THE IMPACT OF WIND ENERGY DEVELOPMENT ON SWEDISH ELSPOT DAY-AHEAD PRICES

Dissertation in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE WITH A MAJOR IN WIND POWER PROJECT MANAGEMENT

UPPSALA UNIVERSITET

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Abstract

The rapid development of wind energy in Sweden created a volatile environment for the electricity market. Variance in the daily prices and the reductions of the average prices over the years due to the merit order effect of intermittent wind energy resulted in increased unpredictability in financial returns, which led to many wind projects being cancelled. In this thesis, in order to shed more light on the impact of wind energy development on spot prices, an artificial neural network (ANN) electricity price forecasting model is designed in order to predict Sweden's four electricity regions Nord Pool Elspot day-ahead electricity spot market prices. The model's final result displayed a mean absolute error of 3.3398 €/MWh. In order for the model to be able to generalize better, a ridge regression regularizer is added to the ANN. Alternative wind scenarios for Sweden are introduced and their spot prices are predicted by the ANN model. The results show that each 10% increase in wind energy production leads to a 0.9% spot price reduction in the Nord Pool Swedish energy market prices.

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1. Introduction

1.1. Background

The world has been depending on the fossil fuels since the industrial revolution. It is an established way of supplying energy; it is energy dense, mobile, and compatible with the developed infrastructure and penetrates every part of the world. However, this situation had been changing due to political, economic and environmental pressures.

Governments learned that depending on the fossil fuels solely costs too much and affects the political autonomy in the times of energy crises as it was in 1970s foundation of OPEC and also during the Iranian Revolution. They are the spark that created awareness in the energy industry and spurred the search of alternative solutions to conventional generation.

There is a continuous effort to reduce the carbon footprint of the world. In 2015, at the COP 21 conference held in Paris many countries have decided to abide by the designated carbon levels set for their country. It resulted in political and thus economical changes that created an environment for renewable energy industries to grow. Recent improvements in technology allowed the wind energy industry to develop in an environmentally responsible way, and also to become economically feasible in many countries.

Wind penetration in energy supply has been increasing globally for the last decade. In 2016, Denmark had a share of 38% wind energy generation over total electricity production and it is expected to rise up to 60% by 2026 (Energinet 2017). Sweden produced approximately 11% of its electricity in 2016 from wind power (Svenska Kraftnet n.d.). Spain, Portugal, Germany, UK are some of the other leading countries in Europe with significant wind power generation capacities. The European Union has set is its target renewable energy consumption to at least 27% by 2030. Therefore, the wind energy industry will continue growing especially in the Nordic countries where there are high wind potentials and low solar potential. An increase in the share of the wind energy production in the Nordic countries also brings new energy producers into the market. They have to sell their energy to potential buyers in the day ahead market if they do not have a bilateral contract. This increase in wind penetration in the energy mix is leading to a more volatile, unpredictable electricity prices for both the producers and consumers of the electricity (Nicolosi & Fürsch 2009).

1.2. Objective

The primary reason for the selection of this investigation of the impact of the wind energy development on electricity prices is to be able to have greater foresight about the potential future revenues of wind farms. Wind farm projects tend to take a long time to obtain permits and begin construction and they often exceed 5 years in Sweden (Pettersson et al. 2010). However, over the years as wind power penetration is increased in the Nord Pool Elspot market, the market prices have decreased (Nord Pool n.d.) along with the potential financial returns of the projects. By the time the project has been realized, the conditions of the electricity market could have changed immensely, which creates financial uncertainty in the project planning. Therefore, having a fuller understanding of the possible future electricity prices depending on the increased wind energy production might be helpful to wind developers while assessing their projects' feasibility.

Most of the electricity production is traded in the day-ahead electricity market and percentile share of the day ahead market in electricity markets has been increasing continuously (Morthorst & Awerbuch 2009). Consequently, day ahead market is the most important market for power producers, because in that electricity market most of the volume is traded, and large portion of the prices are settled. If the current day-ahead market dynamics are simulated and investigated, the relationship between the wind energy production and its impact on the day-ahead electricity prices can be understood better, which can later on be extrapolated for future market conditions considering the Sweden's long term wind production estimates. Wind developers might take the findings of this research into consideration during the selection of their potential wind farm projects.

In this thesis, in order to simulate the day-ahead market dynamics an artificial neural network (ANN) price forecasting model is created, which predicts the Nord Pool Elspot prices of four Swedish electricity regions. Different wind generation scenarios are then structured over a historical time period. By using the ANN model on the wind generation scenarios, how the current day-ahead market reacts to different wind power production values is investigated and the impact of wind energy development on Swedish spot prices is evaluated.

1.3. Outline

In Chapter 2, a literature review is conducted to identify background information on the following topics: intermittency of wind energy, electricity markets, electricity price prediction methods, and the impact of renewable energy development on the electricity prices. In the following Chapter 3, linear & polynomial regression is introduced, model evaluation tools and data selection methodology are explored. Later in the Chapter 3, an ANN price forecasting model is developed with a specific configuration that is more suited for predicting the prices of wind energy scenarios. The predictions of the ANN model on real data and then on altered wind energy scenario data are presented in Chapter 4. These predictions are discussed and evaluated in Chapter 5. Finally, Chapter 6 summarizes the conclusions and highlights the limitations of the thesis and areas for further research.

2. Literature Review

2.1. Introduction

This chapter starts by addressing the intermittency problem of wind energy. Then, the electricity markets are briefly explained in order to have a greater understanding of the merit-order effect and the place of wind energy in the electricity mix. An overview of the different price forecasting models is presented with a detailed focus on the computational intelligence models. In the following sections, the impact of wind energy on electricity prices in different electricity markets are listed and an overview of the current state of the art techniques for the data selection of electricity price forecasting models is presented.

2.2. Intermittency Issue of Wind Power

Modern life requires electricity to work, and as a result demands its constant availability. However, a higher percentage of capacity is not generating any energy due to the increase in renewable sources. Renewable energies such as wind and solar are intermittent, as they depend on external factors such as wind and sun to generate electricity. For solar energy, the production of electricity occurs throughout the day when the consumption is high. However, wind energy might not produce any electricity when it is needed most and might produce more electricity than needed at times, as it is most severely shown in the negative price occurrences of Denmark and Germany (Unger et al. 2017; Fanone et al. 2013). Increasing the share of the wind penetration in the energy supply of a grid network also increases the dependency on the availability of wind energy sources.

Electricity is a largely non-storable commodity. Electricity consumption must always be equal to production in that moment of time (Yamin et al. 2004). Failing to comply with this simple rule would result in would result in technical problems in the grid and even might lead to blackouts. Managing the production of energy power plants is therefore essential in order to match it with consumption.

Energy technologies are classified into two groups. While wind and solar energy technologies are “intermittent” and cannot be controlled by the system operator, fossil fuels and nuclear are “dispatchable” energies, because they can be controlled by the system operator (Joskow 2011). The control of the dispatchable technologies enables them to generate when the energy is most needed, when other production is insufficient. In this way, they can be traded for higher prices. Dispatchable technologies can also function as a baseload if other sources are not available.

Wind power's inability to manage production times creates both abundance and failure, which has set up a dynamic environment for the electricity market and has impacted all its participants. A deeper understanding of the electricity market would create a clearer picture for wind power's place in the energy mix.

2.3. Electricity Markets

2.3.1. Deregulation of the Markets

In most countries of the world, the electricity market formerly consisted of traditional highly regulated procedures have in the most recent decades been restructured following a free market mindset (Amjady & Hemmati 2006). Deregulation of the electricity market has been introduced in many countries in order to let the market manage itself and encourage individual actors to increase the efficiency of the market. The deregulation process is mainly aimed towards achieving a lower cost of electricity by increasing competition among the players of the market. However, the participation of several new players, brokers, and aggregators has resulted in a complex environment.

Price variability is one of the properties of a deregulated electricity market. Introduction of renewable energy systems also increased the volatility of the electricity prices due to their independent nature and inability to be forecasted reliably. The main reasons for this variability, aside from their unpredictability, are generation capacity, demand differences and transmission issues (Benini et al. 2002). Uncertainty inf generation and the uncertainty in prices have been the main issue for these technologies but especially for the wind energy (Eric et al. 2016).

A free market works autonomously. Lack of energy during the peak consumption period financially encourages the electricity producers to generate more energy. Different behaviors of prices and unexpected price spikes occur in the regular operation of the electricity market. It became important to be able to forecast the electricity prices for consumers to be able to use lower priced electricity and for producers to be able to have a predictable income to sustain their financial plans. Electricity distribution companies are especially vulnerable to changing electricity prices, because their consumers are more likely to subscribe to fixed kWh prices and they cannot directly pass the differences between forecasted and real prices to their customers (Joskow 2002).

2.3.2. Supply and Demand Market

There are two main types of contracts in the electricity industry. Pool contracts are handled in the electricity market. Sellers and buyers bid their prices into the supply-demand curve and the point of intersection becomes the value of that hour-block's price. On the other hand, parties can sign a bilateral contract, in which generators can sell their electricity months in advance with a fixed price. By having a predictable electricity price, both buyer and seller reduce their risk from the varying spot prices and achieve an increased financial security (El Khatib & Galiana 2007). However, the behavior of the market of the pool contracts sets the trends and average values of the bilateral contracts, therefore in financial terms they are defined as derivative contracts. Effective forecasting allows electricity producers to manage their production operations more efficiently by enabling them to consider their material and operational costs and make better production decisions. If the electricity prices of the next day are available, a consumer can also plan the usage of electricity by either arranging business operations or on-site electricity production, alternatively integrating it with smart grid technologies. Electricity producers can decide to set their prices close to the predicted spot price if it is feasible, thus maximize their produced and traded electricity output (Ramsay & Wang 1997).

After the deregulation, generated energy can be traded in these different types of markets (Morthorst et al. 2010):

- Bilateral electricity trade: Parties outside of the exchange market participate in the trade and the details are not public.
- Day-ahead market: Bidding closes one day before when the actual physical trade happens. Supply and demand are synchronized in the market and the results are public. Matching the demand and the supply is done mostly in the day ahead market. The auction is done one day before and system operator decides whom generates how much according to the supplier's bids and generation amounts. Every energy producer and trader is given the same information in these auctions.
- Intraday market: In this market, parties can trade their contracts with each other between the end of day-ahead market bidding and the regulating market.

- Regulating power market: This market deals with the imbalances that occur due to the differences between planned day-ahead market production and real demand. The regulating market settles right before the physical deliveries.
- Balancing market: This market deals with the past imbalances of the last 24 hours.

In 2009, approximately 45% of the energy produced in Nordic countries was traded on the Nord Pool ELSPOT spot market, while the rest consisted of long-term bilateral contracts. By contrast, Denmark's volatile wind industry's spot market participation is up to 80% (Morthorst & Awerbuch 2009).

The majority of the electricity prices are decided in the day-ahead market, where the volume of the trade is greatest. Types of energy generation generally act according to their merit order in the market. Merit order shows in which sequence the available energy resources are to be used. Marginal costs of each type of energy create the merit order the market follows, so that the demanded energy is generated with a minimum amount of cost (Morthorst et al. 2010).

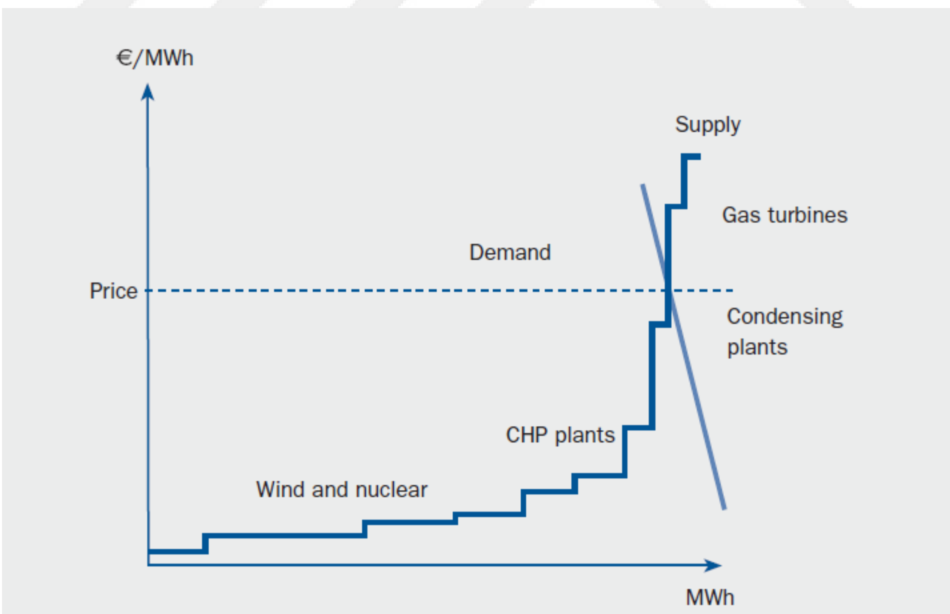


Figure 1: Merit Order Effect with Different Generations (Morthorst & Awerbuch 2009)

In figure 1, general merit order of different electricity sources is presented (Morthorst & Awerbuch 2009). Renewable energies such as wind, solar and run-of-the-river hydropower have high capital costs and almost no marginal production costs. Therefore, they participate in the market independent of the settlement price and they are first generators in the merit order. The impact of the merit order-effect of solar energy on spot prices is especially higher because while both wind and solar energies' production is intermittent, solar energy's production is during daytime hours, where the consumption and therefore displaced fossil fuel usage are higher. Reservoir hydropower is strategically dependent on the other factors; such as time, availability of other generations, and available water reserves and can therefore be placed in any position on the merit-order. Even though operational costs of the nuclear power are not low, stopping and starting the plants have higher costs. For this reason, nuclear power continuously feeds into the network independent of price. Fossil fuels are the last in merit-order with natural gas having the highest marginal costs (Gourvitch 2014; Sensfuss & Ragwittz 2007).

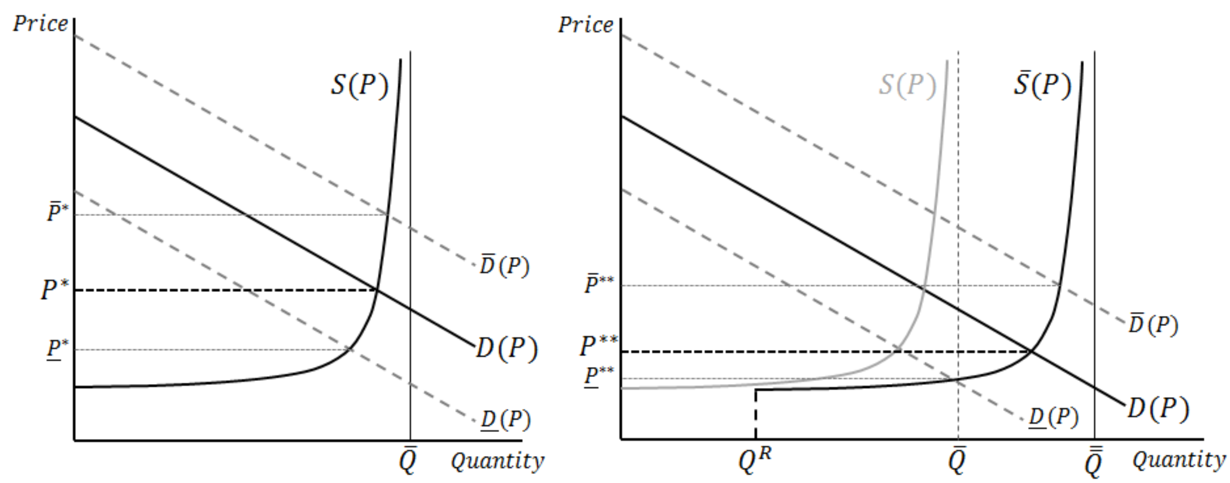


Figure 2a-b: Electricity Price-Quantity Curves. First picture is without wind energy generation. Second one is with wind energy generation (Eric et al. 2016)

Figure 2a shows the case, when there is no wind energy generated. The demand curve is shown with a negative slope because of its price sensitivity and its various forms in different times are denoted as $\bar{D}(P)$ which is higher demand and $\underline{D}(P)$ is the lower demand. The point where the demand line and supply curve intersect is the market's settlement point. The price of the whole traded volume is the settlement price. In figure 2b, wind power is added to the equation. Due to its almost non-existent marginal cost, wind energy enters the merit order first. Therefore, the supply curve shifts to the right, changing the intersection point of demand and supply and reducing the price value of the electricity. In this simple model, we may see the impact of the wind energy theoretically in different demand values. When demand is low, the supply curve is flat and additional wind energy generation does not change the price much as seen from the $(\underline{P}^{**}, \underline{D}(P))$ point, however when demand is high it changes greatly as seen from $(\bar{P}^{**}, \bar{D}(P)$ (Eric et al. 2016).

2.4. Electricity spot price prediction models

There are several different price forecasting techniques currently used in academics and industry. However, studies do not agree on the categories for these techniques (Weron 2014). Methods discussed in this section are the aggregate of the most commonly defined methodologies and the focus will mostly be on the computational methods. While short term forecasts are important for the market efficiency and market players, mid-term and long term forecasters are more oriented toward budgetary, planning and resource management purposes (Weron 2014).

2.4.1. Multi agent models

Models simulate the interaction of energy producers and traders with each other using game theory applications and find the balancing price while matching the supply and demand. The Nash-Cournot framework is the most famous model in this group, even though its popularity is diminishing. Bunn argues that game theory and econometric methods, defined below, are balancing-out, equilibrium methods and they are not fit for daily forecasts (Bunn 2000).

2.4.2. Fundamental models

Fundamental models focus on physical and economic aspect of reality in a more deterministic way. In fundamental models, every plant is specified with its type, production, capacity and efficiency. All the units, flows and capacities are defined if possible. Therefore, they are highly data intensive approaches. They are often used in mid to long term analyses (Keles et al. 2011).

2.4.3. Reduced form models

Statistical properties of electricity prices are characterized and combined with risk management theories. The goal of the reduced form models is not to forecast a specific hour's price, but to define those characteristics, such as price distributions, price dynamics and correlations (Weron 2014). The Markov switching model is the most common in this category. It is more flexible in the stationary time series in the sense that it can contain multiple state definitions. Each point in time belong to one of those states and the specific function for that state is used for the calculations of that point of time (Kuan 2002).

2.4.4. Statistical models

Econometric models and statistical techniques are used in order to determine the electricity prices analytically. Statistical models are the common tools for electricity price forecasting. Statistical approaches prove themselves by capturing the patterns of changes in prices considering the seasonality of energy generation (Aggarwal et al. 2009).

One of the most used statistical models is the autoregressive integrated moving average (ARIMA) model. Most of the varying types of autoregressive (AR) models require stationary data and use the price change and variance in the previous N time step and also the mean of the all series in an equation to predict the current time step’s variance. They are mainly used in weekly average prices predictions, where the influence of the price spikes is lesser. The weekly mean error of ARIMA models that are used in Spanish and Californian electricity markets are around 10-11% (Amjady & Hemmati 2006).

Generalized autoregressive conditional heteroskedasticity (GARCH) considers the variance of the time series changing across time in contrast to AR models’ constant variance assumption. Even though GARCH models can account for the varying price behaviors of the electricity market better than the AR models, Amjady et al.(2006) argue that both GARCH and AR based models are more useful when the variations are low. The error rate of these methods increases quickly as fluctuations and rapid changes occur.

AR, ARIMA and GARCH are linear techniques and cannot accurately account for the nonlinear behavior of the prices. They mostly need the time series to be converted to a stationary form, which might not always be possible (Weron 2014).

2.4.5. Computational intelligence models

A simulation is created using one of the machine learning concepts such as artificial neural networks(ANN), support vector machines or Bayesian networks so that it learns how the market behaves by guessing the electricity price and correcting itself for the later trials. The strength of the computer intelligence methods is their aptitude to manage non-linear effects and sudden spikes.

As a result, computer intelligence models derive better results in the day ahead market (Weron 2014).

The main advantage of an ANN compared to other methods is that neural networks can track nonlinear behavior and can be adjusted to any continuous non-stationary data because of their use of universal learning methods (Amjady & Hemmati 2006). Multilayer perceptron (MLP) neural networks are better for tracking general trends. Radial basis function (RBF) neural networks can notice local differences more accu-rately due to the usage of the radial distance between features as its basis. If N different features such as consumption, wind production etc. are used, each sample in the time series occupies a point in the N-dimensional coordinate space. Radial distances are calculated by taking the Pythagorean distance between the predicted values point and every other sample's coordinate (Broomhead & Lowe 1988). Then, the final price is predicted by using the previous prices and radial distance to those prices.

It has been argued that artificial neural networks will be essential in demand, supply and price forecasting due to their ability to understand non-linear behavior. But they need to be integrated with conventional time series methods for precise forecasting (Bunn 2000).

A three-layered feed-forward system with back propagation has been used in the Victorian electricity market in Australia in 1997 with a daily mean square error of around 15% (Szkuta et al. 2002). Szkuta et al. (2002) also points out that their ANN network outperformed commonly used linear regression methods from that time.

Ramsay & Wang (1997) used a four-layered network with the sigmoid activation function using the day of the week, load, settlement period index, settlement table and prices of the previous days in the UK Power Pool and achieved a 10-18% mean average percentile error (MAPE) depending on the day of the week. The authors also argue that selection of hidden layers and number of neurons is an issue and must be studied further to achieve models with better results. In another study, the same features Ramsay et al.(1997) used are applied to the 2010 Turkish Energy Market data and the results of an ARIMA model and a three layered ANN with hyperbolic tangent as the activation function were compared (Kölmek & Navruz 2015). For the three weeks forecasted, the MAPE error of the ARIMA was 15.6 %, while the error of the ANN was 14.15%. The authors supported the idea of using hybrid models in the future of the electricity price forecasting.

2.4.6. Overview of the models

Even though five different types of price forecasting models exist, statistical methods and computer intelligence methods are primarily used in electricity price forecasts as they seem to give better results than the others (Shahidehpour et al. 2002).

It has been asserted that most of the methods used in forecasting electricity prices are fundamental models. They can all accomplish excellent results however they require extensive data (Keles et al. 2016).

The price in the electricity market's supply and demand cycle are dependent tasks. As Bunn (2000) points out loads and prices are "mutually intertwined activities". Price curves usually share the same trends as loads, however electricity spot prices get affected by numerous other factors. While demand side (load) forecasting techniques are developed and require special emphasis on weather forecasts, research on supply side forecasting is not well developed and requires additional study (Amjady & Hemmati 2006).

As Weron (2014) points out, computational intelligence methods are claimed to be superior by computer science and electrical departments, while statistical models are held as superior by economics departments. Therefore, experience in developing these models is of the utmost importance. Selection of the methodology and the detail given to it highly impacts the outcomes of the studies.

There are also some studies which use more than one category of approach to calculate electricity prices. Hybrid models of computational and econometrics methods might be superior to others through the combination of the precise averaging of econometric models and computational methods ability to recognize price spikes (Kölmek & Navruz 2015).

A major factor for a well-structured model is the variability and availability of different parameters. Some models could yield unsatisfactory results, but they could also give comparatively better results with additional detailed information (Shahidehpour et al. 2002). Therefore, it should also be noted that the true nature of a model cannot be understood effectively unless the information is satisfactory.

2.5. Impact of renewable energy development on electricity prices

There are several different studies which investigate the impact of wind energy generation on electricity prices. Even though they have different assumptions and methodologies they show reduced electricity prices, which was not unexpected. The degree of the reduction changes with the studies reviewed in this section and also with the market which was researched. Among the several studies presented in this section, none of their results show indifference or increase in electricity prices due to wind energy development.

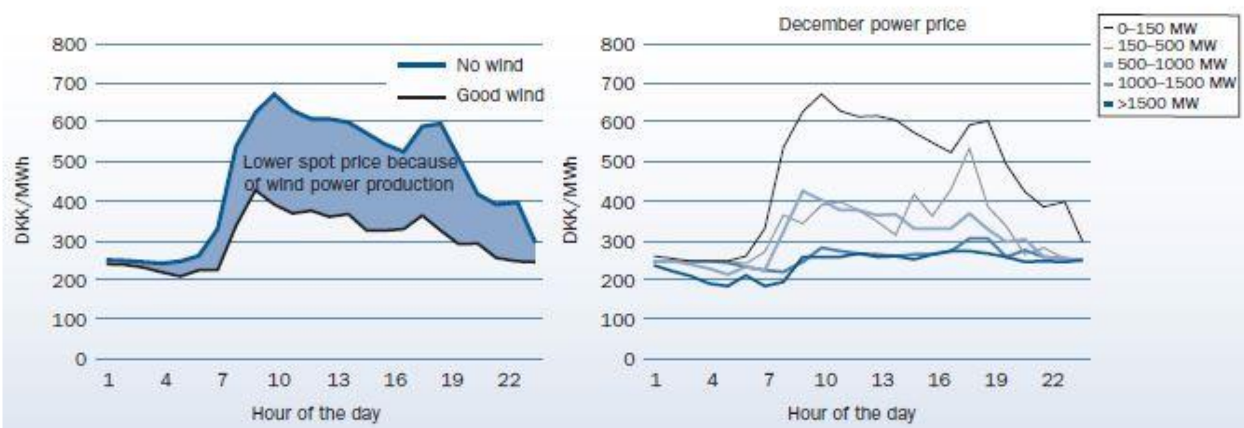


Figure 3: Impact of wind generation on electricity prices on West Denmark in December 2005 (Morthorst & Awerbuch 2009)

Figure 3 shows a study of the impact of wind energy generation electricity prices in the western Denmark region in December 2005 (Morthorst & Awerbuch 2009). The authors assume five different levels of wind generation in their analysis. While early in the morning and late evening, in the off-peak hours, the wind generation does not change the hourly prices that much, the peak hour price in midday decreases greatly with wind generation. Overall, it can be seen that higher wind generation results in lower electricity prices in this study. These findings agree with the investigation of merit order supply-demand curves in Section 2.3.2. The impact of wind energy is higher when the demand is high and lower when the demand is low. Further increases in wind energy generation might also decrease the prices more in the peak hours (Morthorst & Awerbuch 2009). Additionally, it should be noted that these prices are monthly averaged values; therefore, there could be differences in particular days.

The United Kingdom has a renewable energy share goal of 15% by 2020 (International Energy Agency 2012). Another study which followed a particular renewable energy scenario defined by the authors concluded that the electricity prices will be reduced by around 4 £/MWh in 2025 due to the increase in wind energy penetration, although the authors argue also that the derived results will be highly sensitive to the future oil prices and if they differ from author's estimations (Lupo & Kiprakis 2016).

Another study investigated the impact of wind energy development on the Irish electricity prices by using two different methods: an econometric model and a multi-agent model (Denny et al. 2016). The same hourly data from 2009 is used as input in both of these models, which worked independently of each other. The econometric approach showed a savings of 3.40 €/MWh for each additional GWh of wind energy production, while the unit commitment approach resulted in 4.54 €/MWh. Even though, the results between two methods show fairly good agreement, they are higher than the results of other west European energy markets.

In a study on the Netherland's energy market, four different scenarios are given, and the highest price impact found in the outcomes of these scenarios is 2.77 €/MWh. A Belgian study included the forecasting load errors in wind energy generation in the day ahead market and included a smaller simulation which figured the wind energy generation inside its price calculating simulation and accounts for the mistakes in generation amounts (Delarue et al. 2009). The authors concluded that the forecasting errors in energy generation did not significantly impact the prices.

In the south European energy market, it is harder to investigate the impact of wind generation without including solar energy into the analysis, as is the case in Germany. In an Italian case study of renewable energy's impact on the energy market, the results varied greatly each year (Gullì & Balbo 2015). The authors argued that either the econometric model or the simulation is misleading, and the Italian energy market is 'interesting' due to sudden sharp increases in PV generation. Another study showed that the impact of wind energy on the market could be isolated in a complex environment such as Spain with a significant amount of solar generation by using advanced forecasting methods (Geidel & Zareipour 2013). Their study used a similar-day method in order to filter out the differences in days and used the cleaned data in a support vector machine, which is a computer intelligence model. They concluded that the effect of wind energy generation is maximized in peak hours, where the spot prices are highest.

Germany is one of the leading countries in renewable energies, meeting 22% of its electricity demands with renewable energy in 2011 (Policies & Countries 2013). Compared to the countries with low wind energy penetration, the impact of wind energy generation could be observed better in Germany, where the wind penetration is 8.1% of the electricity mix. In one study, the statistical regression model ARMAX is used from the beginning of 2009 to the end of 2013 with the conclusion that 10% of increase in wind energy decreases the spot prices by 1% of what they would have been a given day.(Benhmad & Percebois 2015). This resulted in a 1 €/MWh decrease in spot prices per additional GWh of wind production. The authors also remarked that while the additional generation reduces spot prices, the effect is not full because of the additional costs of balancing fluctuating wind energy. Even though this situation is valid for all the cases, not all research includes this assumption. Another study investigated the years 2008-2012, but included both solar and wind power's effect on electricity prices (Cludius et al. 2014). They used a similar regression model and estimated that each additional GWh of renewable energy generation decreased the price of electricity by 1.10 to 1.30 €/MWh, which correlates well with the previous study considering solar energy generation reduces prices more than wind due to peak electricity prices during the daytime. A comparative study for 2004 to 2005 without any forecasting also suggested a 1.90 to 2.70 €/MWh decrease per additional GWh (Neubarth et al. 2006). While another study, which uses an alternative autoregressive statistical model, showed that an increase in wind energy penetration resulted in a decrease in price volatility in Germany between years 2008 to 2012 (Ketterer 2014). In contrast, assuming an inelastic demand (meaning that demand is fixed and is not affected by price change) resulted in an increase in price volatility for Germany (Nicolosi & Fürsch 2009). However, the current balancing effect of increased wind energy penetration negates the deficit and excess amounts against each other and decreases the variation in electricity prices. (Eric et al. 2016)

Using the historical data from the 2006 German electricity market, wind energy generation versus no wind energy generation scenarios are compared using the agent based PowerACE model (Sensfuß et al. 2008). It resulted in a difference of 7.83 €/MWh between two cases with a renewable energy load variance of 4.4 to 17.7 GW. In another study, the amount saved by the community due to wind energy is investigated instead of wind energy's impact on electricity prices (Weigt 2009). Weigt assumed a case where there is no energy import / export and no other renewable energy generation other than wind energy and his analysis showed that Germany saved 10 €/MWh due to wind energy penetration during the years 2006 to 2008.

Denmark met 20.2% of its electricity demand with wind energy as of 2010 and since then its wind capacity has continued to rapidly increase (IEA 2011). The impact of wind energy should be more apparent in the region, where wind penetration is high. In a 2008 analysis, the renewable subsidy scheme of the country led to an increased consumer price of 0.05–0.6 c€ (Munksgaard & Morthorst 2008). But this increase was actually balanced by the reductions in the electricity market prices. A study about the impact of wind power generation variability in Denmark in the Nord Pool market accounted for the market coupling and balancing of the unavailable power with the hydro energy of Norway in an ARMA-GARCH model to assess the impact of wind energy (Li 2015). It was found that the wind power reduces the spot prices and also decreases the volatility of the Nord Pool day-ahead market. Price elasticity related to the wind energy is calculated as 0.03 in this study.

In the above-mentioned research, wind energy generation is analyzed in closed systems. Some of the studies assume the transaction of energy through the borders via import-export but do not consider the imported wind energy when it is generated abroad. Therefore, increasing the size of the investigation domain would lead to a better analysis of wind energy's impact on electricity prices. However, it also increases the complexity of the problem because of the unavailability of data and also, more importantly, different energy policies.

2.6. Data Selection

ANN creates a relationship between input and output. The quality of the resultant prediction relies on the selection and the quality of input data. Selection of the data and its implementation is found to be highly important for electricity price calculations (Shahidehpour et al. 2002). While any feature can be used as an input to ANN, the features that are known to have a high impact on prices such as demand are essential for an ANN model. For example, for an ANN with four layers, the day of the week, load, settlement period index, settlement table and prices of the previous days were chosen as features (Ramsay & Wang 1997).

Selection of the features that are going to be used in electricity price forecasting is immensely important. While some of the studies found in this literature review have distinctive data, most of them share common features. The majority of the forecasting studies found use consumption and production data, because these features have an essential role in settling the market clearing price and forming the price decisions of the market (Bunn 2000). In day-ahead market price predictions exact values of production and consumption are used, whereas longer term studies might use mean averages or moving averages in a specified time interval.

Szkuta et al. (2002) managed to achieve 15% daily mean error in their predictions by only using production, consumption and price data.

Furthermore, conventional power generations use fossil fuels in order to generate electricity. The cost of these fuels indirectly affects the price of the electricity. Usage of Henry hub gas prices and Nymex oil prices are common in electricity price forecasts and should be included (Amjady & Hemmati 2006).

Keles et al. (2016) has used an ANN by incorporating production and consumption data and also included gas prices, carbon prices, renewable feed-in tariff and demand forecasts for electricity, and achieved a 4.67 €/MWh mean absolute error in 2013 for Germany EPEX spot price predictions.

In an electricity price forecast applied to the Germany EPEX market prices, it has been found that the price movements are different in workdays. Therefore, the information about whether it is a weekday, a weekend or a holiday is included in the forecast (Ziel & Steinert 2017).

Last of all, another key factor that physically impacts the arrangement of the market is the temperature. Most of the impact from temperature is on the load demand variable or on some of the production variables. Therefore, when both demand and supply is incorporated into the model, the impact of the temperature is indirectly included (Ramsay & Wang 1997). Authors also used settlement period index and settlement table number in their study. Settlement period index is the chronological number of the settlement hour in a one-day time period, whereas settlement table number is a binary value that indicates whether the planned production is higher than the planned consumption.

3. Methodology

3.1. Artificial Neural Networks

3.1.1. Introduction

Main reason for the use of a day ahead- market model is to be able to reflect the price dynamics of the day ahead market. By using physical variables such as demand and production, this model will translate the available information into a price equilibrium. Later on, developed model will process varying wind production inputs and produce their corresponding prices. If the market conditions that the model is trained on is assumed to be similar in future, we will have an estimated future electricity price by using the Sweden's long-term wind power production forecasts.

Artificial neural networks (ANN) are loosely inspired by how a brain works. In an ANN, several neurons are defined and connected to each other. All information propagates itself from one neuron to another. They are commonly used in image classification, data compression, natural language processing and time series regression (Muayad & Irtefaa 2016).

ANNs are computationally intensive. Development of faster computers in the last decade is one of the biggest reasons for their increased popularity. While most of the modelling approaches are fit to a specific problem, ANNs have proved to be a universal approximator (Hornik 1991), and therefore they can be used in any type of problem. They can adapt to nonlinear behaviors in contrast to conventional methods (Bunn 2000).

Neural networks are combinations of neurons in several layers. In each neural network there is an input layer, an output layer, and at least one hidden layer in-between (Schmidhuber 2015). Interaction of neurons between the hidden layers can generate abstract relationships between input and output. There are several different versions of artificial neural networks. This thesis will focus on multilayer perceptron (MLP) neural networks. In MLP, all neurons in one layer are connected to every other neuron in the next layer, thus forming a network. There can be any number of hidden layers or number of neurons in a layer. However, they need to be suitable for the problem because of increasing complexity and requirement of extensive data (Haykin 2009).

Neural networks consist of two parts: forward propagation and back propagation. Forward and back suggest the directions of the calculations.

In forward propagation, information from the input will be propagated through the calculations of the hidden layers and reach the output layer. In the output layer the looping calculations in hidden layers come to an end and generate the prediction.

In back propagation, the error between the predictions that were calculated in the forward process and the real target values will be calculated with a predefined error function, in our case mean absolute error. The results of each forward propagation in each iteration will be added to a loss function. The primary aim of the model is to minimize this loss function. It will be achieved by taking the derivative of the loss function with respect to the multiplication coefficients between the neurons and bias coefficients in neurons. The error will be backpropagated through the layers to each coefficient. At the end of back propagation new error coefficients will be generated that would result in a lower loss function value.

3.1.2. Neural Network Forward Propagation

Each layer in a neural network consists of neurons. These neurons are only connected to the neurons in the next layer in a multilayer perceptron as shown in figure 4. The neurons are the calculation points of the network architecture. Information coming to them is processed via an activation function. The activation function is aimed to dampen the information to create a nonlinear impact. The most commonly used activation function is the sigmoid function that is shown in equation 1:

$$\sigma(x) = \frac{1}{1 + e^{-(x)}} \tag{1}$$

The sigmoid function has a limited output between 0 and 1. Figure 5 shows how quickly input values converge to either 0 or 1.

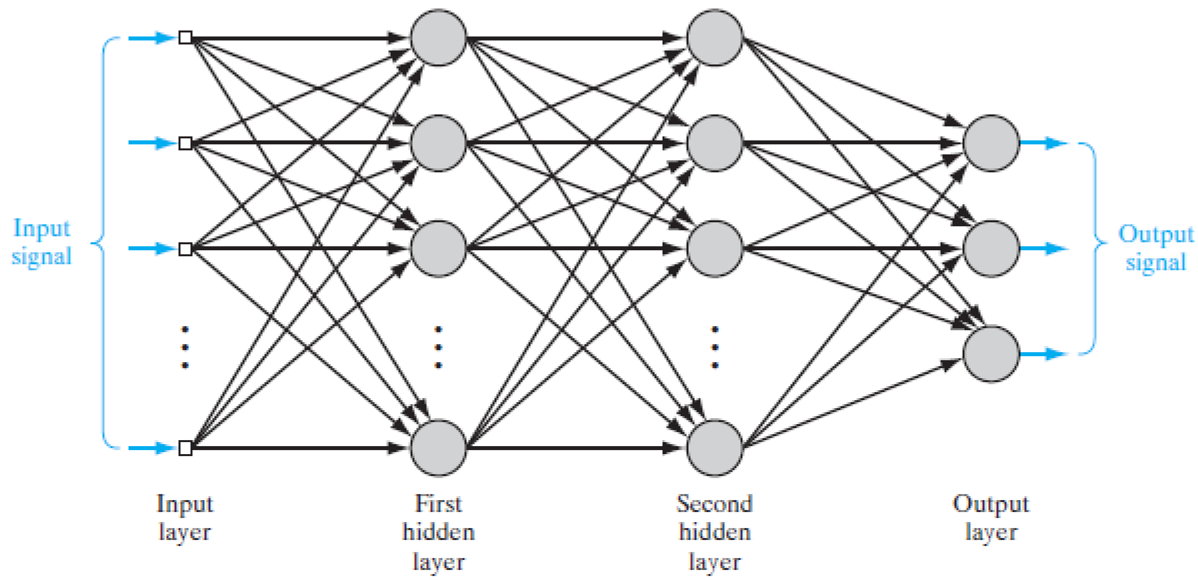


Figure 4: Configuration of a MLP ANN (Haykin 2009)

In order to have a complementary notation over the whole network, input points are also thought to be neurons with activation functions, where the input is multiplied by 1 to give the same input value as a result. Each input neuron shown in figure 4 represents different variables that were chosen as an input. The image representation is the calculation of one sample hour. The same calculations will be carried over to the rest of the dataset.

The arrows between the layers are the multiplication coefficients θ. Each coefficient is different from each other. These coefficients multiply the output of neurons and carry the result to the neuron in the next layer in equation 2. Notation $\theta_{i,j}$ implies the value of the multiplication coefficient of previous layers i^{th} neuron to the current layers j^{th} neuron. After the summation of multiplications of neuron outputs with $\theta_{i,j}$ coefficients, a single bias term will be added to the sum of multiplication to the next layers neuron in order to limit the variance of the model.

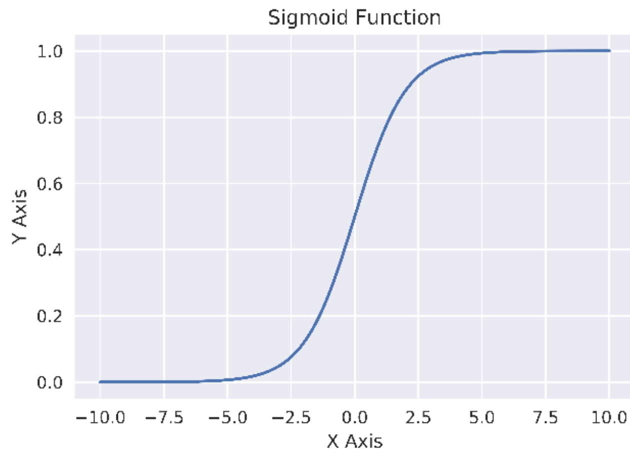


Figure 5: Sigmoid Function

$$a_j = \sum_{i=1}^{N_1} X_i \theta_{ij} + b_j \tag{2}$$

, where a_j is the total input to the neuron. The sigmoid activation function of the neuron will be applied for the output of the neuron.

$$h_j = \sigma(a_j) \tag{3}$$

After obtaining each neuron's output in the first layer, by using h_i instead of X_i, equations 2 and 3 will be iterated to the input of the output layer (Haykin 2009). Because the problem this thesis deals with is a regression problem, using the sigmoid activation function is not possible in the final layer. It would give results between 0 and 1, which is better for classification problems. Therefore, activation function of the neurons in the final layer is the linear function that is used in inputs, which does not change the input value. Predictions are the results of the output layers neurons.

In the first iteration all the coefficients will be randomly assigned with the normal distribution, which would mean that the model will be randomly guessing in the first predictions. Corrections of the coefficients will be handled during the back propagation process.

Neural networks may have any number of hidden layers. If the hidden layer number is high, the network is categorized as a deep neural network. The increase in the number of layers generally requires a higher availability of data. There is no consensus on deciding the number of neurons in a hidden layer either (Sheela & Deepa 2013) and it will be determined through the performance of the various models on the cross validation data. However, one persisting idea is that in each hidden layer the number of neurons must diminish in order for the information to create a bottleneck in the later layers. This would help to generalize the understanding of the model, instead of mimicking individual cases. The ANN that performed best in the cross-validation set consists of 38 input neurons in the input layer, three hidden layers with 500, 250, 80 neurons respectively and a final output layer with 4 neurons. Each output neuron corresponds to the spot price of electricity for regions SE1 to SE4.

3.1.3. Neural Network Back Propagation

The loss function of the ANN model is mean absolute error, which is defined in equation 14. If the derivative of the loss function with respect to θ_{ij} in a specific layer can be found, how much the increase of that coefficient would affect the loss function will be understood. If the coefficients are updated in small steps depending on the loss function's partial derivates with respect to the coefficients, the results of the loss function would converge to smaller values.

The chain rule is a method that is used in order to find the derivatives of the composite functions. By taking the derivatives and applying the chain rule on the loss function, the derivatives of the coefficients in the last hidden layer are found. Then the loss errors in each particular neuron in the last hidden layer are carried over to the previous layer using the derivatives, thus the information will flow back from the output layer to the first input layer's coefficients, hence the name back propagation.

Because the neurons of the output layer do not have sigmoid functions, the loss function can be directly transferred to the weights of the last hidden layer. As an example, considering figure 4's 2 hidden layer configuration, the loss error with respect to a coefficient θ_{ij} that connects neuron i from the first hidden layer to the neuron j in the second layer can be calculated as:

$$\frac{dL}{d\theta_{ij}} = \frac{dL}{dp} * \frac{dp}{dh} * \frac{dh}{d\sigma(a)} * \frac{d\sigma(a)}{da} * \frac{da}{d\theta_{ij}} \tag{4}$$

, where derivative of the loss function is:

$$\frac{dL}{dp} = \begin{cases} +1, & p > y \\ -1, & p < y \end{cases} \tag{5}$$

Furthermore, the derivative of the sigmoid function is as:

$$\frac{d\sigma(a)}{da} = \sigma(a) * \left(1 - \sigma(a)\right) \tag{6}$$

Each coefficient will be updated in a similar way using the above equations. This process optimization of the model parameter by taking the derivative of the loss function is defined as gradient descent (Goodfellow et al. 2016).

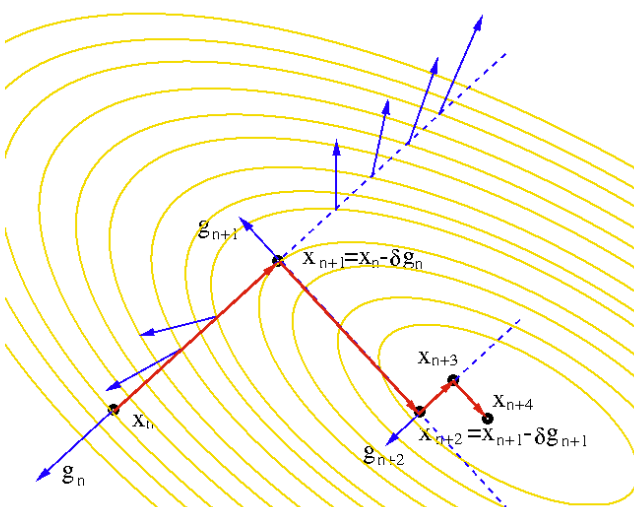


Figure 6: Gradient Descent Loss Topography (Wang 2015)

In figure 6, the loss error counters are drawn. The region in the bottom right of the graph is the local minima. By taking the gradient and reversing it with a predefined magnitude, the model went from loss error position x_n to x_{n+4} in four steps. Similar to the figure, when all of the coefficients are updated in the neural net a new prediction will be calculated using forward propagation and the new lower error will be propagated in many iterations. The result of these iterations will start to converge and would form a graph similar to that in figure 12. It will start to have lower bias and higher variance as the iterations continue. Due to the fact that back propagation, the way the model learns, is applied only to the training data, feed forward predictions of cross validation data will start to generate varied results with higher variance as the iterations increase.

3.1.4. Ridge Regression Coefficient Regularizer

As it has been noted in Section 3.2.3, ridge regression will be incorporated into the model in order to be able to generate more generalized results while using a complex model. The term is also referred to as "weight decay" in machine learning terms since it suppresses the weights closer to zero (Hastie et al. 2009). Some other popular regressions such as LASSO diminish coefficients to zero, but ridge regression converges the coefficients to zero by penalizing the weights. This property was important in the decision of the regularizer selection due to the fact that non-optimum values of regularizer parameter λ would lead to more forgiving results.

$$L_{new} = \frac{1}{n} * \sum_{i}^{N} |y_i - p_i| \; + \; \lambda \sum_{i=o}^{N} \theta_i^2 \tag{7}$$

Ridge regression terms are added to the error loss function shown in Section 3.2.1. as a separate term as shown in Equation 7. After this implementation, θ coefficients are constrained by the additional bounds set by the ridge regression term. Now the model has to minimize the original loss function and also the ridge regression term. In order to minimize the ridge term, the model needs to find θ coefficients closer to zero. Higher values of θ might generate highly varying results, thus adding the ridge regression term ensures that our model is closer to being biased than having variance. Ridge regression is also termed as L2 regularization (Hastie et al. 2009).

3.1.5. Additional Network Settings

A few optimizations have been implemented in the model for quicker computation times that would reach a local optimum faster. Instead of using the input variables' original values, each of them are normalized between -1,1 by substracting the mean of that variable and dividing the resultant to the standard deviation. It would also create more balance in the distribution of the coefficients. The coefficient that is connected to the high value of the consumption numbers would be more heavily penalized in ridge regression than the gas price variable which is a few dollars. Therefore, all inputs are normalized. The same normalization is also applied to results of layers, which is a method called batch normalization.

Additionally, in each iteration cycle some percentage of the neurons in the hidden layers are disabled randomly in order to prevent over-fitting (Shen et al. 2017). This would result in the model to catch the information stored in one neuron to share it with other neurons in the same layer. This was also another attempt to address the generalization requirement of the neural network.

Calculations of each neural network propagation are done in the python programming language with the Keras package using a tensorflow backend on a K80 GPU.

3.2. Data Selection and Exploration

3.2.1. Data Selection

In this section, the features that are used in this model will be presented. Their categories are production, consumption and price data. In total, 43 different features are given as input with their time period ranging between 2013.01.01 and 2017.04.21. Most of the fundamental consumption and production values except hydro reserves are in an hourly format with MWh as their unit.

- Hourly wind, hydro, nuclear, thermal production values of Sweden's four electricity regions in MWh separately
- Hourly consumption values of SE1, SE2, SE3, SE4
- Hourly Elspot day-ahead prices of SE1, SE2, SE3, SE4 and the Nord Pool system price
- Hourly wind energy production values of DK1 and DK2
- Hourly total production and consumption values of Finland, Norway, Estonia, Lithuania, DK1, DK2
- Weekly total hydro reserves of Sweden and Norway
- Hourly net total export value of Sweden
- Daily OPEC crude oil price
- Daily Henry Hub natural gas price

Weekly and daily data are interpolated into hourly sections in order to match to the rest of the data. Additionally, two more variables have been created synthetically.

- Weekday. It is a binary value and returns 1 if it is a weekday, 0 if it is a weekend.
- The average prices of the SE1, SE2, SE3, SE4 regions from 24 hours previously. Even though Swedish spot prices are mostly equal to each other except during peak time congestion, the detail of the differences has been attempted to be included. The reason for selection of a 24 hour delay is that it has the highest correlation between the original price values as seen in the Figure 7. In the figure, the Pearson correlation of the price from the previous timestamps to the current price is shown, which is calculated from the training data. X-axis shows the time lags, and y-axis shows the correlation, which is dimensionless. Correlation of 1 means the highest correlation, -1 is negative correlation and 0 is no correlation at all. When time lag is 0, it shows the highest correlation of current price to

itself which is equal to 1. As the time lag increases, correlation of current price to the previous timestamp's is decreasing up till time lag equals to 24. The figure shows that current prices are highly correlated with the price from 24 hours ago. Every multiple of 24 hour prices follow a similar trend in a diminishing way. That is the reason the price from 24 hour earlier is used as a variable in the calculations. Even though the time lags of 1 and 2 hours have higher correlations than 24 hours', they cannot be used as a variable because the prices of these hours are not known yet.

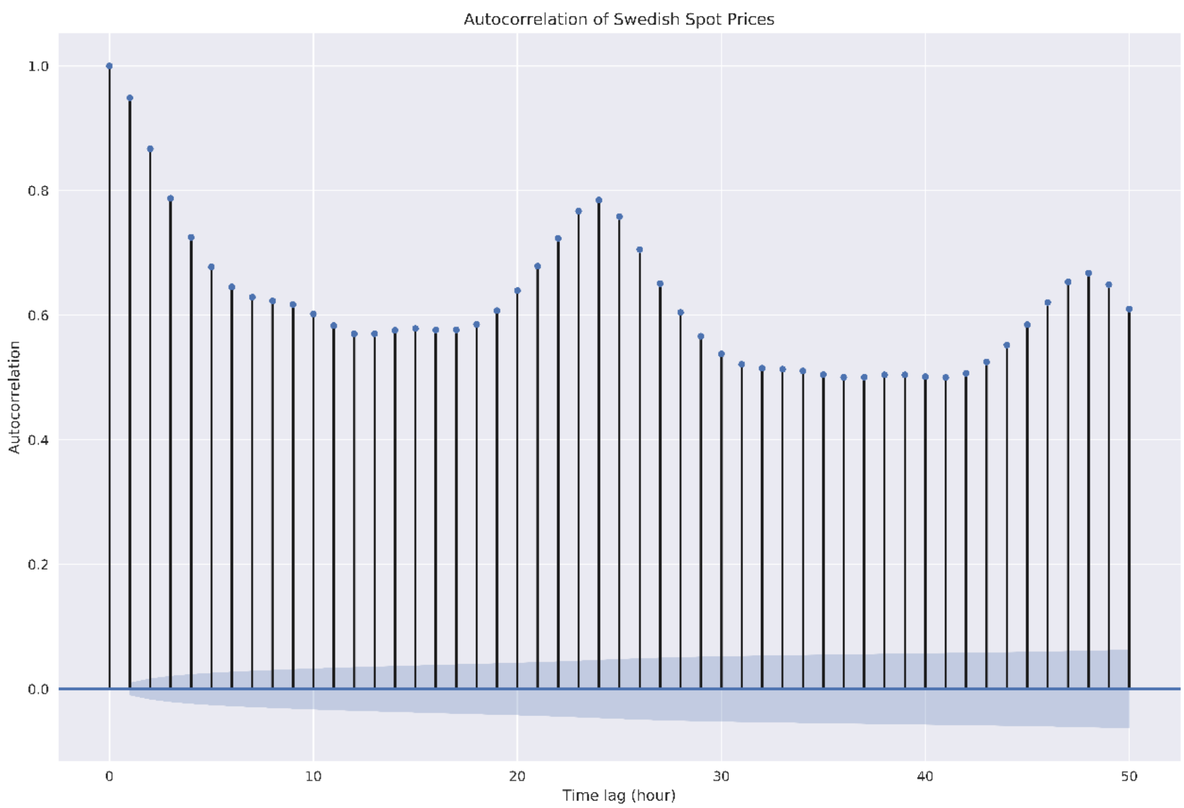


Figure 7: Autocorrelation of the Spot Prices

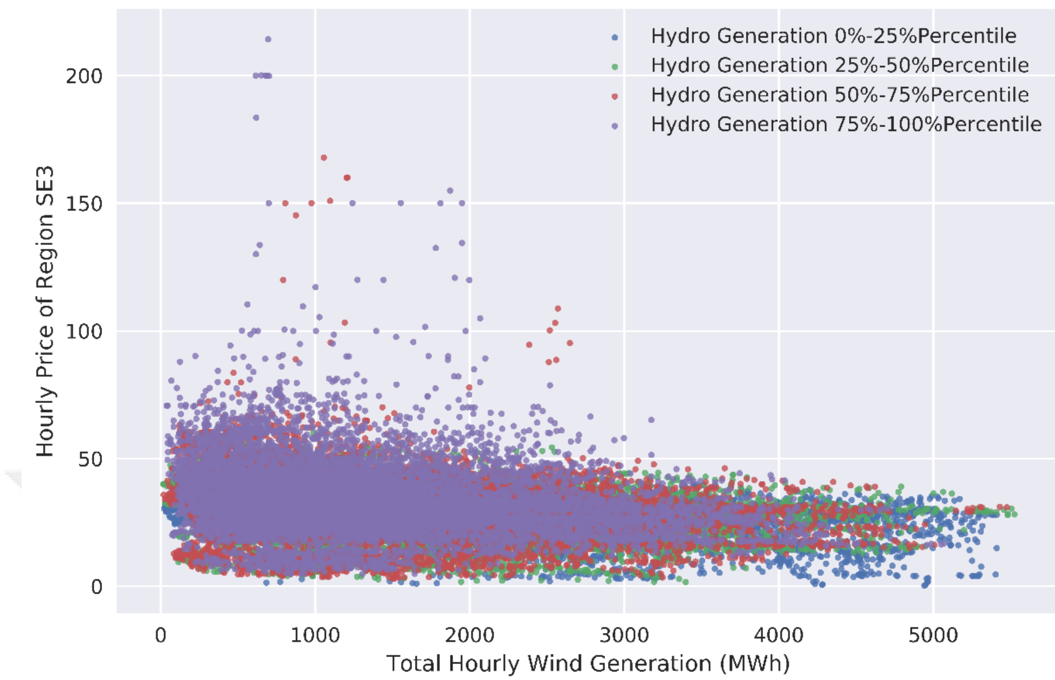


Figure 8: Wind and Hydro Generation Combination versus Price in SE3

Figure 8 shows the hourly prices of the SE3 region versus the total hydro and wind power generation in Sweden. Red and purple dots signify high hydropower generation, whereas the blue and green specify the lower generations. The bottom right corner has high wind generation and low hydro generation with resulting lower spot prices. As wind power decreases in the bottom left part of the graph, the quantity of the purple dots overwhelms the others with an increase in prices.

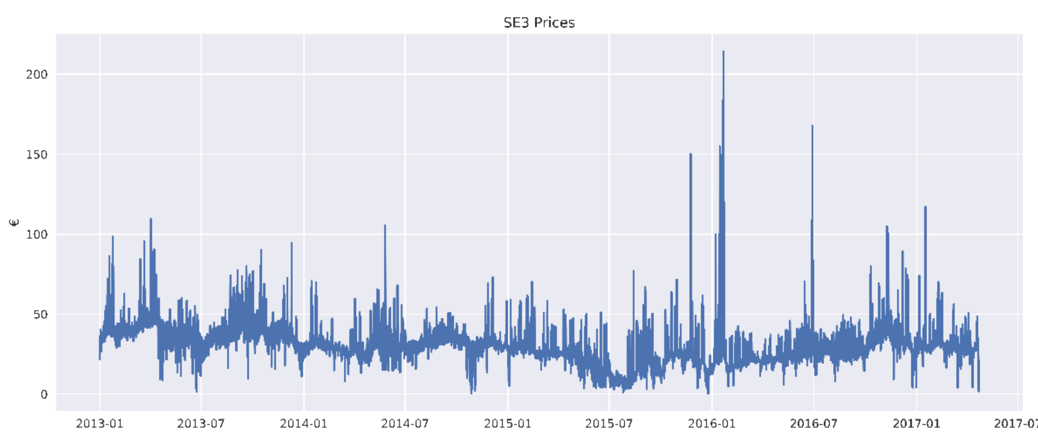


Figure 9: Region SE3 Elspot Spot Prices

The chronological time series of the SE3 price movement has been given in figure 9. There are several price spikes in the winter time followed by a calmer spring season. Only the SE3 region is used as a sample in order for the reader to have an understanding of the price data. Other price time series will not be shown individually. The ANN model will predict the behavior of these prices by only using the relationships between the presented data.

In Table 1, the Pearson correlation test results of different features have been given. Several other features, such as hydro reserves of several countries, price, demand data of Germany have been discarded due to having performed poorly on the model and for also having low correlation scores.

While SE1 and SE2 prices are identical, SE3 and SE4 prices behave differently. One of the interesting notes about these correlations is that hydro reserves of Norway and Sweden do not have any direct relationship with spot prices. One reason for this situation might be that the reserves are abundant. They are still included in the model regardless because of the established relationship between hydro power and wind power (Holttinen 2004).

Data is available from 01.01.2013 to 21.04.2017. The time interval between 21.04.2016 and 21.04.2017 is allocated as test data. The initial 3 years of data is then split into 80% as training and 20% as cross validation data. Cross validation data is chosen by random and was automatically changed in every different model trial.

Table 1: Pearson Correlation of Features

	Price SE1	Price SE2	Price SE3	Price SE4	Price SYS
Consumption DK1	0.39	0.39	0.42	0.45	0.41
Consumption DK2	0.38	0.38	0.40	0.43	0.42
Consumption EE	0.35	0.35	0.37	0.39	0.42
Consumption FI	0.31	0.31	0.33	0.34	0.41
Consumption LT	0.39	0.39	0.41	0.44	0.39
Consumption NO	0.24	0.24	0.26	0.28	0.37
Consumption SE1	0.21	0.21	0.23	0.24	0.30
Consumption SE2	0.27	0.27	0.30	0.31	0.38
Consumption SE3	0.33	0.33	0.35	0.37	0.43
Consumption SE4	0.33	0.33	0.35	0.38	0.43
Henry Hub Gas Price	0.34	0.34	0.31	0.30	0.35
Hydro Reserve NO	-0.04	-0.04	-0.02	-0.02	-0.12
Hydro Reserve SE	-0.12	-0.12	-0.09	-0.09	-0.21
Hydropower SE	0.17	0.17	0.21	0.25	0.17
Hydropower SE1	0.37	0.37	0.40	0.42	0.35
Hydropower SE2	0.09	0.09	0.13	0.17	0.08
Hydropower SE3	-0.12	-0.12	-0.08	-0.05	-0.10
Hydropower SE4	-0.01	-0.01	0.00	0.02	0.09
Net Export	-0.40	-0.40	-0.40	-0.38	-0.39
Nuclear SE3	0.14	0.14	0.12	0.12	0.32
OPEC Barrel Oil	0.44	0.44	0.40	0.38	0.47
Price SE1	1.00	1.00	0.96	0.93	0.91
Price SE2	1.00	1.00	0.96	0.93	0.91
Price SE3	0.96	0.96	1.00	0.97	0.91
Price SE4	0.93	0.93	0.97	1.00	0.88
Price SYS	0.91	0.91	0.91	0.88	1.00
Price AVG 24h Shifted	0.79	0.79	0.77	0.75	0.78
Production DK1	0.22	0.21	0.21	0.21	0.32
Production DK2	0.23	0.23	0.23	0.22	0.36
Production EE	0.56	0.56	0.56	0.56	0.59
Production FI	0.30	0.30	0.32	0.34	0.42
Production LT	0.31	0.31	0.34	0.35	0.32
Production NO	0.28	0.28	0.31	0.35	0.34
Thermal SE	0.23	0.23	0.25	0.25	0.39
Thermal SE1	0.09	0.09	0.09	0.09	0.22
Thermal SE2	0.17	0.17	0.18	0.18	0.32
Thermal SE3	0.26	0.26	0.26	0.27	0.41
Thermal SE4	0.17	0.17	0.20	0.21	0.30
Weekday	0.17	0.17	0.18	0.20	0.16
Wind DK1	-0.19	-0.19	-0.16	-0.17	-0.11
Wind DK2	-0.30	-0.30	-0.26	-0.26	-0.23
Wind SE	-0.28	-0.28	-0.28	-0.27	-0.22
Wind SE1	-0.14	-0.14	-0.11	-0.09	-0.09
Wind SE2	-0.25	-0.25	-0.23	-0.21	-0.21
Wind SE3	-0.23	-0.23	-0.24	-0.24	-0.17
Wind SE4	-0.22	-0.22	-0.23	-0.25	-0.17

3.2.2. Data Acquisition

Consumption, production and wind generation prognosis data since 2013 is made publicly available by Nord Pool (Nord Pool n.d.). Many other features have been provided by the commodity information company MONTEL. Detailed generation types have been taken from Svenska Kraftnät statistics webpage (Svenska Kraftnet n.d.). Lastly, wind power estimations of the DK1 and DK2 regions have been taken from the Energinet website (Energinet n.d.).

3.2.3. Wind Scenarios

6 different Wind scenarios were selected for the model to predict.

Table 2: Wind Generation Scenarios

Scenario	Increased Wind Generation per Hour
W1	+30% Wind Production
W2	+20% Wind Production
W3	+10% Wind Production
W4	-10% Wind Production
W5	-20% Wind Production
W6	-30% Wind Production

Each scenario given in Table 2 is based on the real productions. However, each hourly wind generation will be increased by the given percentages. Therefore, behaviors of the wind will be the same in all scenarios, but with a different magnitude.

However, the increase in wind production must express itself in other features. In the ex-post studies presented in the literature review, most of the research changed the amount of wind energy production without changing the total supply of energy. However, if the energy type wind is replacing is also identified the scenarios would be more coherent with the actual data. Therefore, a basic linear relationship between wind and other generation types has been derived. Changes in the wind productions will be reflected on other generation types by multiplying the change with these coefficients and adding them to the respective generation production amounts.

Table 3: Wind power's linear relationship between other generation types

	Wind Power's Linear Relationship
Nuclear	0.261
Hydro	-0.352
Thermal	0.122

Each change in the wind energy will be multiplied by the coefficients given in Table 3. Normally electricity demand is sensitive to spot prices as shown in figure 1 in Section 2.3.2. Its sensitivity indicates itself in its negative inclination. It is shown by the negative relationship with price, as price increases demand decreases. However, for creating these wind scenarios demand is assumed to be inelastic in order to limit the number of changing features. Therefore, the residual 0.031 from the direct summation of these coefficients will be added to or substracted from the Net Export feature in order to sustain the balance of production and consumption as shown in equation 8.

$$\text{Wind Energy Production} + \text{Hydro} + \text{Thermal} + \text{Nuclear} = \text{Consumption} + \text{Net Export} \tag{8}$$

3.3. Linear - Polynomial Regression

Linear regression will be used to derive a linear relationship between wind power production to one of the other type of productions, while polynomial regression is introduced to for the purposes of explaining the bias and variance relationship more clearly in the later section. Three linear relationships are formed between the production values: wind – nuclear, wind – hydro, wind – thermal. These relationships are used for scenario generation. In linear regression, the relationship between the input and output is linearly proportional. Its form is given as:

$$y = \beta_0 + \beta_1 x_i + \varepsilon \tag{9}$$

, where i is the number of the hourly condition, y is one of the other production types and x is the wind production. While β_0, β_1 are both coefficients of the equation, β_0 is generally referred as the intercept. β_0 is the location of the point, where the line intercepts the y-axis and β_1 is the slope of the line. These coefficients form the best fit line between the input x_1 and the observed target values y.

The error term is the residual amount between the line and the target value. In numerical approximation methods, the main purpose of the algorithms is the minimize the error term.

Given a dataset of $(x\ , y)$, coefficients of the linear regression can be calculated with the Ordinary Least Squares (OLS) method. In equation 2, leaving the error term alone on one side and taking the square of both sides in order to prevent positive and negative instances to cancel out results.

$$\min\left(\sum_i \varepsilon^2\right) = \min\left(\sum_i (y_i - \beta_0 - \beta_1 x_i)^2\right) \tag{10}$$

In order to minimize the error term, the derivate of the right-hand side is taken with respect to β_0, β_1. Equations 11 and 12 are the solutions of the regression by the OLS method.

$$\beta_1 = \sum_i \frac{(x_i - \bar{x}\ )(y_i - \bar{y}\ )}{(x_i - \bar{x}\ )^2} \tag{11}$$

$$\beta_0 = \bar{y} - \beta_1 \bar{x} \tag{12}$$

, where $\bar{x}$ and $\bar{y}$ are their respective averages.

In polynomial regression, input to the problem and its polynomials are linearly multiplied and approximated to the target values. If there is an input-output pair of $(x\ , y)$, they can be represented in polynomial terms as:

$$y = \varepsilon + \beta_0 + \beta_1 x_i^1 + \beta_2 x_i^2 + \beta_3 x_i^3 + \cdots \tag{13}$$

, where i is the number of the sample and ε is the error of the prediction. Linear regression is the first-degree polynomial regression. Polynomial regression's coefficients can be calculated with the OLS method by assuming the powers of the variables as other variables and approaching the problem similar to a multivariate linear regression.

3.4. Model Evaluation & Metrics

3.4.1. Error Metric

Absolute percentage error and mean absolute percentage error are two of the commonly used metrics in forecasts that are comparable across different datasets. However, when the electricity prices are closer to zero, errors become high with small differences and receive too much importance from the forecast (Weron 2014). They also do not make logical interpretations in the cases of negative prices. Furthermore, percentage error metrics do not give enough importance to price spikes, because they would be much less important than the errors when the prices are closer to zero. In this thesis, it is thought to be more meaningful to choose the mean absolute error metric for representing the problem at hand. Its relationship is expressed in equation 14:

$$MAE = \frac{1}{n} * \sum_{i}^{N} |y_i - p_i| \tag{14}$$

, where i is the number of the sample, p_i is the prediction and y is the target value.

3.4.2. Data Separation

The available dataset is commonly split into two pieces in most studies: training data and test data. Training data is used to train the predictive model and test data is used to evaluate the performance of the model. However, when the variations of the model are chosen depending on their performance on the test data, the test data becomes part of the training data. In this case the information would flow back from test data to the model selection process, which is not possible in reality when data is not present (Hastie et al. 2009). Therefore, in this thesis data is divided into three parts: training, cross validation and test data. The models are trained using the training data, their configuration and fine tuning will be handled depending on their performance on cross validation data. The results of the test data will affect the selection of the model, and they will be only discussed during the evaluation of the final model.

3.4.3. Bias vs Variance

Prediction methods estimate the amount of error and aim to minimize it by trying different solutions. One way to understand how and where the predictions fail is to separate the error term into its components.

$$Expected\ Test\ Error\ = Bias + Variance + Noise \tag{15}$$

Bias is the square of the distance between the average of predictions and the average of target values. Low bias indicates the predictions are close to the target values on average. On the other hand, high bias means that the model tends to predict around an incorrect area.

Variance shows how much the predictions vary as its name suggests. The model might be correct on average however might create high spikes due to its high variance error.

Noise is the inherent fluctuations of the data. Different types of data have different types of noises. Noise consists of the error due to the problem itself and due to potential mistakes in data. It cannot be altered and therefore is not considered in this thesis.

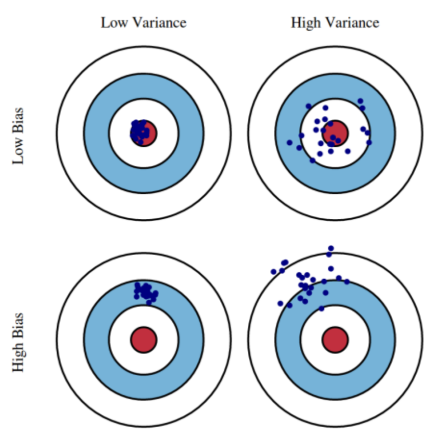


Figure 10: Bias vs Variance Illustrations (Weinberger 2015)

Figure 10 illustrates the meaning of bias and variance in a more intuitive way. In the top left corner, bias and variance are low and the predictions are both accurate and precise. Predictions in the top right corner are around the target values with a correct mean, which suggests a high variance with a low bias. In bottom left predictions are precise but distant to the targets which shows a high bias and low variance. High variance and bias is also represented in the bottom right corner (Weinberger 2015).

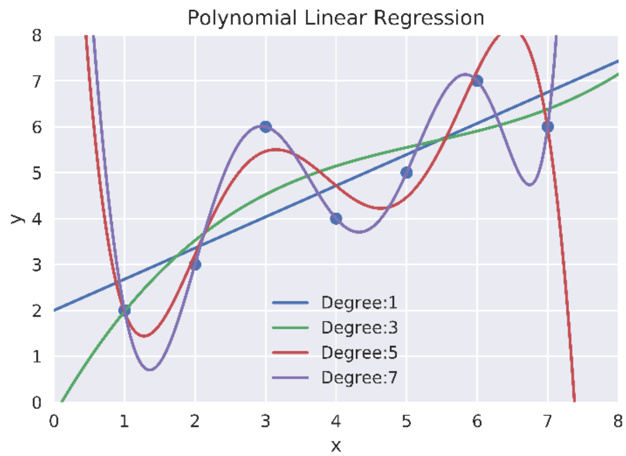


Figure 11: Sample Polynomial Regression with varying degrees

In figure 11, there are four different sample polynomial regression curves the dots representing the given data points. The polynomial line with degree 1 is a linear regression curve and goes between the points. The third-degree polynomial tends to imitate the data points better. While the fluctuations become apparent in fifth order polynomial, seventh order goes right through the points. High degree functions would be able to predict exact values of the trained data, however would predict the newly available points poorly. The opposite is true for simpler models, they will have difficulty in predicting individual points and the predictions they find will be around a similar zone. A simpler model can handle the new data points with much less difficulty. These observations are given in order to illustrate the opposite sides of bias and variance.

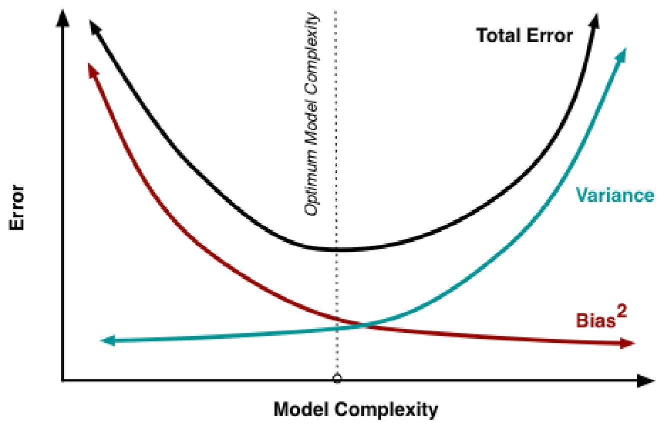


Figure 12: Trade-off between bias and variance(Weinberger 2015)

In general, there is a tradeoff between bias and variance depending on the complexity of the predictive models (Geman & Bienenstock 1992). While constructing the neural network model, training data is presented for the neural network to learn from. Neural networks have the flexibility to result in close to zero error in the training dataset with a correct configuration by training over the dataset several times, thus increasing its complexity. The predictions would overfit through the actual data points and perform poorly on test data. In a model with a simple configuration or with few iterations over the training data, the error will mostly consist of bias term as shown in figure 12. There is an optimum spot between the highly complex model with the high variance that would overfit the data and the simple model with the high bias that would underfit the data. In order to catch these spots each iteration of each network configuration is recorded and compared. However, in this thesis different wind energy production scenarios will be introduced. The model might not account for these artificial data points that it hasn't trained before and might give randomly varying results. Therefore, a ridge regression term that directs the predictions towards the high bias region will be introduced in Section 3.4.4, so that a neural network model with a complex configuration can be trained over the dataset while evading the problems of high variance that would prevent It from obtaining logical outcomes from wind scenarios. The trade-off of this solution is higher mean average errors in the predictions.

3.4.4. Pearson Correlation Test

The Pearson correlation test is the covariance of two variables divided by their respective variances. It shows the strength of the linear relationship between two different variables. The linear relationship of the data will be investigated with the Pearson correlation test and evaluated.

$$\rho(a,b) = \frac{E(ab)}{\sigma_a \sigma_b} \tag{16}$$

, where $E(ab)$ is the cross correlation between variables and σ_a, σ_b values are the variance of the variables. The resultant value lies between -1 and 1. The sign of the Pearson correlation shows the direction of the linear relationship, whereas the value shows the magnitude. A perfect 1 score means all the points of (a, b) can be fit through a line. Values closer to zero indicate that these variables do not have a linear relationship. The Pearson correlation test will be used to evaluate different data features.

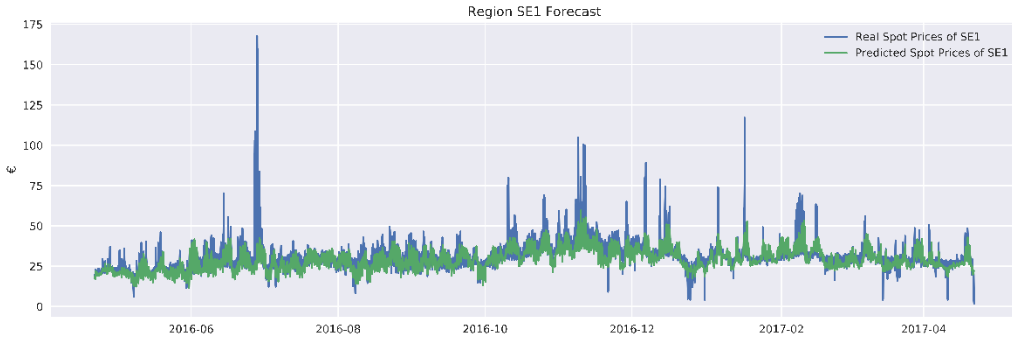
4. Results

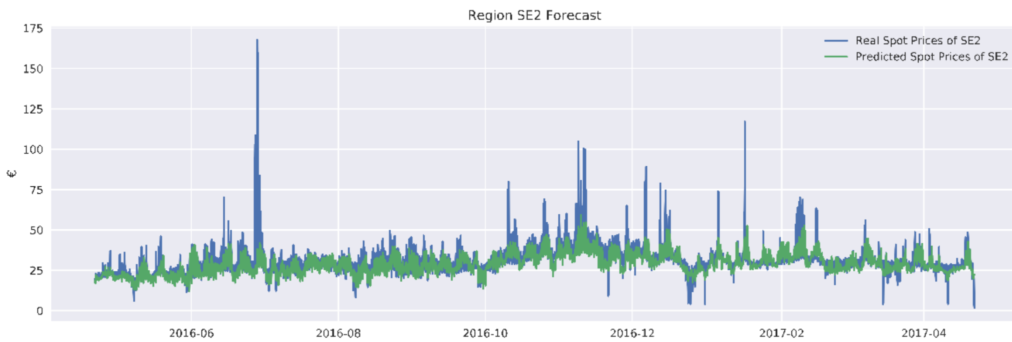
4.1. Day A-head Market Price Forecast

More than 100 different configurations have been tried. The chosen model has 3 hidden layers. 500 neurons in the first hidden layer, 250 neurons in the second layer and 80 neurons in the third hidden layer. Output neurons are the four Swedish region's Elspot prices and the Nord Pool system price. Mean absolute error of the five different output's was 3.3398 €/MWh per prediction where the average prices are around 31€/MWh. All of the predictions resulted in lower values than the actual prices. Details of the model's performances can be seen in more detail in Table 4.

Table 4: Day Ahead Market Forecast Results

Price Region	Percentile Error (%)	Mean Absolute Error (€)
SE1	11.1599	3.5482
SE2	10.9689	3.4983
SE3	10.9615	3.4735
SE4	11.1507	3.6386
System	8.7298	2.5406


Region SE1 Forecast
Real Spot Prices of SE1
Predicted Spot Prices of SE1
€
175
150
125
100
75
50
25
0
2016-06
2016-08
2016-10
2016-12
2017-02
2017-04


Region SE2 Forecast
Real Spot Prices of SE2
Predicted Spot Prices of SE2
€
175
150
125
100
75
50
25
0
2016-06
2016-08
2016-10
2016-12
2017-02
2017-04

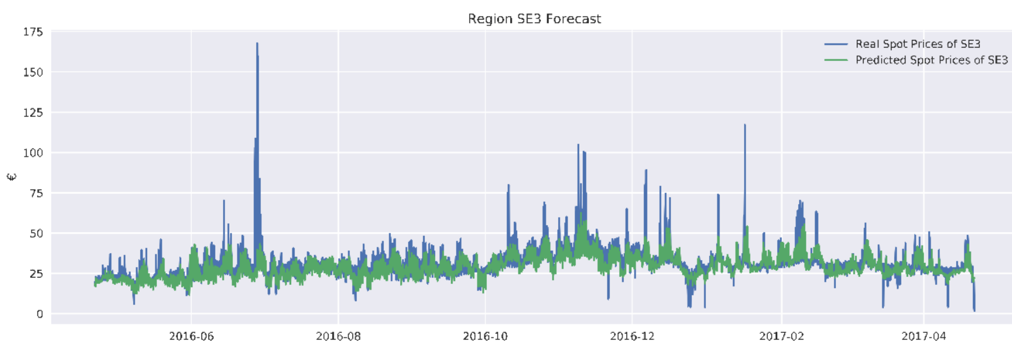

Region SE3 Forecast
Real Spot Prices of SE3
Predicted Spot Prices of SE3
€
175
150
125
100
75
50
25
0
2016-06
2016-08
2016-10
2016-12
2017-02
2017-04

Figure 13: Price forecasts of each Swedish region and the System Price

As can be seen in figure 13 the price forecasts of Swedish spot prices are similar to each other. The occurences of price spikes are understood by the model, however the magnitudes of those price spikes are not forecasted succesfully. The system price forecast performs better with lower mean abosolute error compared to the Swedish regions. While the Swedish spot price forecasts are biased over the mean values, the system price forecast understands the variances significantly better.

4.2. Wind Energy Scenario Forecast

Table 5: Wind Scenario Forecast Results Comparison

Scenario	Wind Energy Increase	Change in Prices			
		Region SE1	Region SE2	Region SE3	Region SE4
W1	+30%	97.20%	97.29%	97.22%	97.21%
W2	+20%	98.14%	98.20%	98.16%	98.15%
W3	+10%	99.08%	99.11%	99.09%	99.08%
W4	-10%	100.91%	100.88%	100.90%	100.91%
W5	-20%	101.81%	101.74%	101.79%	101.80%
W6	-30%	102.71%	102.59%	102.67%	102.69%

The forecast solutions are listed in Table 5. The reference for the price calculation percentiles is the predicted spot prices with original wind production. The results show that each 10% increase in wind energy production would lead to approximately 0.9% spot price reductions in the Nord Pool Swedish energy market. In other terms, these results also suggest that each additional 1 GWh of hourly wind energy production reduces the spot prices by 1.77€/MWh.

In figure 14, the changes of the prices of the W1 and the W6 scenarios with respect to the original predictions are graphed. Opposite scenarios mostly mirror each other about the Δ€=0 horizontal line with a few nuances.

In figure 15, the cases are shown with their differences to each other instead of the reference to the original prediction. In a few cases around 2016-05 and 2017-03 the low wind scenario has lower prices than the high wind scenario which could not be explained.

Figure 14: Price differences of +30%, -30% wind production scenarios compared to the real values

Figure 15: Price Difference between Low wind energy scenario versus High wind scenario

5. Discussion

The day ahead market model has been successful in catching spike behaviors by using the input data. In Section 4.1, the formulated model had biased results towards to the mean of the prices. Directing the model towards the biased region was one of the plans of this study to properly implement the wind scenarios. The impact of this regularization can be seen from the dampening effect on the SE spot prices in Figure 13.

On the other hand, the predictive model was more successful in system price forecasting when compared to the Swedish regions. All of the SE region forecasts are biased towards the mean, while the behavior of the system price forecast is more flexible. It can be argued that there are more features from Nordic countries other than Sweden that affect the system price more directly, while impacting the SE spot prices indirectly.

Due to the fact that only Swedish and Danish wind generations are introduced, it might be possible that the model may think that these values are the sum of whole wind generations in Nordic countries. If the wind energy productions are highly correlated on a large scale in nearby countries as some studies assert (Olauson & Bergkvist 2016), it may not be possible for the model to make the distinction of the other data's unavailability. Therefore, during the course of this thesis the impact of the wind generation has been assumed to be overestimated by the neural network.

An increase of 10% of wind energy production resulted in a 0.9% reduction of the spot prices. The impact of every additional 10% wind energy production also produced a similar reduction, therefore it can be argued that the impact of the increased wind energy production is linearly proportional to the percentile increment of wind energy in total energy production for the defined energy scenarios and time interval in Sweden. In the literature review of this thesis, Benhmad & Percebois(2015) have made almost the same claim. They assert that a 10% increase in wind energy lead to 1% price reductions. Furthermore, for 1GWh of additional renewable energy, the studies presented in the literature review show decreases in the range of 1€ to 3.7€/MWh, which is highly consistent with this study's finding of 1.77 €/MWh.

6. Conclusion

The objective of this thesis was to develop a neural network electricity price spot forecasting model in order to be able to assess the impact of wind energy on Swedish spot prices. Initially, a literature review has been conducted for similar studies. Then, model evaluation methods, metrics and the configuration of the neural network has been investigated. Data, which was gathered across multiple platforms have been presented and explored for a better understanding of the different dynamics that form the balance of the market. With the given dataset the chosen network configuration performed using the desired biased behavior with satisfactory accuracy. The spot prices of the generated wind scenarios are investigated, and the results of the study have been found to be coherent with other studies presented in the literature review.

In 2016, Sweden's yearly total wind production was 15,601 GWh with a penetration of 11% (Svenska Kraftnet n.d.). It has been also reported that in 2030 Sweden is expected to have 31,641 GWh of wind energy production (EWEA 2015) with a penetration of approximately 22% (Wind Europe 2017). This would be an increase of 103% in terms of production and an increase of 100% in terms of wind energy penetration, which are almost identical to each other. Using the results from this thesis, and if the market conditions of 2016-2017 do not change between now and 2030, wind developers in Sweden can expect an approximately 9% reduction in electricity spot prices by 2030 with the assumption that the increase of wind energy production's impact on the spot prices are linearly proportional, as presented in Section 5.2.

The neural network model that was used in this thesis was purposely biased. However, it seems that regularization was applied more than necessary. Training of the models became too computationally intensive as the regularizing terms became rigid barriers that pushed the gradients of the loss function to other regions. Additionally, creating a distinction feature for the system price neuron in the output layer might balance the bias variance difference between the system price and the SE regional spot prices. Also, a more complex algorithm that can capture sequential information, such as recurrent neural networks, might provide better solutions for the day-ahead forecast but potentially would perform poorly in the scenario assessment.

In order to be able to confirm the findings of this thesis, more complex methodology has to be used for the wind energy generation scenarios. In this thesis, the basic linear model has been used which has significant limitations especially considering that it is combined with an advanced neural network model. Another major limitation of the thesis is that while the wind energy productions changed in each scenario, total energy productions stayed almost the same due to the method of scenario generations. Therefore, it is not clear whether a 10% increase in wind energy penetration in total production or a 10% increase in MWh resulted in the 0.9% spot price reduction.

Forecasting electricity spot prices and investigating its effects on the market is important for the market in order for it to be efficient and devise an optimum allocation of resources which would also reduce the prices for the end user consumer. Therefore, it is essential for the relevant data to be publicly available by governmental organizations and TSO's. Investigating, gathering, cleaning, discarding, and combining the data multiple times was the most time consuming portion of this study. Furthermore, some of the data was not consistent between the different data sources such as having different production values for Sweden in Nord Pool and in Svenska Kraftnet for a particular hour. Additionally, almost none of the studies regarding the spot price calculations investigate the relationships between countries. Physical flows, its restrictions and its impact on other elements is also a worthy task to investigate for the better understanding of the market dynamics. Cross-border interactions and inclusion of different policy frameworks into the investigation of price behaviours may also lead to more realistic findings.

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