Kaunas University of Technology

Department of Applied Mathematics

Market energy price forecasting in Australia

Master's Thesis

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Vilnius, 2019

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Business Big Data Analytics (M4106Q51)

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Declaration of academic integrity

I, Adomas Lingevičius, confirm that my final project on "Market energy price forecasting in Australia" is written on my own without any external help, and all results and data included are correct and acquired in a just manner. This work does not include any plagiated parts from any written, internet-based or other sources; all direct and indirect quotations have sources named in the reference list. No payment was made for this work or part of it unless it is stated by law otherwise.

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Baigiamojo bakalauro / magistro projekto užduotis (pagal poreikį)

Projekto tema ______________________________

Reikalavimai ir sąlygos (tikslinti pavadinimą pagal poreikį)

Vadovas / Vadovė ______________________________

(vadovo pareigos, vardas, pavardė, parašas) (data)

Vadovas / Vadovė ______________________________

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Studijų kryptis ir sritis (studijų krypčių grupė): Didžiųjų Verslo Duomenų Analitika.

Reikšminiai žodžiai: energija, elektra, kaina, ilgalaikė, prognozė, PPA, galios pirkimo sutartis, Australija, Viktorija, Naujasis Pietų Velsas.

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Santrauka

Šio projekto tikslas yra sukurti ir panaudoti metodologija, kurios pagalba būtų galima prognozuoti ilgalaikę elektros energijos rinkos kainą, su tikslu vertinti galios pirkimo sutartis. Šios metodologijos poreikis kyla iš elektros energijos vartotojų ir gamintojų apkrovos profilių neatitikimo, ko pasėkoje iškyla detalesnės prognozės poreikis nei mėnesinė ar ketvirtinė prognozė.

Sukurta metodologija yra pritaikoma dviem Australijos valstijoms – Naujajam Pietų Velsui ir Viktorijai. Prognozei panaudojami Australijos Energetikos Rinkos Operatoriaus duomenys (AEMO). Iš viso apmokoma ir ištestuojama 20 metodų, naudojant dviejų lygių testavimo procesą. Rezultatai parodo, kad nors ir savaitinės prognozės panašios į konstantą, laiko formų pritaikymas duomenims leidžią pasiekti reikiamą detalumo lygį abiejuose pritaikymo atvejuose. To pasėkoje tiek energijos vartotojai tiek gamintojai, naudodami tokio tipo prognozę, gali priimti labiau informuotą ir personalizuotą sprendimą, vertinant galios pirkimo sutarties kainą.

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Summary

The aim of this project is to develop and apply a methodology for a long-term energy market price forecast oriented to power purchase agreement price evaluation. The need of a more extensive methodology rises from the imbalance of energy consumers and producers load profiles which in turn requires a more detailed forecast than the usual monthly or quarterly forecasts.

The methodology developed in this thesis is applied to two states in Australia – New South Wales and Victoria using Australian Energy Market Operator (AEMO) data. A total of 20 methods are trained and tested using a two-stage testing process. The results show that even though weekly price average forecasts obtain constant values throughout the forecasted horizon applying time-shapes gives the needed level of detail and variability of the forecast for both states. Thus, letting both energy consumers and producers make a more informed and personalized decisions on the potential value of a PPA.

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Abbreviations:

CFD – a contract for difference.
PPA – power purchase agreement.
AEMO – Australian Energy Market Operator.
ACF – autocorrelation function.
PACF – partial autocorrelation function.
AIC – Akaike's Information Criterion.
AICc – Corrected Akaike's Information Criterion.

Terms:

Contract for difference – "essentially a contract between an investor and an investment bank or a spread-betting firm. At the end of the contract, the parties exchange the difference between the opening and closing prices of a specified financial instrument, including shares or commodities" (see Financial Times Lexicon).

Power purchase agreement – "PPA is a contract to buy power over a period of time at a negotiated price from a particular facility" (Google, 2013). Usually done for 5, 7 or 10 years.

Autocorrelation function - "autocorrelation measures the linear relationship between lagged values of a time series" (Hyndman & Anthanasopoulos, 2018). With a stationary process ξt function itself can be expressed as follows (Kavaliauskas & Rudzkis, 2015):

$$r(\tau) = cor(\xi_{t+\tau}, \xi_t) = \frac{cov(\xi_{t+\tau}, \xi_t)}{\mathbb{D}\,\xi_t} = \frac{R(\tau)}{R(0)}$$

Partial autocorrelation function – measures "the relationship between y_t and y_{t-k} after removing the effects of lags 1,2,3,…,τ-1" (Hyndman & Anthanasopoulos, 2018). With a stationary process ξt function itself can be expressed as follows (Kavaliauskas & Rudzkis, 2015):

$$\widetilde{r}(\tau) = r_{\xi_{t+\tau}\xi_t|(\xi_{t+1},\ldots,\xi_{t+\tau-1})} = cor(\xi_{t+\tau} - \widehat{\mathbb{E}}_{t+1,t+\tau-1}\xi_{t+\tau}, \xi_t - \widehat{\mathbb{E}}_{t+1,t+\tau-1}\xi_t), \quad \tau \in \mathbb{N}$$

Akaike's Information Criterion – "in general terms, the value of AIC for a model *M* is defined as AIC(*M*)=−2 log {*l*(*M*)}+2*D*, where *l*(*M*) is the model likelihood and *D* is a penalty term, which was originally equal to the number of parameters in the model, *p*" (Lombardía, López-Vizcaíno, & Rueda, 2017).

Corrected Akaike's Information Criterion – a bias-corrected version of AIC for a small number of observations used for estimation (Hyndman & Anthanasopoulos, 2018).

Stationarity – "stationary time series is one whose properties do not depend on the time at which the series is observed" (Hyndman & Anthanasopoulos, 2018). Those properties include mean and variance (Hyndman & Anthanasopoulos, 2018).

Introduction

Together with the interest in power purchasing agreements (PPA) grows the need for a detailed long-term market energy price forecast. Long-term forecasts usually have a monthly level of detail; however, energy consumers and producers operate in much more detailed – hourly or even half-hourly markets. Due to different consumption and production profiles a much more detailed level of forecast is needed to evaluate the potential value of a PPA.

This thesis introduces a way to approach the level of detail problem using time-shape extraction and a common methodology for long-term forecasts targeted at PPA clients. The methodology developed in this thesis is applied to two states in Australia – New South Wales and Victoria using Australian Energy Market Operator (AEMO) data. A total of 20 methods were trained and tested using a two-stage testing process. The results show that even though weekly price average forecasts obtain constant values throughout the forecasted horizon applying time-shapes gives the needed level of detail and variability of the forecast for both states. Thus, letting both energy consumers and producers make a more informed and personalized decisions on the potential value of a PPA.

1. Literature review

1.1. Power Purchasing Agreements – a new way to purchase power

During the last decade large corporations and especially technology giants such as Google have encouraged the rise in usage of power purchase agreements (PPAs) and renewable energy (Macdonald, 2016). PPA in its essence is a simple agreement. As Google in its' explanatory article puts it "PPA is a contract to buy power over a period of time at a negotiated price from a particular facility" (Google, 2013). However, PPA is a significantly different approach from the conventional way of purchasing electricity power. In the case of a PPA consumer in most cases is involved in selection of a specific type of electricity and specific facility from which that electricity is bought. Meanwhile, the common way is consumers having an agreement with electricity retailer and pay the bill at the end of each payment period, with little to no knowledge and control over the type of electricity and facilities it has been purchased from. There is more than one reason for this switch from a conventional energy purchase from energy retailers to a more involved purchasing process. Nevertheless, the change of outlook towards sustainability, the problems associated with controlling your energy consumption mix and cost management are the main ones (Google, 2013). Thus, large corporations and in some cases even states are introducing PPAs into their electricity consumption management. Below a graph represents the growth in the amount of energy purchased through corporate PPAs.

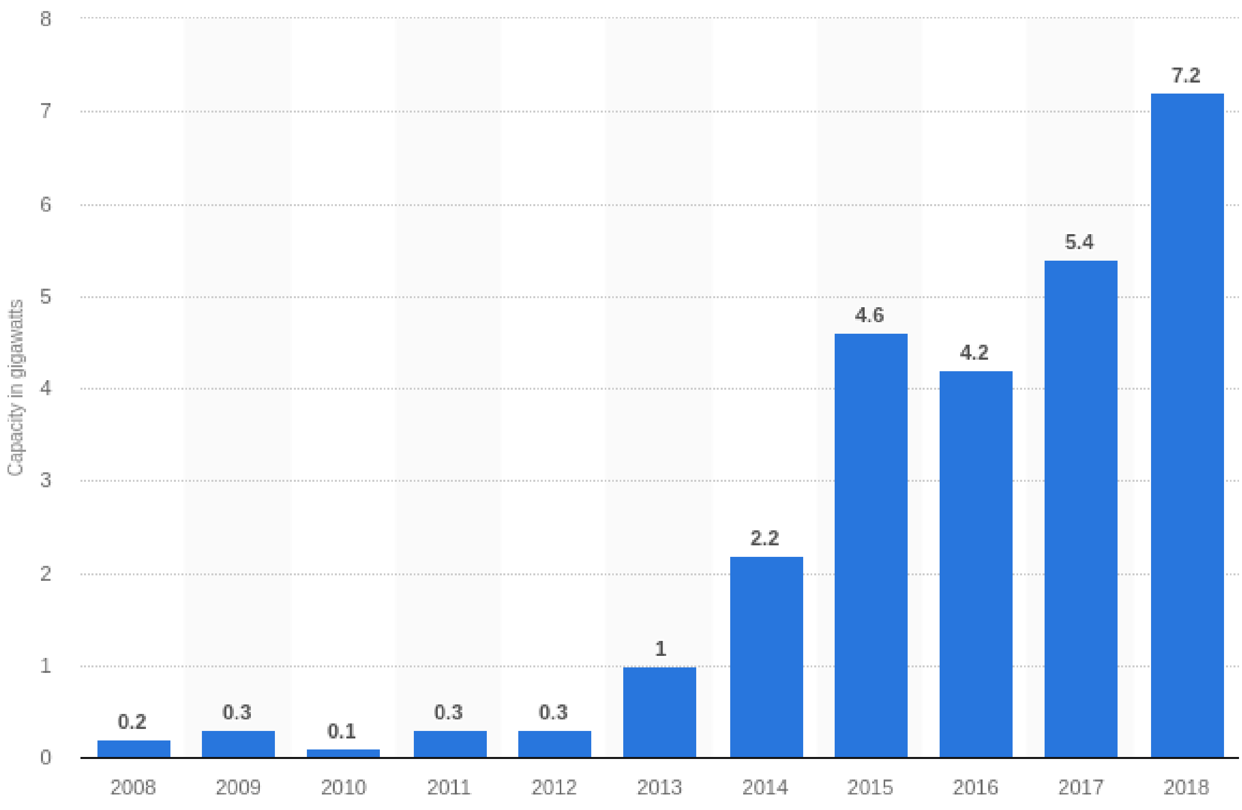


Figure 1. Amount of electricity purchased through PPAs. Source: Statista.

Firstly, this big and in a way quite sudden change is a consequence of changing outlook towards renewable energy and ecology. More and more large corporations switch to renewable energy sources to cover all or a part of their electricity consumption in one way or another (Hashmi, Damanhouri, & Rana, 2015). It is lead and encouraged by changing policies in most of the developed world such as mandatory renewable energy target (European Commision). However, not every country agrees on the topic of sustainability in which case big business takes the lead for renewable energy on themselves (The Economist, 2017). As a result, large corporations and states themselves must and already do change the mix of energy that they use.

Secondly, it is hard for consumer to control the mix of energy that they use. As most of the world is buying electricity through electricity retailers which in turn use state-controlled markets, there is no to little control over what kind of electricity – renewable or otherwise – one buys and uses (Google, 2013). Thus, it is up to state and business itself to encourage and finance the renewable energy infrastructure to increase its size in overall energy pool. Without it achievement of the beforementioned renewable energy targets is questionable at best (Kent & Mercer 2006). States either build the infrastructure themselves or support business via tax exemptions or straight forward financial support in loans and other instruments. As for the business side, some use on-premise renewable energy generation such as solar generation (Demski, 2013). Others try to investigate financial instruments such as PPAs based of contracts for difference (CFD) which in turn enables the market or state to build and develop energy projects such as wind and solar farms (Department for Business, Energy & Industrial Strategy, 2019). Both, building and buying the power through a PPA are options that give the needed control to consumers over the power mix they are using and increase the size of renewable energy produced in overall pool.

Thirdly, depending on the region electricity prices tend to fluctuate dramatically during the years. Below we can see a figure representing average monthly electricity prices in the spot market in Victoria and New South Wales, Australia (AEMO) from 2012 to 2019. Looking at the graph market price during the years fluctuates significantly both year to year and month to month. Due to this fact, electricity retailers expand their margin on electricity resale price to leverage the possible risk associated with a long-term contract, which can cause a significant increase in energy price for the end user (Essential Services Commision, 2013). Thus, corporations are inclined to search for solutions to manage their electricity costs long-term. This is where the PPA and CFD concept comes into place. As PPAs are long term agreements (usually between 5 to 10 years) with a fixed price, which in most cases are regulated either through a contract with an electricity retailer or a CFD, they let to mitigate some of a market effects and fix the price. In turn, this lets consumers to have control on part or all of their electricity cost structure (The Economist, 2017).

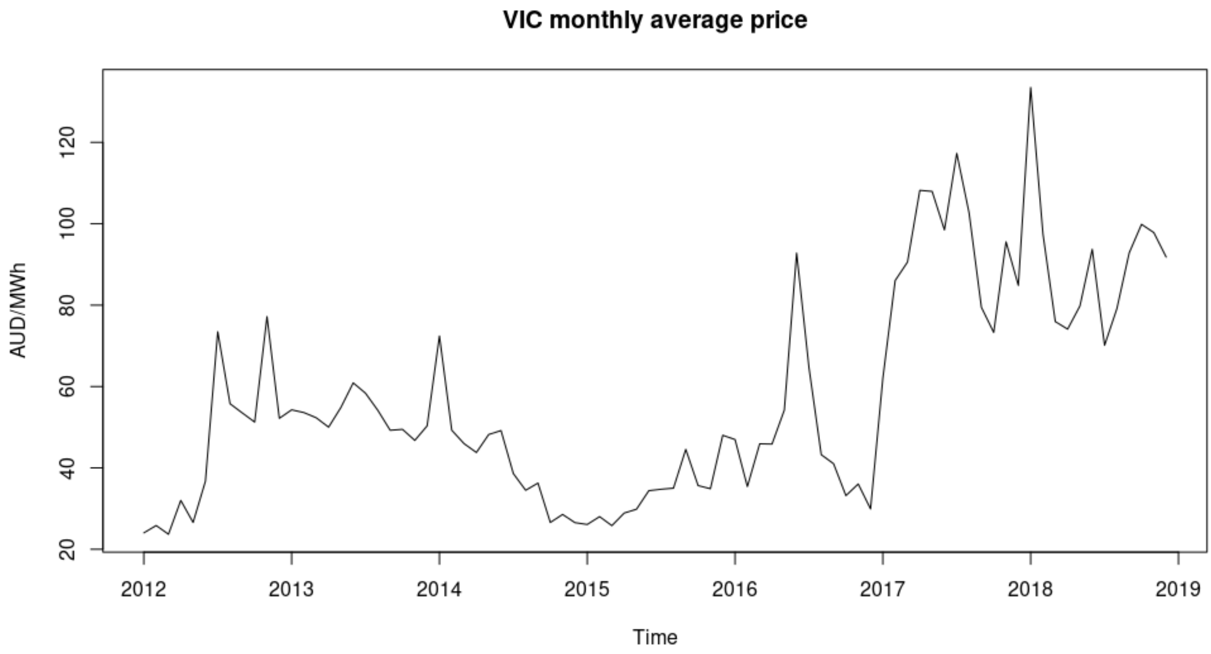


Figure 2. Victoria spot market monthly average price, 2012-2019. Source: AEMO.

PPAs let companies to make impact on the issue of sustainability, take over control over the mix of energy types its consuming and control their energy costs for a long-term period. It looks like an all-around solution for global climate issue. Thus, explaining the rise in its popularity.

The main gain for companies participating in PPAs is financial and environmental. As environmental is fulfilled just by participating, the one this thesis is considering is the financial one. At the producers' side, PPA is the main instrument for project development, as it can settle a constant cashflow to repay the needed funds for the development loan. Since, after signing the producers' side of cashflows is fixed, this thesis is looking only into the problems associated with the consumer side. Thus, the control and evaluation of a PPA from financial side of the consumer.

1.2. Linking PPA and long-term market energy price forecasting

As PPA is a long-term agreement, the need for long-term market price forecast is evident in the definition. However, comparing PPA price to a long-term monthly forecast of the market price is not enough to make the decision. Especially in markets with an unstable price such as Australia (see Fig. 2). Thus, even though PPA looks like a magic remedy that could cure all the problems in one agreement it does not come without issues. As PPA is a long-term agreement it rises a couple of problems directly linked to the long-term part of it, especially when considering renewable energy. To understand the underlying problems in using a PPA it is needed to understand the PPA itself.

1.2.1. PPA structure

As mentioned before, PPA links electricity consumer and producer with a long-term contract which lets them trade electricity for money directly, however, there are two main types of such a relationship (Schneider Electric):

- Direct PPA

- Direct PPA means that electricity is physically delivered to the customer from the producer;
- Both producer and consumer must be in the same grid region;
- Price consists of transmission price and PPA price;
- Additional energy is bought to meet full demand of the customer;
- Depending on the country additional requirements can exist.

Figure 3. Direct PPA structure. Source: Schneider Electric.

– Virtual PPA
  - Virtual PPA means that electricity is delivered from the producer to the grid, and from the grid to the consumer, with no direct link;
  - Consumer and producer both trade with the energy market and just afterwards equalize for the PPA price – meaning that at the end of each payment period if market energy price was lower than that of the PPA consumer pays producer the difference and vice versa (CFD);
  - Purely financial;
  - Can operate through multiple regions;
  - Most of the countries do not have additional requirements.

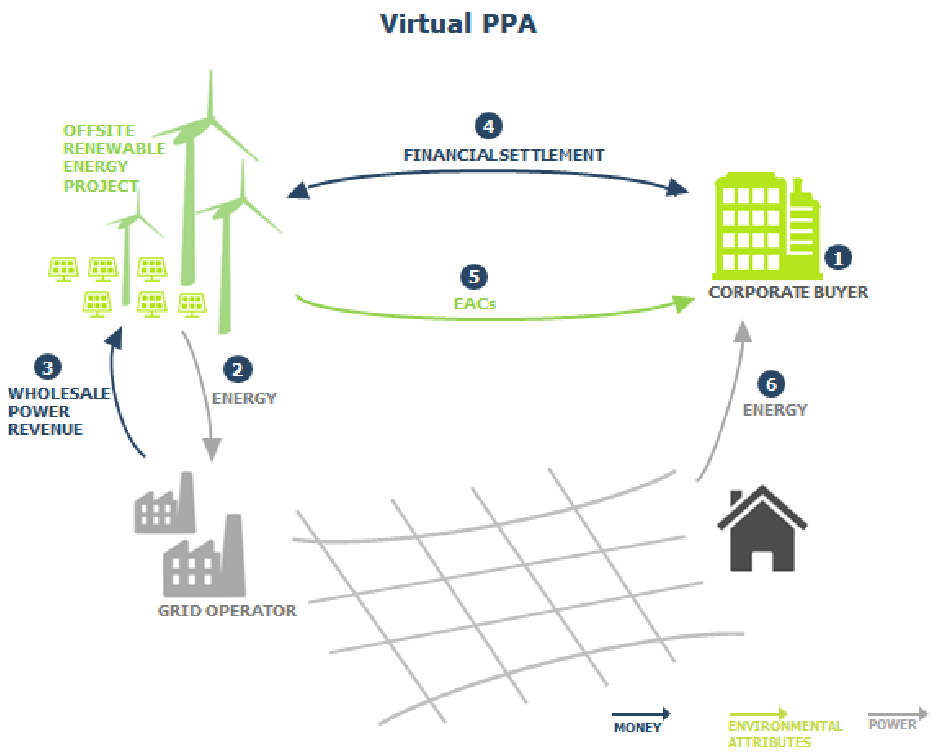


Figure 4. Virtual PPA structure. Source: Schneider Electric.

Then comparing the two main difference is the number of requirements for each to work. As explained, the virtual (financial) PPA is less restricted and in turn more appealing (Schneider Electric). Due to that, the focus of this thesis will be on the virtual PPA (later PPA) for further linking it with the need and specifications of a long-term energy price forecast.

1.2.2. Virtual PPAs and renewable energy production

When setting a PPA agreement both parties agree upon several things such as start date of the delivery, minimum amount delivered per specific term and other, however, the most important for long-term financial gain evaluation are these:

1. Price of the energy – usually in $/MWh, or in Australian case AUD/MWh.
2. Expected delivery timetable – a forecast of producers' production amounts in pre-agreed intervals, usually average hourly production per day per month for each month of the year.
3. Customers consumption forecast – not agreed in the terms of PPA, however important for the financial evaluation.

Price of energy is fixed and agreed for the whole term, however, both expected delivery and customer consumption are variable and quite different, thus, incompatible. The incompatibility arises from the fact that as each hour electricity is produced and consumed it is done so in different amount with a different market price, and as discussed earlier, consumer must pay to the producer if the market price was lower than the PPA price and vice versa. Moreover, consumer has to still balance out his consumption, and in most cases with the help of the energy retailer. For better understanding a graph is provided below (source: AEMO, data is in half-hourly steps, for a week). Here green bars represent solar production, red – consumption and blue line – market price. As seen from the graph, consumption and production do not match, more than that, price differs significantly during the week. As a result, simple evaluation of PPA is nearly impossible due to the factors one needs to consider.

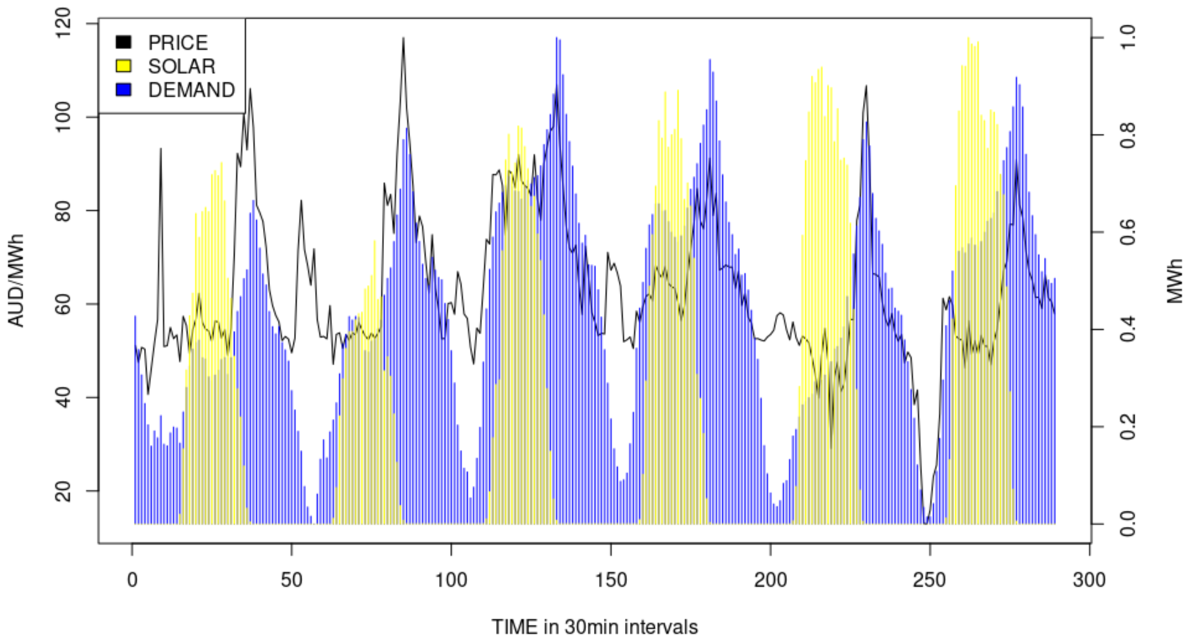


Figure 5. Electricity demand and solar production with prices in NSW. Source: AEMO.

Even though, consumption and production are incompatible in the shown graph, they can be forecasted to some extent for a long period of time. Consumption has 3 cyclical component – variation during the day (night, morning, 2 day peaks) and thus is quite predictable. Production predictability depends on region and production type. Solar is more predictable than wind, however, both require specific knowledge and before signing a PPA are required to be done by experts. Thus, the only variable left is the market price itself.

1.2.3. Renewable PPA specific market price forecast detalization

The need for long-term market price forecast is evident, however, there is some specifics to it as well, mainly the level of detail of the forecast. For that, level of detail of all – production, consumption and price – must be considered. As discussed before, consumption can be represented as an average week with a level of detail of an hour (half-hour for Australia due to market conditions) for each month of the year. The need for monthly division is for year-seasons evaluation, weekday division for business processes defined evaluation and half-hourly due to the specific trading system in Australia. As for production, it is usually provided as an hourly average day for each month of the year, meaning it does not increase the level of detail needed. Regarding the price, the only thing to take into consideration is the Australian trading system, so once again, half-hourly. Taking everything into account the level of detail needed for the forecast is as follows:

Year <- Month <- Weekday <- Time

1.3. Energy market price forecasting

Even though, there is a big body of market price forecasting research in electricity, most of it considers short term forecast to support spot market trading decisions. Nevertheless, the attention to short-term energy price forecasting lead to development of long-term forecasts as well (Ziel & Steinert, 2018). A graph below represents the amount of papers released, where blue represents the long-term ones, which have a horizon of more than one-year (Ziel & Steinert, 2018):

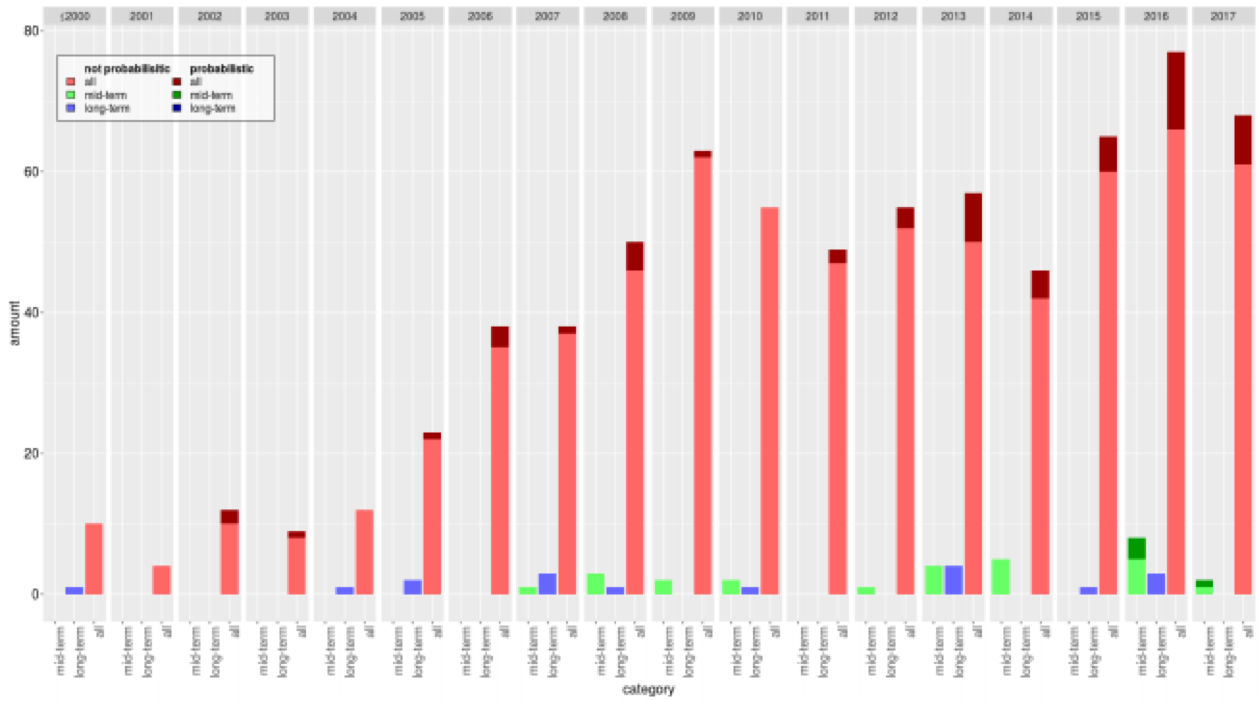


Figure 6. Amount of papers released on energy price forecasting.

The division between long-term energy price forecasting could be set by if a model uses exogenous variables as inputs or not. The models that do either use fuel prices such as natural gas price, coal price (Bello et al., 2016a; Maciejowska & Weron, 2016); or various representation of energy mix in the market as amount of hydro (Torbaghan et al. 2012), number of generators per type (Kosov, 2014) or/and power plant unavailability (Bello et al., 2016a/b); or a mix of all. However, then looking into Australia specific research, exogenous variables are rarely if even seen (Rafiei et al., 2016; Kou et al., 2015, Wan et al., 2017). This could be explained by the high variability of energy mix in Australia, especially at this moment as renewables only start to pick up, despite, mandatory target set as far as 2004 (Kent & Mercer, 2006). Moreover, after a significant change in Australian energy market it became more volatile and unpredictable, which can be caused by "artificial price spikes" (Hutchens, 2018) caused by some of the major electricity producers. Due to this fact, this thesis will focus on models which are time-series specific, i. e. without exogenous variables.

Regarding the horizon of the models, even though elsewhere considered long-term, most them are forecasts up to a year. Despite, some of them do longer horizon forecasts, however it is not uncommon for forecast to be the seasonality component of the price and not the full price itself (Ziel & Steinert, 2018). In the case of price forecasting for PPAs, the horizon must be at least near the lowest possible number of years of a PPA, which is 5 and on average (in Australia) 7. Nevertheless, the testing of such a long-term horizon prove difficult as market situation changed significantly during the period of 2015-2016 (see Fig. 2), (Mcconnell et al., 2016) and the time of writing is 2019. However, for evaluation of the long-term Australian Stock Exchange (ASX) electricity price futures can be used. Even though, they do not provide a robust test sample, they do give an indication where the market is moving gathered through inside information of the market and self-fulfilling prophecy effect. In such case, the horizon used could be 4 years, as ASX has futures contracts up to the end of 2022.

As for the choice of a specific method for long-term forecast focused on energy market price, literature is inconclusive and researchers use a variety of models from SVM and ANN to AR, ARIMAX and GARCH (Ziel & Steinert, 2018). Due to lack of knowledge which specific method to choose, this thesis will try to check as many as possible time-series based methods.

1.3.1. Time-series forecasting methods

Since, no specific method is selected several methods are going to be tested and, thus, discussed in this part of the thesis. These methods include: SVM, ARIMA, ETS, TBATS, regression, mean and naive. Not only the named methods will be tested, but their variations as well.

To start with, the simplest methods are mean, regression, naïve, naive with a seasonal component and naïve with drift. Mean is a method of taking the mean value of selected time-series and using it for all the forecasted points (Vaičiukynas, 2018). Mean is good to forecast quite constant time-series, which do not have high variation. Next up is regression, which takes use of seasonal dummy variables and/or trend. To simply put it, it tries to mimic time-series behavior by mimicking its' trend and seasonality (Vaičiukynas, 2018). Yet another is naïve. Naive is taking the last known value and repeating it for the forecast step, while, seasonal naïve and naïve with drift are its' modifications which add seasonal component to the forecast or drift – change in value from first to last (Vaičiukynas, 2018). While, useful in economic variables for one time step prediction, naïve without drift or seasonal component is hardly usable for longer term predictions. These are the simplest methods which can be used to forecast time-series data.

Furthermore, for more complex time-series ARMA and its derivates such as ARIMA are used. ARMA – autoregressive moving average models. There are two components which constitute the model itself: AR – autoregression; MA – moving average. All together, these parts constitute the ARMA model.

Firstly, AR – the autoregressive part can be described as a process separately. Let's say that **Z** denotes integer set. A stationary process ξ_t is called a p order autoregressive process ($AR(p)$) if it fulfills the following equation (Kavaliauskas & Rudzkis, 2015):

$$\xi_t = \mu + a_1\xi_{t-1} + \cdots + a_p\xi_{t-p} + \varepsilon_t, \quad t \in \mathbb{Z},$$

where ε_t is white noise. If we denote $P(z) = 1 - a_1z - \cdot \cdot \cdot - a_pz^p$, then the previous equation can be rewritten as follows:

$$P(L)\widehat{\xi}_t = \varepsilon_t, \quad \mu = P(1)\,\mathbb{E}\,\xi_t.$$

Each $AR(p)$ process is a reversible process with a finite number of coefficients in the reversed formula, $\alpha_k = -a_k$, $k = 1, \ldots, p$ (Kavaliauskas & Rudzkis, 2015).

Secondly, MA – the moving average part. Let's say that **Z** denotes integers set. A stationary process ξ_t is called a q order moving average process ($MA(q)$) if it fulfills the following equation (Kavaliauskas & Rudzkis, 2015):

$$\xi_t = \mu + \varepsilon_t + b_1\varepsilon_{t-1} + \cdots + b_q\varepsilon_{t-q}, \quad t \in \mathbb{Z},$$

where ε_t is white noise. If we denote $Q(z) = 1 + b_1z + \cdots + b_qz^q$, then the previous equation can be rewritten as follows:

$$\widehat{\xi}_t = Q(L)\varepsilon_t,\ \mu = \mathbb{E}\,\xi_t.$$

Since in the Wold's theorem:

$$\widehat{\xi}_t = \sum_{k=0}^{\infty} c_k\varepsilon_{t-k} = C(L)\varepsilon_t$$

Then the coefficients of *the MA(q)* process are:

$$c_j = \begin{cases} b_j, & j = 0, \ldots, q \\ 0, & j > q. \end{cases}$$

Moving average process is a linear regular process, which is expressed as a white noise filter with a finite number of coefficients *(*Kavaliauskas & Rudzkis, 2015).

Thirdly, ARMA – the autoregressive moving average. Let's say that **Z** denotes integers set. A stationary process ξ_t is called *ARMA*(*p*, q) if it fulfils the following equation (Kavaliauskas & Rudzkis, 2015):

$$\xi_t = \mu + a_1\xi_{t-1} + \cdots + a_p\xi_{t-p} + \varepsilon_t + b_1\varepsilon_{t-1} + \cdots + b_q\varepsilon_{t-q}, \quad t \in \mathbb{Z},$$

where ε_t is white noise. Using the polynoms used for *AR* and *MA* processes we get the following:

$$P(L)\widehat{\xi}_t = Q(L)\varepsilon_t,\ \ \mu = P(1)\,\mathbb{E}\,\xi_t.$$

It is assumed that polynoms *P(z)* and *Q(z)* do not have common square roots since in such case model parameters *p* and *q* would not be unambiguous (Kavaliauskas & Rudzkis, 2015). Such process can exist only then, when polynom *P(z)* does not take on zero values on a unit circle (in a complex number plane), meaning (Kavaliauskas & Rudzkis, 2015):

$$P(z) \neq 0, \quad |z| = 1.$$

Parameters of an *ARMA* process can be selected using the Akaike's information criterion – AIC. Let's assume X=(ξ1, . . . , ξn) distribution density is *p*(*x, θ*), where *θ* is an unknown parameter with *k* dimensions, then criterion can be expressed as (Kavaliauskas & Rudzkis, 2015):

$$AIC(k) = -2\ln p(X, \widehat{\theta}) + 2k,$$

where *θ-hat* is the maximum likelihood estimate. The model with the lowest *AIC*(*k*) value is the recommended model, thus:

$$\widehat{k} = \arg\min_k AIC(k).$$

If ξ_t is expressed as *ARMA(p,q)* process then:

$$\xi_t = \mu + a_1\xi_{t-1} + \cdots + a_p\xi_{t-p} + \varepsilon_t + b_1\varepsilon_{t-1} + \cdots + b_q\varepsilon_{t-q}$$

and in that case:

$$\theta = (\mu, \sigma_\varepsilon^2, a_1, \ldots, a_p, b_1, \ldots, b_q), k = p + q + 2.$$

θ estimate is calculated assuming that ξt is a Gaussian sequence, while, *p* and *q* are selected in such a way that *AIC(k)* → min (Kavaliauskas & Rudzkis, 2015).

ARMA process can be used for forecasting. After calculating *R(τ)* - covariation function, general linear forecasting theory can be used, where *AR(p)* forecast can be calculated recurrently forecasting one step at a time using (Kavaliauskas & Rudzkis, 2015):

$$\widehat{\xi_t} = \mu + a_1\xi_{t-1} + \cdots + a_p\xi_{t-p}.$$

As for the ARIMA it is ARMA derivative with an additional *I* – integrated component part. It is used for non-stationary data which differences behave like stationary data. A process ξ_t is called a *d* order integrated process (denoted *I(d)*) if its' *d* order differences are a stationary process and *d*-1 order differences are non-stationary (Kavaliauskas & Rudzkis, 2015). Thus:

$$\Delta\xi_t = \xi_t - \xi_{t-1} = (1 - L)\xi_t.$$

And in a generalized form:

$$\Delta^d\xi_t = \Delta^{d-1}\xi_t - \Delta^{d-1}\xi_{t-1} = (1 - L)^d\xi_t.$$

Then a process $\xi_t \in I(d)$ is called *ARIMA(p,d,q)* process with *d* order differences and the following equation is true:

$$P(L)(1 - L)^d\widehat{\xi}_t = Q(L)\varepsilon_t,$$

where P(z) and Q(z) are respectively p and q order polynoms and ε_t is white noise (Kavaliauskas & Rudzkis, 2015).

ARMA model and its especially ARIMA are widely used in price forecasting. As overviewed in part 1.3. there is not much research done on long term energy price forecasting, however, quite a few papers discuss ARMA and its derivates being used on other price forecasting or short-term energy price forecasting. Jakasa et al. found ARIMA to be an accurate predictor for the day-ahead energy price forecasting for prices in EPEX power exchange (Jakasa et al. 2011). Meanwhile, Sanchez Lasheras et al. compared accuracy of ARIMA (fitted to ARIMA(1,1,0)) with two different neural networks on the COMEX copper price doing long-term forecasting of coppers closing price and found that ARIMA falls far behind – RMSE of all three models was 0.176, 0.148, 0.107 for ARIMA, multilayer perceptron network and Elman neural network respectively (Sanchez Lasheras et al., 2015). Jarret & Kyper use ARIMA to model Chinese stock prices and "infer that the daily Chinese stock price index contains an autoregressive component" (Jarret & Kyper, 2011), thus, letting to predict stock returns. As noted, ARMA and its derivates are used on a variety of different price forecast research both as a benchmark (Sanchez Lasheras et al., 2015) or as the final model (Jarret & Kyper, 2011), thus, this thesis uses it as well.

Another group of models are exponential smoothing models. These include ETS and Holt-Winters. In short, "exponential smoothing methods [use] weighted averages of past observations, with the weights decaying exponentially as the observations get older" (Hyndman & Anthanasopoulos, 2018). Thus, the older the observation the lower its' weight is and vice versa. These models essentially rely on trend and seasonality and the smoothing method used (Hyndman & Anthanasopoulos, 2018). While, ETS and Holt-Winters both are named as exponential smoothing models, both are considered a form of the first – ETS model - the latter just having a specific name of the researchers. The taxonomy of the models can be found below:

Trend Component	**Seasonal Component**		
	N	**A**	**M**
	(None)	**(Additive)**	**(Multiplicative)**
N (None)	(N,N)	(N,A)	(N,M)
A (Additive)	(A,N)	(A,A)	(A,M)
A_d (Additive damped)	(A_d,N)	(A_d,A)	(A_d,M)

Figure 7. Two-way classification of exponential smoothing methods. Source: Hyndman & Anthanasopoulos, 2018

For a better understanding let's analyze Holt-Winters' additive seasonal method a bit more in depth. This method is used then time-series has trend and seasonality in it. The method can be described as the following forecast, level, trend and seasonal equations (Kavaliauskas & Rudzkis, 2015):

$$
\begin{aligned}
\hat{y}_{t+h|t} &= l_t + hb_t + s_{t-m+((h-1)\bmod\ m)+1} \\
l_t &= \alpha(y_t - s_{t-m}) + (1-\alpha)(l_{t-1} + b_{t-1}) \\
b_t &= \beta^*(l_t - l_{t-1}) + (1-\beta^*)b_{t-1}, \\
s_t &= \gamma^*(y_t - l_{t-1} - b_{t-1}) + (1-\gamma^*)s_{t-m}.
\end{aligned}
$$

here $0 \leq \alpha \leq 1$ – level smoothening parameter, $0 \leq \beta^* \leq 1$ – trend smoothening component, $0 \leq \gamma^* \leq 1$ is the seasonality smoothening parameter and m – seasonality period (m=12 months for yearly data). Here s_t is attributed to each time moment (possibly different) and equals to a revised s_{t-m} value (Kavaliauskas & Rudzkis, 2015). Holt-Winters' seasonal method can written using error correction equations:

$$
\begin{aligned}
l_t &= l_{t-1} + b_{t-1} + \alpha e_t, \\
b_t &= b_{t-1} + \alpha\beta^* e_t = b_{t-1} + \beta e_t, \\
s_t &= s_{t-m} + (1-\alpha)\gamma^* e_t = s_{t-m} + \gamma e_t,
\end{aligned}
$$

Here e_t – is the error of one-step forecast:

$$e_t = y_t - (l_{t-1} + b_{t-1} + s_{t-m}) = y_t - \hat{y}_{t|t-1}$$

For parameter optimization usuallly mean squared error is used, which in this case can be expressed as follows (Kavaliasukas & Rudzkis, 2015):

$$R = \sum_{t=1}^{T} (y_t - \widehat{y}_{t+h|t})^2 = \sum_{t=1}^{T} e_t^2.$$

As for forecasting, the forecast equation is used, which was overview previously:

$$\widehat{y}_{t+h|t} \quad = \quad l_t + hb_t + s_{t-m+((h-1) \bmod m)+1}$$

for each value of h=1, 2, … (Kavaliauskas & Rudzkis, 2015).

Holt-Winters is commonly used for long-term forecasts. Ferbar Tratar & Strmčnik (2016) found it to be the bet model among tested for heat load long term forecasting. Shahin (2017) developed a derivative of Holt-Winters' using multi-seasonality to optimize cloud computing workload. The developed model outperformed others (Shanin, 2017). Due to the nature of Holt-Winters components model performs well in long-term forecasts and is frequently used in studies.

Lastly, some of the less frequently used models for times series forecasting can be tested. Such models are SVM, TBATS, Theta and others. Due to the complex nature of the energy market prices in Australia and recent usage of these models in the time series field, they are going to be tested as well.

As there are a variety of models from which to pick, an understandable and effective measure of goodness should be in place. There are four most common measures for forecast errors: RMSE, MAE, MAPE, MASE. RMSE and MAE both are scale-dependent and are calculated as so:

$$\text{Mean absolute error: MAE} = \text{mean}(|e_t|),$$
$$\text{Root mean squared error: RMSE} = \sqrt{\text{mean}(e_t^2)}.$$

Where e_t is the error – the difference between predicted and actual value. As Hyndman & Anthanasopoulos, 2018, state “method that minimizes the MAE will lead to forecasts of the median, while minimizing the RMSE will lead to forecasts of the mean” as well as it is one of the most popular ways to compare models that use common units. MAPE is a mean absolute percentage error. While having the flexibility to be measured across different units, it also brings some issues when y_t is close to 0 (Hyndman & Anthanasopoulos, 2018). It is given by: MAPE=mean($|p_t|$), where $p_t=100e_t/y_t$. Lastly, MASE is a mean absolute scaled error. Essentially MASE compares forecast to that of an average naïve forecast and if it is <1 then the forecast is better and vice versa (Hyndman & Anthanasopoulos, 2018). Mase is MASE=mean($|q_j|$), where $q_j = \dfrac{e_j}{\dfrac{1}{T-m}\sum_{t=m+1}^{T}|y_t - y_{t-m}|}$ for non-seasonal time series and $q_j = \dfrac{e_j}{\dfrac{1}{T-1}\sum_{t=2}^{T}|y_t - y_{t-1}|}$ for seasonal time series. Since, MAPE has some issues with extreme y_t RMSE and MASE should be used to determine the best fitting model.

To sum up, the final model of the thesis should be a time series model with a time horizon of 4 years and could be at least somewhat testable for that period using Australian Stock Exchange futures prices using RMSE and MASE as forecast error measures. Moreover, methodology should include that a variety of models should be tested and available for testing and forecasting later as situation in the Australian market is far from stable (Mcconnell et al., 2016). Those models include SVM, ARMA, ETS, BATS, regression, mean, naïve and their variations.

1.4. Target states

Since Australia has more than one electricity market price due to the number of states it has, only two are selected. Selection is based on the market size, readiness for PPAs and actual number of PPAs already made. Two states are used for forecasting to compare models for both if different.

Considering market size, Victoria, Queensdale and New South Wales are the biggest consumers as shown in the graph below. Victoria – orange, Queensdale – light blue and New South Wales – deep blue.

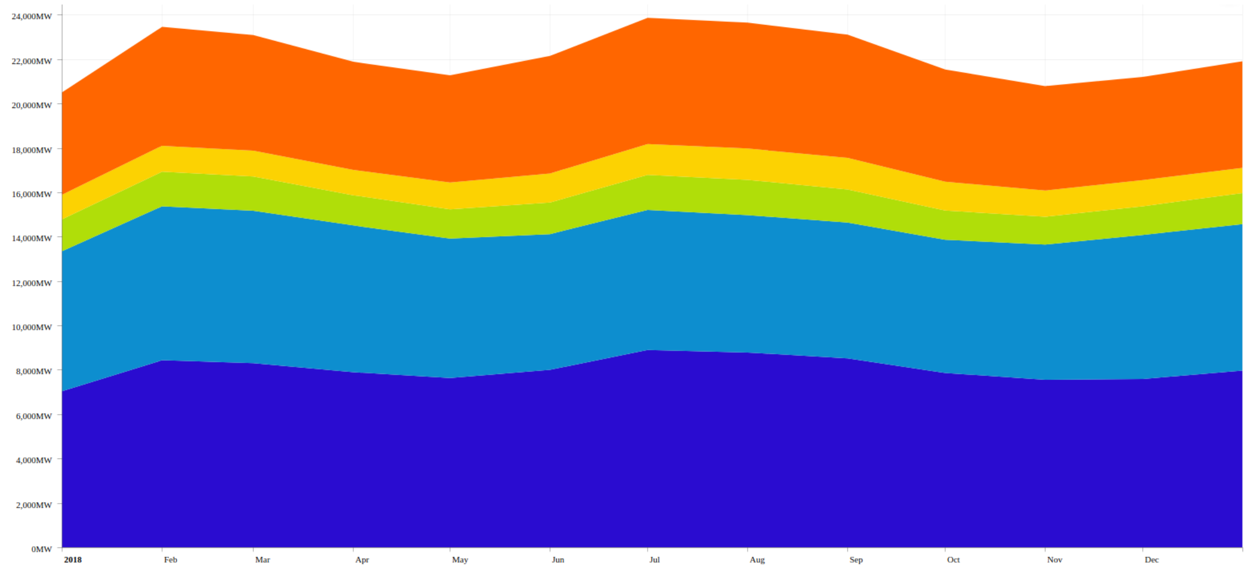


Figure 8. Australia’ electricity consumption distribution by state, 2018. Source: AEMO

As for readiness for PPAs and actual number of PPAs already made a factor of large corporations must be considered. The two biggest cities in Australia are Sydney and Melbourne with populations nearing 5 million people. Sydney is the capital of New South Wales and Melbourne – Victoria. Trailing behind with nearly 3 million residents is Brisbane – the capital of Queensdale. As for the large corporation concentration, both headquarters and other facilities, division reassembles the division of population. Unsurprisingly the number of PPAs per state follows the same track as well, with Victoria and New South Wales in the front (Strasser, 2017).

As other states fall far behind only Victoria, New South Wales and Queensdale were discussed. Of the tree Victoria and New South Wales are chosen due to their market size, readiness for PPAs and the history with PPAs that they already have.

1.5. Aim and objectives of the thesis

The purpose of this thesis is establishing a viable methodology and select the most suited method to forecast the long-term market energy price in Australia, specifically in New South Wales and Victoria. The following objectives must be met for the fulfilment of the named purpose:

- Gather the needed data;
- Data preparation for each model;
- Develop a methodology for long term market price forecasting for PPAs
- Train and test the methods named in 1.3.1.
- Select the best method and methodology to forecast energy prices, which meets these requirements:
    - Has the needed level of detail: Year <- Month <- Weekday <- Time;
    - Has a horizon of 4 years;
    - Does not use exogenous variables;
    - Let's the reader to recreate and improve upon the forecast changing parts of the methodology.

2. Methodology

This part of the thesis will cover methodology for completion of 4-year forecast with needed level of detail. This includes:

- High level overview of the whole process from data mining to a full 4-year forecast
- Price data mining and preparation
- Shape extraction for the needed level of detail
- Two-step model selection
- Forecast transformation to a 4-year forecast with needed level of detail.

The machine used to complete computational task has the listed specifications:

- Intel i7-7500U CPU
- 16 GB of RAM
- 1TB SSD drive
- Manjaro Linux 18.0.4 Illyria

Data preparation, and modelling will be done using R with R-studio.

2.1. High-level overview

The process from data gathering to a full 4-year forecast includes many steps in between, thus a high-level overview of the process is displayed below.

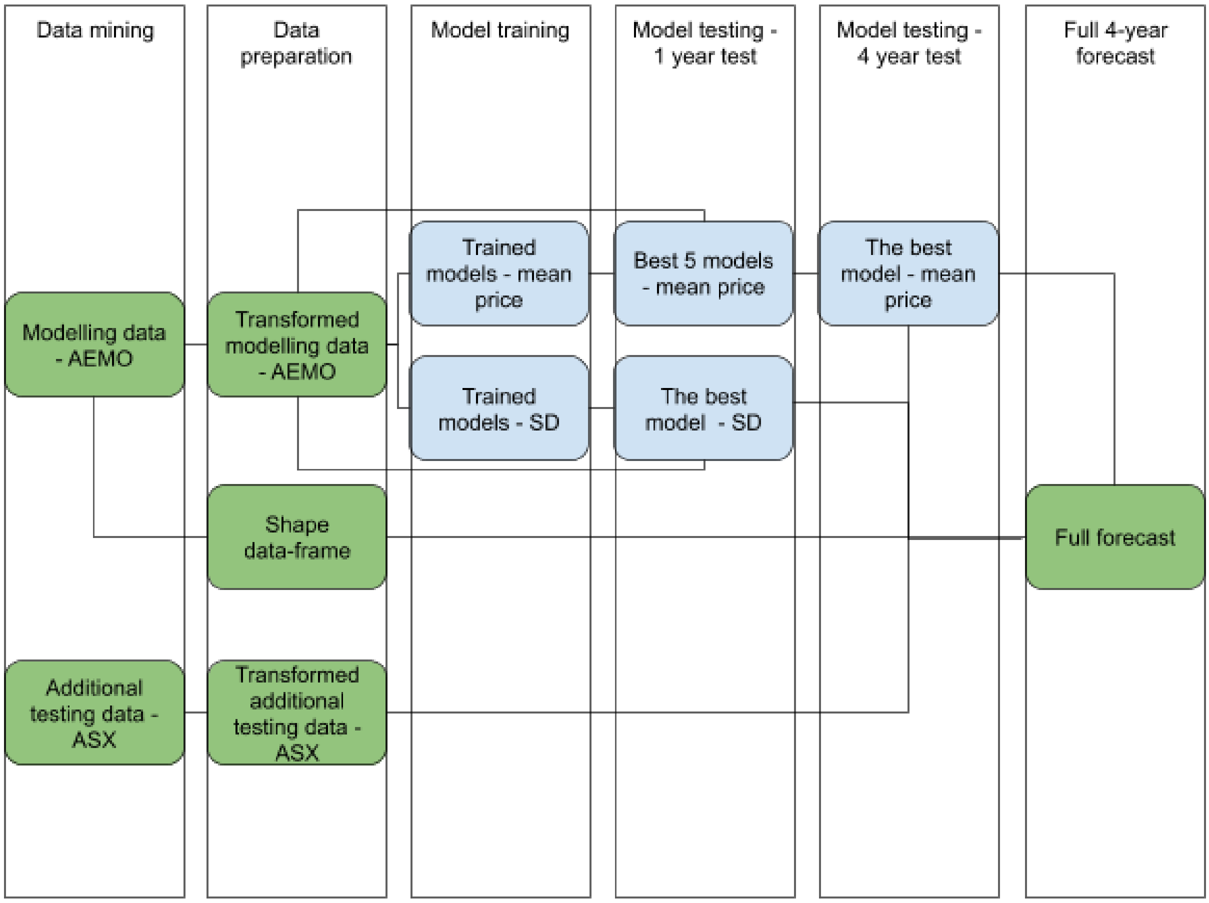


Figure 9. High-level methodology overview

As seen in the figure, the process involves data mining, data preparation, model training, a two-step model testing with different time intervals and lastly a full 4-year forecast with the needed level of detail using price shape data-frame.

2.2. Data

To start model selection and forecasting all the needed data has to be gathered and prepared for modelling.

The data used for modelling is the Australian energy market price. It is a time-series data with a level of detail to half-hour (30 minutes). The interval of data collected is from 2012-01-01 00:00 to 2018-12-31 23:30, Sydney time zone. Two times-series are included for both Victoria and New South Wales states.

Additional data for model testing is used – ASX energy futures prices. It is a time-series data with a level of detail to exact time. The interval of the data collected is for the whole 2018 for 2018 futures prices and 2019-01-01 to 2019-03-14 for 2019-2022 futures prices. Two time-series are included for both Victoria and New South Wales states futures prices.

2.2.1. Data mining

Modelling is gathered from AEMO – Australian energy market operator website, see information resources. Data is displayed as monthly data and can be downloaded as a csv file. Each file for each month of each year of the interval (2012-2018) is then joined with the rest to form a full data-frame of all the prices for the named period for both states.

Additional data for model testing is gathered from ASX – Australian stock exchange, see information resources. Data has time feature to state when the exchange was made.

2.2.2. Data preparation

After modelling data collection some transformations are applied to the data collected. The needed transformations are listed below:

- Data aggregation to monthly price features
  - As mean
  - As standard deviation
- Data aggregation to weekly price features
  - As mean
  - As standard deviation
- Additional time features based on Gregorian calendar
  - Year
  - Month of a year
  - Week of a year
  - Weekday of a week
  - Time of a day
- Month / Weekday / Time shape – additional features with 4032 observations with:
  - 12 months for each month of a year
  - 7 weekdays for each weekday of a year
  - 48 time values for each half-hour of a day
  - Z-score for mean price value of Victoria state based on highest level of detail
  - Z-score for mean price value of New South Wales state based on the highest level of detail
  - Monthly mean price of Victoria state
  - Monthly mean price of New South Wales state
  - Monthly standard deviation of Victoria state
  - Monthly standard deviation of New South Wales state
- Making time-series stationary if it is not
- Training/testing split. Training – 2012-2017, testing –2018.

Additional test data is transformed as well:

- New features including:
  - Year
  - Quarter
  - Mean futures price for the named quarter for Victoria state
  - Mean futures price for the named quarter for New South Wales state

During data preparation time-series are tested for stationarity and transformed to stationary if needed. The process involves testing series using ACF, Ljung-Box test and Augmented Dickey-Fuller test and using differentiation to obtain stationary series if needed. First step of testing for stationarity is a visual evaluation through plot of the series and ACF plot. Time-series plot might show that series has a trend or seasonality in it and, thus, is not stationary. Meanwhile, ACF plot is used as "for a stationary time series, the ACF will drop to zero relatively quickly, while the ACF of non-stationary data decreases slowly" (Hyndman & Anthanasopoulos, 2018). To have a more conclusive result of stationarity testing, this thesis is using two additional tests. Ljung-Box test tests null hypothesis of time-series being a white noise, or in other words is it noncorrelated, and can be expressed as follows (Kavaliauskas & Rudzkis, 2015):

$$Q = n(n+2)\sum_{\tau=1}^{m}\frac{\widehat{r}(\tau)^2}{n-\tau}$$

where *n* is the number of observations, *τ* is the number of lags and *r(τ)* is the autocorrelation function. *Q* has the distribution of χ^2_m, where m is the total number of lags tested, if null hypothesis is not rejected (Hyndman & Anthanasopoulos, 2018). As for Augmented Dickey-Fuller test, it tests the null hypothesis that series are non-stationary, which in turn is $\gamma=0$ in (Holmes et al., 2019):

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + \delta_2 \Delta y_{t-2} + \dots$$

If at least two of the tests (ACF, Ljung-Box and Augmented Dickey-Fuller) lead to a conclusion of non-stationary data series, then differencing is applied, and the tests are done again on the differenced series. Differencing, simply put, is computing "the differences between consecutive observations" (Hyndman & Anthanasopoulos, 2018). When two or more tests result in a conclusion of stationary series, the process of testing and differencing is finished and transformed stationary series are used for modelling and testing.

2.2.3. Shape extraction

As described in the data preparation section additional shape features are formed from modelling data. The shape data-frame is used to achieve the needed level of detail for the forecast as described before – year, month, weekday, time. Shape could be described as an average level of price on specific month, weekday and time. To achieve this z-scores are used. Z-score, also known as standard score, is a simple standardization technique to determine how much a value is above or below the population mean, measured in standard deviations. It is described in mathematical terms below:

$$z = \frac{x - \overline{x}}{s}$$

Where *x* is the value for which the z score is calculated, $\bar{x}$ - sample mean and s - standard deviation of the sample.

In the specific case of this thesis, z-scores for prices are calculated as follows:

- Monthly mean and standard deviation are calculated using half-hourly data for each month and year.
- Mean price for each half-hour, weekday, month and year is calculated.

- Z-score for each half-hour, weekday, month and year is calculated, using monthly mean and standard deviation.
- A mean value of z-scores is derived for each half-hour, weekday, month of the selected years.

This can be represented as follows:

$$z_{twm} = \frac{\sum \frac{\overline{x_{twmy}} - \overline{x_{my}}}{s_{my}}}{y}$$

Where X_{twmy} is the mean price for each half-hour, weekday, month and year, X_{my} is the mean price for each month and year, s_{my} is the standard deviation for each month and year, and y is the total number of the used years. As for iterators – t – stands for half-hour interval in the day (total 48), w – weekday number in the week, m – month number in the year and y – year number. As a result, new series are generated which represent the prices in their z-scores.

After all the needed data is gathered, prepared and in some cases new data is generated, modelling can take place.

2.3. Forecasting

The goal of the forecast is to get the best forecast with a 4-year horizon and a level of detail of year, month, weekday and time. To achieve that a number of models are trained and then tested in a two-step test process and after selecting the best model the full level of the needed detail is recreated for the full 4-year forecast.

2.3.1. Model training

For model training a training dataset is selected from modelling data and all the models are trained using the same dataset. Training dataset for the first test includes all the observations for the first 6 years of data – 2012-2017, and for the second training dataset – all observations for 7 years of data. The level of detail for training data is weekly. The selected models are named below:

- SVM
- Mean
- Naïve
- Seasonal naïve
- Naïve with drift
- Trend
- Trend + season
- ARIMA
- Seasonal ARIMA
- BATS

- TBATS
- ETS
- Holt-Winters

All of the named models are trained for both mean price forecasting and standard deviation forecasting using 6-year training dataset with a weekly level of detail (53 weeks on average per year, thus 318 observations).

Regarding the parameter selection of the models, parameters are mostly selected using AIC/AICc or mean errors. AICc is used for ARIMA and seasonal ARIMA parameter estimation, while, AIC is used for BATS and TBATS parameter estimations. The model within the set of model group (for example, the best ARIMA from all non-seasonal ARIMAs) with the lowest AIC/AICc value is selected. As for SVM, ETS and Holt-Winters parameter values are fitted minimising RMSE for SVM and MSE (mean squared error) for the rest. Other models as mean, naïve and time-series components do not have any specific parameters and, thus, are not optimised in such way.

Weekly level of detail is selected due to an increased number of observations, while comparing it to the monthly level of detail, 53 observations per year versus 12. The selection of observations will be more explained in the results section.

2.3.2. Testing

Testing is divided into two stages. The first test is used for both the mean monthly price and the standard deviation. Meanwhile, the second test is used only for the mean price value. The first test consists of training models using first 6 years of the data as mentioned above and testing the models using the year 2018 data. During the second test models are trained using the full 7 years of data and then tested using the ASX quarterly futures price data and expert opinion on the market. After the second test, the best model for mean price is selected to move forward with the full 4-year forecast with the needed level of detail for PPA evaluation, whereas, the standard deviation model is determined during the first test. For better understanding of the workflow the high-level overview is repeated below:

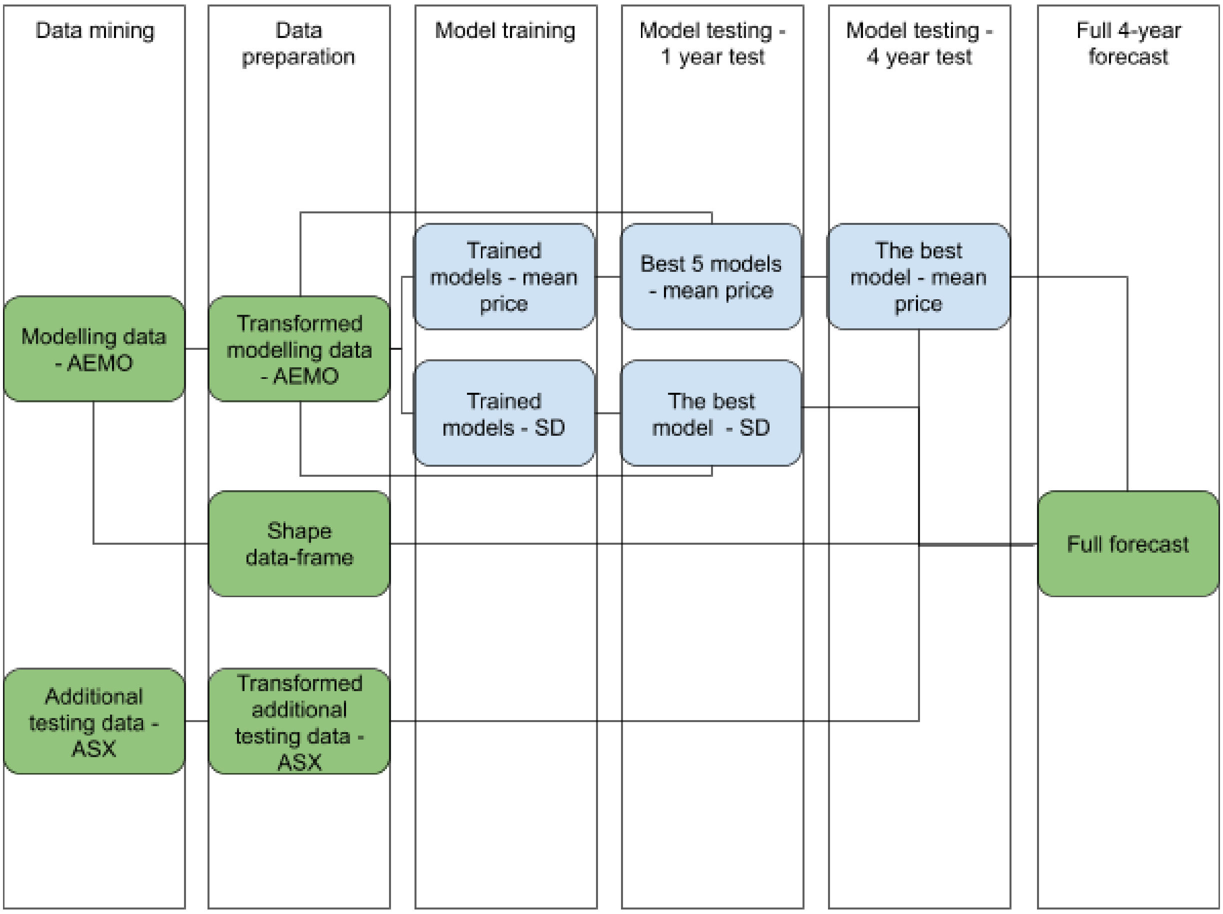


Figure 10. High-level methodology overview

First test is used to lower the number of models for the full forecast selection for mean monthly price and to select the best model for monthly standard deviation. During the first test all the models named in the training section are tested. After the training procedure all models are compared using firstly RMSE and then MASE if the results of RMSE are close or the same. As mentioned, test uses 1 year of data to determine the best models. For the mean price value forecasting 5 best models are selected, while, for the standard deviation – only one best model is selected. After the first test, selected model for the standard deviation is not tested anymore as there is no additional testing data available like ASX data for mean testing.

During the second test only one model is selected from the 5 best models for the mean price value forecasting. After the first test, the selected models are retrained using the full dataset of modelling data. Afterwards, the forecasts of the 5 selected models for the 4-year horizon are made. Forecasts are then aggregated from weekly level of detail to monthly means and compared to the ASX quarterly futures prices for the period of 2019-2022. ASX quarterly prices are transformed to monthly by equating corresponding quarter price to the monthly one. To determine the best fitting model both, plotted values and RMSE measure, are used. As mentioned, in addition to objective measures of fit, expert opinion is included in the determination of the best model. Author of the thesis has 3-year experience in the energy field and, while, not considered as an expert of the industry, has considerable knowledge and experience in the market. For better understanding how evaluation is made, the expert evaluation is summarized into these 4 main criteria:

- Forecast and ASX futures prices do not have opposite slopes;
- Forecast should have either a constant or negative slope;
- If the forecast has a negative slope it should not be as steep as the futures slope;
- It is preferable that the forecast has some seasonality;

At the end of the testing process one model for both mean price value and standard deviation is selected and then used afterwards for the full market price forecast with the needed level of detail.

2.4. Full market price forecast with shapes

Selection of the best fit models is not enough for the fulfilment of the thesis objectives. After selecting the best model for both mean and standard deviation of the energy market price and for both states of Victoria and New South Wales the final forecast must be built. Building the final forecast requires the following resources:

1. Z-score based price shapes.
2. Monthly energy price mean forecast for the 4-year period.
3. Monthly energy price standard deviation forecast for the 4-year period.

Even though some of the requirements are fulfilled before this step, to fulfil all the requirements additional steps have to be taken. Z-score based price shapes are already made during the data preparation process. Monthly energy price mean forecast for the 4-year period is done during the second testing phase. Only the selection of the best model forecast has to be done, to fulfil the second requirement. As for the standard deviation, at this point only the first phase test forecast exists. Due to that, it is needed to train the best model for the standard deviation forecasting using the whole modelling dataset and make a forecast of standard deviation for upcoming 4-years. As the forecast has a level of detail of a week, aggregation is needed to transform the time-series to monthly data. After completing this step, all the needed resources are in place to proceed with the making of the full 4-year market price forecast.

The forecasted values of the price are calculated by calculating the x_{twmy}. It is calculated as follows:

$$x_{twmy} = z_{twmy} \cdot s_{my} + \overline{x_{my}}$$

Which is essentially x expressed from the z-score equation described in the shape extraction section:

$$z = \frac{x - \overline{x}}{s}$$

After calculating x_{twmy} for each t - half-hour interval, w - weekday of the week, m - month and y – year, the full forecast with the needed level of detail is completed.

Following all of the discussed steps in the methodology one should be able to recreate the forecast in the future for further power purchasing agreements evaluation even from scratch. Although each section of the methodology relates to the next one, each of them can be improved upon or changed if, for example, the data source changes, models need to be added or the horizon needs to be expanded.

3. Results

Two datasets are used for the analysis and forecast as described in part 2. Modelling data from AEMO – Australian Energy Market Operator, and additional testing data from ASX – Australian stock exchange. Both are gathered from their corresponding websites.

3.1. Data preparation

At this stage all the named data preparation must be done as noted in the high-level overview (see 2.1). The first two stages of data mining and preparation are shown below:

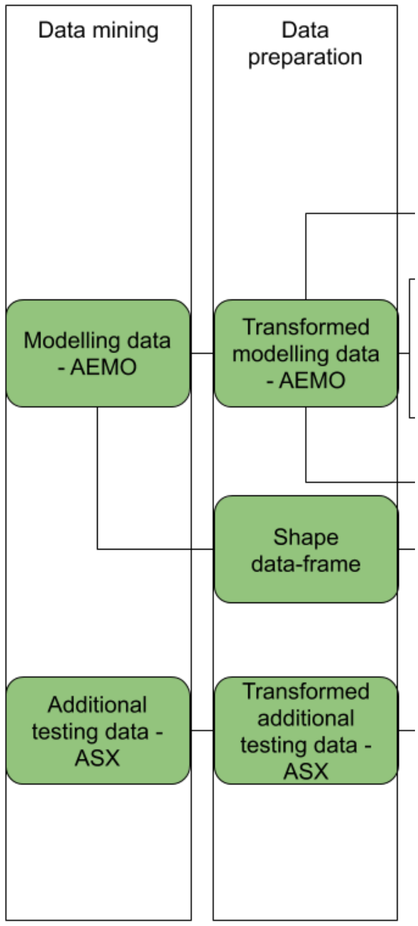


Figure 11. High level overview. Data preparation.

3.1.1. Half-hourly price data from AEMO – modelling data

After gathering the market price data from AEMO, data has the following structure:

- Time in UTC10 as '*01-Jan-2012 00:00*'
- Market price in AUD/MWh as '*25.74*' for Victoria market
- Market price in AUD/MWh as '*25.74*' for New South Wales market

For modelling a couple of transformations and additional features have to be made. They are listed below in the order they are made:

- Additional time features based on Gregorian calendar – for modelling and shape extraction.

  - Year
  - Month of a year
  - Week of a year
  - Weekday of a week
  - Time of a day
- Making time-series stationary if it is not
- Training/testing split. Training – 2012-2017, testing –2018.
- Data aggregation to monthly price data as features - for testing.
  - As mean
  - As standard deviation
- Data aggregation to weekly price data as features – for training.
  - As mean
  - As standard deviation
- Month / Weekday / Time shape – additional features with 4032 observations including:
  - 12 months for each month of a year
  - 7 weekdays for each weekday of a year
  - 48 time values for each half-hour of a day
  - Z-score for mean price value of Victoria state based on highest level of detail
  - Z-score for mean price value of New South Wales state based on the highest level of detail
  - Monthly mean price of Victoria state
  - Monthly mean price of New South Wales state
  - Monthly standard deviation of Victoria state
  - Monthly standard deviation of New South Wales state

It should be noted that Month / Weekday / Time shape and stationarity is done in the exploratory part as not all the years from the train set are used to make the shape and additional test have to be made to check for the stationarity of the series. Both stationarity and shape extraction are explained in Methodology part of the thesis (see 2.2.2. and 2.2.3., respectively).

After finishing the data preparation part for modelling data, modelling stage starts using the aggregated weekly data dataset. Monthly dataset is left for additional testing and shapes are left for the final forecast.

3.1.2. Bid based data from ASX – additional testing data

After gathering data from ASX, data has the following structure:

- Time in UTC10 as '*01-Jan-2018 04:00'*
- Trade price in AUD/MWh as *'68.00'* for Victoria products
- Trade price in AUD/MWh as *'68.00'* for New South Wales products
- Product for which the trade has been done as '*2019Q1'*

As this data is used for additional testing for a 4-year period from 2019 to 2022 a new dataset has to be formed to use it. It consists of the following features:

- Year
- Quarter
- Mean futures price for the named quarter for Victoria state
- Mean futures price for the named quarter for New South Wales state

Even though testing will be done on monthly price basis, only quarterly products for a period this long have a consistently high number in trades for all quarters. Meanwhile, looking at the monthly products, most of the months are missing. Thus, the decision has been made to only take the quarterly products as an additional testing dataset.

3.2. Exploratory analysis

The main goals of the exploratory analysis are as follows:

- Overview of the price data.
- Decision on the year selection for shape extraction for each series (NSW and VIC).
- Check for series stationarity.

3.2.1. Data overview and stationarity

Firstly, Victoria market data is presented. An overview of its weekly mean price time series is presented below.

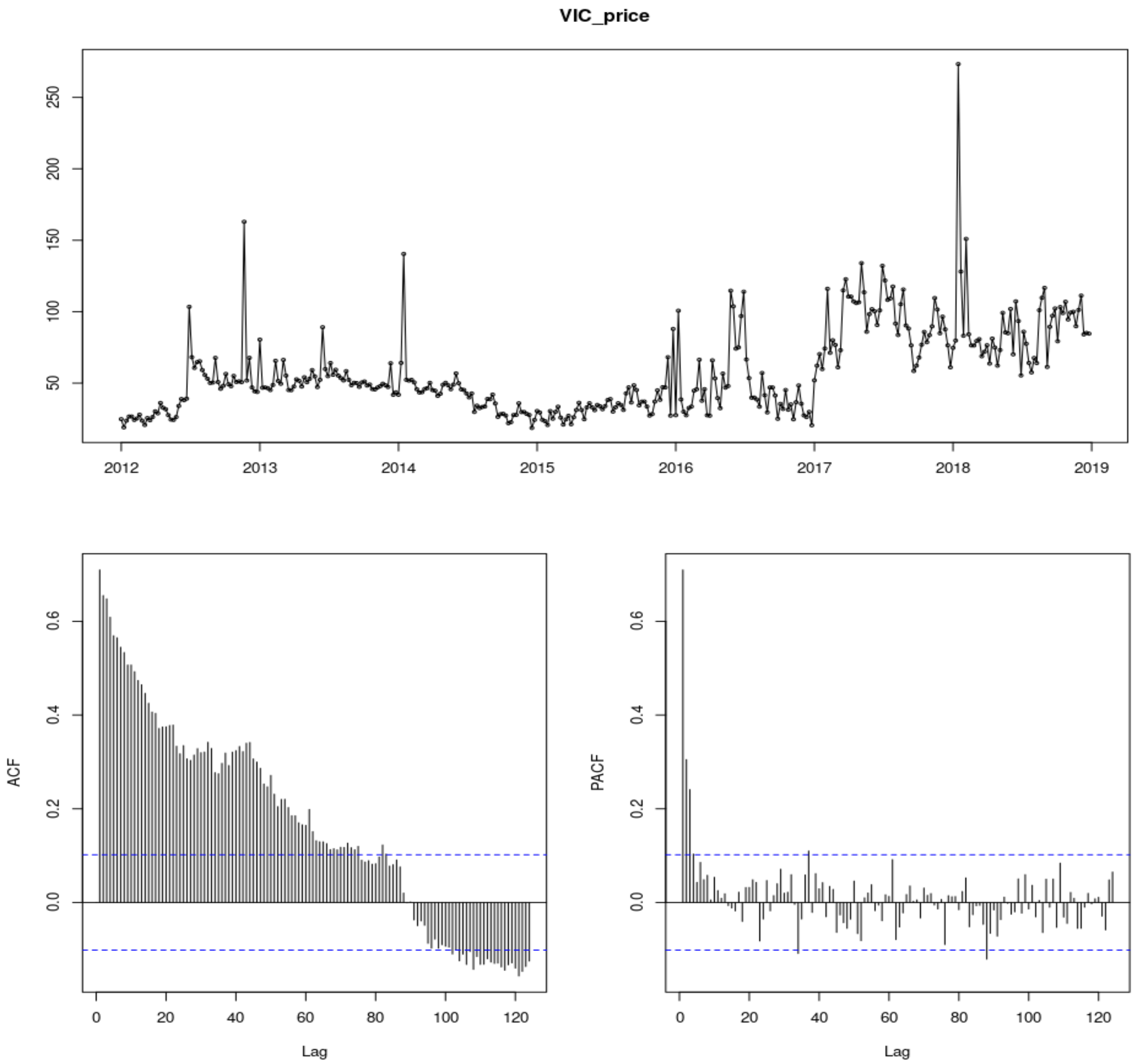


Figure 12. VIC weekly price, 2012-2018.

As it is clearly seen from the series graph, Victoria price had at least three different stages during the last 7 years. There are several time series points, which could be considered as outliers, however, due to the nature of the PPA outliers have to be taken into consideration and should not be removed from the series. As for the autocorrelation (ACF in the graph, see list of terms and abbreviations) and partial autocorrelation (PACF in the graph, see list of terms and abbreviations), deciding from the ACF there are indications of non-stationarity. In order to check for stationarity two tests were used after the initial ACF indications: Ljung-Box test for independence and Augmented Dickey-Fuller test as discussed in methodology (see 2.2.2.). Both tests lead to a conclusion that data is non-stationary (see full test results in Appendix 15). To try and make data stationary a first-order difference is obtained. The results of this transformation are shown below.

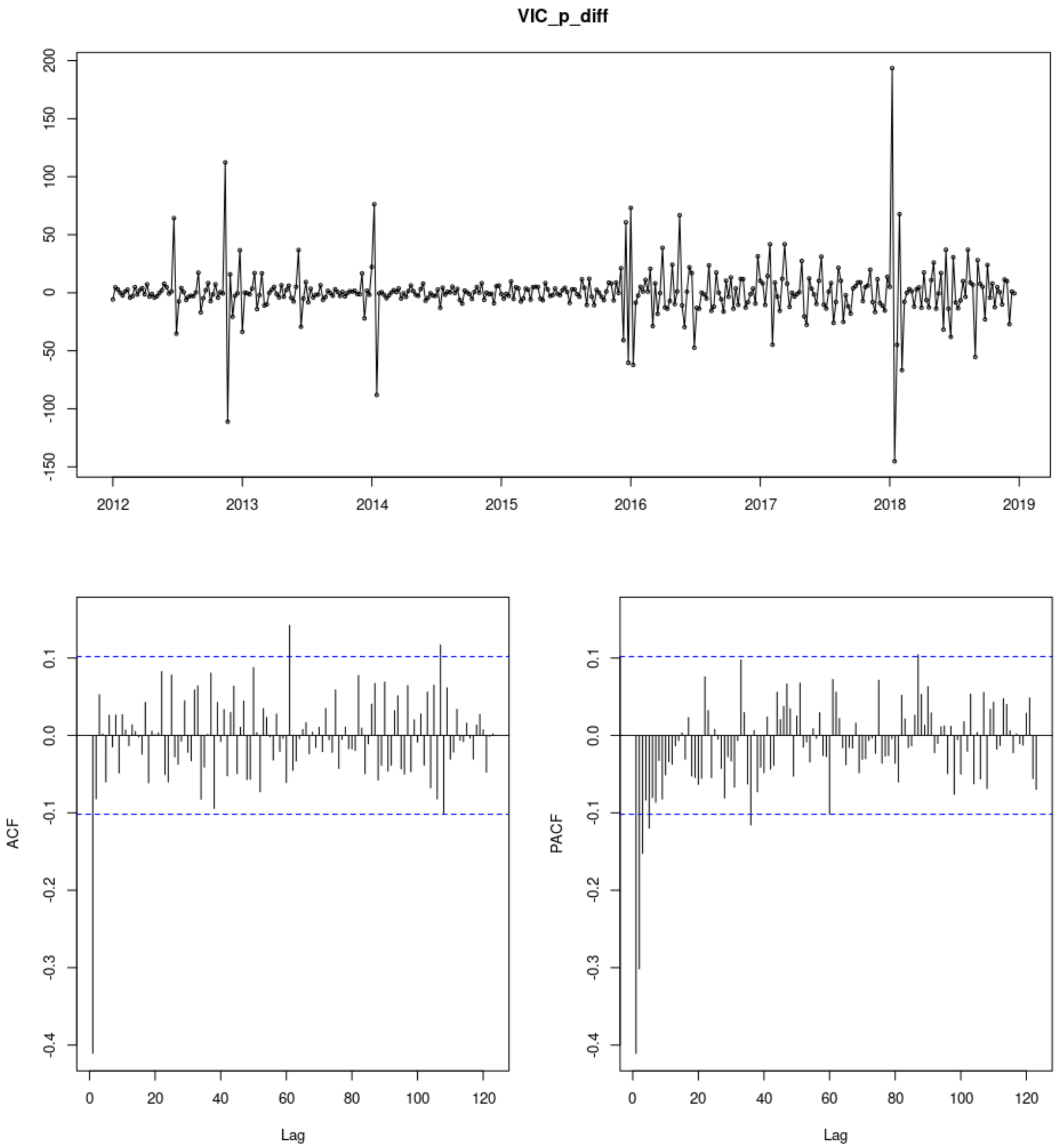


Figure 13. VIC weekly price, first degree difference, 2012-2018.

From a quick look at ACF it looks like series are stationary after transformation. To verify its stationarity tests are done again. Even though, Ljung-Box test still rejects the null hypothesis which would suggest non-correlation, Dickey-Fuller rejects null hypothesis of non-stationarity. Thus, taking the ACF figure and Dickey-Fuller test into account, Victoria weekly average market price first differences are taken as stationary data (see Appendix 15 for full test result).

Additionally, a decomposition of the time series is added. The figure is shown below.

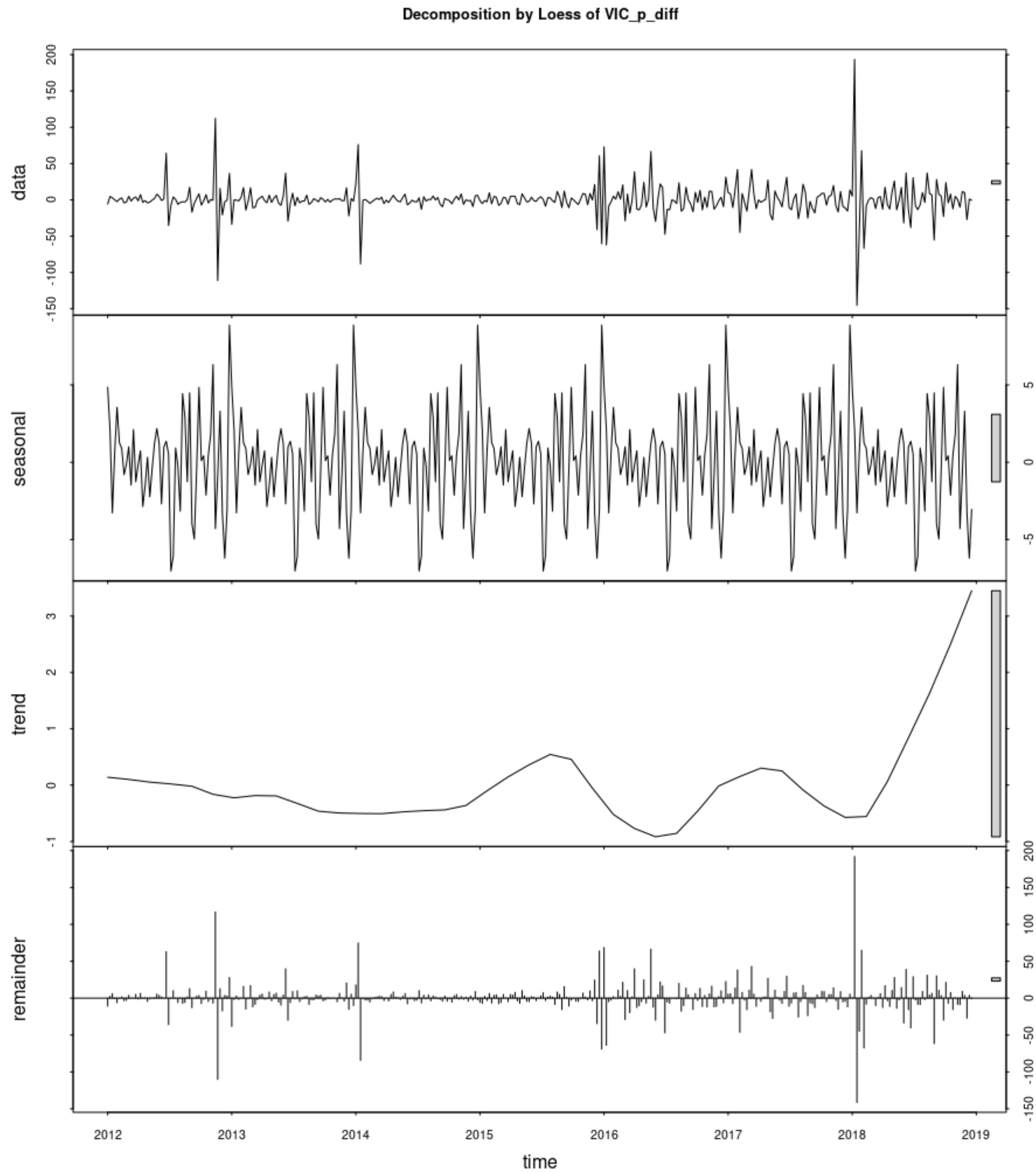


Figure 14. VIC weekly market price first degree difference decomposition.

Decomposition shows that neither trend nor seasonality have any large impact in the series.

As this thesis uses both mean and standard deviation of a time series for forecasting, standard deviation has an overview of its own.

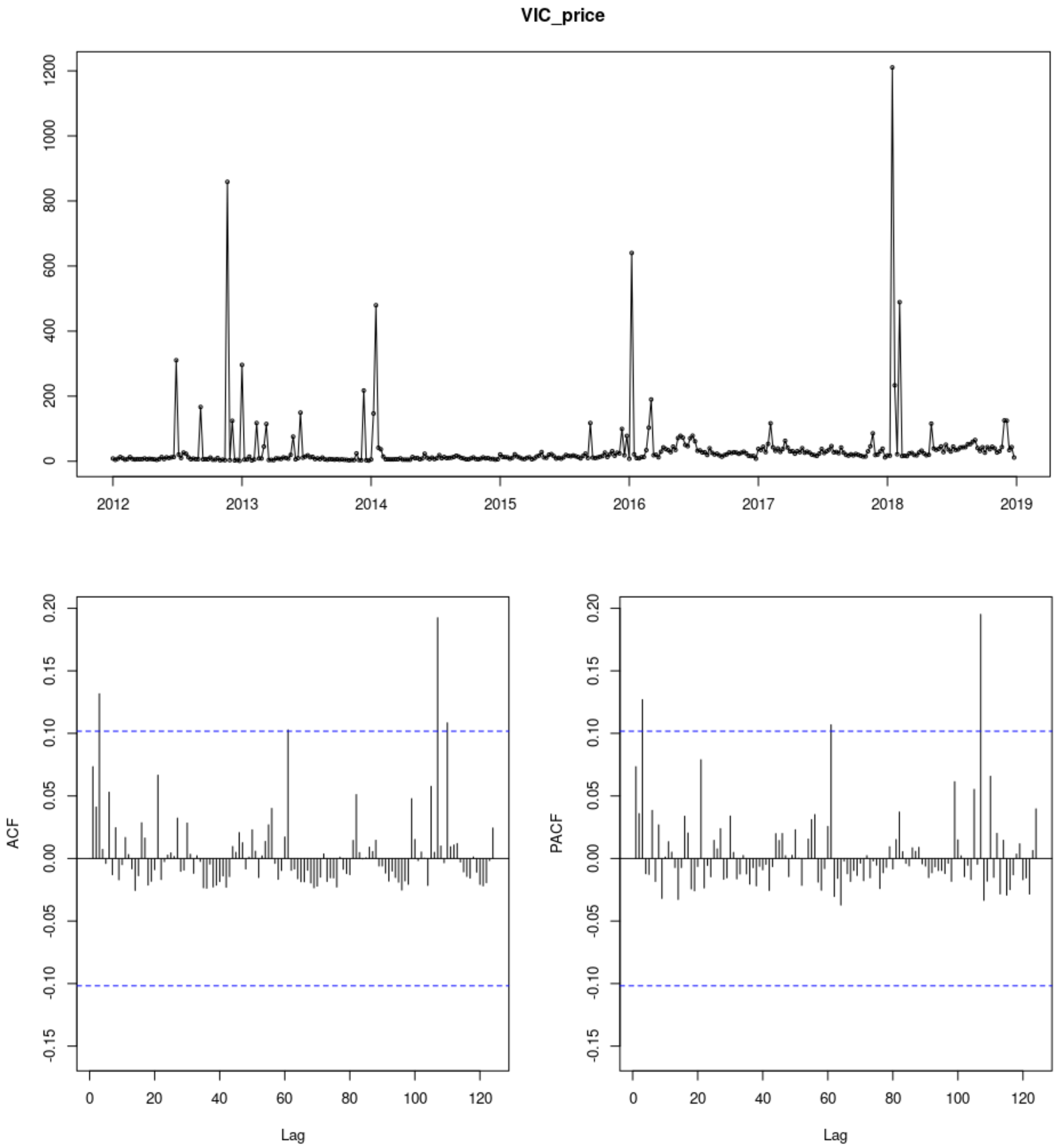


Figure 15. VIC weekly standard deviation. 2012-2018.

As it is seen from the series graph, standard deviation of Victoria market price has outliers as well, however, as discussed before, outliers must be left in the modelling data. Regarding the stationarity of data, it seems that it is stationary and both tests confirm that (for tests results see Appendix 1).

As for decomposition of the series, standard deviation seems to have a strong seasonality to it. See figure below.

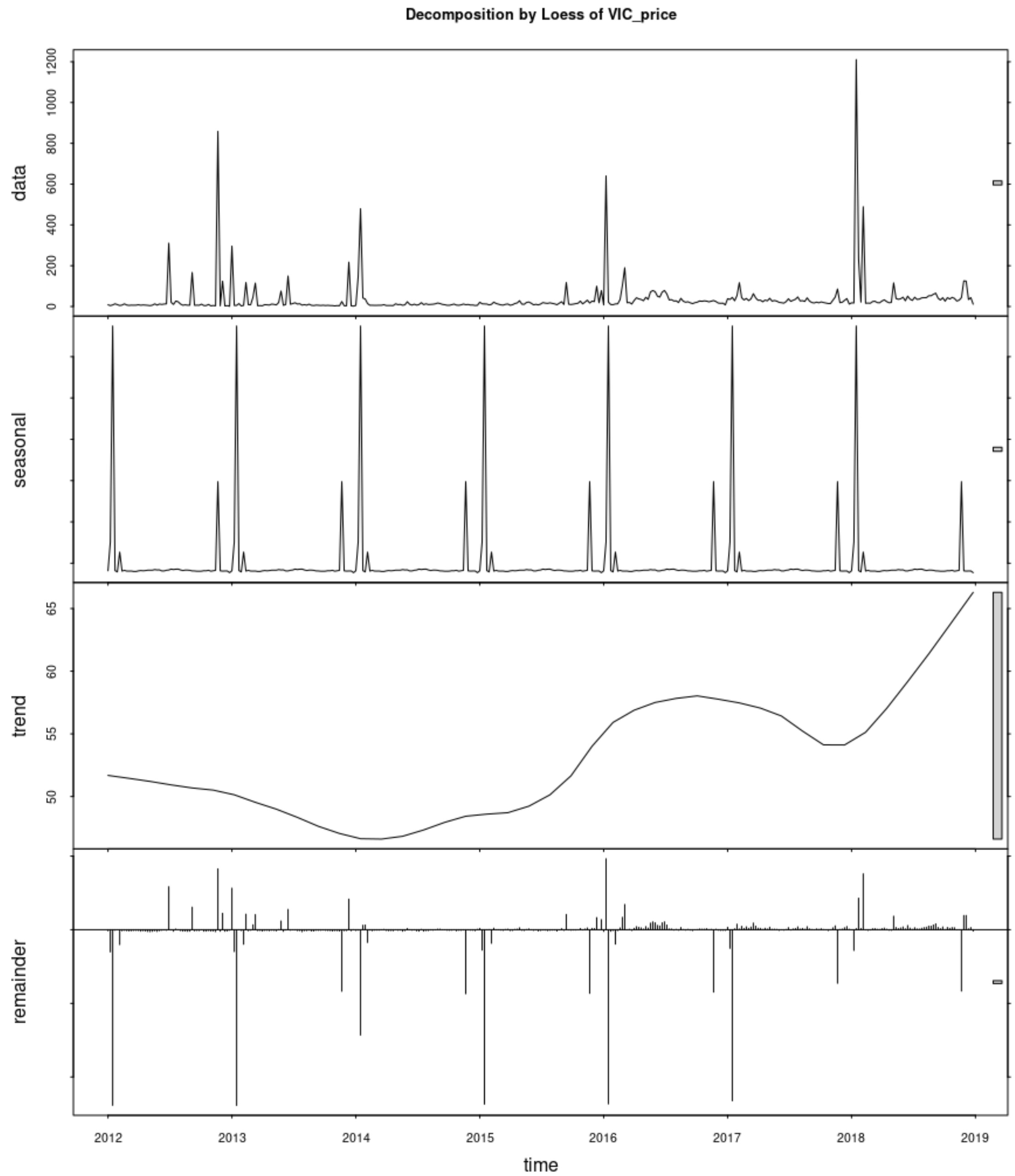


Figure 16. VIC weekly price standard deviation decomposition.

Secondly, an overview of New South Wales data is presented. It follows the same structure as Victoria data, starts with mean market price overview and follows with standard deviation one.

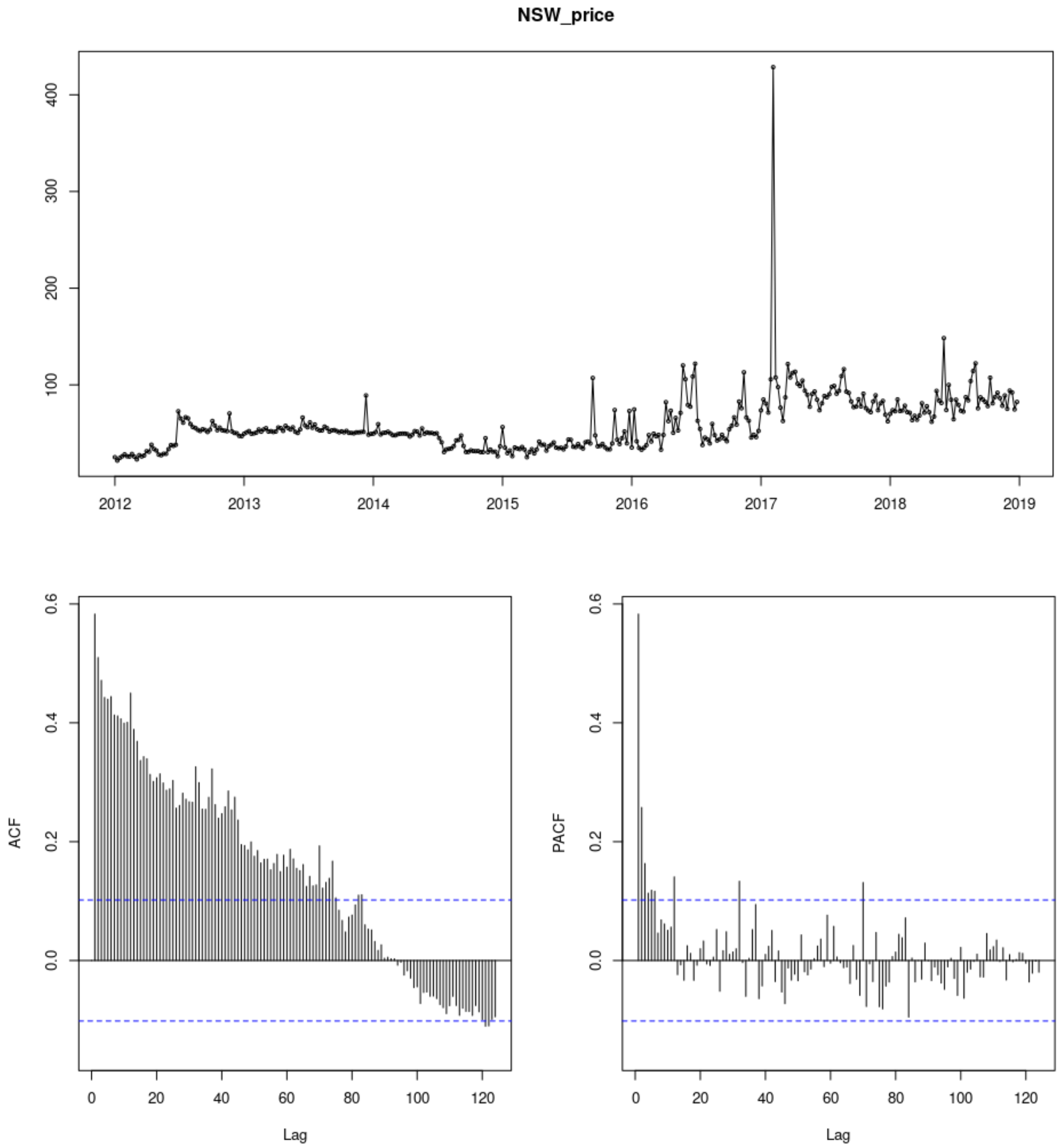


Figure 17. NSW weekly price. 2012-2018.

As with Victoria price, the same is true with the New South Wales. Price series vary a lot, have noticeable outliers and, looking at ACF figure, are non-stationary. To verify that Ljung-Box and Augmented Dickey-Fuller tests are ran of which only the Ljung-Box shows that data is non-stationary (for the results of the tests see Appendix 2). As with Victoria series a first-order difference is done for the series. After transformation series seems to be stationary. The figure of transformed series is displayed below.

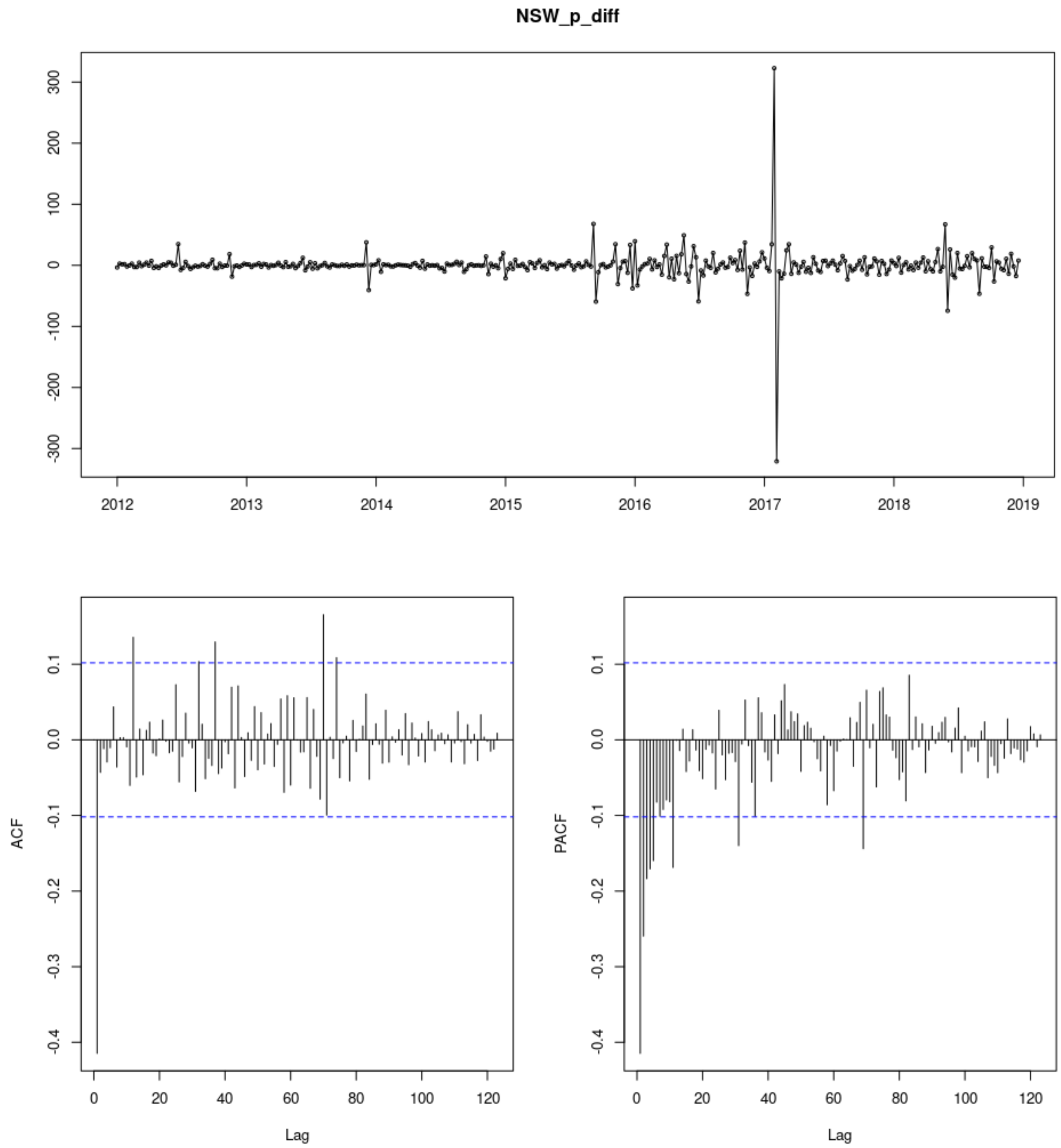


Figure 18. NSW weekly market price first-order differences. 2012-2018.

As seen from the ACF series seem to be stationary after the transformations. Once again stationary tests are done, however, results are inconclusive. Augmented Dickey-Fuller test rejects null-hypothesis that data is non-stationary with the significance of p-value < 0.01, while, Ljung-Box rejects its null-hypothesis that data points are independent (see Appendix 3 for full results). Even though, based on ACF and augmented Dickey-Fuller results NSW first-order difference series are taken as stationary.

Additionally, the decomposition of the series is shown below.

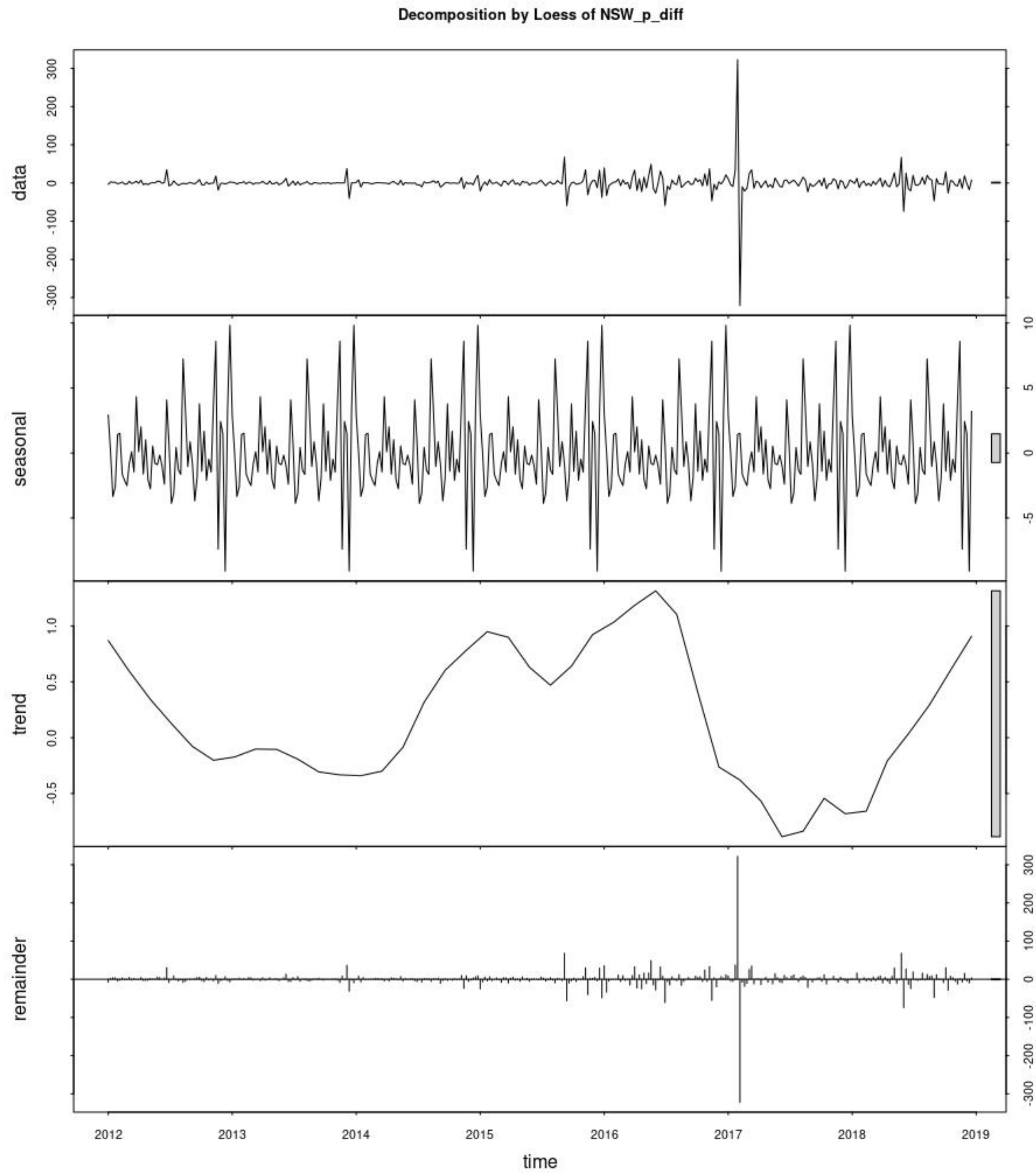


Figure 19. NSW weekly price first-order difference decomposition.

As the figure shows neither trend nor seasonality are significant factors to the price.

Finally, standard deviation overview for New South Wales is presented below.

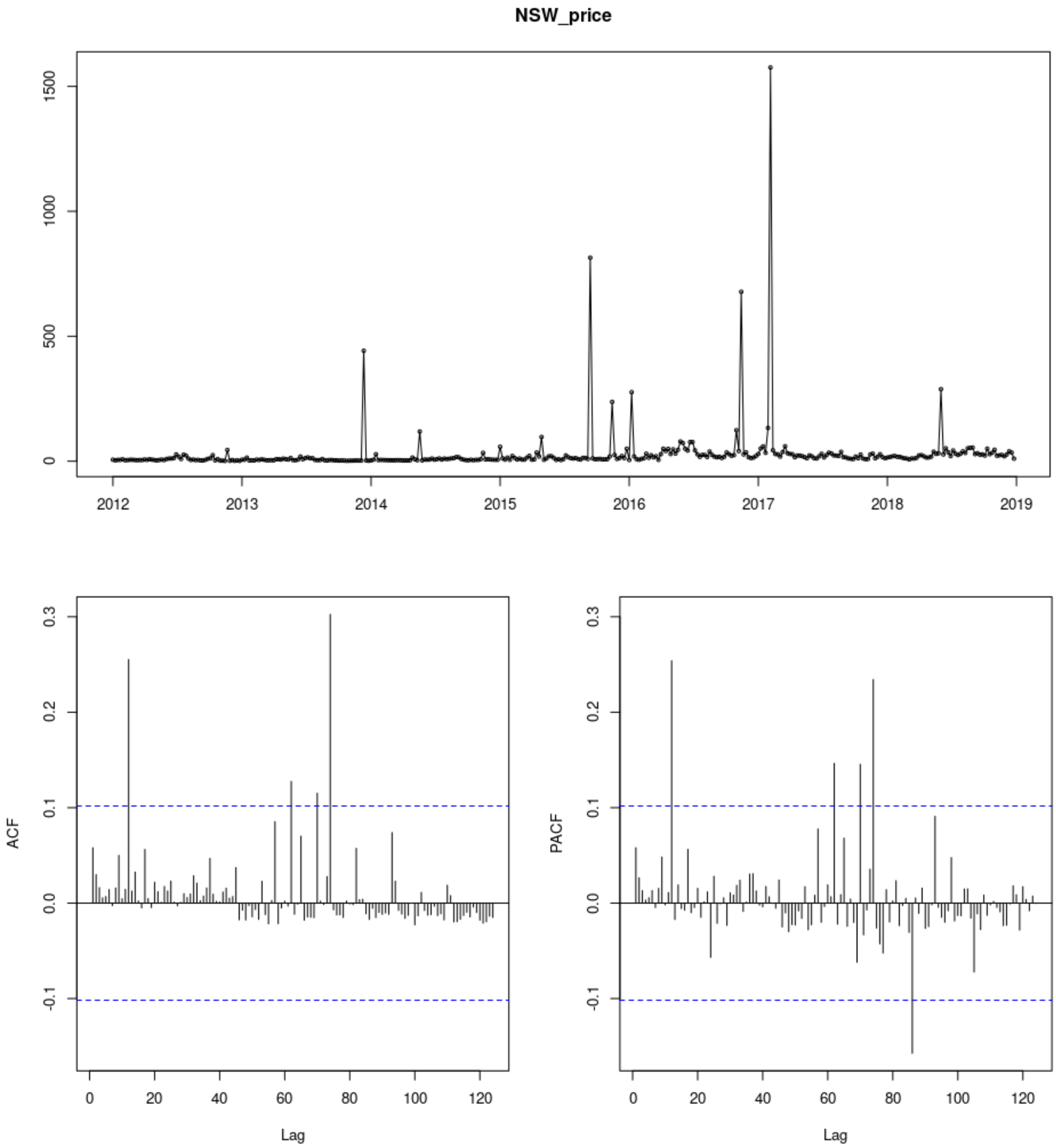


Figure 20. NSW weekly standard deviation. 2012-2018.

As with Victoria standard deviation, New South Wales does not seem much different. There are outliers in the series and ACF seems fine regarding stationarity. To verify, the Ljung-Box and Augmented Dickey-Fuller test are run. Both lead to the same conclusion of stationary data. Decomposition of the series shows that neither seasonality nor trend are present. The figure is shown below.

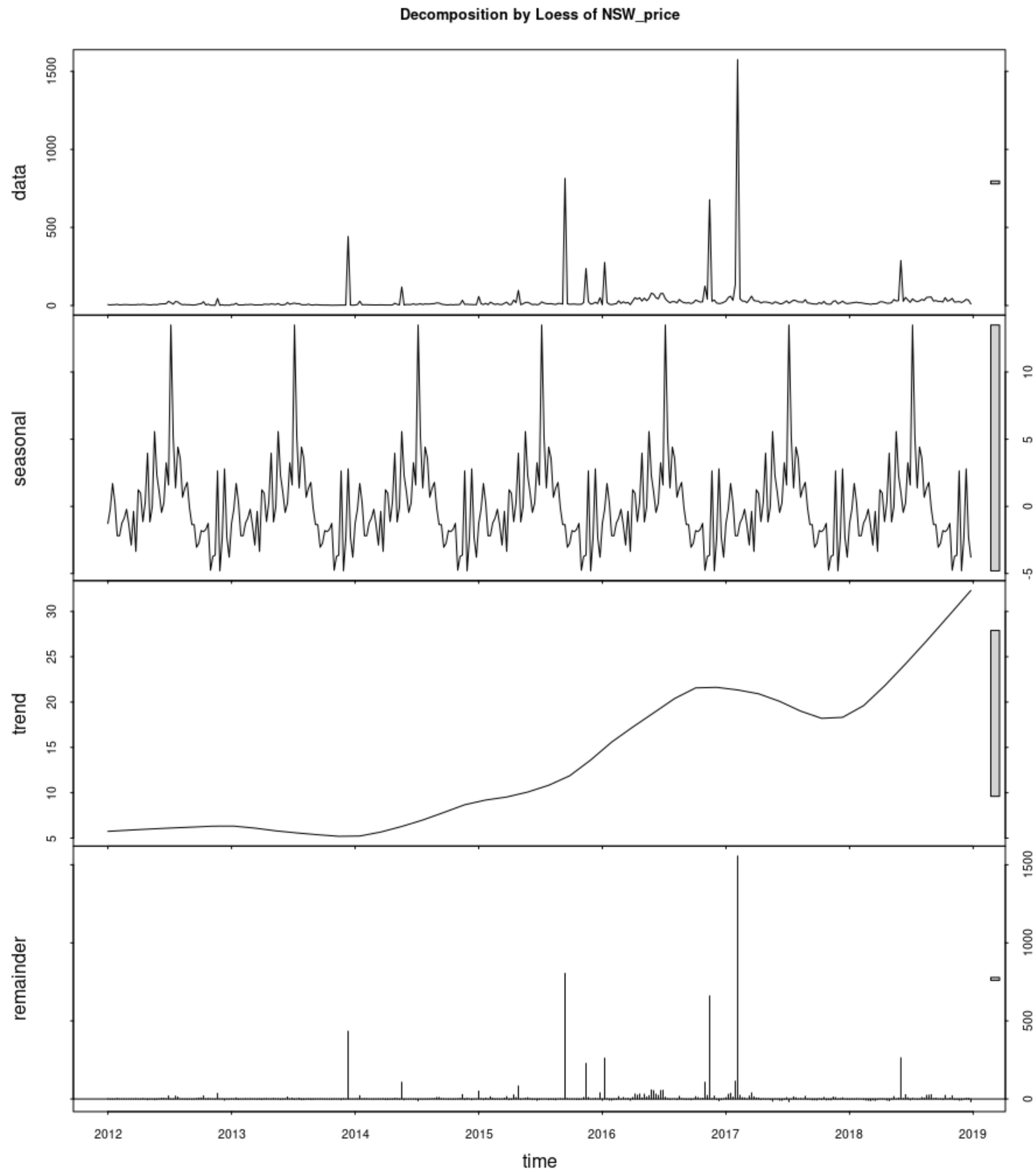


Figure 21. NSW weekly standard deviation decomposition.

To summarize, both weekly mean series needed first-order difference transformations to become stationary and, as for standard deviation, it did not need any transformations. As for time-series decomposition, only VIC standard deviation seems to have some seasonality, other series do not show much signs of seasonality or trend.

3.2.2. Decision on year selection for shape extraction

As shapes to recreate the needed level of detail are needed, an overview of shape extraction is presented. A common decision for both Victoria and New South Wales data is preferred. However, to be as objective as possible, decision is done separately. For both, the decision process is the same. As data is easily interpretable visually, z-scores for each month's average week are compared to check for outlier years. If there are any, those will not be added to the shape calculation. Preferably there should not be any gaps between years selected for shape calculation.

To start with, Victoria z-scores for price market data are presented below. Only the month of July is shown as the situation persists throughout the year.

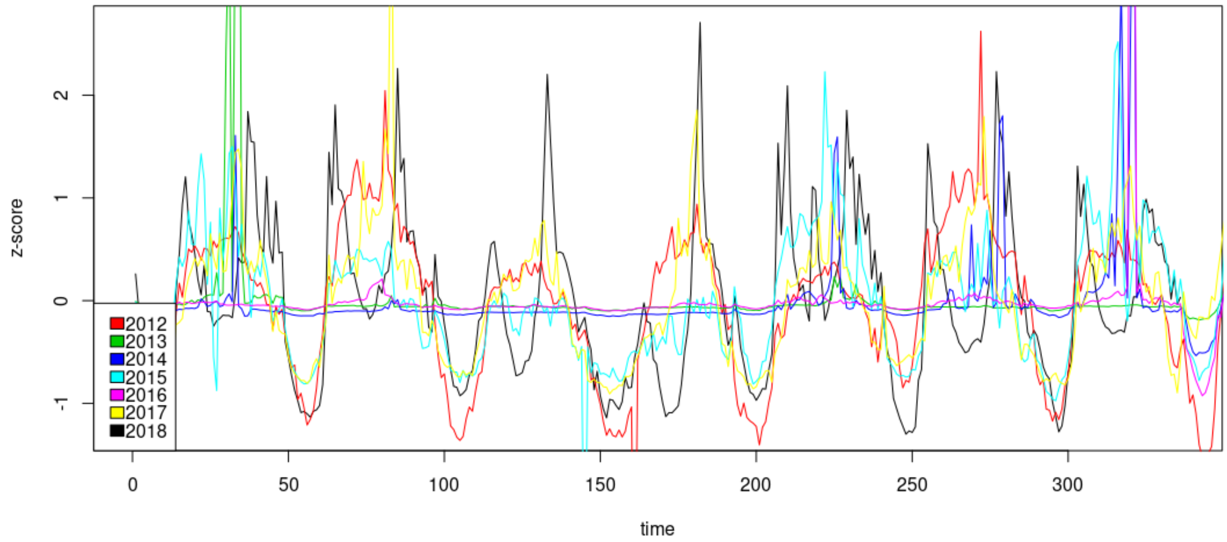


Figure 22. VIC half hourly mean price. July.

In the figure above mean price for each half hour of the week for the month of July for each year is shown. As seen from the figure most of the years seem similar, with the exception of 2016 and 2014. As for the other years, both peaks and off-peaks of the price seem to correspond. Thus, the shapes of 2018 and 2017 will be taken to form the mean shape as they are the most recent years which are similar without a gap year in between.

As for New South Wales shapes, the situation is similar to Victoria. New South Wales z-scores for price market data are presented below. Again, only the month of July is represented as the situation persists throughout each month.

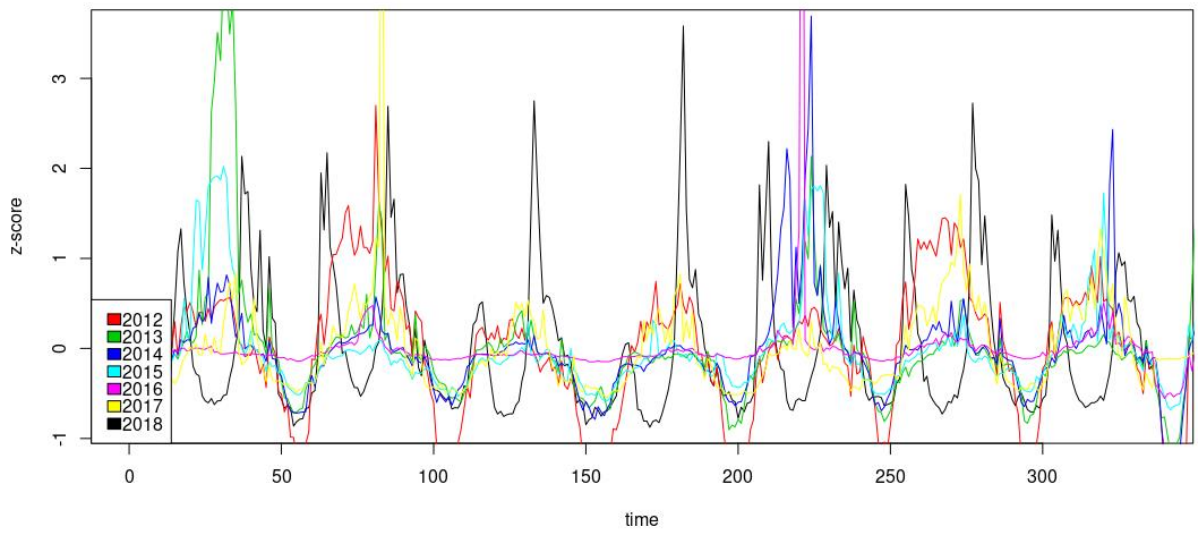


Figure 23. NSW half hourly mean price. July.

In the case of New South Wales, only the year 2016 seems vastly out of place. Again, 2017 and 2018 seem quite similar, thus are selected for the mean shape of New South Wales.

3.3. Modelling and testing

After data preparation is completed modelling and model testing takes place. Both Victoria and New South Wales series are done separately, however, follow the same path provided below (full high-level overview can be found in part 2.1.).

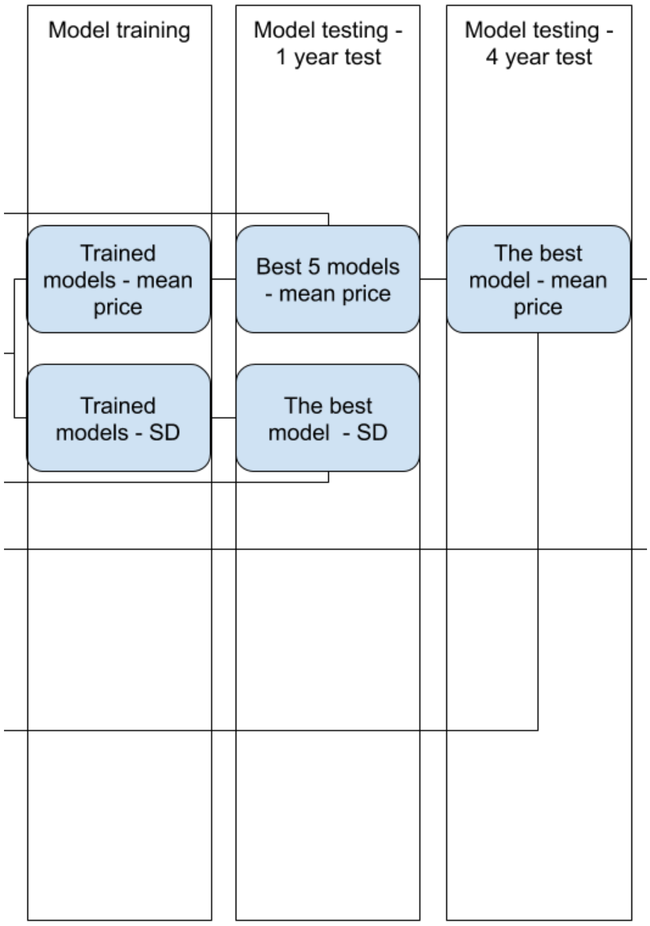


Figure 24. High level overview. Modelling and testing.

It should be noted that the mean value forecast has two stages of testing, while, standard deviation has only one. This occurs due to the fact that there is no additional data for testing standard deviation as there is for the mean value – ASX quarterly prices for the period of 2019-2022.

Each model in the first iteration of training/testing is trained using the data from 2012 to 2017. 2018 is left for testing. For the second iteration of testing models are trained using the full dataset of mean data and then tested using ASX quarterly prices.

In total 20 methods are used to forecast each series in each stage of testing. The full list of the models is provided below.

Method abbreviation	**Full name and short description**
Mean	Mean - mean of the series.
Naive	Naive - last known value.
Naive drift	Naive drift – naive with a drift.
Snaive	Seasonal naive – naive which takes last seasons value instead of the last value in the series.
Regression: trend	Trend component – uses trend component.
Regression: trend + season	Trend and seasonal components – uses trend and seasonal components.
Regression: Q_trend + trend	Quarterly trend and trend components – uses quarterly trend and trend components.
Regression: Q_trend + trend + season	Quarterly trend, trend and seasonal components – uses quarterly trend, trend and seasonal components.
ARIMA	Autoregressive integrated moving average.

Seasonal ARIMA	Seasonal autoregressive integrated moving average - ARIMA with a seasonal component.
STL + ARIMA	Time series decomposition coupled with ARIMA.
STL + ETS	Time series decomposition coupled with exponential smoothening.
ETS	Exponential smoothening.
HoltWinters	Holt-Winter method - a derivative of exponential smoothening.
BATS	Exponential smoothening with Box-Cox transformation and autoregressive moving average for residuals.
TBATS	BATS with trigonometrical seasonality for high frequency seasonality.
SVM	Support vector machines.
baggedModel	Box-Cox transformation coupled with STL decomposition and bagged remainders.
BSM	Basic Structural Model – local trend model with additional seasonal component.
Theta	Theta method – an equivalent to simple exponential smoothening with drift.

Table 1. Method list.

3.3.1. Modelling and testing – Victoria

As noted in data exploration Victoria mean value series are transformed and stationary series of first-order difference are used instead.

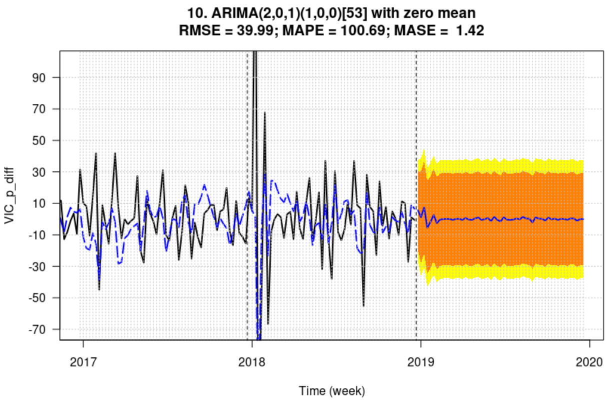
During the first stage of testing RMSE values are quite close and thus the decision on the five selected models is done using RMSE and MASE measures. The list of the five selected models for second stage testing is displayed below.

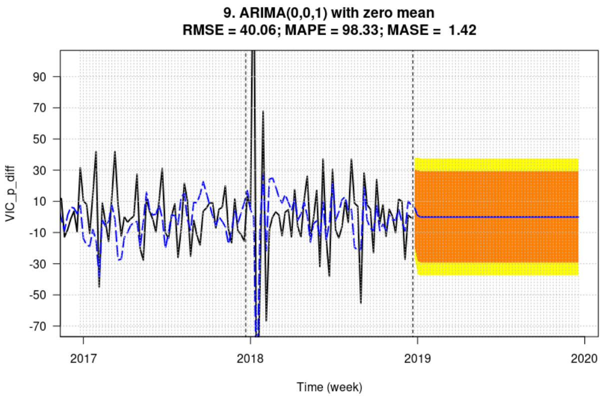
Method name	**RMSE**	**MAPE**	**MASE**
ARIMA(2,0,1)(1,0,0)[53] with zero mean	39.99	100.69	1.42
ARIMA(0,0,1) with zero mean	40.06	98.33	1.42
BATS(1, {0,1}, -, -)	40.07	132.11	1.42
TBATS(1, {0,1}, -, -)	40.07	132.11	1.42
ETS(A,N,N)	40.11	106.6	1.44

Table 2. Top 5 models for VIC mean weekly differences, using 2018 test data.

As seen from the table top models in corresponding order are seasonal ARIMA, ARIMA, BATS, TBATS and exponential smoothening. To check the full table of the test results, see Appendix 5.

The corresponding graphs to the models are displayed below in the same order[1] as in the table above.





[1] Note that 13. BATS is TBATS.

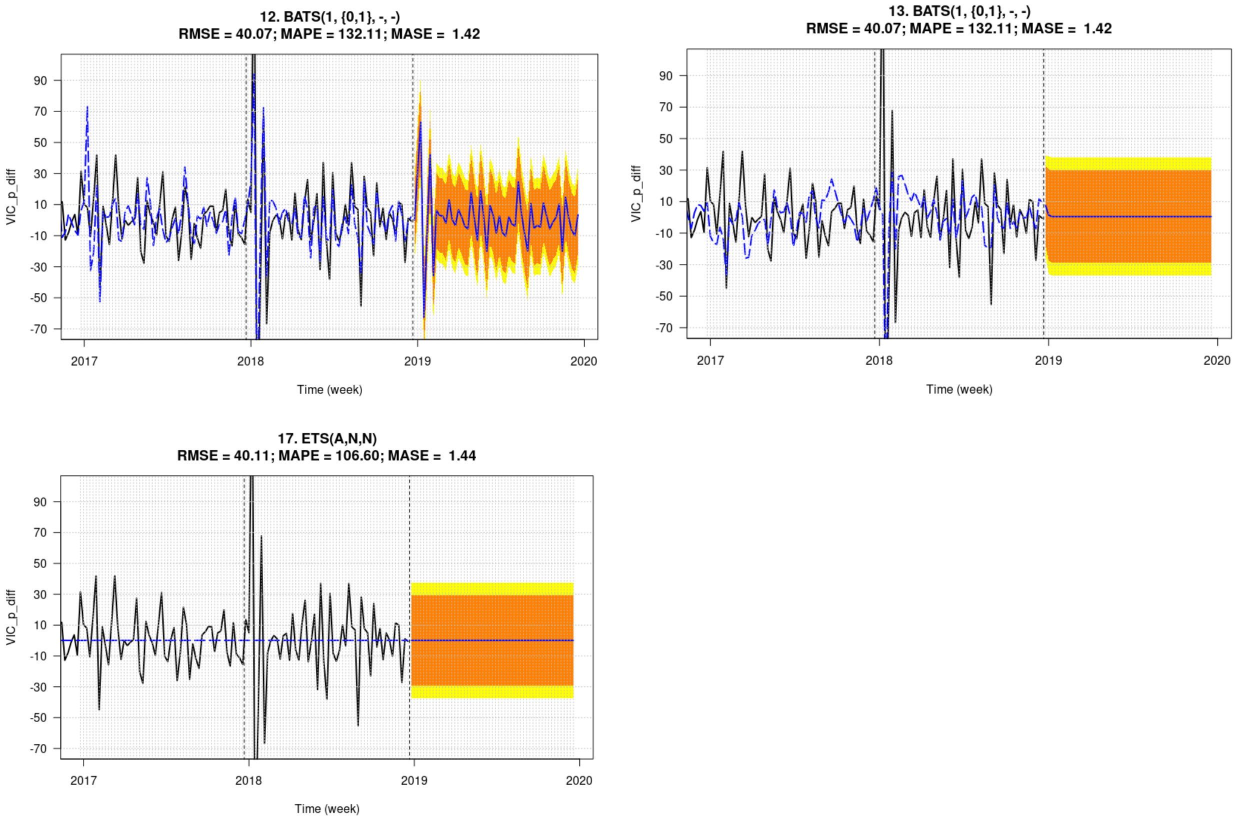


Figure 25. Top 5 models for VIC mean weekly differences, using 2018 test data.

As the final forecast uses monthly values a monthly graph and measures of accuracy are presented below as well.

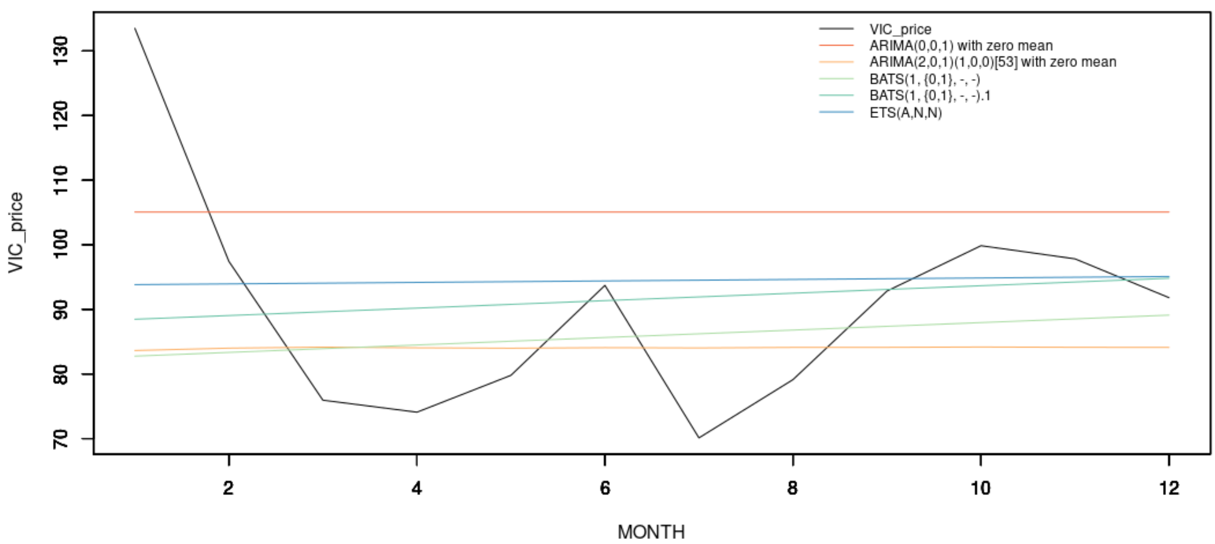


Figure 26. Top 5 models for VIC mean monthly, using 2018 test data.

Method name	RMSE	MAPE
ARIMA(2,0,1)(1,0,0)[53] with zero mean	16.82	13.71
ARIMA(0,0,1) with zero mean	27.55	30.72
BATS(1, {0,1}, -, -)	24.52	25.45

TBATS(1, {0,1}, -, -)	28.30	30.60
ETS(A,N,N)	17.77	15.59

Table 3. Top 5 models for VIC mean monthly, using 2018 test data.

Moving onto the second stage of testing, only the selected 5 methods are used. This time all the modelling data (2012-2018) is used for training and models are tested using 4 years of quarterly futures prices gathered from ASX for the period of 2019-2022. Graph showing monthly forecast is displayed below.

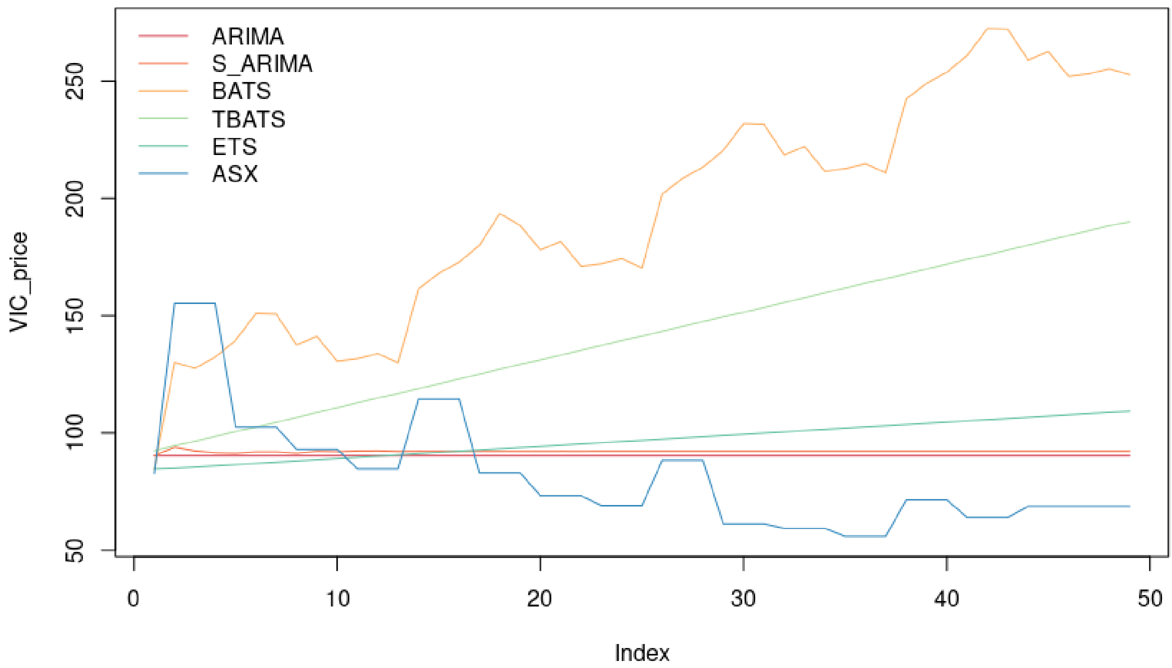


Figure 27. Top 5 models for VIC mean monthly, using 2019-2022 ASX testing data.

As it is clear from a glimpse to the graph both BATS and TBATS diverge into different direction from the ASX data, leaving only ARIMA, ETS and seasonal ARIMA for consideration. In methodology part it was discussed that the final decision on which model to choose will involve a couple of criteria:

- Forecast and ASX futures prices do not have opposite slopes;
- Forecast should have either a constant or negative slope;
- If the forecast has a negative slope it should not be as steep as the futures slope;
- It is preferable that the forecast has some seasonality;

Looking at these only ARIMA and seasonal ARIMA are left. Since seasonal ARIMA does not have observable seasonal variation RMSE of both models for the testing period will determine the best model. When comparing the two ARIMA has RMSE of 25.69 while seasonal ARIMA – 26.26 (see Appendix 6 for a full list of measurements). Taking RMSE and previously mentioned criteria into account ARIMA is constituted as the best fitting model for Victoria mean price forecasting.

As it is ARIMA(0,0,1), it can be expressed as MA(1). As modelling was done using first-order difference of the mean prices the actual model forecasts the difference and not the value itself.

Coefficient can be extracted, and the model can be written as follows (for R output refer to Appendix 13).

$$\Delta Y_t = \epsilon_t - 0.692171\ \epsilon_{t-1}$$

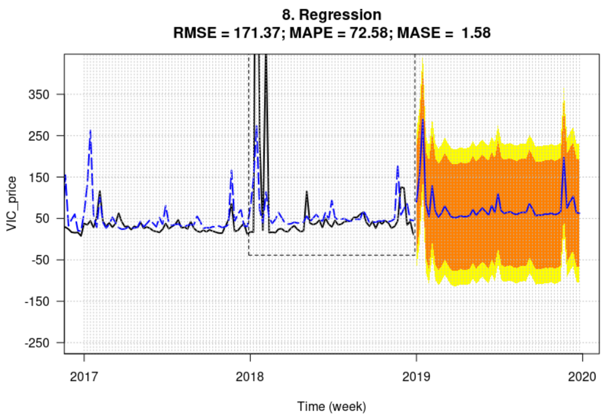
Here ΔY_t is the forecasted difference between series Y_t and Y_{t-1} and ϵ is the white noise. As forecast becomes a constant in 1 step, the full forecast for the period is 90.33 AUD/MWh. If needed refer to the full forecast in Appendix 7.

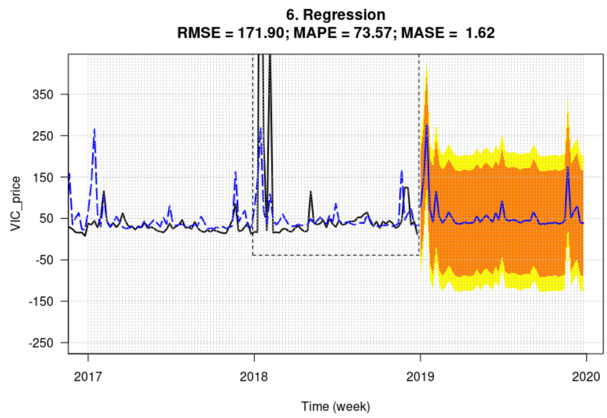
Meanwhile mean is determined through a two-step testing process, standard deviation forecast is tested only once, as there is no additional data to the authors knowledge to evaluate standard deviation in the future. Testing results are shown below (for the full list refer to Appendix 8).

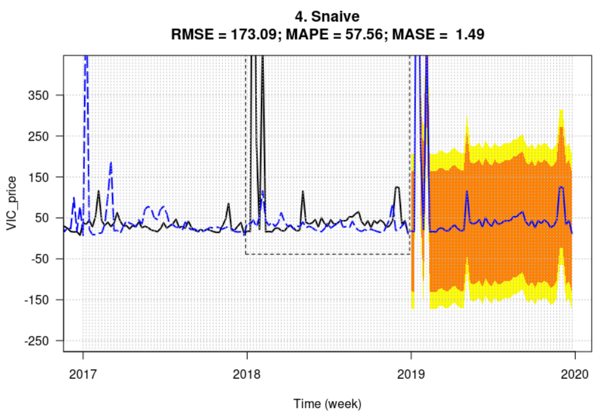
Method name	**RMSE**	**MAPE**	**MASE**
Regression: trend + Q_trend + season	171.37	72.58	1.58
Regression: trend + season	171.9	73.57	1.62
Snaive	173.09	57.56	1.49
baggedModel	175.84	59.48	1.41
BATS(0, {0,0}, 0.955, {53})	175.97	62.95	1.54

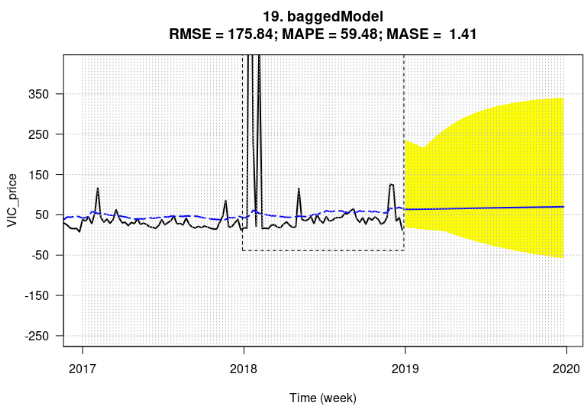
Table 4. Top 5 models for VIC SD weekly, using 2018 test data.

In addition to accuracy measures forecast graphs are provided below in the same order as in the table.









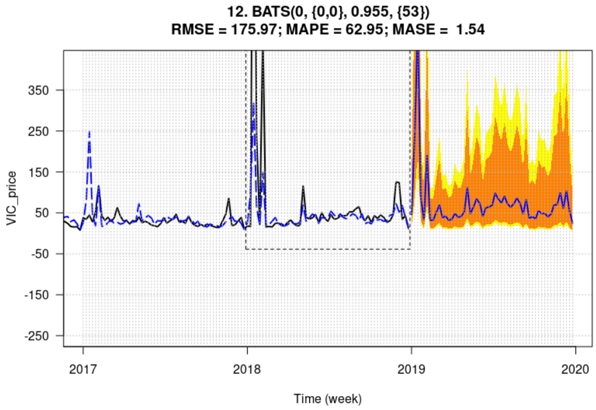


Figure 28. Top 5 models for VIC weekly standard deviation, using 2018 testing data.

As the models act quite similarly between themselves (except for the baggedModel), the decision is made based on RMSE and MASE, which in turn leads to *snaive* selection as it decreases MASE considerable without a considerable loss in RMSE. Retraining the model on full modelling dataset (2012-2018) the forecast is extracted. The coefficients are skipped at this part as snaive repeats the last seasons value, thus, repeating the last year of the series. Full weekly forecast is shown below as a graph and its monthly values are represented in the Appendix 7.

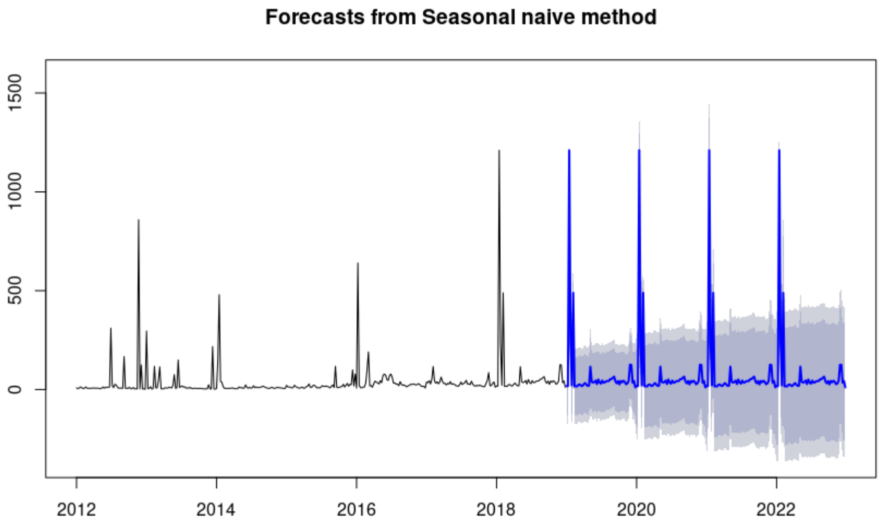


Figure 29. VIC SD weekly forecast for 2019-2022.

3.3.2. Modelling and testing – New South Wales

As noted in data exploration New South Wales mean value series are transformed and stationary series of first-order difference are used instead.

During the first stage of testing RMSE values are quite close and thus the decision on the five selected models is done using RMSE and MASE measures. The list of the five selected models for second stage testing is displayed below.

Method name	**RMSE**	**MAPE**	**MASE**
TBATS(1, {0,2}, -, -)	19.18	99.34	0.92

ARIMA(0,0,2) with zero mean	19.19	98.19	0.92
ETS(A,N,N)	19.21	101.77	0.93
baggedModel	19.21	100.83	0.93
Mean	19.21	100.76	0.93

Table 5. Top 5 models for NSW weekly mean differences, using 2018 test data.

As seen from the table top models in corresponding order are TBATS, ARIMA, exponential smoothening, bagged model and mean. To check the full table of the test results, see Appendix 9.

The corresponding graphs to the models are displayed below in the same order as in the table above.

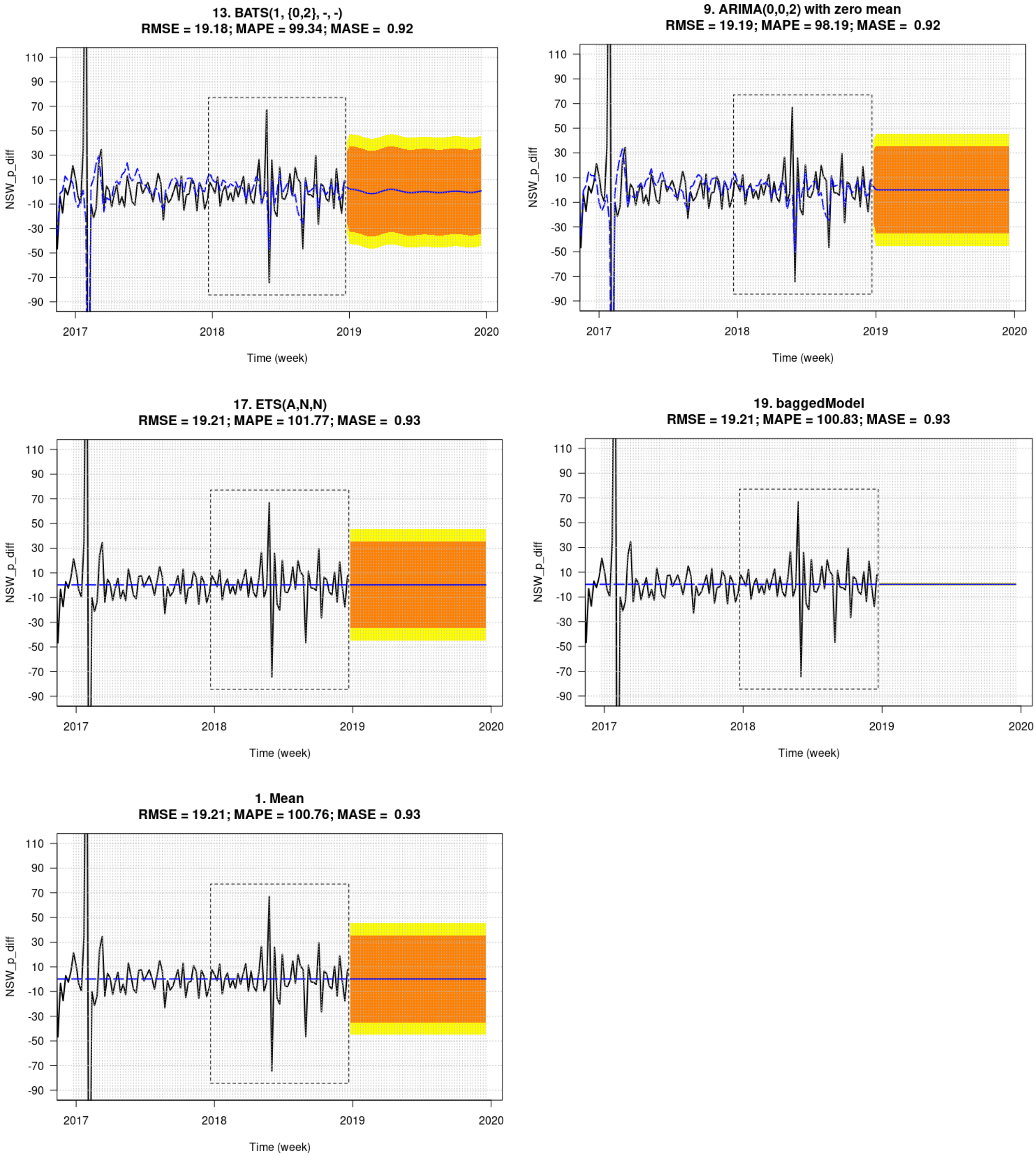


Figure 30. Top 5 models for NSW weekly differences, using 2018 testing data.

Moving onto the second stage of testing, only the selected 5 methods are used. This time all the modelling data (2012-2018) is used for training and models are tested using 4 years of quarterly futures prices gathered from ASX for the period of 2019-2022. Graph showing monthly forecast is displayed below.

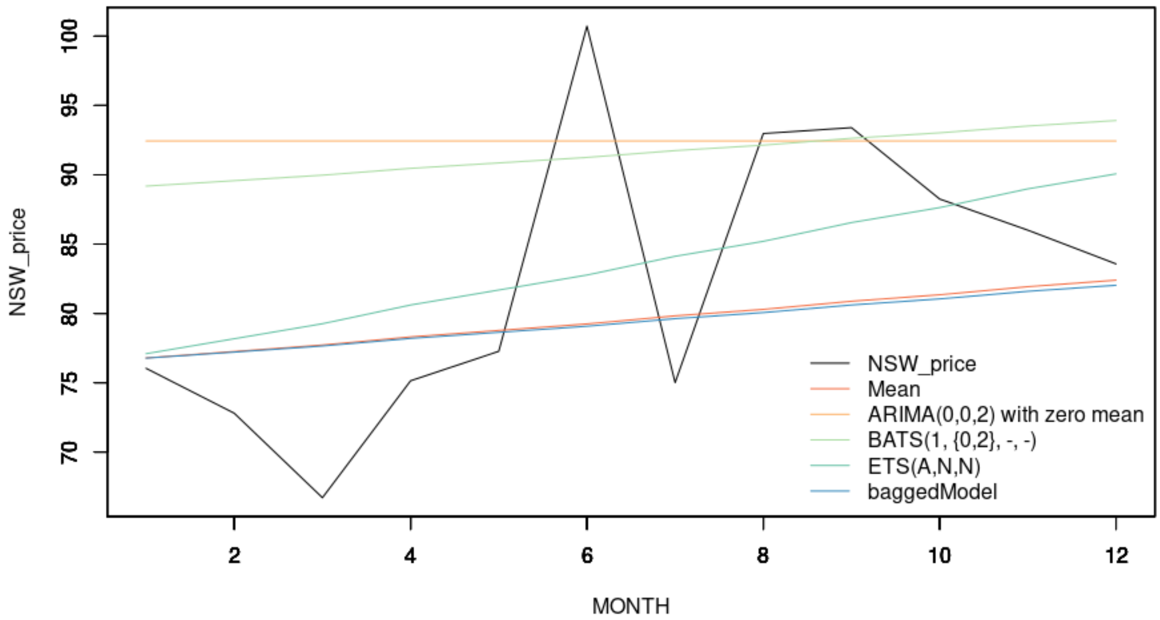


Figure 31. Top 5 models for NSW mean monthly, using 2018 testing data.

Method name	**RMSE**	**MAPE**
TBATS(1, {0,2}, -, -)	12.82	14.43
ARIMA(0,0,2) with zero mean	14.02	15.47
ETS(A,N,N)	8.17	8.18
baggedModel	9.33	8.30
Mean	9.23	8.21

Table 6. Top 5 models for NSW mean monthly, using 2018 test data.

It should be noted that the mean model is second by both metrics, which is above average for an average model.

Moving onto the second stage of testing, only the selected 5 methods are used. This time all the modelling data (2012-2018) is used for training and models are tested using 4 years of quarterly futures prices gathered from ASX for the period of 2019-2022. Graph showing monthly forecast is displayed below.

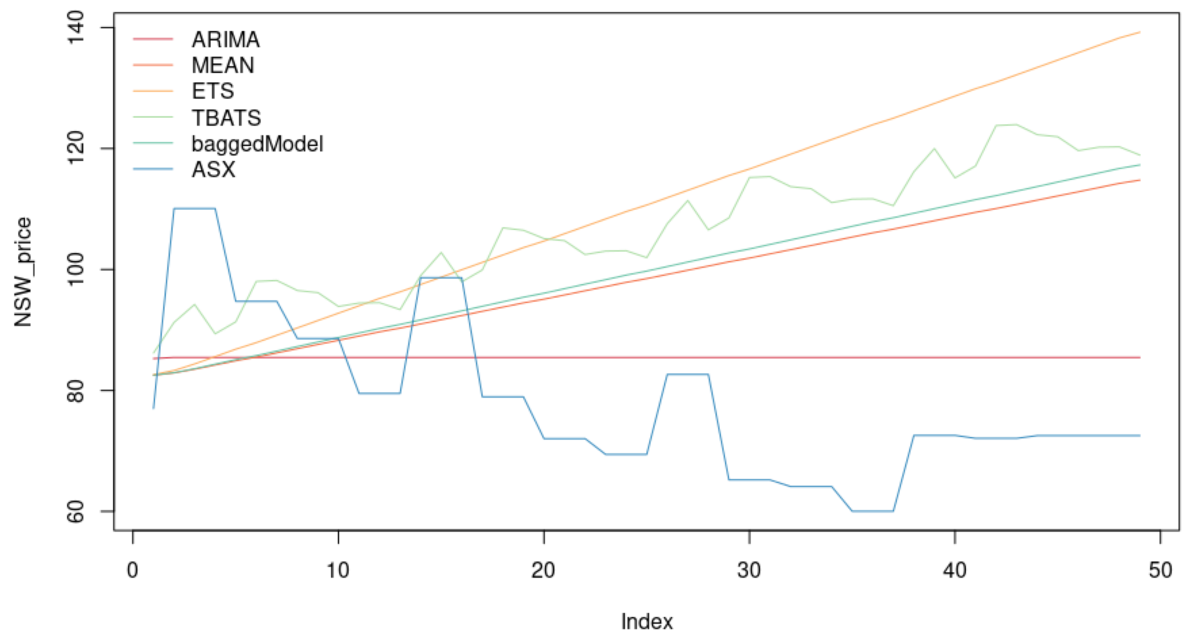


Figure 32. Top 5 models for NSW mean monthly, using 2019-2022 ASX testing data.

As it is clear from a glimpse to the graph both all models except for ARIMA diverge to a different direction from the ASX data. Even though in methodology part it was discussed that the final decision on which model to choose will involve a couple of criteria listed below, only the option of ARIMA is left.

- Forecast and ASX futures prices do not have opposite slopes;
- Forecast should have either a constant or negative slope;
- If the forecast has a negative slope it should not be as steep as the futures slope;
- It is preferable that the forecast has some seasonality;

Looking from the perspective of accuracy ARIMA has the best RMSE leaving far behind second best mean model, 14.86 and 29.18 RMSE respectively (see Appendix 9 for the full list). However, it is not such an average position for an average model.

As for the selected ARIMA(0,0,2) model, it can be expressed as MA(2). As modelling was done using first-order difference of the mean prices the actual model forecasts the difference and not the value itself. Coefficients can be extracted, and the model can be written as follows (for full R output refer to Appendix 14).

$$\Delta Y_t = \epsilon_t - 0.699\,\epsilon_{t-1} - 0.1503\,\epsilon_{t-2}$$

Here ΔY_t is the forecasted difference between series Y_t and Y_{t-1} and ϵ is the white noise. As forecast becomes a constant in 2 steps, the full forecast for the period is 85.46 AUD/MWh. If needed refer to the full forecast in Appendix 11.

Finally, the last forecastable series – NSW standard deviation. The whole process follows the same steps as with the VIC standard deviation. Testing results are shown below (for the full list refer to Appendix 12).

Method name	**RMSE**	**MAPE**	**MASE**
Mean	37.73	52.44	0.42
SVM	38.61	52.68	0.46
ARIMA(0,1,1)	38.94	100.72	0.61
ETS(A,N,N)	39.12	103.47	0.63
BATS(0, {0,0}, -, -)	40.58	41.61	0.48

Table 7. Top 5 models for NSW standard deviation weekly, using 2018 test data.

In addition to accuracy measures forecast graphs are provided below in the same order as in the table.

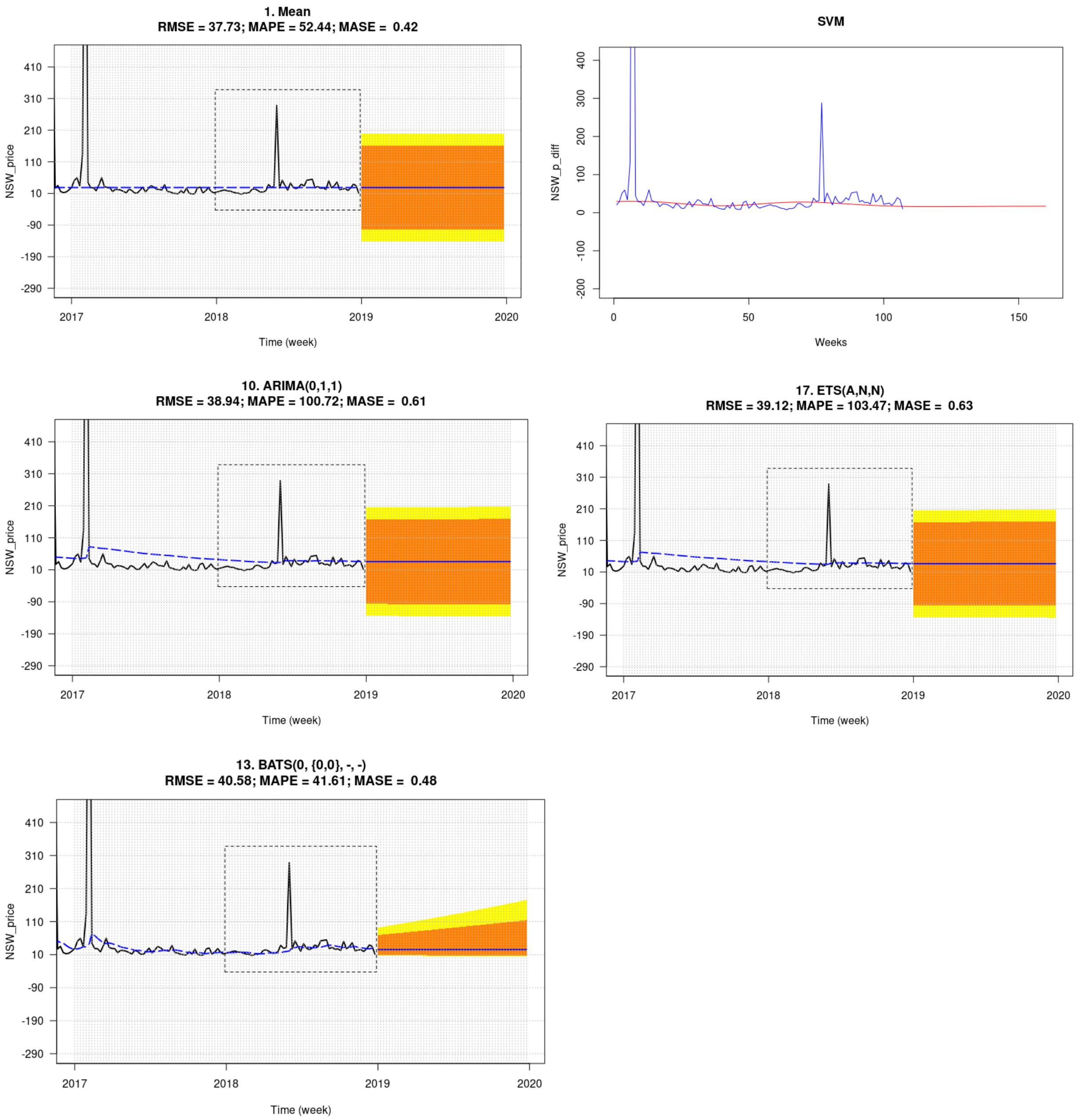


Figure 33. Top 5 models for NSW weekly standard deviation, using 2018 testing data.

As mean in a clear winner with best RMSE and MASE it is selected as the final model. As it is a mean model its expression for weekly value is provided below. The full monthly forecast can be found in Appendix 11.

$$Y_t = \bar{Y} = 28.7$$

3.4. Full forecast

Full forecast requires all the before done components. This can be clearly seen in the high-level overview, where the full forecast is the final step.

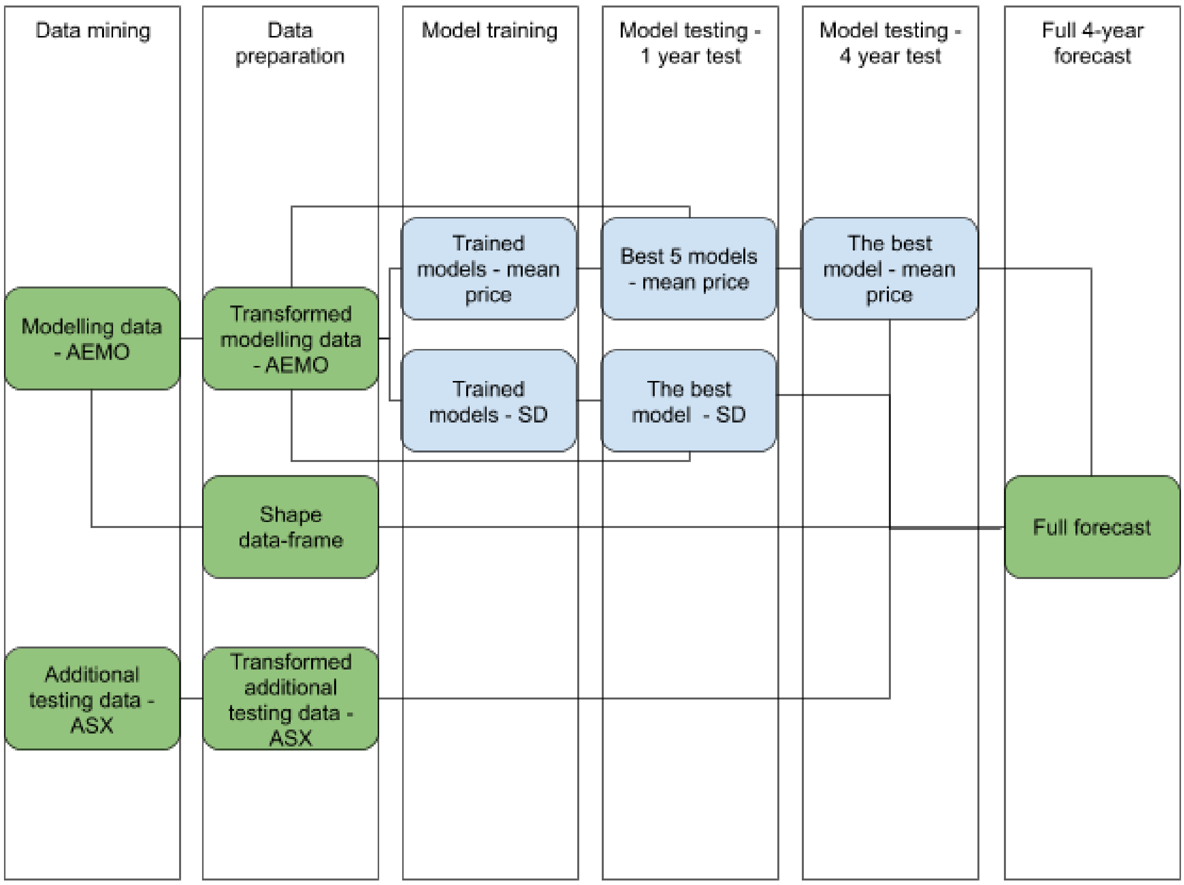


Figure 34. High-level overview.

As seen in the graph 3 main components are required for a full forecast:

1. Z-score based price shapes.
2. Monthly energy price mean forecast for the 4-year period.
3. Monthly energy price standard deviation forecast for the 4-year period.

Z-score based price shapes are determined during data preparation and exploratory analysis, while, mean and standard deviation forecasts are made during modelling and testing part. As all the components are in place a full forecast for each of the series can be made. For that a specific equation is presented at the very end of the methodology and as a reminder here.

$$x_{twmy} = z_{twmy} \cdot s_{my} + \overline{x_{my}}$$

Here x_{twmy} is the full forecast observation at t - half-hour interval, w - weekday of the week, m - month and y – year, while z, s and x arithmetic average, are shape z-score, forecasted standard deviation and mean price, respectively. After calculating x_{twmy} for each t, w, m and y, one gets a full forecast with the needed level of detail.

3.4.1. Victoria

Victoria z-score half-hourly week shapes, forecasted mean and standard deviation are presented below.

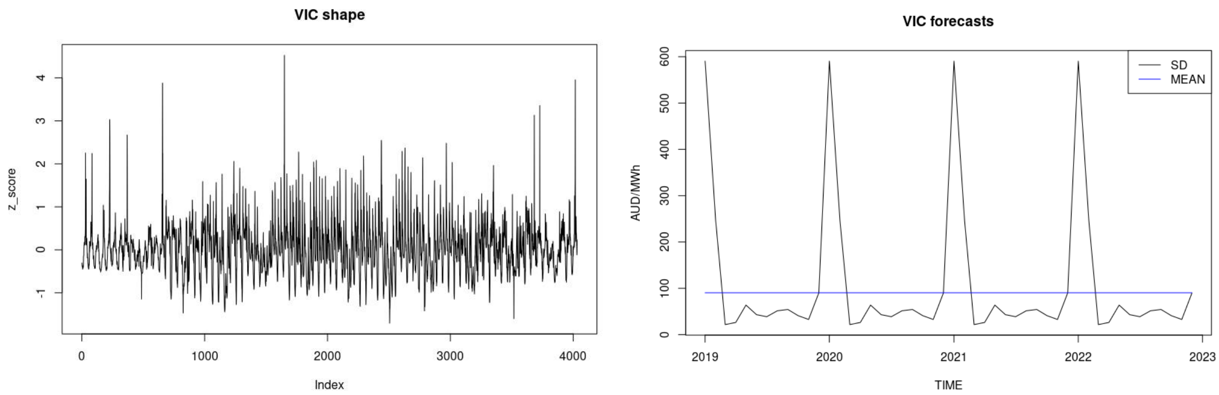


Figure 35. VIC shape, mean and standard deviation.

With shapes, mean and standard deviation forecasts in place the full forecast can be calculated which is displayed below.

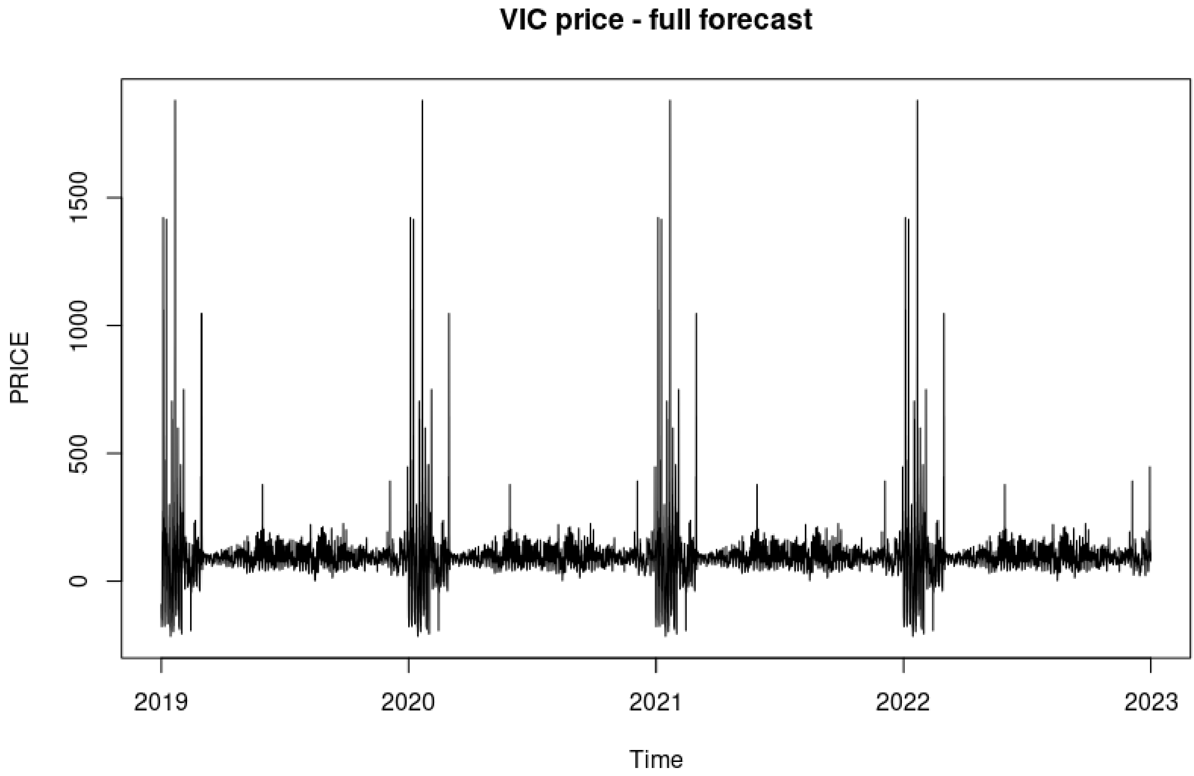


Figure 36. Full VIC price forecast.

Differently than the mean and standard deviation forecasts, a forecast with the half-hourly shapes makes use of seasonal differences and outliers within the weekly shapes to make up a more detailed and variable forecast, thus, letting PPA parties to evaluate their consumption/production profiles in more detail from a financial perspective in accordance to the half-hourly prices.

3.4.2. New South Wales

New South Wales z-score half-hourly week shapes, forecasted mean and standard deviation are presented below.

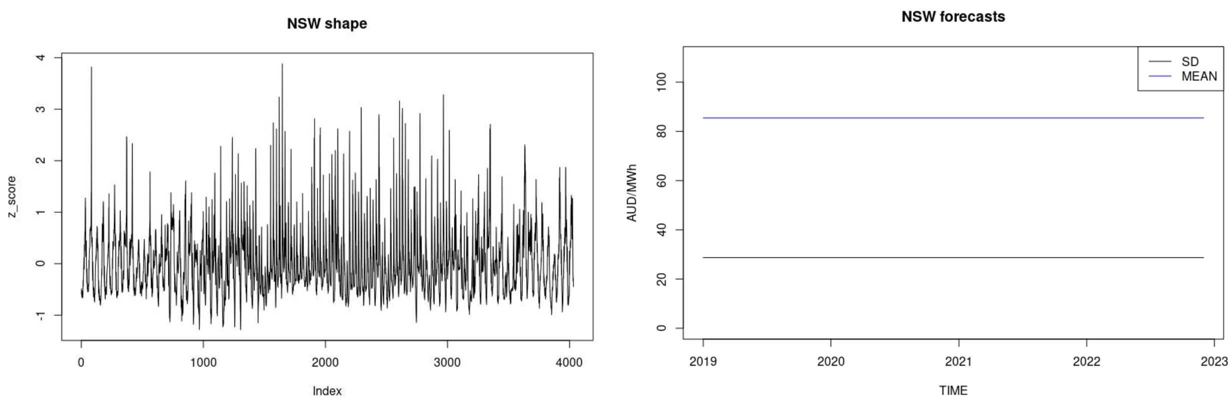


Figure 37. NSW shape, mean and standard deviation.

With shapes, mean and standard deviation forecasts in place the full forecast can be calculated which is displayed below.

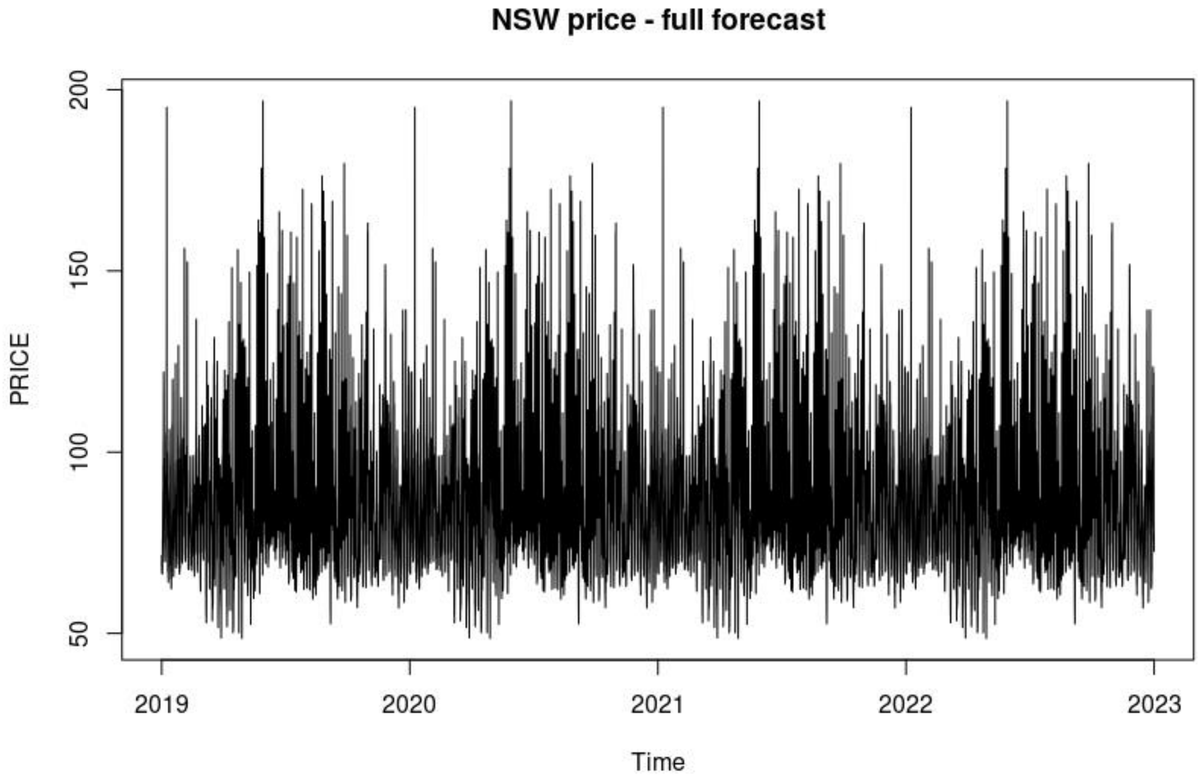


Figure 38. Full NSW price forecast.

As with the VIC full forecast the same conclusions might be drawn here. A forecast with the half-hourly shapes makes up a more detailed and variable forecast letting PPA parties to evaluate their consumption/production profiles in more detail from a financial perspective in accordance to the half-hourly prices.

3.5. Interpretation of the results and final notes

The goal of the results chapter was to take two similar series from the same country but different regions and show that application of a simple methodology lets choose an appropriate method for long-term energy market price forecast and can lead to a more detailed forecast itself which in turn would let PPA parties get a better understanding of how market price could vary in the long-term future.

Considering the methods selected for the series forecast mean market price, both series lean to methods which make use of the last known values of series to determine the level at which the model stays later on. Both series make use of moving average method for their long term mean forecast, which loses variation after q steps of forecasted values, which are 1 and 2, for Victoria and New South Wales respectively. As for the standard deviation, the same is true for New South Wales as mean value of the series was selected as the best method, meanwhile, Victoria standard deviation seems to be best fitted by seasonal naïve. All of the named methods have little to none variation, except for the seasonal naïve which repeats the values of the respective season in the series. Thus, data seems as highly unpredictable, since the best models from all of the tested are the ones which try to find the middle ground between series peaks and off-peaks, instead of trying to lock on its variation patterns. This in turn results in a constant forecast.

All things considered, both Victoria and New South Wales due to their inconsistently variable price and multi-stage historical data mostly benefit from constant-like forms of forecasting which in turn offer little to none variability in the forecast. The most consistent thing is the half-hourly week shapes, which as well point to the changes in the market in the periods around 2014 and 2016, which are visible in the series itself. This is the reason why PPAs require a different look into the market energy price forecasting and why the half-hourly week shapes are introduced in this thesis. Week shapes give another level of risk evaluation for clients as they let them fit their consumption to the market price fluctuations a bit better when making a decision which depends on a highly volatile price of energy.

Conclusions

1. Literature review shows that the needed level of detail for long-term energy forecasts when considering PPA parties is Year <- Month <- Weekday <- Time.
2. A common methodology was built with each part of it (data gathering and preparation, shape extraction, long-term forecasting, full long-term forecast using shapes) being available for change without changing the whole flow of the methodology. Methodology was applied to forecast the market energy price for two states in Australia. In both cases the needed level of detail was achieved.
3. The methodology provided in this thesis provides the needed means for both consumers and producers involved in PPAs to economically evaluate the value of the PPA.
4. Shape usage requires to forecast both the mean value of the price and the standard deviation to achieve the needed level of detail.
5. Long-term forecasts at least in Australia are close to constant throughout the forecasted period.
6. Best models to describe the weekly average energy market price are *moving average* models of order 1 and 2, for Victoria and New South Wales respectively. Best models to describe the weekly energy market standard deviation are *snaive* and *mean*, for Victoria and New South Wales respectively.

List of references

1. Financial Times Lexicon
http://lexicon.ft.com/
2. Hashmi, M., Damanhouri, A., & Rana, A. (2015). Evaluation of Sustainability Practices in the United States and Large Corporations. Journal of Business Ethics, 127(3), 673-681.
3. Kent, & Mercer. (2006). Australia's mandatory renewable energy target (MRET): An assessment. Energy Policy, 34(9), 1046-1062.
4. European Commision. Renewable Energy
https://ec.europa.eu/energy/en/topics/renewable-energy
5. Demski, Jennifer. (2013). Licensing the Sun. Campus Technology, 26(8), 18-20.
6. Macdonald, J. (2016). Low cost solar power is here to stay. Renewable Energy Focus, Renewable Energy Focus.
7. Google. (2013). Google’s Green PPAs: What, How, and Why.
https://storage.googleapis.com/gweb-sustainability.appspot.com/pdf/renewable-energy.pdf
8. The Economist. (2017). Big business sees the promise of clean energy.
https://www.economist.com/business/2017/06/10/big-business-sees-the-promise-of-clean-energy
9. Essential Services Commission. (2013). Retailer Margins in Victoria’s Electricity Market — Discussion Paper, May
10. Department for Business, Energy & Industrial Strategy. (2019). Policy paper: Contracts for Difference.
https://www.gov.uk/government/publications/contracts-for-difference/contract-for-difference
11. Schneider Electric. What is the Difference Between Direct and Financial (Virtual) PPAs?
https://hub.resourceadvisor.com/renewable-energy/what-is-the-difference-between-direct-and-financial-ppas-for-corporate-buyers
12. Maciejowska, K. and Weron, R. (2016). Short-and mid-term forecasting of baseload electricity prices in the uk: The impact of intra-day price relationships and market fundamentals. IEEE Transactions on Power Systems, 31(2):994–1005.
13. Bello, A., Bunn, D., Reneses, J., and Munoz, A. (2016a). Parametric density recalibration of a funda- ˜ mental market model to forecast electricity prices. Energies, 9(11):959.
14. Bello, A., Reneses, J., and Munoz, A. (2016b). Medium-term probabilistic forecasting of extremely ˜ low prices in electricity markets: Application to the spanish case. Energies, 9(3):193.
15. Torbaghan, S. S., Motamedi, A., Zareipour, H., et al. (2012). Medium-term electricity price forecasting. In North American Power Symposium (NAPS), 2012, pages 1–8. IEEE.
16. Kossov, V. (2014). Medium-term forecasting of demand prices on example of electricity prices for industry. Studies on Russian Economic Development, 25(5):456–466.
17. Kou, P., Liang, D., Gao, L., and Lou, J. (2015). Probabilistic electricity price forecasting with variational heteroscedastic gaussian process and active learning. Energy Conversion and Management, 89:298–308.
18. Rafiei, M., Niknam, T., and Khooban, M. H. (2016). A novel intelligent strategy for probabilistic electricity price forecasting: Wavelet neural network based modified dolphin optimization algorithm. Journal of Intelligent & Fuzzy Systems, 31(1):301–312.

19. Wan, C., Niu, M., Song, Y., and Xu, Z. (2017). Pareto optimal prediction intervals of electricity price. IEEE Transactions on Power Systems, 32(1):817–819.
20. Ziel, F. and Steinert, R. (2018). Probabilistic Mid- and Long-Term Electricity Price Forecasting.
21. Mcconnell, D. & Sandiford, M. (2016). Winds of change: An analysis of recent changes in the South Australian electricity market. 10.4225/49/57ABDF310230A.
22. Press, G. (2016). Cleaning Big Data: Most Time-Consuming, Least Enjoyable Data Science Task, Survey Says. *Forbes*
23. Strasser, A. (2017). Corporate PPAs took off in 2017 – who were the leaders? *RenewEconomy* https://reneweconomy.com.au/corporate-ppas-took-off-in-2017-who-were-the-leaders-72117/
24. Hutchens, G. (2018). Australia's high prices 'the new normal', report says. *The Guardian*
25. Vaičiukynas, E. (2018). Laiko eilučių analizė, modeliai ir prognozavimas. [Lecture on univariate time series]
26. Hyndman, R. & Anthanasopoulos, G. (2018). Forecasting principles and practice.
27. Kavaliauskas, M. & Rudzkis R. (2015). Laiko eilučių analizė. Paskaitų konspektas.
28. Lombardía, M., López-Vizcaíno, E., & Rueda, C. (2017). Mixed generalized Akaike information criterion for small area models. *Journal of the Royal Statistical Society: Series A (Statistics in Society),180*(4), 1229-1252.
29. Holmes, E. E., M. D. Scheuerell, & E. J. Ward. (2019) Applied time series analysis for fisheries and environmental data. NOAA Fisheries, Northwest Fisheries Science Center, 2725 Montlake Blvd E., Seattle, WA 98112.
30. Jakasa, T., Androcec, I., & Sprcic, P. (2011). Electricity price forecasting - ARIMA model approach. 2011 8th International Conference on the European Energy Market (EEM), 222-225.
31. Sánchez Lasheras, De Cos Juez, Suárez Sánchez, Krzemień, & Riesgo Fernández. (2015). Forecasting the COMEX copper spot price by means of neural networks and ARIMA models. Resources Policy, 45, 37-43.
32. Jarrett, J., & Kyper, E. (2011). ARIMA Modeling with Intervention to Forecast and Analyze Chinese Stock Prices. International Journal of Engineering Business Management, 3, International Journal of Engineering Business Management, 01 August 2011, Vol.3.
33. Ferbar Tratar, & Strmčnik. (2016). The comparison of Holt–Winters method and Multiple regression method: A case study. Energy, 109, 266-276.
34. Shahin, A. (2017). Using Multiple Seasonal Holt-Winters Exponential Smoothing to Predict Cloud Resource Provisioning. 7(11), (IJACSA) International Journal of Advanced Computer Science and Applications,Vol. 7, No. 11, 2016.

Information resources

1. Australian Energy Market Operator
https://www.aemo.com.au/
2. Statista. Amount of energy sold through PPAs:
https://www.statista.com/statistics/896831/global-ppas-capacity/
3. Australian stock exchange:
https://www.asxenergy.com.au

Appendices

Appendix 1. VIC standard deviation stationarity tests

Augmented Dickey-Fuller Test
data: ts_full
Dickey-Fuller = -6.1909, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

Box-Ljung test
data: ts_full
X-squared = 2.0136, df = 1, p-value = 0.1559

Appendix 2. NSW mean price stationarity tests

Augmented Dickey-Fuller Test
data: ts_full
Dickey-Fuller = -3.9028, Lag order = 7, p-value = 0.01412
alternative hypothesis: stationary

Box-Ljung test
data: ts_full
X-squared = 127.11, df = 1, p-value < 2.2e-16

Appendix 3. NSW mean price with first-order differences stationarity tests

Augmented Dickey-Fuller Test
data: ts_full
Dickey-Fuller = -10.537, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

Box-Ljung test
data: ts_full
X-squared = 64.139, df = 1, p-value = 1.11e-15

Appendix 4. NSW standard deviation stationarity tests

Augmented Dickey-Fuller Test
data: ts_full
Dickey-Fuller = -6.7736, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary

Box-Ljung test
data: ts_full
X-squared = 1.2594, df = 1, p-value = 0.2618

Appendix 5. VIC mean model testing with 2018 data

Method name	RMSE	MAPE	MASE
ARIMA(2,0,1)(1,0,0)[53] with zero mean	39.99	100.69	1.42
ARIMA(0,0,1) with zero mean	40.06	98.33	1.42

BATS(1, {0,1}, -, -)	40.07	132.11	1.42
TBATS(1, {0,1}, -, -)	40.07	132.11	1.42
ETS(A,N,N)	40.11	106.6	1.44
Mean	40.11	106.6	1.44
baggedModel	40.11	105.19	1.44
Regression: Q_trend + trend	40.11	99.73	1.44
Regression: trend	40.11	100.37	1.44
Theta	40.11	99.88	1.44
SVM	39.83	191.05	1.45
STL + ARIMA(0,0,1) with zero mean	40.04	188.41	1.48
BSM	40	191.75	1.49
STL + ETS(A,N,N)	40.08	216.15	1.49
Regression: Q_trend + trend + season	39.61	299.84	1.57
Regression: trend + season	39.61	301.73	1.57
HoltWinters	41.08	478.46	1.66
Snaive	40.55	527.36	1.69
Naive	43.13	1281.5	1.8
Naive drift	43.43	1320.39	1.84

Appendix 6. VIC mean model testing with ASX data

[1] "ARIMA"
ME RMSE MAE MPE MAPE
Test set -8.245321 25.68626 20.97224 -17.67484 27.18671
[1] "S_ARIMA"
ME RMSE MAE MPE MAPE
Test set -10.00849 26.26017 21.88486 -19.96948 28.74837
[1] "BATS"
ME RMSE MAE MPE MAPE
Test set -112.1027 130.1745 115.1954 -162.7497 164.7417
[1] "TBATS"
ME RMSE MAE MPE MAPE
Test set -59.26798 77.16756 66.53606 -90.79243 95.50017
[1] "ETS"
ME RMSE MAE MPE MAPE
Test set -14.79025 33.50741 28.56125 -27.88836 38.26082

Appendix 7. VIC monthly forecast 2019-2022

YEAR	**MONTH**	**MEAN_MA(1)**	**SD_Snaive**
2019	1	90.3295306139423	590.50493226492
2019	2	90.3295306139423	246.659680939768
2019	3	90.3295306139423	21.6392567894831
2019	4	90.3295306139423	26.275405946983
2019	5	90.3295306139423	63.7709496194077
2019	6	90.3295306139423	43.0438059956948
2019	7	90.3295306139423	38.6452506400859
2019	8	90.3295306139423	51.4085161873092
2019	9	90.3295306139423	54.3001038044303
2019	10	90.3295306139423	40.9864355753873
2019	11	90.3295306139423	32.6645888818736
2019	12	90.3295306139423	90.0710357015685
2020	1	90.3295306139423	590.50493226492
2020	2	90.3295306139423	246.659680939768

2020	3	90.3295306139423	21.6392567894831
2020	4	90.3295306139423	26.275405946983
2020	5	90.3295306139423	63.7709496194077
2020	6	90.3295306139423	43.0438059956948
2020	7	90.3295306139423	38.6452506400859
2020	8	90.3295306139423	51.4085161873092
2020	9	90.3295306139423	54.3001038044303
2020	10	90.3295306139423	40.9864355753873
2020	11	90.3295306139423	32.6645888818736
2020	12	90.3295306139423	90.0710357015685
2021	1	90.3295306139423	590.50493226492
2021	2	90.3295306139423	246.659680939768
2021	3	90.3295306139423	21.6392567894831
2021	4	90.3295306139423	26.275405946983
2021	5	90.3295306139423	63.7709496194077
2021	6	90.3295306139423	43.0438059956948
2021	7	90.3295306139423	38.6452506400859
2021	8	90.3295306139423	51.4085161873092
2021	9	90.3295306139423	54.3001038044303
2021	10	90.3295306139423	40.9864355753873
2021	11	90.3295306139423	32.6645888818736
2021	12	90.3295306139423	90.0710357015685
2022	1	90.3295306139423	590.50493226492
2022	2	90.3295306139423	246.659680939768
2022	3	90.3295306139423	21.6392567894831
2022	4	90.3295306139423	26.275405946983
2022	5	90.3295306139423	63.7709496194077
2022	6	90.3295306139423	43.0438059956948
2022	7	90.3295306139423	38.6452506400859
2022	8	90.3295306139423	51.4085161873092
2022	9	90.3295306139423	54.3001038044303
2022	10	90.3295306139423	40.9864355753873
2022	11	90.3295306139423	32.6645888818736
2022	12	90.3295306139423	90.0710357015685

Appendix 8. VIC standard deviation model testing with 2018 data

Method name	RMSE	MAPE	MASE
Regression: trend + Q_trend + season	171.37	72.58	1.58
Regression: trend + season	171.9	73.57	1.62
Snaive	173.09	57.56	1.49
baggedModel	175.84	59.48	1.41
BATS(0, {0,0}, 0.955, {53})	175.97	62.95	1.54
TBATS(0, {0,0}, -, {<53,8>})	176.35	49.88	1.46
Regression: trend + Q_trend	176.61	46.77	1.36
HoltWinters	176.95	77.25	1.69
Regression: trend	177.31	43.2	1.37
Theta	177.34	43.19	1.37
Mean	177.95	41.7	1.39
ARIMA(0,0,0) with non-zero mean	177.95	41.7	1.39
BSM	178.14	41.54	1.4
ARIMA(2,0,0)(1,0,0)[53] with non-zero mean	178.41	40.97	1.4
ETS(M,A,N)	178.56	42.05	1.43

Naive drift	183.21	62.39	1.72
Naive	183.27	63.03	1.73
STL + ETS(A,N,N)	216.18	116.67	2.26
STL + ARIMA(0,0,0) with non-zero mean	216.2	116.86	2.26

Appendix 9. NSW mean testing using 2018 data.

Method name	**RMSE**	**MAPE**	**MASE**
SVM	19.24	93.53	0.93
TBATS(1, {0,2}, -, -)	19.18	99.34	0.92
ARIMA(0,0,2) with zero mean	19.19	98.19	0.92
ARIMA(0,0,2) with zero mean	19.19	98.19	0.92
ETS(A,N,N)	19.21	101.77	0.93
baggedModel	19.21	100.83	0.93
Mean	19.21	100.76	0.93
Theta	19.21	100.18	0.93
Regression: trend	19.21	99	0.93
Regression: trend + Q_trend	19.22	97.57	0.93
Naive	20.54	183.96	1.04
Naive drift	20.64	188.37	1.05
Regression: trend + season	23.14	354.67	1.18
Regression: trend + Q_trend + season	23.15	353.97	1.18
HoltWinters	26.83	488.03	1.3
BATS(1, {0,1}, 0.987, {53})	34.84	732.58	1.58
STL + ETS(A,N,N)	37.17	719.21	1.39
STL + ARIMA(0,0,2) with zero mean	37.24	720.59	1.4
BSM	54.51	1176.94	1.93
Snaive	67.03	1478.87	2.16

Appendix 10. VIC mean model testing with ASX data

[1] "ARIMA"

ME RMSE MAE MPE MAPE

Test set -7.131703 14.87569 13.27783 -11.88755 17.89265

[1] "MEAN"

ME RMSE MAE MPE MAPE

Test set -20.20264 29.18308 25.54754 -30.34616 35.48353
[1] "ETS"
ME RMSE MAE MPE MAPE
Test set -32.39666 42.67908 36.41302 -47.32581 51.10163
[1] "TBATS"
ME RMSE MAE MPE MAPE
Test set -28.34827 35.40884 30.77518 -40.95815 43.18629
[1] "baggedModel"
ME RMSE MAE MPE MAPE
Test set -21.45193 30.5368 26.62444 -32.08574 37.04334

Appendix 11. NSW monthly forecast 2019-2022

YEAR	MONTH	MEAN_MA(2)	SD_Mean
2019	1	85.4587133057258	28.70565
2019	2	85.4587133057258	28.70565
2019	3	85.4587133057258	28.70565
2019	4	85.4587133057258	28.70565
2019	5	85.4587133057258	28.70565
2019	6	85.4587133057258	28.70565
2019	7	85.4587133057258	28.70565
2019	8	85.4587133057258	28.70565
2019	9	85.4587133057258	28.70565
2019	10	85.4587133057258	28.70565
2019	11	85.4587133057258	28.70565
2019	12	85.4587133057258	28.70565
2020	1	85.4587133057258	28.70565
2020	2	85.4587133057258	28.70565
2020	3	85.4587133057258	28.70565
2020	4	85.4587133057258	28.70565
2020	5	85.4587133057258	28.70565
2020	6	85.4587133057258	28.70565
2020	7	85.4587133057258	28.70565
2020	8	85.4587133057258	28.70565
2020	9	85.4587133057258	28.70565
2020	10	85.4587133057258	28.70565
2020	11	85.4587133057258	28.70565
2020	12	85.4587133057258	28.70565
2021	1	85.4587133057258	28.70565
2021	2	85.4587133057258	28.70565
2021	3	85.4587133057258	28.70565
2021	4	85.4587133057258	28.70565
2021	5	85.4587133057258	28.70565
2021	6	85.4587133057258	28.70565
2021	7	85.4587133057258	28.70565
2021	8	85.4587133057258	28.70565
2021	9	85.4587133057258	28.70565
2021	10	85.4587133057258	28.70565
2021	11	85.4587133057258	28.70565
2021	12	85.4587133057258	28.70565
2022	1	85.4587133057258	28.70565
2022	2	85.4587133057258	28.70565
2022	3	85.4587133057258	28.70565

2022	4	85.4587133057258	28.70565
2022	5	85.4587133057258	28.70565
2022	6	85.4587133057258	28.70565
2022	7	85.4587133057258	28.70565
2022	8	85.4587133057258	28.70565
2022	9	85.4587133057258	28.70565
2022	10	85.4587133057258	28.70565
2022	11	85.4587133057258	28.70565
2022	12	85.4587133057258	28.70565

Appendix 12. NSW standard deviation model testing using 2018 data.

Method name	RMSE	MAPE	MASE
Mean	37.73	52.44	0.42
SVM	38.61	52.68	0.46
ARIMA(0,1,1)	38.94	100.72	0.61
ARIMA(0,1,1)	38.94	100.72	0.61
ETS(A,N,N)	39.12	103.47	0.63
BATS(0, {0,0}, -, -)	40.58	41.61	0.48
HoltWinters	41.39	103.12	0.65
Theta	41.72	133.4	0.79
Naive drift	42.19	48.11	0.56
Naive	42.45	49.38	0.57
BATS(0.013, {0,0}, 0.998, {53})	42.63	59.36	0.56
baggedModel	44.35	63.21	0.66
Regression: trend + Q_trend	46.56	175.01	1.03
Regression: trend	48.62	189.7	1.12
STL + ARIMA(0,1,1)	49.71	94.13	0.62
STL + ETS(A,N,N)	49.91	98.38	0.64
BSM	60.03	185.31	1.09
Regression: trend + Q_trend + season	65.63	182.06	1.09
Regression: trend + season	67.46	198.61	1.18
Snaive	218.66	253.33	1.48

Appendix 13. VIC mean. Final model

Forecast method: ARIMA(0,0,1) with zero mean

Model Information:

Series: df

ARIMA(0,0,1) with zero mean

Coefficients:

ma1

-0.6922

s.e. 0.0453

sigma^2 estimated as 372.1: log likelihood=-1619.89

AIC=3243.79   AICc=3243.82   BIC=3251.61

z test of coefficients:

Estimate Std. Error z value Pr(>|z|)

ma1 -0.692171   0.045275 -15.288 < 2.2e-16 ***

---Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Appendix 14. NSW mean. Final model

Forecast method: ARIMA(0,0,2) with zero mean
Model Information:
Series: df
ARIMA(0,0,2) with zero mean
Coefficients:

	ma1	ma2
	-0.6990	-0.1503
s.e.	0.0493	0.0501

sigma^2 estimated as 506.6: log likelihood=-1676.74
AIC=3359.47   AICc=3359.54   BIC=3371.21

z test of coefficients:

	Estimate	Std. Error	z value	Pr(>|z|)	
ma1	-0.699028	0.049269	-14.1881	< 2e-16	***
ma2	-0.150293	0.050079	-3.0011	0.00269	**

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Appendix 15. VIC mean stationarity test

Original series:

Box-Ljung
testdata: ts_full
X-squared = 188.43, df = 1, p-value < 2.2e-16

Augmented Dickey-Fuller
Testdata: ts_full
Dickey-Fuller = -3.1278, Lag order = 7, p-value = 0.1009
alternative hypothesis: stationary

After differencing:

Box-Ljung test
data: ts_full
X-squared = 62.926, df = 1, p-value = 2.109e-15

Augmented Dickey-Fuller Test
data: ts_full
Dickey-Fuller = -9.4389, Lag order = 7, p-value = 0.01
alternative hypothesis: stationary
Warning message:In adf.test(ts_full) : p-value smaller than printed p-value