Risk Assessment due to Load Demand and Electricity Price Forecast Uncertainty

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Declaration of Author's Right

This thesis is the result of the author's original research. It has been composed by the author and has not been previously submitted for examination which has led to the award of a degree.

Signed: Gao Gao

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Abstract

This thesis introduces methodologies for load demand forecasting and electricity price forecasting. The autoregressive integrated moving average (ARIMA) models, seasonal autoregressive integrated moving average (SARIMA) models and artificial neural network (ANN) techniques are introduced to forecast load demand. And the forecasting process of load demand includes monthly, seasonal, annual and multi-step-ahead. Similarly, the same forecasting methods are used for electricity price forecasting. In terms of forecast error analysis method, the root mean square percentage error (RMSPE) and the mean absolute percentage error (MAPE) are used to observe the accuracy of forecasting results. After obtaining the forecasting results, this thesis proposes a risk index method to observe the forecast error more intuitively. The risk indexes are presented based on the load demand forecast errors and electricity price forecast errors respectively.

In addition, this thesis investigates the financial risk by combining the errors made by load demand forecasting and electricity price forecasting. The Value-at-Risk (VaR) and Expected Shortfall (ES) methods in economic theory are used to analyse the financial risks. Moreover, to present the actual risk that the market participants have to bear, the daily, monthly, seasonal and annual total financial risks under three different preconditions are compared.

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Glossary of Terms

PE	Power Exchange
GARCH	Generalized Autoregressive Conditional Heteroskedastic
IPP	Independent Power Producer
NGC	National Grid Company
NETA	New Electricity Trading Arrangements
BETTA	British Electricity Trading and Transmission Arrangements
REC	Regional Monopoly Electricity Company
OFGEM	Office of Gas and Electricity Markets
GBSO	Great Britain System Operator
AI	Artificial Intelligence
AR	Autoregressive
MA	Moving Average
ARMA	Autoregressive Moving Average
ARIMA	Autoregressive Integrated Moving Average
p	Numbers of autoregressive terms
q	Numbers of moving average terms

d	Differencing level
$\emptyset(B)$	Operator of p
$\theta(B)$	Operator of q
B	Backward shift operator
z_t	Historical data at time t
θ_0	Constant term
a_t	Error term
∇z_t	First order difference equation
$\nabla^d z_t$	dth order difference equation
SARIMA	Seasonal Autoregressive Integrated Moving Average
P	Numbers of seasonal autoregressive terms
Q	Numbers of seasonal moving average terms
D	Seasonal differencing level
S	Time periods
$\Phi(B)$	Operator of P
$\Theta(B)$	Operator of Q
ANN	Artificial Neural Network

v_i	Internal activity level
w_{ij}	Weight of the connection from input j to neuron i
x_{ij}	Input signal number from input j to neuron i
w_{i0}	Threshold associated with unit i
FLS	Fuzzy Logic System
ACF	Autocorrelation Function
PACF	Partial Autocorrelation Function
Y	Actual value
$\hat{Y}$	Forecast value
AE	Absolute Error
E	Value of absolute error
MSE	Mean Squared Error
RMSE	Root Mean Square Error
RMSPE	Root Mean Square Percentage Error
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
SD	Standard Deviation

SEM	Standard Error of the Mean
VaR	Value-at-Risk
ΔR	Loss or gain of a financial asset
R_{VaR}	Value at risk at confidence level c
ES	Expected Shortfall
R	Risk index
V	Variation index
D	Load demand
P	Electricity price
A	Transaction amount
F	Financial risk

Chapter 1

Introduction

1.1. Research motivation

In the 1980s, many countries and regions in the world successively carried out market-oriented reforms in the power industry, and the monopoly power industry began to change. A notable feature is to introduce competition to the power industry and provide a market platform for the power generation side. The original intention of the reform is to improve the efficiency of power industry, reduce the generation costs of the power generation companies, and expand the range for power users to choose their power suppliers.

The advantages of the competitive electricity market after the power reform are that the competition of participants can improve production efficiency, and the power industry is no longer a service industry but it is one for profit. The power companies in the competitive electricity market use a variety of physical and financial technologies to increase income and reduce expenditure, boost economic development, and protect the environment.

However, because electricity cannot be stored and its transmission is limited by physical and reliability constraints, the participants in the electricity market have to face various possible risks. Under normal circumstances, risk is the possibility of suffering danger, loss, harm, disadvantage or destruction, and all risks come from uncertainty. But for the risk analysis in this thesis, impact and probability are the two main components of risk analysis, and risk can be defined as a function of impact and probability. Looking at impact versus probability is common in order to categorize and prioritize risks as some risks may have a severe impact on projects objectives but only happen on rare occasions, while other have a moderate impact but occur more frequently. In the electricity market, the participants are affected by many risks, such as:

- Risk of load demand forecast error
- Risk of electricity price forecast error
- Risk of bidding strategy
- Risk of transmission congestions
- Risk of equipment
- Risk within contracts

This thesis mainly investigates load demand forecast and electricity price forecast in electricity market and the financial risk caused by the forecast errors. The data in the UK day-ahead auction electricity market are used as the example, which is obtained from the UK N2EX, Nord Pool [1]. Therefore, among these different risks, the key factors are the load demand and electricity price forecast uncertainties.

In the past many forecasting methods were used in different fields, and this thesis introduces five methods for forecasting load demand and electricity prices — time series, artificial neural network (ANN), fuzzy logic, wavelet transform and grey model. For the time series model, [2], [3] use autoregressive moving average (ARMA) model to forecast the load demand in Greece, but the seasonal factors are not considered. [4] presents the seasonal changes of load demand in England and Wales and it uses the seasonal autoregressive integrated moving average (SARIMA) model to forecast half-hourly ahead electricity demand. Similarly, the electricity price forecast in [5] also present the seasonal changes, and it proposes two SARIMA models to forecast hourly electricity price in the electricity markets of Spain and California. The smallest mean absolute percentage error (MAPE) of electricity price in the California market is 5.21%. In order to improve the forecast accuracy, sometimes the ARMA model can be combined with other models. [6] forecasts day-ahead electricity prices based on the autoregressive integrated moving average (ARIMA) model and wavelet transform. [7] provides an approach to predict next-day electricity prices based on the ARIMA model and Generalized Autoregressive Conditional Heteroskedastic (GARCH) methodology. [8] proposes a price forecasting method based on wavelet transform combined with ARIMA model, and the results from the comparisons show that the proposed method in [8] is more accurate than the other forecast methods.

For the artificial neural network model, [9] presents an ANN model based on the short term load forecasting designed for the Greek Public Power Corporation, and the results show that the ANN model produces accurate load forecasts for both normal days and holidays. [10] uses the ANN model to forecast the electrical energy consumption in Iran. The ARIMA and ANN models are compared and utilized in [11] to formulate forecasting models of the electricity demand in Thailand. [12] uses the ANN model to forecast load demand while also considering electricity price as another input to the neural network, and the results show that the electricity price does have an impact on the performance of a load demand forecasting technique. [13], [14] present the electricity price short-term forecasting implementation using the ANN computing technique. [15] proposes a ANN model to forecast next-week prices in the electricity markets of mainland Spain and California, and the minimum MAPE of electricity price is 5.23% in the Spanish market and 3.09% in the Californian market.

For the fuzzy logic method, [16] proposes a methodology that uses fuzzy logic rules to incorporate historical weather and load data. The results show that in the short-term load demand forecasts, the proposed model has been able to generate forecasts with a MAPE frequently below 2.3% and a holiday model also generated good results. Fuzzy logic can also be combined with other forecasting models. [17] proposes a fuzzy Box-Jenkins approach for modelling and short-term forecasting of the electricity price. The results show that the fuzzy Box-Jenkins method can achieve better performance when the price series do not match the models in the Box-Jenkins method well. [18], [19] combine ANN model and fuzzy logic for short-term price forecasting of electricity markets.

The wavelet transform method is usually used in combination with other methods to forecast load demand and electricity price. A hybrid forecast method combining wavelet transform, neural network and evolutionary algorithm is proposed in [20] to forecast hourly load demand. [21] proposes an approach for short-term electrical load forecasting by combining the wavelet transform and neural networks. The results show the application of the wavelet transform in short-term load forecasting is very encouraging. In addition to load demand forecasting, [6], [8] combine wavelet transform with ARIMA model to forecast electricity price.

For the grey model, [22] presents a trigonometric grey prediction approach by combining the traditional grey model with the trigonometric residual modification technique for forecasting electricity demand. [23] proposes an improved Grey-based prediction algorithm to forecast a very-short-term electric power demand for the demand-control of electricity. A combined model based on combination of the wavelet transform and grey model is presented in [24] for short term electric load forecasting and is improved by particle swarm optimization algorithm. In order to improve the performance of traditional grey models, [25] presents a novel grey model for short-term electricity price forecasting in competitive power markets. The simulation results show that the proposed model is capable of forecasting short-term electricity price efficiently.

From the literature review sections, most of the papers directly use one forecasting model to forecast, without the comparison of different forecasting models. In all these proposed models mentioned above, time series model frequently outperforms other methods, while ANN model is another promising artificial intelligence method. Therefore, the ARIMA and SARIMA model in time series model and the ANN model in artificial intelligence model are selected to forecast load demand and electricity price respectively in this thesis. Then one optimal model is chosen from them. In order to observe the forecast errors more clearly, all of the forecast errors in load demand and electricity price are presented by risk index. In addition, most papers only consider load demand forecast or electricity price forecast in the electricity market, and do not forecast load demand and electricity price in parallel. In this thesis, a further original contribution is the combination of forecast errors in the load demand and electricity price to analyse the financial risk assessment. This opens the dimension of using the errors for risk analysis and anticipation for market participants. The approach can be used to lessen the risk in the bilateral market.

There are two structures in the UK electricity wholesale market — bilateral contract and Power Exchange (PE). In the bilateral contract, the load demand volumes and electricity prices are determined based on the negotiation between the generation side and the demand side, which are fixed. The forecast risks in bilateral contracts are calculated before the contract is sighed. The day-ahead auction electricity market is in the PE, and electricity market participants are bidding for load demand and electricity price here. In the day-ahead auction electricity market, both the generation side and the demand side need to submit their 24-hour load demand volume and electricity price orders for the next trading day. If the actual power generation on the generation side is greater than the purchase amount on the demand side, then the excess power is wasted. If the power bought by the demand side is insufficient, then the power has to be purchased at a higher price in the spot market. In addition, the generation side wants to sell power at a higher price, while the demand side wants to buy power at a lower price. Therefore, load demand and electricity price forecasting need to be applied here because the accurate load demand and electricity price forecasts will help electricity market participants maximize their benefits.

In the first part of this thesis, the monthly, seasonal, annual and multi-step-ahead load demand in the UK day-ahead auction electricity market from March 2015 to February 2016 is forecasted. Due to the different data and waveforms of load demand, all the forecasting process of load demand is carried out. In the monthly forecast, the ARIMA, SARIMA and ANN models are used to forecast the data on weekdays and weekends respectively, and an optimal model will be selected based on the forecast results for the next forecasting processes. In the seasonal forecast, this thesis proposes two methods — the continuous historical data method and the seasonal separation method to forecast seasonal data separately, and the forecasting results for each season of the year can be observed and compared. Then three rolling windows of different sizes are used in the annual forecast, and the effect of the rolling window size on the forecast results is illustrated. Moreover, the comparisons of one-step-ahead forecast and multi-step-ahead forecast are achieved, and the influence of multi-step-ahead forecast on the forecasting results is analysed. In this thesis, the forecasting accuracy is determined by calculating the RMSPE and MAPE.

With the forecasting results of load demand, the forecast errors can be obtained by comparing the actual values and forecast values. In order to observe the forecast error intuitively, all the errors in this thesis are represented by the risk index. In addition, this thesis also proposes a method to observe the risk index through the variation index directly, because the forecasting processes are complicated and the variation index is only related to the changes of the data itself.

In the second part of this thesis, the monthly, seasonal, annual and multi-step-ahead electricity price in the UK day-ahead auction electricity market from March 2015 to February 2016 is forecasted. The same forecasting methods and processes as load demand forecast are also used for electricity price forecasting. Electricity price forecasting is very important because it can directly affect the profits of market participants. According to the actual and forecast values of the electricity price, the electricity price forecast errors can be obtained. Then all the errors are also represented as risk index, and the relationship between the risk index and variation index of electricity price can be observed.

In the third part of this thesis, the financial risks in electricity market are analysed through the combination of load demand forecasting and electricity price forecasting. Financial risk assessment is the main novelty of this thesis. Risk assessment is originally used in the financial industry, but this thesis is used to analyse the financial risks in the electricity market and help market participants to reduce their financial risks. After getting the forecasting results of load demand and electricity price, the actual and forecast electricity transaction amount can be calculated respectively. In this thesis, the error value between the actual transaction amount and the forecast transaction amount is presented as financial risk in monetary value. The Value-at-Risk (VaR) and Expected Shortfall (ES) methods in economics are used to analyse the financial risk. [26] introduces the background of credit risk measurement and presents the VaR and ES methods in detail. [27]–[29] present the research of the VaR method in the banking field. [30] proposes a VaR model for long and short trading positions in oil market to forecast Value at Risk. [31] introduces the financial risk management of electric energy contract evaluation for electricity producers in the electricity market. The comparative analysis methods of VaR and ES are described in [32]–[35]. Originally VaR and ES are measures of the risk of investments. In this thesis they are estimation of the possible loss/gain of financial return due to forecast errors and they are expressed as monetary values. The confidence level of VaR is selected at 90% and 95% in this thesis, which means that 90% and 95% probability of financial risk is desirable, while the remaining 10% and 5% are treated as the wrong data. ES can show the average level of loss suffered as a specific value when the portfolio loss or gain exceeds 90% and 95% VaR threshold. Then the financial risks of electricity market participants will be expressed clearly.

The ultimate goal of risk assessment is to reduce or avoid financial risks, and the total financial risk that adds up all the positive and negative risk values can best reflect the quality of risk assessment. The ideal situation is that all the positive and negative financial risks could offset each other, and then the total financial risk value is zero. [36] calculated the total financial risk in bilateral contracts based on the forecast load demand and the assumed constant electricity price. In this thesis, the total financial risks in the day-ahead auction electricity market are calculated based three different preconditions:

1) Considering the forecasting load demand and electricity price;
2) Considering the forecasting load demand and actual electricity price;
3) Considering the actual load demand and forecasting electricity price.

The analysis results can help the electricity market operators or participants to qualify the risks, improve the accuracy of load demand and electricity price forecasts, and formulate the effective financial hedging strategies to reduce or avoid their financial losses.

In this thesis, all the programs of the ARIMA, SARIMA and ANN models are written in MATLAB language. The basic ARIMA, SARIAM model and ANN toolbox are all one-time forecasting, while this thesis uses the rolling-window forecast method to implement all the forecasting processes. In the ANN model, each of the optimal forecasting results is selected from 1000 cycles. Moreover, the works in the financial risk assessment part are also achieved in MATLAB. Therefore, in addition to the application of the basic models, the author also invested a lot of effort in the program development.

1.2. Objective of the thesis

The objectives of this thesis include:

- To investigate the load demand forecasts in monthly, seasonal, annual and multi-step-ahead. To select the optimal model and method by analysing and comparing the forecasting results of different models, different methods, different sizes of rolling windows and different forecasting steps.

- To investigate the electricity price forecasts in monthly, seasonal, annual and multi-step-ahead. To select the optimal model and method by analysing and comparing the forecasting results of different models, different methods, different sizes of rolling windows and different forecasting steps.

- To develop a risk index analysis method for the load demand forecast uncertainty and propose a variation index analysis method based on the increment in actual load demand.

- To develop a risk index analysis method for the electricity price forecast uncertainty and propose a variation index analysis method based on the increment in actual electricity price.

- To calculate the forecast errors in load demand and electricity price respectively, and combine these errors to investigate the Value-at-Risk and Expected Shortfall.

1.3. Original contributions of the thesis

The main original contributions of this thesis are highlighted in the following:

Contribution 1: Using the ARIMA, SARIMA models in the time series method and the ANN model in the artificial neutral network method for forecasting load demand and electricity price separately. The forecasting process includes monthly, seasonal, annual and multi-step-ahead, and the effects of the forecasting results are used to determine which model or method is the best.

Contribution 2: A risk index method to analyse the forecast errors of load demand is proposed, and a separate risk index method to analyse the forecast errors of electricity price is proposed. Moreover, another contribution related to the risk index is that this thesis also presented a method called variation index. Since the variation index is only related to the increment of the data itself, finding the liner relation between the variation index and risk index can help market participants eliminate the complicated forecasting process to analyse the risk index.

Contribution 3: The forecast error of load demand and the forecast error of electricity price are combined to calculate the financial risk in electricity market. The Value-at-Risk and Expected Shortfall for the market participants are also calculated by combining these two forecast errors. In addition, different preconditions are considered to calculate the total financial risks. This helps market participants choose the appropriate conditions to analyse the financial risks and thus minimize their risks. The application of financial risk assessment in the electricity market is the most important contribution of this thesis.

1.4. Thesis organization

This thesis is made up of seven chapters. They are organized as follows:

Chapter 1 presents the research motivation, objectives, and original contributions in this thesis.

Chapter 2 reviews the background of electricity market. Because the electricity market of the UK is one of the most representative competitive electricity markets, this chapter details the reforms of the UK electricity market and introduces the ongoing new low-carbon electricity market reform. Following that structures of UK electricity wholesale trading market are also introduced.

Chapter 3 illustrates the importance of load demand and electricity price forecasting in the electricity market. Several different forecasting models and their applications are presented, including time series, ANN, fuzzy logic, wavelet transform and grey model. In addition, the parameters determination methods for ARIMA, SARIMA and ANN models are also described in detail.

Chapter 4 introduces the methods for analysing forecast errors and the financial risk assessment methods. It illustrates and compares several common analysis methods of forecast errors. Then a method for converting the forecast errors into risk index is proposed. Furthermore, this chapter investigates the financial risk analysis of electricity market based on Value-at-Risk (VaR) method. The method to evaluate the total financial risk is introduced at last.

Chapter 5 presents the process of load demand forecasting and the comparison of forecast results. Firstly, the rolling-window forecast method is introduced, and the forecasting processes for monthly, seasonal, annual and multi-step forecasts are illustrated. Following that, the parameters selection of ARIMA, SARIMA and ANN models in weekdays and weekends load demand monthly forecast is introduced. Then it compares the monthly forecast results of ARIMA, SARIMA and ANN models and selects the optimal forecasting model. The next section uses continuous historical data method and seasonal separation method to forecast the seasonal load demands separately. Moreover, three annual forecasts with different sizes of input data are implemented and their results are compared. Finally, the one-step-ahead and multi-step-ahead load demand forecasts are achieved and the results are analysed.

Chapter 6 presents the process of electricity price forecasting and the comparison of forecast results. Firstly, the forecasting processes for monthly, seasonal, annual and multi-step forecasts are illustrated. Following that, it details the parameters selection of ARIMA, SARIMA and ANN models in weekdays and weekends monthly electricity price forecasting. After comparing the monthly forecast results of ARIMA, SARIMA and ANN models the optimal forecasting model is selected. Moreover, the seasonal electricity price forecasting is achieved by continuous historical data method and seasonal separation method. Then three annual forecasts with different sizes of input data are implemented and their results are compared. Finally, chapter 6 also carries out the one-step-ahead and multi-step-ahead electricity price forecasts and analyses the results.

Chapter 7 shows the risk index analysis and the financial risk assessment. The risk indexes based on load demand and electricity price forecasting errors are presented. Then a method for evaluating the risk index due to variation index is introduced and achieved in this chapter, and it is found that there is high correlation between the variation index and risk index. Furthermore, the financial risks in electricity market are calculated by VaR method and Expected Shortfall (ES) with 95% and 90% confidence level. At last, in order to observe the individual impact of load demand and electricity price forecasts on financial risks, the total financial risks under three different preconditions are compared and analysed.

Chapter 8 summarizes the conclusions of this thesis, and describes some possible improvements in future work.

1.5. Publications

According to the results of the research work reported in this thesis, the following publications have been published:

- **G. Gao**, K. Lo, J. Lu, and F. Fan, "A Short-Term Electricity Price Forecasting Scheme for Power Market," World Journal of Engineering and Technology, vol. 04, no. 03, pp. 58–65, 2016, Shanghai, China, October 2016.
- **G. Gao**, K. Lo, and F. Fan, "Comparison of ARIMA and ANN Models Used in Electricity Price Forecasting for Power Market," Energy and Power Engineering, vol. 09, no. 04, pp. 120–126, 2017, Chengdu, China, April 2017.

- **G. Gao**, K. Lo, and J. Lu, “Risk assessment due to electricity price forecast uncertainty in UK electricity market,” 52nd International Universities Power Engineering Conference (UPEC) 2017, Heraklion, Greece, August 2017.
- **G. Gao**, K. Lo, “Risk Assessment of Load Demand and Electricity Price Forecast Uncertainty in Power Market,” IET journal paper. (Under preparation)

Chapter 2

Electricity market models and UK electricity market reforms

2.1. Introduction

Electricity market is a place that generators and operators can negotiate with each other to determine their electricity price and load demand. It is a highly complex trading system that consists of the management mechanism, transaction execution system for the coordinated operation of power generation, transmission, distribution, users and other member organizations in the power system based on the principle of fair competition and mutual benefit [37].

As a public utility, the power industry is operating as a vertically integrated monopoly mode for many years. In the 1980s, many economists proposed to relax the regulation of the power industry and introduce market mechanisms. They believe that the competition in the power generation side can promote power generation companies to increase production efficiency, and the competition in power sales side can promote users to save electricity and improve the efficiency of electricity use. Therefore, different modes of competition emerged after the power marketization [38]. In 1996, Hunt and Shuttleworth

[39] proposed that the electricity market can be divided into four models according to the deregulated degree of power generation, transmission, distribution and power sale: monopoly, purchasing agent, wholesale competition, and retail competition. This also reveals the development of the power industry competition model. All these four different kinds of electricity market model have been introduced in this chapter.

The way to change the electricity market models is market reform. The advantage of electricity market reform is that it can improve enterprise efficiency, reduce costs and improve service levels. At present, many electricity markets have been established all around the world, and most of markets are in the process of continuous reform. Compared with the traditional monopoly power management mechanism, the nowadays electricity markets have the openness and competitiveness for electricity supply.

In addition, there is no normative and ideal market economy model that can be directly applied in the electricity market reform process. The national conditions of each country are very different. Some countries have a higher degree of nationalization, and some countries have more free market economics. Moreover, the structure of power installation and power management in different countries are also different. Therefore, each country should choose the market reform process that suits itself according to the actual situation.

The UK electricity market has been reformed three times since 1980s and is now continuing a new round of low carbon reforms. The power reform of UK has promoted the benign competition in the electricity market, allocated resources through market competition, and developed a large number of combined cycle natural gas generators to replace coal-fired generators, which has promoted the production efficiency of the power industry. In this chapter, the process of three reforms in UK electricity market is introduced in detail, and it also presents the trading methods in UK electricity wholesale market.

2.2. Different kinds of electricity market model

All the electricity markets in power industry are categorized into four models: monopoly, purchasing agent, wholesale competition, and retail competition.

2.2.1. Monopoly model

The monopoly model integrates power generation, transmission, distribution and retailing [40]. This model undoubtedly played an important role for a certain period of time in accumulating funds, large-scale rolling development, avoiding duplicated settings, unifying power grid planning, constructing large power grid and improving the stability of power system operation. However, with the expansion of power supply scope, the disadvantages of low economic efficiency, low investment efficiency and low operating efficiency are fully exposed. Monopoly model lacks incentives to increase efficiency, and it focuses too much on the power supply and may be able to even sometimes forget the interests of users.

In the monopolistic mode of operation, there are power transactions among the power companies, such as the electricity trading between France and the United Kingdom. The trading contracts can coordinate the power companies' operating relationships. Through power trading, system backup capacity can be provided to each other, the security of system operation can be enhanced, and the system cost can be reduced. However, under this model, the power companies generally signed the short-term trading contract based on ultra-short-term marginal expenses and split the proceeds in half [41].

2.2.2. Purchasing agent model

In the beginning of introducing competition in the power industry, the utilities no longer monopolize all generating capacity in the system at this time. The Independent Power Producers (IPP) can directly connect to electricity networks and sell electricity to wholesale purchasing agent [42]. With the evolution of this model, the utility no longer owns any power generation company, and needs to purchase all the required power from IPP. This model is called purchasing agent model and it has two characteristics. Firstly, the purchasing agent has sales monopoly power for distribution companies and has purchasing monopoly power for independent power generators. The electricity price set by purchasing agent must be strictly regulated. Secondly, a certain extent of competition among the power generators has been achieved.

2.2.3. Wholesale competition model

The wholesale competition model emerged after the purchasing agent model [7]. In the wholesale competition model, there is no centralized agent responsible for the supply of electricity. Instead, in order to meet the customer's power consumption demand, the distribution companies purchase power directly from power generation companies. This kind of power trading generally takes place in the wholesale electricity market. Except for distribution companies, the large-scale users are also allowed to purchase electricity in the wholesale market directly [8]. This model greatly promoted the competition among the power generation companies. The wholesale electricity price at this time is influenced by both supply and demand. However, small users cannot choose the competitive supplier, the electricity retail prices still have to be monitored [45].

2.2.4. Retail competition model

In the retail competition model, all the power users can choose their own suppliers in the retail competition model [46]. Because of transaction costs, only very large-scale users will choose to purchase electricity directly in the wholesale market. Most of the small and medium-scale users will purchase electricity from retailers, and the retailers then buy electricity at wholesale markets on their behalf. In this model, the only monopoly business in the electricity market is the provision and operation of transmission and distribution network services. The investment cost recovery requires strict supervision. At this time, the electricity retail price is entirely determined by market competition. The implementation requires a considerable amount of measurement, communication and data processing facilities.

2.2.5. Electricity market competition models in different countries

The market competition model adopted by some countries in the world is shown in table 2-1. Malaysia is in the transition period of the power industry reform [47]. The situation in Japan is special, some regions are monopoly model, and some other regions are the retail competition model [48].

Table 2-1: Market models and their corresponding countries [49]

Market Competition Model	Country or Region
Monopoly model	Malaysia, Hong Kong, Colorado in the USA
Purchasing agent model	Thailand, Italy, China, Russia
Wholesale competition model	Singapore, Argentina, South Korea, Philippines, Brazil, New South Wales in Australia
Retail competition model	Nord Pool, UK, Spain, Germany, Victoria in Australia, Michigan and Texas in the USA

2.3. UK electricity market reform

In the late 1980s, UK took the lead in implementing industry privatization reform and proposed deregulation of the electric power supply industry. From 1990 to 2001, the National Grid Company (NGC) was founded, and arrangements called the Electricity Pool operated for the production, purchasing and trading of wholesale electricity [50]. On 27 March 2001, the New Electricity Trading Arrangements (NETA) was put in place, but it only represented the wholesale electricity market for England and Wales [51]. After 2005, the British Electricity Trading and Transmission Arrangements (BETTA) replaced NETA and covered the whole area of the UK [52].

2.3.1. The first electricity market reform

The distinctive feature of the first electricity market reform was the creation of a mandatory electricity pool model based on the NGC, which was established on March 31, 1990 [53]. During that period, the electricity retail market was gradually formed with the opening of power supply options. From April 1990, users with one megawatts (1 MW) peak load were allowed to select their power suppliers from 12 regional monopoly electricity companies (REC), which were the predecessors of power suppliers. The users who have a peak load above 100 kW can choose their power suppliers by 1994. In May 1999, at the end of electricity pool model, the free choice of power supplier was opened to the remaining residents (ie, users with a peak load less than 100 kW), which marked the formal formation of the UK electricity retail market.

In the first electricity market reform, the electricity retail market introduced competition to the electricity selling sector for the first time. This broke the monopoly of regional power companies on local users, which led to the optimization and restructuring of power companies. By 1999 to 2000, 80% of megawatt customers in England and Wales, 67% of medium-load (100 kW to 1 MW) users and 38% of residential users had changed their power supplier at least once [54].

However, the electricity pool model exposed several significant disadvantages after about 10 years of operation. In the electricity pool model, the NGC's functions are too concentrated and lack of physical contracts, which leads to electricity price instability [55]. It cannot reflect the gradual decline in power generation costs, and lack of demand side protection. In this case, the second electricity market reform began with the formal implementation of the New Electricity Trading Arrangements (NETA) on March 27, 2001.

2.3.2. The second electricity market reform

Compared to the previous situation in which a few power generation companies set the uniform electricity pool prices, NETA gives market members freedom of contract and establishes a three-tier trading system with long-term, futures and options, short-term bilateral markets and balancing markets [56]. The reform has further opened up various markets, expanded user participation and market competition. It also improved the reliability of power supply and modestly reduced the retail electricity price. Under the new mechanism with the cessation of the electricity pool, the NGC is no longer responsible for the operation and settlement of electricity transactions, but is only responsible for balancing the market to complete the task of self-dispatching, blocking dispatching and balancing contracts [57].

In this reform, as a participant in the electricity retail market, a more unified and specific power supplier concept was defined by law. Through the contract constraints with power generation company, power suppliers are required to ensure sufficient power purchase quota to meet users' load demand, thus improved the safety and reliability of power supply. The electricity retail market in the NETA also expanded the competition in electricity selling sector. Specifically, the power suppliers who are reorganized from the original regional monopoly power companies further reduced their local market share by 10%. Furthermore, more and more original class 2 power suppliers (subordinate to the original regional monopoly power companies) entered the electricity retail market with a new identity of equal power suppliers [58].

The electricity market reforms in England and Wales under the NETA model achieved remarkable results. However, Scottish Power in Scotland was still constrained by some problems in the electricity pool period, like extremely unbalanced between supply and demand, the lack of competition and high electricity price. Simply synchronizing the power generation price in Scotland region with the NETA model cannot break the monopoly pattern. It also cannot open up a broader market space or provide more choices for the power generation companies in Scotland, especially for the new energy generation companies [59]. Therefore, the Office of Gas and Electricity Markets (Ofgem) proposed a 3rd reform plan to implement the NETA in Britain and establish the British Electricity Trading and Transmission Arrangements (BETTA).

2.3.3. The third electricity market reform

The innovation of the BETTA is reflected in the unification, that is, the nationwide unified electricity trading, balancing and settlement system based on the NETA was established. The unified operation mechanism enables the British electricity market to implement high-efficiency and low-cost expansion, operation, supervision and management [60].

The Great Britain System Operator (GBSO) is the only national operating authority, and it is fully responsible for power dispatching and system operation. The NGC has been adjusted to become one of the owners of British transmission lines [61]. Under BETTA, Scotland’s power suppliers are able to enter the highly competitive electricity wholesale market in the whole of UK, and power generation companies can freely trade with power suppliers in England and Wales. In addition, Scotland’s new energy generation companies would be able to use the England-France intermediaries to sell electricity to the wider European market. The unification of electricity trading and transmission agreements under BETTA laid the foundation for the expansion of the electricity retail market to the whole area of UK, and also introduced the competition to power generation and selling sectors in Scotland [62].

After the first three reforms, the service content and charging mechanism provided by the existing power suppliers have become increasingly uniform. The liberalization and competition of the electricity market has become a more level playing field. In the UK electricity market reform programme announced in 2013, the theme of the ongoing new electricity market reform is to establish a clean, diversified and low carbon emission reduction electricity market [63].

The large-scale entry of new energy power generation companies in the low-carbon reform will not only impact the electricity market but also the electricity retail market. Power suppliers will have more power purchase options and the adjustment of charging mechanism will be imperative. This will activate the competition in the electricity retail market once again. The introduction of diversified smart devices, such as smart meters, will enable power suppliers to calculate users’ bills more accurately, which will have a positive impact on the adjustment of charging mechanism. In addition, the users with solar panels and mini-type wind turbines will change from traditional electricity users to ‘prosumer’ in this reform. The electricity retail market needs to establish a new business model to accommodate this new group [64]. All in all, the low-carbon reform will inject new vitality into the competition of electricity retail market.

2.4. UK electricity wholesale market structures

Electricity is a product that cannot be stored in large quantities. Power supply and demand must always be matched or balanced. In the UK, it is mainly traded by suppliers, generators, traders and customers in the competitive wholesale electricity market [65].

There are two forms of transactions between generators and operators in UK electricity wholesale market — bilateral contract and through a Power Exchange (PE). For the bilateral contract, trade parties sign a bilateral contract by negotiation, and determine the prices and load demand volumes of the transaction. The contract can be signed from one hour to a few years before the actual delivery time, and the settlement period is a half hour. Power Exchange is a centralized power-trade place. Generators and operators submit their offers that contain prices and capacities of energy to be traded. Then PE integrates and clears these offers. The trading in PE is usually started seven days before the power transmission time, and the gate closure happens one hour before the actual transmission hour [66].

2.4.1. Bilateral contract

A bilateral contract in an electricity market is an agreement between a willing buyer and a willing seller to exchange electricity, rights to generating capacity, or a related product under mutually agreeable terms for a specified period of time [67]. Bilateral contracts can provide a stable supply of electricity to power users, while providing long-term stable demand for power producers, and can lock in electricity prices. Therefore, countries in the world have used a large number of bilateral forward contracts for power trading in the early days of power marketization. With the further development of the electricity market, the share of bilateral contract transactions has gradually expanded.

In the UK, under BETTA, bulk electricity is traded "forward" through bilateral contracts, and on one or more power exchanges, such as APX Power UK. Most trading in BETTA takes place in the forward contracts market [68]. In addition to power generators and power sellers, the non-physical traders, such as banks, can also sign electricity trading bilateral contracts for arbitrage. The volume of electricity signed through bilateral contracts and PE is called contracted volume, which cannot be changed after the gate closure. The contracted volume will be reported to the agent that can conduct the unbalance settlement. In the UK, this agent is ELEXON [69].

Bilateral contracts in the electricity market include two categories: power physics contracts and power finance contracts. A power physics contract is a forward contract that has a fixed price and is not related to the contract bidding market. The contracted power in the physics contracts is no longer involved in the spot bid. After signing the physics contracts, the contracted power is reported to the dispatching centre for delivery, and the power producer that signs the power physics contract will reduce the bidding capacity in the bidding power market. Since the power finance contracts are delivered through the spot market and the contract power is still involved in the spot bid, the finance contracts do not affect the competition in the spot market [70]. The power finance contracts that commonly used in the electricity market generally include contracts for difference, optional forward contracts and future contracts.

2.4.2. Power Exchange

There are two major Power Exchanges in the UK, N2EX and APX. N2EX is a solely-invested subsidiary of Nord Pool Spot, which is exclusively responsible for operating in the UK. The volume of power traded through N2EX in day-ahead market achieved 111 TWh in 2017 [71]. APX has Power Exchanges in UK, Netherlands and Belgium. Since the integration of the businesses of the APX Group and EPEX SPOT, APX Power UK operates under the EPEX SPOT brand name. The following mainly describes the trading rules of N2EX. Power Exchange consists of three sub-markets, day-ahead auction, spot market and prompt market, and the latter two are collectively called continuous market. Most of the traded electricity is accomplished by day-ahead auction.

2.4.2.1. Day-ahead auction

The day-ahead auction trades electricity for the 24 hours in the next day. All the market members must submit their orders electronically before the end of the auction, and the orders should include electricity prices and volumes. After the auction, the trading prices and volumes in each trading hour and the market equilibrium point are calculated based on all the received quotes [72].

There are three forms of bids in the day-ahead auction: hourly, block and flexible. The hourly bids are based on the quotations for each delivery hour in the coming day. The hourly bids allow market members to bid in segments, and the trading system forms the bidding curves by linear interpolation according to all the hourly bids. A block bid presents an indivisible amount of quantity for a single price and may be valid for multiple consecutive periods as opposed to hourly bids. When the market members apply for block bid, they need to declare the price, capacity per hour, start-stop transmission hours, and the minimum acceptance ratio (the default is 100%). The flexible bids also represent an indivisible amount of quantity but only for a single period. As opposed to hourly and block bids, flexible bids are not submitted for a particular period and can be evaluated at any period by the market clearing algorithm [73].

2.4.2.2. Spot market

The spot market is opened 48 hours before the power supply and can be traded continuously. After the market members submit their bids, the system will sort and match all the bids in order, and all the matched bids are cleared automatically. The order is sorted by the bid prices, and the bid submitted first is preferred if the prices are the same. The market member can modify or cancel the bid if his submitted bid is not matched [74]. The trading period of N2EX is divided into 10 kinds, such as half an hour, one hour, and four hours. Each trading period can start to submit the bid from 00:00 on the day before the trading period, and the bid submission is stopped about one hour before the trading period. For example, the bid submission time for the period from 17:00 to 17:30 on June 11, 2018 is from 00:00 on June 10, 2018 to 15:45 on June 11, 2018.

2.4.2.3. Prompt market

The prompt market is also a continuous trading market. The trading can be carried out 7 days before the power transmission hour, and the trading system matches all the bids. In N2EX, most of the functions of the prompt market are realized in the spot market, but the bid submission time of these two markets is different. APX's prompt market mainly provides the services for base load and peak load, weekend power use and the combination. There are 7 different contract types: weekend base, base, peak, extended peak, off-peak, blocks 3+4 and overnight [75].

2.5. Summary

This chapter presented four electricity market models from the monopoly model to the retail competition model, which also illustrated the overall development trend of the electricity markets. Following that, three reforms in the UK electricity market was reviewed, and the ongoing new low-carbon electricity market reform was also introduced. Because the experimental processes of this thesis will use the load demand and electricity price in the UK wholesale market, UK electricity market was mainly introduced. The next section described UK electricity wholesale trading market structures. In the UK, there are two types of transaction in the wholesale market before gate closure: bilateral contracts and Power Exchange. Power Exchange includes the day-ahead auction, spot market and prompt market. Most of the electricity trading was completed by bilateral contract, and most of the electricity trading in the Power Exchange was completed by day-ahead auction. The transactions in Power Exchange do not need to consider the network constraints and they are similar to general commodity transactions except that they need to be balanced in different periods. The trading can be applied in multiple markets at the same time, and Power Exchange can provide a different kind of transactions to users.

In Power Exchange, both load demand and electricity price fluctuate over time. In the course of power trading, the ability to accurately forecast fluctuations in load demand and electricity price is significant for market participants. Therefore, the forecasting methods are one of the important research fields in the electricity market.

Chapter 3

Methodology of forecasting models and literature review

3.1. Introduction

In recent years, the power industry has carried out electricity market-oriented reforms all over the world. With the global market trend, the power industry has gradually changed from monopoly mode to competition mode. Electricity can be bought and sold as a normal commodity in the market environment. All the market participants use the ever-changing market demand and price as a basis for electricity trading and settlement. Therefore, load demand and electricity price forecasts have become core elements of the electricity market.

Accurate forecasting results can help electricity market participants to maximize their benefits, and also help market regulators manage the electricity market. The importance of load demand and electricity price forecasting in the electricity market is introduced in this chapter. In order to obtain accurate load demand and electricity price forecasting results, the quality and selection of forecasting models have become the key issue. The development of science and technology provides various theories and methods for load demand and electricity price forecasting, such as time series method, artificial neural network, fuzzy logic, wavelet transform, and grey model. This chapter introduces these above methods in detail, and combined with the literature review, analyses and compares these forecasting methods in terms of applicable conditions, data forms, and calculation methods. The parameter determination methods for ARIMA model, SARIMA model and ANN model are also presented.

3.2. The purpose and significance of load demand and electricity price forecasting

Most of the electricity market is settled at the system marginal price. The system marginal price refers to the uniform price reflecting the short-term supply and demand relationship of power in the electricity market. The marginal price is also the equilibrium price corresponding to the intersection of the power supply curve and the demand curve. It is often referred to as the uniform market clearing price in many pieces of literature [76]. The operating modes of the electricity market in various countries are different from each other, and the formation mechanisms of electricity price are also different. However, due to the basic attributes of commodity prices, the interaction between electricity price and market supply and demand is very close, and the adjustment effect on the market is very significant. The participants in the electricity market trade and settle electricity based on the ever-changing market load demand and electricity price. The electricity price affects the market participants' income directly [77].

In addition, load demand and electricity price in the electricity market have high volatility and randomness due to many factors, which brings risks to the power trading profits [78]. According to the electricity trading market structures, we can find that load demand and electricity price forecasting has become important to promote competition and to guarantee the benefit of participants in the market. As market participants, both generators and operators' intent to contribute more efforts in developing appropriate load demand and electricity price forecasting scheme to maximize their profits. If the load demand and electricity price can be forecasted accurately, the generation side could handle the market dynamically and make an optimal strategy of power generation. In the meanwhile, the demand side could consume the electrical energy within a particular time slot when a lower electricity price is forecasted. Therefore, it could reduce the total cost and improve the market competitiveness. For regulators, grid reference price forecast results can help to improve the monitoring capability of electricity market operation and discover and resolve the problems in the market. Also, the government can formulate related policies by electricity prices and guide electricity market development [79]. Therefore, due to its importance, the research field of load demand and electricity price forecast came into being.

According to the length of the load demand forecast and electricity price forecast period, it can be divided into long-term forecast, medium-term forecast, short-term forecast and ultra-short-term forecast [80], [81]. In general, medium-term forecasts are from a few weeks to a few months and even up to a few years, and long-term forecasts are required to be valid from 3 to 5 years. The medium and long-term forecast contains many uncertain factors and the reliability of the forecast is lower [82]–[86]. Ultra-short-term forecasts are usually from a few minutes to one hour, and short-term forecasts are from one day to one week. Sometimes, both ultra-short-term and short-term forecasts are classified as short-term forecasts [87]. The short-term load demand forecast and short-term electricity price forecast are two important parts of the electricity market. Moreover, short-term load demand and electricity price forecast can provide guidance for the short-term bidding strategies of market participants. The market participants can formulate corresponding bidding parameters and bidding strategies based on the load demand and electricity price forecast results [88], [89]. In the electricity market environment, more and more attention has been paid on short-term load demand and short-term electricity price forecasts, because they play an important role in promoting market competition, safeguarding the interests of participants, improving the efficiency of power system operation and realizing the optimal allocation of resources [90]. Short-term load demand and short-term electricity price forecasts have become the important works in the current electricity market and they are two of the hot issues in the electricity market field.

3.3. Description of the proposed forecast models

In the past, many forecasting methods and models were used in different applications. These methods can be divided into two categories: classical approaches and artificial intelligence (AI) based techniques [91]. Compared to the classical approaches, AI methods can imitate the human brain for intelligent processing, and have adaptive functions for a large number of non-structural and non-deterministic laws. But the forecasting process of the classical approaches is relatively faster than AI methods, and has better adaptability to emergencies. At present, the mature forecasting methods include time series, artificial neural network, fuzzy logic, wavelet transform and grey model. The following content introduces these forecasting methods and their application fields.

3.3.1. Time series model

The historical data of load demand and electricity price are ordered sets that are sampled and recorded at certain time intervals, so they all belong to time series. The time series method refers to using the correlation of existing data itself to establish a time series model for short-term forecasting [92]. The advantages of time series method are that each component of the model has a clear physical meaning, strong explanatory ability and easy to understand. The disadvantages are that the original data must be stationary or stationary after differencing, and the modelling process is complicated [93].

Commonly used time series models include autoregressive (AR) model, moving average (MA) model, autoregressive moving average (ARMA) model and autoregressive integrated moving average (ARIMA) model. At present, the ARMA model and ARIMA model are widely used in short-term forecasting.

The traditional ARIMA model was first studied in the 1920s. George Box and Gwilym Jenkins published their research results in 1970 [94]. ARIMA model is made up of the integrated process and ARMA model. For an $ARIMA(p, d, q)$ model, the orders p and q represent the numbers of autoregressive terms and moving average terms separately and

d is the level of differencing which ensures the stationarity of the time series. The basic ARIMA model can be presented by the following expression:

$$\emptyset(B)(1-B)^d z_t = \theta_0 + \theta(B)a_t \tag{3-1}$$

where $\emptyset(B)$ is the operator of p and $\theta(B)$ is the operator of q respectively. B is the backward shift operator, z_t is the historical electricity price or load demand at time t and θ_0 is the constant term. a_t is the error term which is generally assumed to be independent and its average value is zero.

If the historical data indicates non-stationarity, a differencing step is necessary to be used to convert the data to a stationary time series, which is the integrated part of the model. The differencing step can be applied more than once until the data presents stationarity. The first order and dth order difference can be expressed as:

$$\nabla z_t = z_t - z_{t-1} \tag{3-2}$$

$$\nabla^d z_t = \nabla^{d-1} z_t - \nabla^{d-1} z_{t-1} \tag{3-3}$$

where ∇z_t and $\nabla^d z_t$ are the difference equations for the first order and dth order respectively. In most cases, when the value of d is 1 or 2, the differenced time series could become stationary.

In some situations, there are obvious periodic changes in some time series. The period is caused by seasonal changes (including weekly, monthly, quarterly, etc.), or some other inherent factors. This type of sequence is called a seasonal sequence. One of the expressions for this sequence is a seasonal ARIMA model (SARIMA). Some earlier literature also called it a multiplicative seasonal model [95], [96].

For a SARIMA model $ARIMA(p, d, q)(P, D, Q)_s$, (p, d, q) is the non-seasonal part of the model, $(P, D, Q)_s$ is the seasonal part of the model and s is the number of time periods until the similar series repeats again. The seasonal part of the model consists of terms that are very similar to the non-seasonal components of the model, but they involve backshifts of the seasonal period. The basic SARIMA mode can be expressed as:

$$\emptyset(B)\Phi(B^s)(1-B)^d(1-B^s)^D z_t = \theta(B)\Theta(B^s)a_t \tag{3-4}$$

where $\emptyset$, Φ; θ, Θ are autoregressive and seasonal moving average parameters of the SARIMA model. B is the lag operator. $(1-B)^d$ and $(1-B^s)^D$ are normal and seasonal difference equations. z_t is the historical electricity price or load demand and a_t is the error term [97].

For both ARIMA and SARIMA models, according to the observations of ACF and PACF, different values of orders can be selected to create several models. Then the optimal models with the best result from these models are used to make the forecasting.

ARMA and ARIMA models are widely used in the analysis and forecasting of various fields. [2]–[4] use ARIMA or ARMA model to forecast short-term load demand and [5]–[8], [98] are forecasting electricity price. The time series usually has the characteristics of heteroscedasticity, and normally the models assume that the variance of the time series is constant. The heteroscedasticity of time series can be described by the Generalized Autoregressive Conditional Heteroskedastic (GARCH) model. It holds that the variance of data is related to the historical data and its variance, instead of the normal distribution of random numbers, which is another traditional model in time series theory. Considering the time heteroscedasticity of the electricity price series, [8] and [7] established the ARIMA and GARCH hybrid forecasting model. For load demand and electricity price, the law of change in the same period of each day has strong similarity. [98] and [2] are modelled and forecasted separately in each period of the day, then the forecasting accuracy can be improved because the data in different periods is stable. [99] proposes a fuzzy seasonal ARIMA forecasting model to forecast the production value of a machinery industry and the sales volume of soft drink., which combines the advantages of the SARIMA model and the fuzzy regression model. [100] introduced the ARIMA model to forecast the most possible curve for domestic fossil fuel production of Turkey. [101] used the ARIMA model to forecast traffic flow.

The works presented in [102] and [103] are using the AR model to forecast wind speed. There are 14 and 9 weather locations are selected for wind speed observations In [102] and [103] respectively. The forecast result is not only influenced by historical time series at the target location but also related to its surrounding sampled locations.

3.3.2. Artificial neural network model

The Artificial Neural Network (ANN) is a mathematical tool that simulates the information processing mode of a human brain. It has the advantage of being able to approximate continuous functions with arbitrary precision, and is good at dealing with multivariable and nonlinear problems without assuming the tentative model [104]. There are many factors influencing the load demand and electricity price, and the changes of them may be non-linear. Therefore, many scholars have tried to solve the problem of load demand and electricity price forecasting with the ANN model.

ANN is the research hotspot in the field of artificial intelligence since the 1980s. It can simulate the interaction of biological nerves systems to real-world objects. With the deepening of ANN research work, ANN techniques have been used widely in many different areas, such as the intelligent robot, pattern recognition, automatic control and forecast estimation. The term ANN is used to describe various constructions of highly interconnected simple processing units that deliver an alternative to conventional computing techniques. The difference from the traditional methods is that ANN represents the related objects through learning from sample data rather than modelling calculation processes. The major advantage of ANN is the offline training. However, this exercise is the most time-consuming [105].

In general, the most widely used structure of the ANN model is the multilayer feed-forward network, which includes the input layer, hidden layer and output layer respectively. A three-layer, feed-forward neural network shown in Figure 3-1 is the most widely used ANN structure [106]. This configuration can learn from retrospective information in a process called supervised learning in which the historical data derived from the system are used to train the network and determine the relationship between input and output. In forecast applications, the original data is usually classified into training part and testing part. The training part is used for constructing the neural network, and the testing part can test the trained model.

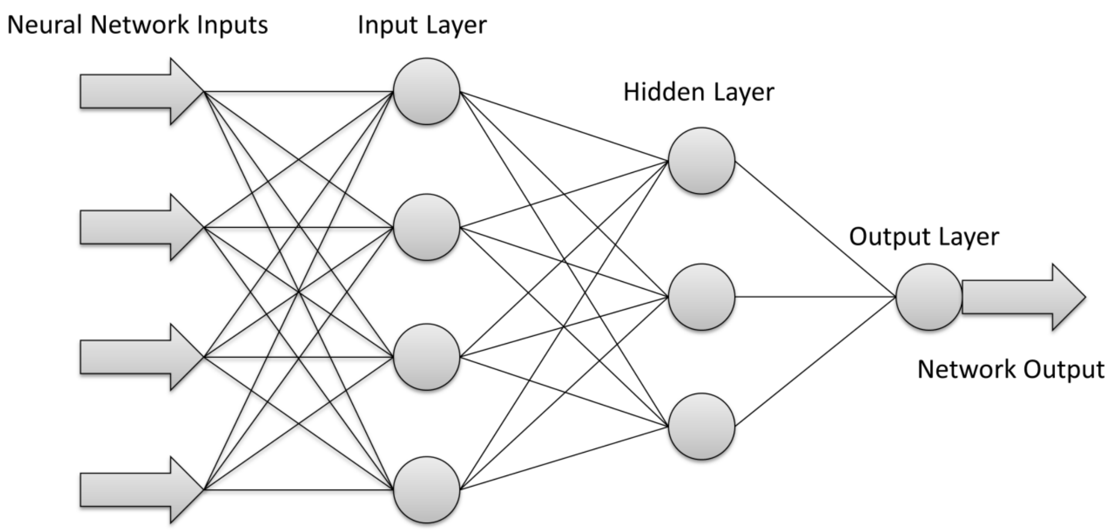


Figure 3-1: Artificial neural network architecture

The neural network is an arithmetic model and composes a large number of neurons. Each neuron represents a specific output function, which is also known as an activation function. The connection between two neurons indicates a weighted value for the signal that is passing through them, and this is equivalent to the memory of ANN. Every neuron in the network sums its weighted inputs to produce an internal activity level v_i

$$v_i = \sum_{j=1}^{n} w_{ij} x_{ij} - w_{i0} \tag{3-5}$$

where w_{ij} is the weight of the connection from input j to neuron i, x_{ij} is the input signal number from j to i, and w_{i0} is the threshold associated with unit i. The output of neuron y_i is expressed as

$$y_i = \varphi(v_i) \tag{3-6}$$

where $\varphi(v_i)$ is the defined function expression. It has many different forms in different situations. During the training process, the network learns by adjusting both the weights connecting the input and hidden layer and the weights connecting the hidden layer and the output, by the gradient multiplied by the learning rate parameter [107].

In recent years, many pieces of literature have studied the forecasting of load demand and electricity price by ANN model. Load demand forecasting in deregulated open power markets using the ANN model is presented in [9]–[12], [108]. [13]–[15], [109]–[112] presented the electricity price short-term forecasting implementation using the ANN computing technique. In some literature, ANN model is not only used but also combined with other methods to achieve more accurate forecasting results, like [18], [19] introduced the method that combines ANN model with fuzzy logic to forecast prices. In [113]–[116], the forecast results of ANN model are used to compare with those of time series model. The experimental results show that sometimes the forecasting results of the ARIMA model are better, and sometimes the ANN model is better. This is because the forecasting performance is affected by the factors such as original data quality, forecasting cycles and the selection of model parameters.

A hybrid ARIMA-ANN model is introduced in [117]–[120], and the purpose of this method is to combine two models to improve the accuracy of forecasting results. The essence is to use ARIMA model to forecast the data so that the linear rule information is included in the forecasting results of the ARIMA model. Then use the ANN model to forecast the errors that produced by ARIMA model, and the nonlinear rule information is included in the forecasting results of ANN model. At last, the forecasting results of

ARIMA and ANN model are added to obtain the final forecasting value of the combined model.

Most short-term load demand and electricity price forecasting are based on ARIMA and ANN models, and some other mathematical methods are used in conjunction with them to reduce the forecast errors.

3.3.3. Fuzzy logic

As mentioned before, [18], [19], [99]combined the forecasting model with fuzzy logic. Fuzzy logic is a concept proposed by American engineer L.A. Zadeh in his 'Fuzzy set and theory' for improving computer programs in 1965. Traditional computers can only recognize binary logics like yes or no, right or wrong, 0 or 1, but they cannot do anything about fuzzy concepts like cold, hot, big and small [121]. With fuzzy logic, the computer can cross the boundary between the poles, work in the "grey" middle ground, and provide accurate answers with limited information. Fuzzy logic system (FLS) is a problem-solving system that provides a way to arrive at a definite conclusion based on the imprecise and incomplete information. It is generally a mapping of an input vector (crisp inputs) into a scalar output (crisp outputs) [122]. As shown in Figure 3-2, FLS is mainly composed of three parts: fuzzifier, inference engine, and defuzzifier.

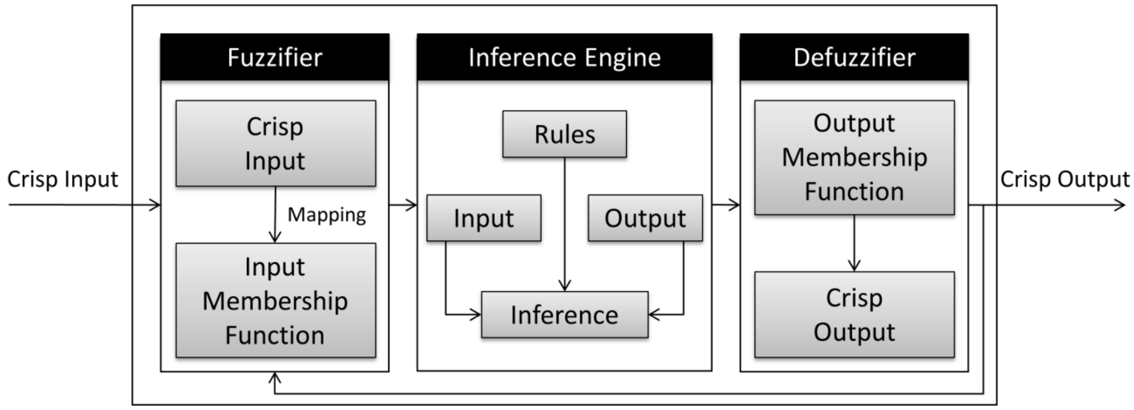


Figure 3-2: Structure of a fuzzy logic system

Assume that there is a batch of expected input and output data $(x_1^1, x_2^1; y^1)$, $(x_1^2, x_2^2; y^2)$, …, where x_1 and x_2 are inputs, y is output. The fuzzy logic method includes the following three steps. Firstly, the input and output spaces are divided into several fuzzy subspaces, each input and output variable fuzzy tags are determined, and then the membership function parameters are primary selected according to the principle that the centre of the membership function is equally divided into input and output data space. Secondly, generate fuzzy rules from learning sample data. In this step it needs to determine the membership degree of the known data in different intervals, give x_1^i, x_2^i, y^i the maximum membership degree in a certain interval, and get a rule from a pair of expected input and output data. Thirdly, assign a membership degree to each rule. The IF-THEN language is a feature of fuzzy logic. When the rule has the same antecedent part (IF) and the consequent part (THEN) is different, the one with the greatest rule strength should work [123]. For each rule R_i: if x_1 is A and x_2 is B, then y is $C(w_i)$, its strength can be expressed as

$$w_i = \mu_a(x_1)\mu_b(x_2)\mu_c(y) \tag{3-7}$$

The method can not only solve the rule conflict problems but also get a simplified rule base [17].

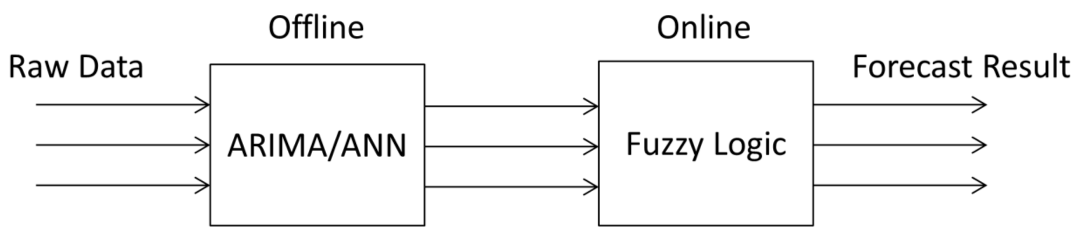


Figure 3-3: The combination of fuzzy logic and ARIMA/ANN models

For both ARIMA and ANN models, fuzzy logic can be used to determine the parameters of the forecasting model or to fine-tune the forecast errors. Figure 3-3 shows the process of combining fuzzy logic with ARIMA or ANN models for forecasting. ARIMA/ANN models use the raw data to forecast, and then the results are imported into the fuzzy logic part. After the fuzzy logic method processes these imported data, the adjusted forecast result can be obtained. The forecasting process of ARIMA/ANN models is the offline part, whose main object is to forecast the load demand and electricity price based on the raw data. The application process of fuzzy logic is the online part, which can adjust the forecast error of load demand and electricity price according to real-time temperature, wind speed, rainfall and other factors, so as to obtain more accurate forecasting result.

3.3.4. Wavelet transform

The concept of wavelet transform was proposed by French geophysicist J.Morlet in 1984. It is called "mathematical microscope" and has been widely used in many fields [124]. Wavelet analysis is an analysis method of adjustable time-frequency window, which can well describe non-stationary signals. The key of wavelet analysis is the wavelet transform. The main characteristics of the wavelet transform are to decompose the non-stationary time series into a much more stable time series than the original sequence and then study each sequence separately to realize the simulation and forecast of the non-stationary time series [125]. A wavelet can be defined as a function $\psi(t)$ with a zero mean

$$\int_{-\infty}^{+\infty} \psi(t)\, dt = 0 \tag{3-8}$$

a signal can be decomposed into many series of wavelets with different scales a and translational value b

$$\psi_{(a,b)}(t) = \frac{1}{\sqrt{a}} \psi\left(\frac{t-b}{a}\right) \tag{3-9}$$

then the wavelet transform of a signal $f(t)$ at scale a and translational value b is expressed by the following integral

$$W_f(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} f(t) \psi\left(\frac{t-b}{a}\right) dt \tag{3-10}$$

the original signal $f(t)$ can be reconstructed by inverse wavelet transform

$$f(t) = \int_0^{\infty} \int_{-\infty}^{+\infty} \frac{1}{a^2} W_f(a,b) \psi_{a,b}(t)\, dbda \tag{3-11}$$

[109], [111] and [126] combined ARIMA and ANN models with wavelet transform. These literature use wavelet transforms to analyse the electricity price and establish the models for electricity price forecasting. According to the time-frequency localization function of the wavelet transform, the original electricity price time series is decomposed into different scales and the subsequence on different scales are forecasted by ARIMA and ANN models respectively. At last, the results on different scales are restored by wavelet reconstruction to obtain the forecasting results of electricity price.

From the signal analysis point of view, electricity load demand can also be considered as a linear combination of different frequencies. Every component of load can be represented by one or several frequencies. [20], [21] decomposed the historical load demand into an approximate part associated with low frequencies and several detail parts associated with high frequencies through the wavelet transform. Then use the ANN model to forecast the approximate part and detail parts separately and finally add the results together to get the final load demand forecasting results.

3.3.5. Grey model

Traditional forecasting methods generally require a large amount of data to construct a model. But sometimes the obtained data is limited, and the forecasting requires a few cogent observations. The grey model forecasting is an appropriate method in this context [127]. The conventional grey model $GM(1,1)$ is a small-data set model for time series data. It employs an accumulating generation operator to obtain a smooth and increasing data series to establish a forecasting model. This is a non-statistical forecasting method that is particularly effective when the number of observations is insufficient. At present, the $GM(1,1)$ model is most commonly used in short-term forecasting, which represents the first order differential equation with 1 variable. However, the forecasting accuracy of the grey model is very limited [128].

The construction of the $GM(1,1)$ model is as follows:

1. Define the observed time series as $x^{(0)} = \left(x^{(0)}(1), x^{(0)}(2), \dots, x^{(0)}(n)\right)$, where n is the number of observations.
2. Define the series $x^{(1)}$ as the following way $x^{(0)} = \left(x^{(0)}(1), x^{(0)}(2), \dots, x^{(0)}(n)\right)$, where

$$x^{(1)}(1) = x^{(0)}(1) \tag{3-12}$$

$$x^{(1)}(k) = \sum_{m=1}^{k} x^{(0)}(m), \quad k = 2, 3, \dots, n \tag{3-13}$$

4. Determine the background values $z^{(1)}(k)$.

$$z^{(1)}(k) = (1-\alpha)x^{(1)}(k-1) + \alpha x^{(1)}(k), \;\; \alpha \in (0,1), \;\; k = 2,3, \dots, n \tag{3-14}$$

5. Estimate the developing coefficient and the grey input by the least-squares method as

$$x^{(0)}(k) + a x^{(1)}(k) = b \tag{3-15}$$

The $GM(1,1)$ model is defined by a first order differential equation

$$\frac{dx^{(1)}(k)}{dk} + ax^{(1)}(k) = b \tag{3-16}$$

The estimated coefficients $[a, b]^T$ can be evaluated by the following equation

$$[a, b]^T = (B^T B)^{-1} B^T Y \tag{3-17}$$

where

$$B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \dots & 1 \\ -z^{(1)}(n) & 1 \end{bmatrix}, \quad Y = \left[x^{(0)}(2), x^{(0)}(3), \dots, x^{(0)}(n)\right]^T \tag{3-18}$$

Use the estimated coefficients and together with the initial condition $x^{(0)}(1) = x^{(1)}(1)$ to solve equation (3-15), and then the forecasting series at step k+1 can be calculated by the following equation

$$\begin{cases} \hat{x}^{(1)}(k+1) = \left(x^{(0)}(1) - \dfrac{b}{a}\right) e^{-ak} + \dfrac{b}{a} \\ \\ \hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k) \end{cases} \tag{3-19}$$

The grey forecasting models are proposed in [22]–[24], [129] to forecast the load demand, where [24] combined the $GM(1,1)$ model with the wavelet transform. The grey model is used to forecast electricity price in [25]. Based on the research of $GM(1,1)$ grey model, this paper used $GM(1,2)$ model to make the short-term electricity price forecasting. [130] achieves short-term forecasting of power generation cost by the grey model. The results of these literature show that the grey models could have a better forecasting accuracy than ARIMA or ANN models when the obtained data is limited.

3.4. The method for determining parameters in forecasting models

The selection of model parameters is the most basic part of the whole forecasting process. If the same set of data is forecasted by the same models with different parameters, the forecasting results will also be different. In these proposed models, time series model is the typical classical approach, while ANN model is the artificial intelligence method. Furthermore, time series method refers to using the correlation of existing data itself to establish a time series model for short-term forecasting, and ANN model represents the related objects through learning from sample data rather than modelling calculation processes. Therefore, the ARIMA and SARIMA model in time series model and the ANN model in artificial neural network model are selected to forecast load demand and electricity price in this thesis.

3.4.1. Parameters determination method for ARIMA model

An $ARIMA(p, d, q)$ model consists of three parts: $AR(p)$, $I(d)$ and $MA(q)$.

- $AR(p)$: AR is the abbreviation of autoregressive, which means that the value of the current time point is equal to the regression of the values of several past time points. It does not depend on other explanatory variables and only depends on its past historical values. If the sequence depends on the most recent p historical values in the past, the order is p and is denoted as the $AR(p)$ model.

- $I(d)$: I is the abbreviation for integrated, which means that the model differences the time series. Because time series analysis requires stationarity, the nonstationary sequence needs to be converted into a stationary sequence by some means, and the general method is differencing. d represents the order of the differencing.
- $MA(q)$: MA is the abbreviation of moving average, indicating that the value of the current time point is equal to the regression of the forecasting errors of several past time points. If the sequence depends on the most recent q historical forecasting errors in the past, the order is q and denoted as $MA(q)$ model.

The time series is not need to be differenced if the initial time series is stationary ($d = 0$), then the $ARIMA(p, d, q)$ model is equivalent to the $ARMA(p, q)$ model [131]. In the ARMA model, autocorrelation function (ACF) and partial autocorrelation function (PACF) are used to check the order of q and p respectively. The moving average order q is determined by ACF, and the autoregressive order p is decided by PACF. For the stationary time series, ACF will decay rapidly to zero with increasing the number of delays. Table 3-1 summarizes standard patterns and provides guidelines for determining the integers p and q, identifying the most influential p observations and q noise terms in an $ARMA(p, q)$ model.

Table 3-1: Standard patterns in the theoretical ACF and PACF of stationary series [132]

Model	ACF	PACF
$\boldsymbol{AR(p)}$	Exponential or sinusoidal decay to zero	Spikes cut off to zero after lag p
$\boldsymbol{MA(q)}$	Spikes cut off to zero after lag q	Exponential or sinusoidal decay to zero
$\boldsymbol{ARMA(p,q)}$	Exponential or sinusoidal decay to zero after lag q	Exponential or sinusoidal decay to zero after lag p

According to Table 3-1, in order to observe and determine the p and q values more intuitively in the ARMA model, Figure 3-4 to 3-9 show several theoretical ACF and PACF graphs.

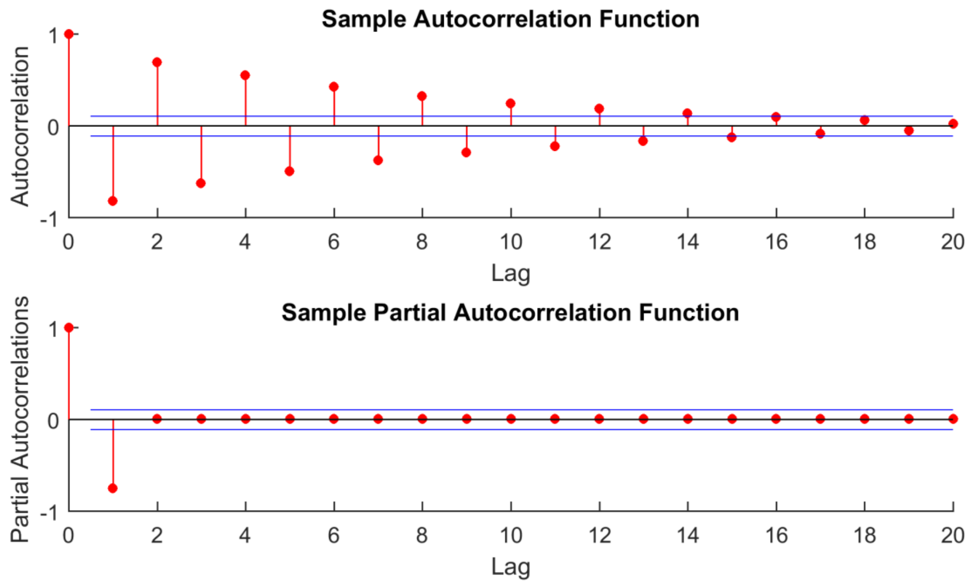


Figure 3-4: Theoretical ACF and PACF of Autoregressive (AR) model in case 1

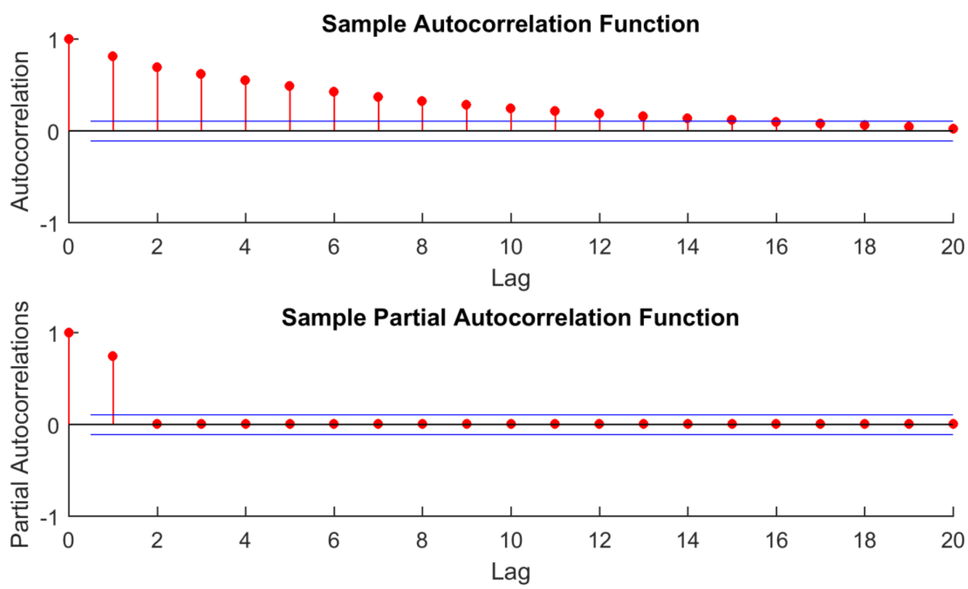


Figure 3-5: Theoretical ACF and PACF of Autoregressive (AR) model in case 2

It can be seen from Figure 3-4 and 3-5 that ACF decays to zero exponentially or sinusoidally, hence $q = 0$, and PACF cuts off at lag p, then the $AR(p)$ model should be selected here.

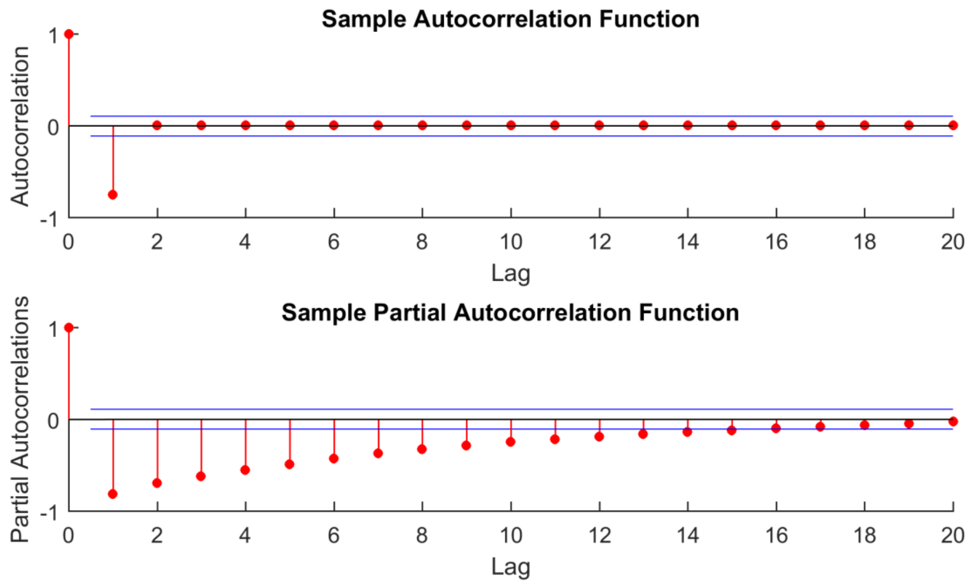


Figure 3-6: Theoretical ACF and PACF of Moving Average (MA) model in case 1

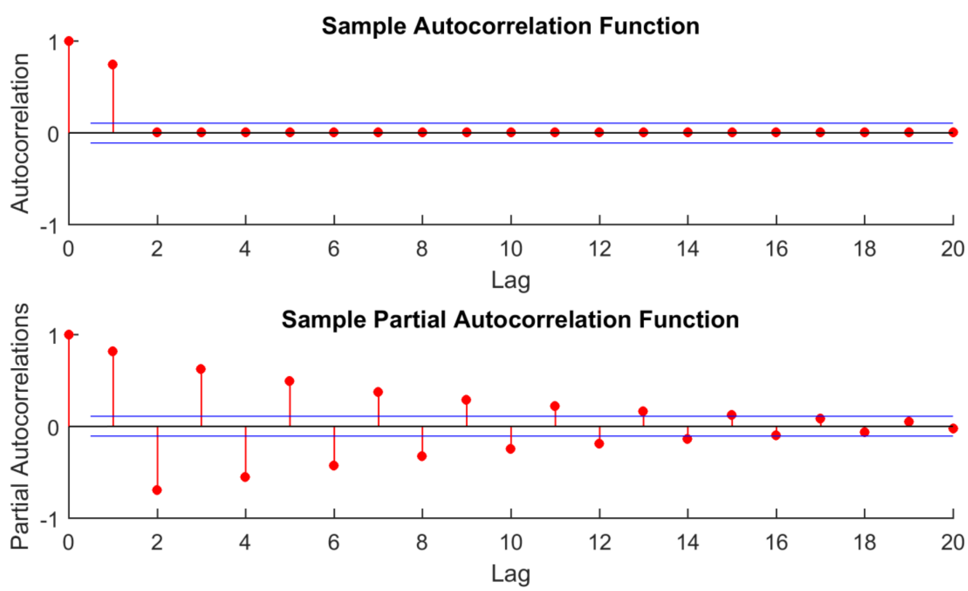


Figure 3-7: Theoretical ACF and PACF of Moving Average (MA) model in case 2

It can be seen from Figure 3-6 and 3-7 that PACF decays to zero exponentially or sinusoidally, hence $p = 0$, and ACF cuts off at lag q, then the $MA(q)$ model should be selected here.

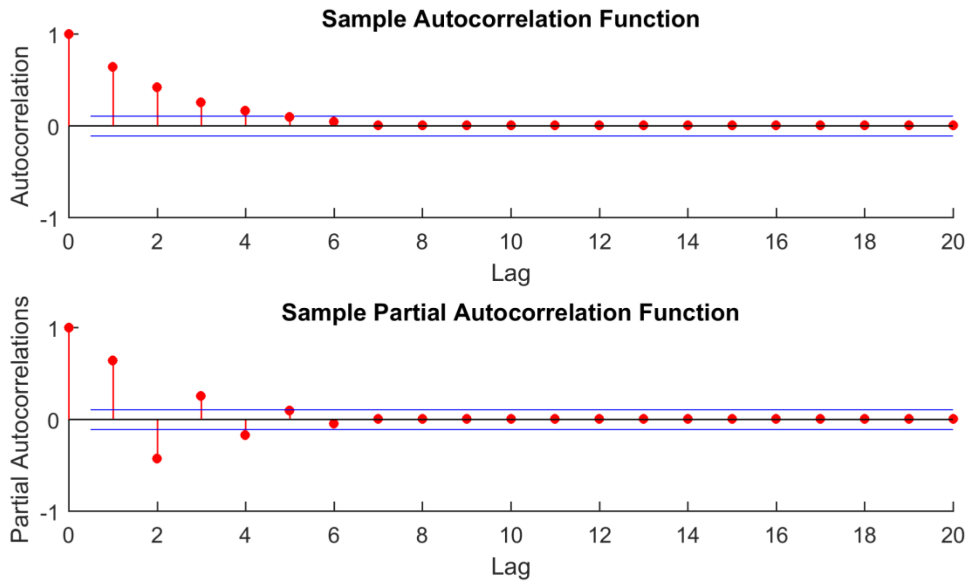


Figure 3-8: Theoretical ACF and PACF of ARMA model in case 1

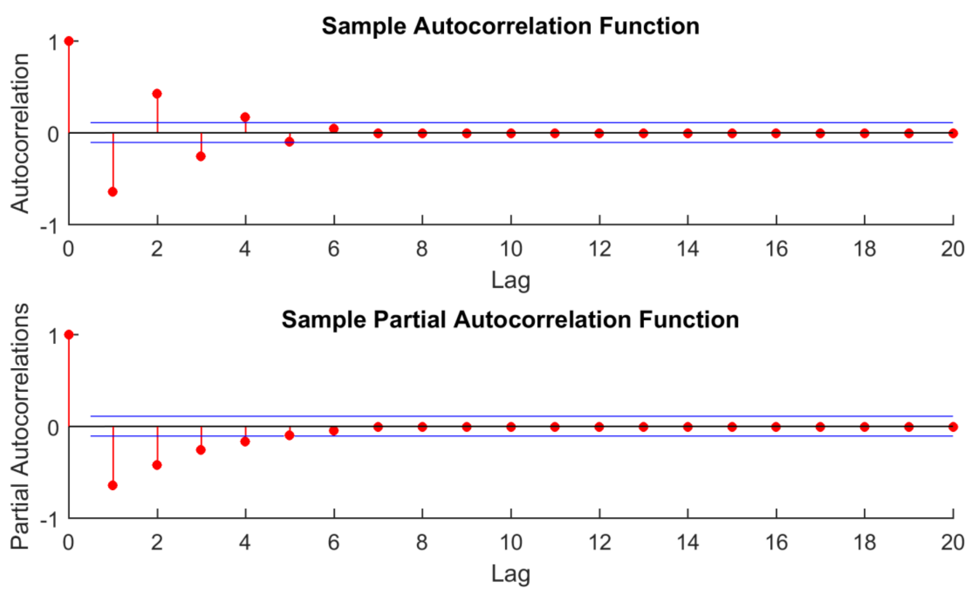


Figure 3-9: Theoretical ACF and PACF of ARMA model in case 2

It can be seen from Figure 3-8 and 3-9 that both ACF and PACF die out and not cut off. ACF and PACF decays to zero exponentially or sinusoidally after lag q and p respectively, then the $ARMA(p, q)$ model should be selected here [94].

In the AR, MA and ARMA models, AR model is the most widely used in forecasts. The ARIMA model turns the non-stationary time series into stationary through differencing at first, and then the selection of parameters p and q is the same as the ARMA model. When the time series is non-stationary, the ACF will show slow decay or even no decay. A slow decay of ACF means that the current value of the series is heavily correlated with the past values. At this point, differencing is needed to convert the time series to stationary. In addition, the blue line above and below the zero axes in Figures 3-1 to 3-6 represents the approximate confidence interval generated by the white noise, with a default of 95% interval. The autocorrelations and partial autocorrelations of values beyond these lines are significantly different from zero. Therefore, it can be considered that the sequence is not decay to zero and is non-stationary when the values of ACF exceed the confidence interval for a period of time.

3.4.2. Parameters determination method for SARIMA model

In addition to the non-seasonal parameters p, d, q in the ARIMA model, the $ARIMA(p,d,q)(P,D,Q)_s$ model also needs to consider seasonal autoregressive terms P, seasonal moving average terms Q and seasonal differencing level D. The premise of the SARIMA model is that the data series must have obvious periodic changes. The change period S is determined by observing the raw data and the plot of ACF and PACF [133]. For the $ARIMA(p,d,q)(P,D,Q)_s$ model, the method of selecting non-seasonal parameters is the same as the $ARIMA(p,d,q)$ model in Figure 3-1 to 3-6, but the selection of seasonal parameters depends on the seasonally differenced ACF and PACF. For the seasonal terms of the AR and MA models, the difference will be seen in the seasonal lags of the ACF and PACF. For example, an $ARIMA(0,0,0)(0,0,1)_{24}$ model will show:

- A spike at lag 24 in the ACF but no other significant spikes;
- Exponential decay to zero in the seasonal lags of the PACF (at lag 24, 48, 72, …).

Similarly, an $ARIMA(0,0,0)(1,0,0)_{24}$ model will show:

- Exponential decay to zero in the seasonal lags of the ACF (at lag 24, 48, 72, …);
- A spike at lag 24 in the PACF but no other significant spikes.

And an $ARIMA(0,0,0)(1,0,1)_{24}$ model will show:

- Exponential decay to zero in the seasonal lags of the ACF (at lag 24, 48, 72, …);
- Exponential decay to zero in the seasonal lags of the PACF (at lag 24, 48, 72, …).

In considering the appropriate seasonal orders for a seasonal ARIMA model, restrict attention to the seasonal lags [134]. The modelling procedure is almost the same as for non-seasonal data, except that it needs to select seasonal AR and MA terms as well as the non-seasonal components of the model. The process is best illustrated via examples. Figure 3-10 and 3-11 show a set of load demand data and its original ACF and PACF.

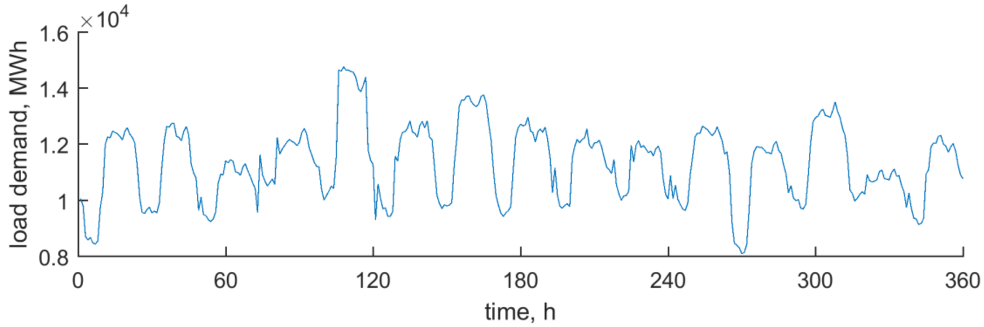


Figure 3-10: A set of load demand data

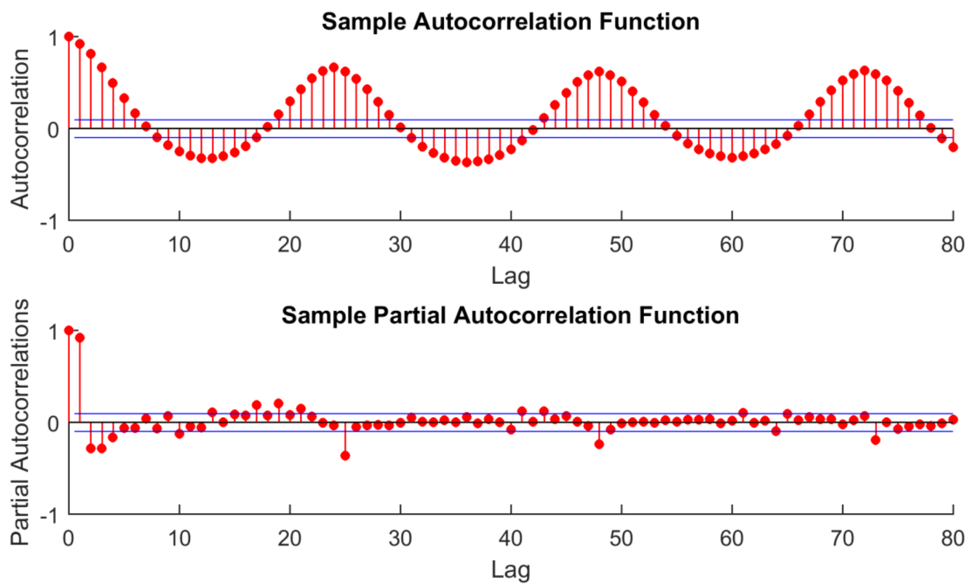


Figure 3-11: Original ACF and PACF of the load demand data

It can be seen from Figure 3-10 that the load demand data has periodic changes and the period is 24 hours. Figure 3-11 shows that the original ACF and PACF also have 24-lag periodic changes. Because ACF indicates a non-stationary process, 1st differencing is applied to the original data and the ACF and PACF of the differenced series are plotted in Figure 3-12.

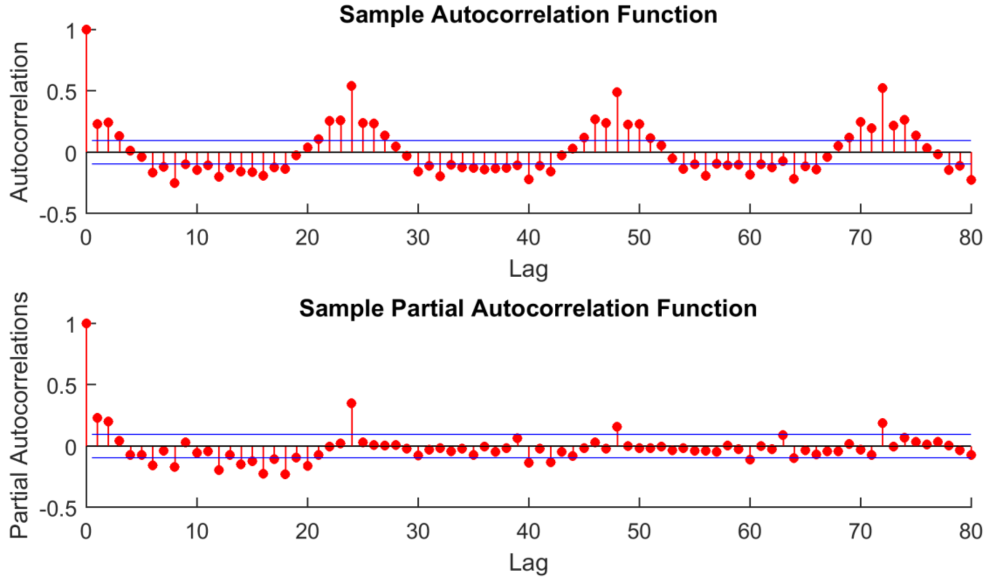


Figure 3-12: ACF and PACF of the load demand data after 1st differencing

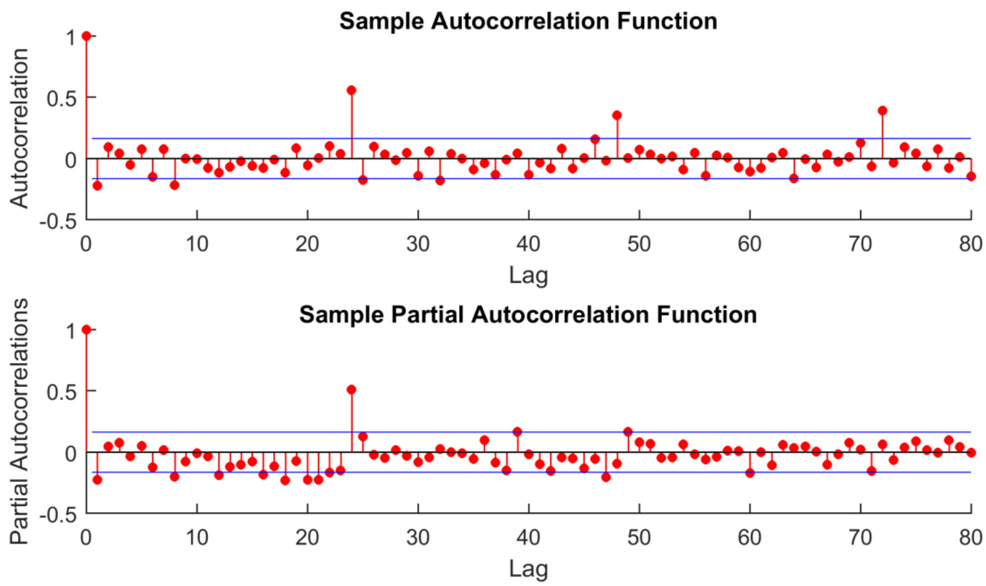


Figure 3-13: ACF and PACF of the load demand data after 1st and 24th differencing

It can be seen in Figure 3-12 that ACF and PACF all have spikes at the seasonal period of lag 24. So an additional 24th seasonal differencing is applied to the series and the ACF and PACF of the seasonal differenced series are plotted in Figure 3-13.

Now the series present stationary and an appropriate SARIMA model can be determined based on the ACF and PACF shown in Figure 3-13. For the non-seasonal terms, only the 1st non-seasonal differencing was applied on the series, so $d = 1$. It can be seen from ACF and PACF that $p = 1$ and $q = 1$. For the seasonal terms, the 24st seasonal differencing was applied on the series, so $D = 1$. There is only one spike at lag 24 in the PACF and the seasonal lags of the ACF decay exponentially, so $P = 1$ and $Q = 0$. Therefore, the SARIMA model $ARIMA(1,1,1)(1,1,0)_{24}$ should be selected in this example.

3.4.3. Parameters determination method for ANN model

The ANN models are different from ARIMA or SARIMA models in that they are mathematical tools originally inspired by the way the human brain processes information. The ANN model is not necessary for the researcher to postulate tentative models because it is able to automatically map the relationship between input and output data with continuous 'training' of the network. Usually, one training session in a neural network cannot give the optimal result, and it is need to constantly debug the parameters and train multiple times to get the optimal result [135]. In this thesis, the nonlinear autoregressive network inside the MATLAB neural network toolbox has been used as the training algorithm.

A classic neural network consists of three layers: input layer, hidden layer and output layer. The input layer is the first layer of the neural network. It receives the input signals and passes them to the next layer, but does not perform any operations on the input signals. Input layer does not have its own weight value and offset value. A hidden layer is a set of vertically stacked neurons. The neurons in the hidden layer convert input signals in different ways, and the last hidden layer passes signal values to the output layer. The output layer is the last layer of the neural network that receives input values from the last hidden layer. The final results within a reasonable range can be obtained through the output layer.

The parameters that need to be debugged in the neural network toolbox are the number of hidden neurons and the number of delays [136]. The hidden neurons are the neurons in the hidden layer, and the delay refers to the number of data that affects the output. For example, if the output is Z_t and the number of delays is 2, then Z_t is related to Z_{t-1} and Z_{t-2}. The default values for hidden neurons and delays are 10 and 2, respectively. Retraining data may improve the forecasting accuracy when training results are not good, or increasing the number of hidden neurons or delays to obtain a better result.

In practical applications, the parameters of the model are probably have several choices and cannot be directly determined no matter for ARIMA, SARIMA or ANN models. When there are several alternative models, this thesis lists all the possible models and uses each model to forecast the target data separately. Then the forecasting results will be compared by analysing the forecast errors to select the optimal parameters of each model.

3.5. Summary

This chapter discussed the importance of load demand and electricity price forecasting for market participants in the electricity market, and compared the characteristics of mid-long-term forecast and short-term forecast. Compared with mid-long-term forecast, short-term load demand and electricity price forecasting have greater advantages in promoting market competition, safeguarding the interests of participants, and improving the efficiency of power system operation. Therefore, this thesis will focus on short-term forecast of load demand and electricity price. Moreover, several proposed forecasting models were introduced, including time series, ANN, fuzzy logic, wavelet transform and grey model. In addition to introducing the basic theory of these models, the method for determining parameters of ARIMA model, SARIMA model and ANN model were also described in detail.

In the process of load demand load and electricity price forecasting, the forecast errors can be obtained after comparing the forecasted value with the actual value. The forecast errors can be used to detect the forecasting accuracy and the quality of the forecasting models, and an in-depth analysis of the forecast errors can also be used to assess the risk of financial losses or gains to electricity market participants.

Chapter 4

The analysis method of forecast errors and risk assessment methodology

4.1. Introduction

Since load demand and electricity price forecasting are the estimates of future values, there are still certain gaps between the forecasted values and the actual values, and these gaps are called the forecast errors. The forecast errors can reflect the accuracy of the forecasting results, and it has important reference value when making decisions with the forecast data. There are various methods to calculate forecast errors. This chapter introduces some of the representative methods, including mean squared error (MSE), root mean square error (RMSE), mean absolute error (MAE) and mean absolute percentage error (MAPE).

These forecast errors could be considered as 'risk' and when using the forecasted values and the process of analysing these risks is called risk assessment. The forecast error is illustrated in Figure 4-1.

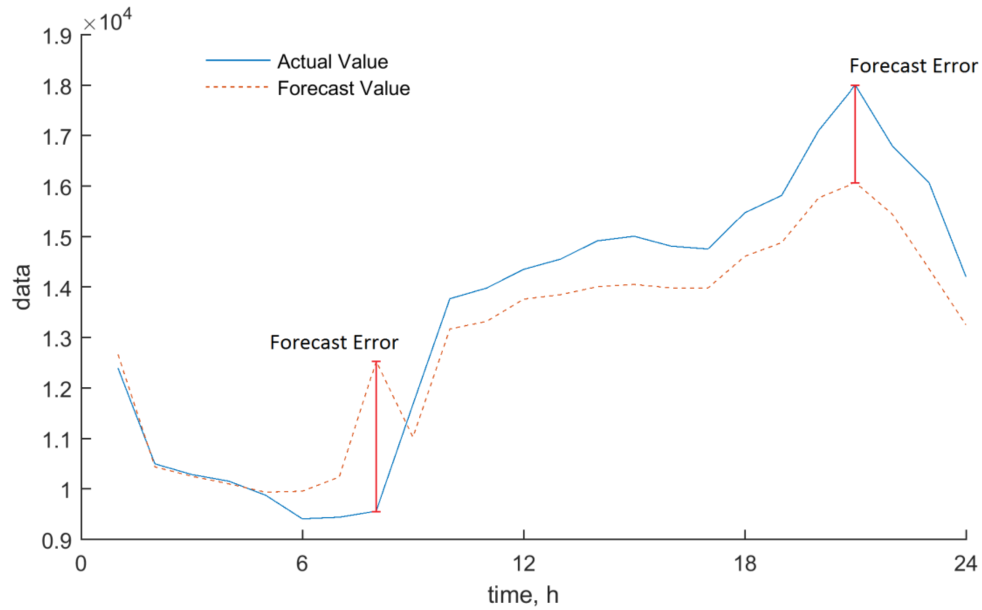


Figure 4-1: Forecast error between the forecast and actual value

In this thesis, risk assessment refers to the assessment of load demand and electricity price forecasts. In addition to observing the errors through mathematical methods, this chapter introduces a risk index to analyse the forecast errors of load demand and electricity price respectively. A method for directly analysing the risk index based on the characteristics of historical data is also proposed.

With the forecasted values and actual values of load demand and electricity price, the financial issues of electricity market participants can be analysed. Due to the uncertainty of the forecasting process, it is possible to bring financial losses or gains to market participants, which are called financial risks. To represent these risks, the Value-at-Risk (VaR) and Expected Shortfall (ES) methods in economic theory are used to analysis. Moreover, the process of analysing financial risks is called the financial risk assessment, which can effectively reflect the positive and negative values of financial risk over a period of time.

4.2. The analysis methods of forecast errors

At present, the widely used methods of calculation and forecasting error analysis include mean absolute percentage error (MAPE), mean squared error (MSE), root mean square error (RMSE) and standard error [137]. These methods have played a role in forecasting error analysis in many fields. However, in order to carry out error analysis more accurately, an appropriate model should be established according to the characteristics of the forecasting model.

4.2.1. The causes of forecast errors

There are many reasons that can create forecast errors, and are mainly the following aspects:

a. Mathematical models are often used to make the forecasting, while most mathematical models only consider the original data of the research object itself, and many secondary factors such as temperature, wind speed and rainfall temperature, wind speed and rainfall can affect the accuracy of load demand forecasts. As for electricity price, the uncertain cause of fuel, generator outage and transmission line congestion can affect the accuracy of electricity price forecasts. The impacts on load demand and electricity price are ever-changing, so the forecast results obtained by these mathematical models will inevitably produce errors with the actual values.

b. For the intricate load demand and electricity price changes, the purposes and requirements of the forecasting are various, so how to choose a proper forecasting method from multiple forecasting methods is particularly important. Each mathematical model has its own advantages and disadvantages. The forecast errors produced by different mathematical models may also be different.

c. A large amount of data is used for load demand and electricity price forecasting, and the data cannot be guaranteed to be accurate and reliable, which could lead to errors. This means there are inherent errors in the original data.

d. The occurrence or sudden change of certain unexpected events may also cause forecast errors, such as constant high temperature weather will have an impact on the forecasting accuracy of load demand, and large power outages due to accidents will have an impact on the forecasting accuracy of electricity price. In addition, due to the difference in calculation or selection, such as the moving average parameter in ARIMA model or the neuron number in ANN model, different parameter selections will also produce different degrees of forecast error [138].

The errors caused by the above reasons may occur at the same time. Therefore, when the error is found to be large and the forecast result is seriously inaccurate, it is necessary to check each of the above reasons one by one to find the root cause.

4.2.2. The methods for analysing forecast errors

There are a lot of methods and indicators to analyse the forecast errors, and some of the most commonly used will be introduced here.

4.2.2.1. Absolute error and relative error

If Y is the actual value, $\hat{Y}$ is the forecast value, and then the absolute error (AE) can be expressed as

$$AE = \left|Y - \hat{Y}\right| \tag{4-1}$$

And the relative error (RE) is

$$RE = \frac{\left|Y - \hat{Y}\right|}{Y} \times 100\% \tag{4-2}$$

The relative error is an intuitive method of error representation and is often used as an assessment index in the electricity market [139].

4.2.2.2. Mean square error and root mean square error

The mean square error (MSE) can be expressed by

$$MSE = \frac{1}{n}\sum_{i=1}^{n} E_i^2 = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2 \tag{4-3}$$

where n is the number of historical data, E_i is the absolute error of the i^{th} forecast value and the actual value. Y_i is the i^{th} actual value and $\hat{Y}_i$ is the i^{th} forecast value. The mean square error is the average of the sum of the forecast error squares. It avoids the problem that the positive and negative errors cannot be added. The root mean square error (RMSE) can be expressed as

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} E_i^2} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2} \tag{4-4}$$

The RMSE is the square root of the MSE. Since the absolute error E_i is squared, the role of large errors in the method is enhanced, thereby improved the sensitivity of this method, which is one of its major advantages [140]. The RMSE is one of the comprehensive index methods of error analysis.

In this thesis, in order to observe the forecast error more intuitively, the RMSE is improved as the root mean square percentage error (RMSPE)

$$RMSPE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\left(Y_i - \hat{Y}_i\right)/Y_i\right)^2} \times 100\% \tag{4-5}$$

This step turns the specific value of RMSE into a percentage value [141]. In this case, the comparison of the forecast errors can be observed clearly when not familiar with the changes of the original data.

4.2.2.3. Mean absolute error and mean absolute percentage error

The mean absolute error (MAE) can be expressed as the following equation

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|E_i| = \frac{1}{n}\sum_{i=1}^{n}\left|Y_i - \hat{Y}_i\right| \tag{4-6}$$

The parameters are the same as above. The mean absolute percentage error (MAPE) is

$$MAPE = \left(\frac{1}{n}\sum_{i=1}^{n}\left|(Y_i - \hat{Y}_i)/Y_i\right|\right) \times 100\% \tag{4-7}$$

Since there are positive and negative errors, in order to avoid the positive and negative values cancellation, MAE and MAPE calculated the absolute value of the error and the average value [142]. The MAPE is also one of the comprehensive index methods of error analysis.

4.2.2.4. Standard deviation and standard error of the mean

The standard deviation (SD) can be expressed as

$$SD = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_i - \bar{Y})^2} \tag{4-8}$$

This formula is similar with RMSE, but here $\bar{Y}$ is the mean value of Y. It means each number of the data is compared with the average value of the data, and the degree of dispersion of this set of data can be seen through the derived values [143].

The standard error of the mean (SEM) is the standard deviation of the sampling distribution of the mean. It can be expressed as

$$SEM = \frac{SD}{\sqrt{n}} \tag{4-9}$$

where SD is the original distribution and n is the sample size [144]. This formula does not assume a normal distribution. However, many of the uses of the formula do assume a normal distribution. The formula shows that the larger the sample size, the smaller the

SEM. More specifically, the size of the SEM is inversely proportional to the square root of the sample size [145].

In practical applications, the purpose of calculating the forecast errors is to compare the forecasting models and select one model with the most accurate result. All the methods mentioned above can be used to analyse the load demand and electricity price forecasting. In these methods, RMSPE and MAPE are used to determine the forecasting model in this thesis, because they can reflect the forecast accuracy between the actual and forecast experimental data.

4.3. Risk index due to the forecast errors

Once the appropriate forecast model is determined, the data that we want to forecast can be forecasted. When the forecast errors are calculated, they are usually represented by curve graphs. The forecast error represents the forecast inaccuracy between actual value and forecasting value, and the forecast inaccuracy can be reflected by the forecast risk. In order to observe the forecast errors more clearly, except for the forecasting models, this thesis investigates the risk index related to load demand and electricity price forecast errors respectively. The risk index is expressed as the ratio between the actual forecast errors in each unit to the maximum forecast errors during the whole observation period. Therefore, the range of risk index is from 0 to 1. When the risk index is 0 it means that the forecast result is perfect, there is no forecast risk in this period. Instead, when risk index is 1 it means that the forecast error reaches the maximum value, and it has the biggest forecast risk in this period.

For example, if the electricity price is updated hourly, then there would be 24 actual electricity price data and 24 forecast electricity price data in one day. Therefore, the one day's electricity price absolute errors can be expressed as

$$E_i = \left|Y_i - \hat{Y}_i\right|, \quad i = 1, 2, \dots, 24. \tag{4-10}$$

where Y_i is the actual value, $\hat{Y}_i$ is the forecast value, and E_i is the forecast errors of the actual and forecast electricity prices. Here, forecast errors on 2nd March 2015 made by ARIMA model is shown in Figure 4-2. It can be seen from the figure that the maximum forecast error is happened at 21:00 o'clock, and its value is 22.87 £/MWh. Then divide the errors at each hour by 22.87 £/MWh to get the daily risk index. Figure 4-3 shows the daily risk index of 2nd March 2015. It can be observed that the high risks occurred at 21:00 and 11:00, the low risks occurred at 2:00, 8:00 and 13:00.

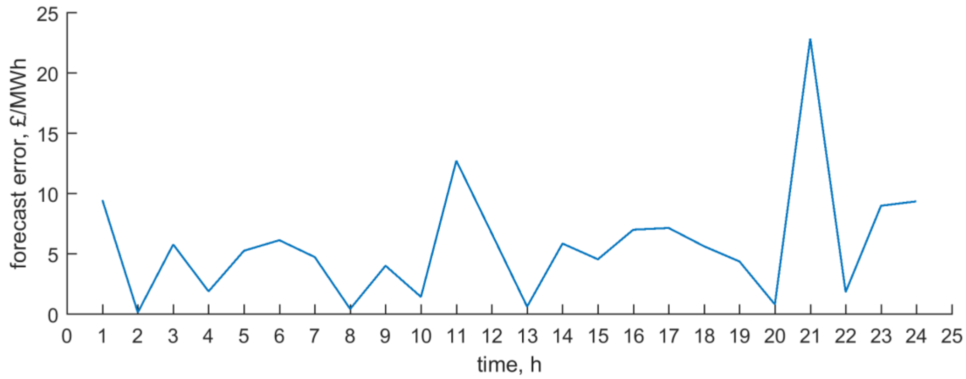


Figure 4-2: Electricity price forecast errors of 2nd March 2015

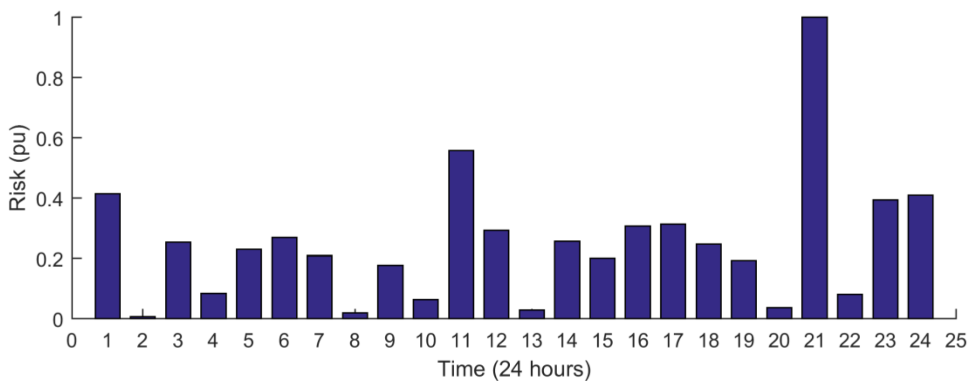


Figure 4-3: Electricity price risk index of 2nd March 2015

With the errors derived from the load demand and electricity price forecasts, the risk indexes under different time sections or seasons can be obtained. However, the electricity price fluctuations and load profiles are not the same in different areas, and the forecasting models they used are also different. Therefore, it becomes meaningful to analyse the risk index based on the data's own characteristics. Hence, this thesis takes the standard deviation of load demand and electricity price increment as the variation index, and then the linear correlation between the variation index and risk index can be found by fitting their data [36]. The variation in the j^{th} time period can be formulated as

$$C_j = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(X_i - \overline{X_\iota})^2} \tag{4-11}$$

where X_i means the one-hour increment in actual load demand or electricity price, which is defined as $X_i = Y_i - Y_{i-1},\ i = 1, 2, \dots, 24$. When $i = 1$, the increment in the first time section is calculated as $X_1 = Y_1 - Y_{24}$. $\overline{X_\iota}$ is the mean value of X_i, and n is the number of experiment data. Then the variation index can be expressed as the ratio between C_j and C_{max}, where C_{max} is the maximum variation over the observation period. At last, the correlation between the variation index and risk index can be expressed as an equation.

The advantage of this method is that the risk index can be identified by the historical data itself, and avoid using the more complex forecasting methods. With a simple linear transformation, the variation risk index in each hour period provides a compact evaluation of the risk index resulting from the actual forecasting errors.

Whether it is for load demand or electricity price, the risk index can convert any unit into a number between 0 and 1, so the risk can be expressed more intuitively. Risk index is a tool for analysing risks, which can be combined with risk management and economic methods for more in-depth research.

4.4. Financial risk analysis of electricity market based on Value-at-Risk method

With the data of load demand and electricity price, the electricity transaction amount can be calculated by multiplying load demand, electricity price and power use time (every hour). Similarly, the forecasting value of transaction amount can also be obtained. The financial risk in this thesis refers to the inaccurate value between the forecast transaction amount and the actual transaction amount. In the electricity market, the market may face huge financial risks while bring the expected benefits to the participants [31]. Therefore, it is of great practical significance to evaluate the financial risks.

In the past years, researchers have quantitatively studied the high fluctuations in short-term load demand and electricity price [146], [147]. Although the financial engineering discipline has developed a number of risk research tools that can be used in financial markets, most of them cannot be directly applied to the electricity market [26]. The reason is that there are many differences between electricity commodities and other goods. For example, where the electricity commodities do not really meet market demand, this can result in a mismatch between supply and demand. This mismatch can be exposed in the form of a financial value, and this may be called the value-at-risk. This thesis intends to use the historical simulation method in Value-at-Risk analysis to analyse the electricity market financial risk, so as to better avoid and prevent market risks, and promote the stable development of the electricity market.

4.4.1. The introduction of Value-at-Risk

In 1994, J.P. Morgan Bank [27] first successfully launched a financial risk analysis tool called risk matrix, which is essentially the Value-at-Risk (VaR) method. Subsequently, the VaR method was rapidly popularized and applied in the international financial system, and soon became one of the most important means for various financial institutions to evaluate financial risks.

Under the normal market fluctuations, the original VaR means the maximum possible loss or gain of a financial asset or portfolios over a specified period of time at a certain probability level. The probability level also can be called as the confidence level. VaR can be expressed as the follow equation

$$Prob(\Delta R > R_{VaR}) = 1 - c \tag{4-12}$$

where ΔR is the loss or gain of a financial asset or portfolios within the holding period Δt. R_{VaR} is the value at risk at confidence level c.

The calculations of VaR mainly involve two factors: target time period and confidence level. The target time means that we calculate the VaR for a time in the future. Its determination depends mainly on the liquidity of the assets in the portfolio, and it could be 1 day, 1 week, 1 month or 1 season. Confidence level is the probability that the overall parameter value falls within a certain range of the sample statistics. The determination of the confidence level depends mainly on the risk attitude of the risk manager, and it is generally taken from 90% to 99.9% [28]. In this thesis, the confidence level is chosen at a more relaxed value of 90% and an average level of 95%.

4.4.2. The theory of historical simulation method

The historical simulation method refers to the market data model adopting the method of simulating history, which is using the observed data changes in a given historical period to represent the data changes in the future. In the estimation model, the historical simulation method re-evaluates related assets based on the historical price level of market data, and calculates the value changes (loss or gain) of related assets in the future. At last, the loss or gain of the asset or portfolios is sorted from small to large to get the loss/gain distribution, and then R_{VaR} can be obtained by the given confidence level. The historical simulation method is intuitive, simple to calculate, and easy to accept. It is a non-parametric method and it does not need to estimate various parameters such as volatility and correlation [30].

For example, for 100 possible loss or gain situations, the last 5 numbers of the asset or portfolios are the maximum loss or gain values under the 95% confidence level. The 95% confidence level indicates that in these 100 possible situations, the first 95 loss or gain values are within the acceptable error range, while the last 5 loss or gain values are outside the acceptable error range.

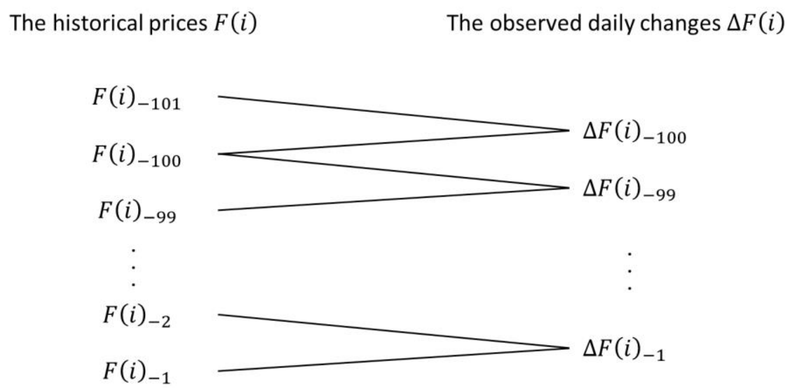


Figure 4-4: Historical prices and daily changes

Figure 4-4 gives a more detailed explanation. If there is a portfolio with market price of $F(i), (i = 1,2, \dots, n)$, here will introduce how to calculate its daily VaR value at 95% confidence level. Firstly, the historical simulation method is used to calculate the daily price volatility, select the historical price series of the market data over the past 101 trading days and get 100 daily price changes.

Assume that these 100 changes may occur on any day in the future. For each market data, add its current price $F(i)$ and the observed changes to get the future possible price, which can be expressed as $A_F(i)_n$:

$$A_F(i)_1 = F(i)_0 + \Delta F(i)_{-1}$$

$$A_F(i)_2 = F(i)_0 + \Delta F(i)_{-2}$$

$$\vdots \qquad \qquad \vdots$$

$$A_F(i)_{100} = F(i)_0 + \Delta F(i)_{-100} \tag{4-13}$$

According to the relevant formula, the current price of the market data and the possible future price can be calculated. Thus, the future loss or gain of the portfolio can be obtained. Then the loss/gain values will be arranged from small to large to get the future loss/gain distribution of the portfolio. Since the confidence level is 95% and there are 100 price change samples, the 95th number is the value of R_{VaR}.

It can be found that VaR is a very important indicator for investors, which can effectively curb the risk of fluctuations in the portfolios. However, VaR also has obvious defects. Firstly, VaR does not consider the severity of extreme loss/gain in the event of an abnormal situation. Just as the above example illustrated, we just determined that the loss/gain of the portfolio will not exceed R_{VaR} by a probability of 95%, but there is still a 5% probability that the loss/gain of the portfolio will exceed R_{VaR}. Once this happens, the extreme loss/gain faced by the portfolio cannot be obtained just through VaR. Secondly, VaR does not satisfy the subadditivity in economics. The subadditivity means the total VaR of the portfolio does not exceed the sum of the VaR of each individual asset in the portfolio. Therefore, using VaR as the risk measurement indicator may result in a situation that the overall risk of the portfolio is greater than the sum of the individual risks of each asset in the portfolio, and this goes against the original intention of reducing the portfolio risk [29].

4.4.3. Expected shortfall

In order to overcome the shortcomings of VaR, Rockafeller and Uryasev [34] first proposed the concept of Expected Shortfall (ES). ES is a common indicator of the extreme portfolio loss/gain risk. ES can show the average level of loss suffered when the portfolio loss or gain exceeds VaR threshold. Because ES further considers the average level of losses in the extreme case, the extreme loss risk of portfolio can be measured more completely. ES is more sensitive to the shape of the tail of the loss/gain distribution.

Compared to the other risk measurement indicators, ES has the following four advantages. Firstly, ES has good mathematical properties and fully meets the requirements of 'Consistent Measures of Risk' proposed by Artzner (1999) [148]. Secondly, the definition of ES is easy to understand, and it is relatively simple in calculation and practical application. Thirdly, ES has the most abundant means to supplement and solve the problems that faced by VaR in the practical application. Finally, under the premise that VaR as the mainstream risk measurement indicator, ES has the closest and most intuitive relationship to VaR [35]. As a result, ES is easier to be accepted and applied by the financial assets and portfolios.

Since the financial risk of the electricity market is mainly caused by fluctuations in load demand and electricity price, the VaR and ES methods can be introduced into the analysis of load demand and electricity price fluctuation in the electricity market, so as to achieve the analysis and calculation of the financial risk of the electricity market. In this thesis, VaR is an estimation of the possible loss/gain of financial return due to forecast error and it is expressed as a monetary value. The error between the actual and forecasting daily electricity transaction amount in Power Exchange is considered as the financial risk. In order to observe the VaR in different seasons, one season is selected as the target time period. Because the confidence level is selected at 90% and 95%, ES is used to calculate the average financial loss/gain at the 90% and 95% confidence level respectively. Therefore, the values of R_{VaR} and ES can be obtained to analyse the size of financial risks in different seasons.

4.5. The total financial risk assessments

Due to the difference between the actual and forecast transaction amount in day-ahead auction market, the financial risks can be calculated and they are all happened in Power Exchange. The values of financial risks could be positive or negative. When the actual transaction amount is bigger than the forecast transaction amount, the financial risk is positive. When the actual transaction amount is smaller than the forecast transaction amount, it shows negative financial risk. The meanings of positive and negative are different for the generator side and demand side. The financial risk behaves positive is good for generation side because that means they can earn more revenue by selling the electricity. For the demand side, the financial risk shows negative is good for them, because that means they can buy the load demand volumes at a lower cost.

If the original data is one year and is updated hourly, in order to observe the financial risks during different periods, the financial risks can be added and then illustrated in daily, monthly and seasonally. In this way, it can be observed which day, month and season have the highest or lowest financial risk. Also, the sum of the annual financial risks can be calculated to evaluate the total accuracy of forecast results. The sum of the financial risks could express the actual risk the participants will have to bear. The best situation is the positive and negative financial risks offset each other, then the risk value is zero.

The financial risk assessments under consideration now are based on the premise of forecasting load demand and forecasting electricity price. In order to observe the separate influence of forecasting load demand and forecasting electricity price on financial risks, this thesis considers two other preconditions for generating financial risks —— forecasting load demand and actual electricity price, and actual load demand and forecasting electricity price. This allows comparing the total financial risks for one year in three different situations. Table 4-1 illustrates all these three situations for analysing total financial risks. Moreover, the RMSPEs and MAPEs between the annual total transaction amount and forecast transaction amount can also be calculated to observe the forecasting accuracies. The smaller values of RMSPEs and MAPEs indicate that the forecast is more accurate.

Table 4-1: Three situations for analysing total financial risks

Situations	**Load demand**	**Electricity price**
1	Forecast	Forecast
2	Forecast	Actual
3	Actual	Forecast

The total financial risk assessments can help electricity market participants to control their costs, and develop reasonable generation and power consumption plans based on actual needs to obtain the maximum profits. Only when the participants understand their financial risks can they make more informed business decisions in the competitive and volatile electricity market environment.

4.6. Summary

In this chapter, various methods to analyse forecast errors are introduced in detail, and each method has its own merits. This thesis will mainly use RMSPE an MAPE to calculate results and select model of forecasting methods to observe the forecasting results. The forecast errors can be obtained from the difference between actual data and forecasting results. Then all the forecast errors are converted to more intuitive risk indexes, because the risk index can represent any size of errors as a specific number from 0 to 1. Thus the high-risk periods can be identified and differnet levels of error risks can be compared. Furthermore, this chapter details the financial risk analysis methods based on Value-at-Risk and Expected Shortfall. Financial risk analysis can help electricity market participants to forecast their financial returns. Finally, the total financial risk assessment is introduced at the last part of this chapter. This approach is able to help market participants assess their monthly, quarterly and annual total financial risks. The practical applications of all these error forecasts and financial risk assessments will be detailed in later chapters. Using the theories of the forecasting models and the error analysis methods, the load demand and electricity price in the electricity market can be forecasted concretely.

Chapter 5

Load demand forecast and simulated results comparison

5.1. Introduction

Load demand forecasting is an important part of ensuring the safe and stable operation in the power systems, and is of great significance for automatic control of power grid dispatching and power production. This chapter introduces the load demand forecasting and the analysis of forecasting results. Since the historical market data in the UK electricity market can be found in the UK N2EX, Nord Pool [1], the load demand data in the UK electricity market are used as an example. The load demand forecasting processes include monthly, seasonal, annual and multi-step-ahead, and the forecasting accuracy is determined by comparing the RMSPE and MAPE of the results.

In the monthly forecasts, the one-year data from March 2015 to February 2016 are divided into 12 months, and the data of each month are divided into weekdays and weekends. For weekdays, the data of three weeks are used for modelling to forecast one-week load demands, and the results are compared to the actual load demands in the fourth week. Similarly, for weekends, the data of three weeks are used for modelling to forecast one-week load demands, and the results are compared to the actual load demands in the fourth week. The monthly forecasts are achieved every month (12 months) from March 2015 to February 2016. The ARIMA, SARIMA and ANN models are all used in these forecasting processes and these forecast results are compared.

In the seasonal forecasts, the load demand of weekdays and weekends are all merged together. In this chapter, there are two different methods are used to forecast the seasonal load demands from March 2015 to February 2016 — continuous historical data method and seasonal separation method. For the continuous historical data method, the 12-month continuous historical data are used for modelling to forecast load demands in the next season (3 months). For the seasonal separation method, the data of the same season in the previous two years are used for modelling to forecast the load demands for the corresponding season (3 months) in the next year. SARIMA models are used in these seasonal forecasting processes and the forecast results are compared.

In the annual forecasts, the load demand of weekdays and weekends are also all merged together. This chapter makes three sets of annual load demand forecasts. Firstly, the one-month data from January to February 2015 are used for modelling to forecast one-year load demands from March 2015 to February 2016. Secondly, the six-month data from September 2014 to February 2015 are used for modelling to forecast one-year load demands from March 2015 to February 2016. Thirdly, the one-year data from March 2014 to February 2015 are used for modelling to forecast one-year load demands from March 2015 to February 2016. These are to observe the effect of the size of the modelling data on the forecasting results.

At last, the comparison of one-step-ahead and multi-step-ahead load demand forecasting is achieved in this chapter. In addition to the basic one-step-ahead forecasting, 6-step-ahead, 12-step-ahead and 24-step-ahead forecasting are also realized. The effect of multi-step-ahead forecasts on the forecasting accuracy is analysed by comparing these forecast results.

5.2. Data preparation for load demand forecast

In this thesis, the rolling-window forecast method is used for all the forecasting processes [149]. If there is a data sample of size T and a rolling window of size m. The rolling window includes an input data of size I and a forecast horizon of size h. The size of the rolling window depends on the data sample size T and periodicity of the data. Every individual forecasts are completed in the rolling window. At the end of each forecast process, the rolling window moves further along to the data sample, picks up a new data at the end and drops off an old data at the front, and then make the next forecast in the new rolling window, and so on. This is called the rolling-window forecast method. All the forecasting processes in this thesis use actual historical data as input to forecast results. Figure 5-1 and 5-2 illustrate the rolling window subsample and the rolling-window forecasting process respectively.

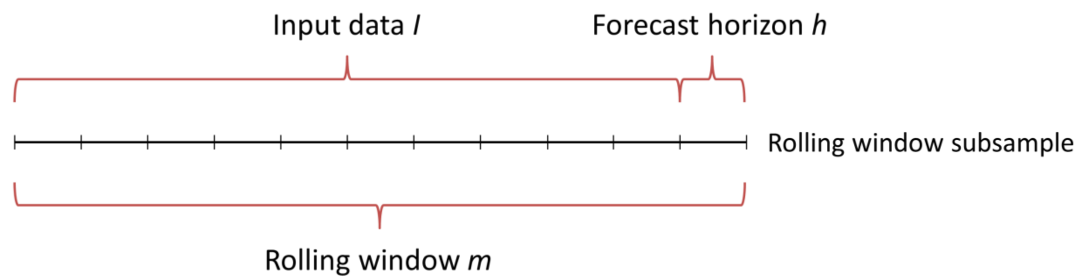


Figure 5-1: Rolling window subsample

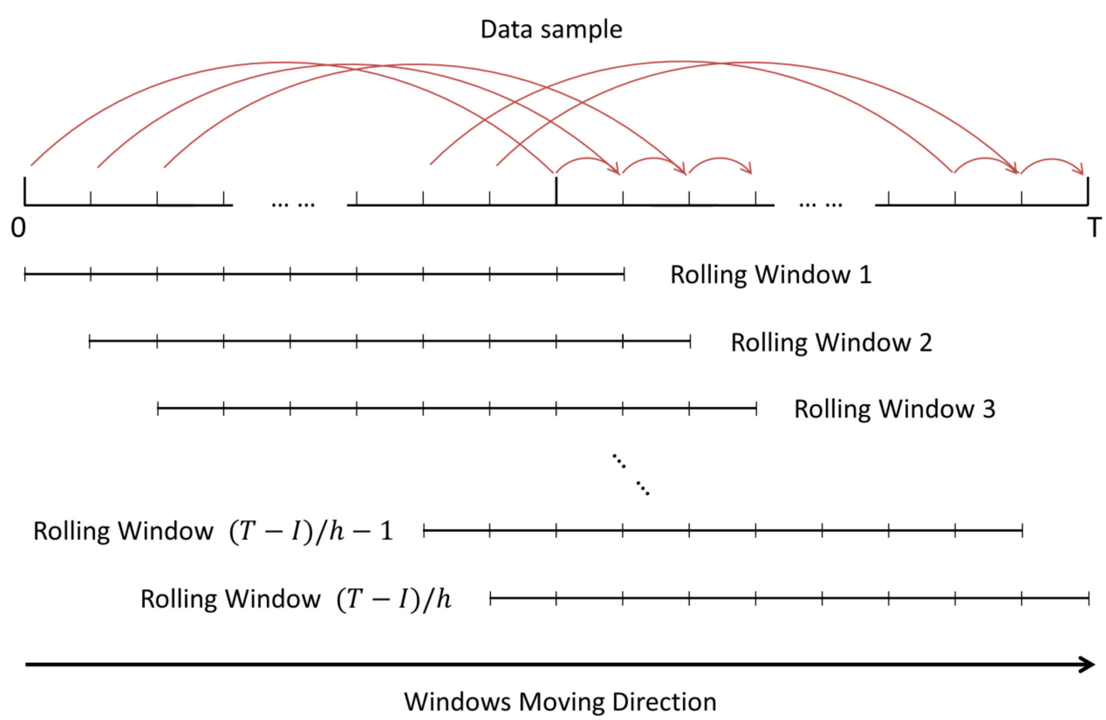


Figure 5-2: Rolling-window forecasting process

For the forecast horizon h, the most basic is one-step-ahead forecasting, and multi-step-ahead forecasting can also be performed according to the actual needs. After the rolling-window forecasting process is completed, the forecast results are compared with the actual data, and the forecast accuracy is analysed based on the calculation results of RMSPE and MAPE.

In this thesis, all the historical one-hour update load demands in the UK electricity wholesale market are obtained from UK N2EX, Nord Pool [150].

5.2.1. Data preparation for monthly forecast

For the monthly forecast, the historical one-hour update load demands from March 2015 to February 2016 in the UK electricity wholesale market are used. In order to make monthly forecasts, the one-year historical load demands are classified into 12 months. For the load demand, the weekday demands are mainly industrial and commercial demands, and the weekend demands are mainly domestic and commercial demands. The load demand waveform is related to the residents' living habits, and the peak times of the weekday and weekend demands are also different. Therefore, the load demand will be forecasted on weekdays and weekends separately in each month over the year.

5.2.1.1. Monthly forecast for weekdays

Generally in each month, the load demands in the first three weeks are used as modelling data, and the load demands in the last week are used as testing data. The forecast data on August 2015 are used as a demonstration example. The calendar for August 2015 is shown in Figure 5-3.

Weekdays | Weekends

Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
					1	2
3	4	5	6	7	8	9
10	11	12	13	14	15	16
17	18	19	20	21	22	23
24	25	26	27	28	29	30
31						

Figure 5-3: The calendar for August 2015

It can be seen from Figure 5-3 that the weekday data for the first three weeks are from 3rd to 21st August and for the fourth week are from 24th to 28th August. That means the historical load demands on weekdays from 3rd to 21st August 2015 (15 days) are used as input data to forecast the results from 24th to 28th August 2015 (5 days).

For the weekday load demand forecast, the historical data is updated hourly and one-step-ahead forecasting is implemented here. Therefore, in the rolling windows for August 2015 weekdays, the input data size I is 360 hours (24 hours × 15 days), the forecast horizon size h is 1 hour, the rolling-window size m is 361 hours (24 hours × 15 days + 1 hour), and the data sample size T is 480 hours (24 hours × 20 days). There are a total of 120 rolling windows ($(T - I)/h$ = (480 – 360)/1). Then ARIMA, SARIMA and ANN models are used for forecasting separately.

5.2.1.2. Monthly forecast for weekends

Similar to the monthly forecast for the weekday, generally in each month, the load demands in the first three weeks are used as modelling data, and the load demands in the last week are used as testing data. The forecast data on August 2015 are used as a demonstration example.

However, it can be seen from Figure 5-3 that there are five weekends in August 2015, in which case the load demands in the first four weeks are used as modelling data, and the load demands in the last week are used as testing data. Therefore, the weekend data for the first four weeks are from 1st to 23rd August and for the fifth week are from 29th to 30th August. That means the historical load demands on weekends from 1st to 23rd August 2015 (8 days) are used as input data to forecast the results from 29th to 30th August 2015 (2 days).

For the weekend load demand forecast, the historical data is updated hourly and one-step-ahead forecasting is implemented here. Therefore, in the rolling windows for August 2015 weekends, the input data size I is 192 hours (24 hours × 8 days), the forecast horizon size h is 1 hour, the rolling-window size m is 193 hours (24 hours × 8 days + 1 hour), and the data sample size T is 240 hours (24 hours × 10 days). There are a total of 48 rolling windows ($(T - I)/\ h$ = (240 – 192)/1). Then ARIMA, SARIMA and ANN models are used for forecasting separately.

The data of August 2015 are used as the demonstration example for monthly load demand forecasting, and the same forecasting methods are achieved in each month over the year from March 2015 to February 2016 (12 months). The purpose of monthly forecast is to compare the load demand forecast results for weekdays and weekends and to determine which model has the best forecasting accuracy in each month.

5.2.2. Data preparation for seasonal forecast

For the seasonal forecast, the historical one-hour update load demands from March 2013 to February 2016 in the UK electricity wholesale market are used. The purpose of the seasonal forecast is to forecast the load demands of four seasons in the year from March 2015 to February 2016 based on the historical data. In seasonal forecasts, the load demands on weekdays and weekends are not separately forecasted and they are combined into continuous data. There are two different methods for forecasting seasonal load demand — continuous historical data method and seasonal separation method, and one-step-ahead forecasting is implemented for both methods.

5.2.2.1. Continuous historical data method

In the continuous historical data method, the load demands from March 2014 to February 2015 are used to forecast the seasonal load demands from March 2015 to February 2016. For each season, the load demands of last year (12 months) are used as modelling data, and the data of next season (3 months) are used as testing data. The Seasonal load demand forecasting process by continuous historical data method is shown in Figure 5-4.

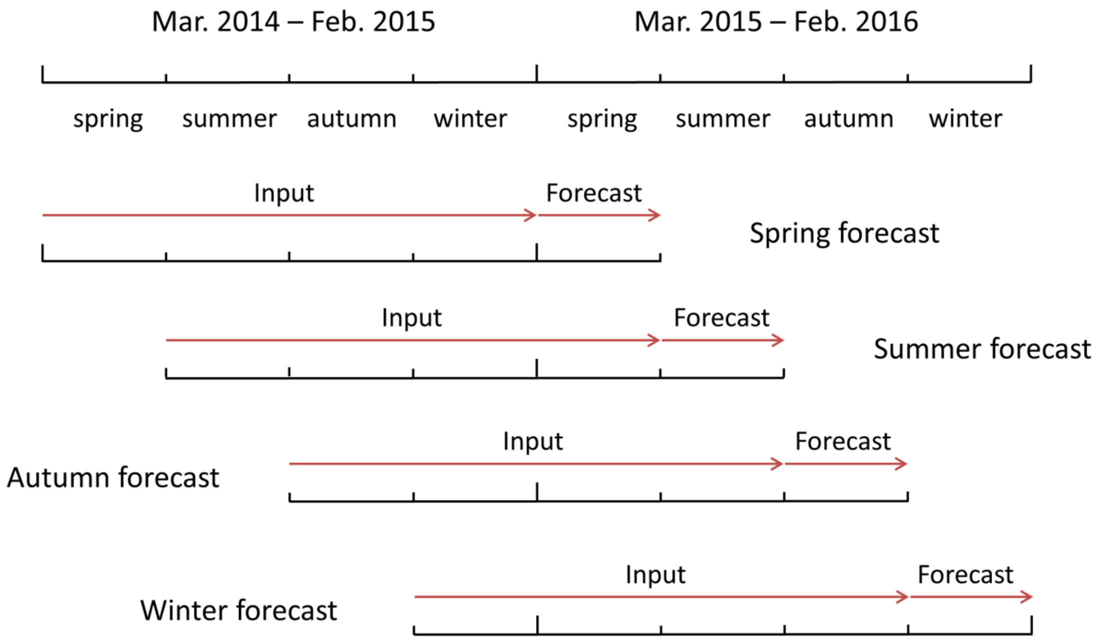


Figure 5-4: Seasonal load demand forecasting process by continuous historical data method

It can be seen from Figure 5-4 that the load demands from March 2014 to February 2015 are used as input data to forecast the results from March to May 2015 (spring forecast). The load demands from June 2014 to May 2015 are used as input data to forecast the results from June to August 2015 (summer forecast). The load demands from September 2014 to August 2015 are used as input data to forecast the results from September to November 2015 (autumn forecast). The load demands from December 2014 to November 2015 are used as input data to forecast the results from December 2015 to February 2016 (winter forecast). Each step of the seasonal forecasting uses the actual load demands of the previous four seasons as input data to forecast the results for the next quarter.

Therefore, the sizes in the rolling window of the continuous historical data method are:

- Spring forecast: the input data size I is 8760 hours (24 hours × 365 days), the forecast horizon size h is 1 hour, the rolling-window size m is 8761 hours (24 hours × 365 days + 1 hour), and the data sample size T is 10968 hours (24 hours × (365 + 92) days). There are a total of 2208 rolling windows ($(T - I)/h$ = (10968 – 8760)/1).
- Summer forecast: the input data size I is 8760 hours (24 hours × 365 days), the forecast horizon size h is 1 hour, the rolling-window size m is 8761 hours (24 hours × 365 days + 1 hour), and the data sample size T is 10968 hours (24 hours × (365 + 92) days). There are a total of 2208 rolling windows ($(T - I)/h$ = (10968 – 8760)/1).
- Autumn forecast: the input data size I is 8760 hours (24 hours × 365 days), the forecast horizon size h is 1 hour, the rolling-window size m is 8761 hours (24 hours × 365 days + 1 hour), and the data sample size T is 10944 hours (24 hours × (365 + 91) days). There are a total of 2184 rolling windows ($(T - I)/h$ = (10944 – 8760)/1).
- Winter forecast: the input data size I is 8760 hours (24 hours × 365 days), the forecast horizon size h is 1 hour, the rolling-window size m is 8761 hours (24 hours × 365 days + 1 hour), and the data sample size T is 10944 hours (24 hours × (365 + 91) days). There are a total of 2184 rolling windows ($(T - I)/h$ = (10944 – 8760)/1).

5.2.2.2. Seasonal separation method

In the seasonal separation method, the load demands from March 2013 to February 2015 are used to forecast the seasonal load demands from March 2015 to February 2016, but the data in different seasons are used separately. For each season, the load demands for the same season in the previous two years (6 months) are used as modelling data, and the data for the corresponding season (3 months) of the next year are used as testing data. The Seasonal load demand forecasting process by seasonal separation method is shown in Figure 5-5.

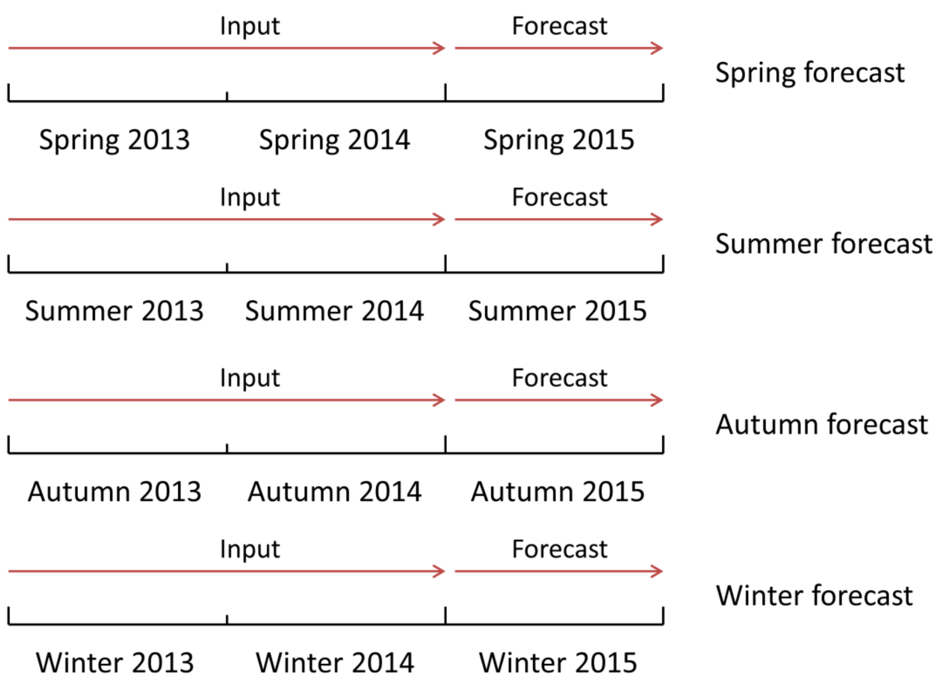


Figure 5-5: Seasonal load demand forecasting process by seasonal separation method

It can be seen from Figure 5-5 that means the load demands from March to May in 2013 and 2014 are used as input data to forecast the results from March to May 2015 (spring forecast). The load demands from June to August in 2013 and 2014 are used as input data to forecast the results from June to August 2015 (summer forecast). The load demands from September to November in 2013 and 2014 are used as input data to forecast the results from September to November 2015 (autumn forecast). The load demands from December to the next February in 2013 and 2014 are used as input data to forecast the results from December 2015 to February 2016 (winter forecast).

Therefore, the sizes in the rolling window of the seasonal separation method are:

- Spring forecast: the input data size I is 4416 hours (24 hours × (92 + 92) days), the forecast horizon size h is 1 hour, the rolling-window size m is 4417 hours (24 hours × (92 + 92) days + 1 hour), and the data sample size T is 6624 hours (24 hours × (92 + 92 + 92) days). There are a total of 2208 rolling windows ($(T - I)/\ h$ = (6624 – 4416)/1).
- Summer forecast: the input data size I is 4416 hours (24 hours × (92 + 92) days), the forecast horizon size h is 1 hour, the rolling-window size m is 4417 hours (24 hours × (92 + 92) days + 1 hour), and the data sample size T is 6624 hours (24 hours × (92 + 92 + 92) days). There are a total of 2208 rolling windows ($(T - I)/\ h$ = (6624 – 4416)/1).
- Autumn forecast: the input data size I is 4368 hours (24 hours × (91 + 91) days), the forecast horizon size h is 1 hour, the rolling-window size m is 4369 hours (24 hours × (91 + 91) days + 1 hour), and the data sample size T is 6552 hours

(24 hours × (91 + 91 + 91) days). There are a total of 2184 rolling windows $((T - I)/\,h$ = (6552 – 4368)$/1)$.

- Winter forecast: the input data size I is 4320 hours (24 hours × (90 + 90) days), the forecast horizon size h is 1 hour, the rolling-window size m is 4321 hours (24 hours × (90 + 90) days + 1 hour), and the data sample size T is 6504 hours (24 hours × (90 + 90 + 91) days). There are a total of 2184 rolling windows $((T - I)/\,h$ = (6504 – 4320)$/1)$.

Only SARIMA model is used for seasonal forecasts, as the SARIMA model performs better forecast results than ARIMA and ANN models in monthly forecasts. The specific forecasting process and comparison of results will be detailed in this chapter.

5.2.3. Data preparation for annual forecast

For the annual forecast, the historical one-hour update load demands from March 2014 to February 2016 in the UK electricity wholesale market are used. The purpose of the annual forecast is to forecast the one-year load demands from March 2015 to February 2016 based on the historical data. In annual forecasts, the load demands on weekdays and weekends are not separately forecasted and they are combined into continuous data. In order to compare the impact of the rolling window size on the forecasting results, the annual forecasts use three sizes of input data to forecast the load demands — one month, six months and one year.

5.2.3.1. Input data for one month

When the input data is one month, the one-month load demands of February 2015 are used to forecast the annual load demands from March 2015 to February 2016. The forecasting process is shown in Figure 5-6.

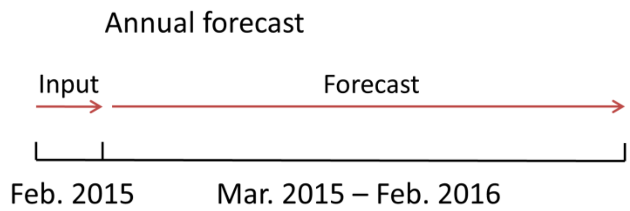


Figure 5-6: Annual load demand forecasting process based on one-month input data

Therefore, in the rolling windows of annual forecast based on input data for one month, the input data size I is 672 hours (24 hours × 28 days), the forecast horizon size h is 1 hour, the rolling-window size m is 673 hours (24 hours × 28 days + 1 hour), and the data sample size T is 9456 hours (24 hours × (28 + 366) days). There are a total of 8784 rolling windows ($(T - I)/\ h$ = (9456 – 672)/1).

5.2.3.2. Input data for six months

When the input data is six months, the six-month load demands from September 2104 to February 2015 are used to forecast the annual load demands from March 2015 to February 2016. The forecasting process is shown in Figure 5-7.

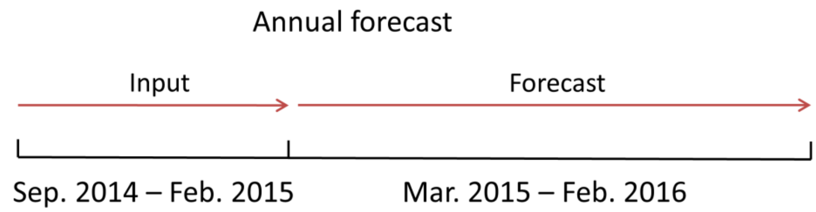


Figure 5-7: Annual load demand forecasting process based on six-month input data

Therefore, in the rolling windows of annual forecast based on input data for six months, the input data size I is 4344 hours (24 hours × 181 days), the forecast horizon size h is 1 hour, the rolling-window size m is 4345 hours (24 hours × 181 days + 1 hour), and the data sample size T is 13128 hours (24 hours × (181 + 366) days). There are a total of 8784 rolling windows ($(T - I)/\ h$ = (13128 – 4344)$/$1).

5.2.3.3. Input data for one year

When the input data is one year, the one-year load demands from March 2014 to February 2015 are used to forecast the annual load demands from March 2015 to February 2016. The forecasting process is shown in Figure 5-8.

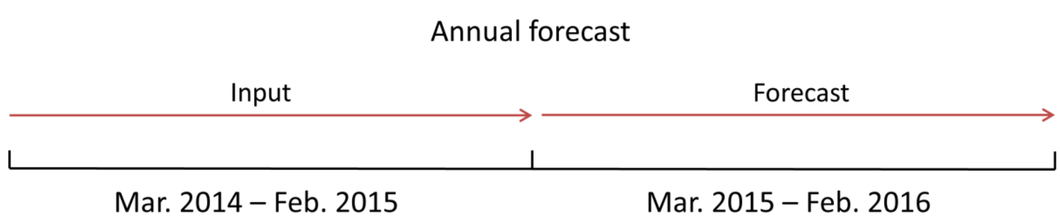


Figure 5-8: Annual load demand forecasting process based on one-year input data

Therefore, in the rolling windows of annual forecast based on input data for one year, the input data size I is 8760 hours (24 hours × 365 days), the forecast horizon size h is 1 hour, the rolling-window size m is 8761 hours (24 hours × 365 days + 1 hour), and the data sample size T is 17544 hours (24 hours × (365 + 366) days). There are a total of 8784 rolling windows ($(T - I)/ h$ = (17544 – 8760)/1).

SARIMA model is used for annual forecasts, and the comparison of results will be detailed in this chapter.

5.2.4. Data preparation for multi-step-ahead forecast

For the multi-step-ahead forecast, the historical one-hour update load demands from March 2014 to February 2016 in the UK electricity wholesale market are used. The purpose of the multi-step-ahead forecast is to compare the impact of one-step-ahead forecast and multi-step-ahead forecast on forecasting results. In the multi-step-ahead forecasts, the load demands from March 2014 to February 2015 are used to forecast the one-year load demands from March 2015 to February 2016 by different forecast horizons. 6-step-ahead forecasting, 12-step-ahead forecasting and 24-step-ahead forecasting are implemented in this chapter. The load demand forecasting processes of 6-step-ahead, 12-step-ahead and 24-step-ahead forecast are shown in Figure 5-9.

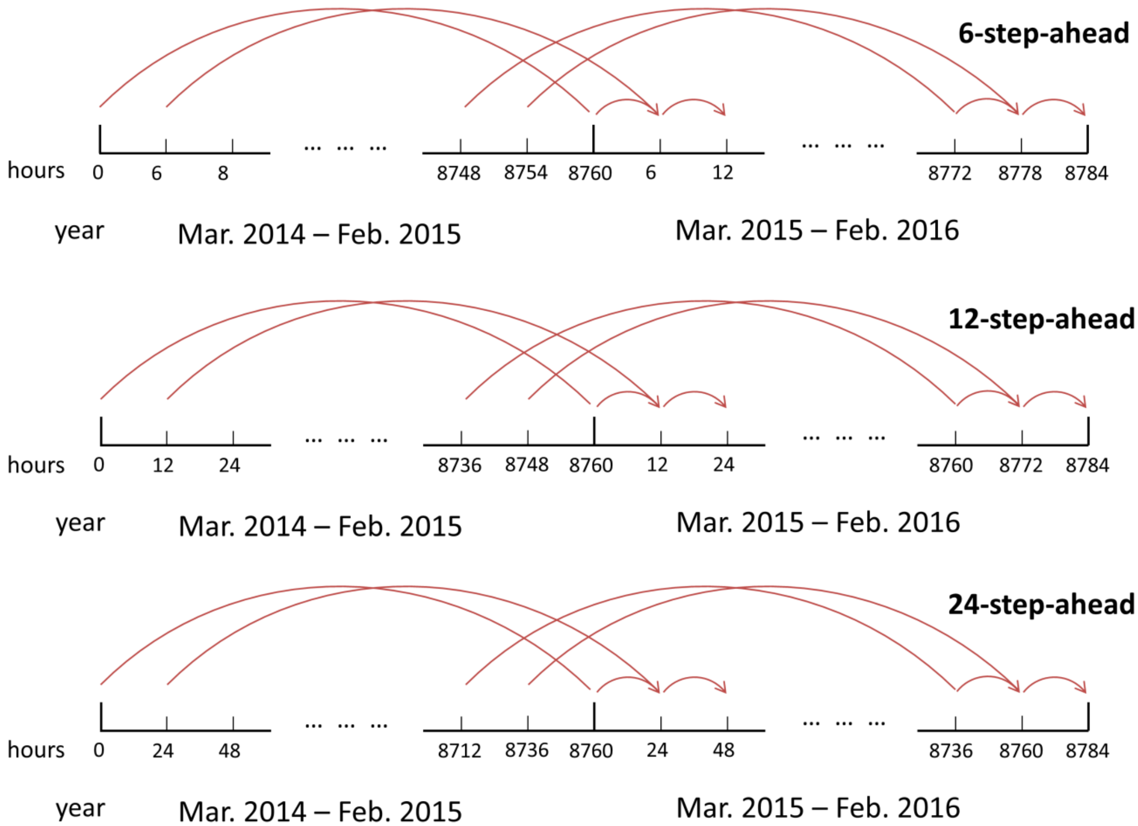


Figure 5-9: The load demand forecasting processes of 6-step-ahead, 12-step-ahead and 24-step-ahead forecast

Therefore, the sizes in the rolling window of 6-step-ahead forecasting, 12-step-ahead forecasting and 24-step-ahead forecasting are:

- 6-step-ahead forecasting: the input data size I is 8760 hours (24 hours × 365 days), the forecast horizon size h is 6 hours, the rolling-window size m is 8766 hours (24 hours × 365 days + 6 hours), and the data sample size T is 17544 hours (24 hours × (365 + 366) days). There are a total of 1464 rolling windows ($(T-I)/h$ = (17544 – 8760)/6).

- 12-step-ahead forecasting: the input data size I is 8760 hours (24 hours × 365 days), the forecast horizon size h is 12 hours, the rolling-window size m is 8772 hours (24 hours × 365 days + 12 hours), and the data sample size T is 17544 hours (24 hours × (365 + 366) days). There are a total of 732 rolling windows ($(T - I)/\ h$ = (17544 – 8760)/12).
- 24-step-ahead forecasting: the input data size I is 8760 hours (24 hours × 365 days), the forecast horizon size h is 24 hours, the rolling-window size m is 8784 hours (24 hours × 365 days + 24 hours), and the data sample size T is 17544 hours (24 hours × (365 + 366) days). There are a total of 366 rolling windows ($(T - I)/\ h$ = (17544 – 8760)/24).

SARIMA model is used for multi-step-ahead forecasts, and the comparison of results will be detailed in this chapter.

For the load demand forecasts in this thesis, all the programs of the ARIMA, SARIMA and ANN models have been written in MATLAB language. The running time of the ARIMA and SARIMA model is less than five minute for one case, and the response time for ANN model is around fifteen minutes because the best result is obtained after 1000 cycles. Therefore, all the models are feasible for other applications.

5.3. Parameter determination process for monthly load demand forecast

The monthly forecasting process of load demand has been introduced before. The load demands from March 2015 to February 2016 are used as the experimental data, and the data for weekdays and weekends are forecasted separately. The monthly forecasts of load demand for August 2015 are used as a demonstration example. Here, the parameter determination process of ARIMA model, SAIMA model and ANN model for August 2015 are presented.

5.3.1. Parameter determination for weekdays of August 2015

For the forecasting on weekdays, the historical load demands from 3rd to 21st August 2015 (15 days) are used as input data to forecast the results from 24th to 28th August 2015 (5 days).

5.3.1.1. ARIMA model

For the parameter determination of ARIMA model on weekdays, load the historical load demands on weekdays from 3rd to 21st August, then plot the sample autocorrelation function (ACF) and sample partial autocorrelation function (PACF) for the load demand series. The original ACF and PACF are shown in Figure 5-10.

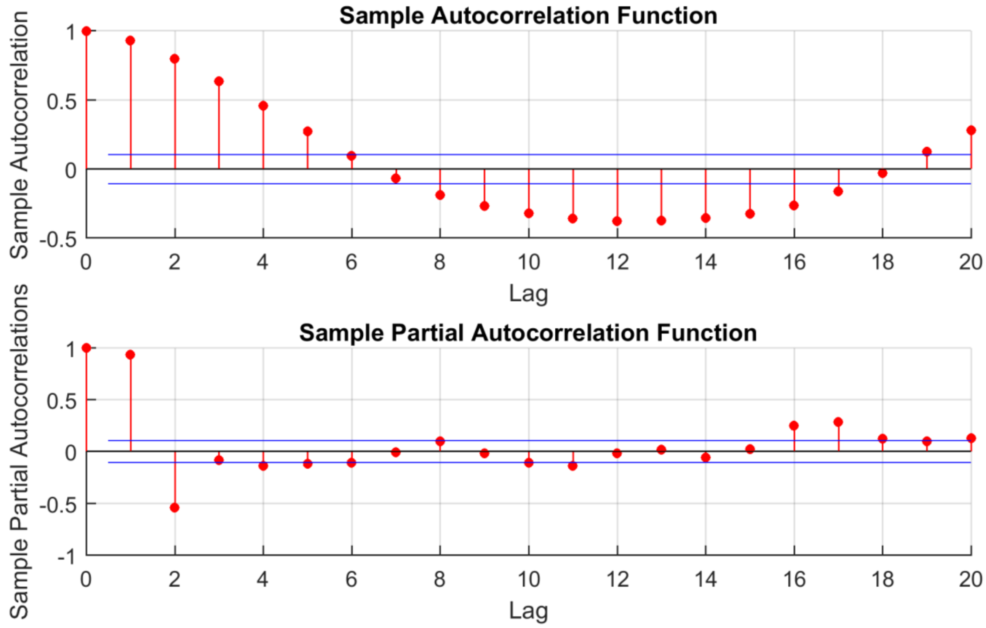


Figure 5-10: Original ACF and PACF of load demand for weekdays in August 2015

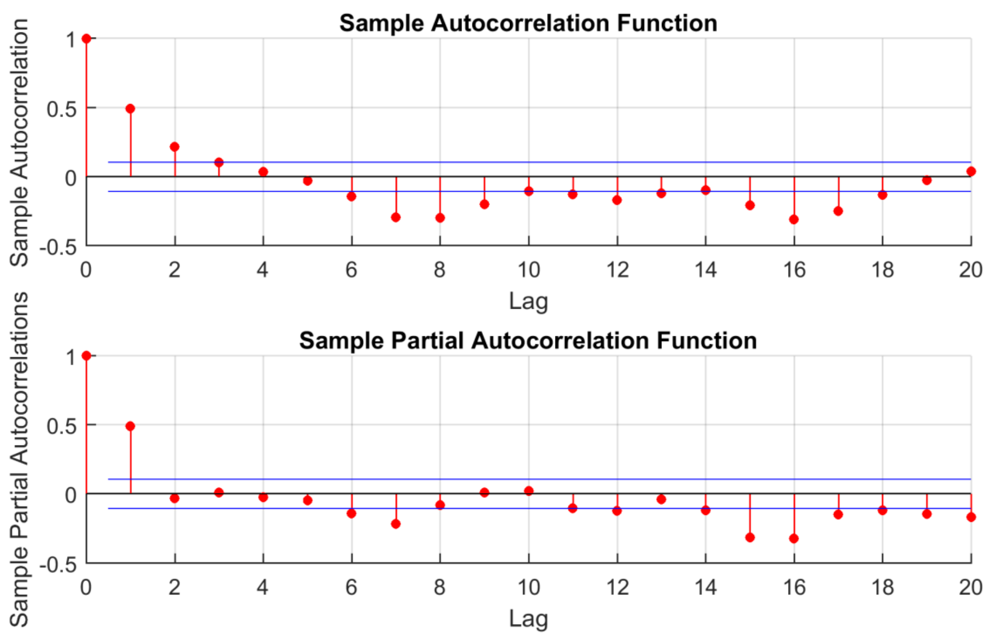


Figure 5-11: ACF and PACF of load demand for weekdays in August 2015 after 1st differencing

It can be seen from Figure 5-10 that the decaying sample ACF indicates a nonstationary process. So the 1st differencing is applied to the original data, and sample ACF and PACF after 1st differencing are plotted in Figure 5-11. But in Figure 5-11, most of the points in ACF are out of the approximate confidence interval, so the ACF also illustrates a nonstationary process. Then another differencing is applied here and the sample ACF and PACF after 2nd differencing are plotted in Figure 5-12.

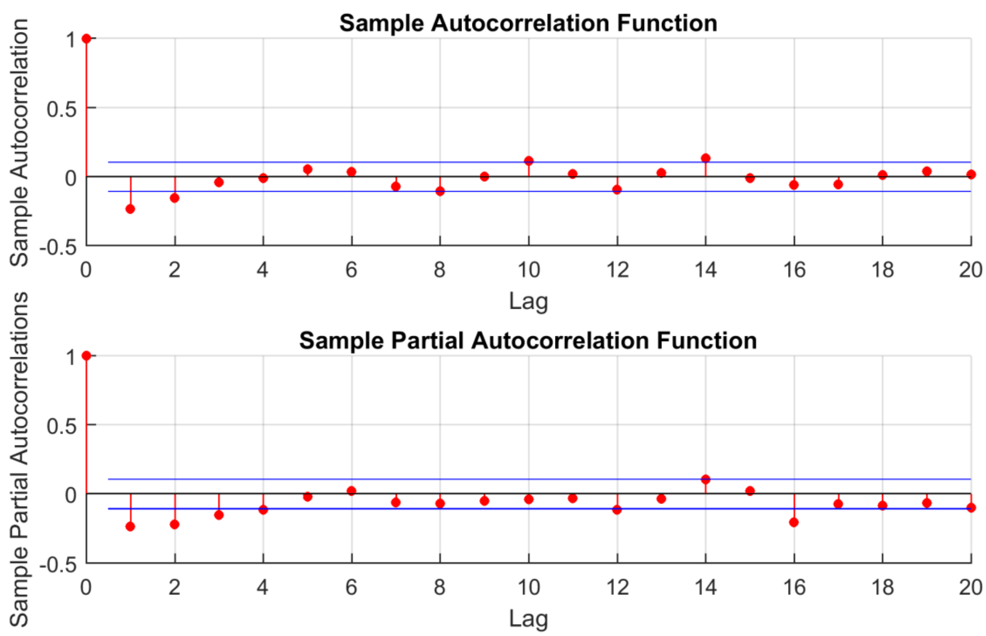


Figure 5-12: ACF and PACF of load demand for weekdays in August 2015 after 2nd differencing

Figure 5-12 shows that the sample ACF and PACF after 2nd differencing are stationary now. The ACF decays to zero after lag 0 or 1, and the PACF decays to zero after lag 0, 1 or 2. As mentioned before, in a $ARIMA(p, d, q)$ model, the moving average order q is determined by ACF, and the autoregressive order p is decided by PACF. Therefore, for the $ARIMA(p, d, q)$ model in this case, d equals to 2, p can be selected in 0, 1 and 2, q can be selected in 0 and 1. That means there are $ARIMA(0, 2, 0)$, $ARIMA(0, 2, 1)$, $ARIMA(1, 2, 0)$, $ARIMA(1, 2, 1)$, $ARIMA(2, 2, 0)$ and $ARIMA(2, 2, 1)$ six models might be appropriate for this set of data. Then use all these six models to forecast the weekdays' load demand from 24th to 28th August, and the results of RMSPE and MAPE are shown in Table 5-1.

Table 5-1: RMSPE and MAPE of different ARIMA models for weekdays' load demand in August 2015

Models	**RMSPE,** %	**MAPE,** %
$ARIMA(0, 2, 0)$	6.07	3.78
$ARIMA(0, 2, 1)$	5.45	3.54
$ARIMA(1, 2, 0)$	5.20	3.43
$ARIMA(1, 2, 1)$	5.23	3.45
$ARIMA(2, 2, 0)$	5.76	3.56
$ARIMA(2, 2, 1)$	5.22	3.44

It can be seen from Table 5-1 that $ARIMA(1, 2, 0)$ model has the smallest RMSPE and MAPE, so $ARIMA(1, 2, 0)$ model is selected as the forecasting model for the weekdays' load demand in August 2015. The formula of $ARIMA(1, 2, 0)$ model can be expressed as

$$(1 - \emptyset_1 B)(1 - B)^2 Z_t = a_t \tag{5-1}$$

where $\emptyset_1$ is the autoregressive operator of p. There is no moving-average operator θ_1 because q is 0. Z_t is the load demands. B is the backward shift operator that defines

$Z_{t-1} = BZ_t$. a_t is the error term with a mean of zero. Thus, the time series forecasting function can be expressed as

$$Z_t = (2 + \emptyset_1)Z_{t-1} - (1 + 2\emptyset_1)Z_{t-2} + \emptyset_1 Z_{t-3} + a_t \qquad (5\text{-}2)$$

where the value of $\emptyset_1$ are changed at each step, because the forecasting process uses the rolling-window forecast method.

5.3.1.2. SARIMA model

For the parameter determination of SARIMA model on weekdays, in addition to the non-seasonal parameters p, d, q in the ARIMA model, the SARIMA model also has the seasonal parameters P, D, Q. The load demand on weekdays from 3rd to 21st August is shown in Figure 5-13. In order to observe the seasonal changes in ACF and PACF, the original ACF and PACF with extended X axes are shown in Figure 5-14.

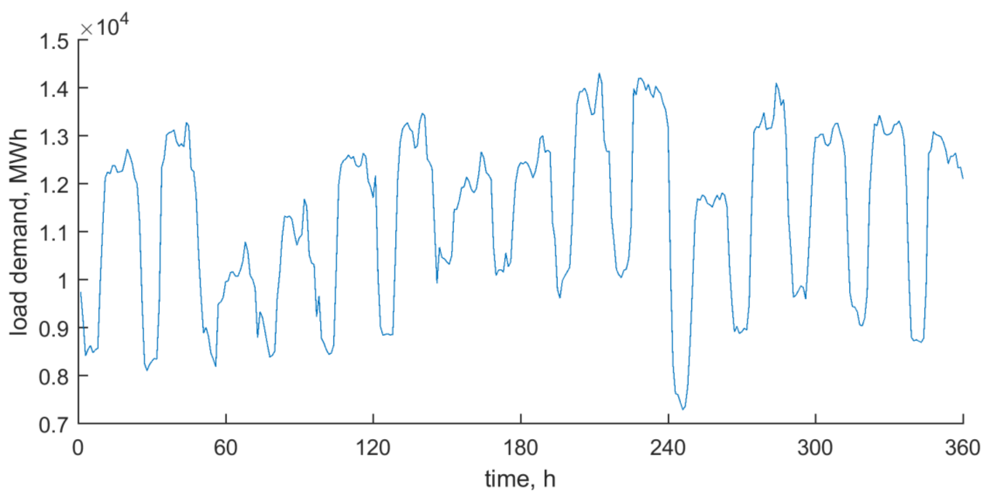


Figure 5-13: Load demand on weekdays from 3rd to 21st August

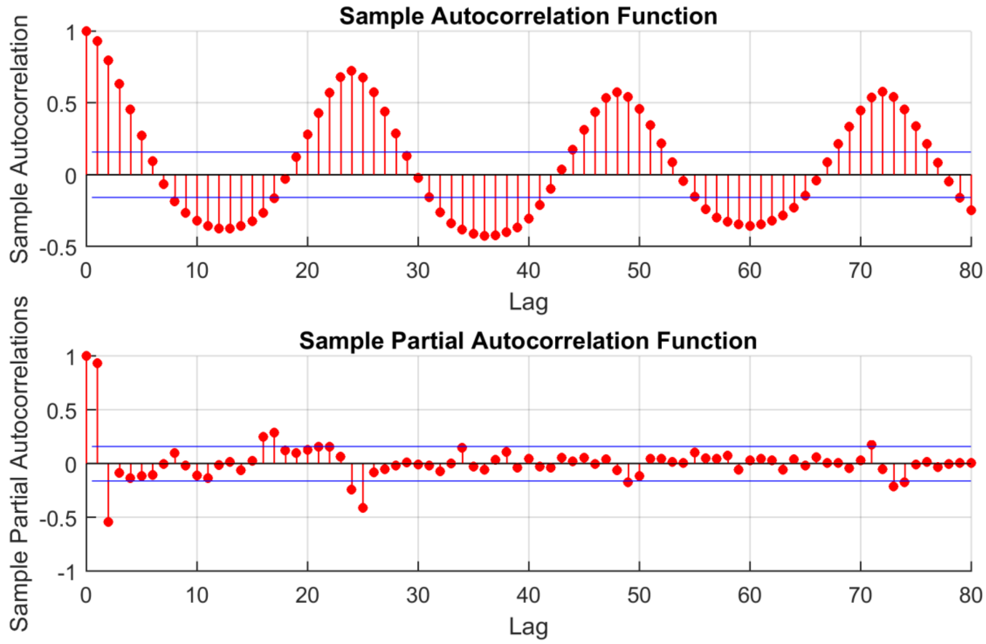


Figure 5-14: Original ACF and PACF of load demand for weekdays in August 2015 (extended X axes)

According to Figure 5-13 and 5-14, there is a seasonal oscillation with the period of 24 hours in the original data and the spikes happened in ACF every 24 lags. Therefore, the seasonal period is 24 hours in this case. The figure of ACF presented non-stationary, so the 1st difference is applied to the original data and the ACF and PACF after 1st differencing are shown in Figure 5-15.

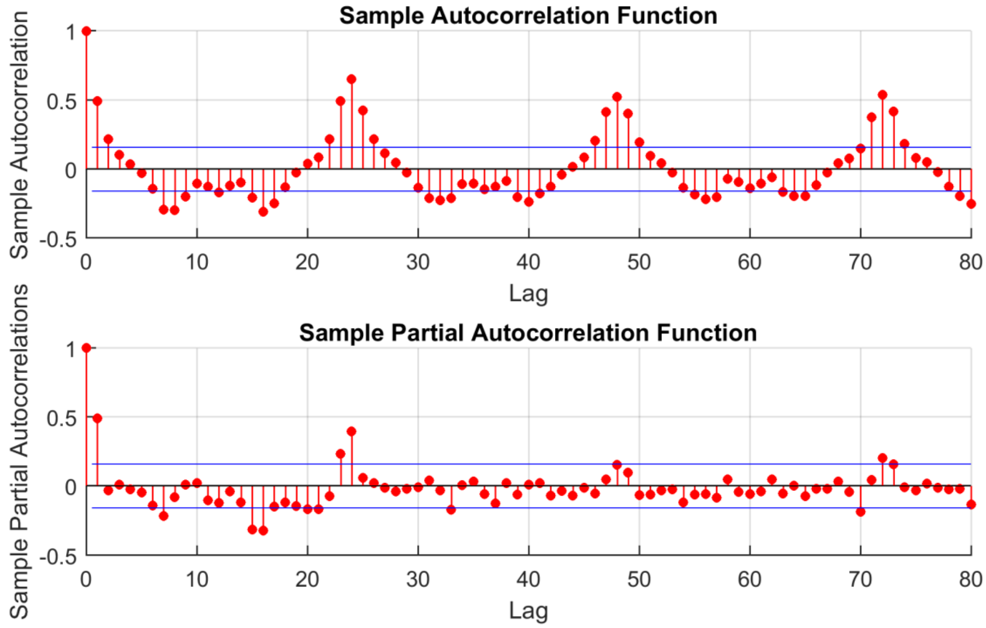


Figure 5-15: ACF and PACF of load demand for weekdays in August 2015 after 1st differencing

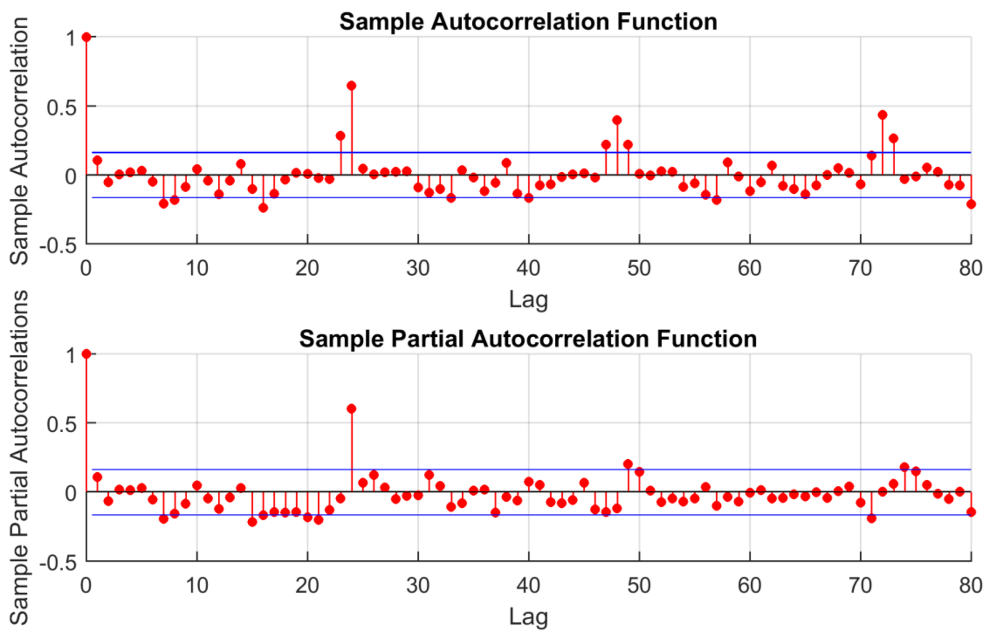


Figure 5-16: ACF and PACF of load demand for weekdays in August 2015 after 1st and 24th differencing

It can be seen in Figure 5-15 that ACF presents nonstationary and has spikes at the seasonal period of lag 24. So an additional 24th seasonal differencing is applied to the series and the ACF and PACF of the seasonal differenced series are plotted in Figure 5-16.

It can be observed in Figure 5-16 that the sample ACF and PACF after the 1st and 24th differencing are stationary process now. According to the differencing times, $d = 1$ and $D = 1$. For the non-seasonal terms, ACF and PACF all decay to zero after lag 0 directly, so $p = 0$ and $q = 0$. For the seasonal terms, the spikes appeared every 24 lags in ACF and there is only one spike at lag 24 in PACF, so $P = 1$ and $Q = 0$. Therefore, $SARIMA(0,1,0)(1,1,0)_{24}$ model is selected as the forecasting model for the weekdays' load demand in August 2015. Its RMSPE and MAPE are 3.58% and 2.01% respectively. The formula of $SARIMA(0,1,0)\ (1,1,0)_{24}$ model can be expressed as

$$(1 - \Phi_1 B^{24})(1 - B)(1 - B^{24})Z_t = a_t \tag{5-3}$$

where Φ_1 is the seasonal autoregressive operator P. Thus, the time series forecasting function can be expressed as

$$Z_t = Z_{t-1} + (1 + \Phi_1)Z_{t-24} - (1 + \Phi_1)Z_{t-25} - \Phi_1 Z_{t-48} + \Phi_1 Z_{t-49} + a_t \tag{5-4}$$

where the value of Φ_1 is changed at each step, because the forecasting process uses the rolling-window forecast method.

5.3.1.3. ANN model

For the parameter determination of ANN model on weekdays, 10 and 20 hidden neurons and 2, 4 and 6 delays are selected separately to find the best forecasting model. Each set of data is trained 1000 times for forecasting and the result with the minimum RMSPE and MAPE are obtained. Then compare these minimum RMSPE and MAPE values to select the best forecasting model. The minimum RMSPE and MAPE of ANN models with different neurons and delays for weekdays' load demand forecasts in August 2015 are shown in Table 5-2.

Table 5-2: The minimum RMSPE and MAPE of different ANN models for weekdays' load demand forecast in August 2015

Models	**RMSPE,** %	**MAPE,** %
ANN(10 neurons, 2 delays)	4.59	3.26
ANN(10 neurons, 4 delays)	4.18	3.03
ANN(10 neurons, 6 delays)	4.02	2.89
ANN(20 neurons, 2 delays)	4.71	3.29
ANN(20 neurons, 4 delays)	4.18	2.86
ANN(20 neurons, 6 delays)	4.33	3.12
ANN(30 neurons, 2 delays)	4.97	3.53
ANN(30 neurons, 4 delays)	4.45	3.33
ANN(30 neurons, 6 delays)	4.45	3.12

It can be seen from Table 5-2 that the ANN model with 10 neurons and 6 delays has the smallest RMSPE and second smallest MAPE. So the ANN model with 10 neurons and 6 delays is selected as the forecasting model for the weekdays' load demand in August 2015. It should be noted that once the optimal forecasting result of the ANN model is obtained, it must be saved or the result of the next set of training will be completely different.

5.3.2. Parameter determination for weekends of August 2015

For the forecasting on weekends, the historical load demands from 1st to 23rd August 2015 (8 days) are used as input data to forecast the results from 29th to 30th August 2015 (2 days).

5.3.2.1. ARIMA model

The parameter determination of ARIMA model on weekends is the same as weekdays. The range of model parameters can be selected based on the original and differenced ACF and PACF figures. Then compare the results of RMSPE and MAPE of these models to get the best model. The sample ACF and PACF after 2nd differencing are plotted in Figure 5-17.

Figure 5-17 shows that the sample ACF and PACF after 2nd differencing are stationary now. It can be seen from Figure 5-17 that $ARIMA(0,2,0)$, $ARIMA(0,2,1)$, $ARIMA(1,2,0)$, $ARIMA(1,2,1)$, $ARIMA(2,2,0)$ and $ARIMA(2,2,1)$ six models might be appropriate for this set of data. Among them, $ARIMA(1,2,1)$ model is selected as the forecasting model for the weekends' load demand in August 2015 because it has the smallest RMSPE and MAPE. Its RMSPE and MAPE are 4.12% and 2.61% respectively.

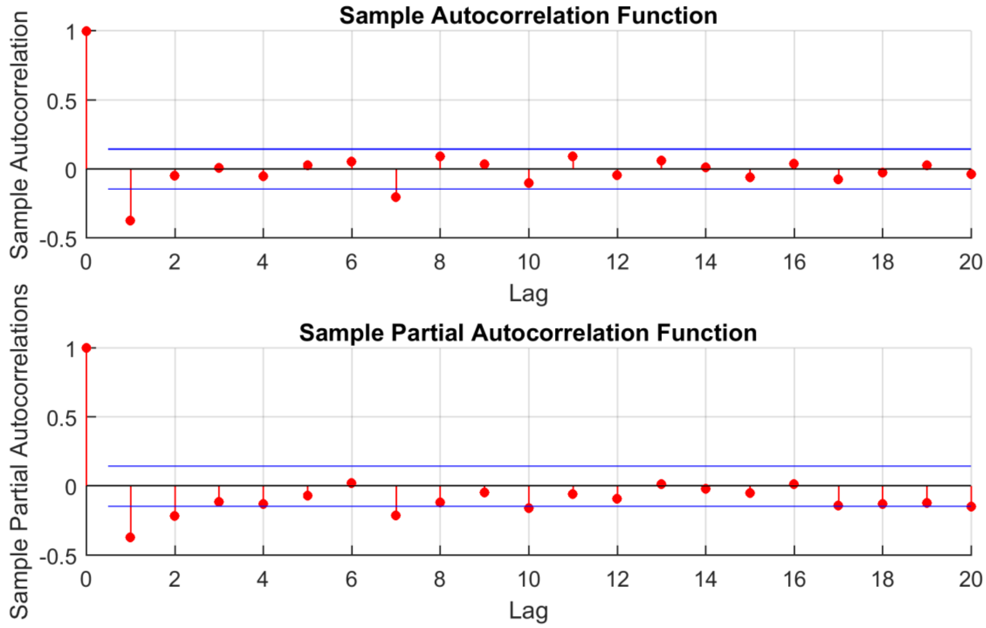


Figure 5-17: ACF and PACF of load demand for weekends in August 2015 after 2nd differencing

The formula of $ARIMA(1, 2, 1)$ model can be expressed as

$$(1 - \emptyset_1 B)(1 - B)^2 Z_t = (1 + \theta_1 B)a_t \tag{5-5}$$

And the time series forecasting function can be expressed as

$$Z_t = (2 + \emptyset_1)Z_{t-1} + (1 - 2\emptyset_1)Z_{t-2} - \emptyset_1 Z_{t-3} + a_t + \theta_1 a_{t-1} \tag{5-6}$$

where the value of $\emptyset_1$and θ_1 are changed at each step, because the forecasting process uses the rolling-window forecast method.

5.3.2.2. SARIMA model

The parameter determination of SARIMA model on weekends is the same as weekdays. In addition to the non-seasonal parameters p, d, q in the ARIMA model, the SARIMA model also has the seasonal parameters P, D, Q. Then compare the results of RMSPE and MAPE of these models to get the best model. The sample ACF and PACF after 1st and 24th differencing are plotted in Figure 5-18.

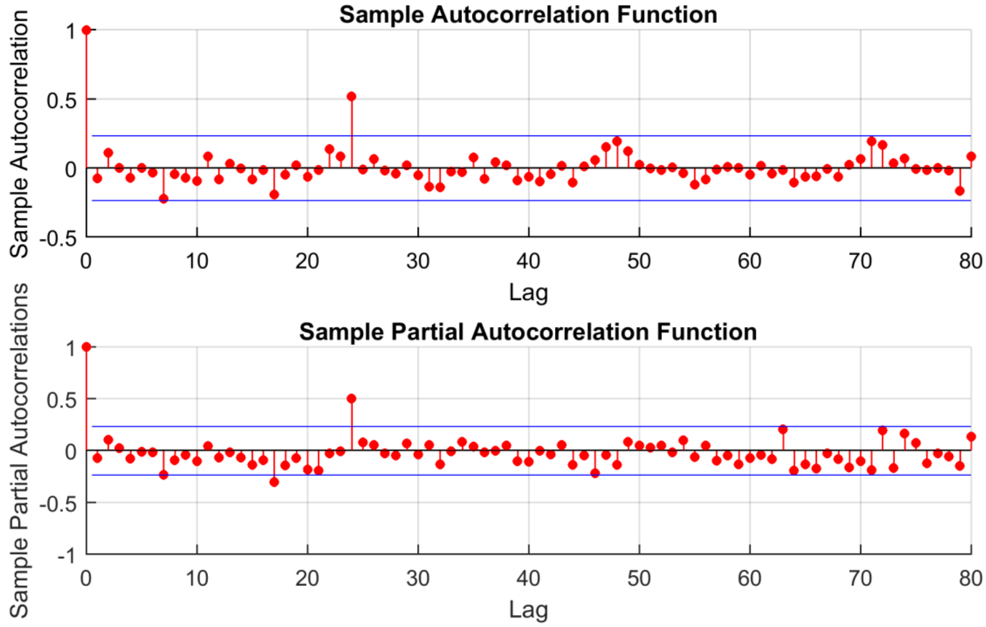


Figure 5-18: ACF and PACF of load demand for weekends in August 2015 after 1st and 24th differencing

It can be seen in Figure 5-18 that the sample ACF and PACF after the 1st and 24th differencing are stationary process now. According to the differencing times, $d = 1$ and $D = 1$. For the non-seasonal terms, ACF and PACF all decay to zero after lag 0 directly, so $p = 0$ and $q = 0$. For the seasonal terms, ACF and PACF exponential decay to zero after the seasonal lag 24, so $P = 1$ and $Q = 1$. Therefore, $SARIMA(0, 1, 0)(1, 1, 1)_{24}$ model is selected as the forecasting model for the weekends' load demand in August 2015. Its RMSPE and MAPE are 2.42% and 1.71% respectively.

The formula of $SARIMA(0, 1, 0)\ (1, 1, 1)_{24}$ model can be expressed as

$$(1 - \Phi_1 B^{24})(1 - B)(1 - B^{24})Z_t = (1 + \Theta_1 B^{24})a_t \tag{5-7}$$

where Φ_1 and Θ_1 are the seasonal autoregressive operator P and moving-average operator Q. Thus, the time series forecasting function can be expressed as

$$Z_t = Z_{t-1} + (1 + \Phi_1)Z_{t-24} - (1 + \Phi_1)Z_{t-25} - \Phi_1 Z_{t-48} + \Phi_1 Z_{t-49}$$

$$+a_t + \Theta_1 a_{t-24} \tag{5-8}$$

where the value of Φ_1 and Θ_1 are changed at each step, because the forecasting process uses the rolling-window forecast method.

5.3.2.3. ANN model

The parameter determination of ANN model on weekends is the same as weekdays. The minimum RMSPE and MAPE of ANN models with different neurons and delays for weekends' load demand forecasts in August 2015 are shown in Table 5-3.

After comparing the minimum RMSPE and MAPE results of different models, it can be found that the ANN model with 10 neurons and 6 delays also has the smallest RMSPE and MAPE, and the values are 3.28% and 2.06% respectively. So it is selected as the forecasting model for the weekends' load demand in August 2015.

Table 5-3: The minimum RMSPE and MAPE of different ANN models for weekends' load demand forecast in August 2015

Models	**RMSPE,** %	**MAPE,** %
ANN(10 neurons, 2 delays)	3.54	2.23
ANN(10 neurons, 4 delays)	3.69	2.52
ANN(10 neurons, 6 delays)	3.28	2.06
ANN(20 neurons, 2 delays)	3.36	2.19
ANN(20 neurons, 4 delays)	3.48	2.26
ANN(20 neurons, 6 delays)	3.67	2.49
ANN(30 neurons, 2 delays)	3.51	2.26
ANN(30 neurons, 4 delays)	3.85	2.67
ANN(30 neurons, 6 delays)	4.03	2.89

All of the above forecasting model parameter determination processes are for the load demand of August 2015. The monthly load demand forecasts are carried out every month in the year from March 2015 to February 2016 and all the parameter determination processes are the same as in August 2015. The optimal ARIMA, SARIMA and ANN models for weekdays' load demand forecast in each month from March 2015 to February 2016 are listed in Appendix A. The optimal models for weekends' load demand are listed in Appendix B.

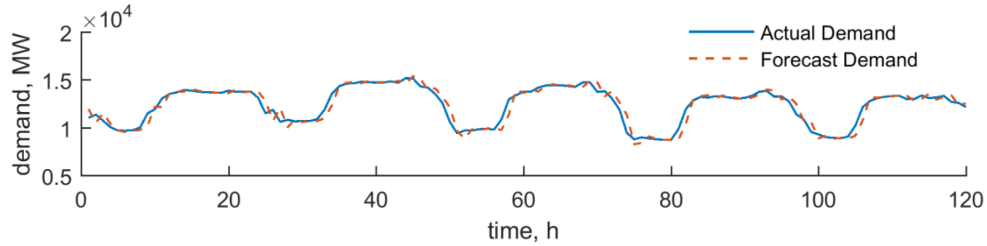
5.4. The comparison of monthly load demand forecasting results

For now, three load demand forecasting models (ARIMA, SARIMA and ANN) for the weekdays and weekends of August 2015 have been determined. This section will compare the one-step-ahead forecasting results of these three models on weekdays and weekends separately. The load demands of August 2015 are still used as the demonstration example. Then the forecasting results of these three models in each month (12 months) of the year from March 2015 to February 2016 will be compared to observe which model has the best performance. The models mentioned below refer to the optimal models that have been selected, and the parameters of the models will not be written in detail.

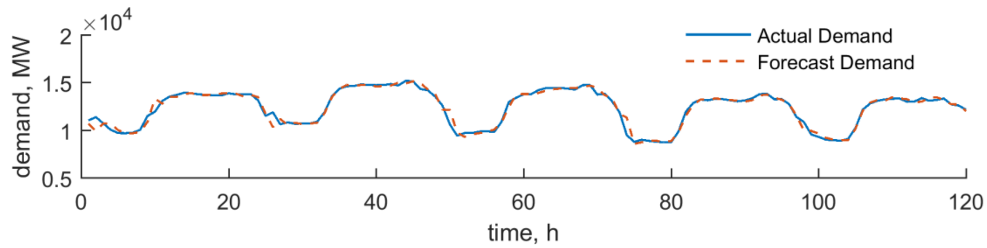
5.4.1. Monthly load demand forecasting results for weekdays

5.4.1.1. Forecasting results of August 2015

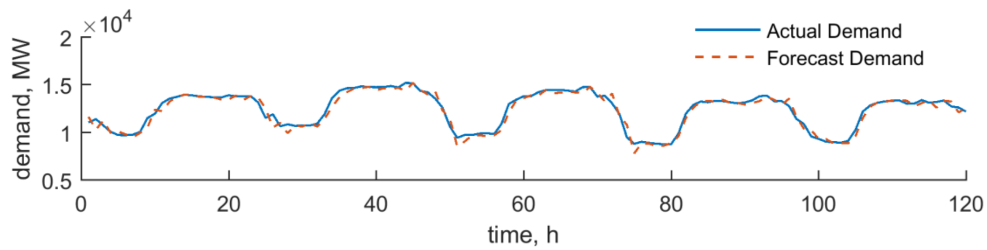
For August 2015, the historical load demand data on weekdays from 3rd to 21st August are used to forecast the results from 24th to 28th August. The forecast results of load demand by ARIMA, SARIMA and ANN models on weekdays are presented in Figure 5-19.



a. ARIMA model



b. SARIMA model



c. ANN model

Figure 5-19: Load demand forecast results on weekdays of August 2015

In figure 5-19, the solid and dashed lines are the actual and forecasting load demand respectively. From these figures it can be observed that all the forecast curves follow the actual curves. But it is difficult to determine which model has the best performance purely by observation. Therefore, the RMSPE and MAPE are used here for analysing forecast errors. Furthermore, in order to observe the MAPE at every hour, all the forecast errors on weekdays from 24th to 28th August are divided into 24 hours in a day. The results of forecast errors are presented in Table 5-4.

Table 5-4: Comparisons between the weekdays' load demand forecast errors by different models for August 2015

Time Period	**MAPE, %**		
	ARIMA	**SARIMA**	**ANN**
00:00–01:00	8.05	2.25	3.98
01:00–02:00	10.55	13.54	9.53
02:00–03:00	8.09	2.99	7.15
03:00–04:00	6.06	3.93	3.82
04:00–05:00	1.63	1.59	1.73
05:00–06:00	1.08	0.81	1.69
06:00–07:00	0.31	0.52	2.20
07:00–08:00	1.63	1.68	1.86
08:00–09:00	10.10	1.70	5.59
09:00–10:00	9.53	4.19	5.29
10:00–11:00	3.06	1.40	3.09
11:00–12:00	0.65	0.43	1.40
12:00–13:00	0.84	0.68	0.54
13:00–14:00	1.27	0.93	0.87
14:00–15:00	0.68	0.48	0.45
15:00–16:00	0.92	0.93	1.56
16:00–17:00	0.46	0.48	1.12
17:00–18:00	1.05	1.12	1.44
18:00–19:00	1.31	1.67	1.27
19:00–20:00	2.58	1.27	4.16
20:00–21:00	1.32	0.58	0.38
21:00–22:00	4.74	2.48	2.35
22:00–23:00	1.95	0.70	2.56
23:00–24:00	4.58	1.77	5.32
Average	3.43	2.01	2.89
RMSPE, %	5.20	3.58	4.02

It can be observed that the MAPE for weekdays stays in a range of 2.01-3.43% and the RMSPE of weekdays is from 3.58-5.20%. The most important point is that the results indicate that the RMSPEs and MAPEs of SARIMA models are all smaller than ARIMA and ANN models. That means on the weekdays' load demand forecasting of August 2015, SARIMA model performed better than the other models.

5.4.1.2. Forecasting results of 12 months

As in August 2015, the 12-month RMSPE and MAPE can be obtained from the forecasting results of each month from March 2015 to February 2016, and all the results are forecasted by their optimal models. Then the 12-month RMSPE and MAPE comparisons of three models for load demand forecast are shown in Table 5-5.

Table 5-5: 12-month RMSPE and MAPE comparisons of different models for weekdays' load demand forecast

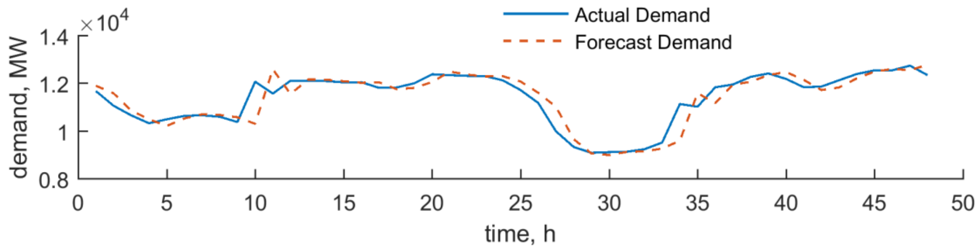
Month	**RMSPE, %**			**MAPE, %**		
	ARIMA	**SARIMA**	**ANN**	**ARIMA**	**SARIMA**	**ANN**
2015.03	4.99	3.71	4.08	3.63	2.43	2.95
2015.04	4.20	2.22	3.94	2.75	1.54	2.52
2015.05	4.33	3.75	4.21	2.98	2.31	2.87
2015.06	4.11	2.58	3.93	2.76	1.65	2.74
2015.07	4.22	4.39	4.80	2.86	2.21	3.27
2015.08	5.20	3.58	4.02	3.43	2.01	2.89
2015.09	4.30	2.88	3.73	3.06	1.70	2.58
2015.10	5.88	4.11	5.57	4.11	2.88	3.99
2015.11	7.11	4.57	7.52	5.31	3.20	6.06
2015.12	8.23	8.67	9.84	5.08	5.02	5.59
2016.01	4.89	3.19	4.39	3.56	2.18	3.11
2016.02	3.56	2.30	3.88	2.50	1.58	2.62

It can be observed from Table 5-5 that almost all the RMSPEs and MAPEs of SARIMA models are smaller than the other two models for the load demand forecast on weekdays. Most of the RMSPEs and MAPEs of ANN models are smaller than ARIMA model. That means in this set of data, the SARIMA models have a better forecasting accuracy than the other two models, and the ANN models have a better forecasting accuracy than the ARIMA models. Thus, SARIMA is the optimal forecasting model for weekdays' load demand forecast. Also it can be observed that the RMSPEs and MAPEs on December 2015 are bigger than the other months. That means the load demand forecast results on weekdays on December 2015 are less accuracy than the other months.

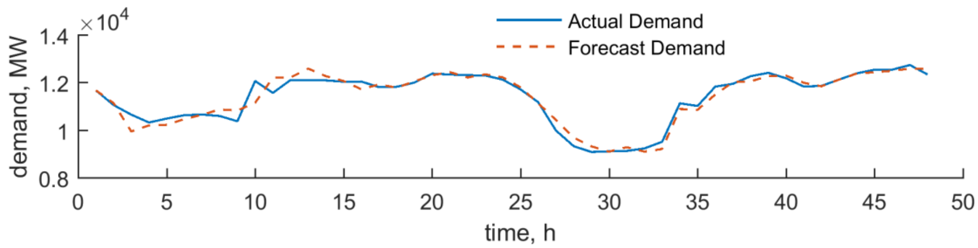
5.4.2. Monthly load demand forecasting results for weekends

5.4.2.1. Forecasting results of August 2015

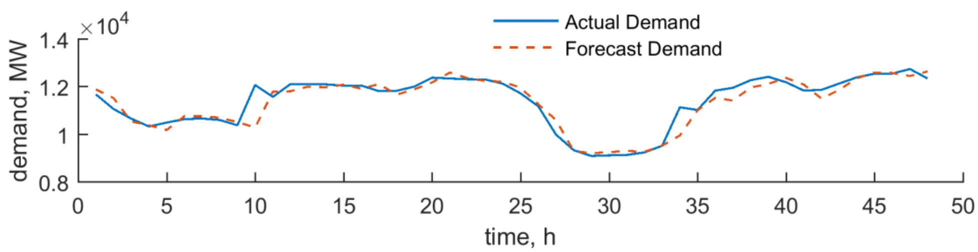
For August 2015, the historical load demand data on weekends from 1st to 23rd August 2015 are used to forecast the results from 29th to 30th August 2015. The forecast results of load demand by ARIMA, SARIMA and ANN models on weekends are presented in Figure 5-20.



a. ARIMA model



b. SARIMA model



c. ANN model

Figure 5-20: Load demand forecast results on weekends of August 2015

In figure 5-20, the solid and dashed lines are the actual and forecasting load demand respectively. From these figures it can be observed that all the forecast curves follow the actual curves. But it is difficult to determine which model has the best performance purely by observation. Therefore, the RMSPE and MAPE are used here for analysing forecast errors. Furthermore, in order to observe the MAPE at every hour, all the forecast errors on weekends from 29th to 30th August are divided into 24 hours in a day. The results of forecast errors are presented in Table 5-6.

Table 5-6: Comparisons between the weekends' load demand forecast errors by different models for August 2015

Time Period	**MAPE, %**		
	ARIMA	**SARIMA**	**ANN**
00:00–01:00	2.49	0.38	1.91
01:00–02:00	4.26	0.57	2.45
02:00–03:00	6.06	5.50	3.60
03:00–04:00	2.56	2.52	0.41
04:00–05:00	1.47	2.54	2.12
05:00–06:00	1.16	0.84	1.29
06:00–07:00	0.22	0.90	1.39
07:00–08:00	0.84	2.03	0.60
08:00–09:00	2.29	3.77	0.67
09:00–10:00	14.21	4.86	12.71
10:00–11:00	6.97	3.47	0.99
11:00–12:00	5.10	1.86	2.53
12:00–13:00	0.28	2.29	2.66
13:00–14:00	1.07	1.61	1.76
14:00–15:00	0.48	0.67	1.37
15:00–16:00	1.29	1.79	1.29
16:00–17:00	2.29	1.14	2.32
17:00–18:00	0.92	0.22	2.22
18:00–19:00	2.05	0.21	1.59
19:00–20:00	2.06	0.32	0.97
20:00–21:00	0.81	0.83	1.21
21:00–22:00	0.43	0.58	0.29
22:00–23:00	0.79	0.78	1.41
23:00–24:00	2.47	1.33	1.57
Average	2.61	1.71	2.06
RMSPE, %	4.12	2.42	3.28

It can be observed that the MAPE for weekends stays in a range of 1.71-2.61% and the RMSPE of weekends is from 2.42-4.12%. The most important point is that the results indicate that the RMSPEs and MAPEs of SARIMA models are all smaller than ARIMA and ANN models. That means on the weekends' load demand forecasting of August 2015, SARIMA model performed better than the other models.

5.4.2.2. Forecasting results of 12 months

As in August 2015, the 12-month RMSPE and MAPE can be obtained from the forecasting results of each month from March 2015 to February 2016, and all the results are forecasted by their optimal models. Then the 12-month RMSPE and MAPE comparisons of three models for load demand forecast are shown in Table 5-7.

Table 5-7: 12-month RMSPE and MAPE comparisons of different models for weekends' load demand forecasts

Month	**RMSPE, %**			**MAPE, %**		
	ARIMA	**SARIMA**	**ANN**	**ARIMA**	**SARIMA**	**ANN**
2015.03	20.97	18.85	18.99	7.49	6.22	7.76
2015.04	4.44	3.10	4.73	3.19	2.04	3.28
2015.05	4.77	3.63	4.44	3.52	2.63	3.25
2015.06	4.72	3.79	4.02	2.64	2.06	2.77
2015.07	3.15	5.85	3.63	2.29	2.95	2.90
2015.08	4.12	2.42	3.28	2.61	1.71	2.06
2015.09	5.14	3.71	3.28	3.58	2.66	2.38
2015.10	4.59	3.94	4.04	3.44	2.85	2.94
2015.11	4.95	4.83	3.95	3.85	3.08	2.78
2015.12	5.15	4.47	4.44	3.71	3.17	3.28
2016.01	5.63	3.24	4.93	3.64	2.14	2.99
2016.02	4.51	2.40	4.07	3.00	1.71	2.97

It can be observed from Table 5-7 that almost all the RMSPEs and MAPEs of SARIMA models are smaller than the other two models for the load demand forecast on weekends. Most of the RMSPEs and MAPEs of ANN models are smaller than ARIMA model. That means in this set of data, the SARIMA models have a better forecasting accuracy than the other two models, and the ANN models have a better forecasting accuracy than the ARIMA models. Thus, SARIMA is the optimal forecasting model for weekends' load demand forecast. Also it can be observed that the RMSPEs and MAPEs on March 2015 are much bigger than the other months. That means the load demand forecast results on weekends on March 2015 are less accuracy than the other months.

5.4.3. Discussion of results

It can be seen from Table 5-5 and 5-7 that except for March and December 2015, the RMSPEs and MAPEs of every month on weekends are similar with weekdays. That means there is not much different between the forecasting accuracy of weekdays and weekends. According to the comparison of RMSPEs and MAPEs for 12 months of the year, it can be found that the SARIMA model also has a better load demand forecasting performance than ARIMA and ANN models, no matter for weekdays or weekends. Therefore it will be only use SARIMA models to forecast the load demand in the following part of this thesis.

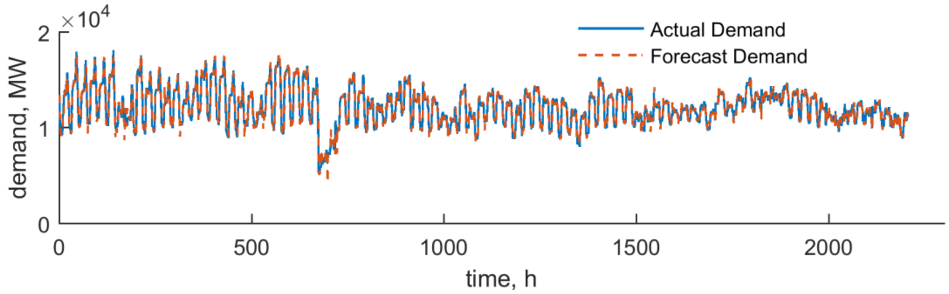
5.5. Seasonal load demand forecasting

For now, the load demand forecasts from March 2015 to February 2016 on weekdays and weekends are already achieved. For separately forecasting the monthly weekdays and weekends load demands, the advantage is that the forecasting accuracy for each month can be clearly observed, and the forecasting accuracy of weekdays and weekends for each month can be compared easily. However, the disadvantage is that the observation data is not enough, especially for the load demands of weekends. Therefore, in order to get more accurate forecasting results and observe the difference in load demand forecasts for four seasons of the year, the seasonal load demand will be forecasted in this section.

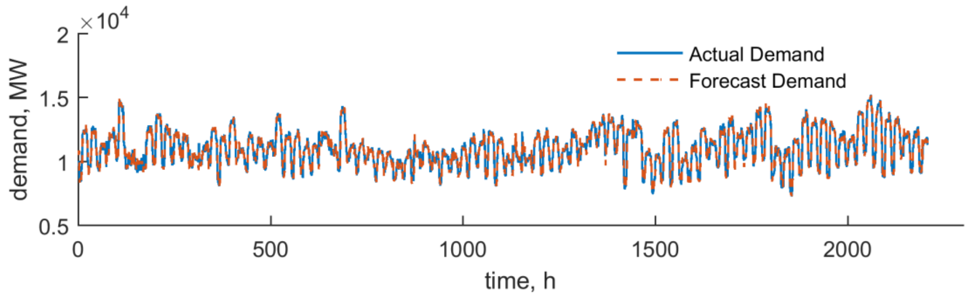
In the seasonal forecasts, the load demands on weekdays and weekends are not separately forecasted and they are combined into continuous data. Two methods are used to forecast the seasonal load demand from March 2015 to February 2016 — continuous historical data method and seasonal separation method. The one-hour-ahead of load demand forecasting is implemented here.

5.5.1. Continuous historical data method

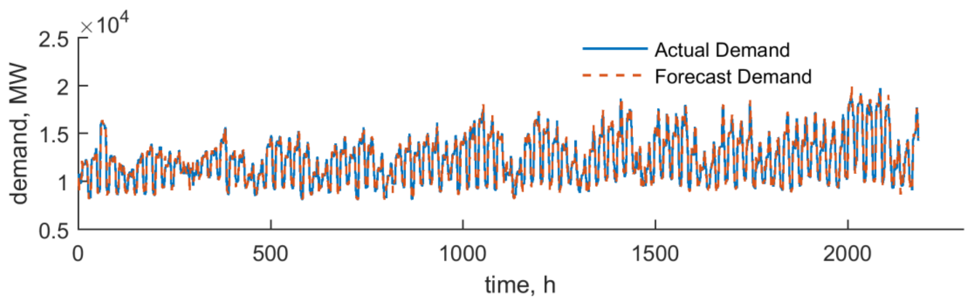
For the continuous historical data method, the load demands from March 2014 to February 2015 are used to forecast the seasonal load demands from March 2015 to February 2016. For each season, the load demands of last year (12 months) are used as input data to forecast the results of next season (3 months). The seasonal load demand forecast results by continuous historical data method are shown in Figure 5-21.



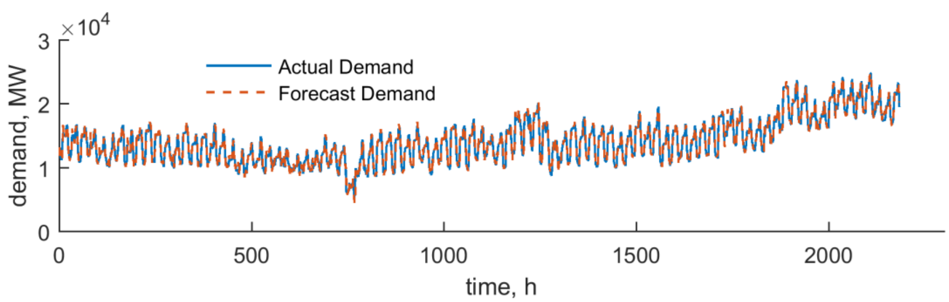
a. spring



b. summer



c. autumn



d. winter

Figure 5-21: Seasonal load demand forecast results by continuous historical data method

After the load demand forecasting for each season, the results of seasonal RMSPE and MAPE from March 2015 to February 2016 are shown in Table 5-8.

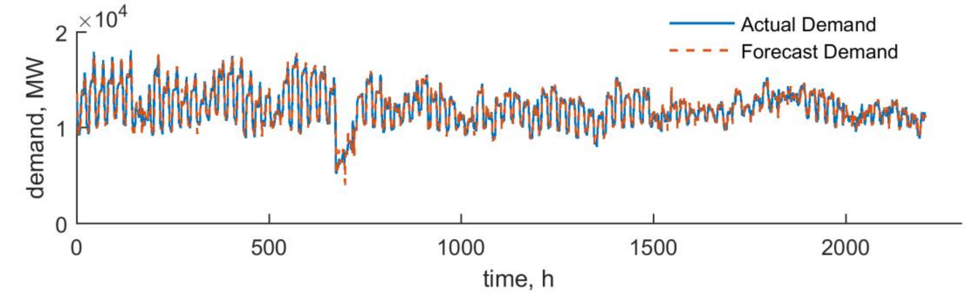
Table 5-8: Seasonal RMSPE and MAPE for load demand forecast by continuous historical data method from March 2015 to February 2016

Seasons	**RMSPE,** %	**MAPE,** %
Spring	4.56	2.42
Summer	3.58	2.15
Autumn	4.37	2.77
Winter	4.53	2.77

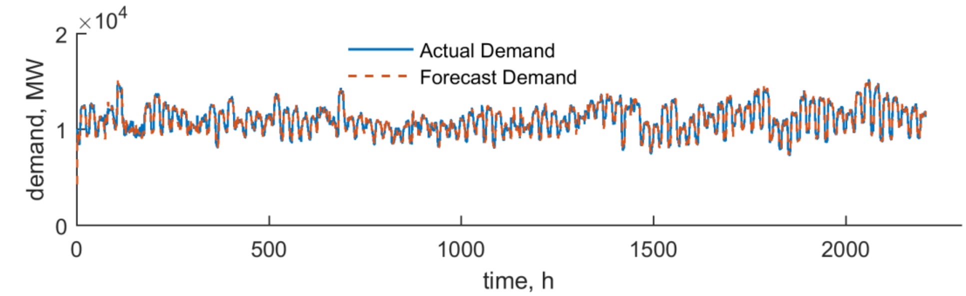
It can be seen from Table 5-8 that the RMSPE and MAPE of spring, autumn and winter are similar. The smallest RMSPE and MAPE are all happened in summer, and the values are 3.58% and 2.15%. That means summer is the most accurate season for load demand forecasting in this year.

5.5.2. Seasonal separation method

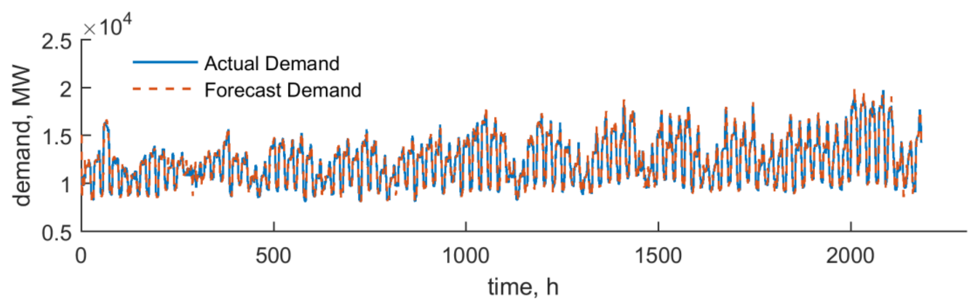
For the seasonal separation method, the load demands from March 2013 to February 2015 to forecast the seasonal load demands from March 2015 to February 2016, but the data in different seasons are used separately. For each season, the load demands for the same season in the previous two years (6 months) are used as input data to forecast the load demands for the corresponding season (3 months) of the next year. The seasonal load demand forecast results by seasonal separation method are shown in Figure 5-22.



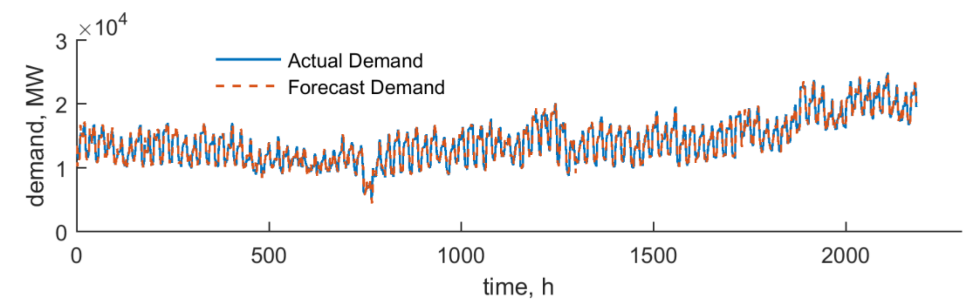
a. spring



b. summer



c. autumn



d. winter

Figure 5-22: Seasonal load demand forecast results by seasonal separation method

After the load demand forecasting for each season by seasonal separation method, the results of seasonal RMSPE and MAPE from March 2015 to February 2016 are shown in Table 5-9.

Table 5-9: Seasonal RMSPE and MAPE for load demand forecast by seasonal separation method from March 2015 to February 2016

Seasons	**RMSPE,** %	**MAPE,** %
Spring	4.64	2.46
Summer	3.88	2.25
Autumn	4.62	2.87
Winter	4.54	2.78

It can be seen from Table 5-9 that forecast results of all the four seasons are similar with Table 5-8. With seasonal separation method, the RMSPE and MAPE of spring, autumn and winter are still similar. Also, the smallest RMSPE and MAPE are all happened in summer, and the values are 3.88% and 2.25%. So after adopting the seasonal separation method, summer is still the most accurate season for load demand forecasting in this year. Furthermore, all of the RMSPE and MAPE in Table 5-9 are bigger than the values in Table 5-8. Thus for this set of data, using the continuous historical data method to forecast the seasonal load demand is better than the seasonal separation method. The forecast results achieved by the continuous historical data method will be used to perform risk analysis in later chapters.

5.6. Annual load demand forecasting

In the annual forecast, the purpose is to forecast the load demand for the year from March 2015 to February 2016 based on the historical input data. In order to compare the impact of different rolling window sizes on forecasting accuracy, the annual forecast uses three different sizes of input data — one month, six months and one year. As with seasonal forecast, the load demands for weekdays and weekends in the annual forecast are not separately forecasted but merged into continuous data.

As introduced before, the annual load demand forecasting processes based on different input data sizes are as follows:

- **Input data for one month:** the one-month load demands of February 2015 are used to forecast the annual load demands from March 2015 to February 2016. The rolling-window size is 673 hours.
- **Input data for six months:** the six-month load demands from September 2014 to February 2015 are used to forecast the annual load demands from March 2015 to February 2016. The rolling-window size is 4345 hours.
- **Input data for one year:** the one-year load demands from March 2014 to February 2015 are used to forecast the annual load demands from March 2015 to February 2016. The rolling-window size is 8761 hours.

After the annual load demand is forecasted based on the input data of one month, six months and one year, the annual RMSPE and MAPE results based on different input data sizes from March 2015 to February 2016 are shown in Table 5-10.

Table 5-10: RMSPE and MAPE for annual load demand forecast by different input data sizes from March 2015 to February 2016

Input data size	**RMSPE,** %	**MAPE,** %
One month	4.38	2.58
Six months	4.29	2.53
One year	4.28	2.53

It can be seen from Table 5-10 that the RMSPE and MAPE for annual forecasts by three different input data sizes are similar. But the minimum RMSPE and MAPE are appeared when the input data is one year, which means the forecast result is more accurate with the one-year input data. Since the rolling window size is proportional to the input data size, the forecast result is more accurate when the rolling window size is larger. Therefore, the one-year input data should be selected to forecast the annual load demand in this thesis.

The annual load demand forecast results based on one year input data are shown in Figure 5-23.

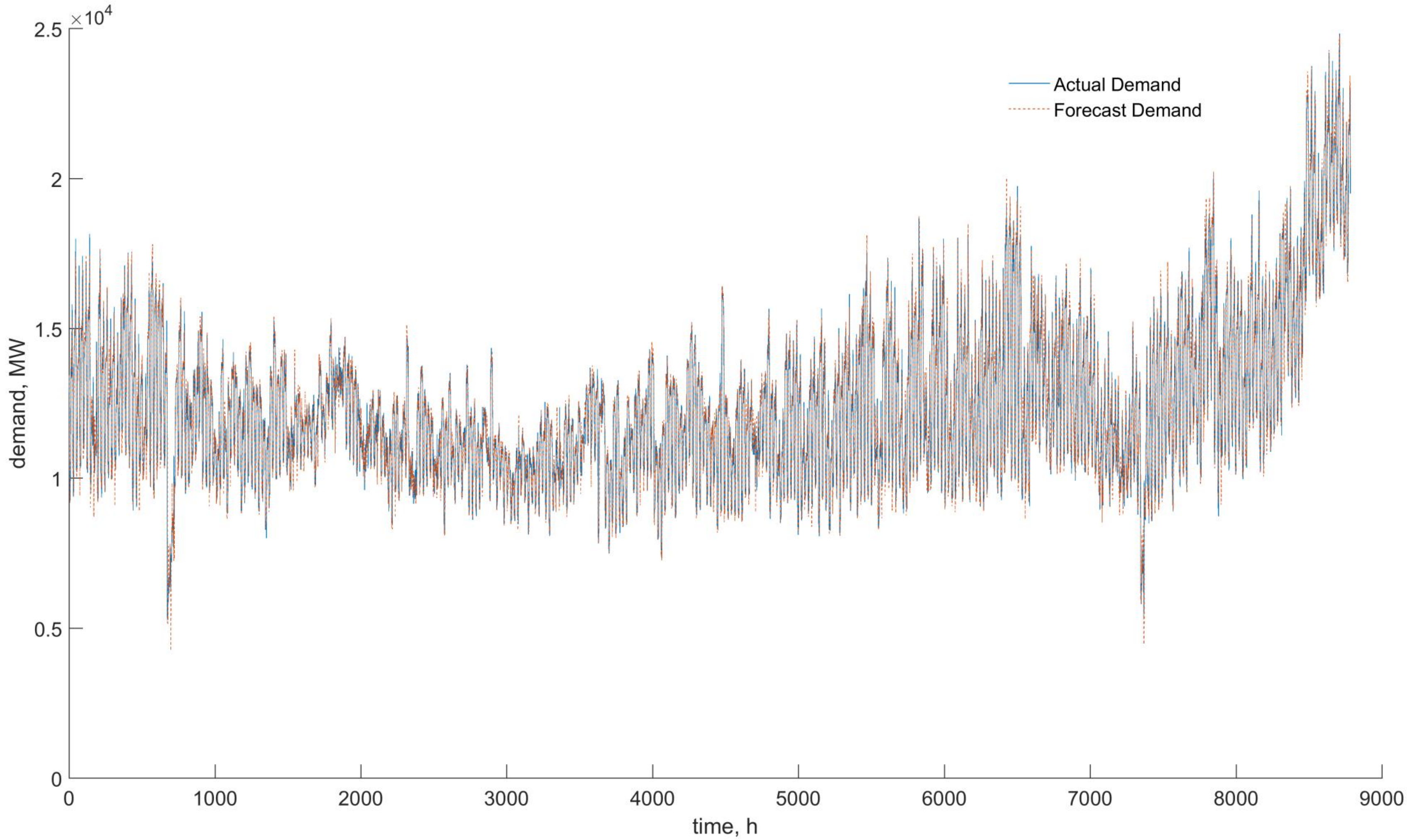


Figure 5-23: Annual load demand forecast results based on one year input data

5.7. Comparison of one-step-ahead and multi-step-ahead load demand forecasting

The one-step-ahead forecasts with rolling-window forecast method have been used in the seasonal load demand forecasting from March 2015 to February 2016. In theory, the one-step-ahead forecasts have the most accurate forecasting results, because each step of the one-step-ahead forecasts is based on the actual historical data, but the multi-step-ahead forecasts are based on the forecasted data of the sub-steps. But the advantage of multi-step-ahead forecasts is that the forecasting range is larger than the one-step-ahead forecasts, and it can forecast the data for a few hours or even days directly [151]. In order to compare the forecasting results by one-step-ahead and multi-step-ahead forecasts, the one-year data from March 2014 to February 2015 are used to forecast the seasonal and annual load demands from March 2015 to February 2016 by one-step-ahead, 6-step-ahead, 12-step-ahead and 24-step-ahead in this section.

The results of one-step-ahead seasonal and annual forecasts have been obtained in section 5.5 and 5.6. For the 6-step-ahead, 12-step-ahead and 24-step-ahead forecasts, the difference to one-step-ahead is that after how many forecast steps the parameters in the SARIMA model will change once based on the actual historical data. The results of seasonal and annual RMSPE and MAPE by one-step-ahead, 6-step-ahead, 12-step-ahead and 24-step-ahead forecasting are shown in Table 5-11 and Table 5-12 respectively.

Table 5-11: Seasonal and annual RMSPE for load demand forecast by one-step-ahead and multi-step-ahead forecasts from March 2015 to February 2016

Time range	**RMSPE,** %			
	1-step-ahead	**6-step-ahead**	**12-step-ahead**	**24-step-ahead**
Spring	4.56	8.97	10.93	14.83
Summer	3.58	7.34	8.28	10.01
Autumn	4.37	9.10	9.42	11.76
Winter	4.53	8.50	9.94	13.05
Annual	4.28	8.50	9.69	12.54

Table 5-12: Seasonal and annual MAPE for load demand forecast by one-step-ahead and multi-step-ahead forecasts from March 2015 to February 2016

Time range	**MAPE,** %			
	1-step-ahead	**6-step-ahead**	**12-step-ahead**	**24-step-ahead**
Spring	2.42	5.28	6.44	9.08
Summer	2.15	4.67	5.44	7.41
Autumn	2.77	6.20	6.69	9.13
Winter	2.77	5.62	6.66	8.63
Annual	2.53	5.44	6.31	8.56

It can be observed from Table 5-11 and 5-12 that the seasonal and annual values of RMSPE and MAPE made by one-step-ahead forecasts are all the smallest. The results of 6-step-ahed forecasting are bigger than one-step ahead forecasting. Then the RMSPEs and MAPEs of 12-step-ahead are bigger than 6-step-ahed forecasting and 24-step-ahead are bigger than 12-step-ahed forecasting. The results proved that the accuracy of one-step-ahead forecasts is the highest, and the forecasting accuracy decreases with the increase of the single forecasting range. Also, it can be found that summer is still the most accurate season for load demand forecasting in all the results.

For the users of the forecasting methods, they can choose whatever they want in the forecasting process. If they want more accurate forecasting results, then choose the on-step-ahead forecasts. If they want to get a farther forecasting range, then choose the multi-step-ahead forecast. This thesis only considers the accuracy of load forecasting, so all the load demand forecasts are adopted by one-step-ahead forecasting.

5.8. Summary

This chapter introduced and assessed the ARIMA, SARIMA and ANN forecasting models for load demand forecasts based on the day-ahead auction data in UK electricity market. Firstly, the rolling-window forecast method was presented, and the rolling windows for the monthly, seasonal, annual and multi-step-ahead load demand forecasts were detailed. In the monthly forecast, the forecasting process was divided into weekday and weekend parts. The load demands are forecasted after determining the parameters of each model. According to the forecasting accuracy in terms of RMSPE and MAPE, SARIMA models show more accuracy than ARIMA and ANN models for both monthly load demand forecasts in weekdays and weekends. Therefore SARIMA model is selected as the optimal model to forecast the load demand in the remaining part of this thesis. The monthly forecasting results also showed that the forecast errors for weekends are similar with weekdays on load demand forecast. Moreover, the seasonal load demands were forecasted by the continuous historical data method and seasonal separation method respectively. The results showed that the forecasts by the continuous historical data method are more accurate than the seasonal separation method. For both methods, summer is the most accurate season for load demand forecasts during the year. Also, the annual load demand forecasts were achieved based on one-month, six-month and one-year input data respectively. It showed that the result is more accurate when the rolling window size is larger. So the one-year input data should be selected to forecast the annual load demand in this thesis. At last, the one-step-ahead and multi-step-ahead forecasts were used to forecast the seasonal and annual load demands. Based on the results of seasonal and annual RMSPE and MAPE, it proved that one-step-ahead forecasts are more accurate than multi-step-ahead forecasts. Therefore, all the load demand forecast results for risk analysis that appear later in this thesis are completed by the one-step-ahead forecasts of SARIMA models based on the one-year continuous historical load demands.

In the UK electricity market, the electricity price is mainly determined based on the load demand forecasting situation and the quotation of the power producer. The electricity price is changed according to the load demand changes in the power system. Therefore, the electricity price will be forecasted after the load demand forecast is completed.

Chapter 6

Electricity price forecast and simulated results comparison

6.1. Introduction

In the electricity market, electricity price forecasting provides significant information which can help the electricity market participants to prepare corresponding bidding strategies to maximize their profits. Electricity prices can reflect the supply and demand relationship in the electricity market. In this chapter, ARIMA, SARIMA and ANN models are used to forecast the monthly electricity prices, and one optimal model will be selected from them. Then the seasonal, annual and multi-step-ahead electricity prices are forecasted. The electricity price data in the UK electricity market are used as an example. The RMSPE and MAPE are used to verify the forecast accuracy of different models.

In the monthly forecasts, the one-year data from March 2015 to February 2016 are divided into 12 months, and the data of each month are divided into weekdays and weekends. For weekdays, the data of three weeks are used for modelling to forecast one-week electricity prices, and the results are compared to the actual electricity prices in the fourth week. Similarly, for weekends, the data of three weeks are used for modelling to forecast one-week electricity prices, and the results are compared to the actual electricity prices in the fourth week. The monthly forecasts are achieved every month (12 months) from March 2015 to February 2016. The ARIMA, SARIMA and ANN models are all used in these forecasting processes and these forecast results are compared.

In the seasonal forecasts, the electricity price of weekdays and weekends are all merged together. In this chapter, there are two different methods are used to forecast the seasonal electricity prices from March 2015 to February 2016 — continuous historical data method and seasonal separation method. For the continuous historical data method, the 12-month continuous historical data are used for modelling to forecast electricity prices in the next season (3 months). For the seasonal separation method, the data of the same season in the previous two years are used for modelling to forecast the electricity prices for the corresponding season (3 months) in the next year. SARIMA models are used in these seasonal forecasting processes and the forecast results are compared.

In the annual forecasts, the electricity price of weekdays and weekends are also all merged together. This chapter makes three sets of annual electricity price forecasts. Firstly, the one-month data from January to February 2015 are used for modelling to forecast one-year electricity prices from March 2015 to February 2016. Secondly, the six-month data from September 2014 to February 2015 are used for modelling to forecast one-year electricity prices from March 2015 to February 2016. Thirdly, the one-year data from March 2014 to February 2015 are used for modelling to forecast one-year electricity prices from March 2015 to February 2016. These are to observe the effect of the size of the modelling data on the forecasting results.

At last, the comparison of one-step-ahead and multi-step-ahead electricity price forecasting is achieved in this chapter. In addition to the basic one-step-ahead forecasting, 6-step-ahead, 12-step-ahead and 24-step-ahead forecasting are also realized. The effect of multi-step-ahead forecasts on the forecasting accuracy is analysed by comparing these forecast results.

6.2. Data preparation for electricity price forecast

Like the load demand forecasting, the rolling-window forecast method is also used for the electricity price forecasting processes. If there is a data sample of size T and a rolling window of size m. The rolling window includes an input data of size I and a forecast horizon of size h. The size of the rolling window depends on the data sample size T and periodicity of the data. For the forecast horizon h, the most basic is one-step-ahead forecasting, and multi-step-ahead forecasting can also be performed according to the actual needs. RMSPE and MAPE are used to analyse the forecasting accuracy.

In this thesis, all the historical one-hour update electricity prices in the UK electricity wholesale market are obtained from UK N2EX, Nord Pool [152].

6.2.1. Data preparation for monthly forecast

For the monthly forecast, the historical one-hour update electricity prices from March 2015 to February 2016 in the UK electricity wholesale market are used. In order to make monthly forecasts, the one-year historical electricity prices are classified into 12 months. Since the load demand waveforms of weekdays and weekends are different, and the electricity price changes with the load demand, the waveforms of electricity price of weekdays and weekends should also be different. Therefore, the electricity price will be forecasted on weekdays and weekends separately in each month over the year.

6.2.1.1. Monthly forecast for weekdays

Generally in each month, the electricity prices in the first three weeks are used as modelling data, and the electricity prices in the last week are used as testing data. The forecast data on August 2015 are used as a demonstration example. The calendar for August 2015 is shown in Figure 6-1.

Weekdays					Weekends	
Monday	**Tuesday**	**Wednesday**	**Thursday**	**Friday**	**Saturday**	**Sunday**
					1	2
3	4	5	6	7	8	9
10	11	12	13	14	15	16
17	18	19	20	21	22	23
24	25	26	27	28	29	30
31						

Figure 6-1: The calendar for August 2015

It can be seen from Figure 6-1 that the weekday data for the first three weeks are from 3^{rd} to 21^{st} August and for the fourth week are from 24^{th} to 28^{th} August. That means the historical electricity prices on weekdays from 3rd to 21st August 2015 (15 days) are used as input data to forecast the results from 24th to 28th August 2015 (5 days).

For the weekday electricity price forecast, the historical data is updated hourly and one-step-ahead forecasting is implemented here. Therefore, in the rolling windows for August 2015 weekdays, the input data size I is 360 hours (24 hours × 15 days), the forecast horizon size h is 1 hour, the rolling-window size m is 361 hours (24 hours × 15 days + 1 hour), and the data sample size T is 480 hours (24 hours × 20 days). There are a total of 120 rolling windows ($(T - I)/ h$ = (480 – 360)/1). Then ARIMA, SARIMA and ANN models are used for forecasting separately.

6.2.1.2. Monthly forecast for weekends

Similar to the monthly forecast for the weekday, generally in each month, the electricity prices in the first three weeks are used as modelling data, and the electricity prices in the last week are used as testing data. The forecast data on August 2015 are used as a demonstration example.

However, it can be seen from Figure 6-1 that there are five weekends in August 2015, in which case the electricity prices in the first four weeks are used as modelling data, and the electricity prices in the last week are used as testing data. Therefore, the weekend data for the first four weeks are from 1st to 23rd August and for the fifth week are from 29th to 30th August. That means the historical electricity prices on weekends from 1st to 23rd August 2015 (8 days) are used as input data to forecast the results from 29th to 30th August 2015 (2 days).

For the weekend electricity price forecast, the historical data is updated hourly and one-step-ahead forecasting is implemented here. Therefore, in the rolling windows for August 2015 weekends, the input data size I is 192 hours (24 hours × 8 days), the forecast horizon size h is 1 hour, the rolling-window size m is 193 hours (24 hours × 8 days + 1 hour), and the data sample size T is 240 hours (24 hours × 10 days). There are a total of 48 rolling windows ($(T - I)/\ h$ = (240 – 192)/1). Then ARIMA, SARIMA and ANN models are used for forecasting separately.

The data of August 2015 are used as the demonstration example for monthly electricity price forecasting, and the same forecasting methods are achieved in each month over the year from March 2015 to February 2016 (12 months). The purpose of monthly forecast is to compare the electricity price forecast results for weekdays and weekends and to determine which model has the best forecasting accuracy in each month.

6.2.2. Data preparation for seasonal forecast

For the seasonal forecast, the historical one-hour update electricity prices from March 2013 to February 2016 in the UK electricity wholesale market are used. The purpose of the seasonal forecast is to forecast the electricity prices of four seasons in the year from March 2015 to February 2016 based on the historical data. In seasonal forecasts, the electricity prices on weekdays and weekends are not separately forecasted and they are combined into continuous data. There are two different methods for forecasting seasonal electricity price — continuous historical data method and seasonal separation method, and one-step-ahead forecasting is implemented for both methods.

6.2.2.1. Continuous historical data method

In the continuous historical data method, the electricity prices from March 2014 to February 2015 are used to forecast the seasonal electricity prices from March 2015 to February 2016. For each season, the electricity prices of last year (12 months) are used as modelling data, and the data of next season (3 months) are used as testing data. The Seasonal electricity price forecasting process by continuous historical data method is shown in Figure 6-2.

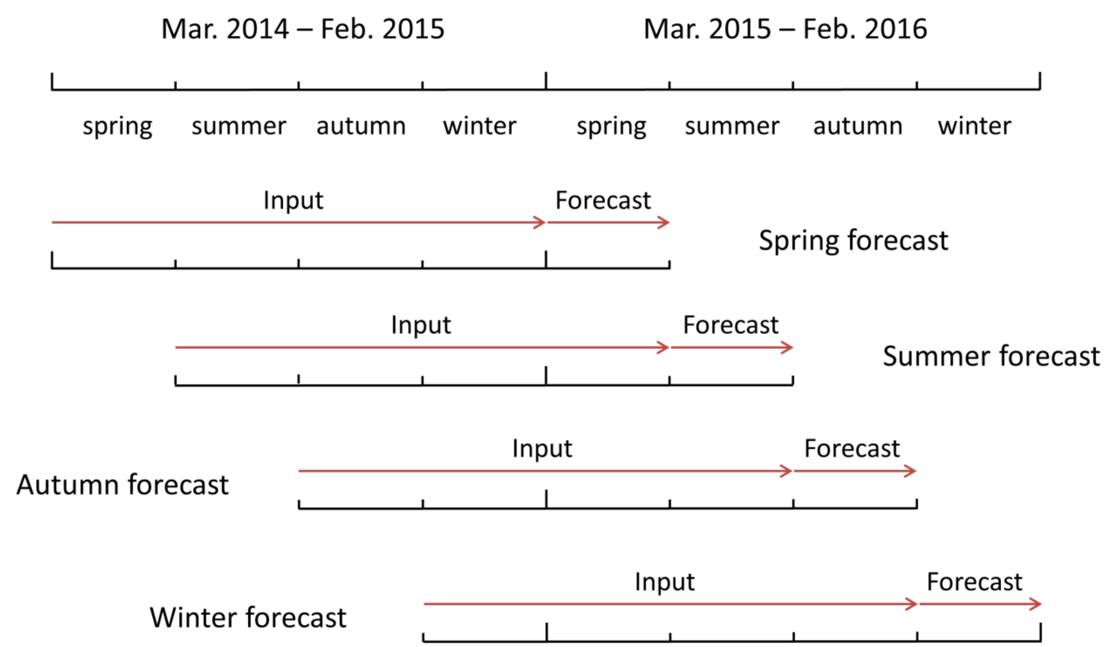


Figure 6-2: Seasonal electricity price forecasting process by continuous historical data method

It can be seen from Figure 6-2 that the electricity prices from March 2014 to February 2015 are used as input data to forecast the results from March to May 2015 (spring forecast). The electricity prices from June 2014 to May 2015 are used as input data to forecast the results from June to August 2015 (summer forecast). The electricity prices from September 2014 to August 2015 are used as input data to forecast the results from September to November 2015 (autumn forecast). The electricity prices from December 2014 to November 2015 are used as input data to forecast the results from December 2015 to February 2016 (winter forecast). Each step of the seasonal forecasting uses the actual electricity prices of the previous four seasons as input data to forecast the results for the next quarter.

Therefore, the sizes in the rolling window of the continuous historical data method are:

- Spring forecast: the input data size I is 8760 hours (24 hours × 365 days), the forecast horizon size h is 1 hour, the rolling-window size m is 8761 hours (24 hours × 365 days + 1 hour), and the data sample size T is 10968 hours (24 hours × (365 + 92) days). There are a total of 2208 rolling windows ($(T-I)/h$ = (10968 – 8760)$/1$).
- Summer forecast: the input data size I is 8760 hours (24 hours × 365 days), the forecast horizon size h is 1 hour, the rolling-window size m is 8761 hours (24 hours × 365 days + 1 hour), and the data sample size T is 10968 hours (24 hours × (365 + 92) days). There are a total of 2208 rolling windows ($(T-I)/h$ = (10968 – 8760)$/1$).
- Autumn forecast: the input data size I is 8760 hours (24 hours × 365 days), the forecast horizon size h is 1 hour, the rolling-window size m is 8761 hours (24 hours × 365 days + 1 hour), and the data sample size T is 10944 hours (24 hours

× (365 + 91) days). There are a total of 2184 rolling windows ($(T - I)/\, h$ = (10944 – 8760)$/1$).

- Winter forecast: the input data size I is 8760 hours (24 hours × 365 days), the forecast horizon size h is 1 hour, the rolling-window size m is 8761 hours (24 hours × 365 days + 1 hour), and the data sample size T is 10944 hours (24 hours × (365 + 91) days). There are a total of 2184 rolling windows ($(T - I)/\, h$ = (10944 – 8760)$/1$).

6.2.2.2. Seasonal separation method

In the seasonal separation method, the electricity prices from March 2013 to February 2015 are used to forecast the seasonal electricity prices from March 2015 to February 2016, but the data in different seasons are used separately. For each season, the electricity prices for the same season in the previous two years (6 months) are used as modelling data, and the data for the corresponding season (3 months) of the next year are used as testing data. The Seasonal electricity price forecasting process by seasonal separation method is shown in Figure 6-3.

It can be seen from Figure 6-3 that means the electricity prices from March to May in 2013 and 2014 are used as input data to forecast the results from March to May 2015 (spring forecast). The electricity prices from June to August in 2013 and 2014 are used as input data to forecast the results from June to August 2015 (summer forecast). The electricity prices from September to November in 2013 and 2014 are used as input data to forecast the results from September to November 2015 (autumn forecast). The electricity prices from December to the next February in 2013 and 2014 are used as input data to forecast the results from December 2015 to February 2016 (winter forecast).

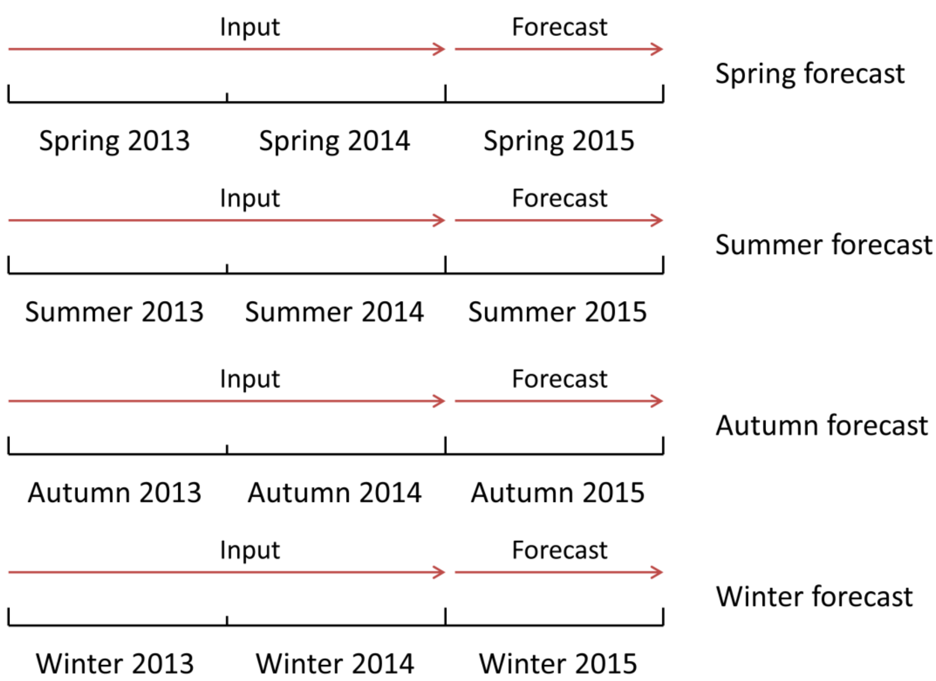


Figure 6-3: Seasonal electricity price forecasting process by seasonal separation method

Therefore, the sizes in the rolling window of the seasonal separation method are:

- Spring forecast: the input data size I is 4416 hours (24 hours × (92 + 92) days), the forecast horizon size h is 1 hour, the rolling-window size m is 4417 hours (24 hours × (92 + 92) days + 1 hour), and the data sample size T is 6624 hours (24 hours × (92 + 92 + 92) days). There are a total of 2208 rolling windows ($(T - I)/\,h$ = (6624 – 4416)/1).

- Summer forecast: the input data size I is 4416 hours (24 hours × (92 + 92) days), the forecast horizon size h is 1 hour, the rolling-window size m is 4417 hours (24 hours × (92 + 92) days + 1 hour), and the data sample size T is 6624 hours (24 hours × (92 + 92 + 92) days). There are a total of 2208 rolling windows ($(T - I)/\ h$ = (6624 – 4416)/1).
- Autumn forecast: the input data size I is 4368 hours (24 hours × (91 + 91) days), the forecast horizon size h is 1 hour, the rolling-window size m is 4369 hours (24 hours × (91 + 91) days + 1 hour), and the data sample size T is 6552 hours (24 hours × (91 + 91 + 91) days). There are a total of 2184 rolling windows ($(T - I)/\ h$ = (6552 – 4368)/1).
- Winter forecast: the input data size I is 4320 hours (24 hours × (90 + 90) days), the forecast horizon size h is 1 hour, the rolling-window size m is 4321 hours (24 hours × (90 + 90) days + 1 hour), and the data sample size T is 6504 hours (24 hours × (90 + 90 + 91) days). There are a total of 2184 rolling windows ($(T - I)/\ h$ = (6504 – 4320)/1).

Only SARIMA model is used for seasonal forecasts, as the SARIMA model performs better forecast results than ARIMA and ANN models in monthly forecasts. The specific forecasting process and comparison of results will be detailed in this chapter.

6.2.3. Data preparation for annual forecast

For the annual forecast, the historical one-hour update electricity prices from March 2014 to February 2016 in the UK electricity wholesale market are used. The purpose of the annual forecast is to forecast the one-year electricity prices from March 2015 to February 2016 based on the historical data. In annual forecasts, the electricity prices on weekdays and weekends are not separately forecasted and they are combined into continuous data. In order to compare the impact of the rolling window size on the forecasting results, the annual forecasts use three sizes of input data to forecast the electricity prices — one month, six months and one year.

6.2.3.1. Input data for one month

When the input data is one month, the one-month electricity prices of February 2015 are used to forecast the annual electricity prices from March 2015 to February 2016. The forecasting process is shown in Figure 6-4.

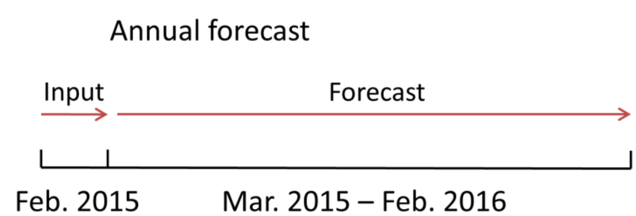


Figure 6-4: Annual electricity price forecasting process based on one-month input data

Therefore, in the rolling windows of annual forecast based on input data for one month, the input data size I is 672 hours (24 hours × 28 days), the forecast horizon size h is 1 hour, the rolling-window size m is 673 hours (24 hours × 28 days + 1 hour), and the data sample size T is 9456 hours (24 hours × (28 + 366) days). There are a total of 8784 rolling windows ($(T - I)/\ h$ = (9456 – 672)/1).

6.2.3.2. Input data for six months

When the input data is six months, the six-month electricity prices from September 2104 to February 2015 are used to forecast the annual electricity prices from March 2015 to February 2016. The forecasting process is shown in Figure 6-5.

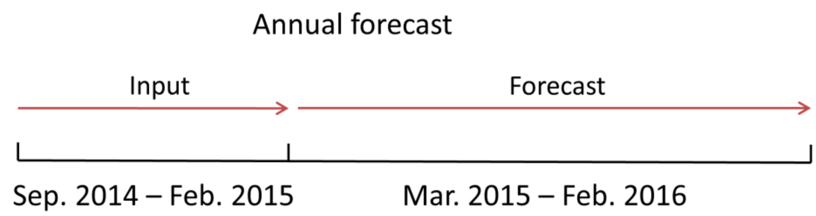


Figure 6-5: Annual electricity price forecasting process based on six-month input data

Therefore, in the rolling windows of annual forecast based on input data for six months, the input data size I is 4344 hours (24 hours × 181 days), the forecast horizon size h is 1 hour, the rolling-window size m is 4345 hours (24 hours × 181 days + 1 hour), and the data sample size T is 13128 hours (24 hours × (181 + 366) days). There are a total of 8784 rolling windows ($(T - I)/ h$ = (13128 – 4344)/1).

6.2.3.3. Input data for one year

When the input data is one year, the one-year electricity prices from March 2014 to February 2015 are used to forecast the annual electricity prices from March 2015 to February 2016. The forecasting process is shown in Figure 6-6.

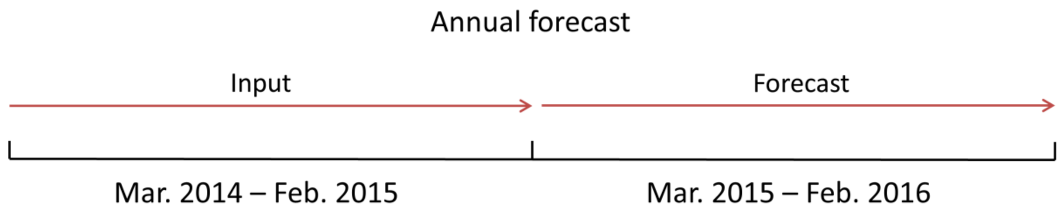


Figure 6-6: Annual electricity price forecasting process based on one-year input data

Therefore, in the rolling windows of annual forecast based on input data for one year, the input data size I is 8760 hours (24 hours × 365 days), the forecast horizon size h is 1 hour, the rolling-window size m is 8761 hours (24 hours × 365 days + 1 hour), and the data sample size T is 17544 hours (24 hours × (365 + 366) days). There are a total of 8784 rolling windows ($(T - I)/\ h$ = (17544 – 8760)$/1$).

SARIMA model is used for annual forecasts, and the comparison of results will be detailed in this chapter.

6.2.4. Data preparation for multi-step-ahead forecast

For the multi-step-ahead forecast, the historical one-hour update electricity prices from March 2014 to February 2016 in the UK electricity wholesale market are used. The purpose of the multi-step-ahead forecast is to compare the impact of one-step-ahead forecast and multi-step-ahead forecast on forecasting results. In the multi-step-ahead forecasts, the electricity prices from March 2014 to February 2015 are used to forecast the one-year electricity prices from March 2015 to February 2016 by different forecast horizons. 6-step-ahead forecasting, 12-step-ahead forecasting and 24-step-ahead forecasting are implemented in this chapter. The electricity price forecasting processes of 6-step-ahead, 12-step-ahead and 24-step-ahead forecast are shown in Figure 6-7.

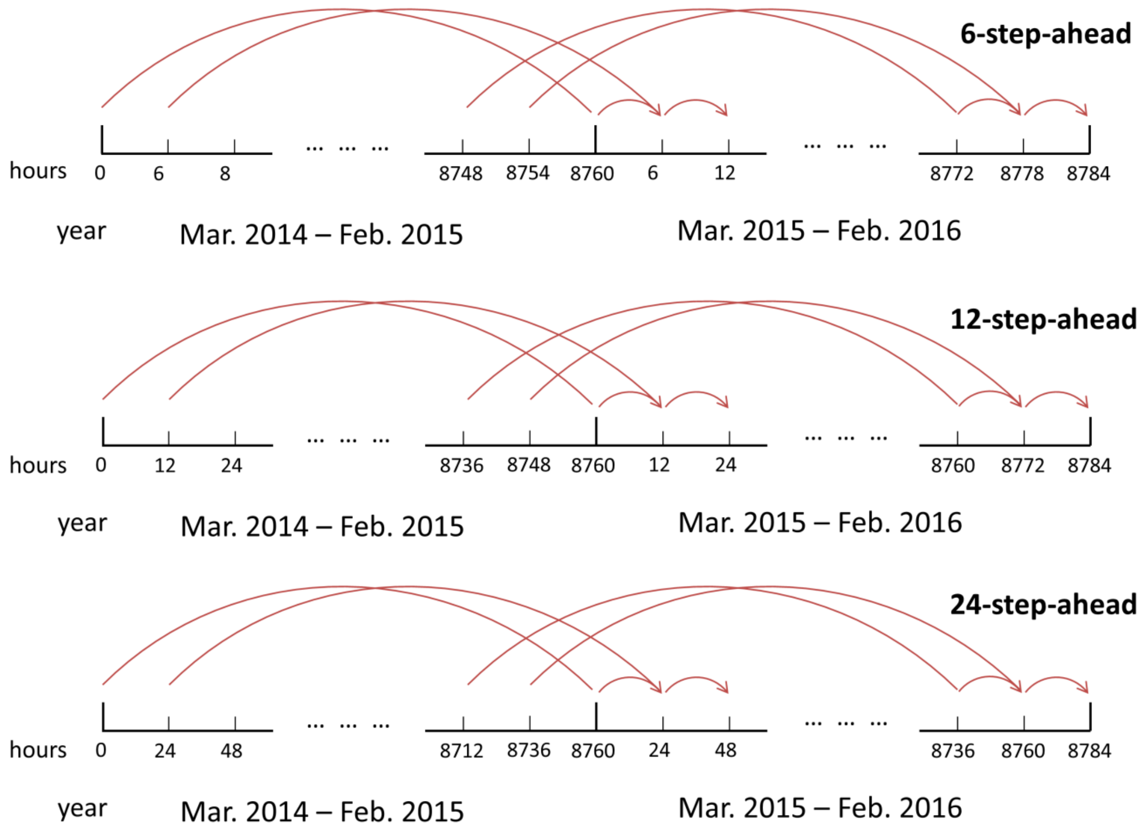


Figure 6-7: The electricity price forecasting processes of 6-step-ahead, 12-step-ahead and 24-step-ahead forecast

Therefore, the sizes in the rolling window of 6-step-ahead forecasting, 12-step-ahead forecasting and 24-step-ahead forecasting are:

- 6-step-ahead forecasting: the input data size I is 8760 hours (24 hours × 365 days), the forecast horizon size h is 6 hours, the rolling-window size m is 8766 hours (24 hours × 365 days + 6 hours), and the data sample size T is 17544 hours

(24 hours × (365 + 366) days). There are a total of 1464 rolling windows ($(T-I)/h$ = (17544 – 8760)/6).

- 12-step-ahead forecasting: the input data size I is 8760 hours (24 hours × 365 days), the forecast horizon size h is 12 hours, the rolling-window size m is 8772 hours (24 hours × 365 days + 12 hours), and the data sample size T is 17544 hours (24 hours × (365 + 366) days). There are a total of 732 rolling windows ($(T-I)/h$ = (17544 – 8760)/12).
- 24-step-ahead forecasting: the input data size I is 8760 hours (24 hours × 365 days), the forecast horizon size h is 24 hours, the rolling-window size m is 8784 hours (24 hours × 365 days + 24 hours), and the data sample size T is 17544 hours (24 hours × (365 + 366) days). There are a total of 366 rolling windows ($(T-I)/h$ = (17544 – 8760)/24).

SARIMA model is used for multi-step-ahead forecasts, and the comparison of results will be detailed in this chapter.

For the electricity price forecasts in this thesis, all the programs of the ARIMA, SARIMA and ANN models have been written in MATLAB language. The running time of the ARIMA and SARIMA model is less than five minute for one case, and the response time for ANN model is around fifteen minutes because the best result is obtained after 1000 cycles. Therefore, all the models are feasible for other applications.

6.3. Parameter determination process for monthly electricity price forecast

The monthly forecasting process of electricity price has been introduced before. The electricity prices from March 2015 to February 2016 are used as the experimental data, and the data for weekdays and weekends are forecasted separately. The monthly forecasts of electricity price for August 2015 are used as a demonstration example. Here, the parameter determination process of ARIMA model, SAIMA model and ANN model for August 2015 are presented.

6.3.1. Parameter determination for weekdays of August 2015

For the forecasting on weekdays, the historical electricity prices from 3^{rd} to 21^{st} August 2015 (15 days) are used as input data to forecast the results from 24^{th} to 28^{th} August 2015 (5 days).

6.3.1.1. ARIMA model

For the parameter determination of ARIMA model on weekdays, load the historical electricity prices on weekdays from 3rd to 21st August, then plot the sample autocorrelation function (ACF) and sample partial autocorrelation function (PACF) for the electricity price series. The original ACF and PACF are shown in Figure 6-8.

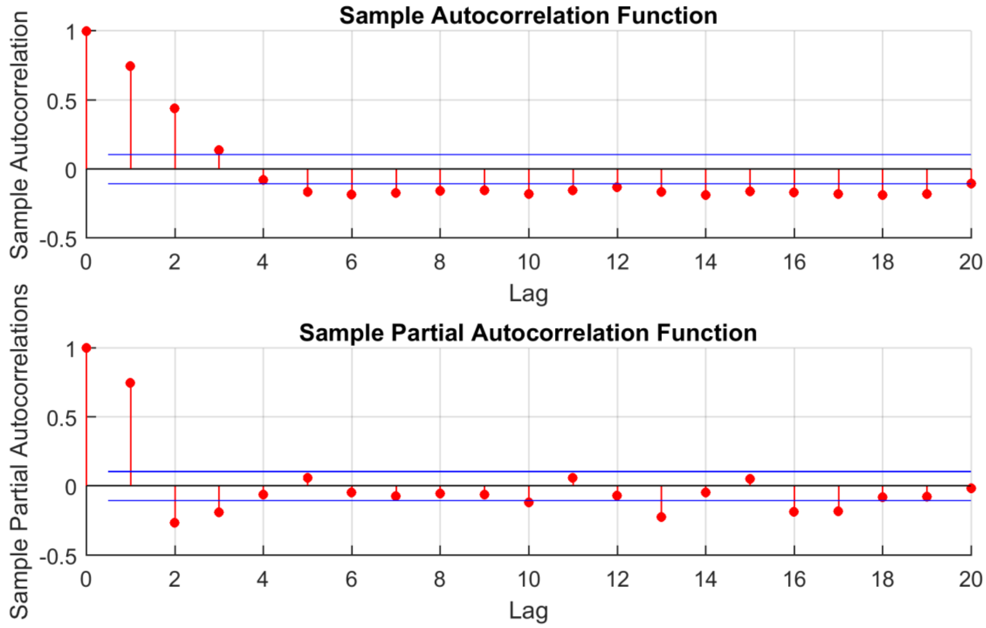


Figure 6-8: Original ACF and PACF of electricity price for weekdays in August 2015

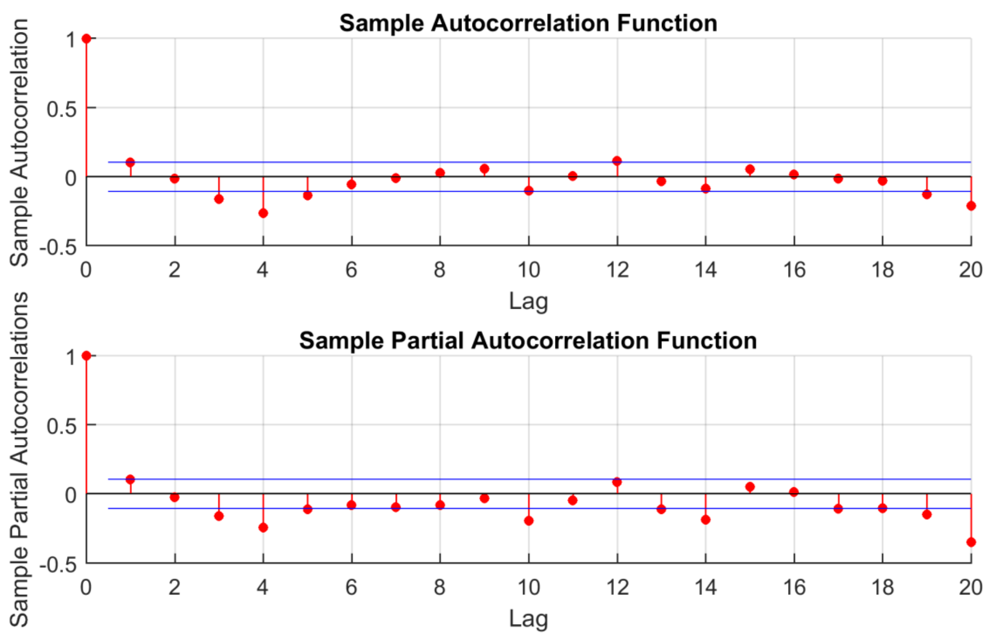


Figure 6-9: ACF and PACF of electricity price for weekdays in August 2015 after 1st differencing

It can be seen from Figure 6-8 that the sample ACF seems to decay to stationary, but most of the points in ACF are out of the approximate confidence interval. This indicates that the sample ACF does not decay to zero and it is not a good stationary process. So the 1st differencing is applied to the original data, and sample ACF and PACF after 1st differencing are plotted in Figure 6-9.

Figure 6-9 shows that the sample ACF and PACF of the differenced series are stationary now. The ACF decays to zero after lag 0 or 1, and the PACF also decays to zero after lag 0 or 1. As mentioned before, in a $ARIMA(p,d,q)$ model, the moving average order q is determined by ACF, and the autoregressive order p is decided by PACF. Therefore, for the $ARIMA(p,d,q)$ model in this case, d equals to 1, p can be selected in 0 and 1, q can be selected in 0 and 1. That means there are $ARIMA(0,1,0)$, $ARIMA(0,1,1)$, $ARIMA(1,1,0)$ and $ARIMA(1,1,1)$ four models might be appropriate for this set of data. Then use all these four models to forecast the weekdays' electricity price from 24th to 28th August, and the results of RMSPE and MAPE are shown in Table 6-1.

Table 6-1: RMSPE and MAPE of different ARIMA models for weekdays' electricity price forecast in August 2015

Models	**RMSPE,** %	**MAPE,** %
$ARIMA(0,1,0)$	10.93	8.81
$ARIMA(0,1,1)$	10.80	8.86
$ARIMA(1,1,0)$	10.83	8.88
$ARIMA(1,1,1)$	10.80	8.84

It can be seen from Table 6-1 that $ARIMA(1,1,1)$ model has the smallest RMSPE and second smallest MAPE, so $ARIMA(1,1,1)$ model is selected as the forecasting model for the weekdays' electricity prices in August 2015. The formula of $ARIMA(1,1,1)$ model can be expressed as

$$(1 - \emptyset_1 B)(1 - B)Z_t = (1 + \theta_1 B)a_t \tag{6-1}$$

where $\emptyset_1$ and θ_1 are the autoregressive operator of p and moving-average operator q. Z_t is the electricity prices. B is the backward shift operator that defines $Z_{t-1} = BZ_t$. a_t is the error term with a mean of zero. Thus, the time series forecasting function can be expressed as

$$Z_t = (1 + \emptyset_1)Z_{t-1} - \emptyset_1 Z_{t-2} + a_t + \theta_1 a_{t-1} \tag{6-2}$$

where the value of $\emptyset_1$ and θ_1 are changed at each step, because the forecasting process uses the rolling-window forecast method.

6.3.1.2. SARIMA model

For the parameter determination of SARIMA model on weekdays, in addition to the non-seasonal parameters p, d, q in the ARIMA model, the SARIMA model also has the seasonal parameters P, D, Q. The electricity price on weekdays from 3rd to 21st August is shown in Figure 6-10. In order to observe the seasonal changes in ACF and PACF, the original ACF and PACF with extended X axes are shown in Figure 6-11.

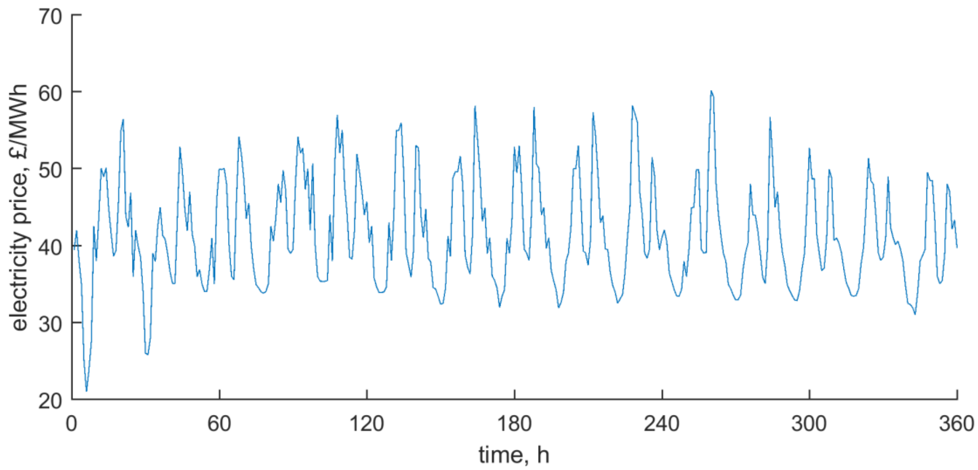


Figure 6-10: Electricity price on weekdays from 3rd to 21st August

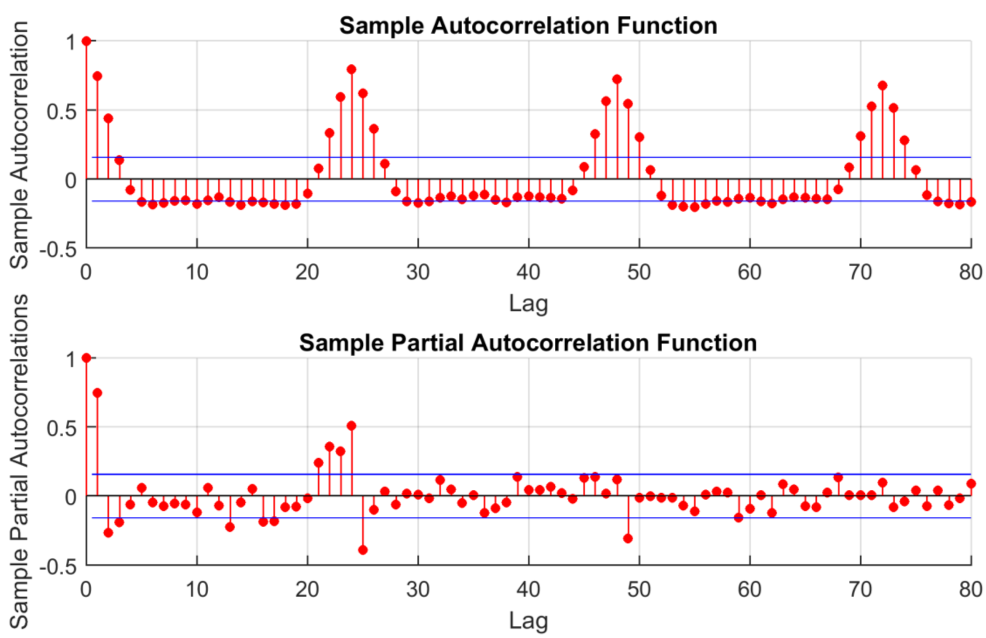


Figure 6-11: Original ACF and PACF of electricity price for weekdays in August 2015 (extended X axes)

According to Figure 6-10 and 6-11, there is a seasonal oscillation with the period of 24 hours in the original data and the spikes happened in ACF every 24 lags. Therefore, the seasonal period is 24 hours in this case. The figure of ACF presented non-stationary, so the 1st difference is applied to the original data and the ACF and PACF after 1st differencing are shown in Figure 6-12.

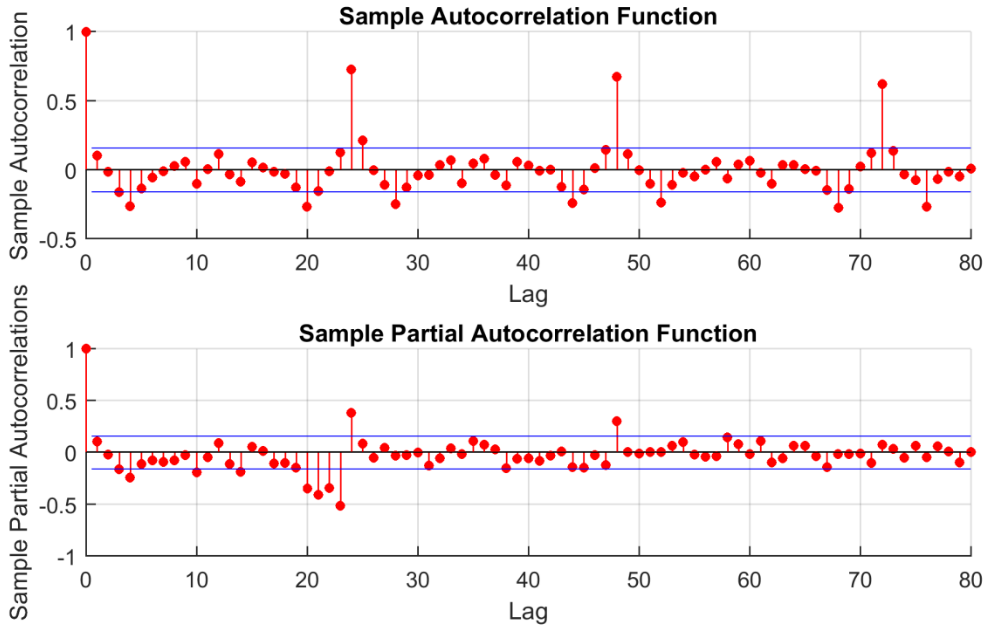


Figure 6-12: ACF and PACF of electricity price for weekdays in August 2015 after 1st differencing

It can be seen in Figure 6-12 that ACF indicates spikes at the seasonal period of lag 24 and some points near the seasonal period are outside the confidence interval, so the sample ACF is not a good stationary process. Then an additional 24th seasonal differencing is applied to the series and the ACF and PACF of the seasonal differenced series are plotted in Figure 6-13.

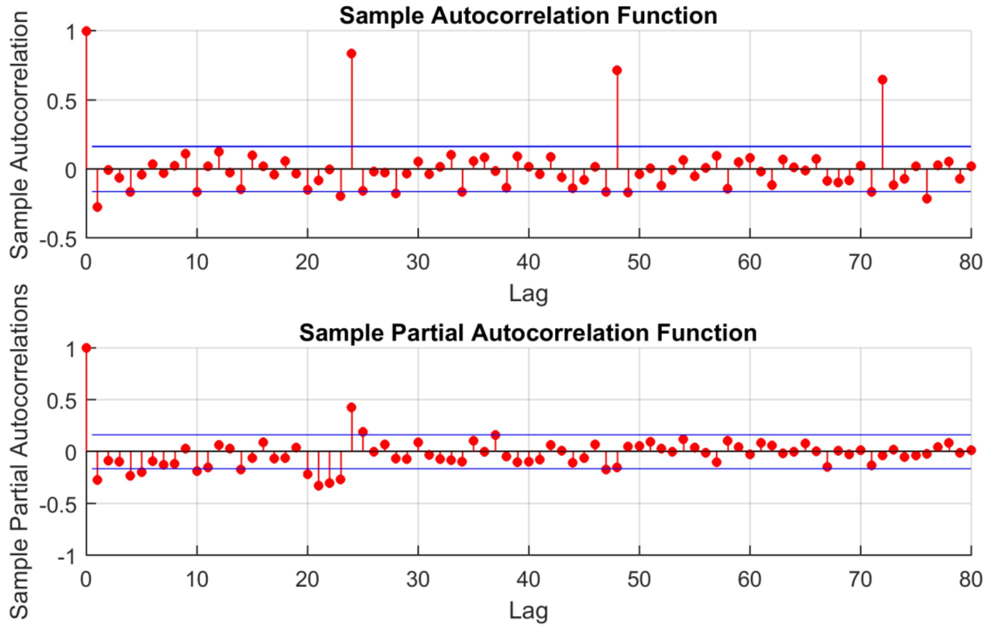


Figure 6-13: ACF and PACF of electricity price for weekdays in August 2015 after 1st and 24th differencing

It can be observed in Figure 6-13 that the sample ACF and PACF after the 1st and 24th differencing are stationary process now. According to the differencing times, $d = 1$ and $D = 1$. For the non-seasonal terms, ACF and PACF all decay to zero after lag 0 or 1, so p and q can be selected from 0 to 1. For the seasonal terms, the spikes appeared every 24 lags in ACF and there is only one spike at lag 24 in PACF, so $P = 1$ and $Q = 0$. So $SARIMA(0,1,0)(1,1,0)_{24}$, $SARIMA(0,1,1)(1,1,0)_{24}$, $SARIMA(1,1,0)(1,1,0)_{24}$ and $SARIMA(1,1,1)(1,1,0)_{24}$ four models might be appropriate for this set of data. Then all these four models are used to forecast the weekdays' electricity prices from 24th to 28th August and the results of RMSPE and MAPE are shown in Table 6-2.

Table 6-2: RMSPE and MAPE of different SARIMA models for weekdays' electricity price forecast in August 2015

Models	**RMSPE,** %	**MAPE,** %
$SARIMA(0,1,0)(1,1,0)_{24}$	6.97	5.77
$SARIMA(0,1,1)(1,1,0)_{24}$	7.10	5.89
$SARIMA(1,1,0)(1,1,0)_{24}$	7.17	5.86
$SARIMA(1,1,1)(1,1,0)_{24}$	6.63	5.43

It can be seen from Table 6-2 that $SARIMA(1,1,1)\ (1,1,0)_{24}$ model has the smallest RMSPE and MAPE, so $SARIMA(1,1,1)\ (1,1,0)_{24}$ model is selected as the forecasting model for the weekdays' electricity price in August 2015. The formula of $SARIMA(1,1,1)\ (1,1,0)_{24}$ model can be expressed as

$$(1-\emptyset_1 B)(1-\Phi_1 B^{24})(1-B)(1-B^{24})Z_t = (1+\theta_1 B)a_t \qquad \text{(6-3)}$$

in addition to the non-seasonal autoregressive operator p and moving-average operator q that already introduced in the ARIMA model, Φ_1 is the seasonal autoregressive operator P. Thus, the time series forecasting function can be expressed as

$$\begin{aligned} Z_t = {} & (1+\phi_1)Z_{t-1} - \phi_1 Z_{t-2} + (1+\Phi_1)Z_{t-24} - (1+\phi_1+\Phi_1+\phi_1\Phi_1)Z_{t-25} \\ & + (\phi_1+\phi_1\Phi_1)Z_{t-26} - \Phi_1 Z_{t-48} + (\Phi_1+\phi_1\Phi_1)Z_{t-49} - \phi_1\Phi_1 Z_{t-50} \\ & + a_t + \theta_1 a_{t-1} \qquad \text{(6-4)} \end{aligned}$$

where the value of $\emptyset_1$, θ_1 and Φ_1 are changed at each step, because the forecasting process uses the rolling-window forecast method.

6.3.1.3. ANN model

For the parameter determination of ANN model on weekdays, 10 and 20 hidden neurons and 2, 4 and 6 delays are selected separately to find the best forecasting model. Each set of data is trained 1000 times for forecasting and the result with the minimum RMSPE and MAPE are obtained. Then compare these minimum RMSPE and MAPE values to select the best forecasting model. The minimum RMSPE and MAPE of ANN models with different neurons and delays for weekdays' electricity price forecasts in August 2015 are shown in Table 6-3.

Table 6-3: The minimum RMSPE and MAPE of different ANN models for weekdays' electricity price in August 2015

Models	**RMSPE,** %	**MAPE,** %
ANN(10 neurons, 2 delays)	9.80	7.73
ANN(10 neurons, 4 delays)	9.43	7.15
ANN(10 neurons, 6 delays)	8.77	6.61
ANN(20 neurons, 2 delays)	10.51	8.12
ANN(20 neurons, 4 delays)	10.05	7.99
ANN(20 neurons, 6 delays)	9.72	7.34
ANN(30 neurons, 2 delays)	10.18	8.28
ANN(30 neurons, 4 delays)	10.71	8.06
ANN(30 neurons, 6 delays)	9.46	7.56

It can be seen from Table 6-3 that the ANN model with 10 neurons and 6 delays has the smallest RMSPE and MAPE. So the ANN model with 10 neurons and 6 delays is selected as the forecasting model for the weekdays' electricity price in August 2015. It should be noted that once the optimal forecasting result of the ANN model is obtained, it must be saved or the result of the next set of training will be completely different.

6.3.2. Parameter determination for weekends of August 2015

For the forecasting on weekends, the historical electricity prices from 1st to 23rd August 2015 (8 days) are used as input data to forecast the results from 29th to 30th August 2015 (2 days).

6.3.2.1. ARIMA model

The parameter determination of ARIMA model on weekends is the same as weekdays. The range of model parameters can be selected based on the original and differenced ACF and PACF figures. Then compare the results of RMSPE and MAPE of these models to get the best model. The sample ACF and PACF after 1st differencing are plotted in Figure 6-14.

Figure 6-14 shows that the sample ACF and PACF after 1st differencing are stationary now. It can be seen from Figure 6-14 that only $ARIMA(0, 1, 0)$ model can be selected in this set of data, because the sample ACF and PACF all decay to zero after lag 0 directly. Therefore, $ARIMA(0, 1, 0)$ model is selected as the forecasting model for the weekends' electricity price in August 2015 and its RMSPE and MAPE are 14.70% and 10.14% respectively.

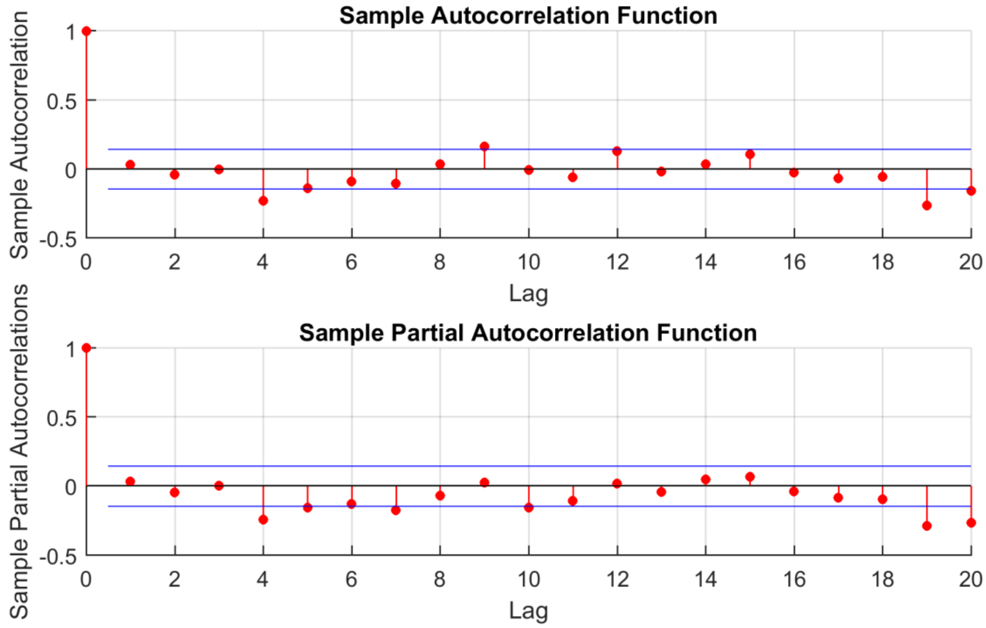


Figure 6-14: ACF and PACF of electricity price for weekends in August 2015 after 1st differencing

The formula of $ARIMA(0, 1, 0)$ model can be expressed as

$$(1 - B)Z_t = a_t \tag{6-5}$$

And the time series forecasting function can be expressed as

$$Z_t = Z_{t-1} + a_t \tag{6-6}$$

the forecasting process uses the rolling-window forecast method.

6.3.2.2. SARIMA model

The parameter determination of SARIMA model on weekends is the same as weekdays. In addition to the non-seasonal parameters p, d, q in the ARIMA model, the SARIMA model also has the seasonal parameters P, D, Q. Then compare the results of RMSPE and MAPE of these models to get the best model. The sample ACF and PACF after 1st and 24th differencing are plotted in Figure 6-15.

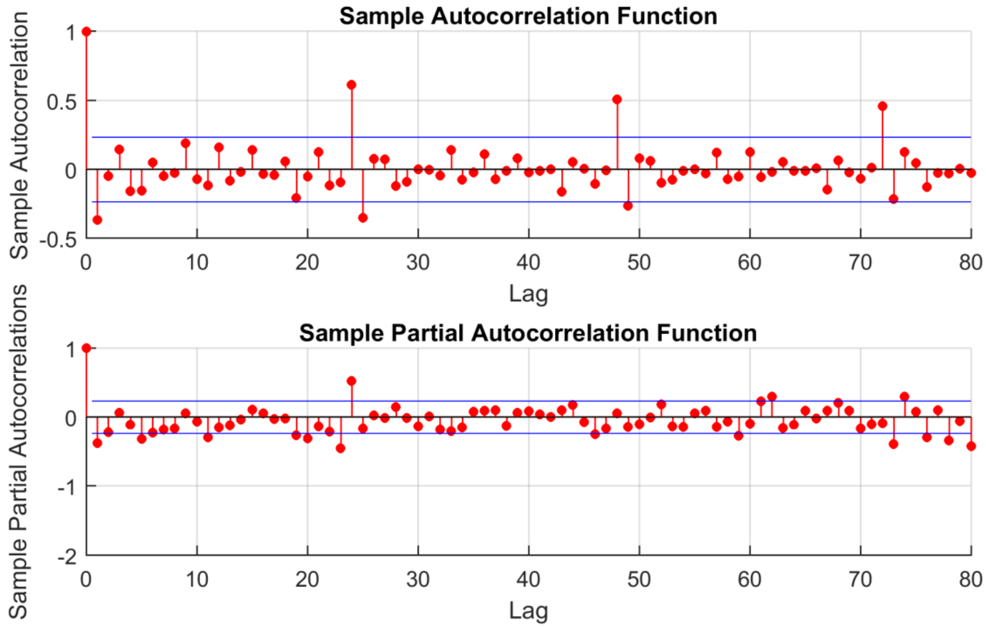


Figure 6-15: ACF and PACF of electricity price for weekends in August 2015 after 1st and 24th differencing

It can be seen in Figure 6-15 that the sample ACF and PACF after the 1st and 24th differencing are stationary process now. According to the differencing times, $d = 1$ and $D = 1$. For the non-seasonal terms, ACF and PACF all decay to zero after lag 0 or 1, so p and q can be selected from 0 to 1. For the seasonal terms, the spikes appeared every 24 lags in ACF and PACF exponential decay to zero after the seasonal lag 24, so $P = 1$ and $Q = 0$. Therefore, $SARIMA(0,1,0)(1,1,0)_{24}$, $SARIMA(0,1,1)(1,1,0)_{24}$, $SARIMA(1,1,0)(1,1,0)_{24}$ and $SARIMA(1,1,1)(1,1,0)_{24}$ four models might be appropriate for this set of data. Then all these four models are used to forecast the weekends' electricity prices from 24th to 28th August and the results of RMSPE and MAPE are shown in Table 6-4.

Table 6-4: RMSPE and MAPE of different SARIMA models for weekends' electricity price forecast in August 2015

Models	**RMSPE,** %	**MAPE,** %
$SARIMA(0,1,0)(1,1,0)_{24}$	9.49	7.76
$SARIMA(0,1,1)(1,1,0)_{24}$	9.84	7.98
$SARIMA(1,1,0)(1,1,0)_{24}$	10.03	8.31
$SARIMA(1,1,1)(1,1,0)_{24}$	9.26	7.61

It can be seen from Table 6-4 that $SARIMA(1,1,1)\ (1,1,0)_{24}$ model has the smallest RMSPE and MAPE, so $SARIMA(1,1,1)\ (1,1,0)_{24}$ model is selected as the forecasting model for the weekends' electricity price in August 2015. Its formula is the same as the above formula 6-3 and 6-4.

6.3.2.3. ANN model

The parameter determination of ANN model on weekends is the same as weekdays. The minimum RMSPE and MAPE of ANN models with different neurons and delays for weekends' electricity price forecasts in August 2015 are shown in Table 6-5.

Table 6-5: The minimum RMSPE and MAPE of different ANN models for weekends' electricity price forecast in August 2015

Models	**RMSPE,** %	**MAPE,** %
ANN(10 neurons, 2 delays)	9.68	7.16
ANN(10 neurons, 4 delays)	9.95	7.36
ANN(10 neurons, 6 delays)	10.34	8.01
ANN(20 neurons, 2 delays)	11.24	8.79
ANN(20 neurons, 4 delays)	10.84	8.57
ANN(20 neurons, 6 delays)	10.33	7.92
ANN(30 neurons, 2 delays)	9.89	7.65
ANN(30 neurons, 4 delays)	11.03	8.67
ANN(30 neurons, 6 delays)	10.05	7.73

After comparing the minimum RMSPE and MAPE results of different models, it can be found that the ANN model with 10 neurons and 2 delays has the smallest RMSPE and MAPE, and the values are 9.68% and 7.16% respectively. So it is selected as the forecasting model for the weekends' electricity price in August 2015.

All of the above forecasting model parameter determination processes are for the electricity price of August 2015. The monthly electricity price forecasts are carried out every month in the year from March 2015 to February 2016 and all the parameter determination processes are the same as in August 2015. The optimal ARIMA, SARIMA and ANN models for weekdays' electricity price forecast in each month from

March 2015 to February 2016 are listed in Appendix C. The optimal models for weekends' electricity price are listed in Appendix D.

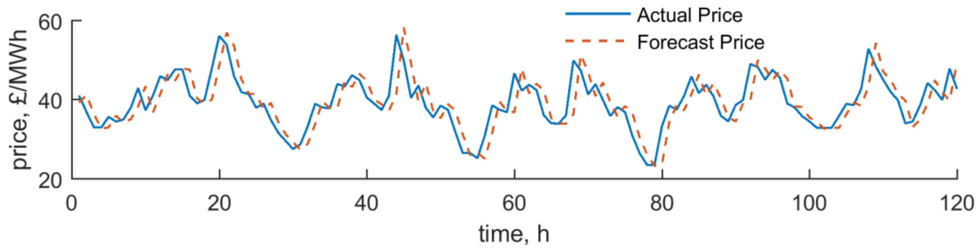
6.4. The comparison of monthly electricity price forecasting results

For now, three electricity price forecasting models (ARIMA, SARIMA and ANN) for the weekdays and weekends of August 2015 have been determined. This section will compare the one-step-ahead forecasting results of these three models on weekdays and weekends separately. The electricity prices of August 2015 are still used as the demonstration example. Then the forecasting results of these three models in each month (12 months) of the year from March 2015 to February 2016 will be compared to observe which model has the best performance. The models mentioned below refer to the optimal models that have been selected, and the parameters of the models will not be written in detail.

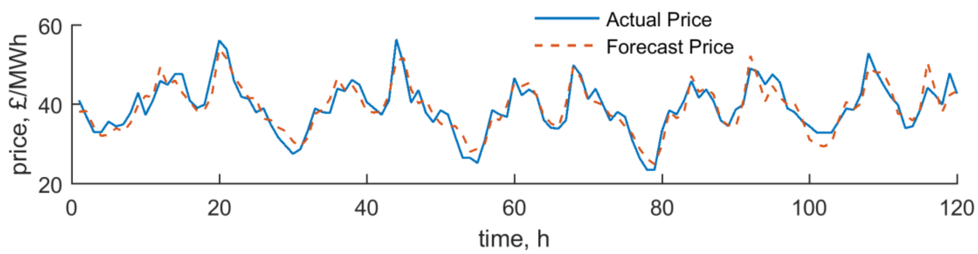
6.4.1. Monthly electricity price forecasting results for weekdays

6.4.1.1. Forecasting results of August 2015

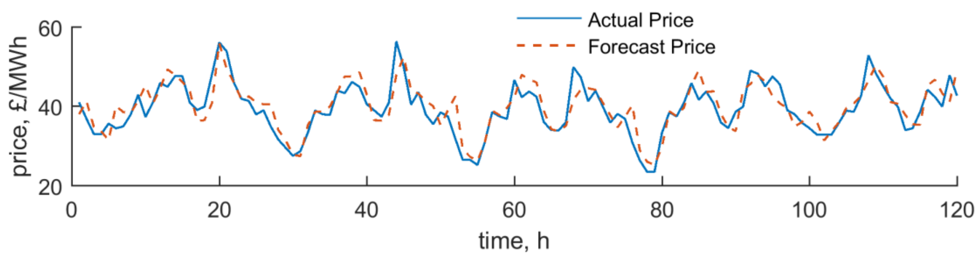
For August 2015, the historical electricity price data on weekdays from 3rd to 21st August are used to forecast the results from 24th to 28th August. The forecast results of electricity price by ARIMA, SARIMA and ANN models on weekdays are presented in Figure 6-16.



a. ARIMA model



b. SARIMA model



c. ANN model

Figure 6-16: Electricity price forecast results on weekdays of August 2015

In figure 6-16, the solid and dashed lines are the actual and forecasting electricity price respectively. From these figures it can be observed that all the forecast curves follow the actual curves. But it is difficult to determine which model has the best performance purely by observation. Therefore, the RMSPE and MAPE are used here for analysing forecast errors. Furthermore, in order to observe the MAPE at every hour, all the forecast errors on weekdays from 24th to 28th August are divided into 24 hours in a day. The results of forecast errors are presented in Table 6-6.

Table 6-6: Comparisons between the weekdays' electricity price forecast errors by different models for August 2015

Time Period	**MAPE, %**		
	ARIMA	**SARIMA**	**ANN**
00:00–01:00	8.87	5.52	6.96
01:00–02:00	6.12	5.69	8.22
02:00–03:00	7.44	4.67	5.53
03:00–04:00	9.56	6.84	17.19
04:00–05:00	10.23	12.30	9.60
05:00–06:00	4.94	8.13	7.13
06:00–07:00	2.67	7.04	5.74
07:00–08:00	15.50	5.35	3.59
08:00–09:00	11.87	4.02	1.50
09:00–10:00	6.16	4.25	5.89
10:00–11:00	5.98	6.47	3.38
11:00–12:00	14.52	5.29	5.28
12:00–13:00	8.60	2.17	10.98
13:00–14:00	5.62	3.40	3.28
14:00–15:00	4.68	5.28	5.80
15:00–16:00	12.01	2.99	5.85
16:00–17:00	5.89	3.62	5.22
17:00–18:00	4.25	4.41	5.42
18:00–19:00	8.58	5.82	8.80
19:00–20:00	19.48	7.08	8.24
20:00–21:00	8.00	3.18	6.18
21:00–22:00	12.60	5.14	5.65
22:00–23:00	9.30	7.68	5.32
23:00–24:00	9.41	3.89	7.97
Average	8.84	5.43	6.61
RMSPE, %	10.80	6.63	8.77

It can be observed that the MAPE for weekdays stays in a range of 5.43-8.84% and the RMSPE of weekdays is from 6.63-10.80%. The most important point is that the results indicate that the MAPEs and RMSPEs of SARIMA models are all smaller than ARIMA and ANN models. That means on the weekdays' electricity price forecasting of August 2015, SARIMA model performed better than the other models.

6.4.1.2. Forecasting results of 12 months

As in August 2015, the 12-month RMSPE and MAPE can be obtained from the forecasting results of each month from March 2015 to February 2016, and all the results are forecasted by their optimal models. Then the 12-month RMSPE and MAPE comparisons of three models for electricity price forecast are shown in Table 6-7.

Table 6-7: 12-month RMSPE and MAPE comparisons of different models for weekdays' electricity price forecast

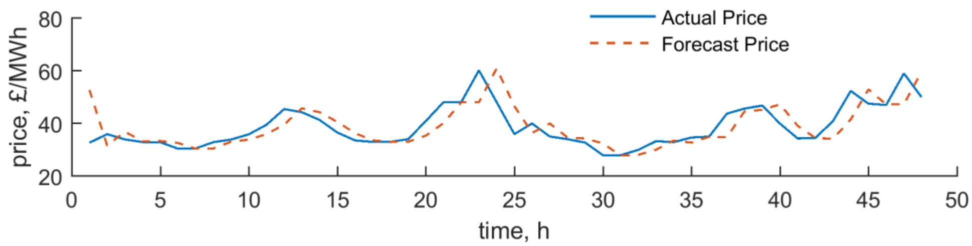
Month	**RMSPE,** %			**MAPE,** %		
	ARIMA	**SARIMA**	**ANN**	**ARIMA**	**SARIMA**	**ANN**
2015.03	16.03	6.75	10.64	11.60	5.07	7.95
2015.04	10.63	6.65	9.11	8.38	4.80	7.22
2015.05	12.83	7.46	10.14	9.45	5.60	7.94
2015.06	10.01	6.89	8.59	7.79	5.63	6.42
2015.07	10.24	7.14	8.78	7.75	5.08	6.55
2015.08	10.80	6.63	8.77	8.84	5.43	6.61
2015.09	13.49	6.63	10.18	10.92	4.91	7.97
2015.10	15.58	11.44	15.22	11.06	7.58	10.55
2015.11	17.35	10.76	13.89	12.98	8.16	10.39
2015.12	23.49	19.27	20.82	16.31	14.08	14.79
2016.01	19.76	13.11	18.57	14.67	9.35	14.01
2016.02	21.84	14.99	26.05	16.19	9.39	14.57

It can be observed from Table 6-7 that all the RMSPEs and MAPEs of SARIMA models are smaller than the other two models for the electricity price forecast on weekdays. Most of the RMSPEs and MAPEs of ANN models are smaller than ARIMA model. That means in this set of data, the SARIMA models have a better forecasting accuracy than the other two models, and the ANN models have a better forecasting accuracy than the ARIMA models. Thus, SARIMA is the optimal forecasting model for weekdays' electricity price forecast. Also it can be observed that the RMSPEs and MAPEs from October 2015 to February 2016 are bigger than the other months. That means the electricity price forecast results on weekdays from October 2015 to February 2016 are less accuracy than the other months.

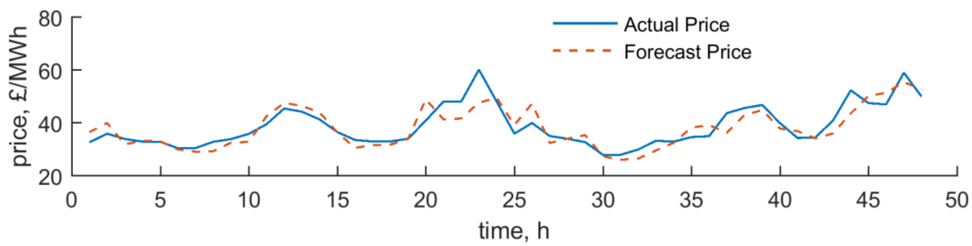
6.4.2. Monthly electricity price forecasting results for weekends

6.4.2.1. Forecasting results of August 2015

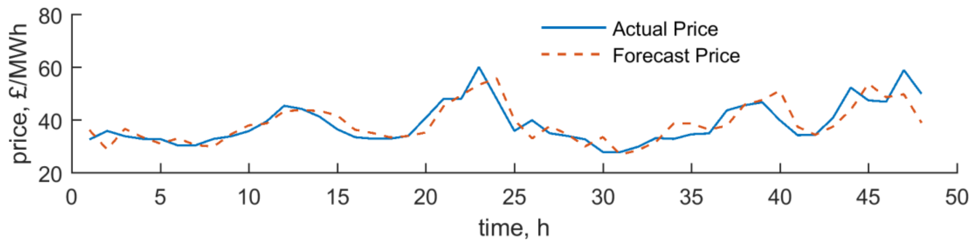
For August 2015, the historical electricity price data on weekends from 1st to 23rd August 2015 are used to forecast the results from 29th to 30th August 2015. The forecast results of electricity price by ARIMA, SARIMA and ANN models on weekends are presented in Figure 6-17



a. ARIMA model



b. SARIMA model



c. ANN model

Figure 6-17: Electricity price forecast results on weekends of August 2015

In figure 6-17, the solid and dashed lines are the actual and forecasting electricity price respectively. From these figures it can be observed that all the forecast curves follow the actual curves. But it is difficult to determine which model has the best performance purely by observation. Therefore, the RMSPE and MAPE are used here for analysing forecast errors. Furthermore, in order to observe the MAPE at every hour, all the forecast errors on weekends from 29th to 30th August are divided into 24 hours in a day. The results of forecast errors are presented in Table 6-8.

Table 6-8: Comparisons between the weekends' electricity price forecast errors by different models for August 2015

Time Period	**MAPE, %**		
	ARIMA	**SARIMA**	**ANN**
00:00–01:00	45.50	10.43	11.43
01:00–02:00	10.53	14.81	18.45
02:00–03:00	11.39	6.76	8.03
03:00–04:00	1.38	0.63	1.85
04:00–05:00	3.05	4.29	6.62
05:00–06:00	11.59	1.70	14.49
06:00–07:00	0.44	5.69	1.85
07:00–08:00	6.73	11.11	6.62
08:00–09:00	6.12	7.53	3.26
09:00–10:00	3.69	4.82	11.92
10:00–11:00	7.31	8.97	6.84
11:00–12:00	6.47	8.30	4.30
12:00–13:00	11.91	11.04	7.08
13:00–14:00	4.70	6.14	2.87
14:00–15:00	7.27	2.20	8.08
15:00–16:00	13.23	7.06	18.25
16:00–17:00	7.92	5.82	7.89
17:00–18:00	0.12	2.30	0.74
18:00–19:00	9.76	6.05	4.12
19:00–20:00	17.06	18.15	14.86
20:00–21:00	13.98	9.92	9.62
21:00–22:00	0.31	11.27	3.24
22:00–23:00	19.86	13.37	13.36
23:00–24:00	23.01	4.19	19.08
Average	10.14	7.61	8.54
RMSPE, %	14.70	9.26	10.79

It can be observed that the MAPE for weekends stays in a range of 7.61-10.14% and the RMSPE of weekends is from 9.26-14.70%. The most important point is that the results indicate that the MAPEMAPEs and RMSPEs of SARIMA models are all smaller than ARIMA and ANN models. That means on the weekends' electricity price forecasting of August 2015, SARIMA model performed better than the other models.

6.4.2.2. Forecasting results of 12 months

As in August 2015, the 12-month RMSPE and MAPE can be obtained from the forecasting results of each month from March 2015 to February 2016, and all the results are forecasted by their optimal models. Then the 12-month RMSPE and MAPE comparisons of three models for electricity price forecast are shown in Table 6-9.

Table 6-9: 12-month RMSPE and MAPE comparisons of different models for weekends' electricity price forecasts

Month	**RMSPE,** %			**MAPE,** %		
	ARIMA	**SARIMA**	**ANN**	**ARIMA**	**SARIMA**	**ANN**
2015.03	22.27	22.97	15.14	17.75	15.86	10.86
2015.04	14.73	11.24	12.40	10.98	8.16	9.50
2015.05	25.04	21.39	21.00	13.45	11.84	12.40
2015.06	13.52	9.24	10.95	9.96	7.06	7.85
2015.07	20.52	21.40	22.93	13.07	14.26	12.66
2015.08	14.70	9.26	10.79	10.14	7.61	8.54
2015.09	19.09	9.61	11.44	11.39	6.68	8.79
2015.10	23.57	15.72	19.45	17.69	11.21	13.49
2015.11	27.42	11.87	19.30	19.46	8.85	15.02
2015.12	37.22	33.40	38.75	26.68	20.59	22.98
2016.01	29.27	22.29	25.22	18.89	15.57	18.57
2016.02	18.43	11.06	15.49	14.07	8.33	11.95

It can be observed from Table 6-9 that almost all the RMSPEs and MAPEs of SARIMA are smaller than the other two models for the electricity price forecasts on weekends. Most of the RMSPEs and MAPEs of ANN models are smaller than ARIMA model. That means in this set of data, the SARIMA models have a better forecasting accuracy than the other two models, and the ANN models have a better forecasting accuracy than the ARIMA models. Thus, SARIMA is the optimal forecasting model for weekends' electricity price forecast. Also it can be observed that the RMSPEs and MAPEs on April, June, August, September, November 2015 and February 2016 is smaller than the other months. That means the electricity price forecast results on weekdays in these months are more accuracy than the other months.

6.4.3. Discussion of results

It can be seen from Table 6-7 and 6-9 that the RMSPEs and MAPEs of every month on weekends are all higher than weekdays. The results indicated that the forecast for weekends are more difficult than weekdays. Also, according to the comparison of RMSPEs and MAPEs for 12 months of the year, it can be found that the SARIMA model has a better electricity price forecasting performance than ARIMA and ANN models, no matter for weekdays or weekends. Therefore it will be only use SARIMA models to forecast the electricity price in the following part of this thesis.

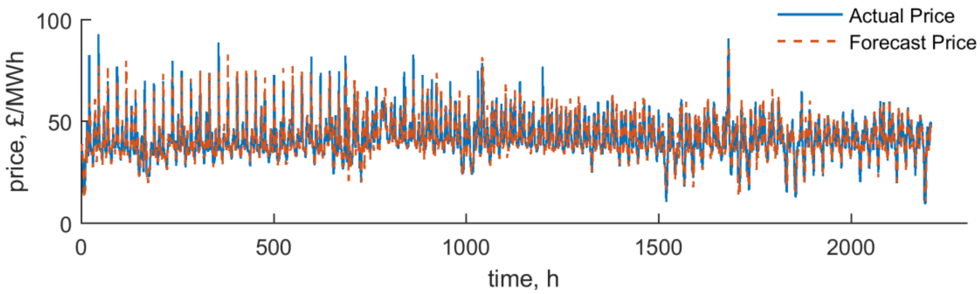
6.5. Seasonal electricity price forecasting

For now, the electricity price forecasts from March 2015 to February 2016 on weekdays and weekends are already achieved. For separately forecasting the monthly weekdays and weekends electricity prices, the advantage is that the forecasting accuracy for each month can be clearly observed, and the forecasting accuracy of weekdays and weekends for each month can be compared easily. However, the disadvantage is that the observation data is not enough, especially for the electricity prices of weekends. Therefore, in order to get more accurate forecasting results and observe the difference in electricity price forecasts for four seasons of the year, the seasonal electricity price will be forecasted in this section.

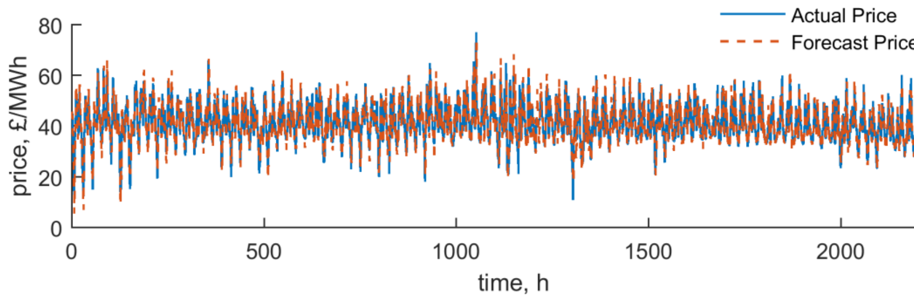
In the seasonal forecasts, the electricity prices on weekdays and weekends are not separately forecasted and they are combined into continuous data. Two methods are used to forecast the seasonal electricity price from March 2015 to February 2016 — continuous historical data method and seasonal separation method. The one-hour-ahead of electricity price forecasting is implemented here.

6.5.1. Continuous historical data method

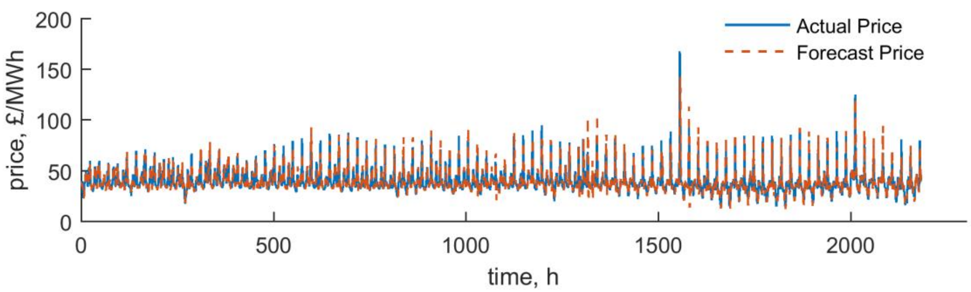
For the continuous historical data method, the electricity prices from March 2014 to February 2015 are used to forecast the seasonal electricity prices from March 2015 to February 2016. For each season, the electricity prices of last year (12 months) are used as input data to forecast the results of next season (3 months). The seasonal electricity price forecast results by continuous historical data method are shown in Figure 6-18.



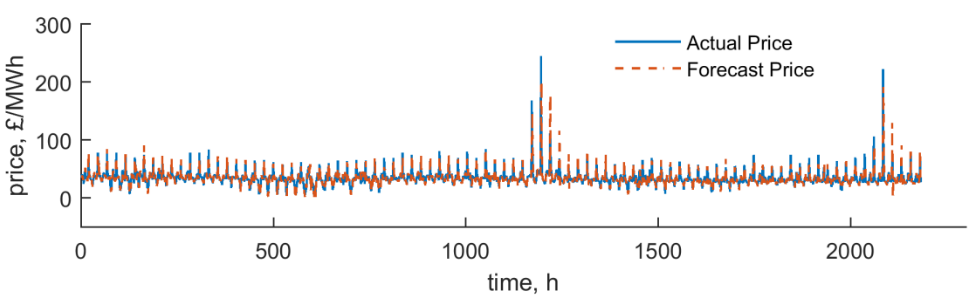
a. spring



b. summer



c. autumn



d. winter

Figure 6-18: Seasonal electricity price forecast results by continuous historical data method

After the electricity price forecasting for each season, the results of seasonal RMSPE and MAPE from March 2015 to February 2016 are shown in Table 6-10.

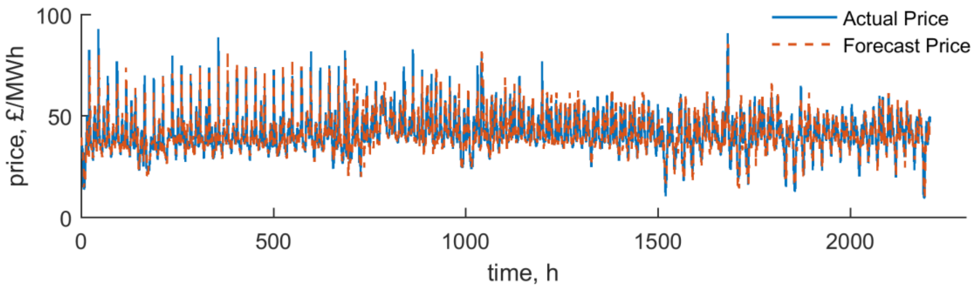
Table 6-10: Seasonal RMSPE and MAPE for electricity price forecast by continuous historical data method from March 2015 to February 2016

Seasons	**RMSPE,** %	**MAPE,** %
Spring	12.60	7.64
Summer	9.67	6.35
Autumn	9.78	6.69
Winter	17.70	9.90

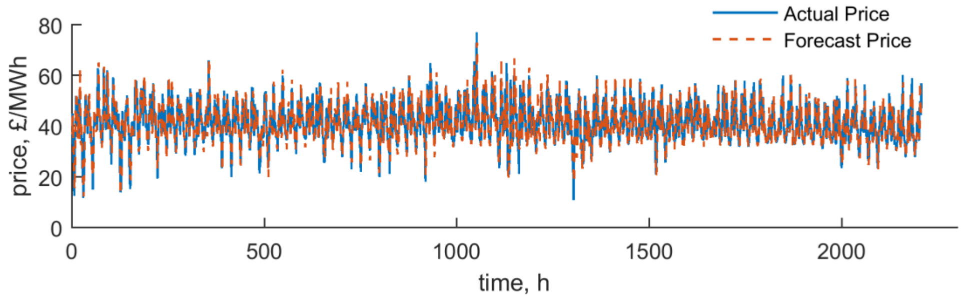
It can be seen from Table 6-10 that the RMSPE of summer and autumn are around 9.7% and the MAPE are around 6.5%. The RMSPE of winter is 17.70% and the MAPE is 9.90%. It means that the electricity forecast for winter of this year is less accurate than other seasons. The smallest RMSPE and MAPE are all happened in summer. So summer is the most accurate season for electricity price forecasting in this year.

6.5.2. Seasonal separation method

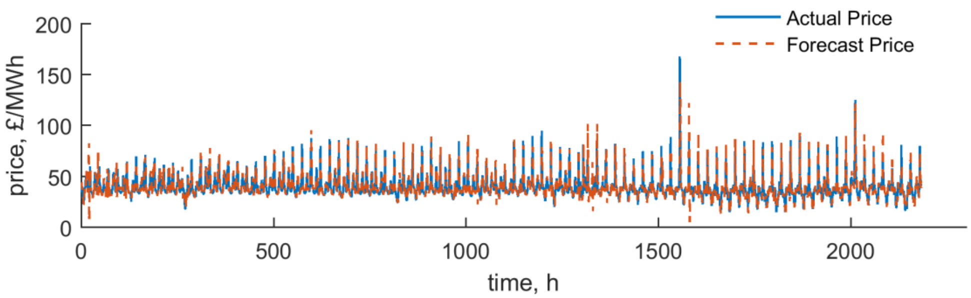
For the seasonal separation method, the electricity prices from March 2013 to February 2015 to forecast the seasonal electricity prices from March 2015 to February 2016, but the data in different seasons are used separately. For each season, the electricity prices for the same season in the previous two years (6 months) are used as input data to forecast the electricity prices for the corresponding season (3 months) of the next year.



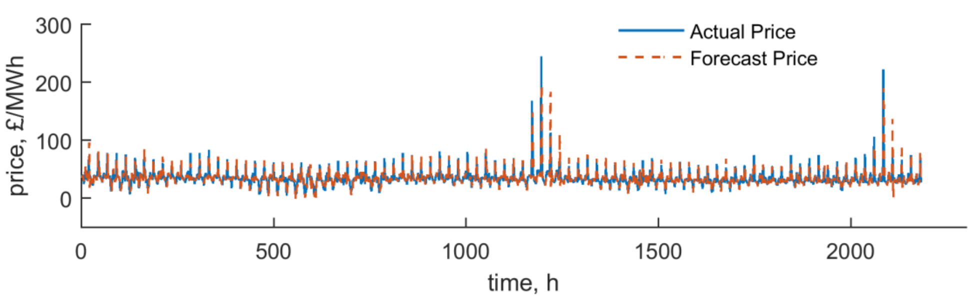
a. spring



b. summer



c. autumn



d. winter

Figure 6-19: Seasonal electricity price forecast results by seasonal separation method

The seasonal electricity price forecast results by seasonal separation method are shown in Figure 6-19. After the electricity price forecasting for each season by seasonal separation method, the results of seasonal RMSPE and MAPE from March 2015 to February 2016 are shown in Table 6-11.

Table 6-11: Seasonal RMSPE and MAPE for electricity price forecast by seasonal separation method from March 2015 to February 2016

Seasons	**RMSPE,** %	**MAPE,** %
Spring	12.36	7.56
Summer	9.96	6.45
Autumn	10.40	7.09
Winter	17.98	10.13

It can be seen from Table 6-11 that forecast results of all the four seasons are similar with Table 6-10. With seasonal separation method, the RMSPE and MAPE of winter is 17.98% and the MAPE is 10.13%. It means that the electricity forecast for winter of this year is still less accurate than other seasons. This inaccurate forecast result may be caused by the electricity price fluctuations and spikes in winter. Also, the smallest RMSPE and MAPE are all happened in summer. So after adopting the seasonal separation method, summer is still the most accurate season for electricity price forecasting in this year. But, except for spring, the RMSPE and MAPE of other seasons in Table 6-11 are bigger than the values in Table 6-10. Thus for this set of data, using a one-year continuous historical electricity prices to forecast the seasonal electricity price is better than the seasonal separation method. The forecast results achieved by the continuous historical data method will be used to perform risk analysis in later chapters.

6.6. Annual electricity price forecasting

In the annual forecast, the purpose is to forecast the electricity price for the year from March 2015 to February 2016 based on the historical input data. In order to compare the impact of different rolling window sizes on forecasting accuracy, the annual forecast uses three different sizes of input data — one month, six months and one year. As with seasonal forecast, the electricity prices for weekdays and weekends in the annual forecast are not separately forecasted but merged into continuous data.

As introduced before, the annual electricity price forecasting processes based on different input data sizes are as follows:

- **Input data for one month:** the one-month electricity prices of February 2015 are used to forecast the annual electricity prices from March 2015 to February 2016. The rolling-window size is 673 hours.
- **Input data for six months:** the six-month electricity prices from September 2014 to February 2015 are used to forecast the annual electricity prices from March 2015 to February 2016. The rolling-window size is 4345 hours.
- **Input data for one year:** the one-year electricity prices from March 2014 to February 2015 are used to forecast the annual electricity prices from March 2015 to February 2016. The rolling-window size is 8761 hours.

After the annual electricity price is forecasted based on the input data of one month, six months and one year, the annual RMSPE and MAPE results based on different input data sizes from March 2015 to February 2016 are shown in Table 6-12.

Table 6-12: RMSPE and MAPE for annual electricity price forecast by different input data sizes from March 2015 to February 2016

Input data size	**RMSPE,** %	**MAPE,** %
One month	13.66	8.29
Six months	13.47	8.25
One year	13.41	8.21

It can be seen from Table 6-12 that the RMSPE and MAPE for annual forecasts by three different input data sizes are similar. But the RMSPE and MAPE of six-month input data is smaller than one-month input data, and the RMSPE and MAPE of one-year input data is smaller than six-month input data, which means the forecast result is more accurate with the one-year input data. Since the rolling window size is proportional to the input data size, the forecast result is more accurate when the rolling window size is larger. Therefore, the one-year input data should be selected to forecast the annual electricity price in this thesis.

The annual electricity price forecast results based on one year input data are shown in Figure 6-20.

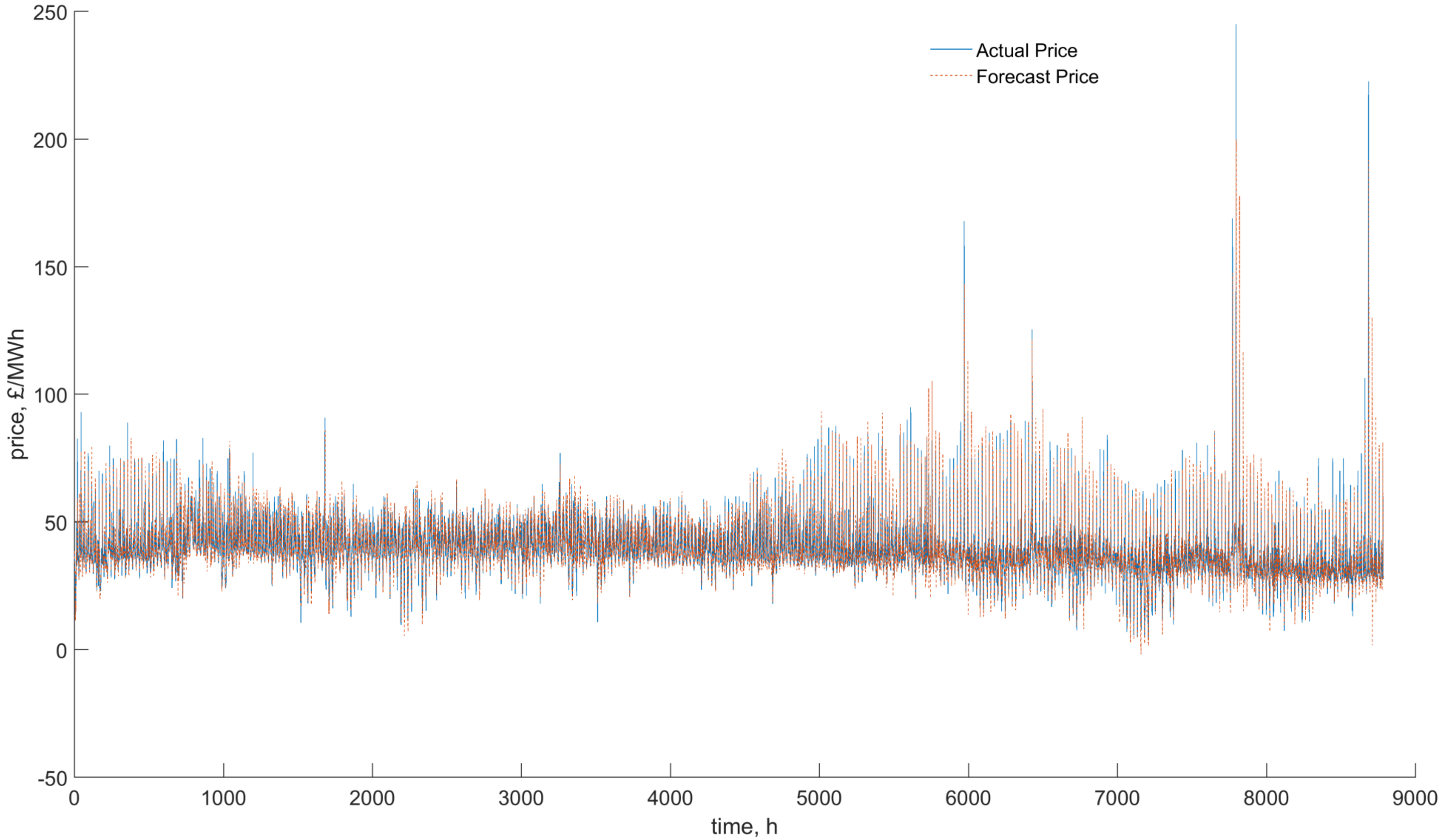


Figure 6-20: Annual electricity price forecast results based on one year input data

6.7. Comparison of one-step-ahead and multi-step-ahead electricity price forecasting

The one-step-ahead forecasts with rolling-window forecast method have been used in the seasonal electricity price forecasting from March 2015 to February 2016. In theory, the one-step-ahead forecasts have the most accurate forecasting results, because each step of the one-step-ahead forecasts is based on the actual historical data, but the multi-step-ahead forecasts are based on the forecasted data of the sub-steps. But the advantage of multi-step-ahead forecasts is that the forecasting range is larger than the one-step-ahead forecasts, and it can forecast the data for a few hours or even days directly. In order to compare the forecasting results by one-step-ahead and multi-step-ahead forecasts, the one-year data from March 2014 to February 2015 are used to forecast the seasonal and annual electricity prices from March 2015 to February 2016 by one-step-ahead, 6-step-ahead, 12-step-ahead and 24-step-ahead in this section.

The results of one-step-ahead seasonal and annual forecasts have been obtained in section 6.5 and 6.6. For the 6-step-ahead, 12-step-ahead and 24-step-ahead forecasts, the difference to one-step-ahead is that after how many forecast steps the parameters in the SARIMA model will change once based on the actual historical data. The results of seasonal and annual RMSPE and MAPE by one-step-ahead, 6-step-ahead, 12-step-ahead and 24-step-ahead forecasting are shown in Table 6-13 and Table 6-14 respectively.

Table 6-13: Seasonal and annual RMSPE for electricity price forecast by one-step-ahead and multi-step-ahead forecasts from March 2015 to February 2016

Time range	**RMSPE, %**			
	1-step-ahead	**6-step-ahead**	**12-step-ahead**	**24-step-ahead**
Spring	12.60	18.72	19.97	19.83
Summer	9.67	12.61	13.53	13.61
Autumn	9.78	11.81	12.22	12.08
Winter	17.70	22.77	23.37	23.13
Annual	13.41	17.08	17.86	17.74

Table 6-14: Seasonal and annual MAPE for electricity price forecast by one-step-ahead and multi-step-ahead forecasts from March 2015 to February 2016

Seasons	**MAPE, %**			
	1-step-ahead	**6-step-ahead**	**12-step-ahead**	**24-step-ahead**
Spring	7.64	10.44	11.03	10.78
Summer	6.35	8.13	8.59	8.66
Autumn	6.69	8.15	8.49	8.31
Winter	9.90	12.95	13.37	13.03
Annual	8.21	9.91	10.37	10.19

It can be observed from Table 6-13 and 6-14 that the seasonal and annual values of RMSPE and MAPE made by one-step-ahead forecasts are all the smallest. The results of 6-step-ahed forecasting are much bigger than one-step ahead forecasting. Then the

RMSPEs and MAPEs of 12-step-ahead and 24-step-ahead forecasting are bigger than 6-step-ahed forecasting. The results proved that the accuracy of one-step-ahead forecasts is the highest, and the forecasting accuracy decreases with the increase of the single forecasting range.

For the users of the forecasting methods, they can choose whatever they want in the forecasting process. If they want more accurate forecasting results, then choose the on-step-ahead forecasts. If they want to get a farther forecasting range, then choose the multi-step-ahead forecast. This thesis only considers the accuracy of electricity price forecasting, so all the electricity price forecasts are adopted by one-step-ahead forecasting.

6.8. Summary

This chapter introduced and assessed the ARIMA, SARIMA and ANN forecasting models for electricity price forecasts based on the day-ahead auction data in UK electricity market. Firstly, the rolling windows for the monthly, seasonal, annual and multi-step-ahead electricity price forecasts were detailed. . In the monthly forecast, the forecasting process was divided into weekday and weekend parts. The electricity prices are forecasted after determining the parameters of each model. According to the forecasting accuracy in terms of RMSPE and MAPE, SARIMA models show more accuracy than ARIMA and ANN models for both monthly electricity price forecasts in weekdays and weekends. Therefore SARIMA model is selected as the optimal model to forecast the electricity price in the remaining part of this thesis. The monthly forecasting results also showed that the forecasting errors for weekends are bigger than weekdays on electricity price forecast. Moreover, the seasonal electricity prices were forecasted by the continuous historical data method and seasonal separation method respectively. The results showed that the forecasts by the continuous historical data are more accurate than the seasonal separation method. For both methods, summer is the most accurate season for electricity price forecasts during the year, and winter is the most inaccurate season. Also, the annual electricity price forecasts were achieved based on one-month, six-month and one-year input data respectively. It showed that the result is more accurate when the rolling window size is larger. So the one-year input data should be selected to forecast the annual electricity price in this thesis. At last, the one-step-ahead and multi-step-ahead forecasts were used to forecast the seasonal and annual electricity prices. Based on the results of seasonal and annual RMSPE and MAPE, it proved that one-step-ahead forecasts are more accurate than multi-step-ahead forecasts. Therefore, all the electricity price forecast results for risk analysis that appear later in this thesis are completed by the one-step-ahead forecasts of SARIMA models based on the one-year continuous historical electricity prices.

In addition, by comparing the monthly, seasonal, annual and multi-step-ahead forecasting results of electricity price and load demand, it can be found that the load demand forecasts are more accurate than the electricity price forecasts for the data from March 2015 to February 2016 in the UK electricity wholesale market. For electricity price forecasts, the forecast results for the weekdays are more accurate than the weekends, but there is no big difference between the weekdays and weekends forecasting results for load demand forecasts. Furthermore, the commonality between these two forecast processes is that the SARIMA model shows the best forecasting results. The forecasts by the continuous historical data method have a better performance for both seasonal load demand and electricity price forecasts. And the annual load demand and electricity price forecasts show that the forecasting results are the most accurate when the input data is one year. Also, the load demand and electricity price forecasts all proved that one-step-ahead forecasts have the most accurate forecasting results. So only the one-step-ahead SARIMA models based on the one-year continuous historical data method are used to forecast load demand and electricity price in this thesis.

With the actual data and forecast results of load demand and electricity price, the forecast errors between the forecasted and actual values can be calculated. Then according to these errors, the risk assessment can be carried out to help electricity market participants analyse the risks they have to bear.

Chapter 7

Analysis of risk index and financial risk

7.1. Introduction

After getting the monthly, seasonal and annual forecasting results of load demand and electricity price, the corresponding forecast errors can be obtained. This chapter analyses the forecast error for the participants in the electricity market, which is expressed by risk index. The financial risk is also analysed according to the transaction amount generated by the actual and forecast values of load demand and electricity price.

The monthly load demand and electricity price forecasting results from March 2015 to February 2016 are used to calculate the risk index. The data in UK electricity market are used as an example. The risk index is divided into two parts: load demand and electricity price. In order to observe the risk index in different time periods more intuitively, all the results are convert to daily and seasonal risk indexes. Additionally, because the monthly forecasting results of load demand and electricity price include weekdays and weekends, the daily and seasonal risk indexes on weekdays and weekends are compared at last.

Since the forecasting processes are complicated, a method based on the daily variation index to evaluate the daily risk index is also been proposed in this chapter. Similar to the daily risk index, the daily variation index is also divided into two parts, load demand and electricity price. Then the relationships between daily risk index and daily variation index on weekdays and weekends are illustrated separately, and their linear regression equations are expressed.

In addition to risk indexes, another important concern is to calculate the financial risks. In this chapter, the Value-at-Risk (VaR) and Expected Shortfall (ES) methods with 95% and 90% confidence level are used respectively to assess the seasonal financial risk from March 2015 to February 2016. According to the seasonal forecasting results of load demand and electricity price, the seasonal financial risks and the VaR threshold with 95% and 90% confidence level are indicated. All the results of VaR threshold and ES in different seasons with positive and negative financial risks are compared.

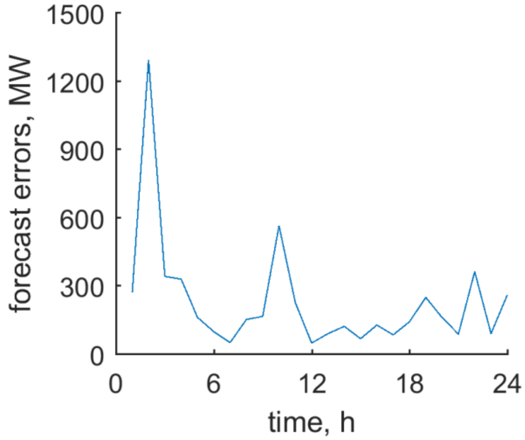
In addition, the daily, monthly, seasonal and annual total financial risks are calculated based on the load demand and electricity price annual forecast results. The total financial risks can present the actual risk that the market participants have to bear in different periods. Moreover, in order to verify the forecasting accuracy of financial risks, the total financial risks under three different situations are compared and analysed:

1) Considering both the forecasting of load demand and of electricity price;
2) Considering the forecasting load demand and actual electricity price;
3) Considering the actual load demand and forecasting electricity price.

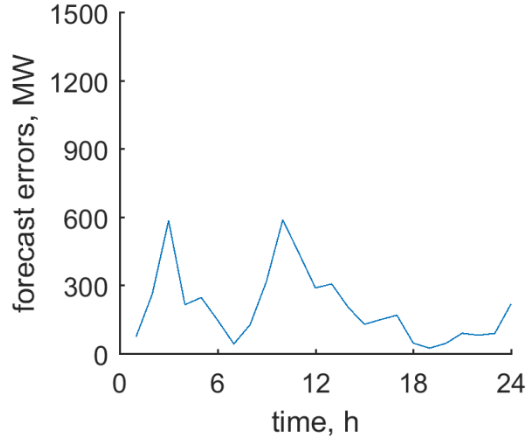
7.2. Daily and seasonal risk index analysis due to load demand and electricity price forecasting errors

The load demand and electricity price from March 2015 to February 2016 in the UK electricity market have been forecasted in Chapter 5 and 6 respectively. The forecasting errors can be obtained by comparing the forecasting results and actual values. The previous forecasting errors were calculated as RMSPE and MAPE to compare the forecasting accuracy of each model. But all the forecasting errors in this chapter will be calculated as the actual error values instead of the RMSPE and MAPE because the actual errors of load demand and electricity price are more meaningful in the analysis of financial risks.

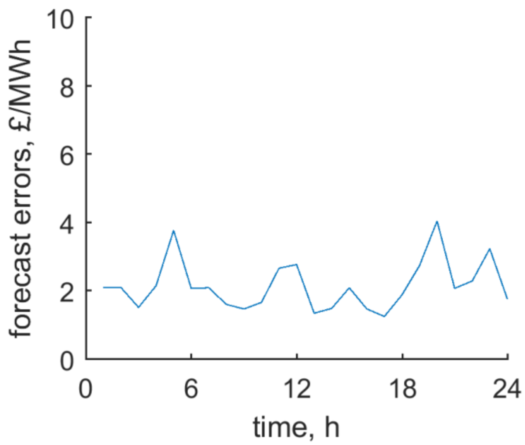
According to the monthly forecasting results that have been accomplished before, the forecasting errors can be calculated for every month during March 2015 to February 2016 for both load demand and electricity price forecast respectively. Then in each month, the errors are averaged to 24 hours in a day to observe the daily forecasting errors for load demand and electricity price. The forecast results on August 2015 are still used as a demonstration example here. The daily load demand and electricity price forecasting errors for weekdays and weekends in August 2015 are shown in Figure 7-1.



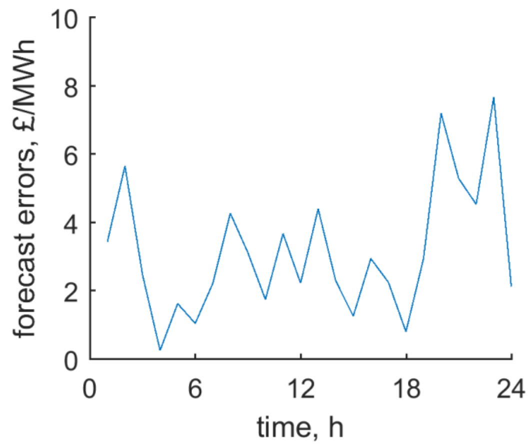
a. load demand errors on weekdays



b. load demand errors on weekends



c. electricity price errors on weekdays



d. electricity price errors on weekends

Figure 7-1: Daily forecasting errors in August 2015

Figure 7-1 illustrates that there are some bigger forecasting errors happened in some specific periods during a whole day. For example in Figure 7-1a, the load demand daily forecasting errors on weekdays, the peak forecast error happened at 2 o'clock and it is around 1300 MW. Another peak forecast error is appeared at 10 o'clock but this is not as big as the first one. Moreover, it can be found that for the load demand forecasts of August 2015, the average daily forecasting errors on weekdays are bigger than weekends, and for the electricity price forecasts of August 2015, the average daily forecasting errors on weekends are bigger than weekdays.

The big forecast error indicates that the forecasting inaccuracy risk is high. However, the same value of an error may be having different meaning for weekdays and weekends. For example, if the load demand forecasting error is 500 MV, it is a very big daily error for weekends, about 83% of the maximum error. But for weekdays it is far from the biggest error, about 38% of the maximum error. This makes it difficult to observe the forecasting inaccuracy risks in different situations. So the risk index brings into use to solve this problem. The risk index can be expressed as

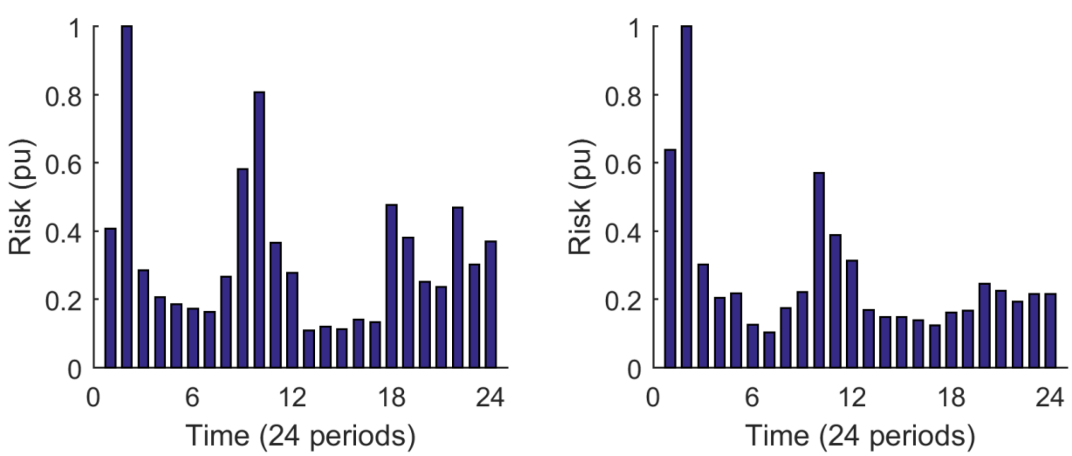
$$Risk\ Index = \frac{Error_i}{Error_{max}} \tag{7-1}$$

where $Error_i$ is the forecast error at time i and $Error_{max}$ is the biggest forecast error during the whole observation period. Therefore the range of risk index is from 0 to 1. The values from 0 to 1 indicate that the forecasting result is from the most accurate to the most inaccurate. The advantage of risk index is that it can change the actual errors in to a number between 0 and 1, so the forecast inaccuracy risk can be observed more intuitively.

7.2.1. Risk index for load demand

7.2.1.1. Daily risk index

The monthly load demand forecasting errors for both weekdays and weekends are used to observe the daily risk index of the year from March 2015 to February 2016. Firstly, the forecast errors in 12 months are added up. The total load demand forecasting errors are averaged in to 24 hours in a day. So the daily errors of the year can be obtained. Then the 24-period risk index of load demand forecasting errors for the whole year can be achieved. The daily risk indexes of load demand forecasting on weekdays and weekends are shown in Figure 7-2.



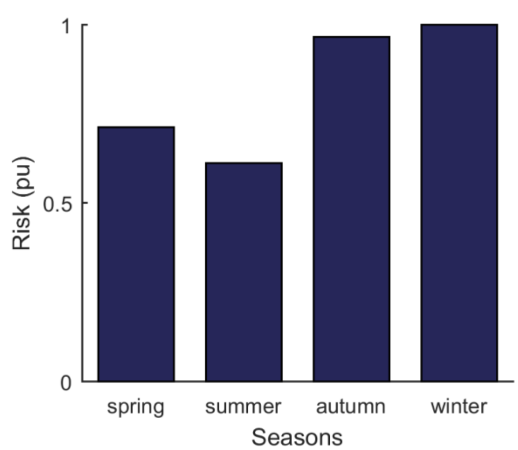
a. weekdays b. weekends

Figure 7-2: Load demand daily risk index

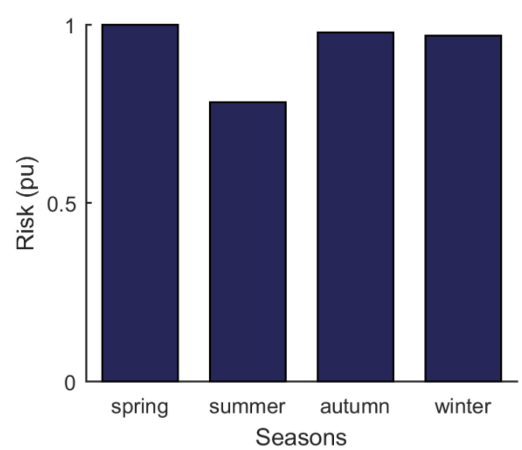
It can be seen from Figure 7-2 that the high risks occurred at 2:00 and the period from 9:00 to 10:00 for the daily risk index on weekdays. The peak daily risk index on weekends happened in the period from 1:00 to 2:00 and 10:00. The daily load demand risk indexes from 18:00 to 24:00 on weekdays are bigger than weekends.

7.2.1.2. Seasonal risk index

The monthly load demand forecasting errors for both weekdays and weekends are also used to observe the seasonal risk index of the year from March 2015 to February 2016. Firstly, the monthly forecasting errors are divided into four seasons. The monthly forecasting errors in each season are added up separately. Then the seasonal risk index of load demand forecasting errors for the whole year can be achieved. The seasonal risk indexes of load demand forecasting on weekdays and weekends are shown in Figure 7-3.



a. weekdays



b. weekends

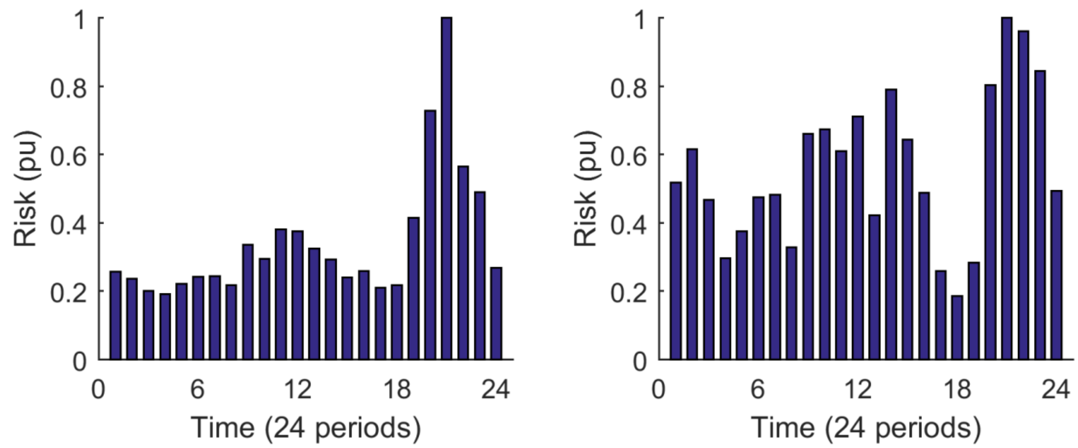
Figure 7-3: Load demand seasonal risk index

For the seasonal load demand risk index shown in Figure 7-3, the highest risk appeared at winter on weekdays, and then followed by autumn. Summer is the season with smallest risk index on weekdays. For weekends, spring, autumn and winter all have high risk index and the biggest risk index is happened in spring. Summer also has the smallest risk index for weekends. It can be found that the average seasonal risk index on weekends is bigger than weekdays.

7.2.2. Risk index for electricity price

7.2.2.1. Daily risk index

Similar to load demand, the monthly electricity price forecasting errors for both weekdays and weekends are used to observe the daily risk index of the year from March 2015 to February 2016. Firstly, the forecast errors in 12 months are added up. The total electricity price forecasting errors are averaged in to 24 hours in a day. So the daily errors of the year can be obtained. Then the 24-period risk index of electricity price forecasting errors for the whole year can be achieved. The daily risk indexes of electricity price forecasting on weekdays and weekends are shown in Figure 7-4.



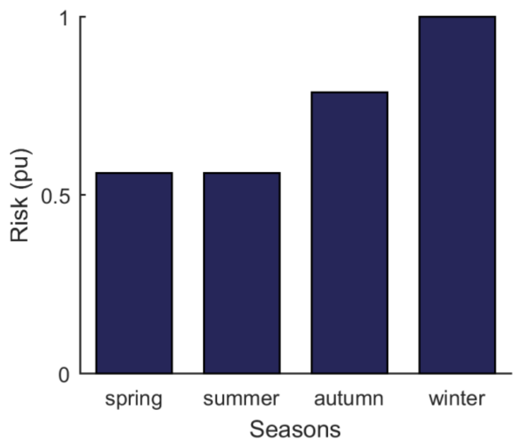
a. weekdays b. weekends

Figure 7-4: Electricity price daily risk index

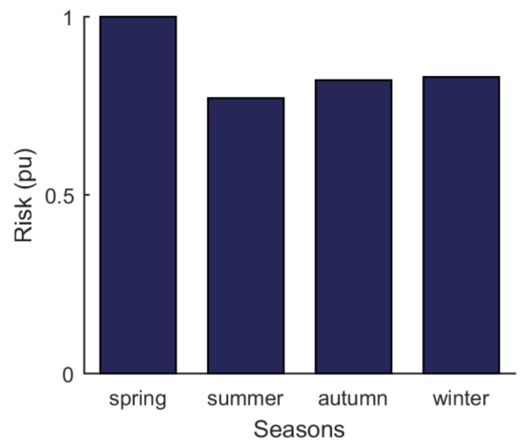
It can be observed from Figure 7-4 that there is more irregular risk peaks appeared on weekends. These bigger fluctuations indicate that the electricity price forecasts on weekends are more difficult than weekdays. The high risks on weekdays happen in the period from 19:00 to 23:00. For weekends, the high risks happen in the period from 20:00 to 23:00, but the periods from 9:00 to 12:00 and 14:00 to 15:00 also show high risks. Their value all peaked at 21:00. It means the big forecast risks of electricity price are more likely to happen around 21:00 o'clock in a day for both weekdays and weekends.

7.2.2.2. Seasonal risk index

Similar to load demand, the monthly electricity price forecasting errors for both weekdays and weekends are also used to observe the seasonal risk index of the year from March 2015 to February 2016. Firstly, the monthly forecasting errors are divided into four seasons. The monthly forecasting errors in each season are added up separately. Then the seasonal risk index of electricity price forecasting errors for the whole year can be achieved. The seasonal risk indexes of electricity price forecasting on weekdays and weekends are shown in Figure 7-5.



a. weekdays



b. weekends

Figure 7-5: Electricity price seasonal risk index

In Figure 7-5, the risk indexes of electricity price forecast errors are shown in different seasons. For weekdays, the risk index in winter is higher than the other seasons. The risk index in autumn is also very high. Spring and summer have the same smallest risk index here. For weekends, the peak value occurs in spring and is flowed by winter and autumn. Summer also has the smallest risk index for weekends. Moreover, it can be found that the average value of seasonal risk index on weekends is bigger than weekdays.

7.3. The method for evaluating the daily risk index due to daily variation index

The daily and seasonal risk indexes of load demand and electricity price on weekdays and weekends have been achieved. But the processes of getting these risk indexes are very complicated. The accurate risk index requires the accurate forecasting results, and the forecasting results are related to the original load demand and electricity price data. The load demand and electricity price profiles and characters in different times and different areas are also different. All these factors make it difficult to calculate the risk indexes. Hence, the method for evaluating the risk index due to variation index is used here to solve these problems.

The variation means the standard deviation of load demand or electricity price increment. It can be expressed as the following equation:

$$C_j = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(X_i - \overline{X_i})^2} \tag{7-2}$$

where C_j is the variation in the jth time period. X_i is the one-hour increment in actual load demand or electricity price, which is defined as $X_i = Y_i - Y_{i-1},\ i = 1, 2, \dots, 24$. When $i = 1$, the increment in the first time section is calculated as $X_1 = Y_1 - Y_{24}$. $\overline{X_i}$ is the mean value of X_i, and n is the number of experiment data. Then, the variation index can be calculated as

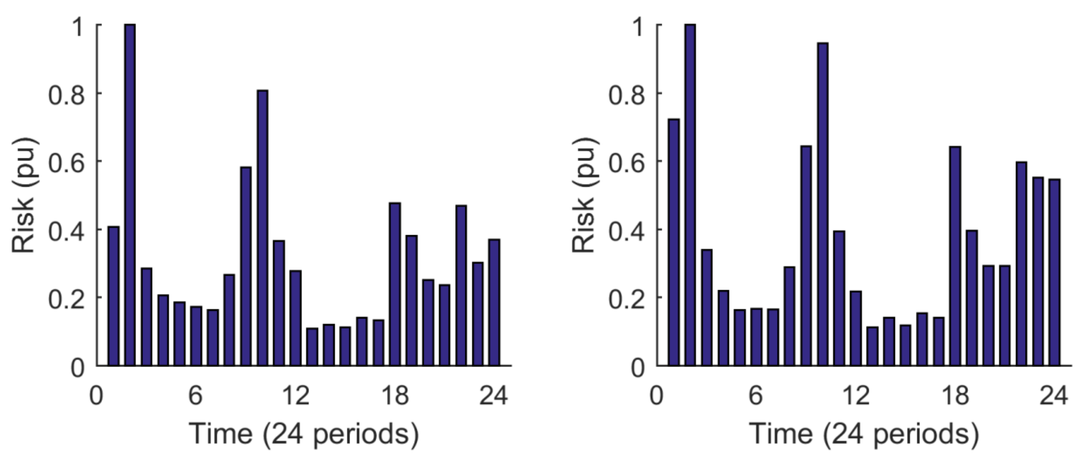
$$V_j = \frac{C_j}{C_{max}} \tag{7-3}$$

where V_j is the variation index at time period j. C_j is the variation in the j^{th} time period and C_{max} is the maximum variation during the whole observation period. Based on this algorithm, all the daily variation indexes of load demand and electricity price on weekdays and weekends from March 2015 to February 2016 are calculated.

7.3.1. Relationship between daily risk index and daily variation index for load demand

7.3.1.1. Weekdays relationship

In order to observe the relationship between daily risk index and daily variation index, the comparison of daily risk index and daily variation index for load demand on weekdays is shown in Figure 7-6.



a. daily risk index b. daily variation index

Figure 7-6: Daily risk index and daily variation index for load demand on weekdays

It can be seen from Figure 7-6 that there is a high correlation between the daily risk index and daily variation index for load demand on weekdays. The fluctuations and peaks of these two indexes are very similar. Then Figure 7-7 indicates the relationship between these two indexes and fitted their data.

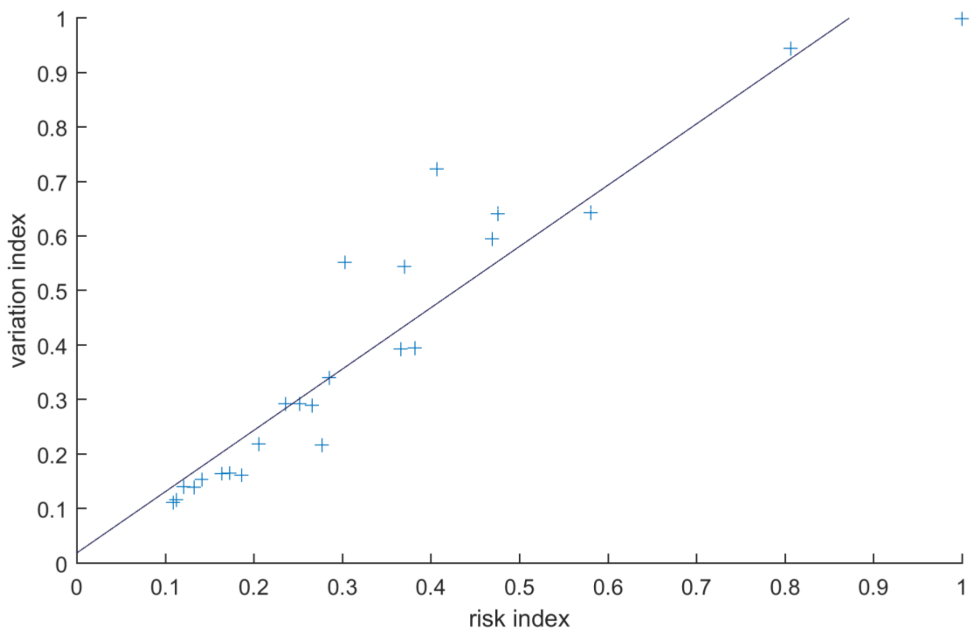


Figure 7-7: Relationship between the daily risk index and daily variation index for load demand on weekdays

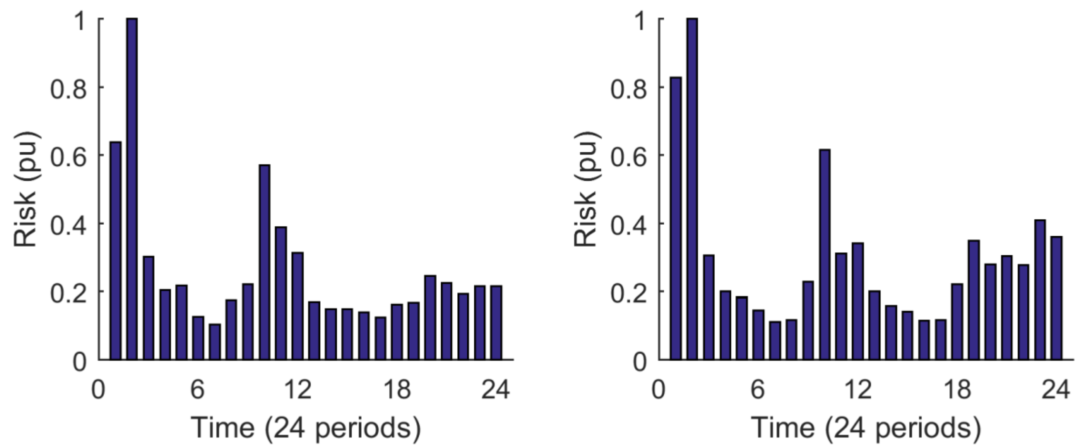
In Figure 7-7, the X axis is the daily risk index and Y axis is the daily variation index. The linear regression equation of the daily risk index and daily variation index for load demand on weekdays is shown below:

$$V = 1.1242 * R + 0.0190 \tag{7-4}$$

where R is the daily risk index and V is the daily variation index.

7.3.1.2. Weekends relationship

Similarly, the comparison of daily risk index and daily variation index for load demand on weekends is shown in Figure 7-8.



a. daily risk index b. daily variation index

Figure 7-8: Daily risk index and daily variation index for load demand on weekends

It can be seen from Figure 7-8 that there is a high correlation between the daily risk index and daily variation index for load demand on weekends. The fluctuations and peaks of these two indexes are very similar. Then Figure 7-9 indicates the relationship between these two indexes and fitted their data.

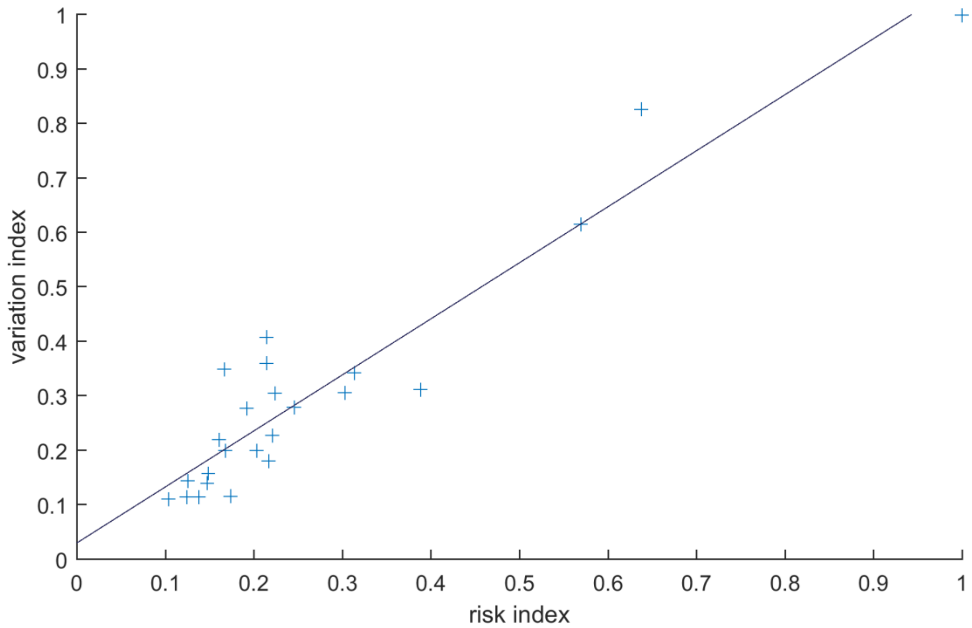


Figure 7-9: Relationship between the daily risk index and daily variation index for load demand on weekends

In Figure 7-9, the X axis is the daily risk index and Y axis is the daily variation index. The linear regression equation of the daily risk index and daily variation index for load demand on weekends is shown below:

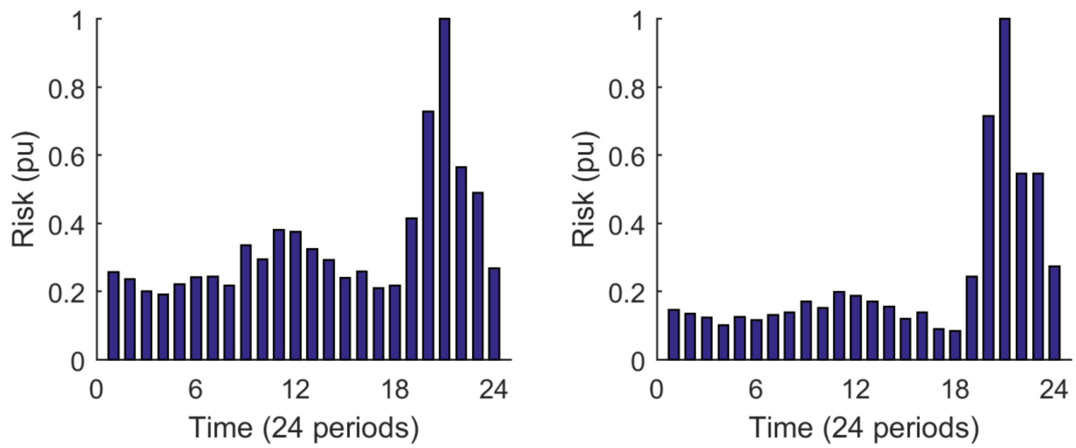
$$V = 1.0286 * R + 0.0301 \tag{7-5}$$

where R is the daily risk index and V is the daily variation index.

7.3.2. Relationship between daily risk index and daily variation index for electricity price

7.3.2.1. Weekdays relationship

Same as the load demand, in order to observe the relationship between daily risk index and daily variation index, the comparison of daily risk index and daily variation index for electricity price on weekdays is shown in Figure 7-10.



a. daily risk index b. daily variation index

Figure 7-10: Daily risk index and daily variation index for electricity price on weekdays

It can be seen from Figure 7-10 that there is a high correlation between the daily risk index and daily variation index for electricity price on weekdays. The fluctuations and peaks of these two indexes are very similar. Then Figure 7-11 indicates the relationship between these two indexes and fitted their data.

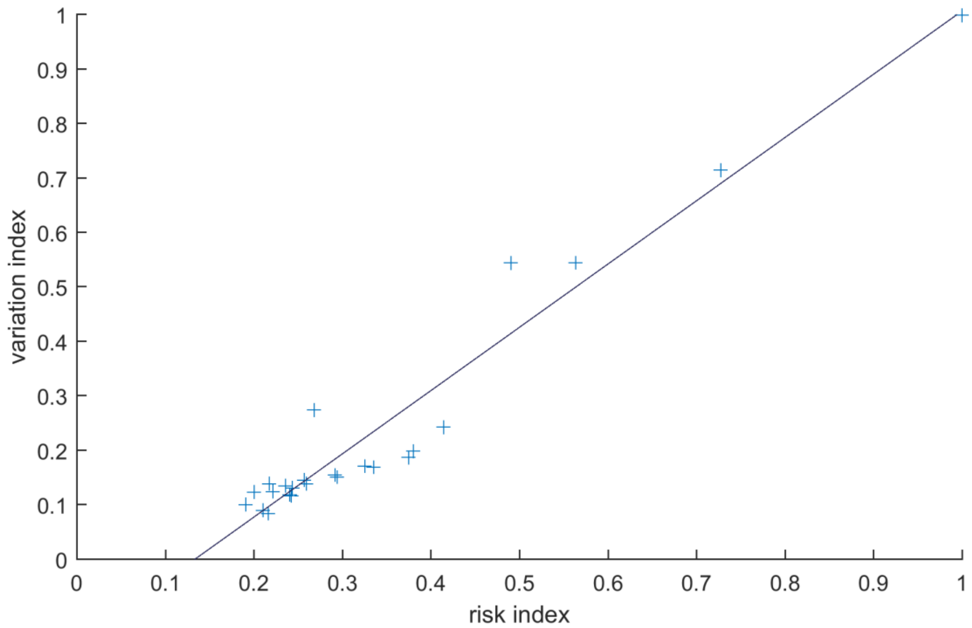


Figure 7-11: Relationship between the daily risk index and daily variation index for electricity price on weekdays

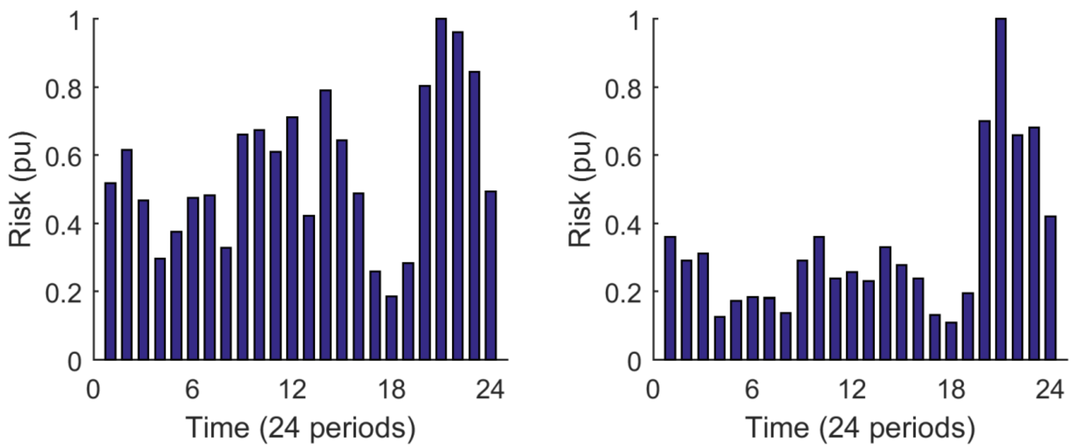
In Figure 7-11, the X axis is the daily risk index and Y axis is the daily variation index. The linear regression equation of the daily risk index and daily variation index for electricity price on weekdays is shown below:

$$V = 1.1613 * R - 0.1547 \tag{7-6}$$

where R is the daily risk index and V is the daily variation index.

7.3.2.2. Weekends relationship

Similarly, the comparison of daily risk index and daily variation index for electricity price on weekends is shown in Figure 7-12.



a. daily risk index b. daily variation index

Figure 7-12: Daily risk index and daily variation index for electricity price on weekends

It can be seen from Figure 7-12 that the correlation between the daily risk index and daily variation index for electricity price on weekends is not high as on weekdays. The daily risk index has a greater fluctuation than daily variation index. But their peak times and the overall waveforms are similar. So they also have some relationships with each other. Then Figure 7-13 indicates the relationship between the electricity price daily risk index and daily variation index on weekends.

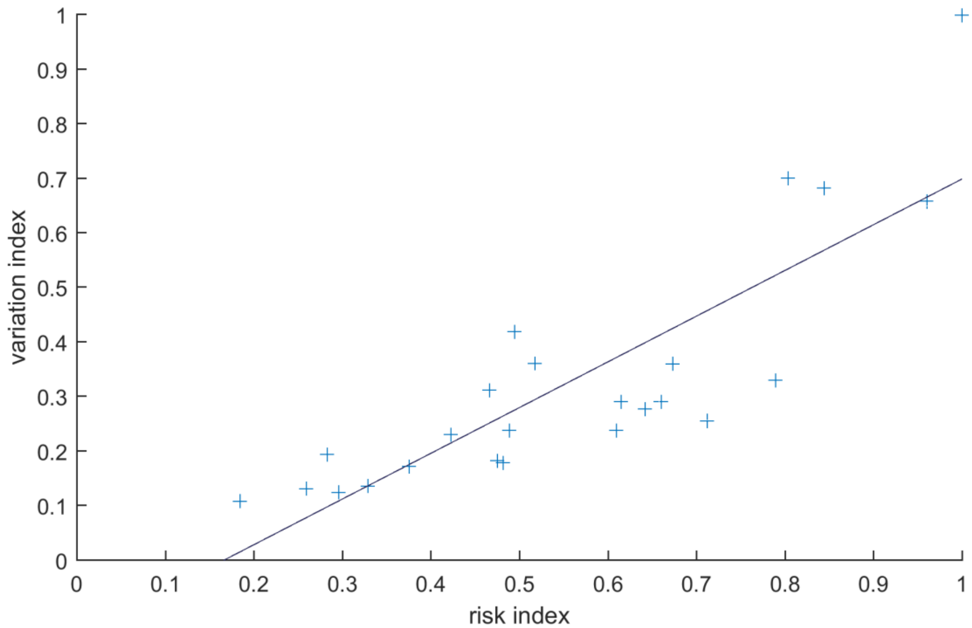


Figure 7-13: Relationship between the daily risk index and daily variation index for electricity price on weekends

In Figure 7-13, the X axis is the daily risk index and Y axis is the daily variation index. The linear regression equation of the daily risk index and variation index for electricity price on weekends is shown below:

$$V = 0.8379 * R - 0.1391 \tag{7-7}$$

where R is the daily risk index and V is the daily variation index.

It can be seen from these figures that the relationship between the electricity price daily risk index and daily variation index on weekends is not as good as the other three sets of data. This is may be because the unstable electricity price fluctuations on weekends lead to the inaccurate forecasting results, but there is still a linear correlation between them.

Therefore for both for load demand and electricity price, the daily risk index and variation index on weekdays or weekends all have very strong correlations between tach other.

The strength of the proposed method lies in its ability to identify the risk index accordingly from historical load demand and electricity price data, and avoid using complex forecasting processes. With a simple linear transformation, the variation index V in each hour period provides a compact evaluation of the risk index R resulting from actual forecasting errors. The weakness of the proposed method is that the obtained risk index may not as accurate as the results by the accrual forecasting errors.

7.4. Seasonal value-at-risk and expected shortfall analysis

Based on the risk index, it is now possible to analyse the financial risk measurement due to the load demand and electricity price forecast uncertainty. The financial risk refers to the estimated financial loss or gain risk of power market participants due to the load demand and electricity price forecast errors. In this section, the seasonal load demand and electricity price forecasting results that have been obtained before are used to analyse the seasonal financial risk from March 2015 to February 2016.

There are a number of financial tools have been used in the risk measurement for power market. One of the most important methods is value-at-risk (VaR) measurement. Originally VaR is a measure of the risk of investments. In this thesis it is an estimation of the possible loss/gain of financial return due to forecast error and it is expressed as a monetary value. It estimates the maximum expected loss or gain due to market element changes within a given confidence interval, during the asset portfolio holding period. Expected shortfall (ES) is a common indicator of the extreme portfolio loss/gain risk. ES can show the average level of loss suffered when the portfolio loss or gain exceeds VaR threshold. Because ES further considers the average level of losses in the extreme case, the extreme loss risk of portfolio can be measured more completely.

The total transaction amount in the market is the product of load demand, electricity price and one hour. The actual and forecast transaction amount can be shown as

$$A_{actual} = D_{actual} \times P_{actual} \times 1\ hour \tag{7-8}$$

$$A_{forecast} = D_{forecast} \times P_{forecast} \times 1\ hour \tag{7-9}$$

where D_{actual} and $D_{forecast}$ are the actual and forecast load demand respectively. P_{actual} and $P_{forecast}$ are the actual and forecast electricity price respectively. A_{actual} and $A_{forecast}$ are the actual and forecast transaction amount respectively. According to the forecast errors, the actual transaction amount may bigger or smaller to the forecast value. Therefore, the financial risk relationship between the total actual and forecast transaction amount for the generation side is expressed below

$$F_{positive} = A_{actual} - A_{forecast} \quad \text{if} \quad A_{actual} > A_{forecast} \tag{7-10}$$

$$F_{negative} = A_{forecast} - A_{actual} \quad \text{if} \quad A_{forecast} > A_{actual} \tag{7-11}$$

where $F_{positive}$ and $F_{negative}$ are the financial risk caused by forecasting errors when the actual transaction amount is bigger and smaller to the forecast value respectively. For the generation side in the power market, when the actual transaction amount is bigger than the forecast value, which means the total price they sold is more than expected and the financial return is profitable. In this situation the financial risk errors are presented as positive. If the actual transaction amount is smaller than the forecast value, which means the total price they sold is less than expected and it expresses the loss of financial return. In this situation the financial risk errors are presented as negative. The demand side presents an opposite results to the generation side because they buy electricity from Power Exchange. This thesis only considers the financial risk of generation side in the power market.

Depending on equation 7-10 and 7-11, all the forecasting results can be divided into positive and negative errors. In one day, adding all the positive errors to get one-day positive financial risk, and adding all the negative errors to get one-day negative financial risk. Figure 7-14 shows the calculation process of one-day positive and negative financial risk on March 1, 2015.

After calculating the financial risk for each day of the year from March 2015 to February 2016, the seasonal financial risks can be obtained. Figure 7-15 shows the positive and negative financial risks in spring 2015.

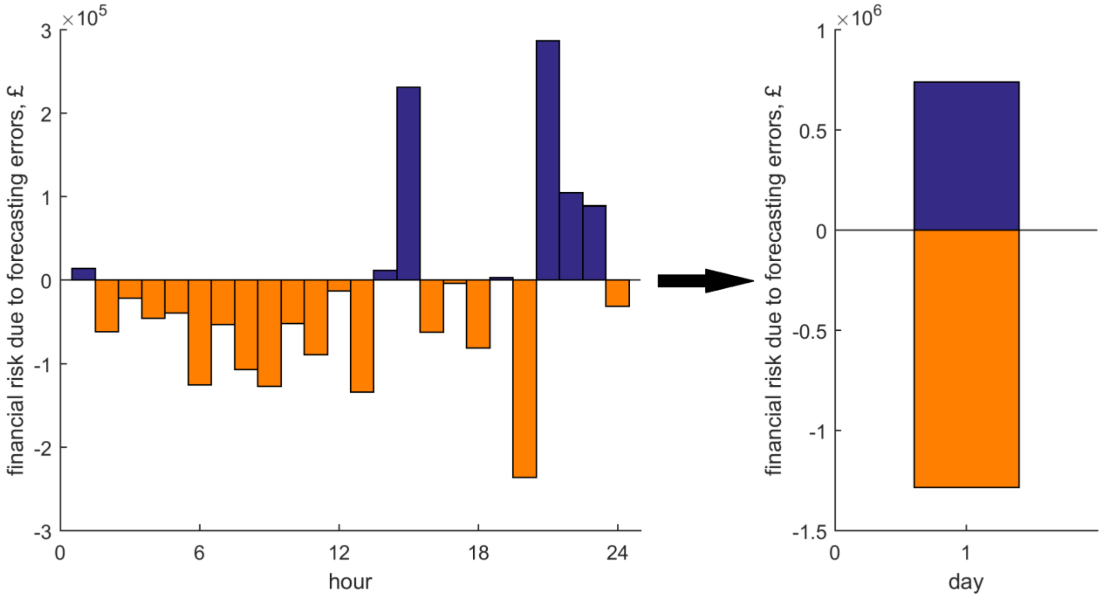


Figure 7-14: The calculation process of one-day positive and negative financial risk on March 1, 2015

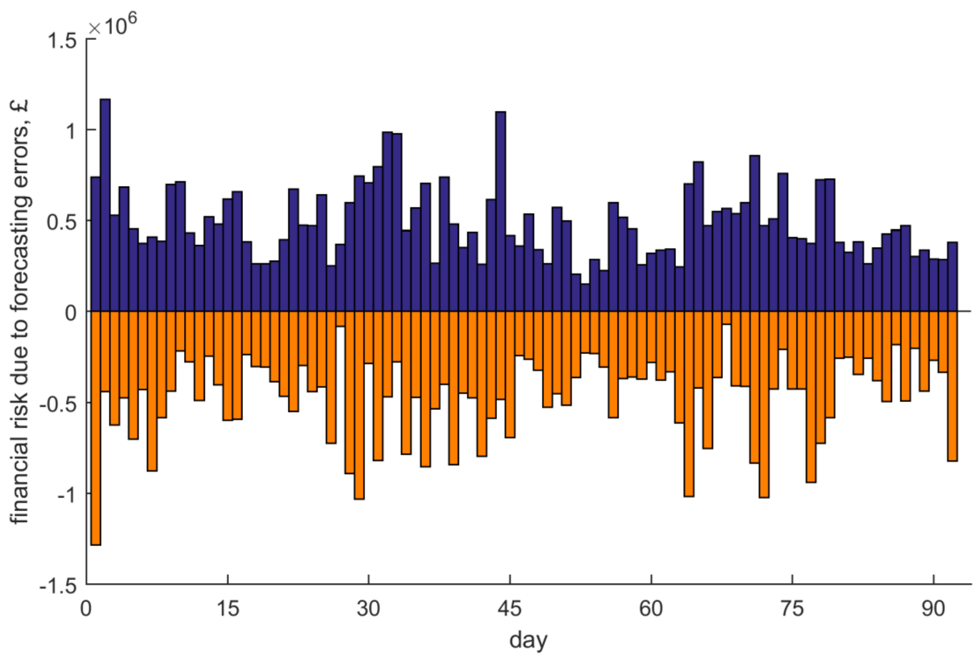
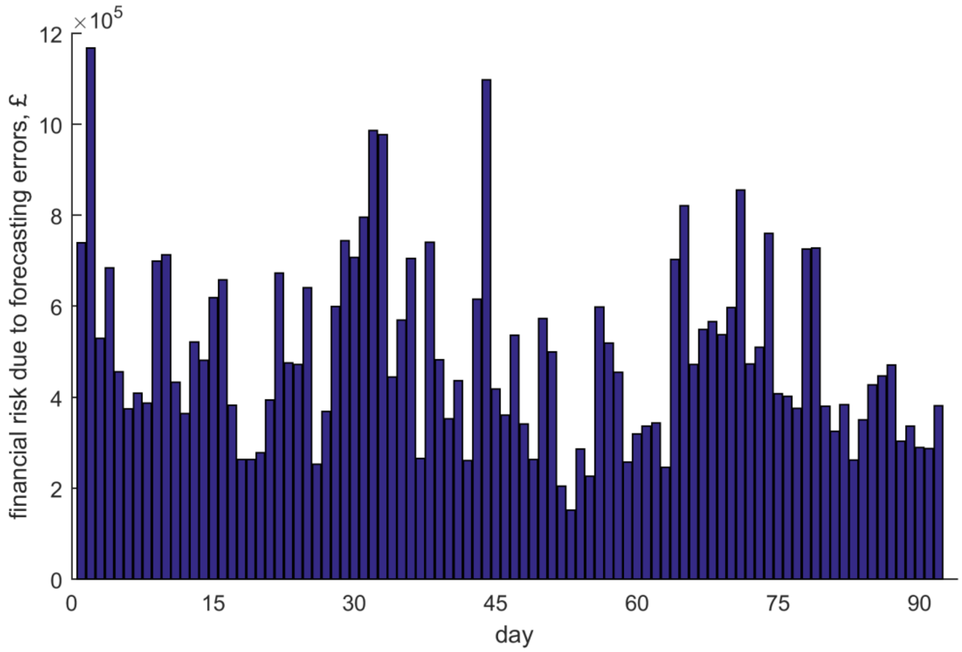


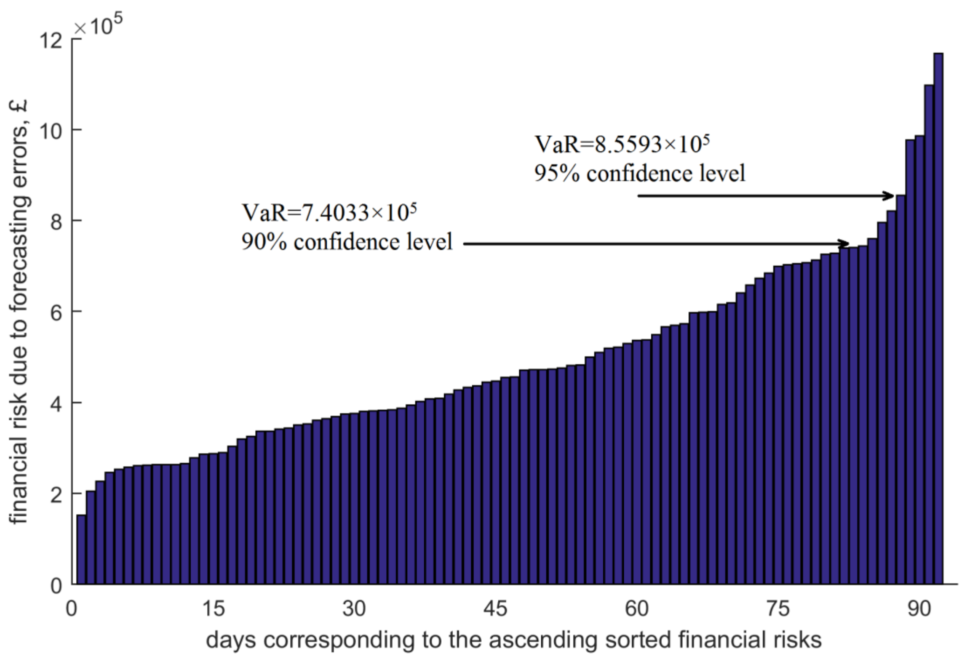
Figure 7-15: Positive and negative financial risks in spring 2015

In order to calculate the values of VaR and ES in each season, all the positive and negative financial risks are sorted in ascending order respectively. For the VaR method which used in the seasonal financial risks from March 2015 to February 2016, the holding period is one day, the observation period is one season, and the confidence level selected 95% and 90%.

Here, the original positive financial risks and the ascending sorted positive financial risks in spring 2015 and the VaR threshold with 95% and 90% confidence level are shown in Figure 7-16. The original negative financial risks and the ascending sorted negative financial risks in spring 2015 and the VaR threshold with 95% and 90% confidence level are shown in Figure 7-17. For ease of observation, all the negative financial risk values are taken in absolute terms.

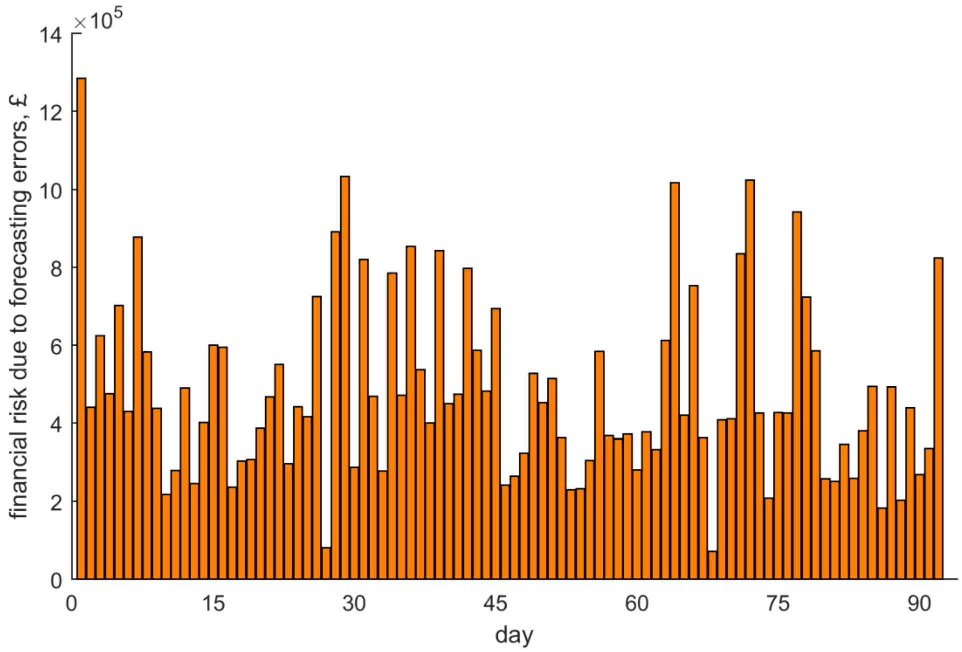


a. original

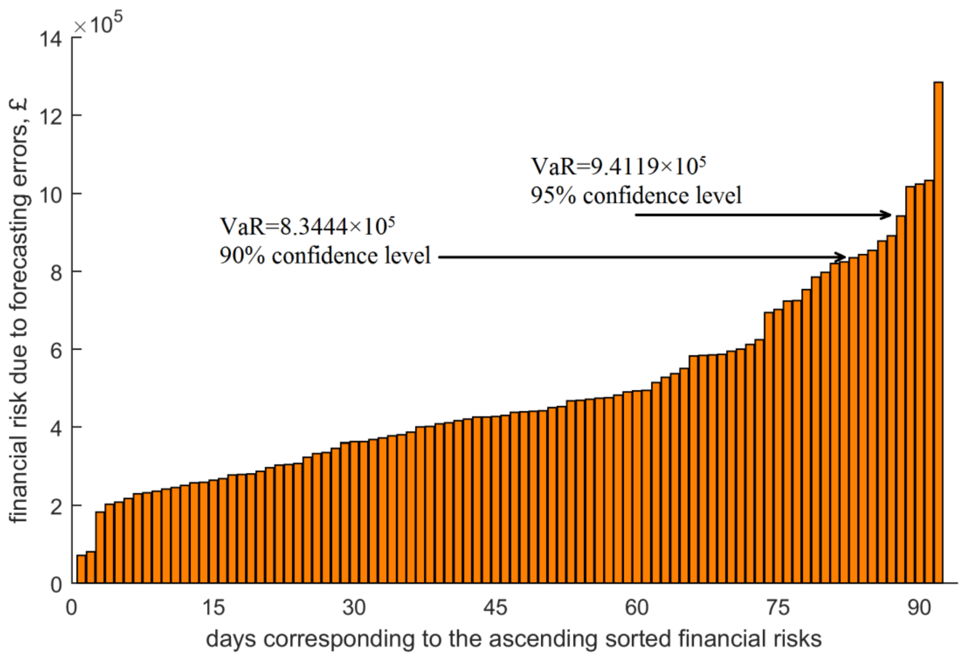


b. ascending sorted

Figure 7-16: The positive financial risks in spring 2015



a. original



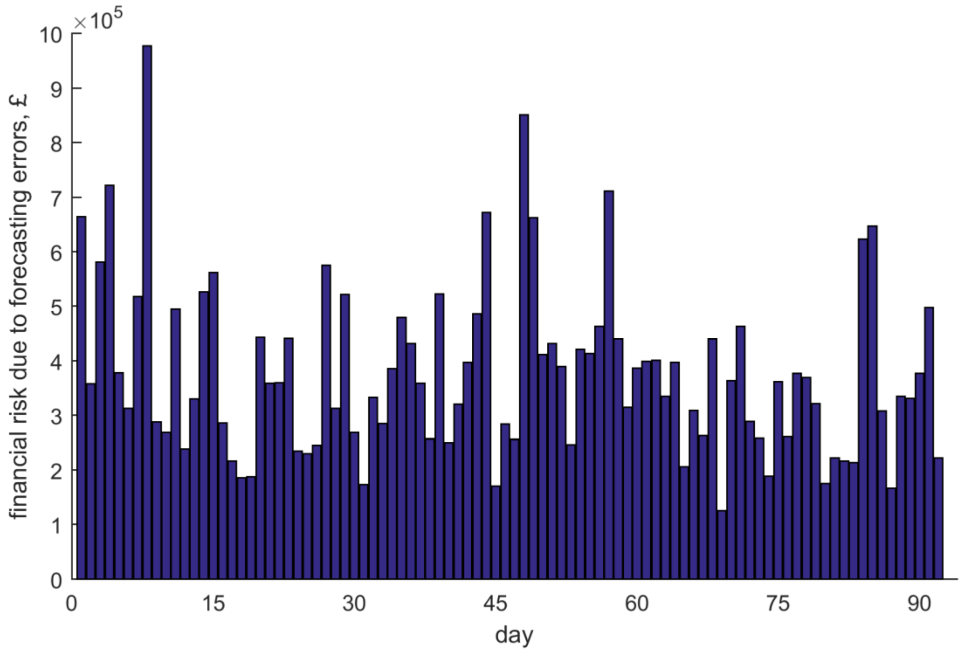
b. ascending sorted

Figure 7-17: The negative financial risks in spring 2015

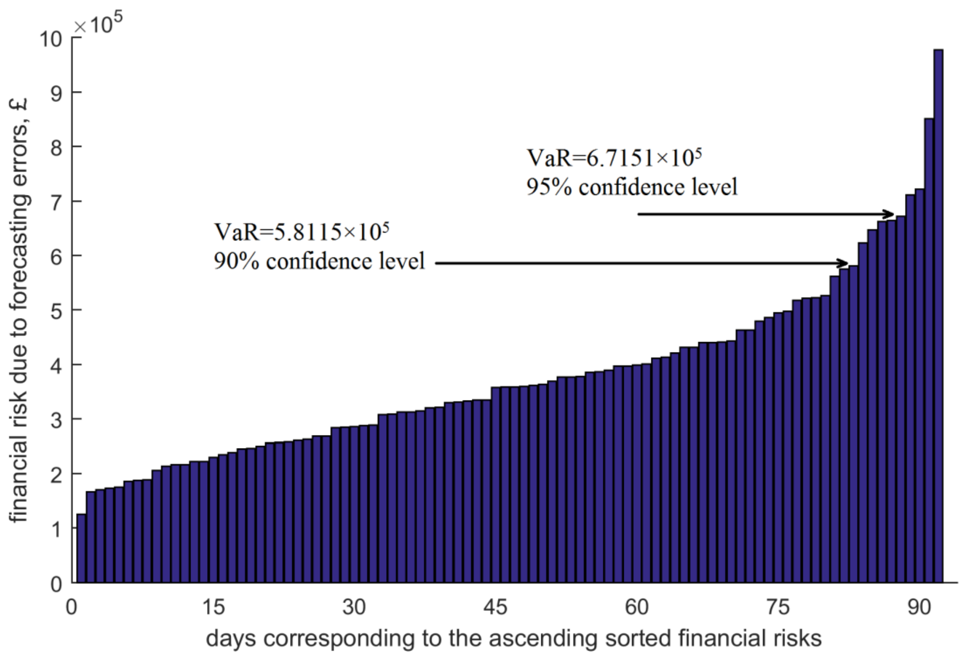
Based on the historical VaR method, for the positive financial risks in Figure 7-16b, the daily VaR of transaction amount in spring 2015 is £8.5593×10^5 at 95% confidence level and £7.4033×10^5 at 90% confidence level. That means there are 5% probability the daily positive financial errors will exceed £8.5593×10^5, 10% probability will exceed £7.4033×10^5. For the negative financial risks, the daily VaR of transaction amount is £9.4119×10^5 at 95% confidence level and £8.3444×10^5 at 90% confidence level. That means there are 5% probability the daily negative financial errors will exceed £9.4119×10^5, 10% probability will exceed £8.3444×10^5. It can be found that in spring 2015, the VaR of negative risks is bigger than positive risks no matter it is for 95% or 90% confidence level.

Expected shortfall presents the average value of errors when the risk exceed VaR threshold. So the ES in spring 2015 is £1.0168×10^6 at 95% confidence level and £8.9465×10^5 at 90% confidence level for the positive financial risks. For the negative risks, the ES is £1.0602×10^6 at 95% confidence level and £9.5988×10^5 at 90% confidence level. It can be found that in spring 2015, the ES of negative risks is also bigger than positive risks for both 95% and 90% confidence level.

In order to observe the seasonal financial risks from March 2015 to February 2016, the VaR and ES methods which used in spring are also achieved in summer, autumn and winter. The positive and negative financial risks in summer, autumn and winter are shown in Figure 7-18 to 7-23 respectively.

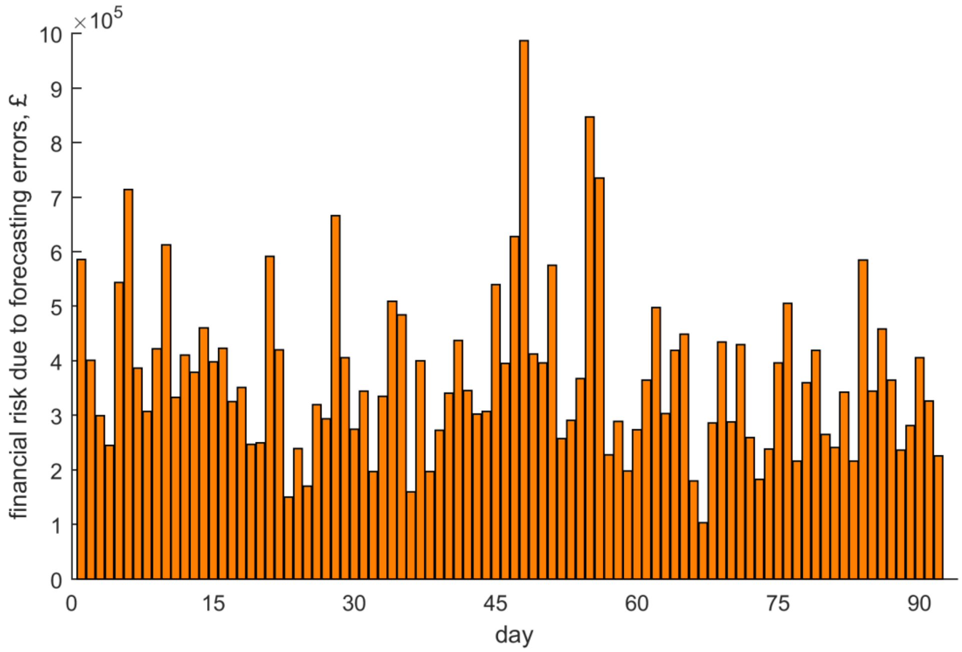


a. original

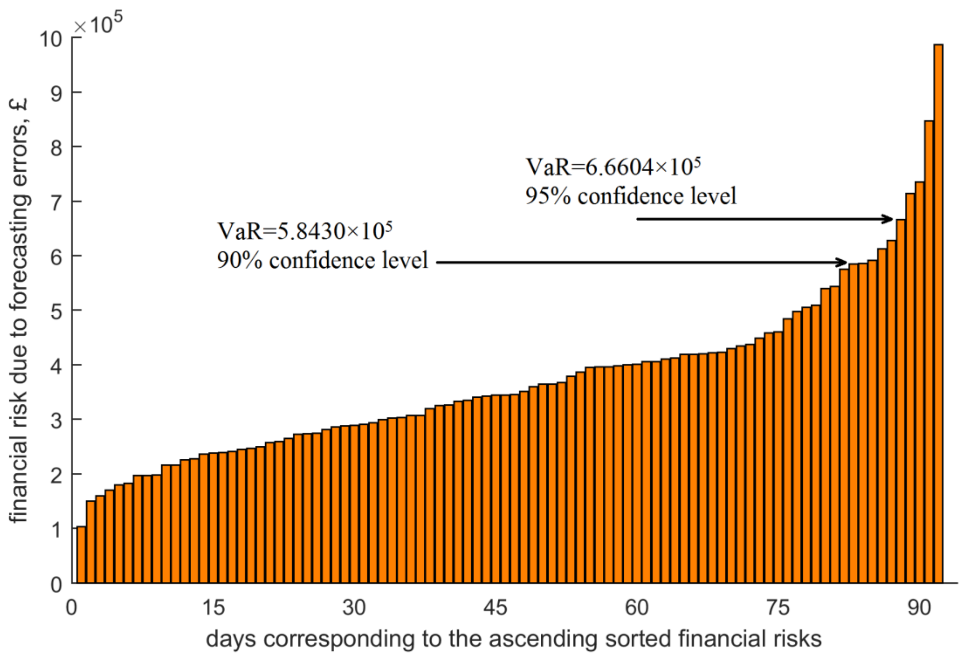


b. ascending sorted

Figure 7-18: The positive financial risks in summer 2015

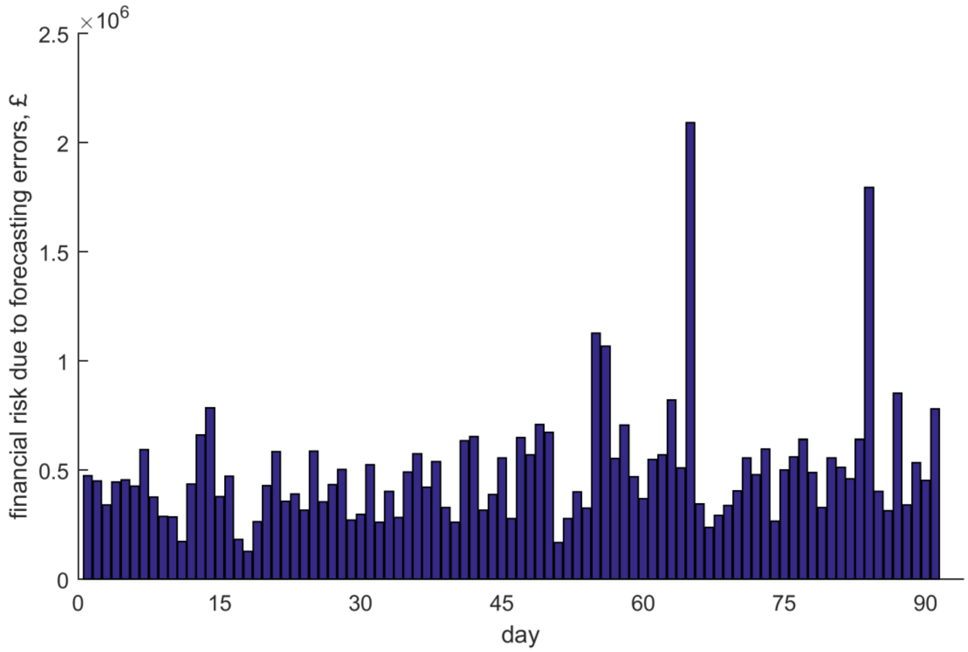


a. original

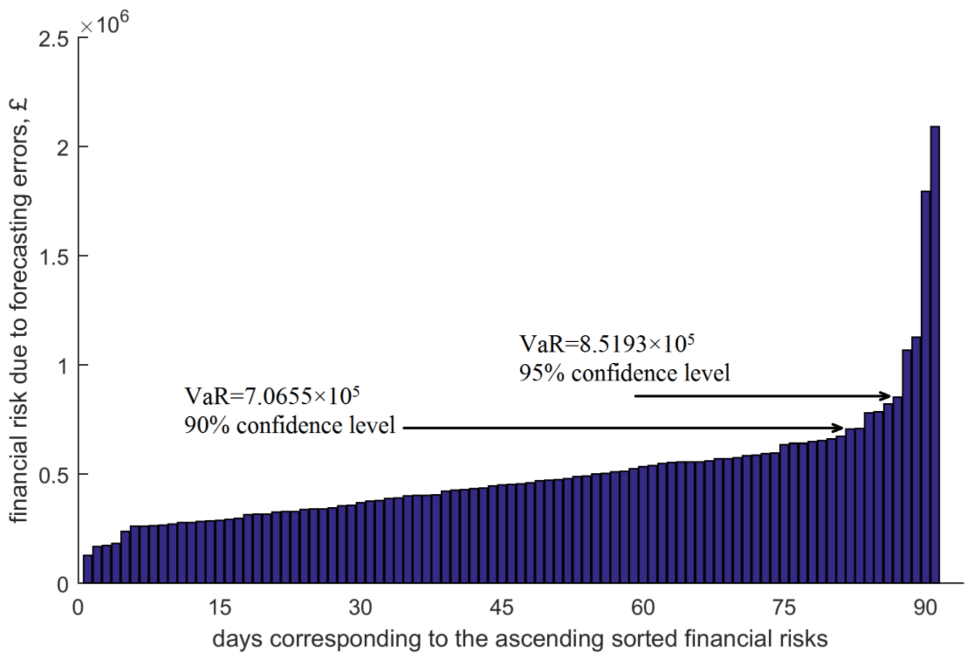


b. ascending sorted

Figure 7-19: The negative financial risks in summer 2015

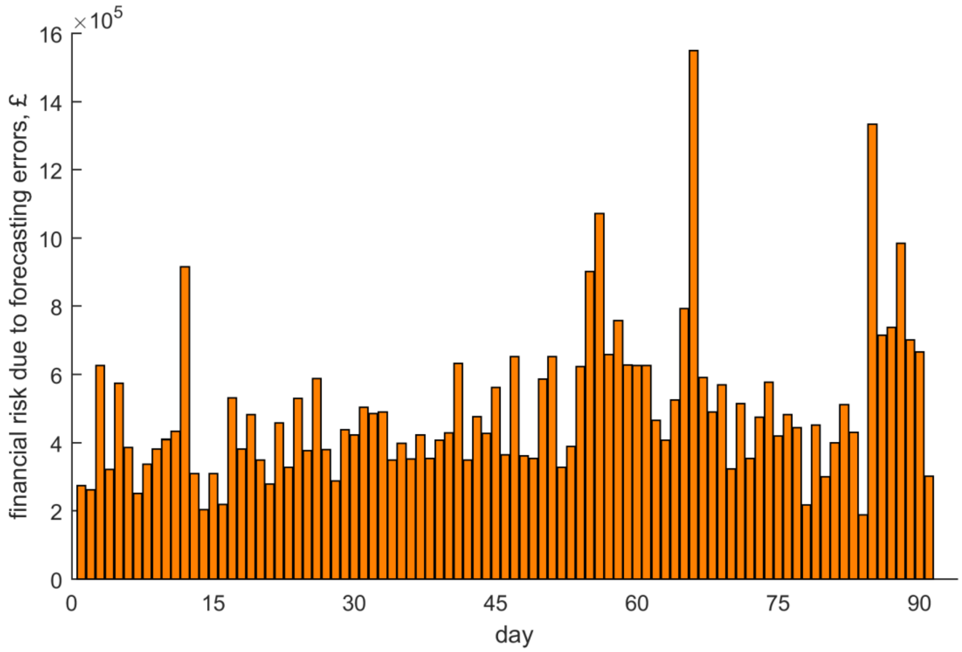


a. original

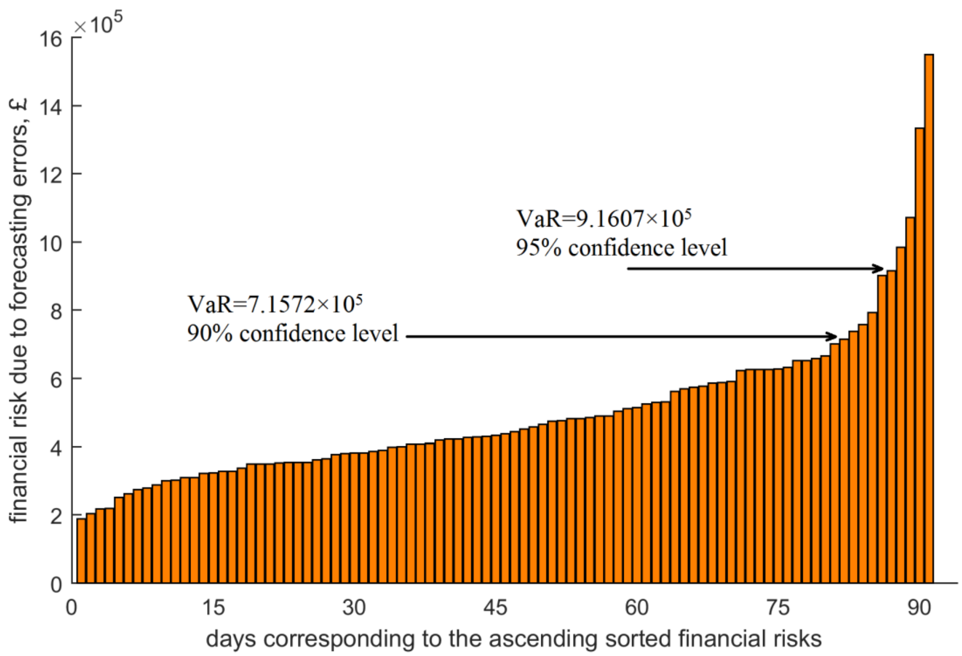


b. ascending sorted

Figure 7-20: The positive financial risks in autumn 2015

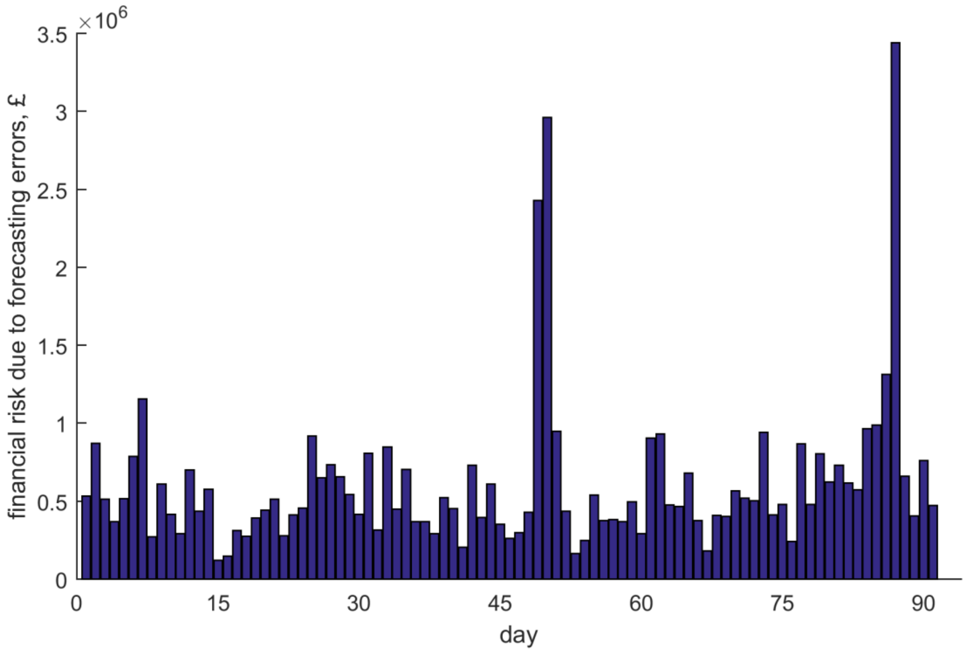


a. original

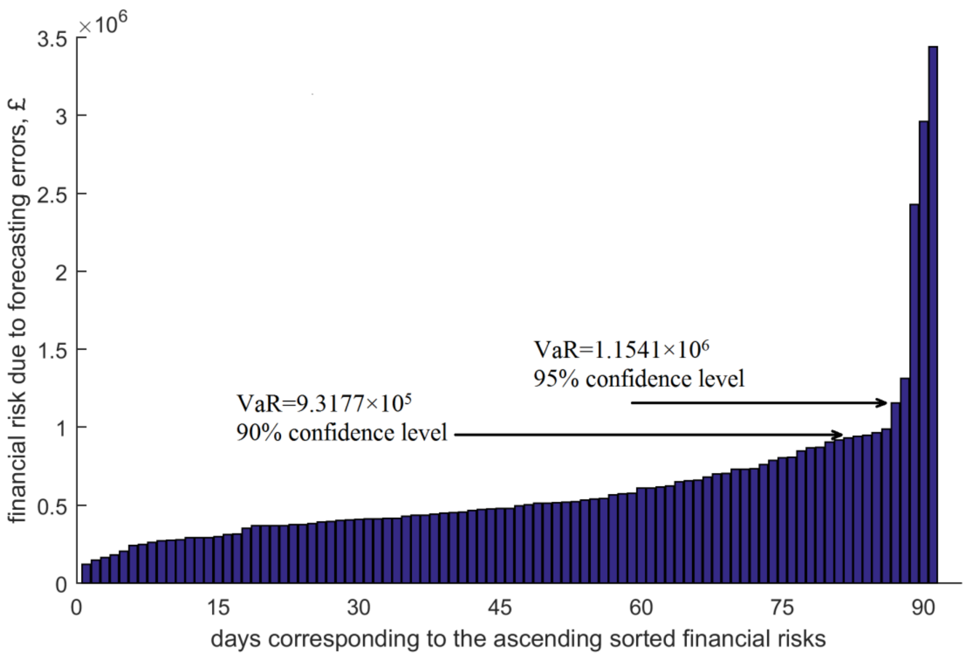


b. ascending sorted

Figure 7-21: The negative financial risks in autumn 2015

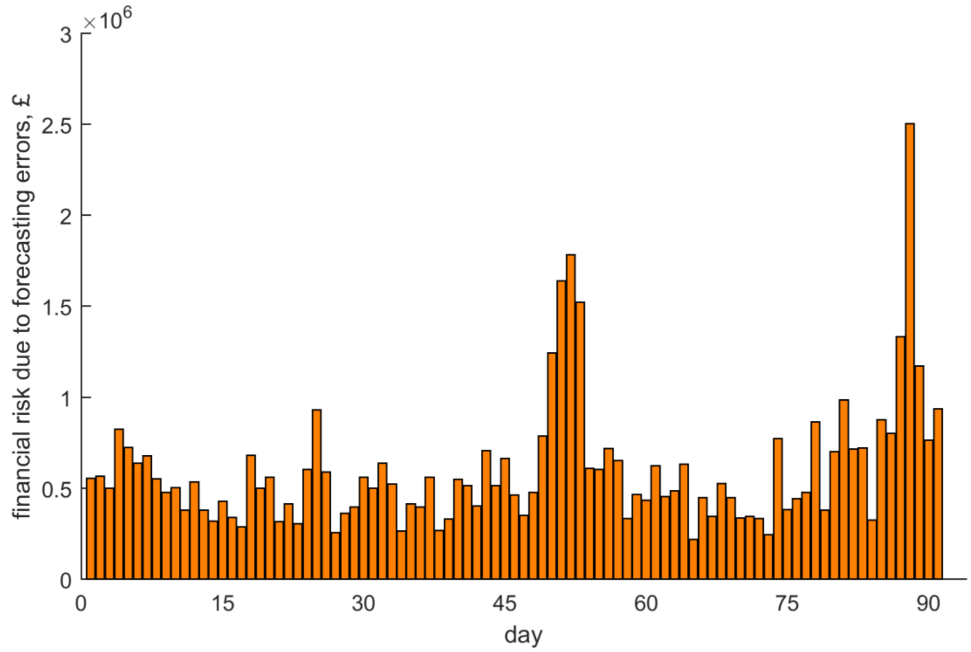


a. original

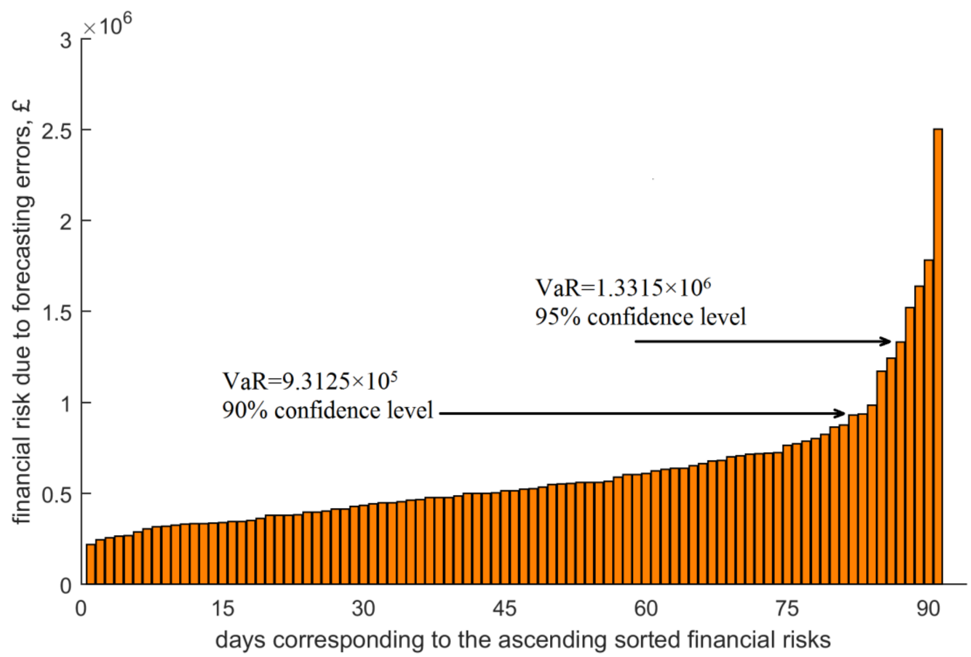


b. ascending sorted

Figure 7-22: The positive financial risks in winter 2015



a. original



b. ascending sorted

Figure 7-23: The negative financial risks in winter 2015

All the results of VaR threshold and ES in different seasons with positive and negative financial risks are listed in Table 7-1 and 7-2.

Table 7-1: VaR threshold and ES in different seasons when financial risks are positive

Confidence level	**Seasons**	**VaR,** £	**ES,** £
95%	spring	8.5593×10^5	1.0168×10^6
	summer	6.7151×10^5	7.8624×10^5
	autumn	8.5193×10^5	1.3861×10^6
	winter	1.1541×10^6	2.2591×10^6
90%	spring	7.4033×10^5	8.9465×10^5
	summer	5.8115×10^5	7.1091×10^5
	autumn	7.0655×10^5	1.0732×10^6
	winter	9.3177×10^5	1.6070×10^6

Table 7-2: VaR threshold and ES in different seasons when financial risks are negative

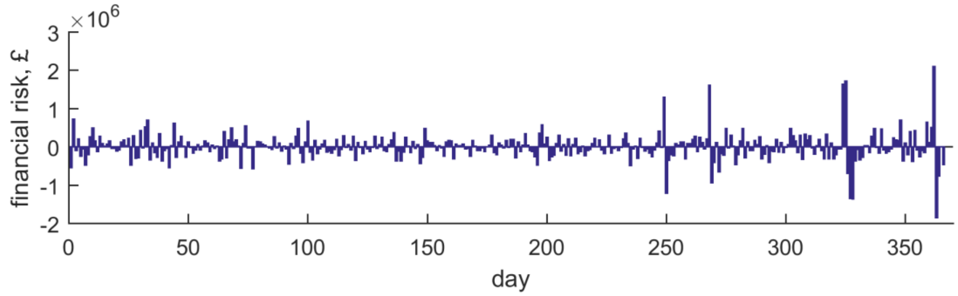
Confidence level	**Seasons**	**VaR,** £	**ES,** £
95%	spring	9.4119×10^5	1.0602×10^6
	summer	6.6604×10^5	7.8967×10^5
	autumn	9.1607×10^5	1.1714×10^6
	winter	1.3315×10^6	1.7560×10^6
90%	spring	8.3444×10^5	9.5988×10^5
	summer	5.8430×10^5	6.9493×10^5
	autumn	7.1572×10^5	9.7635×10^5
	winter	9.3125×10^5	1.4048×10^6

It can be seen from Table 7-1 that for the positive financial risks with 95% and 90% confidence level, summer all has the smallest VaR threshold and the smallest ES. The biggest value of VaR threshold and ES are all appeared in winter. Table 7-2 illustrates the VaR threshold and ES with 95% and 90% confidence level for negative financial risks. It can be observed that summer is also the season which has the smallest VaR threshold and ES. The biggest value of VaR threshold and ES are also appeared in winter. Therefore, for both positive and negative seasonal financial risks in the year from March 2015 to February 2016, summer and winter are the seasons that have the minimum and maximum VaR threshold and ES respectively, no matter the confidence level is 95% or 90%.

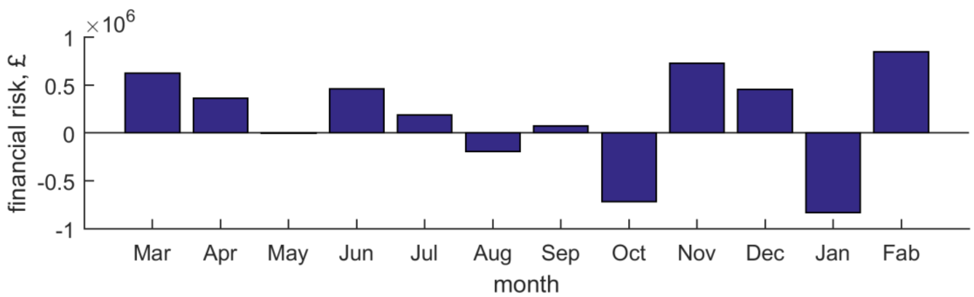
7.5. The total financial risk assessment in different situations

The financial risks in different seasons from March 2015 to February 2016 due to the seasonal forecasting results of load demand and electricity price have been calculated. In order to evaluate the total accuracy of the financial risks, the annual load demand and electricity price forecasting results that have been obtained before are used to analyse the daily, monthly, seasonal and annual total financial risk from March 2015 to February 2016.

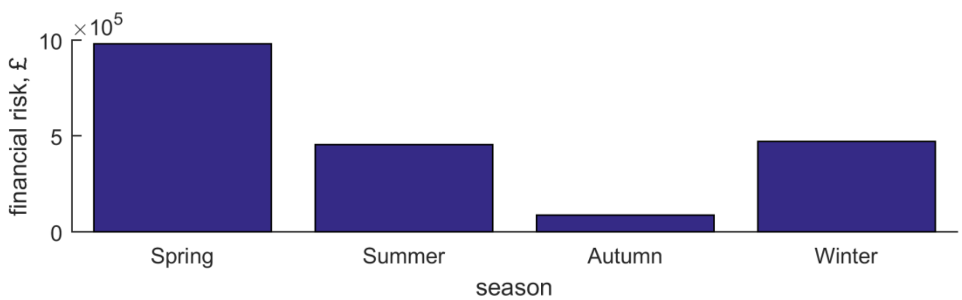
The daily, monthly and seasonal financial risks of the year from March 2015 to February 2016 are illustrated in Figure 7-24. Also, the annual total financial risk for the whole year has been calculated, which can present the actual risk that the market participants will have to bear. The best situation is that all the positive and negative financial risks could offset each other, and then the annual total financial risk value is zero.



a. daily financial risks



b. monthly financial risks

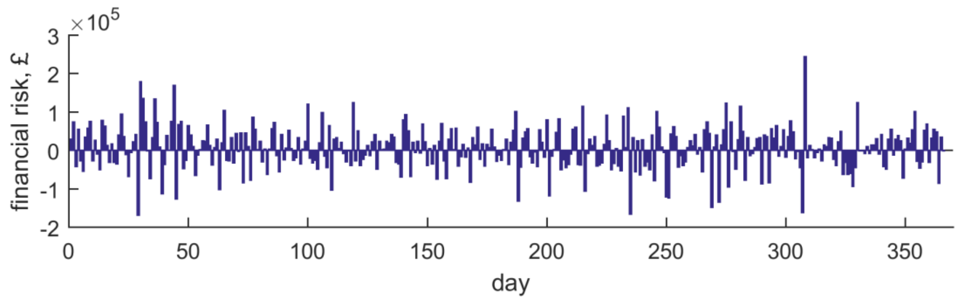


c. seasonal financial risks

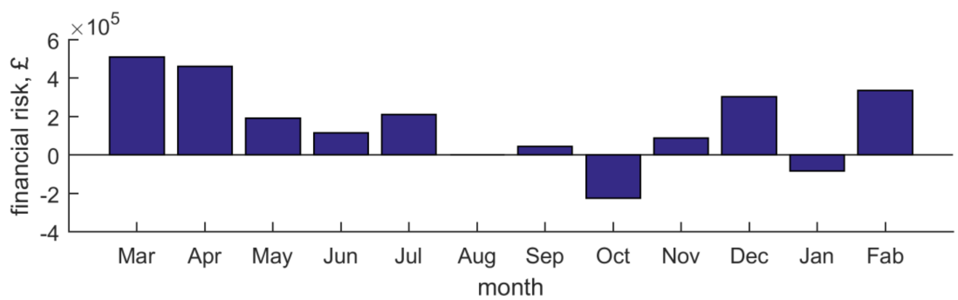
Figure 7-24: Financial risks of the year from Mar. 2015 to Feb. 2016 due to forecasting load demand and forecasting electricity price

It is shown in Figure 7-24a that the bigger daily financial risks are appeared at the beginning and ending of the year. The maximum daily financial risk is happened at day 362 and the value is £2.1069×10^6. The minimum daily financial risk is happened at day 221 and the value is -£1.2770×10^3. For the monthly financial risks in Figure 7-24b, the maximum risk £8.4803×10^5 appeared on February 2016 and the minimum risk £1.2123×10^3 appeared on May 2015. Figure 7-24c shows that the financial risk of autumn is the smallest in these four seasons, and its value is £8.7670×10^4. Spring has the biggest financial risk with £9.8192×10^5. The financial risk values for summer and winter are very close. Moreover, the annual total financial risk is calculated and the value is £1.9959×10^6.

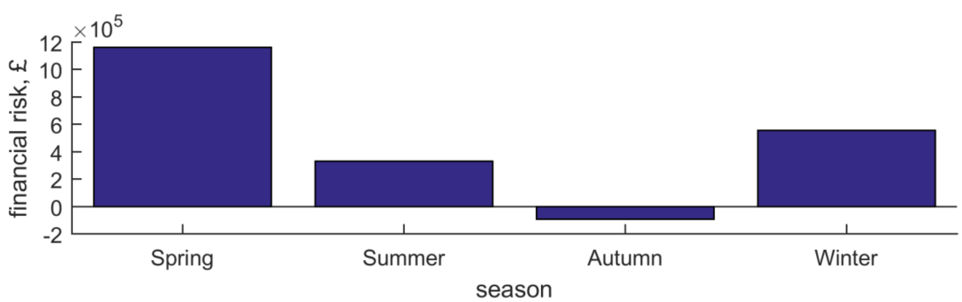
All the data we have achieved by now are depending on both load demand and electricity price forecasting results. However, if the load demand or electricity price historical data is not good enough, it will lead to an inaccurate forecasting result. At this time, the financial risks derived from the consideration of load demand and electricity price forecasting results will also be inaccurate. In this case, the forecast data of load demand or electricity price can be ignored and replaced by the actual data. Therefore, the total financial risk can be assessed in three different preconditions. Firstly, the forecasting load demand and electricity price are considered (situation 1), which has been calculated in Figure 7-24. Secondly, the forecasting load demand and actual electricity price are considered (situation 2). Thirdly, the actual load demand and forecasting electricity price are considered (situation 3). Simultaneously, situation 2 and 3 can also observe the individual impact of forecasting load demand and forecasting electricity price on financial risks. Here, the daily, monthly and seasonal financial risks of the year from March 2015 to February 2016 under situation 2 and 3 are shown in Figure 7-25 and 7-26 respectively. Also, their annual total financial risks of the year have been calculated.



a. daily financial risks

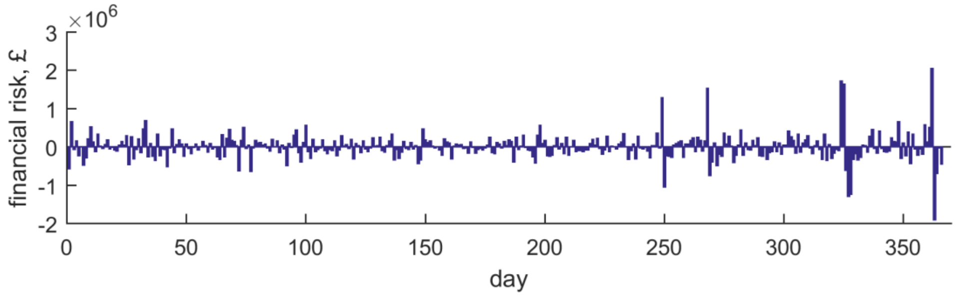


b. monthly financial risks

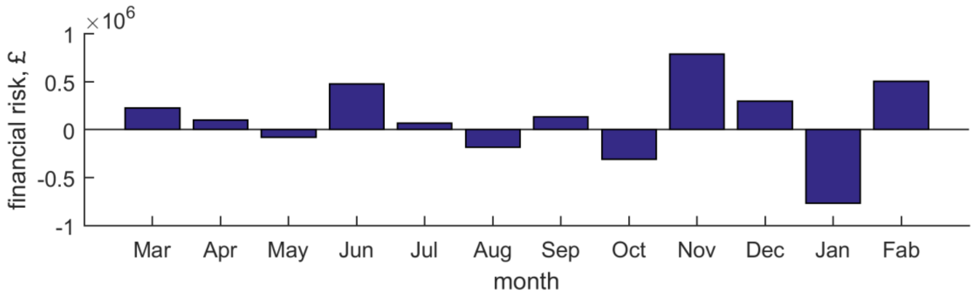


c. seasonal financial risks

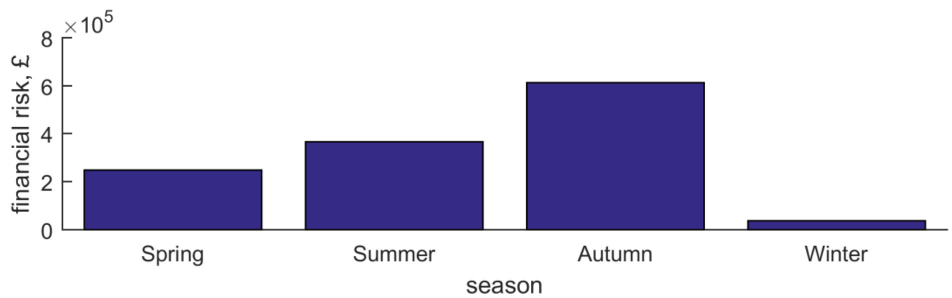
Figure 7-25: Financial risks of the year from Mar. 2015 to Feb. 2016 due to forecasting load demand and actual electricity price



a. daily financial risks



b. monthly financial risks



c. seasonal financial risks

Figure 7-26: Financial risks of the year from Mar. 2015 to Feb. 2016 due to actual load demand and forecasting electricity price

It can be observed from Figure 7-25 that when considering the forecasting load demand and actual electricity price, the daily and monthly financial risk values are all smaller than the other two situations. The maximum daily financial risk in Figure 7-25a is

£2.4422×10^5 and the maximum monthly financial risk in Figure 7-25b is £5.1003×10^5. But its spring financial risk is £1.1611×10^6 in Figure 7-25c, which is the biggest single seasonal financial risk in all these three situations. The minimum seasonal financial risk is happened in autumn, which is the same as situation 1. The annual total financial risk is £1.9537×10^6.

In Figure 7-26, the daily and seasonal financial risks in situation 3 are similar to those in situation 1. The bigger daily financial risks are all appeared at the beginning and ending of the year. But its maximum seasonal financial risk occurs in autumn, which is exactly the opposite of the other two situations. The minimum seasonal financial risk happened in winter. The annual total financial risk is £1.2616×10^6 for situation 3.

Furthermore, the RMSPEs and MAPEs between the annual total transaction amount and forecast transaction amount are calculated to compare the financial risk forecast accuracy under different situations. The results are shown in Table 7-3.

Table 7-3: The comparison of forecast results of financial risks under three different situations

Situations	**Annual total financial risk,** £	**RMSPE,** %	**MAPE,** %
1	1.9959×10^6	14.23	8.51
2	1.9537×10^6	4.28	2.53
3	1.2616×10^6	12.93	7.64

It can be seen from Table 7-3 that the biggest annual total financial risk, RMSPE and MAPE are all appeared in situation 1. That means when considering the forecasting load demand and electricity price, the results is less accurate than the other situations. Because situation 1 combines load demand and electricity price forecast errors together. When considering the forecasting load demand and actual electricity price, situation 2 presented the most accurate forecast results. Its RMSPE is 4.28% and MAPE is 2.53%. The annual total financial risk is a little smaller than situation 1. When considering the actual load demand and forecasting electricity price, the smallest annual total financial risk is occurred in situation 3. But the RMSPE and MAPE of situation 3 is in the middle between situation 1 and 2.

Therefore, the results indicate that a more accuracy forecast result not necessarily has a smaller annual total financial risk, because the financial risks could be positive or negative. In this set of data, when considering the forecasting load demand and electricity price, the forecast result is the most inaccurate and the annual total financial risk is also the greatest. Moreover, Table 7-3 shows that all the annual total financial risks are positive. That means no matter which situation is considered, for the generation side, the actual transaction amount is bigger than the forecast value in most of time during this year.

For the positive and negative financial risks introduced in section 7.4, the VaR and ES of the positive financial risks can show the maximum possible gains on power generation side when only considering that the actual values of the transaction amount are greater than the forecast values. The VaR and ES of the negative financial risks can show the maximum possible losses on power generation side when only considering that the actual values of the transaction amount are smaller than the forecast values. However, the total financial risk introduced in this section does not calculate VaR and ES, which is the result of directly adding positive and negative financial risks, and it can express the total risk that the market participants will ultimately bear. Moreover, the total financial risk is the closest to the real situation, because the total financial risk considers the two cases where the actual values of the transaction amount are greater and smaller than the forecast values. Therefore, the total financial risk is of great importance to power market participants.

7.6. Summary

The risk assessment for risk index and financial risk on load demand and electricity price forecast is presented in this chapter. With the monthly forecasting results of load demand and electricity price, the daily and seasonal risk indexes on weekdays and weekends are illustrated. Thus the daily and seasonal high-risk periods of forecast inaccuracy can be observed from risk indexes. In addition, a simple method called variation index on risk assessment is proposed. It is based on calculating the standard deviation of load demand and electricity price increment as the variation index. Then the linear relationships between the daily risk index and daily variation are expressed. The results showed that for load demand and electricity price, the daily risk index and variation index on weekdays or weekends all have very strong correlations between tach other. Moreover, this chapter presents Value-at-Risk and Expected Shortfall with 95% and 90% confidence level in different seasons for the generation side based on the seasonal forecast results of load demand and electricity price. The results indicated that summer and winter are the seasons that have the minimum and maximum VaR threshold and ES respectively. Finally, the daily, monthly, seasonal and annual total financial risks under three different situations are illustrated. The RMSPE and MAPE are used to analyse the forecast accuracy of financial risks. The results showed that more accurate forecasts do not necessarily have a smaller annual total financial risk because the financial risks have positive and negative values.

The contribution of risk assessment is to provide market participants an opportunity for easily quantifying their risk exposure and making optimal trading strategies in the competitive electricity market.

Chapter 8

Conclusions and future work

8.1. Conclusions and contributions

This thesis uses the ARIMA, SARIMA and ANN models to forecast load demand and electricity price respectively. The optimal models and methods are selected from the monthly, seasonal, annual and multi-step-ahead forecasting processes. Moreover, in order to observe the errors more intuitively, all the forecast errors in this thesis are expressed as risk index. A new method named variation index is also presented. The advantage of variation index is that the risk index can be analysed by the data itself. Finally, the VaR and ES methods commonly used in the financial industry are used in the electricity market to assess the financial risk for market participants. This opens up new ideas for financial analysis of the electricity market. All the research results in this thesis have been analysed and presented in detail. The well-proven software tools MATLAB supports the study.

8.1.1. Load demand forecast and electricity price forecast

For the load demand forecast, the forecasting models are based on the monthly load demand. In the demonstration example of August 2015, the results indicate that the

RMSPEs and MAPEs of SARIMA models are all smaller than ARIMA and ANN models. In the 12-month forecasting results on weekdays and weekends from March 2015 to February 2016, the accuracy of load demand forecasts on weekdays are similar with weekends. Almost all the RMSPEs and MAPEs of SARIMA models are smaller than the ARIMA and ANN models. Thus the SARIMA model is selected as the optimal model to forecast the load demand.

The continuous historical data method and seasonal separation method are used to forecast the seasonal load demand. The results show that all of the seasonal RMSPE and MAPE by seasonal separation method are bigger than the values by continuous historical data method. So the continuous historical data method is selected to forecast the seasonal load demand. The input data for one-month, six-month and one-year are used to forecast the annual load demand. The results show that the forecast result is more accurate with the one-year input data. It also proves that the forecast result is more accurate when the rolling window size is larger. Therefore, the one-year input data are selected to forecast the annual load demand. In the multi-step-ahead forecast, the seasonal and annual load demands from March 2015 to February 2016 are forecasted by one-step-ahead, 6-step-ahead, 12-step-ahead and 24-step-ahead. The results illustrate that all of the seasonal and annual values of RMSPE and MAPE made by one-step-ahead forecasts are much smaller than others. The annual RMSPE of one-step-ahead forecast is 4.28%, which is 8.26% more accurate than the 12.54% annual RMSPE of 24-step-ahead. Similarly, the annual MAPE of one-step-ahead forecast is 2.53%, which is

6.03% more accurate than the 8.56% annual MAPE of 24-step-ahead. The results proved that the one-step-ahead load demand forecasts have the most accurate forecasting results.

The same forecasting methods are used to forecast the electricity price. In the demonstration example of August 2015, the monthly forecasting results indicate that the RMSPEs and MAPEs of SARIMA models are all smaller than ARIMA and ANN models. In the 12-month forecasting results on weekdays and weekends from March 2015 to February 2016, electricity price forecasts on weekdays are more accurate than weekends. Almost all the RMSPEs and MAPEs of SARIMA models are smaller than the ARIMA and ANN models. Thus the SARIMA model is selected as the optimal model to forecast the electricity price.

In the seasonal electricity price forecast, the results show that all of the seasonal RMSPE and MAPE by seasonal separation method are bigger than the values by continuous historical data method. So the continuous historical data method is selected to forecast the seasonal electricity price. In the annual electricity price forecast, the results show that the forecast result is more accurate with the one-year input data. It also proves that the forecast result is more accurate when the rolling window size is larger. Therefore, the one-year input data are selected to forecast the annual electricity price. In the multi-step-ahead electricity price forecast, the results illustrate that all of the seasonal and annual values of RMSPE and MAPE made by one-step-ahead forecasts are smaller than others. The annual RMSPE of one-step-ahead forecast is 13.41%, which is 4.45% more accurate than the 17.86% annual RMSPE of 12-step-ahead. Similarly, the annual MAPE of one-step-ahead forecast is 8.21%, which is 2.16% more accurate than the 10.37%

annual MAPE of 12-step-ahead. The results of 24-step-ahead forecast are not as big as 12-step-ahead forecast, but they are also close. The results proved that the one-step-ahead forecasts have the most accurate forecasting results.

Therefore, the one-step-ahead SARIMA models based on the one-year continuous historical data method are used for both load demand and electricity price forecasts. By comparing the load demand and electricity price forecasting results, it can be found that the load demand forecast is more accurate than the electricity price forecast. The annual RMSPE for one-step-ahead load demand forecast is 4.28%, which is 9.13% more accurate than the 13.41% annual RMSPE for one-step-ahead electricity price forecast. Similarly, the annual MAPE for one-step-ahead load demand forecast is 2.53%, which is 5.68% more accurate than the 8.21% annual MAPE for one-step-ahead electricity price forecast.

The results indicate that by comparing different models and selecting one optimal forecasting model, the accuracy of load demand forecasting and electricity price forecasting can be greatly improved. But not every time the same model produces the most accurate results. When using the data of load demand and electricity price from different countries, the forecasting process needs to be adjusted and the optimal model may also change. In addition, the different methods in seasonal, annual and multi-step-ahead forecasting provide market participants with a broader range of ideas that can forecast load demand and electricity price in different ways.

8.1.2. Risk index based on the forecasting errors

The forecasting errors in load demand and electricity price are expressed as risk indexes respectively. For the load demand risk index, the highest daily risk index on weekdays and weekends all occurred at 2:00 o'clock. Winter and spring are the seasons with highest seasonal risk index for weekdays and weekends respectively, and summer has the smallest seasonal risk index for both weekdays and weekends.

For the electricity price risk index, the highest daily risk index on weekdays and weekends all occurred at 21:00 o'clock, but the high-risk indexes appeared more frequently on weekends than on weekdays. The highest seasonal risk indexes for weekdays and weekends are happened in winter and spring respectively, and the smallest seasonal risk indexes are all appeared in summer.

Another method of calculating the risk index trough the variation index has also been proposed. The results illustrate that for both for load demand and electricity price, the daily risk index and variation index all have very strong correlations no matter for weekdays or weekends.

Risk index reflects all the forecast errors more intuitively than the specific values, so the magnitude of risks can be directly observed. According to the results displayed by risk index, the market participants are able to prepare for the period of high-risk index in advance, thereby reducing the forecast errors that they may face. The risk index accurately represents the forecast errors but requires a large number of forecasting processes. While the variation index is able to identify the risk index accordingly from historical load demand and electricity price data, and avoid using complex forecasting processes. Therefore, variation index can be selected to reflect the forecast errors when the forecasting results are not satisfactory.

8.1.3. Financial risk in electricity market

The financial transaction amount in the electricity market can be obtained through load demand and electricity price. Then the estimated value of the possible loss/gain of financial return due to forecast error is expressed as the financial risk and it is shown as a monetary value. The Value-at-Risk method at 95% and 90% confidence level are used to analyse the financial risk. Then assume that each loss/gain has the same weight, and use Expected Shortfall to investigate the mean value of the tail financial loss/gain. The results illustrate that the minimum and maximum financial risks occur on summer and winter respectively in the year from March 2015 to February 2016. For the positive financial risks, the maximum Expected Shortfall with 95% confidence level is £2.2591×10^6 and with 90% confidence level is £1.6070×10^6. For the negative financial risks, the maximum Expected Shortfall with 95% confidence level is £1.7560×10^6 and with 90% confidence level is £1.4048×10^6.

Finally, the thesis shows the daily, monthly and seasonal total financial risks of the year, and the annual total financial risks are calculated. Moreover, in addition to considering both the load demand and electricity price forecasting results, the one-year forecast errors and the total financial risks in the other two situations are also illustrated: considering load demand forecasting results and actual electricity price data, and considering actual load demand data and electricity price forecasting results. From the results analysis, it can be found that the smallest annual total financial risk is £1.2616×10^6, which happens when considering the actual load demand and forecasting electricity price. The smallest annual total financial risk is £7.3431×10^5 less than the largest annual total financial risk of £1.9959×10^6. However, the RMSPE and MAPE are the smallest when considering the forecasting load demand and actual electricity price. The smallest RMSPE is 4.28%, which is 9.95% more accurate than the 14.23% biggest RMSPE. The smallest MAPE is 2.53%, which is 5.98% more accurate than the 8.51% biggest MAPE. Therefore, the results indicate that a more accuracy forecast result not necessarily has a smaller annual total financial risk, because the financial risks could be positive or negative.

Market participants can utilize the financial risk presented in this thesis to predict their possible gain or loss. They can use the risk index to adjust their commitment in purchase/selling of electricity energy. This can be in the form of long purchase or short purchase depending on their own situation. The application of VaR and ES in financial risk expands new space for market participants to use forecasting errors on risk analysis. Market participants can make risk response decisions based on the results of financial risks in advance. Furthermore, the total financial risks under different situations help market participants to select the forecasting preconditions based on the quality of history data and actual conditions. These financial risk analysis methods can be used to reduce the risk in electricity market.

8.2. Future Work

Due to the time constraints, some problems were not resolved in this research. This section suggests possible improvement or ways to expand the research work in this thesis. These include:

- **Improvements of forecasting model:** This thesis introduces the separate ARIMA, SARIMA and ANN models to forecast load demand and electricity price. Several other forecasting models are also detailed, like fuzzy logic, wavelet transform and grey model. According to different characteristics of each model, combining two or more forecasting models into a new forecasting method may result in a more accurate forecasting result. For example, the ARIMA model can be used to forecast the history data and get the forecasting results and errors. The fuzzy logic is then applied to adjust the forecasting errors by editing the IF-THEN language based on the relationship between the forecasting errors and the actual values. Finally, combining the forecasting results of ARIMA model with the adjusted forecasting errors of fuzzy logic to obtain the final forecasting results. Moreover, the deep learning algorithms are also can be used to forecast electricity data and load demand. The advantage of the deep learning algorithm is that it is good at dealing with nonlinear features when the forecasting range is increased.

- **Load demand and electricity price forecasting:** The load demand and electricity price forecasts in this thesis only consider the changes in historical data themselves. It is necessary to find out the relationships between load demand and the external factors, or electricity price profiles demand and the external factors. Like the relation between load demand and wind speed when considering renewable energy input, the relation between electricity price and international crude oil price, and the relation between electricity price and stock price. Another way is to take these external factors into account when building the forecasting models. The purpose is to increase the accuracy of the forecasting results and help electricity participants determine their bidding strategies.

- **More kinds of risk:** This thesis investigates the risk of load demand forecast errors, the risk of electricity price forecast errors, and the financial risk arising from load demand and electricity price forecasting errors. However, there are other risks in the electricity market, such as the risk within bilateral contracts, the risk of transmission constraints and the equipment operating risk. If these possible risks can be considered when computing the financial return risks in the electricity market, the results obtained may be closer to the real loss/gain. The financial risks can be calculated not only from the power generation side, but also from the power demand side.

- **Financial risk analysis methods:** The measurement of financial risk is of great significance to the asset portfolio and risk control of electricity market participants. According to different risk sources and risk management objectives, different risk analysis methods are generated. Except for the Value-at-Risk method and

Expected Shortfall method, there are also some methods of measuring financial risk in modern financial market, such as volatility method, sensitivity analysis method, coherent measure of risk, and entropy information theory. All these methods have their own pros and cons and reflect the different characteristics of risk. Therefore, in the electricity market risk management, different risk analysis methods should be integrated to calculate the risks from different angles, so as to better identify and control the financial risks.

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Appendix A

Optimal models for load demand forecast on weekdays

A.1 ARIMA model

Table A-1: 12 month optimal ARIMA models for weekdays' load demand forecast

Month	**ARIMA model**
2015.03	$ARIMA(1,2,1)$
2015.04	$ARIMA(1,2,1)$
2015.05	$ARIMA(2,2,1)$
2015.06	$ARIMA(2,2,0)$
2015.07	$ARIMA(1,2,1)$
2015.08	$ARIMA(1,2,0)$
2015.09	$ARIMA(1,2,1)$
2015.10	$ARIMA(1,2,0)$
2015.11	$ARIMA(1,2,1)$
2015.12	$ARIMA(1,2,1)$
2016.01	$ARIMA(1,2,1)$
2016.02	$ARIMA(1,2,1)$

A.2 SARIMA model

Table A-2: 12 month optimal SARIMA models for weekdays' load demand forecast

Month	SARIMA model
2015.03	$SARIMA(0,1,0)\ (2,1,0)_{24}$
2015.04	$SARIMA(0,1,0)\ (1,1,0)_{24}$
2015.05	$SARIMA(1,1,1)\ (2,1,0)_{24}$
2015.06	$SARIMA(1,1,1)\ (1,1,0)_{24}$
2015.07	$SARIMA(1,1,1)\ (1,1,0)_{24}$
2015.08	$SARIMA(0,1,0)\ (1,1,0)_{24}$
2015.09	$SARIMA(0,1,0)\ (1,1,0)_{24}$
2015.10	$SARIMA(0,1,0)\ (1,1,0)_{24}$
2015.11	$SARIMA(0,1,0)\ (1,1,0)_{24}$
2015.12	$SARIMA(0,1,0)\ (2,1,0)_{24}$
2016.01	$SARIMA(0,1,0)\ (1,1,0)_{24}$
2016.02	$SARIMA(0,1,0)\ (2,1,0)_{24}$

A.3 ANN model

Table A-3: 12 month optimal ANN models for weekdays' load demand forecast

Month	ANN model
2015.03	ANN(20 neurons, 6 delays)
2015.04	ANN(20 neurons, 4 delays)
2015.05	ANN(10 neurons, 4 delays)
2015.06	ANN(20 neurons, 6 delays)
2015.07	ANN(10 neurons, 6 delays)
2015.08	ANN(10 neurons, 6 delays)
2015.09	ANN(10 neurons, 4 delays)
2015.10	ANN(20 neurons, 6 delays)
2015.11	ANN(20 neurons, 4 delays)
2015.12	ANN(10 neurons, 2 delays)
2016.01	ANN(10 neurons, 6 delays)
2016.02	ANN(10 neurons, 6 delays)

Appendix B

Optimal models for load demand forecast on weekends

B.1 ARIMA model

Table B-1: 12 month optimal ARIMA models for weekends' load demand forecast

Month	**ARIMA model**
2015.03	$ARIMA(1, 2, 1)$
2015.04	$ARIMA(1, 2, 0)$
2015.05	$ARIMA(1, 1, 1)$
2015.06	$ARIMA(1, 1, 0)$
2015.07	$ARIMA(0, 1, 0)$
2015.08	$ARIMA(1, 2, 1)$
2015.09	$ARIMA(2, 2, 1)$
2015.10	$ARIMA(1, 2, 0)$
2015.11	$ARIMA(1, 2, 1)$
2015.12	$ARIMA(1, 2, 1)$
2016.01	$ARIMA(1, 2, 1)$
2016.02	$ARIMA(1, 1, 0)$

B.2 SARIMA model

Table B-2: 12 month optimal SARIMA models for weekends' load demand forecast

Month	SARIMA model
2015.03	$SARIMA(0,1,0)\ (1,1,0)_{24}$
2015.04	$SARIMA(0,1,0)\ (1,1,1)_{24}$
2015.05	$SARIMA(1,1,1)\ (2,1,2)_{24}$
2015.06	$SARIMA(1,1,1)\ (1,1,2)_{24}$
2015.07	$SARIMA(2,1,1)\ (0,1,1)_{24}$
2015.08	$SARIMA(0,1,0)\ (1,1,1)_{24}$
2015.09	$SARIMA(0,1,0)\ (1,1,1)_{24}$
2015.10	$SARIMA(0,1,0)\ (1,1,1)_{24}$
2015.11	$SARIMA(0,1,0)\ (0,1,0)_{24}$
2015.12	$SARIMA(0,1,0)\ (2,1,1)_{24}$
2016.01	$SARIMA(0,1,0)\ (0,1,1)_{24}$
2016.02	$SARIMA(0,1,0)\ (2,1,2)_{24}$

B.3 ANN model

Table B-3: 12 month optimal ANN models for weekends' load demand forecast

Month	ANN model
2015.03	ANN(10 neurons, 4 delays)
2015.04	ANN(20 neurons, 2 delays)
2015.05	ANN(20 neurons, 4 delays)
2015.06	ANN(10 neurons, 6 delays)
2015.07	ANN(20 neurons, 4 delays)
2015.08	ANN(10 neurons, 6 delays)
2015.09	ANN(30 neurons, 4 delays)
2015.10	ANN(10 neurons, 6 delays)
2015.11	ANN(10 neurons, 6 delays)
2015.12	ANN(20 neurons, 4 delays)
2016.01	ANN(20 neurons, 6 delays)
2016.02	ANN(30 neurons, 2 delays)

Appendix C

Optimal models for electricity price forecast on weekdays

C.1 ARIMA model

Table C-1: 12 month optimal ARIMA models for weekdays' electricity price forecast

Month	**ARIMA model**
2015.03	$ARIMA(2,1,0)$
2015.04	$ARIMA(2,2,1)$
2015.05	$ARIMA(0,1,0)$
2015.06	$ARIMA(1,1,1)$
2015.07	$ARIMA(0,1,0)$
2015.08	$ARIMA(1,1,1)$
2015.09	$ARIMA(2,2,1)$
2015.10	$ARIMA(1,1,0)$
2015.11	$ARIMA(0,1,0)$
2015.12	$ARIMA(1,1,1)$
2016.01	$ARIMA(1,1,1)$
2016.02	$ARIMA(2,1,1)$

C.2 SARIMA model

Table C-2: 12 month optimal SARIMA models for weekdays' electricity price forecast

Month	SARIMA model
2015.03	$SARIMA(2,1,1)\ (1,1,0)_{24}$
2015.04	$SARIMA(2,1,0)\ (1,1,0)_{24}$
2015.05	$SARIMA(1,1,1)\ (1,1,0)_{24}$
2015.06	$SARIMA(1,1,1)\ (1,1,0)_{24}$
2015.07	$SARIMA(2,1,1)\ (1,1,0)_{24}$
2015.08	$SARIMA(1,1,1)\ (1,1,0)_{24}$
2015.09	$SARIMA(1,1,0)\ (1,1,0)_{24}$
2015.10	$SARIMA(2,1,0)\ (0,1,0)_{24}$
2015.11	$SARIMA(2,1,1)\ (2,1,0)_{24}$
2015.12	$SARIMA(2,1,1)\ (1,1,0)_{24}$
2016.01	$SARIMA(1,1,1)\ (0,1,0)_{24}$
2016.02	$SARIMA(2,1,1)\ (2,1,0)_{24}$

C.3 ANN model

Table C-3: 12 month optimal ANN models for weekdays' electricity price forecast

Month	ANN model
2015.03	ANN(20 neurons, 4 delays)
2015.04	ANN(30 neurons, 2 delays)
2015.05	ANN(10 neurons, 2 delays)
2015.06	ANN(10 neurons, 6 delays)
2015.07	ANN(10 neurons, 4 delays)
2015.08	ANN(10 neurons, 6 delays)
2015.09	ANN(20 neurons, 6 delays)
2015.10	ANN(10 neurons, 6 delays)
2015.11	ANN(20 neurons, 2 delays)
2015.12	ANN(30 neurons, 2 delays)
2016.01	ANN(10 neurons, 4 delays)
2016.02	ANN(20 neurons, 2 delays)

Appendix D

Optimal models for electricity price forecast on weekends

D.1 ARIMA model

Table D-1: 12 month optimal ARIMA models for weekends' electricity price forecast

Month	**ARIMA model**
2015.03	$ARIMA(0,1,0)$
2015.04	$ARIMA(0,1,0)$
2015.05	$ARIMA(0,1,0)$
2015.06	$ARIMA(1,1,1)$
2015.07	$ARIMA(0,1,0)$
2015.08	$ARIMA(0,1,0)$
2015.09	$ARIMA(0,1,0)$
2015.10	$ARIMA(2,1,0)$
2015.11	$ARIMA(1,1,0)$
2015.12	$ARIMA(0,1,0)$
2016.01	$ARIMA(1,1,2)$
2016.02	$ARIMA(2,1,0)$

D.2 SARIMA model

Table D-2: 12 month optimal SARIMA models for weekends' electricity price forecast

Month	SARIMA model
2015.03	$SARIMA(2,1,1)\ (1,1,0)_{24}$
2015.04	$SARIMA(1,1,0)\ (1,1,0)_{24}$
2015.05	$SARIMA(1,1,1)\ (1,1,1)_{24}$
2015.06	$SARIMA(0,1,0)\ (1,1,1)_{24}$
2015.07	$SARIMA(1,1,1)\ (1,1,0)_{24}$
2015.08	$SARIMA(1,1,1)\ (1,1,0)_{24}$
2015.09	$SARIMA(0,1,0)\ (1,1,2)_{24}$
2015.10	$SARIMA(2,1,1)\ (0,1,2)_{24}$
2015.11	$SARIMA(2,1,1)\ (1,1,0)_{24}$
2015.12	$SARIMA(1,1,1)\ (1,1,0)_{24}$
2016.01	$SARIMA(1,1,1)\ (1,1,0)_{24}$
2016.02	$SARIMA(0,1,0)\ (1,1,0)_{24}$

D.3 ANN model

Table D-3: 12 month optimal ANN models for weekends' electricity price forecast

Month	ANN model
2015.03	ANN(10 neurons, 2 delays)
2015.04	ANN(10 neurons, 6 delays)
2015.05	ANN(10 neurons, 6 delays)
2015.06	ANN(20 neurons, 4 delays)
2015.07	ANN(10 neurons, 4 delays)
2015.08	ANN(10 neurons, 2 delays)
2015.09	ANN(20 neurons, 6 delays)
2015.10	ANN(10 neurons, 4 delays)
2015.11	ANN(10 neurons, 2 delays)
2015.12	ANN(20 neurons, 6 delays)
2016.01	ANN(20 neurons, 2 delays)
2016.02	ANN(10 neurons, 4 delays)