MSc Data Analytics Dissertation

MTH797P 2019/20

Seasonal Effects in Spot Price Market Data

Rishanie Rajkumar

Student Number = 140298682

Supervisor = Dr Wolfram Just

School of Mathematical Sciences

Abstract

In my dissertation, I will be analysing the Nord Pool electricity spot prices from January 1999 to January 2007 to see if the results are as expected. For example, in which hour or month we will expect electricity prices to be higher or lower. We will be discussing the trends hourly, daily, monthly and yearly. We will also be investigating the time series of Nord Pool with a sampling rate of an hour over the eight-year period. The project evaluates the daily return and studies the correlations and effects by external data. Quantitative indicators will be employed to measure daily variations in spot price market data.

Declaration of original work

I, Rishanie Rajkumar, hereby declare that the work in this thesis is my original work. I have not copied from any other students' work, work of mine submitted elsewhere, or from any other sources except where due reference or acknowledgement is made explicitly in the text, nor has any part been written for me by another person.

Referenced text has been flagged by:

1. Using italic fonts or by referencing the author together with the year of publication in square brackets, and
2. Using quotation marks "...", and
3. Explicit mentioning of the sources in the last section of this thesis

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Chapter 1

Introduction

In this thesis, we will be looking at the effects in spot price using the time series of Nord Pool. Many concepts influence and affect the cost of electricity. The commodity costs, carbon costs, demand, weather, season, and supply constraints are examples of the electricity market's effects. It is vital to analyse financial data to help predict future business proposals and prevent businesses from being vulnerable. Using past datasets, we can observe risk factors and try to accommodate unexpected events accordingly.

However, we cannot always predict what the future can hold. For example, with the current Covid-19 pandemic, there have been drastic changes to the demand for electricity. In terms of commercial, the demand has gone down as many industries, schools, and offices are closed. As businesses were closed, there was also a sudden rise in unemployment.

On the other hand, there is a rise in demand for domestic use following lockdown. As people were encouraged to work from home by the government and schools were shut, households' power usage increased. The morning peaks during weekdays decreased, and the use of electronic appliances spread during the day. According to frontier economics, the total electricity demand fell by 13% in the week of March 23rd compared to March 9th. The total electricity demand continued to drop over the next few weeks. As lockdown measures eased, the electricity demand starts to increase; however, it is still lower than 2019 levels. [Hussain & Jian, 2020]

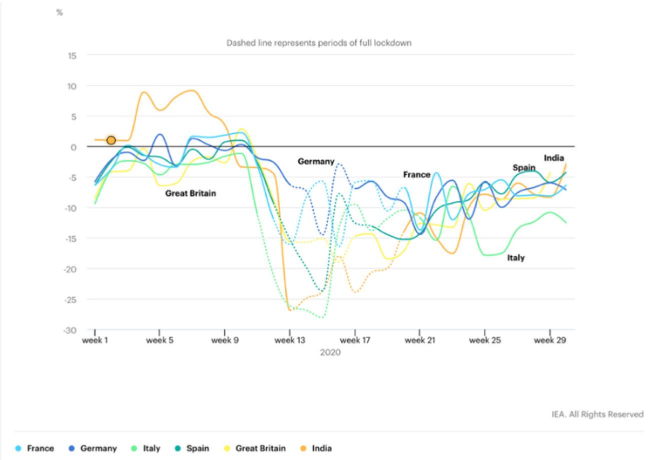


Illustration by

IEA, 2020: Year-on-year change in weekly electricity demand, weather corrected, in selected countries, 2020. [*https://www.iea.org/data-and-statistics/charts/year-on-year-change-in-weekly-electricity-demand-weather-corrected-in-selected-countries-2020*](https://www.iea.org/data-and-statistics/charts/year-on-year-change-in-weekly-electricity-demand-weather-corrected-in-selected-countries-2020)

In the chart above from IEA, we see the weekly effects of electricity demand in 6 countries. We can see the severe drop in demand from week 9 to week 13 in Great Britain. During the lockdown, the demand continues to fall and rise. It has a repeated pattern of falling and rising, but the overall trend is increasing.

Here, we see the importance of analysing datasets from previous years and comparing them to the current situation. Scrutinizing datasets helps us understand how events such as a pandemic impact on the electricity market.

On top of the current situation, Brexit is another major factor that will have a high effect on electricity prices. Although the United Kingdom has left the European Union, the transition period is set to end on December 31st, 2020. As said by Moneysupermarket.com, the three main ways in which leaving the EU could potentially push up energy bills in the UK are:

- A reduction in EU investment and increased transportation costs
- Leaving the EU Emission Trading System
- Not having a replacement body for European Atomic Energy Community

[Moneysupermarket.com, 2020]

Another component that can affect electricity prices is natural disasters. Especially the ones that occur in a country where resources such as oil and gas are mainly manufactured. Their ability to produce fuel will lead to higher demand. Natural disasters therefore create competition for resources and results to business electricity prices rising.
[exchangeutility.com, 2020]

We will be exploring the electricity prices from January 1st, 1999 to January 26th, 2007. We will analyse the data daily, hourly, monthly, and yearly and examine how the prices are affected. Before we do this, we will cover the general concept of the electricity market and Nord Pool. We will also evaluate the daily returns and study the correlations and effects using time series analysis. Lastly, we will conclude with the findings from our analysis.

Chapter 2

2.1 Electricity Generation, Transmission and Distribution

Depending on fuel prices, the volume of electricity generated is different every year. Electricity can be generated in numerous ways. For example, it can be produced by burning non-renewable energy resources such as fossil fuels or renewable energy resources such as wind power. The advantages of renewable resources are that they can be replaced quickly and will not run out. National Grid predicted that zero-carbon electricity (wind, nuclear, solar, and hydro) would generate more electricity than fossil fuels during 2019. [Evans, 2019]

Electricity is usually produced in power stations and then fed through a complicated system, most commonly known as the grid, to be transmitted efficiently to consumers. It can be carried over long distances at a lower cost through high-voltage transmission lines. There needs to be the same amount of electricity transmitted into the grid and the quantity of electricity consumed. If not, it will cause a blackout. It is also not possible to store large amounts of electricity over long periods; therefore, conventional power plants have to compensate for the constant fluctuations. [EIA, 2020]

The flow of the electricity market, according to Erbach, consists of electricity suppliers, consumers, transmission system operators, distribution network operators, and regulators. The electricity supplies buy electricity from generators and sell via bills to consumers. Transmission system operators pay for long-distance transportation and ensure system stability. Distribution network operators pay for delivering electricity to consumers, and lastly, regulators set rules and oversee the functioning of the market. [Erbach 2016]

In 2019, the EU adopted the 'Clean Energy for all Europeans package' to help EU market rules become a reality. As we know, it is predicted that the share of electricity produced by renewable energy resources is expected to grow. According to the European Commission, it is expected to grow from 25% more than 50% by 2030. Therefore, markets need to be improved, and electricity must be produced and sufficient quantities when there is no wind or sun. [European Commission, 2019]

The increase in renewable resource production means that a factor that is highly relied upon is the weather. Higher temperatures will result in higher energy demand and changes to electricity production. For example, warmer weather means more air conditioning, and colder weather means more use of central heating. The actual and predicted weather also affects spot market prices and short-term contracts. [Diversegy, 2014]

2.2 Financial Market

"Financial markets are a type of marketplace that provides an avenue for the sale and purchase of assets such as bonds, stocks, foreign exchange, and derivatives." There are various types of financial markets, such as the stock market, derivatives market, commodities market, etc. There is at least one financial market in every country, and they vary in size. Some of which are well known internationally and some of which are small. New York Stock Exchange (NYSE) is the largest securities exchange and trades trillions of dollars on a daily basis. [CFI Education Inc, 2015-2020]

Types of Market

1. Bond Markets offers companies and the government the opportunity to finance an investment or project. Investors buy bonds from a company. The company then returns the amount of the bond and interest within an agreed time. [CFI Education Inc, 2015-2020]

2. Derivatives markets involve derivatives or contracts where the value is based on the market value of the asset being traded. [CFI Education Inc, 2015-2020]

3. Stock Markets trade shares of public company ownerships. The investor makes money with stocks if they perform well in the market as each claim comes with a price.
[CFI Education Inc, 2015-2020]

4. The commodities market is where traders and investors buy and sell commodities such as gold, old, etc. As prices are unpredictable, it has its specific market.
[CFI Education Inc, 2015-2020]

Spot Market

"The spot market is where financial instruments, such as commodities, currencies, and securities, are traded for immediate delivery." [Investopedia, 2019] A spot market contract is an agreement between two individuals to buy or sell goods. In terms of electricity, spot contract is achieved when the supplier has delivered the electricity or when the buyer has accepted the supply. The payment of a spot contract usually clears on the same day as the delivery. With electricity, it is commonly paid for one exchange-trading before it is delivered.

"Spot prices refer to the current price of a security at which it can be bought or sold at a particular place and time." [Bennett, Coleman & Co. Ltd. 2020] In the energy sector, the spot price lets generators know how much electricity is required at any moment in time. The generators ensure that the power system is in balance.

Generators upgrade their output to sell extra power to the market when the spot goes up. If the spot price falls, more expensive generators are not used, or a smaller percentage is used. "Spot prices are currently updated every thirty minutes, but this will move to every five minutes in 2021." [AEMC, 2020] Generally, prices are lower during early mornings as before people are awake or businesses are running. During the afternoon and evening, prices are higher, as most power is usually used.

Households or small businesses are offered a contract from retailers for supplying electricity. This plan entails how customers will be charged over a fixed period of time. In order to do this, retailers have contracts with generators in order to buy electricity at a fixed price. Going into contracts helps manage financial risks and provides more certainty with wholesale energy costs. [AEMC, 2020]

Contract prices are usually based on the average expectations of future spot prices. This leads to supply and demand. If spot prices increase due to the demand being tighter, this will have become apparent with rising contact prices. Here, we see the importance of contract prices as it gives a rough estimate of how much electricity needs to be generated and where. [AEMC, 2020]

2.3 Supply and Demand

As mentioned previously, we must ensure that the electricity supply and demand are equal at all times, which may lead to risks of systems breaking down or power outages. For the average level of electricity use, non-flexible generators are used. On the other hand, flexible generators are used when there is a peak in meeting demands. More flexible generators are required in order to satisfy demand as more renewable energy resources are used. [Erbach, 2016]

Primary reserves, secondary reserves, and tertiary reserves are used when balancing supply and demand in the short term. Primary reserves are activated within seconds, secondary reserves are activated within a few minutes, and tertiary reserves are activated within 15 minutes. [Erbach, 2016]

2.4 Nord Pool Timeline

[Nordpool.com, 2020]

1991 - The Norwegian parliament decided to deregulate the market for trading of electrical energy.

1993 - An independent company Statnett Marked AS is established.

1995 - An integrated Nordic power market contract framework is made to the Norwegian Parliament.

1996 - Nord Pool ASA is established. This is a joint Norwegian-Swedish power exchange.

1998 - Finland joins Nord Pool ASA. A Nord Pool office is opened in Odense, Denmark.

1999 - Elbas market is launched and Elspot* area trade begun on 1st July. Elbas markets is a continuous hourly market for balance adjustment.

2000 - Denmark joins the exchange and the Nordic Market becomes fully integrated.

2002 - Nord Pool Spot AS (a separate company) opens for Nord Pool's spot market activities.

2004 - Eastern Denmark joins the Elbas market.

2005 - Nord Pool Spot opens the Kontek bidding area in Germany.

2006 - Nord Pool Spot launches Elbas in Germany.

2007 - Western Denmark joins the Elbas market. The new Elspot, SESAM, trading system is set into production.

* Elspot is the spot market for electrical energy. Auction based market for the trading of electrical power for delivery the next day. "72% of the total consumption of electrical energy in the Nordic countries is traded on the Elspot-market." [Nordpool.com, 2020]

2.5 Nordic Electricity Market

As we see from the Nord Pool timeline, the electricity markets in Denmark, Finland, Norway, and Sweden opened up for competition in generation and retailing purposes. Hence, they integrated into a single Nordic electricity market between 1991 and 2000.

As stated by Amundsen and Bergman, the general opinion among power industry representatives and electricity market analysis is that the Nordic electricity market works well. There have been occasions were demand and supply were severely affected; however, the market did not collapse.

Wholesale prices have increased due to the new European system of carbon dioxide emission permits. The new system has caused some issues for the power-consuming industries as consumers were not happy with the price change. A political decision causes the issue that affects electricity prices; therefore, this does not affect the electricity market's functionality. [Amundsen & Bergmen, 2006]

The total power generation in Nordic countries is about 50 percent created by and relied on upon hydropower. [Amundsen & Bergmen, 2006] Here, a standard hydroelectric plant is a system consisting of a power plant, a dam that can control the water flow, and a reservoir for the water storage. The water pushes against the turbine, which causes the blades to turn, and thus, the generators produce electricity. The system depends heavily on water. The changes in climatic situations might instigate difficulties with balancing the supply and demand, especially when there is a high hydropower portion. Electric heating is also used more frequently. [Nunez, C, 2019]

For example, the "supply shock" that occurred from Autumn 2002 to February 2003. The inconsistencies of rain and inflow to hydro reservoirs make the power generation face uncertainties. Typically, the producers predicted the level of water and rain; however, there was a sudden drop. As a result of the shortfall of hydropower, the spot prices started to increase. The spot price was double or triple the usual amount until February 2003. The rise in spot price led to contract prices also increasing. [Amundsen & Bergmen, 2006]. The Nordic electricity market still managed to function, which shows the importance of forecasting data.

2.6 Nord Pool's Products, Services and Trading

The Nord Pool is owned 50-50 by two transmission system operators, Statnett SF in Norway and Svenska Kraftnat in Sweden. Nord Pool operates primarily under a Norwegian license, giving them the nonexclusive right to organise physical trade in energy. [Fehr & Harbord, 1998]

Referring back to the Nord Pool timeline, Elspot and Elbas are mentioned. These are products and services that are offered by the Nordic electricity market. Elspot offers spot market trade-in power contracts for next-day physical delivery. There is a double auction system for each hour in the day, used to determine electricity prices. Sweden, West, and East Denmark, and Finland established one separate Elspot area each. The division occurred due to transmission demand and power production. [Nordpoolgroup.com, 2020]

At present, Nord Pool delivers day-ahead and intraday trading, clearing, and settlements to customers. The day-ahead market is when consumers can sell or buy energy for the next 24 hours. "You can trade day-ahead in 14 countries and across 21 bidding zones". The availability of interconnectors and in the grid are published, and then the buyers and sellers have 2 hours to submit their final bid for the auction. The orders are then matched according to the single price for each hour and the bidding one. [Nordpoolgroup.com, 2020]

Similarly, there is the intraday market. "This is a continuous market, with trading taking place every day around the clock until one hour before delivery." The transmission system operators provide the availabilities, and then the capacity is determined by the day-ahead auction results. [Nordpoolgroup.com, 2020]

2.7 General Effects on Electricity Prices

As stated in the introduction, there are many concepts that influence and affect the cost of electricity. In general, the more electricity supply, the cheaper the electricity price and vice versa. We also know that the higher the demand, the higher the prices will be and the lower the demand the cheaper the prices will be.

Some examples of affects are the commodity costs, carbon costs, demand, weather, season, and supply constraints. Let us now further look into commodity costs and weather.

Commodity Costs

According to Business Juice, "the commodity markets largely drives the cost of electricity". For example, the demand for nuclear, gas, oil and coal will affect the consumption of electricity. It is a given that, the price of electricity will be partly driven by the price of gas. The commodity market itself is affected by the production costs, transportation costs and etc. Again, the higher the demand for commodity, the higher the prices.

Weather

The weather has a high impact on both the supply and demand of electricity. As mentioned earlier, the majority of electricity generation is by renewable resources such as wind and solar. For example, a storm could cause a power outage by damaging power lines. Also, electricity prices tend to be the highest during Summer. As there is a higher demand, expensive generators are used to meet the demand. [Business Juice, 2017]

In recent news, we see that the UK electricity prices spiked. This was caused by high demand and low winds. The low winds had also affected all of Western Europe as well. Thus, became an issue as the countries were unable to trade across the interconnectors. [Grundy, 2020] The 'Storm Ellen' also affected the electricity consumption in the Ireland. There were power cuts because of the high winds and rain. "The forced winds had caused significant and widespread damage to the electricity market affecting more than 194,000 homes, farms and businesses ". Storm Ellen is an example of extreme impacts caused by the weather. [BBC News, 2020]

Chapter 3

3.1 Time Series

"A time series is a collection of random variables indexed according to the order they are obtained in time." Using time-series, we can plot data and observe the different variations, see if there is a trend or seasonality, and look out for any outliers. We can also construct statistical models in order to have a better understanding of the dataset. Using this model, we can predict future observations and try to control future outcomes.

The four main features in times series are the trend, seasonality, variation, and unusual features. According to William Yoo,

Trend -

- indicates a long-term change of the mean.

- we model it as a function in time t, i.e., mt

- polynomial (linear, quadratic, cubic, etc.), exponential, sigmoid, etc.

Seasonality

- shows a pattern repeating in time
- the amount of time for it to repeat itself is called period (e.g., monthly, yearly, quarterly, etc.)
- we model it using a periodic function in time t, i.e., st
- sinusoids (sine and cosine), trigonometric polynomials, indicator variable, etc.

Heterogenous variation, e.g., increasing or decreasing volatility

- we model it using variance stabilizing transformations.

Unusual features, e.g., sudden single peak, outlier, change-point, etc.

- we model these using ad hoc methods.

3.2 Analysis of Returns

In finance, the return suggests whether an asset has performed well in percentages.

$$R = \frac{S_1 - S_0}{S_0} = \frac{S_1}{S_0} - 1$$

With time series we will get a sequence of returns. The formula for a sequence of return is as follows:

$$R_1 = \frac{S_1 - S_0}{S_0}, R_2 = \frac{S_2 - S_1}{S_1}, \ldots, R_m = \frac{S_m - S_{m-1}}{S_{m-1}}$$

where S_0 is the initial value.

Log-returns are preferred over simple returns as log-returns tend to add up adequately. The simple return and log return are usually quite similar unless the values are large.

$$R = \ln\left(\frac{S_1}{S_0}\right)$$

[Sebastian del Bano Rollin, 2019-2020]

3.3 Stationarity

A vital factor of time series analysis is our dataset's stationarity, as it is easier to evaluate. Before we define stationarity, let us look at the mean and covariance function.

Mean function

"Let $\{Xt\}$ be a time series with $E[X_t] < \infty$. The mean function is μ(t) = E[X_t]."

Covariance function

"The covariance function of $\{X_t\}$ is $\gamma(r,s) = Cov(\mathrm{X_r}, \mathrm{X_s}) = E\{[\mathrm{X_r} - \mu(r)][\mathrm{X_s} - \mu(s)]\}$, for all integers r and s. "

[Yoo, W, 2019-20]

Definition - Weakly Stationary

Let X_t be the observations at time $-\infty < t < \infty$. We say that $\{X_t\}$ is weakly stationary if

1. μt is independent of t

2. $\gamma(t+h,t)$ is independent of t for each h.

This definition means that the covariance function is invariant to shift in time, thus,

$$\gamma(t+h,t) = \gamma(h,0) = \gamma(h).$$

[Yoo, W, 2019-20]

Definition - Strongly/Strictly Stationary

A stationary process $\{ X_t , t \in N \}$ is said to be strictly or strongly stationary if its statistical distributions remain unchanged after a shift on the time scale. "If in every n, every choice of times t1, t2, …, tn∈**N** and every time lag k such that ti+k∈**N**, the n-dimensional random vector (Xt1+k, Xt2+k ,…, Xtn+k) has the same distribution as the vector (Xt1, Xt2, …, Xtn), then the process is strictly stationary. " [Salin KC, 2018]

3.4 Autocovariance and Autocorrelation Function

Let $\{X_t\}$ be a stationary time series. The autocovariance function (ACVF) of $\{X_t\}$ at lag h is $\gamma(h) = Cov(X_{t+h}, X_t)$.

Autocorrelation function (ACF) of $\{X_t\}$ at lag h is $\rho(h) = \frac{\gamma(h)}{\gamma(0)} = corr(X_{t+h}, X_t)$.

This means that if the time series is stationary then the ACF only depends on the lag and not on t. We know that $\gamma(0) = Var(X_t)$.

[Yoo, W, 2019-20]

3.5 Time Series Analysis Methodology

As mentioned previously, a time series can be used to construct models and predict future values by forecasting. Before we start the analysis on our dataset, let's first look at the steps we will take.

Firstly, we will visualise the time series by plotting the dataset. We will identify patterns such as trend and seasonality. Then, we will check if our time series is stationary. Stationary data exhibits statistical measurements of the data, such as averages and variances have a constant pattern over time-period [Shrestha, 2018]. Stationary data is easier to work with, and it helps obtain meaningful sample statistics such as mean and variances. The means and variances will help foresee future electricity prices. Unit root loops with the help of "Augmented Dickey-Fuller" (ADF) test is applied to assess whether the dataset is stationary or not.

Next, we need to find optimal parameters for the stationary model. We can do this by evaluating the ACF and PACF plots. The autocorrelation function (ACF) plot describes how well the present value is compared to its past values. "The ACF gives the value of the auto-correlation of any series with its lagged values." The partial autocorrelation function finds the correlation of the residuals [Salvi, 2019].

Following this, we can try to fit an ARIMA model to understand our time series pattern better. As this only works on stationary data, we need to make sure the dataset is stationary. [Chauhan, 2019].

A process $\{X_t\}$ is said to be ARIMA (p, d, q) if

$$\nabla^d X_t = (1 - B)^d X_t$$

is ARMA (p, q).

Finally, using this model, we make estimates of future electricity spot prices.

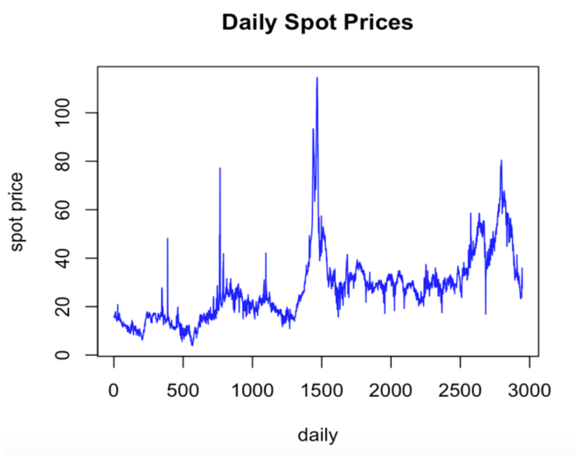
Chapter 4 - Nord Pool Analysis

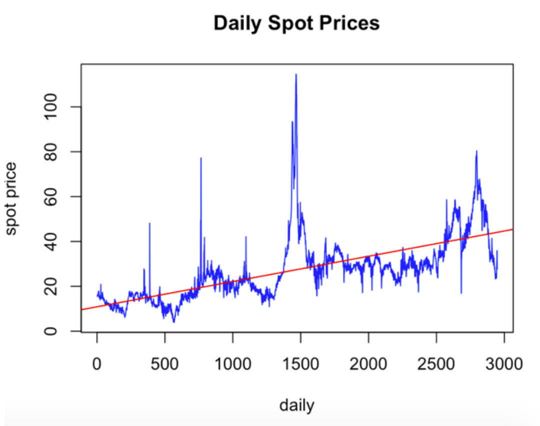
4A. Time Series Analysis of Daily Variations in Spot Price Market Data

4A.1 Graphical Representation of Daily Spot Prices

Using the excel function 'OFFSET' and 'AVERAGE,' I split the hourly dataset into daily electricity spot prices. In R, I used the following code to help plot the Nord Pool electricity spot prices' time series.

```
setwd("/Users/rishanierajkumar/Desktop/")
spdaily = read.table("BEUR daily.txt", header=TRUE)
spdailytimeseries <- ts(spdaily)
plot.ts(spdailytimeseries, main = "Daily Spot Prices", xlab = "daily", ylab="spot price", col=4)
```



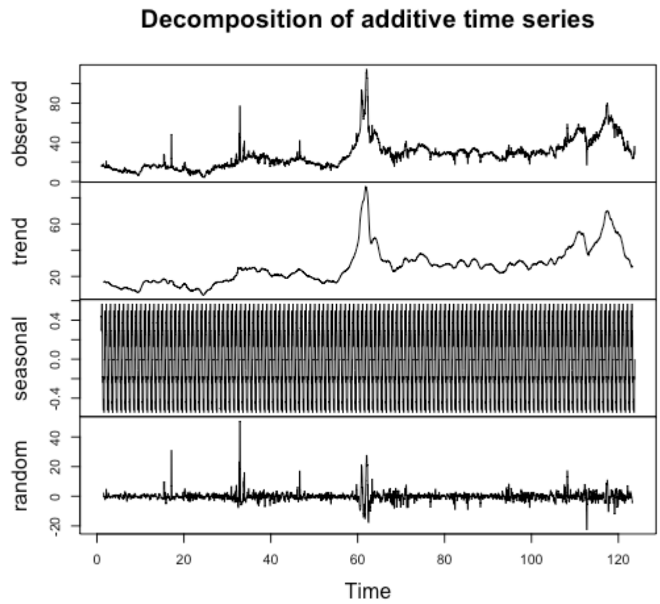


From the analysis of daily spot prices, it is identified that there is a lot of variations in everyday spot prices. We clearly see bunches of high variation in different times where spot prices strike positively in the market. Observation# 500, near to 800, 1500, and after 2500 observations, we see that the daily spot prices change rapidly in the market. We can also see that there is an overall upward trend.

A classical decomposition model is the additive decomposition model.

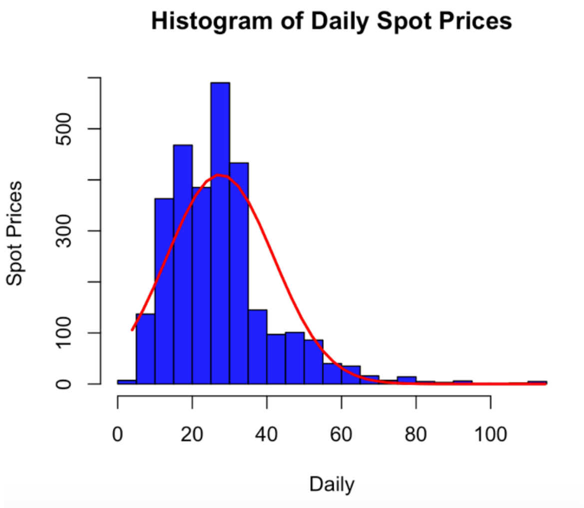
$$X_t = m_t + s_t + Y_t, \quad t = 1,2,\dots,n$$

In this case, m_t is the trend component, s_t is the seasonal component and Y_t is the random/stochastic component. [Yoo, W, 2019-20]



Here, we have the decomposition of the additive time series on our dataset. Looking at the trend, we can see that there is an overall increasing trend. We can also see that there is seasonality, as there is a repeating cycle.

4A.2 Descriptive Analysis




```
> summary(spdailytimeseries)
  X15.37458333
 Min.    :  3.887
 1st Qu.: 16.750
 Median : 26.236
 Mean    : 27.480
 3rd Qu.: 32.731
 Max.    :114.614
> sd(spdailytimeseries)
[1] 14.32674
> skewness(spdailytimeseries)
[1] 1.589287
> kurtosis(spdailytimeseries)
[1] 4.502937
```

Data on daily spot prices indicate that the average everyday spot price is found to be 27.48, with a variation of 14.33. Data is not homogenous as highlighted in the output values of skewness of data and kurtosis, which do not lie in the range ("±1.06 and ±0.2"), respectively, and is higher than this. The skewness is greater than 0, and the mean is greater than the median; therefore, it has a positive skew. In other words, more than half of the spot prices of electricity are priced lower than the average electricity spot price. The kurtosis measures the sharpness of the peak. In our case, the kurtosis is more significant than three; therefore, the data is heavily tailed in comparison to the normal distribution.

4A.3. Stationarity of Behaviour of Time Series for Daily Spot Prices

An Augmented Dickey-Fuller test (ADF) is a statistical test used to see if a time series is stationary or not.

H0: The behaviour of time series for daily spot prices is non-stationary

H1: The behaviour time series for daily spot prices is stationary

```
> adf.test(spdailytimeseries, k=24)

        Augmented Dickey-Fuller Test

data:  spdailytimeseries
Dickey-Fuller = -3.3053, Lag order = 24, p-value = 0.06973
alternative hypothesis: stationary
```

We have checked the stationary condition of daily spot prices with the help of the "Augmented Dickey-Fuller" test (ADF). We have found that daily spot prices are non-stationary in behaviour because the significant p-value is 0.06973, which is higher than the 0.05 significance level. Hence, we apply the first-order differencing.

First order differencing is used to detrend the time series model itself by using differencing. It is defined as $\nabla X_t = X_t - X_{t-1.}$

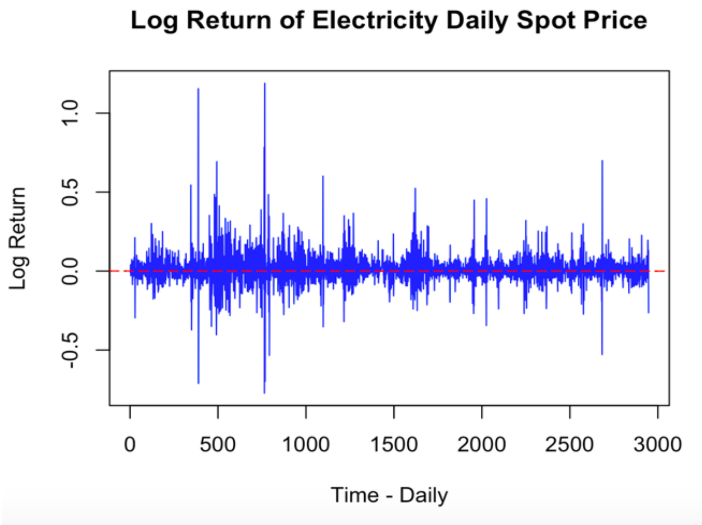
In our case, this is what we find:

```
        Augmented Dickey-Fuller Test

data:  firstdiff
Dickey-Fuller = -7.4837, Lag order = 24, p-value = 0.01
alternative hypothesis: stationary

Warning message:
In adf.test(firstdiff, k = 24) : p-value smaller than printed p-value
```

We observe that daily spot prices are now stationary because the significant probability value is less than 0.05 level of significance.

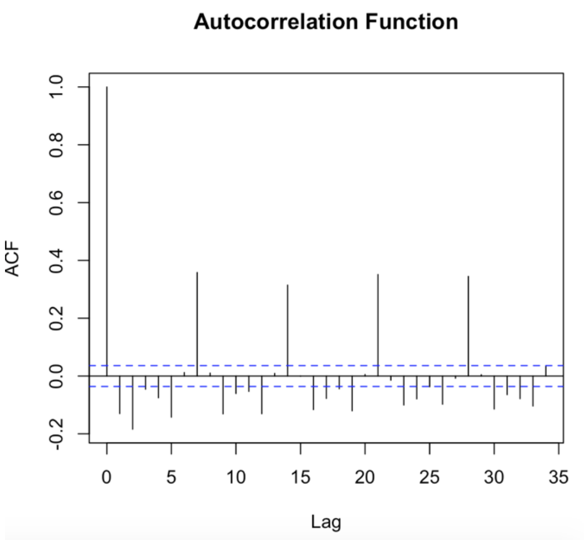
4A.4 Graph of log return of daily spot prices

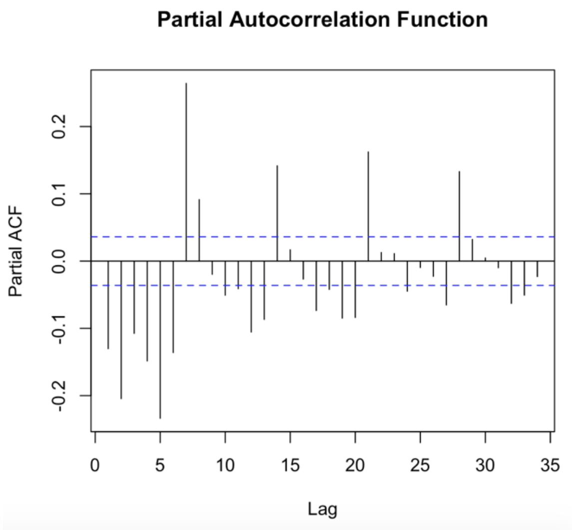
The log-returns of daily spot prices show stationary behaviour. It is clear by seeing bunches of clusters around mean 0 and constant variance.



4A.5 Auto-Covariances, Autocorrelations & Partial Autocorrelations

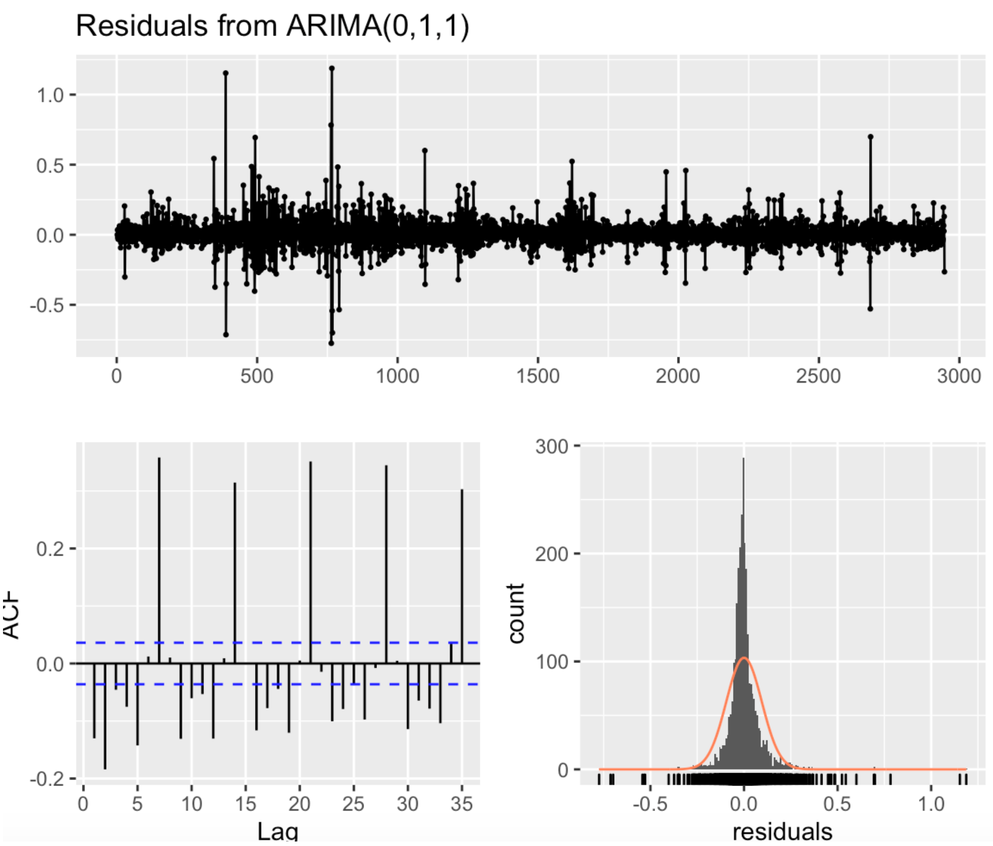
Here, I have plot the autocorrelation function (ACF) and partial autocorrelation function (PACF) of the log return. In our ACF, we notice that there seems to be repeated peaks at lag 7, lag 14, lag 21 and so forth.





4A.6 ARIMA Model

Firstly, we are going to try and model the standard ARIMA(0,1,1) model and observe the results.



Above, we still notice the peaks at lag 7, lag 14 and so forth. We see that our residuals are also normally distributed. The p-value from the Ljung box test is small than 2.2e^-6.

```
        Ljung-Box test

data:  Residuals from ARIMA(0,1,1)
Q* = 674.35, df = 9, p-value < 2.2e-16

Model df: 1.   Total lags used: 10
```

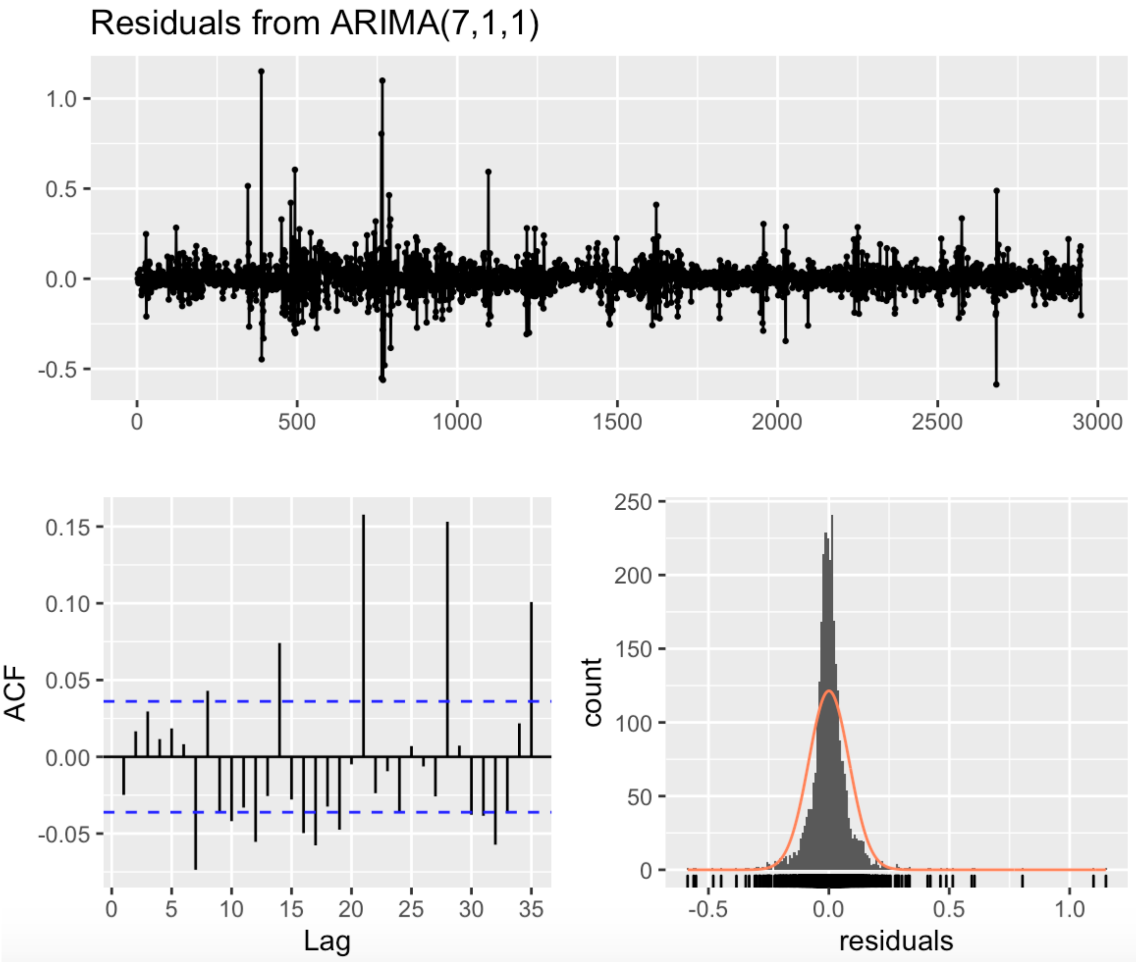
"The Ljung Box test is a way to test for the absence of serial autocorrelation, up to a specified lag k". The test determines whether there is a significant lack of fit in our model. In our case, the p-value is very small therefore there the model does not show a significant lack of fit.

[Stephanie, 2018]

As we noticed the lag 7 in the ACF, we will try to fit an ARIMA(7,1,1) model. I computed the below in R:

```
(fit <- Arima(diff(log(spdailytimeseries)), order=c(7,1,1)))
checkresiduals(fit)
autoplot(forecast(fit))
```

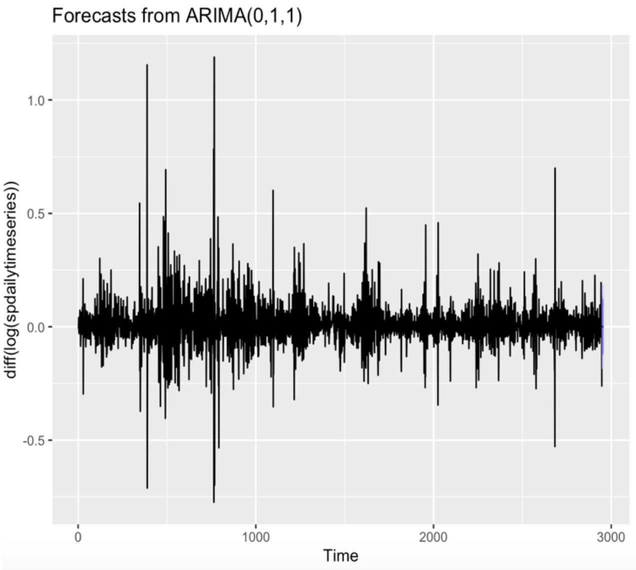
These are the results that we get.



In comparison to ARIMA(0,1,1), we observe that the ACF is different. The peaks are not as consistent, and that more lines are within the blue dotted lines. We also notice that with the normally distributed curve the peak is higher.

We also look at the p-value for the Ljung Box test and notice that the p-value (7.72e^-09) is still very small and that the model does not show a significant lack of fit.

Now, using this, we will try to forecast. The blue lines, in the end, show the predicted values. We will also compare both ARIMA(0,1,1) and ARIMA(7,1,1).

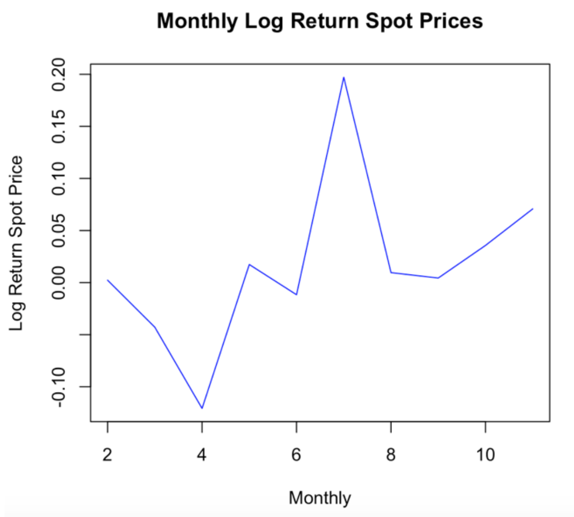


We notice that both models have a predicted similar value for the future. The last recorded electricity spot price was on the 26th of January 2007. We would expect that the electricity prices will be relatively the same as in previous years. However, from 2007 to 2009 is when the 'Great Recession' occurred. The crisis was not expected and may have impacted the spot prices.

"The Great Recession is a term that represents the sharp decline in economic activity during the late 2000s." [Investopedia - Chappelow, 2020]. Although this mainly affected the USA, it had impacts on Norway. This global economic activity leads to increases in the interest rates in 2007 and 2008. The activity had damped household energy consumptions and residential investments. [Saltmarsh, 2009].

4B. Time Series Analysis of Monthly Variations in Spot Price Market Data

4A.1 Graphical Representation of Monthly Spot Prices and Log Return of Monthly Spot Prices



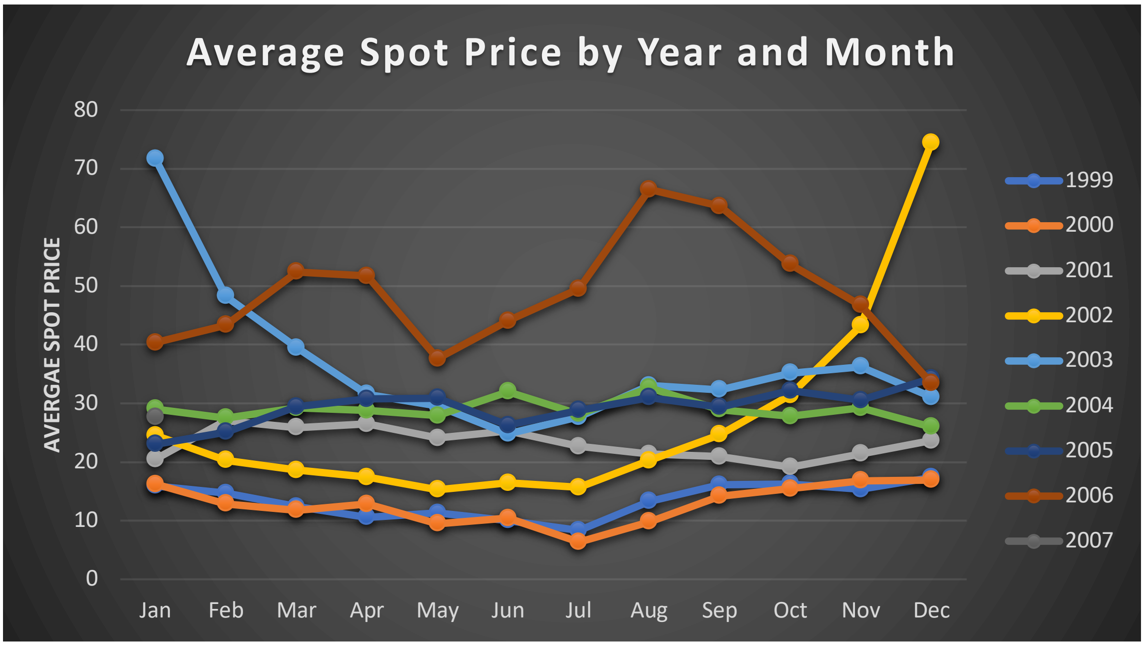
From the first graph, we can see that the overall yearly trend is increasing. We see that the average spot price is generally smaller from April to June compared to the other months. This is expected as during spring, and the weather tends to be relatively neutral, neither too cold nor too hot. The electricity prices are much higher during the period of September to January as this is when the weather is much colder. This leads to more electricity consumption, such as heating. Electricity prices are also exceptionally high through summer periods as consumers use fans, ACs, and so forth.

Looking at the log return spot price, we can see that there it has a fluctuating pattern that shows the variations within our dataset. Before we look at the log-returns for the months of January, July, and December in more depth, let us plot (using excel) the average spot price by year and month.

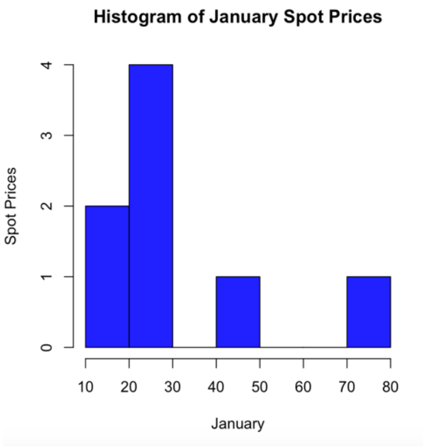
The below line graph shows us how the average spot price has changed over the years. The average spot prices seemed to be very small in 1999 and 2000 in comparison to the rest of the years. The prices appear to be the highest overall in the year 2006, although the most elevated spot price value was at the end of 2002 and beginning of 2003. The high prices were because of the crisis that occurred in 2002, which is mention earlier in the thesis.

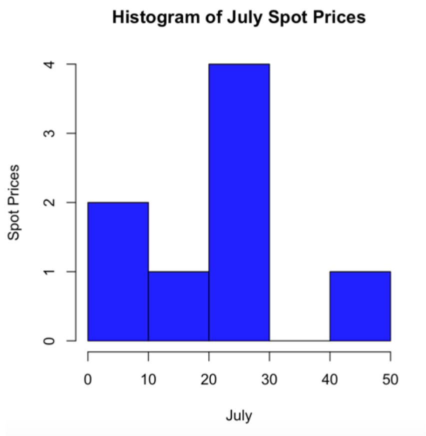
We see that electricity every year has an overall upward trend expected in 2003 and 2006. In 2003, we noticed that the spot price was very high in January, and then it dropped drastically in February and continued to fall steadily from March to June. Then, the prices started to rise and fall from July to December. This was when the market was slowly recovering from the "supply shock." In 2002, we saw that the spot prices were steadily decreasing from January to May and then from July onwards it was steadily increasing until it reached the months of October to December.

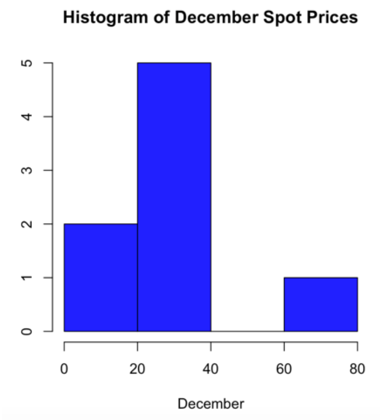
Overall, in the rest of the years, there were small fluctuations within the months.



4B.2 Descriptive Analysis







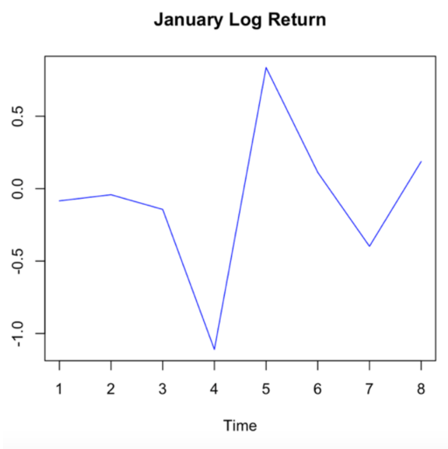
We found that monthly spot prices are 29.87 for January, 23.39 for July 32.12 for December, with variations 17.34, 13.7, and 18.35, which is a high variation. Data is homogenous, as indicated by skewness and values of kurtosis.

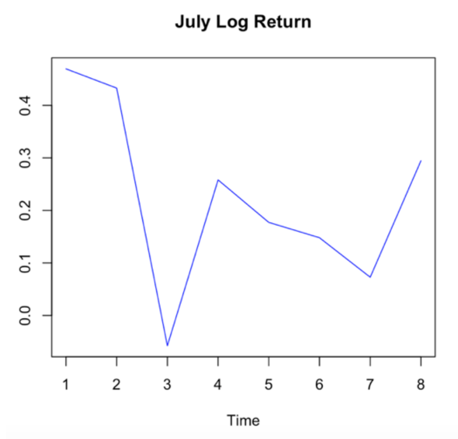
```
> summary(monthly$Jan)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
  15.95   19.40   23.77   30.15   31.86   71.68
> sd(monthly$Jan)
[1] 18.52203
> skewness(monthly$Jan)
[1] 1.291567
> kurtosis(monthly$Jan)
[1] 0.2668025
```

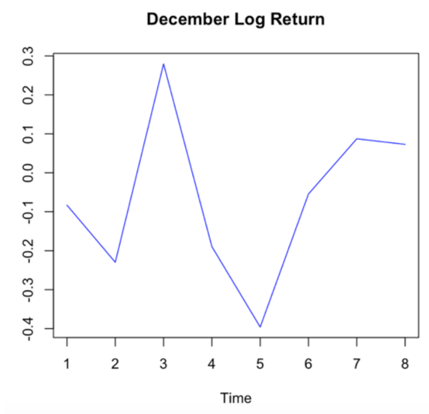
```
> summary(monthly$Jul)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
  6.352  13.828  25.140  23.391  28.320  49.518
> sd(monthly$Jul)
[1] 13.78636
> skewness(monthly$Jul)
[1] 0.4465011
> kurtosis(monthly$Jul)
[1] -0.8997175
```

```
> summary(monthly$Dec)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
  16.92   22.05   28.51   32.13   33.64   74.43
> sd(monthly$Dec)
[1] 18.35143
> skewness(monthly$Dec)
[1] 1.377945
> kurtosis(monthly$Dec)
[1] 0.6493442
```

Here, we observe that the skewness for January, July, and December is 1.29, 0.45, 1.38, respectively, to 2 decimal places. The distributions for January and December are highly skewed as the value are greater than 1. The distribution for July is approximately symmetric, as the value lies between -0.5 and 0.5. The kurtosis is 0.27, -0.9, and 0.65 respectively to decimal places. The kurtosis value for July is negative; therefore, the tails are thinner than a normal distribution curve.







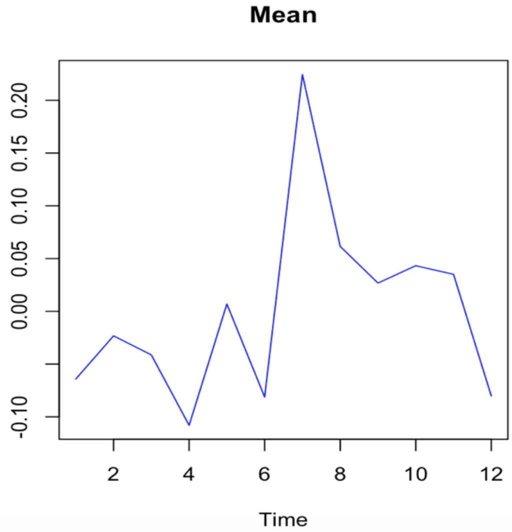
Looking at the log returns, we see that there are variations. The mean in January, July, and December is -0.0641, 0.2244, and -0.0802, respectively. The variances for January, July, and December are 0.0448, 0.0315, and 0.3021. In January and December, we see a negative mean indicating that the average spot price is decreasing. July has a positive mean, so the spot price is increasing. In terms of variances, the variance in January and July are relatively small, showing the there isn't much spread in the dataset. The variance for December is relatively high, which means that the dataset is spread out and outliers may affect the data.

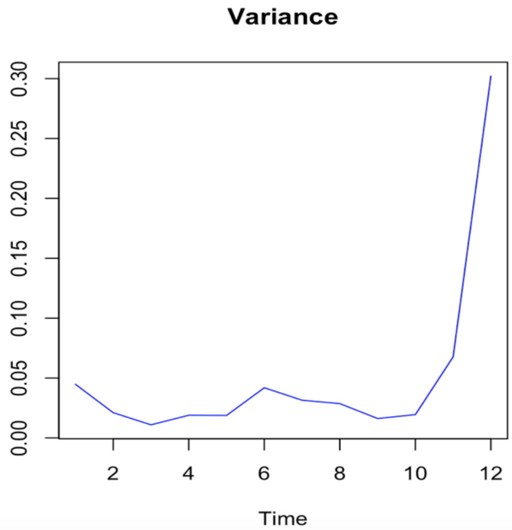
Before we take a look at the means and variances for the months overall, let us describe mean and variance. "The mean is the average of the numbers. It is a calculated central value of a set of numbers. Variance is defined as the average of the squared differences from the mean." [mathsisfun.com, 2017] The variance tells us how close we are to the mean.

Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
-0.06	-0.02	-0.04	-0.11	0.01	-0.08	0.22	0.06	0.03	0.04	0.04	-0.08

The variances for the months are:

Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
0.045	0.021	0.011	0.012	0.019	0.042	0.031	0.029	0.016	0.019	0.068	0.302



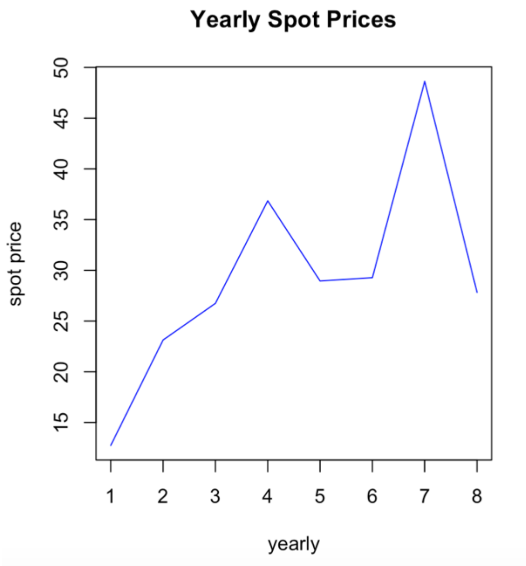


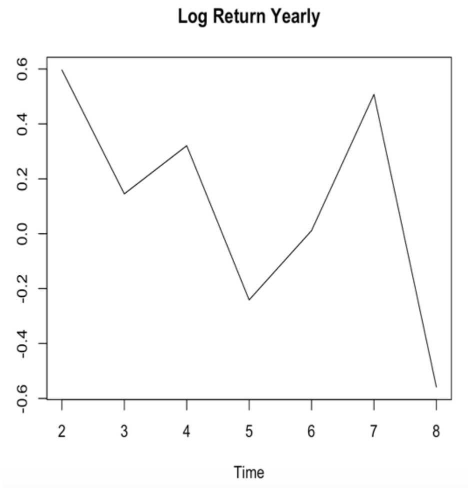
Here, I have plotted the mean and variance of the log-returns monthly to investigate the pattern further. From the means, we see that there are both positive values that show that the electricity spot prices are fluctuating monthly. The mean has a range from -0.11 and 0.22. We can see that the price drops the most from March to April. As discussed before, we would expect electricity prices to drop in April as the weather is relatively neutral. We notice from the plot that the mean tends to rise and fall frequently. The highest mean is in July, which shows that electricity prices have increased the most from June to July. The means for specific months seems quite expected; however, we would have predicted that the mean would be higher from November to December as it is winter. People will use central heating and electrical appliances more. As we know, Christmas is in December; therefore, people tend to put up Christmas lights and keep them on during the nights.

Looking at the variance, we see that there is spread within our data set. The variance values are between 0.011 and 0.302. We see that the variance is the highest in December and lowest in March. From the plot, we notice that the variance is reasonably low and continuously changing until it reaches December.

4C. Time Series Analysis of Yearly Variations in Spot Price Market Data

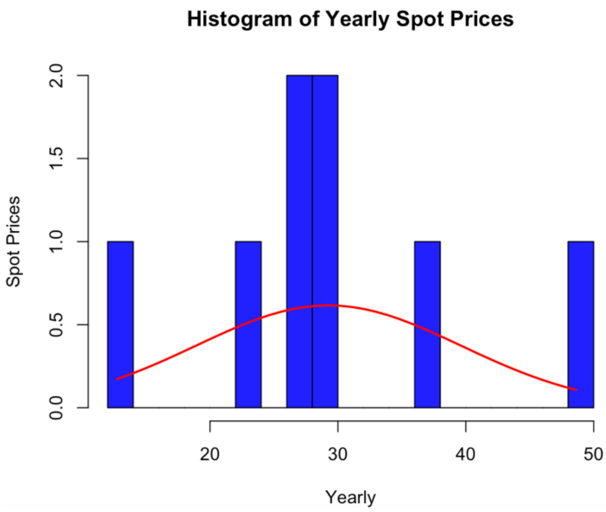
4C.1 Graphical Representation of Yearly & Log Return Spot Prices





We can see that over the years, electricity prices have increased. The prices started relatively cheap in the earlier years. We can see the rise in 2003 and 2006. We saw this earlier when we were observing the monthly spot prices. As we are aware, 'The Great Recession' occurred in 2007. This was a significant event that affected market majorly. This, again, stresses the importance of analysing data and forecasting.

4C.2 Descriptive Analysis

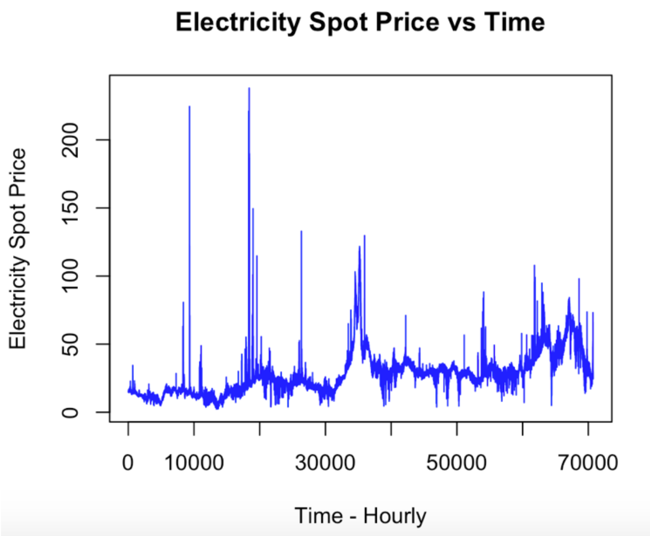


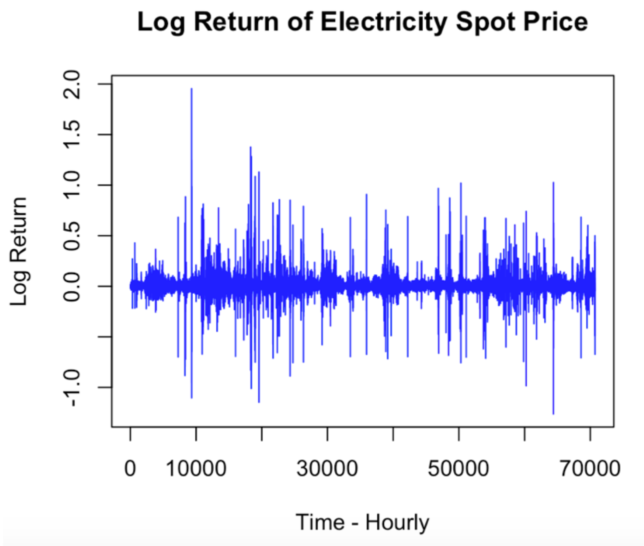

```
> summary(spyearlytimeseries)
  X13.4625879
 Min.   :12.74
 1st Qu.:25.84
 Median :28.39
 Mean   :29.27
 3rd Qu.:31.17
 Max.   :48.62
> sd(spyearlytimeseries)
[1] 10.36142
> skewness(spyearlytimeseries)
[1] 0.3284265
> kurtosis(spyearlytimeseries)
[1] -0.6169714
```

The mean of the yearly spot price is 29.27, and the standard deviation is 10.36142. We notice that the skewness is 0.3284265. The value means that the distribution is approximately symmetric, which is outlined in our histogram plot. The kurtosis for our yearly spot prices is -0.6169714. We have a negative value therefore, our distribution is platykurtic. Platykurtic means that the distribution has thinner tails than a normal distribution.

4D. Time Series Analysis of Hourly Variations in Spot Price Market Data

4D.1 Graphical Representation of Hourly Spot Prices/ Descriptive Analysis





Here, I have plotted the entire hourly dataset. We see an overall increasing trend along with fluctuations. We have found high variation in yearly spot prices as compared to daily spot prices. The variations can be seen from the clusters of the variations overtime period. We also notice that there is seasonality. Looking at the log return, we notice that the values are close to 0. Therefore, we observe stationarity.

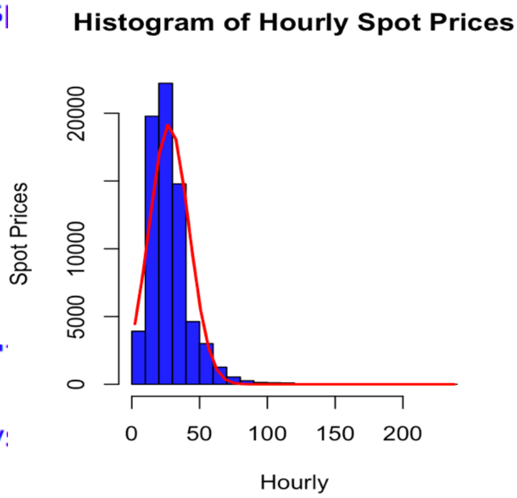
4D.2 Stationarity of Behaviour of Time Series for Hourly Spot Prices

```
        Augmented Dickey-Fuller Test

data:  electricityspotpricestimeseries
Dickey-Fuller = -27.755, Lag order = 0, p-value = 0.01
alternative hypothesis: stationary
```

Observing the Augmented Dickey-Fuller test, we reject Ho therefore the time series is stationary.

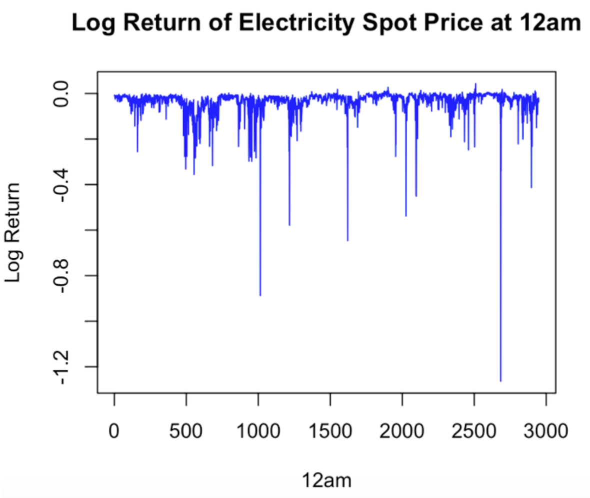
4D.3 Descriptive Analysis

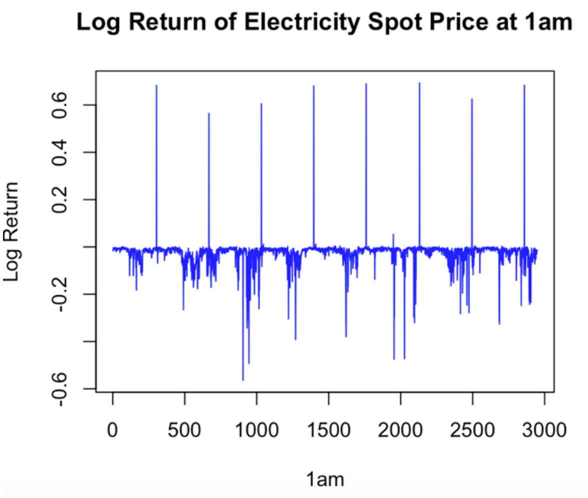
```
> summary(electricitys
  SpotPrice
 Min.   :  2.33
 1st Qu.: 16.75
 Median : 25.88
 Mean   : 27.48
 3rd Qu.: 32.79
 Max.   :238.01
> sd(electricityspotpr
[1] 14.71368
> skewness(electricity
[1] 1.76682
```



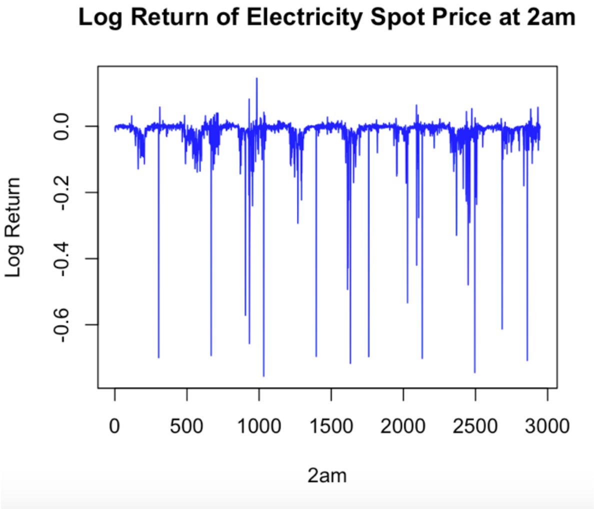
From the histogram, we notice that the dataset is positively skewed. We also see that the skewness is 1.77 to 2 decimal places, which is greater than 1.5, so the distribution is highly skewed. Our dataset's mean and standard deviation is 27.48 and 12.71, respectively, to 2 decimal places. The kurtosis of the dataset is 6.75. This value is greater than 5; therefore, it is heavily tailed compared to the normal distribution curve.

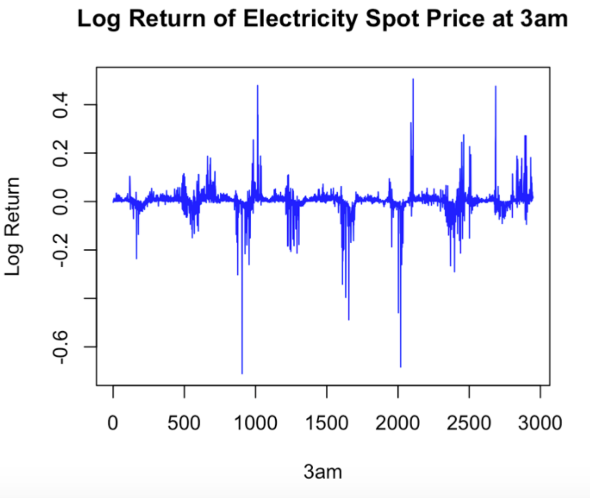
4D.4 Log Returns of Hourly Spot Prices



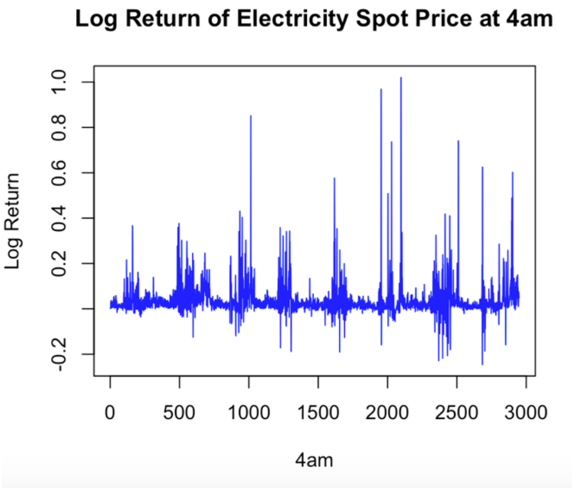


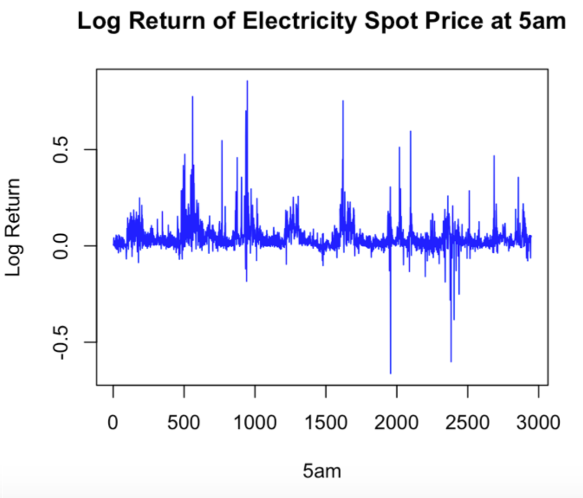
The first plot conveys that the electricity spot prices decrease. This is expected as people tend to be asleep from 12 am to 5 am. Therefore, the majority of households will not be using electricity. When looking at the plot for 1 am, we notice that some positive events occur quite frequently and periodically. Our data is over an eight-year period, and we observe that there are about eight times when the spot price has increased. Rather than it being an event caused by demand, it may be a yearly system update. It is ideal for updates to take place during this time as the need for electricity is not high. Overall, on average, the electricity price goes down. The mean for 12 am and 1 am is -0.0358 and -0.0257 (4 decimal places), respectively. The mean for both is negative, which, along with the plot, shows that the prices are decreasing. Similarly, the variances for 12 am and 1 am are 0.0029 and 0.0030 (4 decimal places), respectively. Here, the variance is very close; therefore, there isn't much change in the data spread.



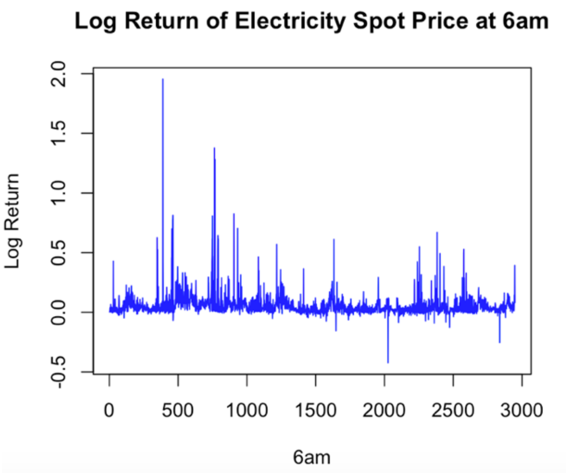


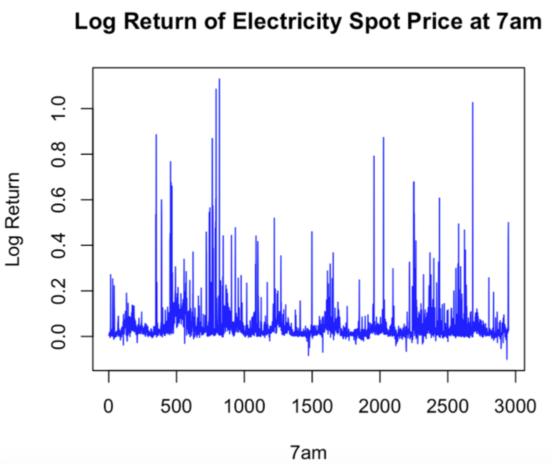
The plot for 2 am is quite similar to the plot for 1 am; however, there isn't a periodic positive spike. In general, the prices drop down quite drastically at some points where it reaches about -0.7, but it doesn't seem to have a constant occurrence. Again, we would expect electricity prices to go down, as this is when people are asleep. From the 3 am plot, it is indicated that there are both positive and negative events. We wouldn't expect prices from 3 am to be very different from 2 am as it is still considered an off-peak hour. The mean for 2 am and 3 am is -0.0178 and 0.0042, respectively. The variance for 1 am and 2 am is 0.0033 and 0.0027, respectively. From the mean, we can see that the price starts to go up at 3 am as it is a positive mean and is higher than the mean for 2 am. The variance is again similar; therefore, the spread of the prices is still constant.



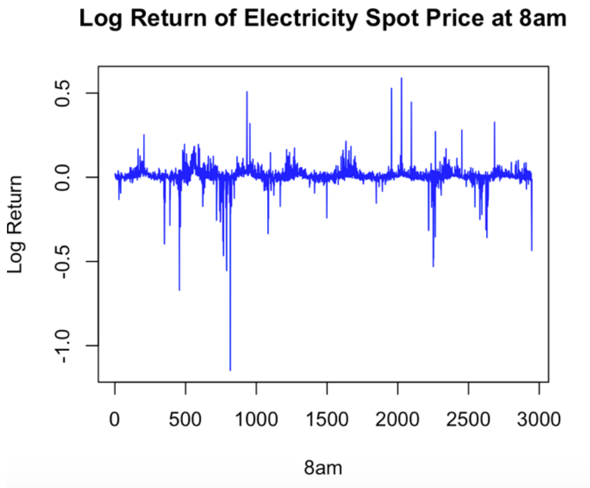


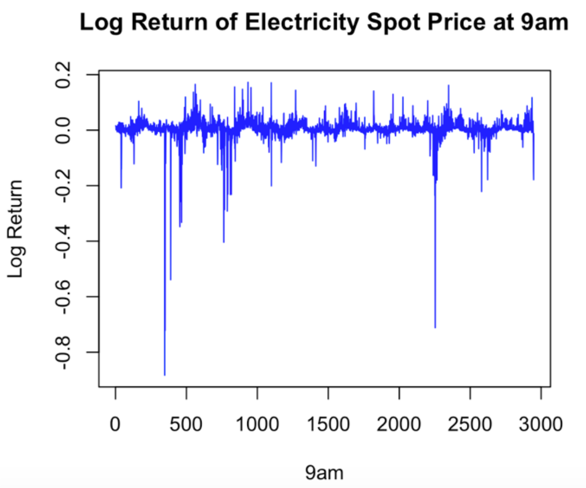
At 4 am, the prices are beginning to go up as indicated by the positive events. We would assume that prices will start to increase as people may wake up during this hour. More electricity would be used, especially at 5 am. As we see from the 5 am plot, the prices are going up from 4 am to 5 am as there are extremely positive events. This is the time when some people would start getting ready for work/school, meaning that electrical appliances and heating would be used. The mean for 4 am and 5 am is 0.0412 and 0.0487, respectively. Both means are positive and much higher than from 3 am to 4 am; therefore, it confirms that prices increase. The variance for 4 am and 5 am is 0.0049 and 0.0052. Compared to the variance from 12 am to 4 am, the variance is slightly higher, showing that the prices are starting to fluctuate.



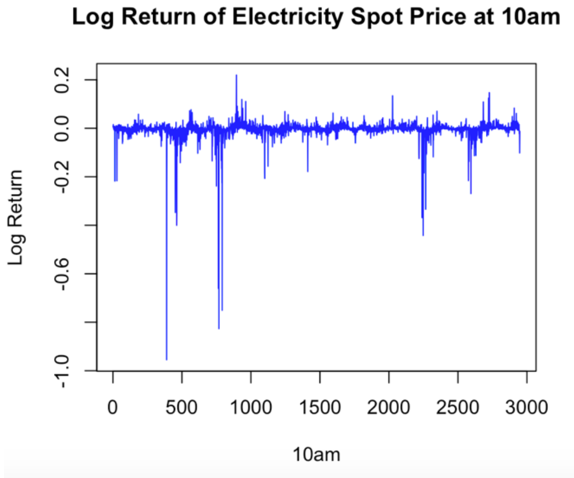


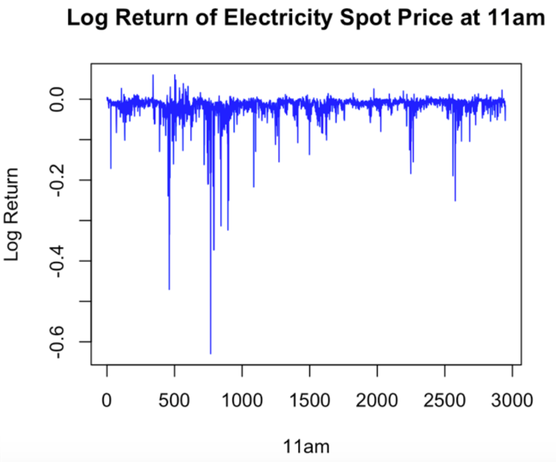
The plot for 6 am to reasonably close to the plot for 5 am showing that prices are still going up from 5 am to 6 am. The 7 am plot indicates the extreme price increase as we have extreme positive events. The price increase from 6 am to 7 am is highly predicted as 7 am is known to be the peak hour. This is the time where the majority of the population will be awake and will get ready to leave the household for education and work purposes. This is also the time that electricity consumption in offices will increase. The mean at 6 am and 7 am is 0.0614 and 0.0497, respectively. We notice that the mean at 6 am is higher than 5 am and smaller than 7 am. The mean at 6 am is the highest we have seen so far. The variance at 6 am and 7 am is 0.0093 and 0.0076, respectively. The variance of 6 am compared to 5 am is much higher. This is expected at the electricity prices start to fluctuate more at 6 am. This also shows that the market is highly volatile at this point. We would expect the variance to be higher at 7 am as there are sharper peaks in the plot, which show a much higher increase in prices. However, looking more in-depth at the plot, we notice that the highest peak at 6 am is around 1.9 and the highest peak at 7 am is about 1.4. Therefore, the fluctuation of prices at 7 am is lower than at 6 am. But overall, from 6 am to 7 am, the electricity prices are increasing the most.



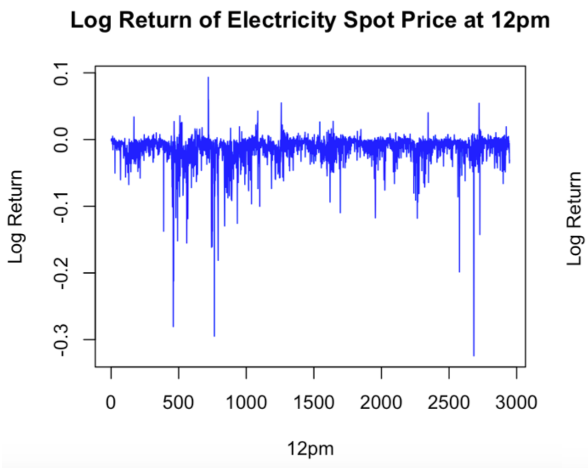


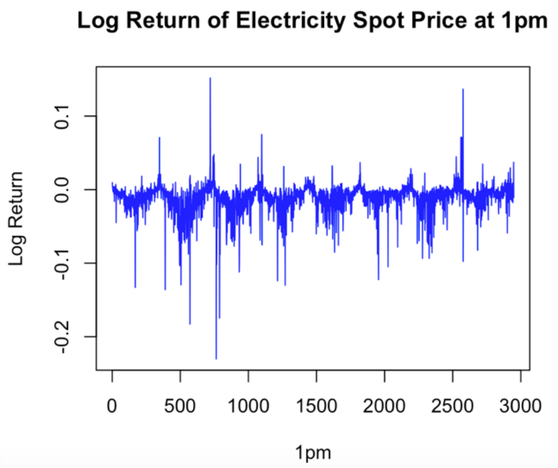
From the 8 am plot, we notice that there are both positive and negative events. There doesn't seem to be many extreme events, and so the prices are quite constant. At 9 am, we see that a few negative events indicate that the prices are starting to go down from 8 am to 9 am. The spikes don't appear to have a repeated pattern but occur quite randomly. The mean at 8 am and 9 am is 0.0487 and 0.0022. The mean for both 8 am and 9 am is smaller compared to 7 am. Both means are positive, indicating that the average electricity prices are fluctuating and going up. The mean for 9 am is relatively small compared to 8 am so the prices are going down from 8 am to 9 am. The variance at 8 am and 9 am is 0.0052 and 0.0019. We can see the decrease in variance from 8am to 9 am, indicating that the prices are starting to become constant and have fewer outliers. The random drops at 9 am might be an event that has affected electricity prices at that point, such as weather or supply constraints.



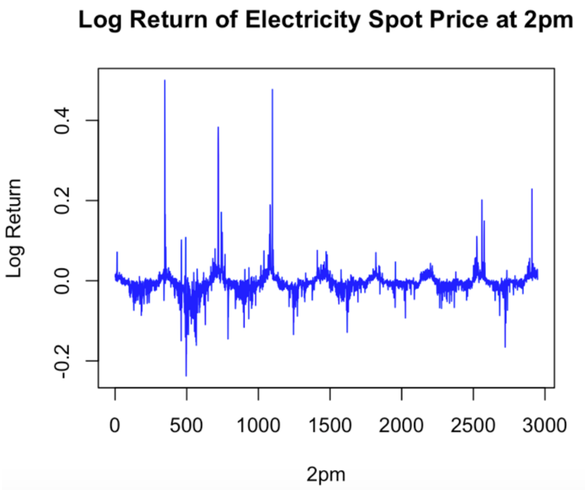


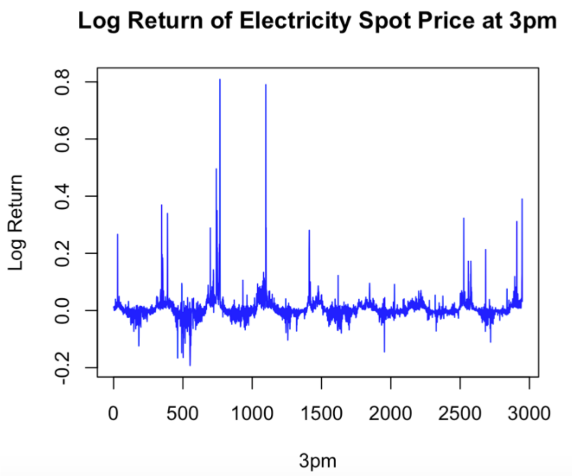
We notice that the plot for 9 am and 10 am look quite similar. The electricity prices appear to be uniform with the random drops. With the 11 am plot, we observe that the electricity prices are starting to decrease. We would expect this as electricity consumption will generally begin to decrease during this hour as people will be at work/school during this hour. The mean at 10 am and 11 am is -0.0078 and -0.0174, respectively. We notice that both means are negative, so the electricity prices are falling. The variance at 10 am and 11 am is 0.0018 and 0.0010. The variance at 9 am and 10 am is very close and very small, which indicates that the data is quite close to the mean, and therefore the prices are quite constant.



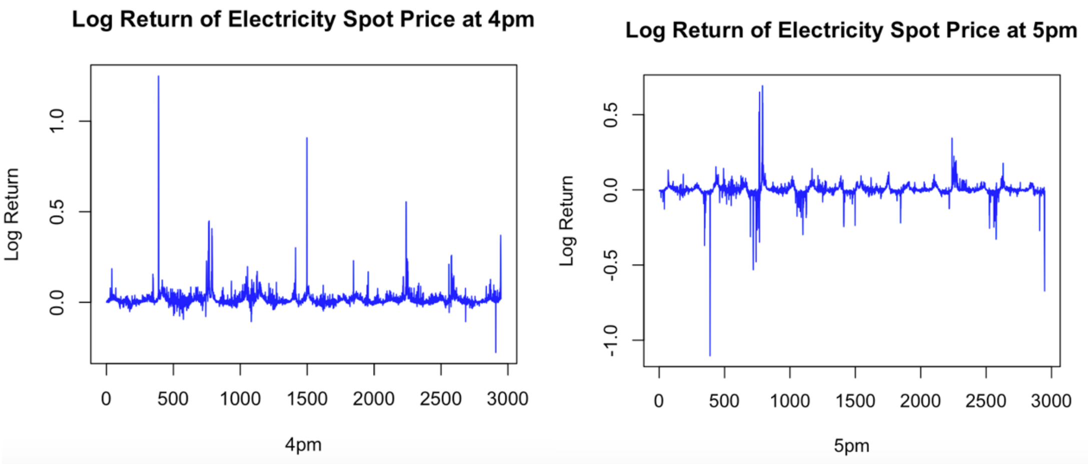


At noon, we observe that the electricity prices are decreasing from 11 am. There are a few extreme negative events. The 11 am and 12 pm plot are quite alike so that the price changes will be similar. The difference between the two is the extreme drops at 11 am and 12 pm as the drop at 11 am is higher than noon. At 1 pm, we see the same structure as at noon. There are a few positive events. The mean at 12 pm and 1 pm is -0.0133 and -0.0106, respectively. We have negative means which show that the electricity prices are decreasing. The means are the same as two decimal places; therefore, there isn't much change. The variance at 12 pm and 1 pm is 0.0005 and 0.0004. Here, the variances are very small and close to one another. This conveys that we do not see any severe changes within our dataset.

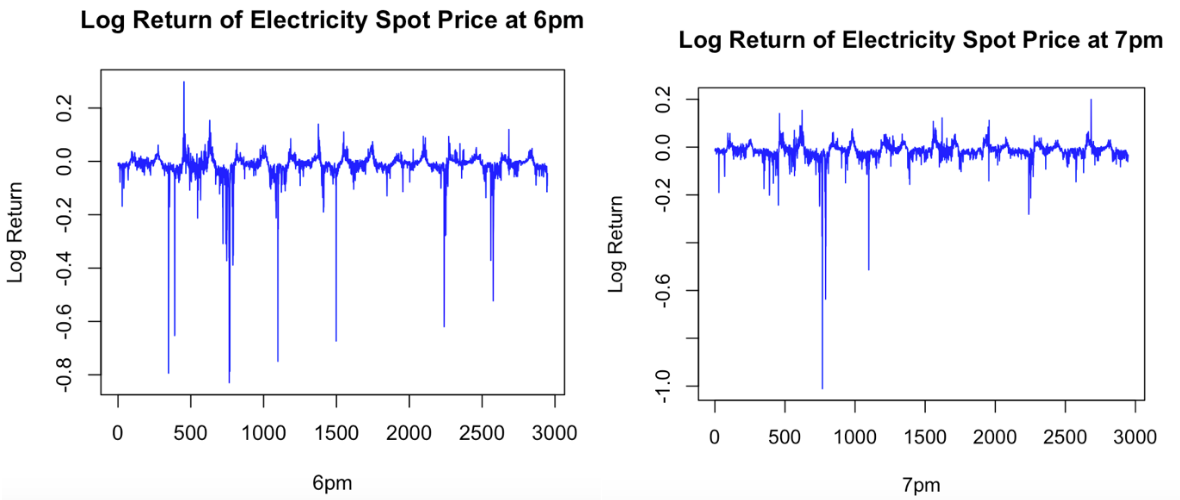




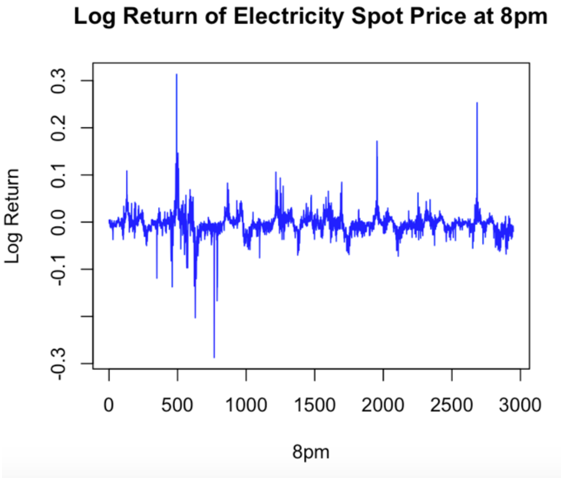
From both plots, we notice that the plots are fairly alike. They have a similar pattern; however, the peaks are much higher at 2 pm (about 0.5) than at 3pm (about 0.8). The mean at 2 pm and 3 pm is -0.0055 and 0.0059, respectively. The variance at 2 pm and 3 pm is 0.0010 and 0.0019. Looking at the mean, we see that there is a negative mean at 2 pm and a positive mean at 3 pm. We would expect prices to start going up at 3 pm as this is when school usually finishes, meaning that electricity consumption at households will begin to increase. We also notice that the mean at 2 pm is smaller than at 1 pm. The variance for both 2 pm and 3 pm is very close.

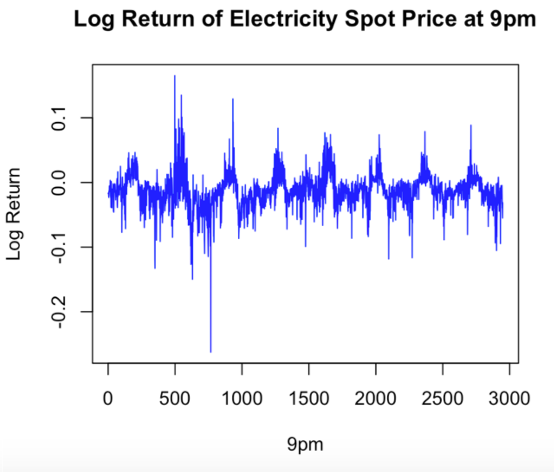


At 4 pm, we see positive events, which means that the prices increase from 3 pm. As mentioned before, this is predicted as most of the population will use more electricity during this hour. At 5 pm, we see fluctuations as there are both positive and negative events. The mean at 4 pm and 5 pm is 0.0183 and -0.0001, respectively. The variance at 4 pm and 5 pm is 0.0027 and 0.0032, respectively. The variance at 4 pm and 5 pm is 0.0027 and 0.0032, respectively.

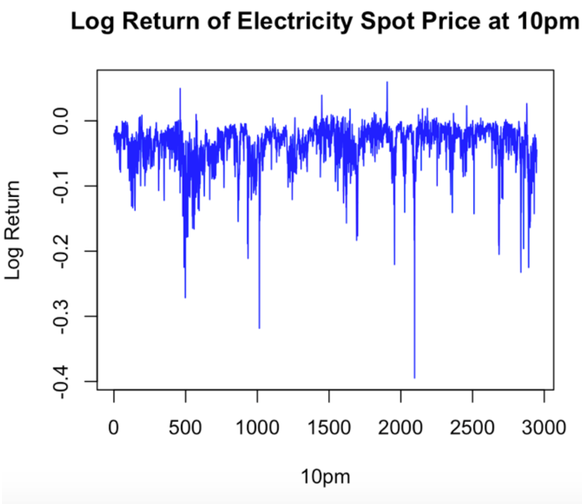


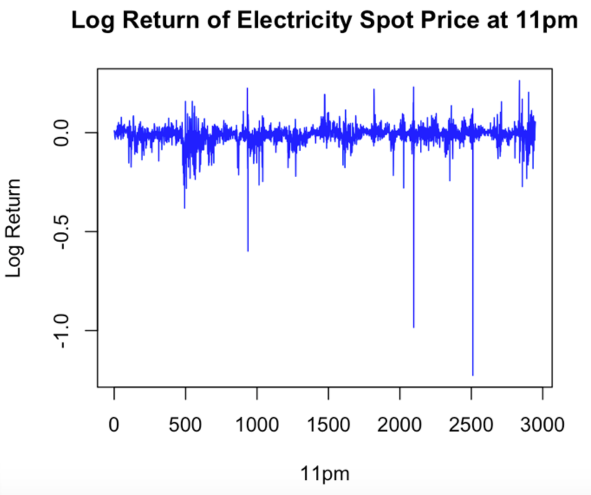
We notice that the electricity spot prices begin to drop from 5 pm to 7 pm. We would not expect this, as these are the times that people will start to go home. We would predict that people will be using electrical appliances more. As a reason for electricity prices to possibly drop is that it may be bright outside. Electricity is usually used more when it is darker outside, as consumers will not need to use as much light in households. The mean at 6 pm and 7 pm is -0.0163 for both rounded to 4 decimal places. As we see, the mean is negative, which indicates that prices are going down. The variance at 6 pm and 7 pm is 0.0032 and 0.0017, respectively. Both times, the variances are quite small, showing that the dataset is quite close to the mean.





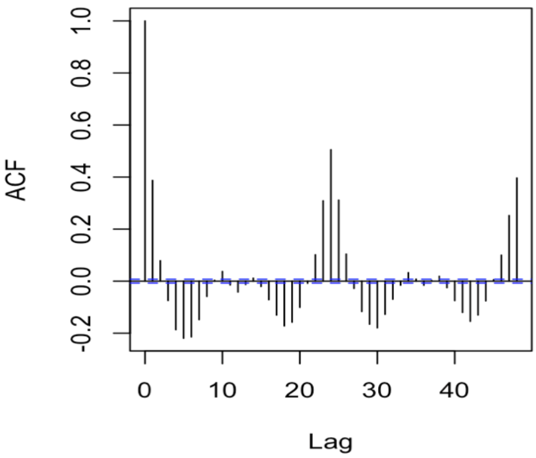
As seen by both plots, electricity prices have a mixture of positive and negative events. This shows that the prices are fluctuating during these hours. From calculations, the mean at 8 pm and 9 pm is -0.0042 and -0.0139, respectively. We see that the means are both negative, indicating that the prices are dropping. This is something that we would expect seeming as it is later at night. The variance at 8 pm and 9 pm is 0.0006 and 0.0007, respectively. The two variances for 8 pm and 9m are very small. This shows that the dataset is not spread out that much and that there aren't many outliers.

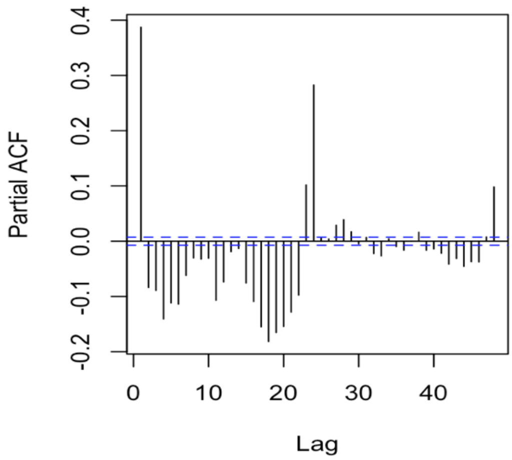




Lastly, let us look at the plots for 10 pm and 11 pm. As we can see, the electricity prices start to drop down again. One would expect to see this as it is the time that the vast majority of people will begin to fall asleep: especially children and those who wake up early for the next morning. The mean at 10 pm and 11 pm is -0.0376 and -0.0136. The negative means again show that the prices are going down. The variance at 10 pm and 11 pm is 0.0011 and 0.0030, respectively. The variance is also quite small but not as little as 8 pm and 9 pm.

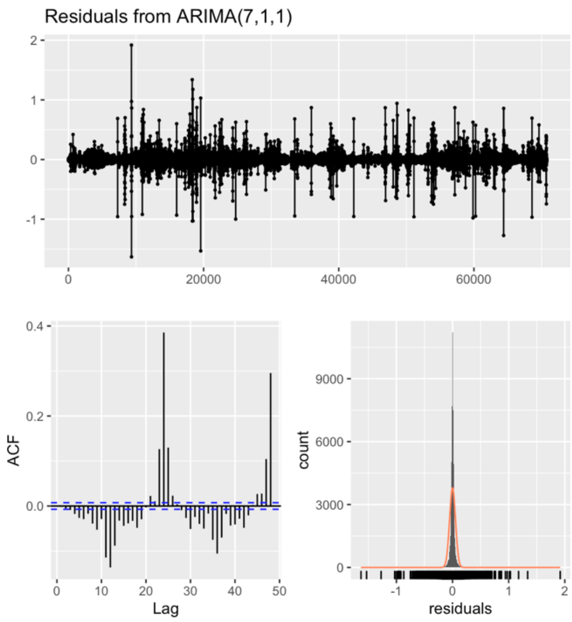
4D.5 ACF and PACF





4D.6 ARIMA Model

I tried the same model as I did for the daily spot prices to make a comparison. Below, I have plotted the ARIMA(7,1,1) plot.



Here, we see that the distribution of the residuals is the same except for the count. The ACF is very different however we see a repeated pattern. From the first plot of the residuals we see that the values are fluctuating around 0.

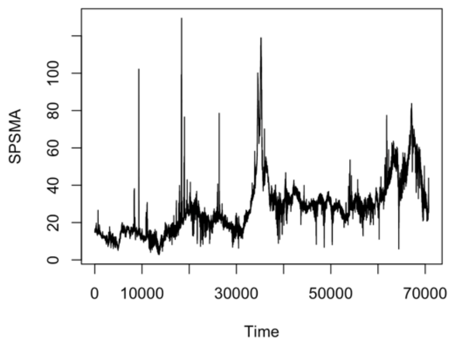
4E. Smoothing the Nord Pool Dataset

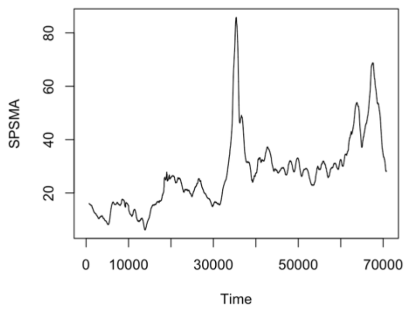
Finally, I have decided to smooth the hourly dataset. This will help see the patterns and trend more clearly.

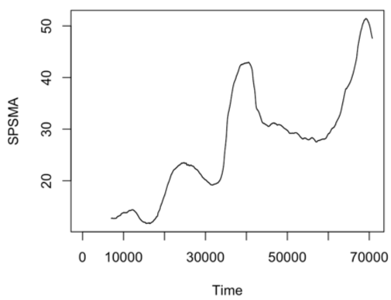
Firstly, a method that can be used to smooth or dataset is the simple moving average.
As defined by Woo,
Let q be a positive integer. We call

$$W_t = \frac{1}{2q+1}\sum_{j=-q}^{q} X_{t+j}$$

a symmetric two-sided simple moving average of the time series $\{X_t\}$. Here the tuning parameter is q and larger q corresponds to smoother W_t. In other words, the simple moving average calculates the average overs a number of time periods. Time series tend to be quite noisy therefore simple moving average is commonly used to smooth the dataset and to remove the noise.







Above, I have plotted 3 time series graphs. The first is a 7-point moving average, the second is a 70-point moving average and the last is a 7000-point moving averages. In the first plot, we identify that there hasn't been much change from the original time series. With the 70-point moving average, we notice that the time series is easier to read. We can see the overall upward trend and the fluctuations are more evident. The last plot illustrates oscillating curves with an increasing trend.

Chapter 5 - Conclusion

Overall, in my thesis, we have gathered Nord Pool data set of daily, hourly, monthly, and yearly spot prices and have analysed through time series behaviour. It is interesting to see the effects over the eight-year period that have affected the dataset the most—observing the means and variances assisted with the conclusions drawn from the dataset. Using ARIMA models to model and forecast future values has helped better understand the time-series. ARIMA models tend not to overfit and make the models more flexible.

From the results of our analysis, we see that there is high variation in yearly spot prices than daily spot prices. Also, spot prices change hourly and monthly time frameworks. The descriptive analysis also shows that variance has a high value and data is non-homogeneous, indicating that there is a change in the daily, hourly, monthly and yearly spot prices over some time.

In conclusion, some results were as predicted, and some were quite different. For example, we notice that electricity prices go down at some peak hours, such as 5 pm. We would also expect prices to go up from November to December as it tends to be colder in December.

We were also able to observe how the electricity spot prices were increasing over the years and how some events made a massive impact such as the "supply shock". This again emphasises on the importance of analysing financial datasets although as I stated at the beginning, the future cannot always be predicted.

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