39.99	36.04	38.41	35.71	30.85	32.51	59.81	96.42	95.58	67.38	48.58	46.06	83.53	53.99	54.07	49.28	50.02	35.39	31.46	31.98	32.45	30.85
13-Dec-07	70.16	65.02	77.76	77.53	74.80	67.46	37.29	41.91	77.64	76.40	148.97	72.75	57.61	53.26	71.28	62.97	56.77	42.28	50.16	40.68	33.13	33.77	33.18	31.61
14-Dec-07	66.38	53.74	45.37	41.90	48.17	46.24	34.33	37.17	54.61	67.75	80.00	68.71	61.91	57.51	60.06	56.48	45.53	44.96	51.06	44.59	39.91	39.04	33.28	32.46
15-Dec-07	36.06	35.00	37.52	35.41	34.22	35.04	28.39	29.87	30.16	37.72	62.68	57.27	49.45	33.35	50.94	42.27	41.17	37.09	44.68	47.06	39.41	39.29	37.33	33.13
16-Dec-07	50.06	45.95	40.04	32.04	29.98	28.01	35.29	32.85	40.64	43.38	66.01	75.21	68.60	46.59	60.00	46.14	41.43	37.54	51.55	39.97	36.32	30.32	31.61	34.93
17-Dec-07	67.71	65.10	30.18	32.06	41.77	40.55	38.97	40.87	93.69	165.66	272.25	222.11	83.74	73.93	97.99	65.08	70.66	50.69	44.51	45.36	43.47	39.76	37.90	37.67
18-Dec-07	40.15	39.20	38.79	40.00	41.66	41.01	38.52	39.94	51.32	114.32	147.85	151.92	75.78	74.10	99.50	60.33	62.33	48.86	73.20	45.56	43.40	35.57	50.00	47.15
19-Dec-07	124.01	103.83	99.20	68.21	67.07	68.91	48.26	55.52	125.16	359.52	380.93	353.29	221.81	156.97	176.73	95.09	114.83	99.76	64.91	54.61	46.59	41.02	41.97	34.81
20-Dec-07	122.11	67.19	68.59	91.42	89.00	59.59	39.64	63.93	200.00	198.86	296.11	256.45	196.71	173.39	81.58	55.99	61.84	47.06	41.96	36.69	33.04	32.78	38.81	42.01
21-Dec-07	44.12	42.11	35.00	34.03	34.06	34.31	33.04	34.19	40.98	49.39	69.87	49.46	39.05	37.16	62.41	43.38	38.41	35.86	35.00	33.49	34.20	34.91	41.95	35.75
22-Dec-07	41.53	41.55	31.88	31.57	30.06	31.79	30.01	32.08	35.42	45.02	149.34	135.73	91.48	54.34	56.00	42.67	38.06	35.94	39.68	36.69	36.45	37.62	34.64	33.44
23-Dec-07	54.38	57.09	30.18	45.35	45.00	35.00	33.63	33.89	46.89	72.31	91.00	92.00	83.19	55.02	56.14	54.76	48.71	40.22	43.66	41.13	36.81	36.85	38.82	37.38
24-Dec-07	58.57	40.65	36.05	25.00	32.82	30.63	33.90	33.14	34.43	57.91	71.33	75.59	62.05	44.36	52.65	49.39	47.29	35.33	40.28	41.20	31.26	29.65	35.75	34.63
25-Dec-07	48.12	61.98	54.21	36.50	29.54	26.47	26.36	25.53	26.00	28.21	26.50	29.86	27.42	26.73	27.51	28.08	25.25	25.48	26.77	24.96	24.00	25.96	25.08	27.46
26-Dec-07	35.39	35.12	35.84	34.50	34.28	31.59	27.54	27.58	35.04	46.06	55.43	45.92	36.90	37.92	39.19	34.44	34.21	28.77	30.51	30.37	29.92	28.52	26.21	25.85
27-Dec-07	37.87	36.03	32.90	31.43	30.00	29.54	29.56	32.02	35.10	74.02	57.74	95.48	69.93	41.41	52.87	41.27	33.26	32.67	33.72	35.10	33.78	32.84	27.79	26.76
28-Dec-07	50.11	47.94	44.33	38.39	42.45	39.50	32.52	32.37	37.11	61.98	117.65	75.00	73.21	50.88	82.99	56.60	41.00	40.06	43.52	39.09	36.08	34.89	28.26	28.27
29-Dec-07	29.56	28.60	27.79	27.81	27.63	27.25	28.05	28.38	29.27	38.39	57.74	94.86	66.92	33.85	52.55	44.05	31.03	31.19	40.35	30.04	29.96	29.82	27.08	27.19
30-Dec-07	37.41	35.99	30.03	29.74	29.78	29.30	28.48	28.85	31.68	43.73	82.86	70.44	39.22	35.33	45.35	41.69	43.51	40.71	40.26	32.48	29.83	28.89	27.01	27.52
31-Dec-07	38.14	37.44	30.12	29.73	30.32	30.01	30.09	29.01	30.29	30.83	57.74	43.25	40.36	32.47	39.24	31.70	31.69	31.26	31.22	31.00	29.00	32.10	27.51	27.95

The rest of reference data (from Feb. 2007 to Nov. 2007) are omitted from the appendix. Please see the public website for more details of the data.

## II. Calculation of Best Parameters for SVM Training A

[local] 3 -4 -4 0.902113 (best c=8.0, g=0.0625, p=0.0625, mse=0.902113)  
[local] 3 -4 -6 0.89629 (best c=8.0, g=0.0625, p=0.015625, mse=0.89629)  
[local] 3 -4 -2 0.923075 (best c=8.0, g=0.0625, p=0.015625, mse=0.89629)  
[local] 3 -4 -7 0.894357 (best c=8.0, g=0.0625, p=0.0078125, mse=0.894357)  
[local] 3 -4 -3 0.889109 (best c=8.0, g=0.0625, p=0.125, mse=0.889109)  
[local] 3 -4 -5 0.889398 (best c=8.0, g=0.0625, p=0.125, mse=0.889109)  
[local] 3 -4 -1 1.00389 (best c=8.0, g=0.0625, p=0.125, mse=0.889109)  
[local] 3 -4 -8 0.892531 (best c=8.0, g=0.0625, p=0.125, mse=0.889109)  
[local] 3 -2 -4 2.20952 (best c=8.0, g=0.0625, p=0.125, mse=0.889109)  
[local] 3 -2 -6 2.19105 (best c=8.0, g=0.0625, p=0.125, mse=0.889109)  
[local] 3 -2 -2 2.1439 (best c=8.0, g=0.0625, p=0.125, mse=0.889109)  
[local] 3 -2 -7 2.17867 (best c=8.0, g=0.0625, p=0.125, mse=0.889109)  
[local] 3 -2 -3 2.1756 (best c=8.0, g=0.0625, p=0.125, mse=0.889109)  
[local] 3 -2 -5 2.20568 (best c=8.0, g=0.0625, p=0.125, mse=0.889109)  
[local] 3 -2 -1 2.15052 (best c=8.0, g=0.0625, p=0.125, mse=0.889109)  
[local] 3 -2 -8 2.17385 (best c=8.0, g=0.0625, p=0.125, mse=0.889109)  
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[local] 3 -7 -6 4.14178 (best c=8.0, g=0.0625, p=0.125, mse=0.889109)  
[local] 3 -7 -2 4.13478 (best c=8.0, g=0.0625, p=0.125, mse=0.889109)  
[local] 3 -7 -7 4.14273 (best c=8.0, g=0.0625, p=0.125, mse=0.889109)  
[local] 3 -7 -3 4.07896 (best c=8.0, g=0.0625, p=0.125, mse=0.889109)  
[local] 3 -7 -5 4.13944 (best c=8.0, g=0.0625, p=0.125, mse=0.889109)  
[local] 3 -7 -1 4.30742 (best c=8.0, g=0.0625, p=0.125, mse=0.889109)  
[local] 3 -7 -8 4.13966 (best c=8.0, g=0.0625, p=0.125, mse=0.889109)  
[local] 3 -1 -4 3.12575 (best c=8.0, g=0.0625, p=0.125, mse=0.889109)  
[local] 3 -1 -6 3.13818 (best c=8.0, g=0.0625, p=0.125, mse=0.889109)  
[local] 3 -1 -2 3.15727 (best c=8.0, g=0.0625, p=0.125, mse=0.889109)  
[local] 3 -1 -7 3.13838 (best c=8.0, g=0.0625, p=0.125, mse=0.889109)  
[local] 3 -1 -3 3.126 (best c=8.0, g=0.0625, p=0.125, mse=0.889109)  
[local] 3 -1 -5 3.13414 (best c=8.0, g=0.0625, p=0.125, mse=0.889109)  
[local] 3 -1 -1 3.28838 (best c=8.0, g=0.0625, p=0.125, mse=0.889109)  
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[local] 3 -6 -4 1.88255 (best c=8.0, g=0.0625, p=0.125, mse=0.889109)  
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[local] 3 -6 -8 1.88173 (best c=8.0, g=0.0625, p=0.125, mse=0.889109)  
[local] 3 -3 -4 1.43809 (best c=8.0, g=0.0625, p=0.125, mse=0.889109)  
[local] 3 -3 -6 1.4557 (best c=8.0, g=0.0625, p=0.125, mse=0.889109)  
... ..  
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[local] 5 -7 -8 0.4623 (best c=32.0, g=0.0078125, p=0.015625, mse=0.458636)  
[local] 5 -1 -4 3.11205 (best c=32.0, g=0.0078125, p=0.015625, mse=0.458636)  
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[local] 5 -1 -2 3.15868 (best c=32.0, g=0.0078125, p=0.015625, mse=0.458636)  
[local] 5 -1 -7 3.13139 (best c=32.0, g=0.0078125, p=0.015625, mse=0.458636)  
[local] 5 -1 -3 3.11167 (best c=32.0, g=0.0078125, p=0.015625, mse=0.458636)  
[local] 5 -1 -5 3.12267 (best c=32.0, g=0.0078125, p=0.015625, mse=0.458636)  
[local] 5 -1 -1 3.27597 (best c=32.0, g=0.0078125, p=0.015625, mse=0.458636)  
[local] 5 -1 -8 3.13307 (best c=32.0, g=0.0078125, p=0.015625, mse=0.458636)  
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[local] 5 -6 -6 0.161443 (best c=32.0, g=0.015625, p=0.015625, mse=0.161443)  
[local] 5 -6 -2 0.273508 (best c=32.0, g=0.015625, p=0.015625, mse=0.161443)  
[local] 5 -6 -7 0.157421 (best c=32.0, g=0.015625, p=0.0078125, mse=0.157421)  
[local] 5 -6 -3 0.185611 (best c=32.0, g=0.015625, p=0.0078125, mse=0.157421)  
[local] 5 -6 -5 0.166659 (best c=32.0, g=0.015625, p=0.0078125, mse=0.157421)  
[local] 5 -6 -1 0.395725 (best c=32.0, g=0.015625, p=0.0078125, mse=0.157421)  
[local] 5 -6 -8 0.15632 (best c=32.0, g=0.015625, p=0.00390625, mse=0.15632)  
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 [local] 0 -4 -2 5.74414 (best c=32.0, g=0.015625, p=0.00390625, mse=0.15632)  
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 [local] 0 -1 -8 4.96592 (best c=32.0, g=0.015625, p=0.00390625, mse=0.15632)  
 [local] 0 -6 -4 11.8989 (best c=32.0, g=0.015625, p=0.00390625, mse=0.15632)  
 ... ..  
 [local] -1 -3 -4 7.03019 (best c=64.0, g=0.015625, p=0.03125, mse=0.0882816)  
 [local] -1 -3 -6 7.02373 (best c=64.0, g=0.015625, p=0.03125, mse=0.0882816)  
 [local] -1 -3 -2 7.23903 (best c=64.0, g=0.015625, p=0.03125, mse=0.0882816)  
 [local] -1 -3 -7 7.02788 (best c=64.0, g=0.015625, p=0.03125, mse=0.0882816)  
 [local] -1 -3 -3 7.07354 (best c=64.0, g=0.015625, p=0.03125, mse=0.0882816)  
 [local] -1 -3 -5 7.01914 (best c=64.0, g=0.015625, p=0.03125, mse=0.0882816)  
 [local] -1 -3 -1 7.34216 (best c=64.0, g=0.015625, p=0.03125, mse=0.0882816)

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[local] -1 -8 -4 17.4413 (best c=64.0, g=0.015625, p=0.03125, mse=0.0882816)  
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[local] -1 -8 -8 17.4682 (best c=64.0, g=0.015625, p=0.03125, mse=0.0882816)  
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[local] -1 0 -3 8.19376 (best c=64.0, g=0.015625, p=0.03125, mse=0.0882816)  
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[local] -1 0 -1 8.31917 (best c=64.0, g=0.015625, p=0.03125, mse=0.0882816)  
[local] -1 0 -8 8.22675 (best c=64.0, g=0.015625, p=0.03125, mse=0.0882816)  
[local] -1 -5 -4 12.2766 (best c=64.0, g=0.015625, p=0.03125, mse=0.0882816)  
[local] -1 -5 -6 12.2562 (best c=64.0, g=0.015625, p=0.03125, mse=0.0882816)  
[local] -1 -5 -2 12.3937 (best c=64.0, g=0.015625, p=0.03125, mse=0.0882816)  
[local] -1 -5 -7 12.2554 (best c=64.0, g=0.015625, p=0.03125, mse=0.0882816)  
[local] -1 -5 -3 12.3199 (best c=64.0, g=0.015625, p=0.03125, mse=0.0882816)  
[local] -1 -5 -5 12.2576 (best c=64.0, g=0.015625, p=0.03125, mse=0.0882816)  
[local] -1 -5 -1 12.4874 (best c=64.0, g=0.015625, p=0.03125, mse=0.0882816)  
[local] -1 -5 -8 12.2597 (best c=64.0, g=0.015625, p=0.03125, mse=0.0882816)

**64.0 0.015625 0.03125 0.0882816**

### III. Calculation of Best Parameters for SVM Training B

```
[local] 3 -4 -4 8.06378 (best c=8.0, g=0.0625, p=0.0625, mse=8.06378)
[local] 3 -4 -6 8.10882 (best c=8.0, g=0.0625, p=0.0625, mse=8.06378)
[local] 3 -4 -2 8.10268 (best c=8.0, g=0.0625, p=0.0625, mse=8.06378)
[local] 3 -4 -7 8.11612 (best c=8.0, g=0.0625, p=0.0625, mse=8.06378)
[local] 3 -4 -3 8.06293 (best c=8.0, g=0.0625, p=0.125, mse=8.06293)
[local] 3 -4 -5 8.09116 (best c=8.0, g=0.0625, p=0.125, mse=8.06293)
[local] 3 -4 -1 7.92555 (best c=8.0, g=0.0625, p=0.5, mse=7.92555)
[local] 3 -4 -8 8.11976 (best c=8.0, g=0.0625, p=0.5, mse=7.92555)
[local] 3 -2 -4 27.1932 (best c=8.0, g=0.0625, p=0.5, mse=7.92555)
[local] 3 -2 -6 27.2226 (best c=8.0, g=0.0625, p=0.5, mse=7.92555)
[local] 3 -2 -2 26.8256 (best c=8.0, g=0.0625, p=0.5, mse=7.92555)
[local] 3 -2 -7 27.2268 (best c=8.0, g=0.0625, p=0.5, mse=7.92555)
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[local] 3 -2 -8 27.2288 (best c=8.0, g=0.0625, p=0.5, mse=7.92555)
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[local] 3 -7 -6 16.6384 (best c=8.0, g=0.0625, p=0.5, mse=7.92555)
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[local] 3 -7 -7 16.6641 (best c=8.0, g=0.0625, p=0.5, mse=7.92555)
[local] 3 -7 -3 16.4678 (best c=8.0, g=0.0625, p=0.5, mse=7.92555)
[local] 3 -7 -5 16.5998 (best c=8.0, g=0.0625, p=0.5, mse=7.92555)
[local] 3 -7 -1 17.0761 (best c=8.0, g=0.0625, p=0.5, mse=7.92555)
[local] 3 -7 -8 16.675 (best c=8.0, g=0.0625, p=0.5, mse=7.92555)
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[local] 3 -1 -6 48.4982 (best c=8.0, g=0.0625, p=0.5, mse=7.92555)
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[local] 3 -1 -7 48.5201 (best c=8.0, g=0.0625, p=0.5, mse=7.92555)
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```

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 ... ..  
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 [local] 6 -5 -4 1.45949 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] 6 -5 -6 1.4264 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] 6 -5 -2 1.50725 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] 6 -5 -7 1.41281 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] 6 -5 -3 1.46738 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] 6 -5 -5 1.44551 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] 6 -5 -1 1.54186 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] 6 -5 -8 1.40717 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -4 -4 76.3944 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -4 -6 76.3802 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -4 -2 76.5495 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -4 -7 76.3789 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -4 -3 76.3924 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -4 -5 76.3841 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -4 -1 77.1944 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -4 -8 76.3825 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -2 -4 90.9765 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -2 -6 90.9533 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -2 -2 90.9622 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -2 -7 90.9446 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -2 -3 91.0008 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -2 -5 90.9618 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -2 -1 91.3918 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -2 -8 90.9398 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -7 -4 147.574 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -7 -6 147.654 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -7 -2 146.968 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -7 -7 147.677 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -7 -3 147.425 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)



[local] -1 -7 -5 147.638 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -7 -1 146.582 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -7 -8 147.685 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -1 -4 107.398 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -1 -6 107.276 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -1 -2 107.678 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -1 -7 107.256 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -1 -3 107.561 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -1 -5 107.319 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -1 -1 107.681 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -1 -8 107.249 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -6 -4 122.686 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -6 -6 122.648 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -6 -2 122.794 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -6 -7 122.633 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -6 -3 122.904 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -6 -5 122.678 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -3 -1 122.475 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -6 -8 122.626 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -3 -4 78.5668 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -3 -6 78.6234 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -3 -2 78.618 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -3 -7 78.6374 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -3 -3 78.5724 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -3 -5 78.6022 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -3 -1 79.0702 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -3 -8 78.6437 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -8 -4 163.927 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -8 -6 163.876 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -8 -2 163.193 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -8 -7 163.873 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -8 -3 163.693 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -8 -5 163.9 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -8 -1 162.652 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -8 -8 163.873 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 0 -4 129.734 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 0 -6 129.778 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 0 -2 129.469 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 0 -7 129.779 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 0 -3 129.649 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 0 -5 129.773 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 0 -1 128.897 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 0 -8 129.781 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -5 -4 95.4482 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -5 -6 95.5956 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -5 -2 95.1433 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -5 -7 95.621 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -5 -3 95.3484 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -5 -5 95.5443 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -5 -1 94.7727 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)  
 [local] -1 -5 -8 95.6301 (best c=64.0, g=0.0078125, p=0.25, mse=0.33015)

**64.0 0.0078125 0.25 0.33015**

## IV. Experimental Results

Date		16 – Jun - 07		17 – Jun - 07		18 – Jun - 07		19 – Jun - 07		20 – Jun - 07	
Time	Periods	Ref.	ANNs	Ref.	ANNs	Ref.	ANNs	Ref.	ANNs	Ref.	ANNs
HH_1	00.00-00.30	21.77	17.98	19.57	17.61	16.45	15.63	16.32	14.15	16.11	16.04
HH_2	00.30-01.00	18.98	17.74	18.12	18.11	16.12	16.38	15.75	13.00	15.74	15.39
HH_3	01.00-01.30	20.00	17.84	17.50	17.26	16.07	15.88	14.93	14.57	13.68	14.97
HH_4	01.30-02.00	20.00	18.74	17.94	17.68	15.70	17.90	14.38	13.60	13.77	13.72
HH_5	02.00-02.30	16.80	16.59	15.99	17.09	16.00	14.21	13.28	13.97	13.09	12.75
HH_6	02.30-03.00	16.33	16.60	15.99	17.35	15.39	14.35	13.41	14.08	12.30	13.47
HH_7	03.00-03.30	15.88	16.45	15.22	16.87	15.40	13.34	13.16	12.01	12.43	13.05
HH_8	03.30-04.00	15.98	16.53	15.36	17.08	17.44	13.47	12.40	10.94	12.57	13.06
HH_9	04.00-04.30	15.83	15.90	15.50	16.93	14.21	13.25	11.72	12.29	12.68	12.98
HH_10	04.30-05.00	15.44	16.23	15.99	16.77	14.00	13.27	9.65	11.39	11.82	12.07
HH_11	05.00-05.30	15.74	16.06	17.81	17.44	13.61	13.66	10.25	13.07	12.48	14.21
HH_12	05.30-06.00	14.99	16.17	11.00	17.00	14.68	13.23	13.59	12.72	12.25	13.56
HH_13	06.00-06.30	16.49	17.29	20.67	17.79	17.20	17.98	17.04	17.12	16.87	15.49
HH_14	06.30-07.00	15.81	17.08	14.00	17.96	17.16	18.71	16.79	15.60	15.56	14.92
HH_15	07.00-07.30	16.35	19.09	17.51	16.61	16.77	18.78	20.86	21.25	18.12	19.24
HH_16	07.30-08.00	19.15	19.45	16.59	16.54	25.00	21.08	23.50	24.23	19.35	17.50
HH_17	08.00-08.30	20.27	23.96	15.81	16.67	38.20	34.64	33.65	30.13	17.63	21.70
HH_18	08.30-09.00	22.22	28.29	17.43	17.02	44.44	44.39	33.62	29.90	17.94	20.17
HH_19	09.00-09.30	25.76	31.31	17.93	16.36	45.81	48.88	42.57	40.68	26.75	25.20
HH_20	09.30-10.00	44.26	37.95	18.03	18.05	59.32	60.57	39.79	41.72	29.04	29.64
HH_21	10.00-10.30	51.91	53.48	18.08	20.67	77.51	75.59	46.29	46.65	33.62	32.60
HH_22	10.30-11.00	69.88	65.14	22.95	24.11	87.50	90.46	64.16	61.43	37.27	34.62
HH_23	11.00-11.30	73.75	75.49	27.16	28.50	102.60	101.66	73.08	73.88	52.43	52.47
HH_24	11.30-12.00	70.73	73.51	31.95	29.01	98.53	100.99	76.00	71.02	77.05	76.85
HH_25	12.00-12.30	74.14	76.78	38.72	29.34	97.28	99.79	74.14	76.36	76.38	77.29
HH_26	12.30-13.00	55.13	49.51	29.30	23.21	72.29	75.33	58.78	59.47	80.74	81.71
HH_27	13.00-13.30	45.22	42.05	23.85	27.35	93.26	92.47	62.99	70.33	70.00	74.75
HH_28	13.30-14.00	38.63	41.11	20.40	27.54	98.00	89.80	65.00	67.41	70.25	68.90
HH_29	14.00-14.30	33.48	37.41	20.20	26.23	94.83	81.62	55.40	63.32	62.70	66.41
HH_30	14.30-15.00	30.63	33.53	20.29	24.60	67.60	71.86	64.20	59.98	65.77	60.81
HH_31	15.00-15.30	32.35	28.80	21.38	21.20	59.16	58.76	63.78	63.96	64.66	62.51
HH_32	15.30-16.00	41.66	30.23	20.23	21.22	59.75	61.22	73.34	67.32	59.37	66.22
HH_33	16.00-16.30	28.94	34.73	19.86	18.32	28.94	38.10	72.65	70.32	89.96	85.99
HH_34	16.30-17.00	39.26	39.60	19.96	25.04	71.07	67.66	77.40	76.65	95.70	94.09
HH_35	17.00-17.30	36.88	36.72	21.89	21.76	65.13	65.02	80.24	80.24	72.26	72.22
HH_36	17.30-18.00	35.92	35.91	21.11	20.75	43.14	43.30	74.79	74.69	47.86	47.89
HH_37	18.00-18.30	24.93	24.86	19.10	19.72	27.27	26.79	33.63	33.93	40.39	40.42
HH_38	18.30-19.00	19.60	19.56	17.50	16.85	24.70	25.10	31.86	31.38	40.29	40.14
HH_39	19.00-19.30	19.33	19.35	20.38	20.12	23.23	22.86	42.64	42.67	47.22	47.17
HH_40	19.30-20.00	18.27	25.02	19.37	18.52	21.37	22.03	26.49	29.42	45.68	42.81
HH_41	20.00-20.30	20.00	13.60	19.96	17.18	19.75	19.27	20.74	23.79	44.27	43.11
HH_42	20.30-21.00	18.50	17.54	21.35	17.82	19.14	20.05	18.96	18.95	35.47	35.55
HH_43	21.00-21.30	17.50	23.45	20.33	17.35	22.44	21.35	21.00	22.15	29.13	26.92
HH_44	21.30-22.00	22.82	22.33	21.19	18.39	17.97	19.40	23.93	23.67	29.43	25.75
HH_45	22.00-22.30	23.60	21.38	21.85	18.92	18.00	20.42	18.13	20.31	25.59	24.80
HH_46	22.30-23.00	19.93	20.32	20.92	19.09	18.27	20.78	18.23	16.77	21.96	21.11
HH_47	23.00-23.30	24.39	21.63	19.80	18.01	18.43	22.41	17.56	18.75	18.56	19.93
HH_48	23.30-24.00	25.26	20.49	20.52	17.71	18.75	21.36	17.71	18.49	17.99	19.85

**Table A (a)** Forecasting results by ANNs (16<sup>th</sup> -20<sup>th</sup> June 2007)

Date Time Periods	21 – Jun - 07		22 – Jun - 07		23 – Jun - 07		24 – Jun - 07		25 – Jun - 07	
	Ref.	ANNs	Ref.	ANNs	Ref.	ANNs	Ref.	ANNs	Ref.	ANNs
HH_1 00.00-00.30	15.87	17.13	18.66	14.36	18.10	15.67	16.12	12.93	15.06	13.23
HH_2 00.30-01.00	16.02	16.17	17.10	13.85	16.31	15.35	15.65	12.94	12.93	12.05
HH_3 01.00-01.30	16.43	16.75	16.64	14.92	17.71	15.67	14.48	12.85	11.97	12.71
HH_4 01.30-02.00	14.97	14.93	13.81	15.25	16.43	15.50	14.11	12.50	10.49	9.80
HH_5 02.00-02.30	14.00	13.16	12.84	14.85	14.90	15.42	10.29	12.75	9.85	11.49
HH_6 02.30-03.00	14.03	12.49	12.16	14.64	15.09	15.36	10.00	12.84	9.95	11.98
HH_7 03.00-03.30	15.00	15.85	11.00	14.14	21.00	15.48	11.24	12.68	11.66	11.24
HH_8 03.30-04.00	14.96	15.68	10.90	13.75	14.59	15.38	10.52	12.61	11.54	10.54
HH_9 04.00-04.30	14.50	16.03	10.73	13.89	14.31	15.34	8.60	12.87	12.54	12.05
HH_10 04.30-05.00	17.11	16.23	10.00	14.02	13.67	15.39	17.11	12.62	12.88	10.56
HH_11 05.00-05.30	14.75	14.98	10.09	13.75	13.50	15.31	9.93	13.05	10.39	12.90
HH_12 05.30-06.00	15.58	15.59	12.54	14.04	13.49	15.44	8.00	12.87	11.87	12.28
HH_13 06.00-06.30	18.32	16.45	15.41	15.12	16.62	15.37	8.27	13.38	15.10	14.94
HH_14 06.30-07.00	16.30	17.15	15.62	14.66	15.55	15.15	9.28	13.34	16.06	13.92
HH_15 07.00-07.30	22.54	24.25	18.30	16.74	15.65	16.43	11.00	13.61	20.49	19.51
HH_16 07.30-08.00	28.01	29.34	18.36	17.52	17.43	16.45	11.40	13.94	22.09	20.56
HH_17 08.00-08.30	60.00	60.75	18.60	18.81	17.11	17.18	12.11	15.22	24.38	26.90
HH_18 08.30-09.00	78.47	79.18	23.09	19.68	17.64	17.45	13.91	15.08	22.58	23.86
HH_19 09.00-09.30	100.60	99.26	24.62	21.88	17.84	18.75	14.67	16.56	31.41	35.15
HH_20 09.30-10.00	89.96	90.01	25.84	25.65	18.05	18.65	16.15	15.88	33.03	32.02
HH_21 10.00-10.30	111.27	112.30	27.52	30.06	19.59	18.95	16.12	17.14	43.91	42.06
HH_22 10.30-11.00	118.78	118.41	31.71	35.91	18.26	19.51	18.43	18.08	47.05	47.57
HH_23 11.00-11.30	123.92	123.55	42.47	40.16	20.08	19.26	19.98	21.13	65.72	66.83
HH_24 11.30-12.00	121.38	119.91	46.47	41.65	18.83	17.90	22.42	23.34	69.51	72.94
HH_25 12.00-12.30	113.52	114.83	45.06	43.32	19.10	18.99	23.66	23.28	77.78	76.50
HH_26 12.30-13.00	99.12	98.29	35.45	26.60	16.91	22.20	23.37	18.88	63.26	63.53
HH_27 13.00-13.30	78.46	82.04	25.01	27.45	17.25	18.37	24.26	21.48	76.21	66.27
HH_28 13.30-14.00	69.26	68.91	19.45	27.65	19.61	17.71	20.63	20.71	60.79	58.84
HH_29 14.00-14.30	70.53	71.02	20.06	25.30	16.84	17.60	19.00	20.78	57.57	59.85
HH_30 14.30-15.00	64.62	64.95	20.60	24.18	16.07	17.42	17.47	20.37	56.94	57.89
HH_31 15.00-15.30	70.28	70.22	19.96	23.69	25.12	18.51	22.00	21.31	69.97	68.65
HH_32 15.30-16.00	72.96	73.43	19.00	24.69	17.20	18.98	18.12	21.65	74.78	72.07
HH_33 16.00-16.30	82.63	76.71	21.00	23.75	17.64	23.68	28.94	20.82	80.46	86.67
HH_34 16.30-17.00	85.83	86.40	25.07	23.86	19.97	21.46	20.00	23.22	88.60	89.33
HH_35 17.00-17.30	71.94	72.03	25.66	25.60	17.56	17.39	20.00	20.29	57.74	57.64
HH_36 17.30-18.00	62.90	62.95	21.02	20.64	18.93	19.15	18.51	17.98	74.65	74.66
HH_37 18.00-18.30	65.43	65.43	18.25	19.01	17.50	17.36	17.40	17.58	37.56	37.45
HH_38 18.30-19.00	44.93	45.12	18.15	17.19	16.88	16.95	17.11	17.93	29.83	29.84
HH_39 19.00-19.30	39.87	39.81	19.58	19.73	16.88	15.78	17.91	17.66	22.39	22.45
HH_40 19.30-20.00	32.72	31.81	21.04	17.78	17.47	18.96	17.02	15.00	32.50	32.78
HH_41 20.00-20.30	27.35	29.04	21.47	19.92	17.50	19.23	16.74	16.39	29.65	26.70
HH_42 20.30-21.00	23.50	23.46	18.60	18.66	15.04	18.28	16.27	14.77	19.46	19.04
HH_43 21.00-21.30	24.97	24.55	22.90	17.65	15.45	17.55	16.84	13.08	19.00	21.07
HH_44 21.30-22.00	18.49	17.24	18.83	17.01	16.21	16.97	16.83	13.50	17.00	20.84
HH_45 22.00-22.30	19.90	18.49	19.56	15.58	16.25	16.37	17.24	13.57	16.20	19.24
HH_46 22.30-23.00	18.11	16.59	19.30	14.86	16.36	15.73	16.18	13.27	16.00	15.24
HH_47 23.00-23.30	18.04	16.44	17.80	17.15	22.29	16.20	17.79	12.80	17.35	13.97
HH_48 23.30-24.00	18.88	21.68	19.60	16.26	20.78	16.15	16.93	13.22	15.40	16.06

Table A (b) Forecasting results by ANNs (21<sup>st</sup> -25<sup>th</sup> June 2007)

Date	26 – Jun - 07		27 – Jun - 07		28 – Jun - 07		29 – Jun - 07		30 – Jun - 07	
Time Periods	Ref.	ANNs	Ref.	ANNs	Ref.	ANNs	Ref.	ANNs	Ref.	ANNs
HH_1 00.00-00.30	20.84	16.71	17.10	15.89	17.39	16.16	17.61	16.84	17.25	14.97
HH_2 00.30-01.00	19.82	16.65	17.77	15.52	15.71	16.08	19.54	16.92	16.08	14.31
HH_3 01.00-01.30	17.94	16.52	14.99	15.86	15.49	16.10	19.20	16.77	16.15	15.47
HH_4 01.30-02.00	15.88	16.14	15.00	15.89	15.33	16.04	11.83	16.88	15.29	15.56
HH_5 02.00-02.30	15.24	15.97	14.59	15.28	14.34	15.75	13.42	16.44	13.72	15.37
HH_6 02.30-03.00	15.21	16.11	14.24	15.22	14.67	15.75	14.37	16.47	12.99	15.15
HH_7 03.00-03.30	14.56	16.13	14.00	15.16	14.16	15.94	14.64	16.64	13.00	14.98
HH_8 03.30-04.00	14.29	16.13	13.76	15.02	13.05	15.96	14.22	16.72	13.00	14.64
HH_9 04.00-04.30	14.62	16.28	13.84	14.93	13.11	15.89	14.43	16.59	12.92	14.71
HH_10 04.30-05.00	14.87	16.01	17.11	15.01	12.82	15.91	12.64	16.61	12.95	14.89
HH_11 05.00-05.30	16.26	16.45	13.43	15.01	13.07	15.87	11.83	16.61	12.87	14.41
HH_12 05.30-06.00	16.91	16.28	13.28	15.11	13.71	15.91	13.53	16.59	11.30	14.82
HH_13 06.00-06.30	18.66	16.99	18.88	15.64	17.57	15.99	19.00	16.75	14.01	15.22
HH_14 06.30-07.00	17.00	17.06	16.98	15.28	16.40	16.04	16.61	16.92	16.08	14.78
HH_15 07.00-07.30	17.47	17.83	17.99	17.22	18.40	16.60	18.19	17.00	17.39	17.07
HH_16 07.30-08.00	17.62	17.95	18.41	17.81	20.05	16.61	17.86	16.87	16.57	17.30
HH_17 08.00-08.30	24.63	20.95	22.26	20.48	19.28	18.34	26.73	18.56	18.03	17.65
HH_18 08.30-09.00	25.29	21.67	23.31	22.29	20.21	19.31	25.67	19.67	19.14	17.78
HH_19 09.00-09.30	30.00	23.83	22.97	25.15	21.46	20.21	25.49	20.13	18.05	19.38
HH_20 09.30-10.00	25.08	24.67	23.43	25.35	20.87	20.55	25.82	22.18	20.64	22.58
HH_21 10.00-10.30	22.87	29.19	30.43	26.40	21.79	21.61	28.57	27.94	27.45	26.54
HH_22 10.30-11.00	23.77	30.53	32.91	30.15	23.82	21.64	28.51	29.56	29.07	29.69
HH_23 11.00-11.30	44.00	36.07	32.00	30.58	21.62	22.60	30.21	32.82	29.48	31.30
HH_24 11.30-12.00	40.07	39.92	28.01	27.77	28.00	24.33	39.93	31.84	27.78	28.76
HH_25 12.00-12.30	38.04	39.23	28.92	29.37	28.11	23.85	39.53	32.17	32.53	31.27
HH_26 12.30-13.00	35.48	33.36	26.00	31.56	22.72	24.46	25.37	25.68	25.11	23.88
HH_27 13.00-13.30	35.50	34.42	27.27	27.33	22.67	22.68	22.18	24.95	23.66	21.07
HH_28 13.30-14.00	31.94	32.49	24.60	26.34	21.49	21.67	16.84	24.12	23.18	20.88
HH_29 14.00-14.30	31.53	32.18	23.60	25.10	22.46	21.48	17.05	23.63	20.75	19.55
HH_30 14.30-15.00	31.30	30.66	20.20	23.77	20.98	20.70	17.29	22.49	19.02	19.22
HH_31 15.00-15.30	25.66	31.14	20.05	23.70	18.57	20.61	17.08	21.37	18.00	20.15
HH_32 15.30-16.00	27.76	31.97	22.49	24.60	19.81	20.99	19.60	21.69	17.44	21.03
HH_33 16.00-16.30	34.55	32.29	33.79	29.87	23.38	22.41	20.90	21.06	17.49	23.85
HH_34 16.30-17.00	38.78	36.50	33.95	29.81	25.38	23.36	18.80	23.70	20.00	20.55
HH_35 17.00-17.30	36.33	36.33	36.45	35.98	23.63	24.34	21.98	22.35	23.44	23.45
HH_36 17.30-18.00	27.13	26.90	22.93	22.75	19.65	19.60	23.28	23.18	24.55	24.46
HH_37 18.00-18.30	21.50	22.17	18.01	18.85	18.15	17.00	20.89	20.89	42.43	42.56
HH_38 18.30-19.00	19.39	19.13	17.94	16.80	18.41	20.43	19.21	18.68	17.75	17.33
HH_39 19.00-19.30	19.24	19.26	18.61	18.37	19.50	21.13	20.96	22.22	21.90	21.98
HH_40 19.30-20.00	17.94	21.13	20.53	21.21	19.35	18.43	21.55	18.94	20.88	18.09
HH_41 20.00-20.30	17.49	20.03	18.70	17.83	19.61	18.38	20.94	21.59	19.36	17.99
HH_42 20.30-21.00	17.18	18.68	16.49	17.82	18.96	17.78	20.08	20.43	18.33	17.42
HH_43 21.00-21.30	17.06	18.43	19.67	19.16	16.84	17.43	20.26	17.83	20.75	18.61
HH_44 21.30-22.00	17.38	17.95	17.88	18.65	15.68	16.69	21.14	17.08	19.97	17.12
HH_45 22.00-22.30	17.09	18.20	17.00	17.67	15.00	16.73	21.80	17.41	18.00	15.73
HH_46 22.30-23.00	16.00	17.66	17.02	16.62	17.21	16.49	21.09	17.41	17.03	14.96
HH_47 23.00-23.30	19.66	17.24	17.65	17.34	17.42	16.56	17.79	17.39	18.72	17.19
HH_48 23.30-24.00	20.22	17.72	19.40	17.10	17.99	16.69	18.99	17.42	20.41	16.46

Table A (c) Forecasting results by ANNs (26<sup>th</sup> -30<sup>th</sup> June 2007)

Date	01 – Dec - 07		02 – Dec - 07		03 – Dec - 07		04 – Dec - 07		05 – Dec - 07	
Time Periods	Ref.	ANNs	Ref.	ANNs	Ref.	ANNs	Ref.	ANNs	Ref.	ANNs
HH_1 00.00-00.30	31.26	25.55	27.55	24.00	24.13	25.57	31.73	26.62	25.55	26.68
HH_2 00.30-01.00	30.15	23.44	25.14	22.84	24.07	24.39	31.43	27.24	27.94	25.97
HH_3 01.00-01.30	29.97	24.34	25.36	23.17	28.00	24.63	25.01	25.66	24.05	26.06
HH_4 01.30-02.00	29.95	23.54	25.19	22.69	23.52	24.13	25.00	25.65	22.77	25.75
HH_5 02.00-02.30	22.00	24.29	23.50	22.89	23.00	24.21	25.00	23.74	22.80	25.73
HH_6 02.30-03.00	22.62	23.85	22.02	22.63	23.50	23.94	24.56	23.75	22.75	25.57
HH_7 03.00-03.30	21.72	23.24	21.33	22.34	23.71	23.66	24.47	24.21	23.62	25.41
HH_8 03.30-04.00	22.15	23.51	21.87	22.38	22.60	23.64	23.51	23.28	22.45	25.36
HH_9 04.00-04.30	21.92	23.77	21.47	22.45	22.56	23.68	22.42	22.67	23.17	25.37
HH_10 04.30-05.00	22.55	23.00	21.53	22.09	22.60	23.34	22.15	23.35	22.37	25.18
HH_11 05.00-05.30	24.73	22.94	19.00	22.30	23.02	23.71	26.37	25.37	24.58	25.47
HH_12 05.30-06.00	22.66	22.90	19.13	22.33	22.79	23.77	26.07	25.79	25.66	25.53
HH_13 06.00-06.30	27.50	24.61	22.35	24.20	27.28	26.19	34.12	32.64	30.09	27.28
HH_14 06.30-07.00	20.84	25.00	22.18	24.35	27.83	26.31	30.05	32.02	29.40	27.33
HH_15 07.00-07.30	25.20	23.09	22.96	23.49	30.54	25.54	39.23	34.04	29.65	26.91
HH_16 07.30-08.00	25.49	22.65	22.59	23.86	31.77	26.27	43.05	39.03	36.76	27.55
HH_17 08.00-08.30	25.46	23.15	22.63	26.37	33.61	30.09	57.86	56.56	42.18	30.53
HH_18 08.30-09.00	26.76	24.21	26.19	27.07	33.70	30.87	59.33	57.20	40.07	31.04
HH_19 09.00-09.30	26.56	24.40	27.19	27.83	34.58	32.03	56.00	62.35	40.55	31.94
HH_20 09.30-10.00	29.06	28.13	28.61	31.47	36.56	36.63	72.76	73.80	37.98	35.20
HH_21 10.00-10.30	33.78	34.57	32.11	30.96	36.83	36.71	80.45	71.11	35.93	36.35
HH_22 10.30-11.00	33.31	32.42	31.40	31.51	36.79	35.65	69.52	68.93	35.51	39.49
HH_23 11.00-11.30	33.78	29.34	34.67	33.29	35.82	36.63	61.12	58.59	33.74	32.55
HH_24 11.30-12.00	32.13	32.72	37.36	37.39	36.33	37.76	52.39	53.09	32.46	32.79
HH_25 12.00-12.30	32.45	36.59	36.13	37.51	36.59	35.75	52.83	55.37	33.76	31.35
HH_26 12.30-13.00	30.39	37.70	38.36	29.76	35.46	33.49	35.00	41.93	33.00	33.00
HH_27 13.00-13.30	29.95	36.86	45.00	32.73	31.25	35.86	36.03	43.08	28.63	33.65
HH_28 13.30-14.00	26.45	34.20	30.00	31.01	28.31	33.97	34.03	41.92	29.64	32.44
HH_29 14.00-14.30	26.32	34.96	30.97	31.53	29.73	34.56	37.67	42.56	29.37	32.84
HH_30 14.30-15.00	27.38	32.67	30.00	30.03	29.69	32.90	37.65	41.33	31.02	31.76
HH_31 15.00-15.30	23.98	27.13	25.42	25.56	29.72	27.55	31.27	31.65	28.78	28.09
HH_32 15.30-16.00	25.30	28.25	30.25	26.40	31.74	28.54	33.05	33.17	29.22	28.76
HH_33 16.00-16.30	35.01	38.16	37.79	35.08	34.55	39.19	66.85	55.85	32.41	36.19
HH_34 16.30-17.00	46.65	46.13	48.02	47.79	99.20	96.55	126.72	126.30	55.71	56.78
HH_35 17.00-17.30	122.46	122.53	90.30	90.50	90.43	90.47	165.54	165.57	69.75	69.60
HH_36 17.30-18.00	133.40	133.74	73.23	72.44	61.72	61.02	109.13	108.78	53.54	53.64
HH_37 18.00-18.30	78.48	56.58	36.70	42.63	34.61	45.37	40.88	30.00	33.46	39.13
HH_38 18.30-19.00	44.03	38.59	32.99	33.47	32.87	36.66	39.00	40.69	32.96	33.80
HH_39 19.00-19.30	39.55	39.33	37.89	37.32	47.69	48.34	55.00	54.76	42.59	43.13
HH_40 19.30-20.00	37.33	38.55	33.93	36.82	50.27	40.71	44.80	45.51	41.28	37.27
HH_41 20.00-20.30	34.89	34.64	32.58	35.89	35.90	35.75	29.88	36.13	35.89	34.81
HH_42 20.30-21.00	32.32	34.73	29.03	30.30	31.68	32.67	29.62	33.68	30.57	31.36
HH_43 21.00-21.30	31.83	34.48	30.69	31.22	33.32	34.20	35.33	42.08	29.76	32.60
HH_44 21.30-22.00	27.61	30.51	25.77	28.17	36.58	30.63	32.98	36.66	28.81	30.19
HH_45 22.00-22.30	26.69	28.76	24.18	26.40	28.86	28.37	29.93	30.77	27.38	28.57
HH_46 22.30-23.00	25.17	25.53	24.32	23.98	26.96	25.55	30.40	26.61	26.96	26.67
HH_47 23.00-23.30	26.52	27.01	28.03	24.96	24.05	26.64	29.35	27.52	26.05	27.38
HH_48 23.30-24.00	27.17	26.73	24.96	24.69	24.04	26.29	28.65	26.62	24.87	27.13

**Table B (a)** Forecasting results by ANNs (1<sup>st</sup> -5<sup>th</sup> December 2007)

Date	06 – Dec - 07		07 – Dec - 07		08 – Dec - 07		09 – Dec - 07		10 – Dec - 07	
Time Periods	Ref.	ANNs	Ref.	ANNs	Ref.	ANNs	Ref.	ANNs	Ref.	ANNs
HH_1 00.00-00.30	24.44	24.12	23.96	25.85	28.50	26.67	29.54	27.19	26.78	28.47
HH_2 00.30-01.00	24.20	24.11	24.26	25.51	31.22	24.43	28.70	25.22	25.50	27.35
HH_3 01.00-01.30	23.82	23.66	25.00	25.35	25.78	25.33	29.23	26.08	25.37	27.47
HH_4 01.30-02.00	22.65	23.57	24.98	25.16	24.87	24.47	28.38	25.33	24.41	26.98
HH_5 02.00-02.30	22.47	22.98	22.68	24.90	24.15	25.20	25.69	26.06	23.95	26.92
HH_6 02.30-03.00	22.44	22.94	23.20	24.80	24.36	24.72	26.41	25.64	24.04	26.65
HH_7 03.00-03.30	21.61	23.04	22.05	24.76	25.41	24.09	26.82	25.07	25.21	26.40
HH_8 03.30-04.00	20.21	22.74	23.16	24.61	24.88	24.34	24.81	25.34	23.78	26.32
HH_9 04.00-04.30	19.50	22.56	23.56	24.53	22.71	24.60	23.67	25.60	23.53	26.32
HH_10 04.30-05.00	21.04	22.71	23.83	24.51	22.58	23.79	23.67	24.86	23.19	26.03
HH_11 05.00-05.30	22.03	23.41	24.07	24.96	22.93	23.81	23.55	24.77	24.60	26.53
HH_12 05.30-06.00	22.53	23.55	24.49	25.05	23.16	23.78	23.69	24.73	25.19	26.62
HH_13 06.00-06.30	26.01	26.11	27.85	27.01	24.29	25.89	24.17	26.21	28.18	29.51
HH_14 06.30-07.00	26.89	25.94	27.36	26.96	23.35	26.28	26.36	26.59	27.81	29.59
HH_15 07.00-07.30	28.49	26.44	26.84	26.99	24.09	24.30	24.43	24.77	29.51	28.96
HH_16 07.30-08.00	29.83	28.13	32.26	28.03	24.23	24.03	25.48	24.29	34.93	30.04
HH_17 08.00-08.30	34.22	34.28	37.20	32.17	26.68	25.25	25.04	24.48	36.76	35.06
HH_18 08.30-09.00	34.34	34.61	37.17	32.56	29.33	26.42	27.18	25.45	41.95	35.88
HH_19 09.00-09.30	30.59	36.42	37.23	33.79	30.07	26.83	27.85	25.54	33.37	37.39
HH_20 09.30-10.00	33.28	40.80	35.97	37.27	33.59	31.31	28.89	28.83	49.34	42.76
HH_21 10.00-10.30	35.48	40.95	36.89	36.26	37.96	36.31	29.91	32.21	51.28	45.68
HH_22 10.30-11.00	41.66	42.82	39.40	39.88	41.69	41.41	32.91	35.08	57.12	55.54
HH_23 11.00-11.30	40.86	43.22	39.37	40.88	35.28	34.40	31.00	35.00	59.27	56.34
HH_24 11.30-12.00	50.32	46.67	38.29	34.81	33.33	33.26	37.48	36.52	59.80	60.64
HH_25 12.00-12.30	42.46	42.55	37.66	39.06	35.88	37.00	39.45	34.77	52.48	54.70
HH_26 12.30-13.00	43.96	31.08	30.54	30.57	36.43	39.09	39.11	35.92	45.13	39.68
HH_27 13.00-13.30	32.16	31.03	29.34	32.20	30.18	39.55	36.90	37.45	41.37	39.84
HH_28 13.30-14.00	33.72	30.34	27.05	31.34	32.70	36.59	31.05	34.99	39.75	37.88
HH_29 14.00-14.30	33.65	30.64	29.49	31.66	34.96	37.42	33.55	35.69	34.57	38.52
HH_30 14.30-15.00	29.60	29.97	29.21	30.86	33.18	34.90	31.92	33.58	31.71	36.79
HH_31 15.00-15.30	26.29	26.03	27.87	27.36	27.84	28.56	29.47	28.57	30.85	30.79
HH_32 15.30-16.00	27.70	26.67	29.03	27.97	28.05	29.82	30.43	29.59	33.50	31.88
HH_33 16.00-16.30	27.45	35.59	30.97	35.45	32.16	41.38	41.96	38.46	35.97	44.06
HH_34 16.30-17.00	44.33	46.06	86.87	89.04	48.62	48.55	75.07	73.24	58.91	66.20
HH_35 17.00-17.30	68.40	68.18	84.78	84.77	120.15	120.12	107.80	107.99	74.90	74.48
HH_36 17.30-18.00	41.49	40.79	45.46	45.65	132.47	132.56	110.07	109.49	69.96	71.12
HH_37 18.00-18.30	31.30	28.54	34.54	33.70	68.82	60.25	62.39	55.98	40.41	48.35
HH_38 18.30-19.00	28.96	30.10	32.93	31.10	43.71	42.99	32.63	38.55	41.31	39.54
HH_39 19.00-19.30	42.88	42.76	43.01	43.27	42.83	42.79	35.51	34.93	66.22	66.45
HH_40 19.30-20.00	43.68	34.57	38.62	41.22	34.63	31.87	40.62	45.77	62.37	51.22
HH_41 20.00-20.30	32.77	31.57	37.22	36.01	33.67	32.65	35.74	39.43	47.91	44.06
HH_42 20.30-21.00	27.67	27.57	36.17	29.56	34.97	36.90	37.78	35.66	35.37	36.05
HH_43 21.00-21.30	29.47	30.48	34.29	31.43	36.00	36.97	31.11	35.30	46.73	38.16
HH_44 21.30-22.00	28.94	28.12	32.00	29.29	36.08	32.40	29.32	31.64	40.08	34.21
HH_45 22.00-22.30	26.03	25.89	28.97	27.54	34.35	30.28	30.08	30.10	32.23	31.55
HH_46 22.30-23.00	25.09	24.11	28.77	25.84	32.47	26.65	27.32	27.17	31.80	28.45
HH_47 23.00-23.30	26.06	24.58	24.18	26.39	26.57	28.27	29.41	28.53	28.12	29.60
HH_48 23.30-24.00	24.80	24.24	23.83	26.12	25.27	27.93	28.18	28.28	26.14	29.19

**Table B (b)** Forecasting results by ANNs (6<sup>th</sup> -10<sup>th</sup> December 2007)

Date Time Periods	11 – Dec - 07		12 – Dec - 07		13 – Dec - 07		14 – Dec - 07		15 – Dec - 07	
	Ref.	ANNs	Ref.	ANNs	Ref.	ANNs	Ref.	ANNs	Ref.	ANNs
HH_1 00.00-00.30	28.50	28.66	31.56	29.70	30.89	32.17	34.80	35.06	35.48	34.10
HH_2 00.30-01.00	27.23	29.09	28.70	28.00	32.59	30.27	35.60	33.76	34.61	34.32
HH_3 01.00-01.30	27.24	27.84	27.94	28.48	33.65	30.01	35.18	33.83	40.17	34.03
HH_4 01.30-02.00	28.98	27.80	26.78	27.79	29.47	29.08	36.23	33.24	33.55	34.08
HH_5 02.00-02.30	27.76	26.26	26.37	28.08	29.62	28.37	36.26	33.08	33.82	33.75
HH_6 02.30-03.00	28.11	26.26	26.38	27.70	29.87	27.88	35.70	32.76	33.67	33.78
HH_7 03.00-03.30	26.65	26.61	25.50	27.26	27.11	27.56	30.86	32.49	34.29	33.88
HH_8 03.30-04.00	25.79	25.86	25.10	27.32	27.98	27.11	33.27	32.35	31.39	33.73
HH_9 04.00-04.30	25.17	25.37	24.38	27.44	27.51	26.92	28.94	32.31	31.00	33.62
HH_10 04.30-05.00	24.93	25.90	24.24	26.90	27.62	26.59	29.05	32.00	30.42	33.77
HH_11 05.00-05.30	26.35	27.55	25.18	27.22	27.85	28.17	29.57	32.70	31.85	34.07
HH_12 05.30-06.00	26.96	27.90	26.04	27.26	28.41	28.47	32.86	32.83	31.98	34.14
HH_13 06.00-06.30	32.95	33.55	33.64	30.00	33.79	36.00	39.96	36.59	37.53	35.05
HH_14 06.30-07.00	33.48	33.06	33.67	30.22	33.64	35.94	36.68	36.65	23.88	34.93
HH_15 07.00-07.30	31.79	34.64	32.04	28.95	33.20	35.41	32.13	36.00	32.03	35.35
HH_16 07.30-08.00	36.23	38.71	33.82	29.51	37.23	39.00	33.48	37.53	34.06	36.11
HH_17 08.00-08.30	60.89	53.08	36.34	33.18	38.50	53.87	41.89	44.35	34.62	38.67
HH_18 08.30-09.00	61.31	53.63	36.54	34.21	42.73	55.60	41.00	45.35	34.91	38.70
HH_19 09.00-09.30	73.91	57.86	30.79	35.33	51.27	60.03	50.35	47.39	38.72	39.46
HH_20 09.30-10.00	72.68	67.37	31.48	40.67	69.37	73.65	63.44	54.33	37.38	40.93
HH_21 10.00-10.30	52.44	66.98	31.81	43.36	87.10	84.52	64.38	57.60	41.29	39.44
HH_22 10.30-11.00	47.74	48.51	32.50	30.43	101.16	101.07	67.62	70.08	48.06	44.44
HH_23 11.00-11.30	51.64	55.15	37.30	38.16	72.59	71.17	74.17	73.52	47.57	45.25
HH_24 11.30-12.00	55.24	55.05	41.67	39.50	66.77	68.07	79.21	74.66	42.85	42.18
HH_25 12.00-12.30	52.98	48.96	35.88	38.09	70.16	70.65	66.38	69.85	36.06	42.20
HH_26 12.30-13.00	42.20	43.26	32.61	41.19	65.02	63.24	53.74	49.15	35.00	35.07
HH_27 13.00-13.30	35.00	42.54	39.99	42.49	77.76	58.54	45.37	49.36	37.52	35.88
HH_28 13.30-14.00	32.51	41.47	36.04	39.97	77.53	54.50	41.90	46.98	35.41	35.86
HH_29 14.00-14.30	31.23	42.02	38.41	40.74	74.80	55.88	48.17	47.76	34.22	35.91
HH_30 14.30-15.00	35.04	40.94	35.71	38.54	67.46	52.27	46.24	45.65	35.04	35.86
HH_31 15.00-15.30	31.69	32.83	30.85	31.99	37.29	38.06	34.33	38.06	28.39	34.75
HH_32 15.30-16.00	34.38	34.11	32.51	33.23	41.91	40.57	37.17	39.43	29.87	34.91
HH_33 16.00-16.30	40.43	53.00	59.81	45.96	77.64	70.37	54.61	54.98	30.16	37.68
HH_34 16.30-17.00	81.46	79.33	96.42	95.34	76.40	75.09	67.75	68.82	37.72	40.72
HH_35 17.00-17.30	109.52	109.38	95.58	95.74	148.97	149.13	80.00	80.38	62.68	62.21
HH_36 17.30-18.00	56.21	56.28	67.38	66.46	72.75	72.77	68.71	69.66	57.27	58.21
HH_37 18.00-18.30	34.88	32.50	48.58	57.03	57.61	70.28	61.91	58.84	49.45	32.78
HH_38 18.30-19.00	46.15	41.18	46.06	44.01	53.26	59.35	57.51	49.29	33.35	35.61
HH_39 19.00-19.30	84.44	84.44	83.53	83.74	71.28	71.27	60.06	59.78	50.94	50.66
HH_40 19.30-20.00	49.07	49.90	53.99	52.82	62.97	69.35	56.48	60.89	42.27	41.15
HH_41 20.00-20.30	48.61	40.67	54.07	45.00	56.77	57.48	45.53	54.93	41.17	39.28
HH_42 20.30-21.00	41.43	34.78	49.28	38.93	42.28	48.50	44.96	44.37	37.09	34.61
HH_43 21.00-21.30	47.71	41.68	50.02	40.28	50.16	55.11	51.06	47.29	44.68	35.86
HH_44 21.30-22.00	39.24	37.04	35.39	35.82	40.68	46.00	44.59	42.36	47.06	35.29
HH_45 22.00-22.30	34.84	32.16	31.46	33.22	33.13	39.19	39.91	38.92	39.41	34.53
HH_46 22.30-23.00	29.44	28.65	31.98	29.68	33.77	32.13	39.04	35.04	39.29	34.10
HH_47 23.00-23.30	28.54	29.44	32.45	31.12	33.18	34.55	33.28	36.45	37.33	34.15
HH_48 23.30-24.00	27.25	28.70	30.85	30.71	31.61	33.50	32.46	35.91	33.13	34.03

**Table B (c)** Forecasting results by ANNs (11<sup>th</sup> -15<sup>th</sup> December 2007)

Date		16 – Jun - 07		17 – Jun - 07		18 – Jun - 07		19 – Jun - 07		20 – Jun - 07	
Time	Periods	Ref.	SVM	Ref.	SVM	Ref.	SVM	Ref.	SVM	Ref.	SVM
HH_1	00.00-00.30	21.77	21.10	19.57	19.16	16.45	16.41	16.32	15.91	16.11	14.98
HH_2	00.30-01.00	18.98	18.51	18.12	17.98	16.12	15.70	15.75	15.29	15.74	14.83
HH_3	01.00-01.30	20.00	19.14	17.50	18.08	16.07	17.46	14.93	15.86	13.68	15.88
HH_4	01.30-02.00	20.00	19.12	17.94	17.36	15.70	16.87	14.38	15.20	13.77	15.01
HH_5	02.00-02.30	16.80	17.80	15.99	17.06	16.00	16.32	13.28	14.04	13.09	13.71
HH_6	02.30-03.00	16.33	17.08	15.99	16.63	15.39	15.40	13.41	13.62	12.30	14.08
HH_7	03.00-03.30	15.88	15.76	15.22	15.38	15.40	15.12	13.16	12.94	12.43	12.21
HH_8	03.30-04.00	15.98	15.78	15.36	15.37	17.44	16.23	12.40	12.23	12.57	12.89
HH_9	04.00-04.30	15.83	15.79	15.50	15.68	14.21	14.73	11.72	12.06	12.68	13.07
HH_10	04.30-05.00	15.44	15.14	15.99	15.39	14.00	13.50	9.65	10.03	11.82	11.50
HH_11	05.00-05.30	15.74	15.60	17.81	16.72	13.61	14.12	10.25	11.62	12.48	12.86
HH_12	05.30-06.00	14.99	15.40	11.00	13.42	14.68	14.60	13.59	13.39	12.25	13.62
HH_13	06.00-06.30	16.49	16.90	20.67	17.98	17.20	16.80	17.04	16.96	16.87	15.91
HH_14	06.30-07.00	15.81	16.09	14.00	15.20	17.16	18.33	16.79	17.89	15.56	16.23
HH_15	07.00-07.30	16.35	17.00	17.51	17.28	16.77	18.46	20.86	21.23	18.12	18.56
HH_16	07.30-08.00	19.15	18.21	16.59	16.28	25.00	25.79	23.50	24.11	19.35	18.67
HH_17	08.00-08.30	20.27	21.49	15.81	17.18	38.20	31.94	33.65	28.85	17.63	20.08
HH_18	08.30-09.00	22.22	25.35	17.43	17.87	44.44	39.36	33.62	34.13	17.94	23.16
HH_19	09.00-09.30	25.76	29.68	17.93	18.02	45.81	48.50	42.57	40.23	26.75	27.93
HH_20	09.30-10.00	44.26	39.65	18.03	19.46	59.32	57.74	39.79	46.62	29.04	33.09
HH_21	10.00-10.30	51.91	48.67	18.08	21.97	77.51	67.22	46.29	49.73	33.62	39.05
HH_22	10.30-11.00	69.88	55.96	22.95	23.66	87.50	76.64	64.16	56.42	37.27	45.58
HH_23	11.00-11.30	73.75	61.04	27.16	27.25	102.60	78.53	73.08	61.69	52.43	55.05
HH_24	11.30-12.00	70.73	64.04	31.95	28.67	98.53	84.32	76.00	68.10	77.05	63.71
HH_25	12.00-12.30	74.14	66.69	38.72	30.59	97.28	96.26	74.14	76.78	76.38	77.61
HH_26	12.30-13.00	55.13	58.88	29.30	27.84	72.29	90.00	58.78	72.77	80.74	78.05
HH_27	13.00-13.30	45.22	46.61	23.85	24.35	93.26	78.86	62.99	64.45	70.00	68.47
HH_28	13.30-14.00	38.63	40.49	20.40	21.80	98.00	74.60	65.00	58.52	70.25	60.25
HH_29	14.00-14.30	33.48	35.12	20.20	20.62	94.83	66.98	55.40	56.77	62.70	58.78
HH_30	14.30-15.00	30.63	32.96	20.29	20.32	67.60	58.98	64.20	54.09	65.77	54.56
HH_31	15.00-15.30	32.35	32.62	21.38	19.90	59.16	53.47	63.78	55.65	64.66	54.11
HH_32	15.30-16.00	41.66	33.80	20.23	20.15	59.75	52.03	73.34	58.13	59.37	55.69
HH_33	16.00-16.30	28.94	31.18	19.86	20.22	28.94	51.59	72.65	55.64	89.96	55.34
HH_34	16.30-17.00	39.26	37.38	19.96	23.20	71.07	64.79	77.40	66.44	95.70	65.28
HH_35	17.00-17.30	36.88	39.20	21.89	30.96	65.13	54.97	80.24	55.37	72.26	57.51
HH_36	17.30-18.00	35.92	31.74	21.11	29.82	43.14	38.09	74.79	38.98	47.86	40.13
HH_37	18.00-18.30	24.93	26.41	19.10	25.43	27.27	29.14	33.63	32.47	40.39	35.19
HH_38	18.30-19.00	19.60	20.96	17.50	21.50	24.70	29.84	31.86	32.34	40.29	36.60
HH_39	19.00-19.30	19.33	21.86	20.38	24.23	23.23	26.97	42.64	30.87	47.22	35.16
HH_40	19.30-20.00	18.27	21.46	19.37	22.25	21.37	20.89	26.49	23.33	45.68	29.89
HH_41	20.00-20.30	20.00	17.15	19.96	19.29	19.75	18.83	20.74	19.52	44.27	28.63
HH_42	20.30-21.00	18.50	18.79	21.35	20.36	19.14	18.05	18.96	17.37	35.47	28.86
HH_43	21.00-21.30	17.50	18.17	20.33	20.55	22.44	23.01	21.00	22.07	29.13	28.97
HH_44	21.30-22.00	22.82	22.95	21.19	21.08	17.97	17.72	23.93	22.29	29.43	26.43
HH_45	22.00-22.30	23.60	22.57	21.85	21.66	18.00	17.67	18.13	18.57	25.59	24.28
HH_46	22.30-23.00	19.93	20.14	20.92	20.79	18.27	18.12	18.23	17.93	21.96	20.95
HH_47	23.00-23.30	24.39	23.12	19.80	19.58	18.43	20.03	17.56	18.32	18.56	19.05
HH_48	23.30-24.00	25.26	23.85	20.52	20.09	18.75	17.02	17.71	17.19	17.99	17.77

Table C (a) Forecasting results by SVM (16<sup>th</sup> -20<sup>th</sup> June 2007)



Date Time Periods	21 – Jun - 07		22 – Jun - 07		23 – Jun - 07		24 – Jun - 07		25 – Jun - 07	
	Ref.	SVM	Ref.	SVM	Ref.	SVM	Ref.	SVM	Ref.	SVM
HH_1 00.00-00.30	15.87	16.68	18.66	17.98	18.10	17.99	16.12	15.63	15.06	14.11
HH_2 00.30-01.00	16.02	15.05	17.10	16.08	16.31	17.03	15.65	15.17	12.93	13.13
HH_3 01.00-01.30	16.43	16.74	16.64	15.34	17.71	17.03	14.48	14.67	11.97	14.08
HH_4 01.30-02.00	14.97	16.24	13.81	14.19	16.43	16.69	14.11	13.54	10.49	12.52
HH_5 02.00-02.30	14.00	14.74	12.84	13.41	14.90	16.19	10.29	12.00	9.85	11.62
HH_6 02.30-03.00	14.03	15.07	12.16	12.91	15.09	15.93	10.00	11.99	9.95	12.13
HH_7 03.00-03.30	15.00	14.96	11.00	11.15	21.00	19.01	11.24	11.31	11.66	11.60
HH_8 03.30-04.00	14.96	14.92	10.90	10.80	14.59	14.88	10.52	10.76	11.54	11.70
HH_9 04.00-04.30	14.50	14.81	10.73	10.66	14.31	14.31	8.60	10.31	12.54	12.94
HH_10 04.30-05.00	17.11	15.11	10.00	10.33	13.67	13.69	17.11	14.63	12.88	11.60
HH_11 05.00-05.30	14.75	14.48	10.09	10.50	13.50	13.57	9.93	10.02	10.39	11.56
HH_12 05.30-06.00	15.58	15.78	12.54	12.07	13.49	13.94	8.00	9.53	11.87	13.04
HH_13 06.00-06.30	18.32	16.83	15.41	16.06	16.62	15.68	8.27	8.91	15.10	15.24
HH_14 06.30-07.00	16.30	19.46	15.62	15.49	15.55	15.59	9.28	9.47	16.06	17.05
HH_15 07.00-07.30	22.54	22.07	18.30	17.95	15.65	16.13	11.00	11.56	20.49	20.46
HH_16 07.30-08.00	28.01	32.28	18.36	18.06	17.43	16.48	11.40	10.58	22.09	20.99
HH_17 08.00-08.30	60.00	46.46	18.60	20.10	17.11	16.78	12.11	11.75	24.38	23.10
HH_18 08.30-09.00	78.47	57.66	23.09	22.52	17.64	17.70	13.91	14.76	22.58	27.46
HH_19 09.00-09.30	100.60	72.05	24.62	23.21	17.84	17.72	14.67	14.67	31.41	33.16
HH_20 09.30-10.00	89.96	76.95	25.84	26.22	18.05	19.15	16.15	16.86	33.03	38.92
HH_21 10.00-10.30	111.27	84.60	27.52	28.05	19.59	20.02	16.12	17.70	43.91	43.85
HH_22 10.30-11.00	118.78	95.17	31.71	30.60	18.26	19.52	18.43	18.12	47.05	48.50
HH_23 11.00-11.30	123.92	83.55	42.47	36.51	20.08	20.30	19.98	19.29	65.72	57.86
HH_24 11.30-12.00	121.38	99.03	46.47	38.48	18.83	18.36	22.42	20.65	69.51	64.85
HH_25 12.00-12.30	113.52	107.36	45.06	39.12	19.10	17.86	23.66	23.27	77.78	75.58
HH_26 12.30-13.00	99.12	100.73	35.45	34.31	16.91	18.75	23.37	24.55	63.26	74.57
HH_27 13.00-13.30	78.46	75.47	25.01	27.16	17.25	17.88	24.26	22.05	76.21	67.37
HH_28 13.30-14.00	69.26	70.01	19.45	22.90	19.61	18.01	20.63	20.53	60.79	58.10
HH_29 14.00-14.30	70.53	60.02	20.06	20.87	16.84	17.96	19.00	19.13	57.57	57.00
HH_30 14.30-15.00	64.62	55.43	20.60	20.27	16.07	18.19	17.47	18.29	56.94	52.25
HH_31 15.00-15.30	70.28	60.45	19.96	20.08	25.12	19.95	22.00	19.51	69.97	57.50
HH_32 15.30-16.00	72.96	59.10	19.00	20.60	17.20	19.74	18.12	19.47	74.78	59.11
HH_33 16.00-16.30	82.63	59.71	21.00	20.62	17.64	19.20	28.94	19.50	80.46	55.81
HH_34 16.30-17.00	85.83	70.74	25.07	22.78	19.97	21.25	20.00	19.37	88.60	65.74
HH_35 17.00-17.30	71.94	59.49	25.66	22.98	17.56	25.05	20.00	19.25	57.74	52.79
HH_36 17.30-18.00	62.90	37.85	21.02	20.65	18.93	25.61	18.51	19.52	74.65	36.52
HH_37 18.00-18.30	65.43	32.01	18.25	21.38	17.50	22.86	17.40	24.67	37.56	32.52
HH_38 18.30-19.00	44.93	33.11	18.15	20.92	16.88	19.09	17.11	23.58	29.83	32.09
HH_39 19.00-19.30	39.87	34.66	19.58	20.26	16.88	21.30	17.91	20.90	22.39	28.52
HH_40 19.30-20.00	32.72	24.35	21.04	18.90	17.47	18.05	17.02	16.39	32.50	21.49
HH_41 20.00-20.30	27.35	23.21	21.47	16.74	17.50	16.95	16.74	15.68	29.65	18.99
HH_42 20.30-21.00	23.50	20.94	18.60	20.00	15.04	16.26	16.27	16.60	19.46	16.70
HH_43 21.00-21.30	24.97	24.81	22.90	23.08	15.45	15.52	16.84	17.28	19.00	20.47
HH_44 21.30-22.00	18.49	17.64	18.83	19.15	16.21	16.10	16.83	16.83	17.00	16.95
HH_45 22.00-22.30	19.90	19.27	19.56	19.44	16.25	16.35	17.24	16.78	16.20	16.38
HH_46 22.30-23.00	18.11	17.66	19.30	19.23	16.36	16.45	16.18	16.51	16.00	16.32
HH_47 23.00-23.30	18.04	20.37	17.80	18.00	22.29	21.03	17.79	17.13	17.35	17.96
HH_48 23.30-24.00	18.88	16.75	19.60	19.06	20.78	20.11	16.93	17.32	15.40	15.91

Table C (b) Forecasting results by SVM (21<sup>st</sup> -25<sup>th</sup> June 2007)

Date	26 – Jun - 07		27 – Jun - 07		28 – Jun - 07		29 – Jun - 07		30 – Jun - 07	
Time Periods	Ref.	SVM	Ref.	SVM	Ref.	SVM	Ref.	SVM	Ref.	SVM
HH_1 00.00-00.30	20.84	19.53	17.10	17.33	17.39	16.82	17.61	18.48	17.25	16.97
HH_2 00.30-01.00	19.82	18.77	17.77	16.67	15.71	15.71	19.54	17.90	16.08	15.68
HH_3 01.00-01.30	17.94	17.98	14.99	15.90	15.49	15.50	19.20	17.37	16.15	15.76
HH_4 01.30-02.00	15.88	16.28	15.00	15.04	15.33	15.28	11.83	13.73	15.29	15.23
HH_5 02.00-02.30	15.24	15.89	14.59	15.27	14.34	14.96	13.42	14.40	13.72	14.46
HH_6 02.30-03.00	15.21	15.88	14.24	14.73	14.67	14.65	14.37	14.54	12.99	13.66
HH_7 03.00-03.30	14.56	14.60	14.00	14.03	14.16	13.88	14.64	14.44	13.00	12.89
HH_8 03.30-04.00	14.29	14.31	13.76	13.83	13.05	13.01	14.22	14.05	13.00	12.91
HH_9 04.00-04.30	14.62	14.75	13.84	14.43	13.11	13.14	14.43	14.00	12.92	12.94
HH_10 04.30-05.00	14.87	14.67	17.11	15.90	12.82	12.77	12.64	13.06	12.95	12.84
HH_11 05.00-05.30	16.26	16.26	13.43	13.70	13.07	13.20	11.83	12.31	12.87	12.66
HH_12 05.30-06.00	16.91	16.68	13.28	14.14	13.71	13.80	13.53	13.47	11.30	12.03
HH_13 06.00-06.30	18.66	18.63	18.88	17.71	17.57	17.17	19.00	18.11	14.01	14.57
HH_14 06.30-07.00	17.00	17.25	16.98	17.22	16.40	16.62	16.61	16.87	16.08	15.65
HH_15 07.00-07.30	17.47	17.58	17.99	17.99	18.40	18.42	18.19	18.08	17.39	17.00
HH_16 07.30-08.00	17.62	18.71	18.41	18.26	20.05	19.00	17.86	19.02	16.57	16.66
HH_17 08.00-08.30	24.63	22.53	22.26	21.27	19.28	19.98	26.73	23.38	18.03	17.73
HH_18 08.30-09.00	25.29	23.59	23.31	23.03	20.21	20.46	25.67	25.03	19.14	19.21
HH_19 09.00-09.30	30.00	25.52	22.97	23.33	21.46	21.01	25.49	24.36	18.05	19.17
HH_20 09.30-10.00	25.08	26.92	23.43	26.21	20.87	22.21	25.82	26.93	20.64	22.47
HH_21 10.00-10.30	22.87	27.71	30.43	27.12	21.79	22.21	28.57	27.49	27.45	24.28
HH_22 10.30-11.00	23.77	30.08	32.91	28.11	23.82	22.43	28.51	28.69	29.07	25.65
HH_23 11.00-11.30	44.00	36.36	32.00	29.21	21.62	24.82	30.21	31.21	29.48	27.88
HH_24 11.30-12.00	40.07	36.45	28.01	29.33	28.00	25.06	39.93	32.85	27.78	27.90
HH_25 12.00-12.30	38.04	37.90	28.92	28.99	28.11	24.94	39.53	32.53	32.53	28.41
HH_26 12.30-13.00	35.48	36.75	26.00	26.89	22.72	23.45	25.37	27.01	25.11	25.77
HH_27 13.00-13.30	35.50	33.46	27.27	25.39	22.67	22.28	22.18	23.07	23.66	23.46
HH_28 13.30-14.00	31.94	30.98	24.60	23.48	21.49	21.24	16.84	19.79	23.18	21.42
HH_29 14.00-14.30	31.53	29.94	23.60	22.94	22.46	21.11	17.05	18.38	20.75	19.92
HH_30 14.30-15.00	31.30	28.99	20.20	21.52	20.98	20.40	17.29	17.94	19.02	19.30
HH_31 15.00-15.30	25.66	25.71	20.05	20.57	18.57	18.79	17.08	18.27	18.00	18.11
HH_32 15.30-16.00	27.76	26.83	22.49	21.16	19.81	19.44	19.60	18.89	17.44	18.33
HH_33 16.00-16.30	34.55	27.76	33.79	22.29	23.38	20.18	20.90	19.46	17.49	18.61
HH_34 16.30-17.00	38.78	33.71	33.95	26.10	25.38	23.47	18.80	21.13	20.00	21.14
HH_35 17.00-17.30	36.33	35.70	36.45	29.61	23.63	25.35	21.98	27.65	23.44	23.78
HH_36 17.30-18.00	27.13	32.73	22.93	27.86	19.65	25.10	23.28	25.98	24.55	24.18
HH_37 18.00-18.30	21.50	27.21	18.01	23.86	18.15	23.53	20.89	23.36	42.43	25.35
HH_38 18.30-19.00	19.39	24.47	17.94	22.06	18.41	22.13	19.21	21.66	17.75	24.07
HH_39 19.00-19.30	19.24	25.42	18.61	23.47	19.50	22.41	20.96	24.69	21.90	22.69
HH_40 19.30-20.00	17.94	20.96	20.53	19.75	19.35	19.19	21.55	21.87	20.88	19.78
HH_41 20.00-20.30	17.49	17.61	18.70	16.73	19.61	17.60	20.94	18.45	19.36	17.22
HH_42 20.30-21.00	17.18	16.49	16.49	16.54	18.96	18.46	20.08	19.67	18.33	18.81
HH_43 21.00-21.30	17.06	17.26	19.67	19.75	16.84	16.90	20.26	20.48	20.75	20.95
HH_44 21.30-22.00	17.38	17.25	17.88	17.94	15.68	15.77	21.14	21.16	19.97	19.76
HH_45 22.00-22.30	17.09	16.99	17.00	16.98	15.00	15.51	21.80	21.72	18.00	17.93
HH_46 22.30-23.00	16.00	16.33	17.02	17.08	17.21	16.91	21.09	20.84	17.03	17.16
HH_47 23.00-23.30	19.66	19.28	17.65	17.90	17.42	17.67	17.79	18.06	18.72	18.65
HH_48 23.30-24.00	20.22	19.77	19.40	19.13	17.99	17.57	18.99	18.55	20.41	19.74

Table C (c) Forecasting results by SVM (26<sup>th</sup> -30<sup>th</sup> June 2007)

Date Time Periods	01 – Dec - 07		02 – Dec - 07		03 – Dec - 07		04 – Dec - 07		05 – Dec - 07	
	Ref.	SVM	Ref.	SVM	Ref.	SVM	Ref.	SVM	Ref.	SVM
HH_1 00.00-00.30	31.26	29.38	27.55	26.06	24.13	25.14	31.73	30.33	25.55	26.10
HH_2 00.30-01.00	30.15	28.74	25.14	25.29	24.07	24.95	31.43	29.12	27.94	25.82
HH_3 01.00-01.30	29.97	28.21	25.36	25.12	28.00	25.57	25.01	27.53	24.05	24.73
HH_4 01.30-02.00	29.95	26.76	25.19	23.73	23.52	24.60	25.00	25.81	22.77	24.51
HH_5 02.00-02.30	22.00	23.69	23.50	22.09	23.00	23.37	25.00	25.20	22.80	23.29
HH_6 02.30-03.00	22.62	23.64	22.02	21.93	23.50	23.14	24.56	24.51	22.75	22.95
HH_7 03.00-03.30	21.72	22.68	21.33	21.95	23.71	23.37	24.47	24.45	23.62	22.96
HH_8 03.30-04.00	22.15	22.43	21.87	21.76	22.60	22.70	23.51	23.58	22.45	22.58
HH_9 04.00-04.30	21.92	22.24	21.47	21.20	22.56	22.49	22.42	22.61	23.17	22.64
HH_10 04.30-05.00	22.55	22.54	21.53	21.13	22.60	22.31	22.15	22.44	22.37	22.60
HH_11 05.00-05.30	24.73	23.69	19.00	19.78	23.02	23.02	26.37	25.58	24.58	24.57
HH_12 05.30-06.00	22.66	23.28	19.13	19.58	22.79	23.01	26.07	26.28	25.66	25.03
HH_13 06.00-06.30	27.50	25.73	22.35	22.54	27.28	26.79	34.12	32.41	30.09	29.47
HH_14 06.30-07.00	20.84	22.82	22.18	21.95	27.83	27.57	30.05	32.22	29.40	29.39
HH_15 07.00-07.30	25.20	24.65	22.96	22.54	30.54	29.70	39.23	37.07	29.65	30.19
HH_16 07.30-08.00	25.49	24.96	22.59	22.72	31.77	31.75	43.05	44.47	36.76	34.78
HH_17 08.00-08.30	25.46	26.13	22.63	23.87	33.61	33.84	57.86	54.22	42.18	39.56
HH_18 08.30-09.00	26.76	26.87	26.19	24.66	33.70	33.56	59.33	57.03	40.07	39.14
HH_19 09.00-09.30	26.56	28.16	27.19	26.19	34.58	34.08	56.00	58.59	40.55	38.26
HH_20 09.30-10.00	29.06	28.96	28.61	27.97	36.56	36.92	72.76	68.01	37.98	39.83
HH_21 10.00-10.30	33.78	32.17	32.11	31.52	36.83	36.79	80.45	67.51	35.93	38.14
HH_22 10.30-11.00	33.31	34.40	31.40	33.76	36.79	38.60	69.52	70.55	35.51	38.70
HH_23 11.00-11.30	33.78	32.75	34.67	35.66	35.82	38.27	61.12	64.98	33.74	36.97
HH_24 11.30-12.00	32.13	32.67	37.36	36.85	36.33	37.75	52.39	58.77	32.46	35.38
HH_25 12.00-12.30	32.45	31.83	36.13	37.61	36.59	35.90	52.83	52.48	33.76	34.60
HH_26 12.30-13.00	30.39	28.78	38.36	35.78	35.46	32.94	35.00	40.39	33.00	31.24
HH_27 13.00-13.30	29.95	29.21	45.00	35.33	31.25	31.57	36.03	37.38	28.63	30.72
HH_28 13.30-14.00	26.45	27.41	30.00	32.22	28.31	29.29	34.03	35.66	29.64	28.77
HH_29 14.00-14.30	26.32	26.62	30.97	31.72	29.73	31.02	37.67	39.61	29.37	30.45
HH_30 14.30-15.00	27.38	25.82	30.00	29.52	29.69	30.55	37.65	37.39	31.02	30.19
HH_31 15.00-15.30	23.98	25.16	25.42	28.19	29.72	29.59	31.27	33.12	28.78	28.04
HH_32 15.30-16.00	25.30	26.15	30.25	29.08	31.74	30.49	33.05	34.60	29.22	28.85
HH_33 16.00-16.30	35.01	29.44	37.79	31.68	34.55	34.93	66.85	41.75	32.41	32.64
HH_34 16.30-17.00	46.65	43.55	48.02	42.29	99.20	49.86	126.72	73.47	55.71	45.71
HH_35 17.00-17.30	122.46	60.63	90.30	53.04	90.43	65.19	165.54	97.38	69.75	61.87
HH_36 17.30-18.00	133.40	59.89	73.23	49.36	61.72	57.63	109.13	84.91	53.54	54.44
HH_37 18.00-18.30	78.48	47.23	36.70	38.89	34.61	40.81	40.88	49.41	33.46	37.06
HH_38 18.30-19.00	44.03	37.28	32.99	31.68	32.87	37.09	39.00	45.21	32.96	37.21
HH_39 19.00-19.30	39.55	44.22	37.89	38.48	47.69	53.14	55.00	69.86	42.59	54.55
HH_40 19.30-20.00	37.33	36.39	33.93	33.59	50.27	43.78	44.80	54.25	41.28	43.37
HH_41 20.00-20.30	34.89	33.63	32.58	30.56	35.90	35.96	29.88	38.65	35.89	34.59
HH_42 20.30-21.00	32.32	31.08	29.03	28.69	31.68	31.59	29.62	31.11	30.57	30.01
HH_43 21.00-21.30	31.83	31.83	30.69	30.23	33.32	35.42	35.33	35.75	29.76	31.36
HH_44 21.30-22.00	27.61	28.13	25.77	26.00	36.58	34.61	32.98	32.61	28.81	28.89
HH_45 22.00-22.30	26.69	26.21	24.18	24.21	28.86	28.99	29.93	30.75	27.38	27.48
HH_46 22.30-23.00	25.17	25.23	24.32	24.12	26.96	27.10	30.40	30.21	26.96	26.78
HH_47 23.00-23.30	26.52	27.44	28.03	27.16	24.05	25.42	29.35	30.10	26.05	26.71
HH_48 23.30-24.00	27.17	28.18	24.96	25.98	24.04	24.48	28.65	29.20	24.87	25.69

Table D (a) Forecasting results by SVM (1<sup>st</sup> -5<sup>th</sup> December 2007)

Date Time Periods	06 – Dec - 07		07 – Dec - 07		08 – Dec - 07		09 – Dec - 07		10 – Dec - 07	
	Ref.	SVM	Ref.	SVM	Ref.	SVM	Ref.	SVM	Ref.	SVM
HH_1 00.00-00.30	24.44	24.81	23.96	24.74	28.50	28.30	29.54	29.50	26.78	26.74
HH_2 00.30-01.00	24.20	24.00	24.26	24.76	31.22	28.42	28.70	28.60	25.50	25.94
HH_3 01.00-01.30	23.82	23.71	25.00	24.87	25.78	26.89	29.23	28.59	25.37	25.89
HH_4 01.30-02.00	22.65	23.02	24.98	25.00	24.87	25.82	28.38	27.61	24.41	25.55
HH_5 02.00-02.30	22.47	22.09	22.68	23.24	24.15	23.97	25.69	25.28	23.95	24.11
HH_6 02.30-03.00	22.44	21.95	23.20	22.94	24.36	24.13	26.41	25.30	24.04	24.18
HH_7 03.00-03.30	21.61	21.25	22.05	22.86	25.41	24.75	26.82	25.75	25.21	24.60
HH_8 03.30-04.00	20.21	20.61	23.16	22.90	24.88	23.99	24.81	24.78	23.78	23.81
HH_9 04.00-04.30	19.50	20.46	23.56	23.20	22.71	23.12	23.67	23.97	23.53	23.55
HH_10 04.30-05.00	21.04	20.70	23.83	23.37	22.58	22.82	23.67	23.78	23.19	23.23
HH_11 05.00-05.30	22.03	22.13	24.07	24.18	22.93	23.12	23.55	23.75	24.60	24.47
HH_12 05.30-06.00	22.53	22.35	24.49	24.16	23.16	22.70	23.69	23.34	25.19	24.70
HH_13 06.00-06.30	26.01	25.98	27.85	27.54	24.29	24.38	24.17	25.33	28.18	28.15
HH_14 06.30-07.00	26.89	26.40	27.36	27.34	23.35	23.84	26.36	25.35	27.81	27.93
HH_15 07.00-07.30	28.49	27.65	26.84	27.37	24.09	24.40	24.43	25.20	29.51	29.44
HH_16 07.30-08.00	29.83	29.82	32.26	31.28	24.23	24.63	25.48	25.15	34.93	33.37
HH_17 08.00-08.30	34.22	32.76	37.20	35.80	26.68	27.39	25.04	25.80	36.76	37.76
HH_18 08.30-09.00	34.34	32.92	37.17	36.09	29.33	28.60	27.18	26.68	41.95	39.76
HH_19 09.00-09.30	30.59	33.42	37.23	36.15	30.07	29.99	27.85	27.55	33.37	41.38
HH_20 09.30-10.00	33.28	35.92	35.97	39.07	33.59	33.96	28.89	29.57	49.34	48.28
HH_21 10.00-10.30	35.48	38.16	36.89	38.03	37.96	36.36	29.91	32.55	51.28	50.04
HH_22 10.30-11.00	41.66	40.90	39.40	40.52	41.69	39.86	32.91	35.20	57.12	56.13
HH_23 11.00-11.30	40.86	42.33	39.37	39.95	35.28	38.36	31.00	36.06	59.27	56.68
HH_24 11.30-12.00	50.32	43.12	38.29	38.58	33.33	37.60	37.48	37.35	59.80	55.72
HH_25 12.00-12.30	42.46	42.65	37.66	35.70	35.88	35.57	39.45	37.76	52.48	51.83
HH_26 12.30-13.00	43.96	37.62	30.54	31.34	36.43	33.09	39.11	35.46	45.13	43.79
HH_27 13.00-13.30	32.16	34.12	29.34	30.69	30.18	33.47	36.90	34.49	41.37	40.44
HH_28 13.30-14.00	33.72	31.43	27.05	28.68	32.70	31.47	31.05	31.69	39.75	37.24
HH_29 14.00-14.30	33.65	32.04	29.49	29.57	34.96	31.98	33.55	32.26	34.57	37.19
HH_30 14.30-15.00	29.60	29.98	29.21	29.14	33.18	30.40	31.92	31.34	31.71	33.91
HH_31 15.00-15.30	26.29	27.81	27.87	27.51	27.84	28.28	29.47	30.12	30.85	32.01
HH_32 15.30-16.00	27.70	27.79	29.03	28.53	28.05	29.23	30.43	30.87	33.50	31.97
HH_33 16.00-16.30	27.45	30.89	30.97	32.98	32.16	33.41	41.96	34.06	35.97	36.16
HH_34 16.30-17.00	44.33	42.08	86.87	46.19	48.62	50.59	75.07	50.04	58.91	54.99
HH_35 17.00-17.30	68.40	53.93	84.78	61.12	120.15	71.21	107.80	68.39	74.90	73.46
HH_36 17.30-18.00	41.49	47.23	45.46	54.44	132.47	67.77	110.07	65.72	69.96	64.97
HH_37 18.00-18.30	31.30	34.51	34.54	38.46	68.82	50.39	62.39	50.35	40.41	47.70
HH_38 18.30-19.00	28.96	33.97	32.93	36.18	43.71	38.90	32.63	38.50	41.31	46.65
HH_39 19.00-19.30	42.88	48.20	43.01	50.94	42.83	47.06	35.51	47.34	66.22	64.18
HH_40 19.30-20.00	43.68	39.59	38.62	42.43	34.63	39.69	40.62	39.48	62.37	53.06
HH_41 20.00-20.30	32.77	32.04	37.22	36.69	33.67	37.01	35.74	35.69	47.91	43.51
HH_42 20.30-21.00	27.67	28.46	36.17	33.58	34.97	33.34	37.78	33.39	35.37	38.08
HH_43 21.00-21.30	29.47	30.04	34.29	36.04	36.00	37.19	31.11	32.87	46.73	45.59
HH_44 21.30-22.00	28.94	28.68	32.00	31.63	36.08	35.57	29.32	29.69	40.08	38.77
HH_45 22.00-22.30	26.03	26.03	28.97	29.07	34.35	33.30	30.08	29.08	32.23	32.62
HH_46 22.30-23.00	25.09	25.00	28.77	28.31	32.47	31.82	27.32	27.57	31.80	31.03
HH_47 23.00-23.30	26.06	25.97	24.18	25.37	26.57	27.19	29.41	29.63	28.12	28.31
HH_48 23.30-24.00	24.80	25.14	23.83	24.46	25.27	26.43	28.18	28.86	26.14	26.89

**Table D (b)** Forecasting results by SVM (6<sup>th</sup> -10<sup>th</sup> December 2007)

Date	11 – Dec - 07		12 – Dec - 07		13 – Dec - 07		14 – Dec - 07		15 – Dec - 07	
Time Periods	Ref.	SVM	Ref.	SVM	Ref.	SVM	Ref.	SVM	Ref.	SVM
HH_1 00.00-00.30	28.50	28.42	31.56	30.43	30.89	32.42	34.80	35.43	35.48	36.50
HH_2 00.30-01.00	27.23	27.08	28.70	28.71	32.59	31.25	35.60	34.28	34.61	34.88
HH_3 01.00-01.30	27.24	27.79	27.94	28.35	33.65	32.37	35.18	35.75	40.17	36.46
HH_4 01.30-02.00	28.98	28.77	26.78	27.62	29.47	30.27	36.23	36.00	33.55	36.04
HH_5 02.00-02.30	27.76	26.21	26.37	25.62	29.62	28.57	36.26	32.21	33.82	31.78
HH_6 02.30-03.00	28.11	25.62	26.38	25.25	29.87	27.77	35.70	31.06	33.67	31.42
HH_7 03.00-03.30	26.65	26.26	25.50	25.48	27.11	27.09	30.86	30.79	34.29	32.28
HH_8 03.30-04.00	25.79	25.48	25.10	25.08	27.98	27.43	33.27	30.76	31.39	30.87
HH_9 04.00-04.30	25.17	24.96	24.38	24.50	27.51	26.98	28.94	28.92	31.00	29.39
HH_10 04.30-05.00	24.93	24.53	24.24	24.35	27.62	26.94	29.05	28.48	30.42	29.38
HH_11 05.00-05.30	26.35	26.58	25.18	25.50	27.85	27.21	29.57	29.74	31.85	30.39
HH_12 05.30-06.00	26.96	26.94	26.04	25.83	28.41	28.01	32.86	30.41	31.98	29.57
HH_13 06.00-06.30	32.95	33.33	33.64	32.56	33.79	33.72	39.96	37.44	37.53	33.64
HH_14 06.30-07.00	33.48	32.52	33.67	32.35	33.64	33.07	36.68	35.09	23.88	27.46
HH_15 07.00-07.30	31.79	32.45	32.04	31.80	33.20	33.82	32.13	33.76	32.03	32.45
HH_16 07.30-08.00	36.23	40.41	33.82	33.86	37.23	36.87	33.48	35.79	34.06	32.36
HH_17 08.00-08.30	60.89	52.66	36.34	36.63	38.50	43.64	41.89	41.60	34.62	35.10
HH_18 08.30-09.00	61.31	57.48	36.54	35.85	42.73	48.14	41.00	46.54	34.91	36.81
HH_19 09.00-09.30	73.91	58.71	30.79	34.91	51.27	54.96	50.35	51.09	38.72	39.72
HH_20 09.30-10.00	72.68	64.73	31.48	36.51	69.37	66.45	63.44	61.66	37.38	44.25
HH_21 10.00-10.30	52.44	58.22	31.81	35.54	87.10	74.92	64.38	63.98	41.29	44.74
HH_22 10.30-11.00	47.74	61.68	32.50	37.28	101.16	81.68	67.62	71.11	48.06	49.66
HH_23 11.00-11.30	51.64	60.66	37.30	39.57	72.59	80.98	74.17	72.48	47.57	47.66
HH_24 11.30-12.00	55.24	57.15	41.67	39.04	66.77	79.49	79.21	70.94	42.85	45.91
HH_25 12.00-12.30	52.98	51.15	35.88	37.17	70.16	78.42	66.38	65.14	36.06	40.54
HH_26 12.30-13.00	42.20	41.78	32.61	35.57	65.02	68.36	53.74	52.14	35.00	34.68
HH_27 13.00-13.30	35.00	37.30	39.99	37.19	77.76	68.13	45.37	47.68	37.52	37.18
HH_28 13.30-14.00	32.51	34.94	36.04	34.69	77.53	68.03	41.90	44.39	35.41	34.19
HH_29 14.00-14.30	31.23	37.04	38.41	37.26	74.80	69.46	48.17	47.13	34.22	35.33
HH_30 14.30-15.00	35.04	35.80	35.71	36.82	67.46	60.38	46.24	44.73	35.04	33.56
HH_31 15.00-15.30	31.69	32.11	30.85	32.97	37.29	43.51	34.33	36.10	28.39	29.71
HH_32 15.30-16.00	34.38	33.13	32.51	32.60	41.91	45.40	37.17	35.75	29.87	29.83
HH_33 16.00-16.30	40.43	37.29	59.81	38.66	77.64	52.85	54.61	40.15	30.16	32.00
HH_34 16.30-17.00	81.46	61.70	96.42	59.41	76.40	88.88	67.75	70.83	37.72	52.06
HH_35 17.00-17.30	109.52	83.67	95.58	81.79	148.97	116.77	80.00	101.80	62.68	82.93
HH_36 17.30-18.00	56.21	72.62	67.38	73.83	72.75	102.44	68.71	95.94	57.27	82.74
HH_37 18.00-18.30	34.88	48.95	48.58	55.30	57.61	71.82	61.91	71.37	49.45	64.15
HH_38 18.30-19.00	46.15	54.16	46.06	50.46	53.26	61.41	57.51	61.62	33.35	53.71
HH_39 19.00-19.30	84.44	76.85	83.53	70.11	71.28	82.59	60.06	81.46	50.94	68.90
HH_40 19.30-20.00	49.07	61.34	53.99	56.48	62.97	63.87	56.48	61.42	42.27	52.27
HH_41 20.00-20.30	48.61	45.89	54.07	48.35	56.77	48.68	45.53	48.50	41.17	43.02
HH_42 20.30-21.00	41.43	39.20	49.28	44.22	42.28	41.98	44.96	43.29	37.09	38.16
HH_43 21.00-21.30	47.71	47.06	50.02	48.33	50.16	48.93	51.06	50.00	44.68	46.03
HH_44 21.30-22.00	39.24	38.14	35.39	35.25	40.68	38.74	44.59	42.66	47.06	43.52
HH_45 22.00-22.30	34.84	33.85	31.46	31.97	33.13	33.54	39.91	38.49	39.41	38.14
HH_46 22.30-23.00	29.44	30.40	31.98	31.40	33.77	32.84	39.04	37.57	39.29	37.54
HH_47 23.00-23.30	28.54	30.48	32.45	32.49	33.18	33.42	33.28	35.90	37.33	37.62
HH_48 23.30-24.00	27.25	28.14	30.85	31.28	31.61	31.63	32.46	33.40	33.13	34.46

**Table D (c)** Forecasting results by SVM (11<sup>th</sup> -15<sup>th</sup> December 2007)

Date		16 – Jun - 07		17 – Jun - 07		18 – Jun - 07		19 – Jun - 07		20 – Jun - 07	
Time	Periods	Ref.	Tests	Ref.	Tests	Ref.	Tests	Ref.	Tests	Ref.	Tests
HH_1	00.00-00.30	21.77	20.37	19.57	18.81	16.45	17.01	16.32	16.23	16.11	16.53
HH_2	00.30-01.00	18.98	19.08	18.12	17.45	16.12	16.90	15.75	15.30	15.74	14.66
HH_3	01.00-01.30	20.00	19.76	17.50	17.53	16.07	16.65	14.93	15.91	13.68	14.35
HH_4	01.30-02.00	20.00	19.51	17.94	17.60	15.70	15.68	14.38	14.56	13.77	13.94
HH_5	02.00-02.30	16.80	17.26	15.99	16.75	16.00	16.36	13.28	13.76	13.09	14.16
HH_6	02.30-03.00	16.33	16.70	15.99	15.93	15.39	15.28	13.41	13.94	12.30	12.82
HH_7	03.00-03.30	15.88	16.47	15.22	15.88	15.40	15.84	13.16	13.44	12.43	13.45
HH_8	03.30-04.00	15.98	16.30	15.36	15.57	17.44	16.73	12.40	12.45	12.57	12.57
HH_9	04.00-04.30	15.83	15.83	15.50	15.49	14.21	14.24	11.72	11.80	12.68	12.71
HH_10	04.30-05.00	15.44	15.76	15.99	16.04	14.00	14.41	9.65	10.63	11.82	12.66
HH_11	05.00-05.30	15.74	15.70	17.81	16.16	13.61	13.88	10.25	11.13	12.48	12.71
HH_12	05.30-06.00	14.99	15.05	11.00	11.40	14.68	14.76	13.59	13.65	12.25	12.42
HH_13	06.00-06.30	16.49	18.06	20.67	19.59	17.20	17.48	17.04	18.15	16.87	17.79
HH_14	06.30-07.00	15.81	16.39	14.00	14.50	17.16	17.09	16.79	17.56	15.56	16.08
HH_15	07.00-07.30	16.35	16.44	17.51	17.54	16.77	16.82	20.86	20.71	18.12	17.96
HH_16	07.30-08.00	19.15	19.15	16.59	16.63	25.00	25.16	23.50	23.76	19.35	19.34
HH_17	08.00-08.30	20.27	20.97	15.81	15.78	38.20	35.55	33.65	32.24	17.63	17.55
HH_18	08.30-09.00	22.22	22.59	17.43	18.42	44.44	40.07	33.62	32.08	17.94	17.67
HH_19	09.00-09.30	25.76	25.62	17.93	19.11	45.81	40.94	42.57	38.69	26.75	26.37
HH_20	09.30-10.00	44.26	40.79	18.03	19.67	59.32	57.27	39.79	36.34	29.04	28.00
HH_21	10.00-10.30	51.91	56.70	18.08	19.55	77.51	61.00	46.29	44.79	33.62	32.06
HH_22	10.30-11.00	69.88	58.58	22.95	22.41	87.50	67.14	64.16	59.37	37.27	35.71
HH_23	11.00-11.30	73.75	58.54	27.16	27.85	102.60	75.70	73.08	66.57	52.43	60.76
HH_24	11.30-12.00	70.73	52.73	31.95	30.43	98.53	56.58	76.00	59.83	77.05	58.20
HH_25	12.00-12.30	74.14	73.12	38.72	36.65	97.28	71.51	74.14	67.63	76.38	68.09
HH_26	12.30-13.00	55.13	60.90	29.30	27.39	72.29	67.49	58.78	68.04	80.74	71.02
HH_27	13.00-13.30	45.22	50.02	23.85	23.39	93.26	76.14	62.99	59.84	70.00	71.29
HH_28	13.30-14.00	38.63	35.45	20.40	20.65	98.00	84.22	65.00	64.81	70.25	67.89
HH_29	14.00-14.30	33.48	31.85	20.20	19.85	94.83	76.03	55.40	52.48	62.70	60.27
HH_30	14.30-15.00	30.63	29.68	20.29	20.10	67.60	67.64	64.20	61.58	65.77	58.12
HH_31	15.00-15.30	32.35	30.52	21.38	20.46	59.16	76.52	63.78	75.20	64.66	73.13
HH_32	15.30-16.00	41.66	36.37	20.23	19.56	59.75	62.41	73.34	51.51	59.37	57.80
HH_33	16.00-16.30	28.94	26.54	19.86	19.72	28.94	27.22	72.65	59.56	89.96	60.40
HH_34	16.30-17.00	39.26	37.05	19.96	19.94	71.07	68.90	77.40	77.55	95.70	78.54
HH_35	17.00-17.30	36.88	36.52	21.89	21.81	65.13	62.16	80.24	58.34	72.26	59.88
HH_36	17.30-18.00	35.92	34.51	21.11	21.02	43.14	41.81	74.79	54.74	47.86	50.63
HH_37	18.00-18.30	24.93	24.68	19.10	19.36	27.27	26.53	33.63	31.96	40.39	39.03
HH_38	18.30-19.00	19.60	19.50	17.50	18.97	24.70	23.67	31.86	27.61	40.29	35.05
HH_39	19.00-19.30	19.33	18.63	20.38	20.92	23.23	23.98	42.64	38.37	47.22	43.53
HH_40	19.30-20.00	18.27	19.22	19.37	20.37	21.37	22.47	26.49	26.35	45.68	54.29
HH_41	20.00-20.30	20.00	21.37	19.96	20.38	19.75	21.33	20.74	19.99	44.27	41.06
HH_42	20.30-21.00	18.50	19.18	21.35	21.05	19.14	20.07	18.96	19.60	35.47	28.61
HH_43	21.00-21.30	17.50	17.59	20.33	20.34	22.44	22.33	21.00	20.91	29.13	28.82
HH_44	21.30-22.00	22.82	23.02	21.19	20.35	17.97	18.09	23.93	23.19	29.43	27.81
HH_45	22.00-22.30	23.60	23.54	21.85	21.73	18.00	18.00	18.13	18.12	25.59	25.49
HH_46	22.30-23.00	19.93	19.32	20.92	19.37	18.27	17.59	18.23	17.60	21.96	18.70
HH_47	23.00-23.30	24.39	24.24	19.80	19.72	18.43	18.44	17.56	17.57	18.56	18.57
HH_48	23.30-24.00	25.26	25.07	20.52	20.45	18.75	18.73	17.71	17.75	17.99	17.97

Table E (a) Forecasting results by hybrid model (16<sup>th</sup> -20<sup>th</sup> June 2007)

Date	21 – Jun - 07		22 – Jun - 07		23 – Jun - 07		24 – Jun - 07		25 – Jun - 07	
Time Periods	Ref.	Tests	Ref.	Tests	Ref.	Tests	Ref.	Tests	Ref.	Tests
HH_1 00.00-00.30	15.87	16.44	18.66	17.88	18.10	18.34	16.12	16.98	15.06	14.82
HH_2 00.30-01.00	16.02	14.82	17.10	16.04	16.31	15.08	15.65	15.09	12.93	12.94
HH_3 01.00-01.30	16.43	16.58	16.64	16.00	17.71	17.05	14.48	14.47	11.97	12.07
HH_4 01.30-02.00	14.97	15.16	13.81	13.94	16.43	16.78	14.11	14.39	10.49	12.18
HH_5 02.00-02.30	14.00	15.47	12.84	13.60	14.90	15.75	10.29	12.63	9.85	12.67
HH_6 02.30-03.00	14.03	14.75	12.16	13.24	15.09	15.46	10.00	10.79	9.95	11.25
HH_7 03.00-03.30	15.00	15.85	11.00	12.21	21.00	19.90	11.24	12.71	11.66	12.45
HH_8 03.30-04.00	14.96	14.97	10.90	10.98	14.59	14.57	10.52	10.58	11.54	11.59
HH_9 04.00-04.30	14.50	14.51	10.73	11.03	14.31	14.15	8.60	9.06	12.54	12.43
HH_10 04.30-05.00	17.11	16.99	10.00	11.08	13.67	14.54	17.11	16.62	12.88	12.46
HH_11 05.00-05.30	14.75	15.06	10.09	10.77	13.50	13.62	9.93	10.25	10.39	10.75
HH_12 05.30-06.00	15.58	15.52	12.54	13.44	13.49	14.47	8.00	9.77	11.87	12.72
HH_13 06.00-06.30	18.32	19.11	15.41	16.38	16.62	17.30	8.27	13.10	15.10	15.64
HH_14 06.30-07.00	16.30	16.19	15.62	16.30	15.55	16.39	9.28	12.30	16.06	16.32
HH_15 07.00-07.30	22.54	22.45	18.30	18.36	15.65	15.70	11.00	11.19	20.49	20.41
HH_16 07.30-08.00	28.01	27.91	18.36	18.35	17.43	17.48	11.40	11.51	22.09	22.66
HH_17 08.00-08.30	60.00	55.94	18.60	18.50	17.11	17.06	12.11	12.13	24.38	24.43
HH_18 08.30-09.00	78.47	62.99	23.09	23.45	17.64	18.37	13.91	13.86	22.58	22.94
HH_19 09.00-09.30	100.6	83.10	24.62	24.88	17.84	18.73	14.67	15.37	31.41	29.89
HH_20 09.30-10.00	89.96	73.15	25.84	24.96	18.05	18.13	16.15	16.79	33.03	31.21
HH_21 10.00-10.30	111.2	76.52	27.52	27.56	19.59	21.41	16.12	17.49	43.91	41.58
HH_22 10.30-11.00	118.7	79.16	31.71	32.40	18.26	19.49	18.43	19.77	47.05	59.76
HH_23 11.00-11.30	123.9	59.08	42.47	40.10	20.08	21.41	19.98	21.40	65.72	60.85
HH_24 11.30-12.00	121.3	75.69	46.47	61.49	18.83	19.75	22.42	23.22	69.51	63.70
HH_25 12.00-12.30	113.5	99.36	45.06	41.47	19.10	19.87	23.66	24.08	77.78	68.09
HH_26 12.30-13.00	99.12	87.25	35.45	35.43	16.91	17.74	23.37	23.00	63.26	58.89
HH_27 13.00-13.30	78.46	77.76	25.01	24.66	17.25	18.28	24.26	24.04	76.21	66.67
HH_28 13.30-14.00	69.26	59.85	19.45	20.97	19.61	19.20	20.63	20.20	60.79	73.54
HH_29 14.00-14.30	70.53	58.71	20.06	20.49	16.84	17.50	19.00	19.76	57.57	65.03
HH_30 14.30-15.00	64.62	71.05	20.60	19.98	16.07	18.67	17.47	18.18	56.94	62.81
HH_31 15.00-15.30	70.28	74.26	19.96	20.30	25.12	24.25	22.00	21.81	69.97	74.61
HH_32 15.30-16.00	72.96	65.04	19.00	19.10	17.20	17.19	18.12	18.83	74.78	55.34
HH_33 16.00-16.30	82.63	72.18	21.00	20.59	17.64	17.58	28.94	27.15	80.46	80.39
HH_34 16.30-17.00	85.83	83.64	25.07	24.90	19.97	19.92	20.00	19.96	88.60	66.82
HH_35 17.00-17.30	71.94	59.89	25.66	25.54	17.56	17.59	20.00	19.94	57.74	56.39
HH_36 17.30-18.00	62.90	69.51	21.02	20.85	18.93	18.63	18.51	18.56	74.65	62.87
HH_37 18.00-18.30	65.43	58.63	18.25	18.32	17.50	17.70	17.40	17.42	37.56	37.39
HH_38 18.30-19.00	44.93	65.06	18.15	19.53	16.88	20.62	17.11	19.22	29.83	27.36
HH_39 19.00-19.30	39.87	38.27	19.58	19.91	16.88	18.11	17.91	19.36	22.39	23.43
HH_40 19.30-20.00	32.72	31.40	21.04	21.48	17.47	17.63	17.02	18.41	32.50	30.04
HH_41 20.00-20.30	27.35	27.97	21.47	23.45	17.50	20.04	16.74	19.05	29.65	29.64
HH_42 20.30-21.00	23.50	21.23	18.60	18.61	15.04	15.27	16.27	16.63	19.46	20.06
HH_43 21.00-21.30	24.97	24.81	22.90	22.85	15.45	15.64	16.84	16.89	19.00	19.90
HH_44 21.30-22.00	18.49	18.65	18.83	18.62	16.21	16.97	16.83	17.33	17.00	17.19
HH_45 22.00-22.30	19.90	19.91	19.56	19.43	16.25	16.58	17.24	17.28	16.20	16.25
HH_46 22.30-23.00	18.11	17.26	19.30	17.70	16.36	17.73	16.18	16.38	16.00	16.01
HH_47 23.00-23.30	18.04	18.05	17.80	17.81	22.29	22.21	17.79	17.80	17.35	17.36
HH_48 23.30-24.00	18.88	18.80	19.60	19.63	20.78	20.72	16.93	16.94	15.40	15.42

**Table E (b)** Forecasting results by hybrid model (21<sup>st</sup> -25<sup>th</sup> June 2007)

Date	26 – Jun - 07		27 – Jun - 07		28 – Jun - 07		29 – Jun - 07		30 – Jun - 07	
Time Periods	Ref.	Tests	Ref.	Tests	Ref.	Tests	Ref.	Tests	Ref.	Tests
HH_1 00.00-00.30	20.84	19.03	17.10	16.73	17.39	17.27	17.61	17.00	17.25	16.44
HH_2 00.30-01.00	19.82	16.83	17.77	16.19	15.71	16.21	19.54	18.83	16.08	17.13
HH_3 01.00-01.30	17.94	16.48	14.99	15.22	15.49	14.80	19.20	18.01	16.15	14.95
HH_4 01.30-02.00	15.88	16.62	15.00	15.92	15.33	15.72	11.83	13.76	15.29	15.86
HH_5 02.00-02.30	15.24	15.93	14.59	15.27	14.34	14.60	13.42	13.77	13.72	14.32
HH_6 02.30-03.00	15.21	15.37	14.24	15.11	14.67	15.04	14.37	14.58	12.99	13.47
HH_7 03.00-03.30	14.56	15.13	14.00	14.71	14.16	15.06	14.64	15.11	13.00	13.67
HH_8 03.30-04.00	14.29	14.31	13.76	13.79	13.05	13.09	14.22	14.21	13.00	13.05
HH_9 04.00-04.30	14.62	14.59	13.84	13.92	13.11	13.38	14.43	14.88	12.92	12.81
HH_10 04.30-05.00	14.87	14.87	17.11	16.12	12.82	13.50	12.64	13.18	12.95	13.14
HH_11 05.00-05.30	16.26	16.15	13.43	13.64	13.07	13.27	11.83	12.11	12.87	13.16
HH_12 05.30-06.00	16.91	16.52	13.28	14.11	13.71	14.54	13.53	14.04	11.30	12.72
HH_13 06.00-06.30	18.66	18.42	18.88	18.80	17.57	17.83	19.00	18.82	14.01	14.43
HH_14 06.30-07.00	17.00	17.03	16.98	17.37	16.40	16.41	16.61	16.58	16.08	16.09
HH_15 07.00-07.30	17.47	17.60	17.99	18.03	18.40	18.45	18.19	18.10	17.39	17.51
HH_16 07.30-08.00	17.62	17.61	18.41	18.41	20.05	20.04	17.86	17.76	16.57	16.57
HH_17 08.00-08.30	24.63	24.27	22.26	22.09	19.28	19.94	26.73	25.45	18.03	17.94
HH_18 08.30-09.00	25.29	24.67	23.31	25.43	20.21	19.98	25.67	25.37	19.14	20.10
HH_19 09.00-09.30	30.00	28.77	22.97	23.28	21.46	21.48	25.49	25.40	18.05	18.59
HH_20 09.30-10.00	25.08	24.76	23.43	23.01	20.87	21.82	25.82	25.79	20.64	20.47
HH_21 10.00-10.30	22.87	22.78	30.43	29.38	21.79	21.50	28.57	27.64	27.45	26.51
HH_22 10.30-11.00	23.77	23.77	32.91	31.01	23.82	24.63	28.51	28.36	29.07	29.22
HH_23 11.00-11.30	44.00	39.57	32.00	31.30	21.62	21.56	30.21	30.43	29.48	29.21
HH_24 11.30-12.00	40.07	39.11	28.01	27.78	28.00	27.96	39.93	38.13	27.78	26.99
HH_25 12.00-12.30	38.04	36.22	28.92	28.98	28.11	28.30	39.53	36.83	32.53	30.72
HH_26 12.30-13.00	35.48	32.60	26.00	25.28	22.72	23.21	25.37	25.15	25.11	25.13
HH_27 13.00-13.30	35.50	33.96	27.27	26.63	22.67	22.37	22.18	22.57	23.66	23.61
HH_28 13.30-14.00	31.94	30.50	24.60	23.50	21.49	21.20	16.84	17.56	23.18	23.04
HH_29 14.00-14.30	31.53	29.78	23.60	22.25	22.46	21.99	17.05	17.07	20.75	20.86
HH_30 14.30-15.00	31.30	31.11	20.20	20.20	20.98	20.43	17.29	18.76	19.02	20.27
HH_31 15.00-15.30	25.66	24.41	20.05	20.16	18.57	18.73	17.08	17.24	18.00	17.99
HH_32 15.30-16.00	27.76	27.15	22.49	22.67	19.81	20.05	19.60	19.81	17.44	18.08
HH_33 16.00-16.30	34.55	31.49	33.79	30.23	23.38	23.04	20.90	20.63	17.49	17.44
HH_34 16.30-17.00	38.78	36.06	33.95	31.22	25.38	25.98	18.80	18.73	20.00	19.96
HH_35 17.00-17.30	36.33	36.28	36.45	36.29	23.63	23.40	21.98	21.78	23.44	23.25
HH_36 17.30-18.00	27.13	26.49	22.93	22.64	19.65	19.93	23.28	23.29	24.55	25.46
HH_37 18.00-18.30	21.50	21.68	18.01	18.07	18.15	18.35	20.89	21.04	42.43	42.17
HH_38 18.30-19.00	19.39	20.34	17.94	19.01	18.41	18.79	19.21	19.04	17.75	18.20
HH_39 19.00-19.30	19.24	20.57	18.61	20.26	19.50	19.55	20.96	21.27	21.90	21.05
HH_40 19.30-20.00	17.94	19.73	20.53	21.04	19.35	19.42	21.55	22.07	20.88	21.22
HH_41 20.00-20.30	17.49	19.42	18.70	20.27	19.61	20.56	20.94	21.90	19.36	20.11
HH_42 20.30-21.00	17.18	17.70	16.49	17.19	18.96	19.43	20.08	20.43	18.33	18.74
HH_43 21.00-21.30	17.06	17.54	19.67	20.18	16.84	18.10	20.26	20.72	20.75	21.30
HH_44 21.30-22.00	17.38	17.36	17.88	18.00	15.68	15.71	21.14	21.10	19.97	19.95
HH_45 22.00-22.30	17.09	17.08	17.00	17.04	15.00	15.22	21.80	21.23	18.00	17.75
HH_46 22.30-23.00	16.00	16.01	17.02	17.03	17.21	17.25	21.09	21.00	17.03	17.06
HH_47 23.00-23.30	19.66	19.60	17.65	17.62	17.42	17.43	17.79	17.79	18.72	18.71
HH_48 23.30-24.00	20.22	20.18	19.40	19.40	17.99	17.99	18.99	18.98	20.41	20.34

Table E (c) Forecasting results by hybrid model (26<sup>st</sup> -30<sup>th</sup> June 2007)



Date	01 – Dec - 07		02 – Dec - 07		03 – Dec - 07		04 – Dec - 07		05 – Dec - 07	
Time Periods	Ref.	Tests	Ref.	Tests	Ref.	Tests	Ref.	Tests	Ref.	Tests
HH_1 00.00-00.30	31.26	30.76	27.55	27.26	24.13	24.04	31.73	31.28	25.55	25.45
HH_2 00.30-01.00	30.15	29.66	25.14	24.83	24.07	23.89	31.43	30.57	27.94	27.31
HH_3 01.00-01.30	29.97	25.87	25.36	23.55	28.00	24.55	25.01	24.83	24.05	23.89
HH_4 01.30-02.00	29.95	26.73	25.19	23.02	23.52	21.94	25.00	23.42	22.77	21.60
HH_5 02.00-02.30	22.00	20.19	23.50	21.38	23.00	21.61	25.00	23.26	22.80	21.70
HH_6 02.30-03.00	22.62	20.86	22.02	20.98	23.50	23.32	24.56	24.40	22.75	22.61
HH_7 03.00-03.30	21.72	20.82	21.33	20.88	23.71	23.31	24.47	23.97	23.62	23.22
HH_8 03.30-04.00	22.15	21.07	21.87	20.46	22.60	21.36	23.51	22.38	22.45	21.30
HH_9 04.00-04.30	21.92	20.74	21.47	21.34	22.56	22.37	22.42	22.28	23.17	23.01
HH_10 04.30-05.00	22.55	21.66	21.53	20.75	22.60	21.68	22.15	21.34	22.37	21.39
HH_11 05.00-05.30	24.73	23.81	19.00	18.70	23.02	22.66	26.37	25.69	24.58	24.53
HH_12 05.30-06.00	22.66	21.70	19.13	18.65	22.79	21.22	26.07	24.73	25.66	23.97
HH_13 06.00-06.30	27.50	26.00	22.35	21.42	27.28	26.01	34.12	31.66	30.09	28.75
HH_14 06.30-07.00	20.84	22.40	22.18	22.90	27.83	27.17	30.05	29.55	29.40	29.11
HH_15 07.00-07.30	25.20	25.16	22.96	23.01	30.54	30.35	39.23	43.45	29.65	29.45
HH_16 07.30-08.00	25.49	25.42	22.59	22.59	31.77	31.58	43.05	42.22	36.76	36.45
HH_17 08.00-08.30	25.46	25.50	22.63	22.72	33.61	33.39	57.86	49.14	42.18	43.17
HH_18 08.30-09.00	26.76	26.79	26.19	26.23	33.70	33.55	59.33	51.91	40.07	44.14
HH_19 09.00-09.30	26.56	26.60	27.19	27.12	34.58	34.30	56.00	50.95	40.55	41.17
HH_20 09.30-10.00	29.06	28.95	28.61	28.51	36.56	41.02	72.76	58.19	37.98	41.21
HH_21 10.00-10.30	33.78	33.53	32.11	31.89	36.83	37.85	80.45	58.91	35.93	38.18
HH_22 10.30-11.00	33.31	39.36	31.40	31.23	36.79	41.11	69.52	51.13	35.51	39.84
HH_23 11.00-11.30	33.78	37.91	34.67	35.55	35.82	41.08	61.12	49.67	33.74	38.96
HH_24 11.30-12.00	32.13	32.07	37.36	38.80	36.33	42.78	52.39	49.77	32.46	32.37
HH_25 12.00-12.30	32.45	32.37	36.13	44.60	36.59	41.78	52.83	47.20	33.76	33.67
HH_26 12.30-13.00	30.39	30.34	38.36	39.37	35.46	39.14	35.00	38.27	33.00	32.91
HH_27 13.00-13.30	29.95	29.94	45.00	46.93	31.25	31.23	36.03	41.15	28.63	28.61
HH_28 13.30-14.00	26.45	26.44	30.00	29.95	28.31	28.26	34.03	33.99	29.64	29.62
HH_29 14.00-14.30	26.32	26.31	30.97	30.88	29.73	29.67	37.67	43.68	29.37	29.39
HH_30 14.30-15.00	27.38	27.33	30.00	29.91	29.69	29.63	37.65	42.50	31.02	30.93
HH_31 15.00-15.30	23.98	23.97	25.42	25.39	29.72	29.64	31.27	31.16	28.78	28.65
HH_32 15.30-16.00	25.30	25.35	30.25	30.20	31.74	31.68	33.05	32.97	29.22	29.20
HH_33 16.00-16.30	35.01	34.95	37.79	40.43	34.55	34.47	66.85	58.08	32.41	32.36
HH_34 16.30-17.00	46.65	50.07	48.02	47.33	99.20	103.57	126.72	114.03	55.71	50.76
HH_35 17.00-17.30	122.46	129.38	90.30	96.43	90.43	98.32	165.54	149.56	69.75	54.02
HH_36 17.30-18.00	133.40	134.40	73.23	60.67	61.72	51.79	109.13	147.79	53.54	50.75
HH_37 18.00-18.30	78.48	60.15	36.70	36.59	34.61	34.52	40.88	44.79	33.46	33.38
HH_38 18.30-19.00	44.03	44.50	32.99	32.88	32.87	32.70	39.00	38.63	32.96	32.84
HH_39 19.00-19.30	39.55	39.45	37.89	37.76	47.69	48.38	55.00	55.84	42.59	43.04
HH_40 19.30-20.00	37.33	37.09	33.93	33.71	50.27	48.14	44.80	44.81	41.28	43.10
HH_41 20.00-20.30	34.89	34.70	32.58	32.43	35.90	35.69	29.88	29.79	35.89	35.81
HH_42 20.30-21.00	32.32	32.24	29.03	28.99	31.68	31.60	29.62	29.56	30.57	30.54
HH_43 21.00-21.30	31.83	31.73	30.69	30.55	33.32	33.23	35.33	35.29	29.76	29.77
HH_44 21.30-22.00	27.61	27.62	25.77	25.83	36.58	36.46	32.98	32.93	28.81	28.77
HH_45 22.00-22.30	26.69	26.71	24.18	24.17	28.86	28.84	29.93	29.85	27.38	27.38
HH_46 22.30-23.00	25.17	25.15	24.32	24.26	26.96	26.83	30.40	30.20	26.96	26.84
HH_47 23.00-23.30	26.52	26.47	28.03	27.94	24.05	23.99	29.35	29.17	26.05	25.95
HH_48 23.30-24.00	27.17	27.07	24.96	24.90	24.04	24.02	28.65	28.54	24.87	24.81

Table F (a) Forecasting results by hybrid model (1<sup>st</sup> -5<sup>th</sup> December 2007)

Date	06 – Dec - 07		07 – Dec - 07		08 – Dec - 07		09 – Dec - 07		10 – Dec - 07	
Time Periods	Ref.	Tests	Ref.	Tests	Ref.	Tests	Ref.	Tests	Ref.	Tests
HH_1 00.00-00.30	24.44	24.31	23.96	23.91	28.50	28.25	29.54	29.22	26.78	26.59
HH_2 00.30-01.00	24.20	23.86	24.26	23.95	31.22	27.05	28.70	25.62	25.50	21.94
HH_3 01.00-01.30	23.82	23.65	25.00	24.78	25.78	25.60	29.23	28.92	25.37	25.14
HH_4 01.30-02.00	22.65	21.35	24.98	23.43	24.87	23.58	28.38	26.46	24.41	22.58
HH_5 02.00-02.30	22.47	21.37	22.68	21.91	24.15	22.58	25.69	23.46	23.95	23.36
HH_6 02.30-03.00	22.44	22.25	23.20	23.04	24.36	24.20	26.41	26.22	24.04	23.86
HH_7 03.00-03.30	21.61	21.39	22.05	21.79	25.41	24.87	26.82	26.49	25.21	23.37
HH_8 03.30-04.00	20.21	20.49	23.16	22.33	24.88	23.04	24.81	23.51	23.78	22.47
HH_9 04.00-04.30	19.50	19.48	23.56	23.37	22.71	22.55	23.67	23.51	23.53	23.35
HH_10 04.30-05.00	21.04	20.29	23.83	22.92	22.58	21.88	23.67	23.19	23.19	22.87
HH_11 05.00-05.30	22.03	22.07	24.07	23.94	22.93	22.85	23.55	23.44	24.60	24.42
HH_12 05.30-06.00	22.53	21.20	24.49	22.82	23.16	21.60	23.69	21.87	25.19	23.27
HH_13 06.00-06.30	26.01	25.19	27.85	26.43	24.29	24.91	24.17	24.77	28.18	28.76
HH_14 06.30-07.00	26.89	26.80	27.36	27.19	23.35	23.65	26.36	26.41	27.81	27.73
HH_15 07.00-07.30	28.49	28.38	26.84	26.78	24.09	24.12	24.43	24.42	29.51	29.32
HH_16 07.30-08.00	29.83	29.63	32.26	32.02	24.23	24.26	25.48	25.47	34.93	34.64
HH_17 08.00-08.30	34.22	33.93	37.20	43.24	26.68	26.66	25.04	25.13	36.76	41.87
HH_18 08.30-09.00	34.34	34.20	37.17	43.88	29.33	29.32	27.18	27.19	41.95	42.84
HH_19 09.00-09.30	30.59	30.45	37.23	43.18	30.07	29.94	27.85	27.80	33.37	33.16
HH_20 09.30-10.00	33.28	33.05	35.97	39.78	33.59	33.42	28.89	28.77	49.34	45.48
HH_21 10.00-10.30	35.48	36.76	36.89	38.30	37.96	42.55	29.91	29.81	51.28	52.05
HH_22 10.30-11.00	41.66	43.23	39.40	38.88	41.69	40.34	32.91	32.67	57.12	48.82
HH_23 11.00-11.30	40.86	40.97	39.37	39.74	35.28	40.99	31.00	30.96	59.27	47.33
HH_24 11.30-12.00	50.32	53.02	38.29	44.21	33.33	33.17	37.48	39.80	59.80	53.38
HH_25 12.00-12.30	42.46	42.22	37.66	39.38	35.88	38.21	39.45	42.22	52.48	47.31
HH_26 12.30-13.00	43.96	46.13	30.54	30.48	36.43	41.48	39.11	41.76	45.13	43.32
HH_27 13.00-13.30	32.16	32.05	29.34	29.31	30.18	30.15	36.90	39.62	41.37	43.07
HH_28 13.30-14.00	33.72	33.66	27.05	27.03	32.70	32.55	31.05	30.99	39.75	47.11
HH_29 14.00-14.30	33.65	33.58	29.49	29.42	34.96	34.81	33.55	33.38	34.57	34.45
HH_30 14.30-15.00	29.60	29.51	29.21	29.10	33.18	32.93	31.92	31.79	31.71	31.61
HH_31 15.00-15.30	26.29	26.26	27.87	27.84	27.84	27.81	29.47	29.41	30.85	30.78
HH_32 15.30-16.00	27.70	27.70	29.03	29.03	28.05	28.08	30.43	30.44	33.50	33.49
HH_33 16.00-16.30	27.45	27.46	30.97	30.94	32.16	32.11	41.96	45.47	35.97	35.87
HH_34 16.30-17.00	44.33	43.48	86.87	62.46	48.62	47.17	75.07	59.85	58.91	51.72
HH_35 17.00-17.30	68.40	56.10	84.78	64.65	120.15	128.55	107.80	140.06	74.90	58.19
HH_36 17.30-18.00	41.49	43.68	45.46	46.89	132.47	122.33	110.07	130.99	69.96	57.22
HH_37 18.00-18.30	31.30	31.23	34.54	34.48	68.82	57.35	62.39	60.67	40.41	42.75
HH_38 18.30-19.00	28.96	28.88	32.93	32.82	43.71	47.98	32.63	32.52	41.31	40.33
HH_39 19.00-19.30	42.88	47.21	43.01	44.18	42.83	46.41	35.51	35.37	66.22	62.02
HH_40 19.30-20.00	43.68	43.79	38.62	38.41	34.63	34.46	40.62	44.87	62.37	60.67
HH_41 20.00-20.30	32.77	32.71	37.22	37.05	33.67	33.49	35.74	35.63	47.91	51.12
HH_42 20.30-21.00	27.67	27.66	36.17	36.06	34.97	34.81	37.78	37.42	35.37	35.21
HH_43 21.00-21.30	29.47	29.46	34.29	34.15	36.00	35.90	31.11	31.06	46.73	49.65
HH_44 21.30-22.00	28.94	28.91	32.00	31.93	36.08	35.86	29.32	29.30	40.08	39.94
HH_45 22.00-22.30	26.03	26.03	28.97	28.96	34.35	34.24	30.08	30.04	32.23	32.15
HH_46 22.30-23.00	25.09	25.06	28.77	28.66	32.47	32.26	27.32	27.18	31.80	31.53
HH_47 23.00-23.30	26.06	25.96	24.18	24.10	26.57	26.45	29.41	29.24	28.12	27.97
HH_48 23.30-24.00	24.80	24.74	23.83	23.73	25.27	25.08	28.18	27.87	26.14	25.87

**Table F (b)** Forecasting results by hybrid model (6<sup>th</sup> -10<sup>th</sup> December 2007)

Date	11 – Dec - 07		12 – Dec - 07		13 – Dec - 07		14 – Dec - 07		15 – Dec - 07	
Time Periods	Ref.	Tests	Ref.	Tests	Ref.	Tests	Ref.	Tests	Ref.	Tests
HH_1 00.00-00.30	28.50	28.19	31.56	30.63	30.89	30.07	34.80	33.83	35.48	34.45
HH_2 00.30-01.00	27.23	23.14	28.70	24.69	32.59	28.03	35.60	30.84	34.61	28.01
HH_3 01.00-01.30	27.24	26.93	27.94	27.63	33.65	33.16	35.18	34.70	40.17	34.82
HH_4 01.30-02.00	28.98	25.66	26.78	23.77	29.47	24.98	36.23	30.32	33.55	28.36
HH_5 02.00-02.30	27.76	25.87	26.37	23.98	29.62	26.42	36.26	31.48	33.82	29.53
HH_6 02.30-03.00	28.11	27.74	26.38	26.09	29.87	29.46	35.70	32.40	33.67	30.36
HH_7 03.00-03.30	26.65	24.82	25.50	23.60	27.11	24.86	30.86	28.48	34.29	31.72
HH_8 03.30-04.00	25.79	23.28	25.10	22.57	27.98	24.88	33.27	29.14	31.39	27.69
HH_9 04.00-04.30	25.17	24.90	24.38	24.20	27.51	25.92	28.94	27.34	31.00	29.47
HH_10 04.30-05.00	24.93	24.14	24.24	23.47	27.62	26.59	29.05	28.23	30.42	29.37
HH_11 05.00-05.30	26.35	25.98	25.18	24.94	27.85	27.47	29.57	29.09	31.85	31.41
HH_12 05.30-06.00	26.96	25.17	26.04	24.29	28.41	26.35	32.86	30.47	31.98	30.21
HH_13 06.00-06.30	32.95	32.82	33.64	33.17	33.79	32.87	39.96	43.22	37.53	36.46
HH_14 06.30-07.00	33.48	33.03	33.67	32.98	33.64	32.82	36.68	35.63	23.88	23.94
HH_15 07.00-07.30	31.79	31.52	32.04	31.84	33.20	32.89	32.13	31.87	32.03	31.77
HH_16 07.30-08.00	36.23	35.90	33.82	33.57	37.23	36.85	33.48	33.31	34.06	33.86
HH_17 08.00-08.30	60.89	49.04	36.34	36.09	38.50	43.06	41.89	45.35	34.62	34.43
HH_18 08.30-09.00	61.31	50.82	36.54	44.19	42.73	44.57	41.00	44.47	34.91	34.69
HH_19 09.00-09.30	73.91	60.56	30.79	30.67	51.27	49.34	50.35	47.53	38.72	40.59
HH_20 09.30-10.00	72.68	56.68	31.48	31.28	69.37	57.35	63.44	53.54	37.38	39.43
HH_21 10.00-10.30	52.44	47.05	31.81	31.63	87.10	58.30	64.38	50.53	41.29	43.04
HH_22 10.30-11.00	47.74	42.75	32.50	32.27	101.16	104.14	67.62	51.68	48.06	43.34
HH_23 11.00-11.30	51.64	45.03	37.30	39.73	72.59	51.66	74.17	55.30	47.57	42.76
HH_24 11.30-12.00	55.24	51.43	41.67	42.62	66.77	54.92	79.21	63.61	42.85	48.89
HH_25 12.00-12.30	52.98	49.00	35.88	37.40	70.16	57.96	66.38	53.15	36.06	35.32
HH_26 12.30-13.00	42.20	44.58	32.61	32.57	65.02	59.33	53.74	51.64	35.00	39.98
HH_27 13.00-13.30	35.00	40.12	39.99	43.05	77.76	60.29	45.37	48.80	37.52	42.69
HH_28 13.30-14.00	32.51	32.41	36.04	41.56	77.53	64.35	41.90	46.91	35.41	42.05
HH_29 14.00-14.30	31.23	31.12	38.41	42.04	74.80	62.43	48.17	51.08	34.22	34.10
HH_30 14.30-15.00	35.04	34.90	35.71	35.52	67.46	59.55	46.24	46.09	35.04	34.90
HH_31 15.00-15.30	31.69	31.63	30.85	30.82	37.29	41.60	34.33	34.28	28.39	28.36
HH_32 15.30-16.00	34.38	34.28	32.51	32.49	41.91	42.02	37.17	39.92	29.87	29.87
HH_33 16.00-16.30	40.43	42.09	59.81	58.24	77.64	65.29	54.61	47.67	30.16	30.12
HH_34 16.30-17.00	81.46	58.82	96.42	114.03	76.40	55.77	67.75	55.05	37.72	37.58
HH_35 17.00-17.30	109.52	145.56	95.58	130.88	148.97	162.55	80.00	64.08	62.68	52.92
HH_36 17.30-18.00	56.21	48.36	67.38	53.16	72.75	55.71	68.71	57.26	57.27	53.94
HH_37 18.00-18.30	34.88	34.78	48.58	48.75	57.61	54.94	61.91	57.56	49.45	50.26
HH_38 18.30-19.00	46.15	44.14	46.06	49.76	53.26	48.73	57.51	52.32	33.35	33.23
HH_39 19.00-19.30	84.44	78.01	83.53	78.63	71.28	69.06	60.06	60.84	50.94	50.71
HH_40 19.30-20.00	49.07	52.65	53.99	53.31	62.97	60.45	56.48	57.48	42.27	46.45
HH_41 20.00-20.30	48.61	51.63	54.07	54.38	56.77	57.99	45.53	49.26	41.17	44.86
HH_42 20.30-21.00	41.43	41.15	49.28	48.02	42.28	45.49	44.96	47.55	37.09	36.85
HH_43 21.00-21.30	47.71	49.66	50.02	48.71	50.16	49.11	51.06	51.06	44.68	46.47
HH_44 21.30-22.00	39.24	39.10	35.39	35.30	40.68	40.52	44.59	46.86	47.06	46.83
HH_45 22.00-22.30	34.84	34.76	31.46	31.39	33.13	32.99	39.91	39.59	39.41	38.97
HH_46 22.30-23.00	29.44	29.29	31.98	31.79	33.77	33.52	39.04	38.68	39.29	38.94
HH_47 23.00-23.30	28.54	28.42	32.45	32.27	33.18	32.98	33.28	33.04	37.33	36.89
HH_48 23.30-24.00	27.25	26.99	30.85	30.42	31.61	31.19	32.46	32.04	33.13	32.64

Table F (c) Forecasting results by hybrid model (11<sup>th</sup> -15<sup>th</sup> December 2007)

## Publications

- [1] Linlin Hu, Gareth Taylor, Malcolm Irving, "A Fuzzy-logic Based Bidding Strategy for Participants in the UK Electricity Market," *43rd International Universities Power Engineering Conference*, Padova, Sep. 1 - 4, 2008.
- [2] Linlin Hu, Gareth Taylor, Malcolm Irving, "A Review of Short-term Electricity Price Forecasting Techniques in Deregulated Electricity Markets," *44th International Universities Power Engineering Conference*, Glasgow, Sep. 1 - 4, 2009.
- [3] Linlin Hu, Gareth Taylor, Malcolm Irving, "A Novel Hybrid Technique for Short-Term Electricity Price Forecasting in Deregulated Electricity Markets," *International Journal of Electrical Power and Energy Systems* (Submitted February 2010).