Development of an Electricity Spot Market Model based on Aggregated Supply and Demand Functions for Future Solar and Wind Power Deployment

Reza Fachrizal
Abstract

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This master thesis aims to develop an electricity spot market model for simulating hourly day-ahead market prices, and use it to study future deployment scenarios for solar and wind power as well as the potential of nuclear phase out in the Swedish and the whole Nordic and Baltic power systems.

The share of intermittent renewable energy (IRE) in Swedish power system is increasing and this is expected to continue in the next decades. The share of wind power has rapidly increased from less than 1% in 2005 to more than 10% of the total generation in 2013. Even though solar power generation is currently still very low in Sweden, the Swedish Energy Agency has estimated that solar power can cover up to 10% of the electricity demand in 2040. With an increasing share of intermittent renewable energy and the potential of a nuclear phase out, the prices on the electricity spot market are likely to change in the future.

In this thesis, statistical approaches are used to find the correlations of the existing market prices to several physical parameters such as temperature, hydro reservoir level, nuclear power generation, IRE, etc., and these are used to construct the proposed market model and to simulate the future scenarios.

The results show that there is a strong dependency of the system price on the hydro reservoir level, as well as firm correlations between the system price with nuclear generation, temperature, electricity consumption and IRE. Using the model, it is possible to show that the substitution of nuclear power generation with realistic shares of wind and solar power will not lead to a fundamental change in the market. However, it will be a different case if the solar power share is higher. High solar penetration in the market makes the system prices much more dynamic both on an hourly and a seasonal basis.

Keywords: spot market, day-ahead prices, modeling, solar and wind deployment, nuclear phase out, future simulations
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1. Introduction

The Swedish electricity system has since 1985 been dominated by nuclear and hydro power, each of them contributing with nearly 45% of the national electricity generation. However, during the last years, a break in the trend can be seen. Since 2005 the share of wind power has rapidly increased from less than 1% in 2005 to more than 10% of the total generation in 2015. Solar power generation is still very low in Sweden, with a contribution of less than 0.1% in 2016, but with future price reductions for photovoltaic (PV) systems and more widespread interest in the technology, this share could rise significantly. The Swedish Energy Agency has estimated that 5-10% of the Swedish electricity demand can be covered by solar electricity in 2040 [1]. Besides the increasing share of renewable power sources, Sweden will most likely phase out baseload nuclear power in the future. The electricity market players will have to deal with substantial changes both regarding technical and market aspects in the future [2].

Exactly how the adoption of PV systems in Sweden will develop depends on electricity market prices. Due to the intermittent nature of wind and solar power together with low variable generation costs, the influence of wind and solar power on the spot market price of electricity might be large in the future. This, in turn, is likely to influence the willingness to invest in new generation capacity. Hence, if the spot market price has a crucial impact on the profitability of solar power, deployment of new generation units should be a self-regulating process, with willingness to invest in new capacity decreasing with each new installed unit. In order to make realistic scenarios for PV and wind power deployment for use in power system integration studies with also taking account nuclear power removal potential, a computationally efficient electricity market model is needed.

1.1 Objectives

The aim of this master thesis is to develop an electricity day-ahead market model for simulating hourly spot market prices, and use it to study future deployment scenarios for solar and wind power in the Nordic power system. The following more specific tasks are to be performed:

1. Statistically analyze how system market prices, supply curves and demand curves in the NordPool Spot market depend on different parameters such as temperature, water level, nuclear power, electricity consumption, intermittent renewable energy.
2. Propose a mathematical model in which (preliminarily) system prices are obtained from supply and demand curves in the system market modeled explicitly based on the parameters studied above.
3. Create scenarios for solar and wind power and study, with the electricity market model, how different volumes of these power sources affect the electricity prices as well as taking account of the potential of nuclear phase out
1.2 Limitations

This master thesis focuses on the electricity day-ahead market in the Nordic-Baltic region. The physical parameters used in this thesis are specific for the Nordic-Baltic region. Thus, some adjustments will be needed if one wants to apply the results from this thesis to different markets and areas.

The technical aspects are discussed in this thesis to some extent. They are undoubtedly important aspects for this study as an electricity market will develop only if it is technically feasible. However, this thesis will not propose detailed technical solutions for future scenarios with high solar and wind power in the systems since this thesis will focus more on how different volumes of these power sources affect the electricity prices.

1.3 Report Structure

Section 2 provides the background information behind this thesis, i.e., the Nordic electricity market, the current electricity mix in the Nordic-Baltic power market, brief theory about technical aspects of power plants per source and their effects on the system pricing. Section 3 explains the methodology of the modeling. Section 4 presents the model validation results and future scenario simulations. Section 5 highlights the main conclusions of this thesis and provides some suggestions regarding future research related to this master thesis.
2. Background

This chapter presents the general background for the research. The background on Swedish and Nordpool electricity systems and markets are reviewed in Section 2.1-2.3. The technical and market aspects of the existing power plants in the Nordic-Baltic regions are presented in Section 2.4 and 2.5.

2.1 Swedish Electricity System

The electricity generation in Sweden is currently dominated by hydro and nuclear power as shown in Figure 2.1. However, since the beginning of the deregulation of the electricity market in 1996, the Swedish electricity system cannot be studied as a sole system as it is now integrated to neighbouring countries and becomes a part of larger systems. Now all the electricity trades in Nordic and Baltic regions are technically done through Nord Pool.

![Electricity production per source in Sweden since 1970](image)

*Figure 2.1. Electricity production per source in Sweden since 1970 [3].*

2.2 Nord Pool Market

Nord Pool is Europe's leading power market and offers trading, clearing, settlement and associated services in both day-ahead and intraday markets across nine European countries. Nord Pool is owned by the Nordic transmission system operators Statnett SF, Svenska kraftnät, Fingrid Oyj, Energinet.dk and the Baltic transmission system operators Elering, Litgrid and Augstsprieguma tikls (AST) [4].

In the common market, there are at least three usual players: the producers, the retailers and the end users. For liberalized electricity markets like NordPool Power Market, a more advanced trading pattern quickly develops. Figure 2.2 illustrates the electricity exchange between the players including the brokers and the traders [5].
There are many routes from the producers to the end users with involvements of traders and brokers. For example, the trader may buy electricity from a producer and then sell it to a retailer. The trader may also choose to buy electricity from one retailer and sell it to another retailer. The brokers play the same part in the electricity market except they own no commodities.

The current Nord Pool electricity market consists of a number of specific underlying markets based on a timeline for the bidding offers. Figure 2.3 illustrates the major components of this market. In this thesis, the modeling will only focus on NordPool day-ahead market. There are currently 2 different day-ahead markets which Nord Pool hosts; the first one is Nordic-Baltic elspot market which covers Denmark, Finland, Sweden, Norway, Estonia, Lithuania and Latvia. The second one is UK N2EX market which covers United Kingdom region. This master thesis only covers elspot market.

**2.2.1 Elspot Market**

Elspot is Nord Pool Spot’s day-ahead auction market, where electrical power is traded. Players who want to trade power on the elspot market for the following day must send their purchase bids to Nord Pool at the latest at 12.00 CET the day before.
the power is delivered to the grid. The sellers, for example a hydropower plant owner, must estimate how much they can sell to the grid at specific hours and at what price. The buyers need to estimate which electricity volume it will need to meet the demand in the following day [5]. Hourly prices are typically announced to the market at 12:42 CET or later. Once the market prices have been calculated, trades are settled. From 00:00 CET the next day, each players must fulfill the contract agreed upon [7].

Besides supply and demand, transmission capacity also plays an important role. A seller may not be able to deliver the power to the buyer if the transmission has reached its capacity. Thus, different prices areas are introduced. There are currently 15 bidding areas in Nordic Baltic Nord Pool market region. To define the area prices, each supply and demand orders are aggregated per bidding areas instead of from the whole market. When the transmission is much congested, the price is raised to reduce demand in the importing area. Thus, the exporting areas have lower price than the importing area. If the power transmitted in the transmission line has not reached a limit that the TSO has set, area prices in these different bidding areas will be identical [7].

### 2.2.2 System Price and Trading Procedure

A system price is calculated after area prices have been calculated for all bidding areas. All orders from Nordic and Baltic regions are included in the system price calculation. It is calculated without any congestion restrictions by setting capacities to infinity. Flows between the Nordic countries and the Netherlands/Germany from area price calculation are taken into account in system price calculation [5] [7].

An example of the trading procedure in [5] is presented as follows:

Figure 2.4 illustrates the example of orders made by a retailer for a certain hour in the following day. A retailer expects that the customers will consume 50 MWh at certain hour. The retailer’s own generation facility can generate power up to 80 MWh, so the retailer can choose whether

- to buy 50 MWh from the market and not to generate anything with his power plant.
- to buy some electricity and generate the rest with his power plant.
- to generate exactly 50 MWh.
- to generate more than 50 MWh and sell the excess generation to the market.

Considering the cost-benefit, the retailer tells Nord Pool that he will buy 10 MWh if the spot price is in the range of 20 – 40 €. If the spot price turns out to be less than 20 €, the retailer will buy all the 50 MWh power from the market. If the spot price is higher than 50 €, the retailer will start to sell power to the market. If the price is 60 € and higher, the retailer will generate the maximum power that his power plant can generate.
Another example is illustrated in Figure 2.5. A nuclear power producer submits an inelastic selling offer for whatever the price is since shutting down a running nuclear power is not beneficial. A load consuming industry which does not have its own generation facility submits an inelastic buying bid for whatever the price is for the sake of their industrial production.

One must note that there is no obligation to include the whole electricity generation and consumption into the exchange market. For example, a player has their own cheap production which they can directly utilize for themselves. Those kinds of production and consumption are still included in total production and consumption statistics but not included in the market supply and demand volumes. Thus there will always be mismatch between total consumption and market demand.
At Nord Pool elspot market, the purchase bids are aggregated to a demand curve. The sale offers are aggregated to a supply curve as illustrated in Figure 2.6. The intersection of the two curves defines the system price and the volume traded in one specific hour [5].

![Graph showing demand and supply curves](image)

*Figure 2.6. Illustration of aggregated supply and demand curves. The figure is inspired by document [4].*

### 2.3 Nordic Baltic Electricity Mix

Electricity mix in the Nordic and Baltic region is quite diverse and dominated by carbon free sources. Figure 2.7 and 2.8 show the pie chart of Nordic Baltic region electricity mix in 2015 divided on generation types and countries. Figure 2.9 summarizes the electricity mix per country in the Nordic Baltic region in 2015.

In 2015, the Nordic-Baltic region generated around 425 TWh over the year. Sweden had the largest power generation shares with 162 TWh (38%) followed by Norway with 145 TWh (34%). Finland, Denmark and Baltic region generated 68 TWh (16%), 29 TWh (7%) and 21 TWh (5%) respectively.

In terms of power sources, the Nordic-Baltic region is gifted with abundant hydropower sources. Hydropower accounted for more than half of the electricity generation in 2015. That year was considered as a wet year which led to electricity price drops [8]. Norway is the biggest contributor of hydropower generation followed by Sweden. Nuclear power comes in second place with an 18% share which is contributed mostly by Sweden and to a lesser extent by Finland. Wind power contributes with 10% to the electricity mix and is expected to increase in the coming years. Denmark interestingly is dominated by wind power even though the amount of its wind power production in TWh is comparable with Sweden. The solar power share is hardly noticeable, but like wind, it is expected to increase and in the coming years.
Figure 2.7. Nordic Baltic region electricity mix in 2015 [9].

Figure 2.8. Electricity production per country in the Nordic-Baltic region in 2015 [9].

Figure 2.9. Nordic Baltic region electricity divided on (a) Sweden (b) Norway (c) Finland (d) Denmark (e) Baltic Countries [9].
2.4 Electricity Generation and Load

The electricity demand varies from moment to moment depending on industrial and residential activities as well as the weather conditions. Generally, on a working day, the demand begins to rise in the morning and creates a first peak between morning and mid-day. It decreases between mid-day and afternoon, and then it gets the highest peak in the afternoon. Then it cools down in the late evening. The load shapes within a working day resemble the shape of a camel hump as illustrated in Figure 2.10.

![Figure 2.10. Schematic illustration of the load within a working day.](image)

Energy cannot be stored in electrical form, so once a plant generates electric power, it must be used directly. Otherwise, the energy will be stored in kinetic form in the systems’ generators and creates frequency rise in the power systems. Oppositely, if electric load is higher than the electric generation, the system frequency will drop. These situations are avoided as the systems demand a stable system frequency within a narrow tolerable range. Thus, there must be a balance between power generated and power consumed all the time.

The electricity load can be divided into 3 categories as shown in Figure 2.10. The first one is baseload, where the minimum load occurs throughout the day. The baseload demand is ideally handled by a baseload power plant which has low variable operating cost and slow ramp-rate. In cold countries where the share of electric power to heat is high, the temperature will have a strong correlation with the baseload power. The second one is intermediate load which is usually met by more flexible power plant. The intermediate power plant can adjust its power output better than the baseload power plants. The third one is peak load which only occurs in a shorter period in a day. Thus, peak load is met by the most flexible power plants which can be turned on and off quickly without complicated procedures [10]. The really highest peaks occur only in a shorter period in a year and are usually covered by expensive generation units. Figure 2.11 from svenska kraftnät illustrates how the power generation per source in Nordic Baltic within a day varies following the load. In the NordPool market, the balancing power within the operating hours is traded in a different market from the elspot market called the regulating power market. However,
the elspot market covers most of the power traded in the NordPool market since the scheduled power productions and consumptions are traded there.

![Figure 2.11. NordPool Market estimated generation per source on 22-02-2017. The specific numbers shown are for the generation at 09.00 [11].](image)

### 2.5 Power Plant Characteristics

Every type of power plant has different marginal cost. This marginal cost can be one of the sellers’ considerations in deciding the price of their generated power. Figure 2.12 illustrates the share of different types of generation in the Nordic Baltic region based on their marginal cost.

![Figure 2.12 Illustration of Nordic Baltic region power supply based on power marginal cost [12]](image)

However, this is not always the case. Another important sellers’ consideration is the power plant technical characteristics. The following sections cover the technical-financial characteristics of existing power plants in Nordic Baltic power market which will be a major guidance in the model construction phase.
2.5.1 Hydropower

Hydroelectric power plants use the flowing water to drive a turbine and generate electricity. Hydropower generation is very low cost, relatively clean and the fastest dispatchable power source as it can reach its maximum generation capacity within only 16 seconds [13]. It is a great advantage if a power system has large share of hydropower as the power quality becomes better and the systems become more reliable. Many countries are having difficulty to handle high penetration of IRE since they do not have much share of high ramp rate power plants. This is not the case with the Nordic. The Nordic system is gifted with abundant hydropower resources. Around 55% of the Nordic and Baltic electricity demand is met by hydropower. From a technical point of view, high IRE penetration in the Nordic electricity system should therefore not be as problematic as in other countries.

In general, hydropower is used to meet the demand in the peak hours due to its flexibility. However, since the hydropower is abundant, hydropower is used to meet any kind of load, which makes the electricity price in Nordic relatively cheap. The use of expensive peaking power plant such as gas turbine can be avoided except for very few moments of high peak powers.

Even though water as fuel is free, hydro station operators have to consider not only how much water is available, but also how much will be available in upcoming weeks [10]. The existence of hydropower stations also should not sacrifice other water demands such as drinking water supply, irrigation and recreation. The hydrology and climate forecasting is one of the most important factors to define the hydropower dispatch decisions, which indirectly affect the hydropower generation price.

2.5.2 Nuclear

Nuclear power plants use the heat produced by nuclear fission to produce steam. The steam drives a turbine to generate electricity. Nuclear plants are characterized by high investment costs but low variable operating costs, including low fuel expense. [10]

Even though the nuclear generation marginal cost is a bit higher than hydropower, nuclear power stations’ owners are the most affected players if the demand goes very low. While hydropower generation can be shut down and started up anytime due to its easy and low-cost procedure, nuclear power is not as flexible. Nuclear power plants are very expensive to stop and start, but it becomes cheap when it can go on running. It is also more safe and efficient if the nuclear power production is kept fixed. Thus, the nuclear power operators will want to have their power plant running the whole year, except for some scheduled shut down. It makes the nuclear power plant owners not bother selling their power for negative prices for few hours.

To sum up, nuclear power plants are categorized as must-run power plants which are used to meet the base load demand. It is easy to predict the nuclear power generation as it is inelastic. The negative price bids in the supply curve of the electricity spot market are presumably contributed by must-run power plant owners.
2.5.3 Thermal

Thermal power plants use the heat produced by fuel combustion to produce steam. In this thesis, biomass, waste, coal power plants as well as combined heat and power plants are categorized as thermal power plants. Thermal power plants with solid fuel such as coal and biomass can be fired up from cold within a few hours [13]. Thermal power plants are characterized by high investment cost but low variable operating costs. Like nuclear power, thermal power is usually used as baseload power plants. However, even though the ramp rate is low, thermal power plants can still be controlled, and thus they can also be used as intermediate power plants with some scheduling strategies. Thus, the thermal power production in NordPool market within a day is not as inelastic as nuclear power production. Varying thermal power productions within a day are often seen in Denmark, Finland and Baltic countries.

2.5.4 Gas and Diesel

Gas and oil can be used as fuels for thermal based power plant or combusting turbine based power plant. Gas and diesel power plants which uses combusting turbine to generate electricity are commonly used as peaking power plants as it can be ramped up within minutes [13]. Even though gas and diesel power plants are relatively cheap to build, they depend on very expensive fuels and are considered inefficient [10]. Thus, the use of gas and diesel power plants is usually avoided.

2.5.5 Intermittent Renewable Energy

Intermittent renewable energy (IRE) source is a renewable source of energy that is not continuously available for conversion to electricity as its energy source is dependent on environment conditions e.g weather. Solar, wind, and wave power are categorized as intermittent renewable energy sources. IRE power can be forecasted but not fully dispatched when the electric power systems need it. Since power systems must always meet the load all the time, IRE cannot be categorized as either baseload, intermediate and peaking plants. There is no guarantee that the plants can generate a specific load level at a given time [10]. Instead, they are more suitable to be categorized as negative load in the power systems. Total load of electricity minus intermittent renewable energy (IRE) are often called residual load or net-load. Previous studies from [14] and [15] have concluded that residual load has stronger correlation than total load to the electricity system price.

Regarding financial aspects, IRE power plants have very low variable cost since the fuel is free. Thus, they are ideally used to replace generation with very high variable cost such as gas and diesel. If IRE generation is available when the demand is low, it can replace thermal and nuclear generation [10].
3. Methodology

This chapter covers and explains the modeling strategy and methodology used in this thesis work. Section 3.1 discusses the overall strategy and motivation of the model construction. Section 3.2 describes the data used in this thesis. Section 3.3 presents the supply and demand curves parameters breakdown. Statistical analysis of supply demand curves against some key physical parameters is performed in Section 3.4. The elspot market model is constructed in Section 3.5. Finally, the future simulations set-up is presented in Section 3.6.

From this section until the end of this thesis, many symbols are used and presented. Two of the most important and repeated are $x$ which stands for electricity volume, and $y$ which stands for electricity price.

3.1 Overall Strategy and Motivation

First of all, all available aggregated supply and demand curves data in different years from NordPool website will be observed to capture the players’ bidding strategies in the market. The aggregated supply and demand curves data from 2015 to the day the author writes this thesis is available on NordPool website. No data before 2015 is available. The statistical analysis will be performed to capture the trend of supply and demand curves based on several physical parameters. Then the electricity market model will be constructed in reference to the statistical analysis results.

An overview of the elspot price modeling strategy in this thesis can be described as follows

1. Extracting important values in the real supply and demand curves.
2. Statistically analyzing the correlation and fitting the respective values as a function of
   a. hourly pattern in holidays and working days
   b. real or prognosis of electricity consumption
   c. nuclear generation
   d. temperature
   e. hydropower reserve
   f. IRE
3. Modeling the supply and demand function based on the fitted values.
4. Defining the model price based on the intersection of the supply and demand function models.

3.2 Data

The historical data used in this thesis are: system prices, supply demand curves, hydro reserve levels, electricity consumptions, temperatures, nuclear generations and wind generations.

In reference to what has been presented in Section 2.3 and 2.5, from the available conventional power production data, this thesis uses only nuclear power generation data for statistical and modeling purpose and only Sweden and Finland use nuclear
power in the Nordic Baltic region. For the IRE data, this thesis only uses wind generation hourly data from Denmark, Sweden and Finland considering the data availability and the fact that in these countries’ wind power production shares in the Nordic-Baltic electricity mix are more significant than in other countries.

In this thesis, the temperature data is for Stockholm, with a simplified assumption that geographically Stockholm represents the temperature in the NordPool power market area. Furthermore, since Stockholm is the most populated area in the NordPool area and Sweden has more than 3 times electricity usage compared to its direct heating usage [9], one can reasonably assume that there is a large share of power to heat. In that case the correlation between the temperature in Stockholm and Nordic Baltic region’s baseload power should be strong.

The data in this thesis are obtained from the several sources. The sources and the data provided are listed as follows:

- NordPool [16]: system price, supply demand curve, hydro reserves level and electricity consumption data.
- Swedish Meteorological and Hydrological Institute [17]: temperature data in Stockholm.
- Svenska Kraftnät [18]: nuclear and wind generation data in Sweden.
- Energia Finland [19]: nuclear and wind generation data in Finland.
- Denmark Energy Data Service [20]: wind generation data in Denmark.

At the time of finalizing the model, only data in 2015 and 2016 were complete on full-year basis. Table 3.1 shows the availability of the data in each full-year time series.

<table>
<thead>
<tr>
<th>Year</th>
<th>System Price</th>
<th>Supply Demand Curves</th>
<th>Hydroreserves Level</th>
<th>Temperature (Stockholm)</th>
<th>Nuclear and Wind Generation (Sweden)</th>
<th>Nuclear and Wind Generation (Finland)</th>
<th>Wind Generation (Denmark)</th>
<th>Electricity Consumption and the Prognosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>2013</td>
<td>V</td>
<td>X</td>
<td>V</td>
<td>V</td>
<td>V</td>
<td>V</td>
<td>V</td>
<td>V</td>
</tr>
<tr>
<td>2014</td>
<td>V</td>
<td>X</td>
<td>V</td>
<td>V</td>
<td>V</td>
<td>V</td>
<td>V</td>
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<tr>
<td>2015</td>
<td>V</td>
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<td>V</td>
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<tr>
<td>2016</td>
<td>V</td>
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<td>2017</td>
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<td>V</td>
<td>V</td>
<td>X</td>
<td>V</td>
<td>V</td>
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<td>V</td>
</tr>
</tbody>
</table>

### 3.3 Supply and Demand Functions Structures

In this section the existing supply and demand curves are analyzed. Figure 3.1 shows a sample of existing supply demand curves and their intersection point where the system price and the traded volume is agreed. As can be seen, the price level varies depending on the electricity volume.

The changing trend of the shape is captured in the model by considering some selected points as indicated in Figure 3.2. The selection of highlighted points is presented in more detail in Section 3.3.1 and 3.3.2.
Figure 3.1. Supply demand curves for the 1st hour on 25/10/16 point out: more narrow range on vertical axis (a) whole data and (b) highlights.

3.3.1 Supply Function Components

The highlighted points in the supply curve are shown in Figure 3.2. Every highlighted point is described as follows:

- **$x_{floor}$** is the minimum selling volume bid.
- **$x_{min20}$** is the selling volume bid when the price is -20 €/MWh.
- **$x_{zero}$** is the selling volume bid when the price is 0 €/MWh.
- **$x_{shift}$** is the selling volume bid when the price shifts from cheap price to regular price.
- **$x_{steady}$** is the selling volume bid when the price starts to be more steady in the longest interval of the bidding volume.
- **$x_{extreme}$** is the selling volume bid when the price starts to increase extremely.
- **$x_{cap}$** is the maximum selling volume bid.
- **$y_{shift}$** is the selling price bid when the price shifts from cheap price to regular price.
- **$y_{steady}$** is the selling price bid when the price starts to be more steady in the longest interval of the bidding volume.
- **$y_{extreme}$** is the selling price bid when the price starts to increase extremely.
As can be seen, the price increases are not the same in every volume increase; instead it varies depending on ranges. The range between $x_{\text{steady}}$ and $x_{\text{extreme}}$ is the widest range in the supply curve. It means the probability of the system price within $y_{\text{steady}}$ and $y_{\text{extreme}}$ range is higher than within the other ranges.

### 3.3.2 Demand Function Components

The highlighted points in the demand curve are shown in Figure 3.3. Every highlighted point is described as follows:

- $x_{\text{Dfloor}}$ is the minimum buying volume bid
- $x_{\text{Dcap}}$ is the maximum buying volume bid
- $x_{\text{Dzero}}$ is the buying volume bid when the price is 0 €/MWh
As can be seen, even though the demand varies depending on the system price, the demand curve is much more inelastic than the supply curve.

3.4 Statistical Analysis

In this section, the correlation between the physical parameters listed in Section 3.1 and the supply and demand curve parameters is analyzed. The physical parameters are temperature, nuclear generation, hydropower reservoir, and real electricity consumption. However, the first step is to capture the hourly trend in order to categorize peak and off-peak hour. Stronger correlation is expected with the peak and off-peak hours’ categorization.

Among all supply parameters, $x_{zero}$ and $x_{cap}$ are chosen to be examined against the physical parameters. It is essential to estimate $x_{cap}$ accurately since it represents the maximum capacity the market can provide. It is also essential to estimate $x_{zero}$ accurately instead of $x_{floor}$ because it can be concluded that the real market starts from $x_{zero}$. Even though $x_{floor}$ represents the minimum capacity of electricity the market must sell, a negative system price never occurred in previous 5 years which makes it unnecessary to estimate $x_{floor}$ very accurately. Negative area price occurred in the Denmark region few times, but the reason for that is the transmission constrains which prevents the export of high excess of wind power production. Thus the price in the neighbor areas did not go negative. More importantly, $x_{zero}$ is closer to the other important parameters (i.e., $x_{shift}$ and $x_{steady}$). Thus, examining $x_{zero}$ will give a more accurate estimation of $x_{shift}$ and $x_{steady}$ than examining $x_{floor}$.

Since the demand curves are much more inelastic than the supply curves, the demand volume estimation will be more simplified. The $x_{Dcap}$ will be excluded from the examination for the same reason with exclusion of $x_{floor}$ of supply curve, the negative system price never happened. Only $x_{Dfloor}$ and $x_{Dzero}$ will be examined, and it is only against real electricity consumption.

3.4.1 Hourly Pattern

The players’ bidding strategies within a day would depend on hourly conditions. For example, consider a camel hump shaped load during a day. For the morning peak hours, many players plan to turn on their power plant at that time to reach the market demand. As the load decreases between two peaks, shutting down already-running power plant can be disadvantageous for many as some power plant are expensive to start and cheaper to keep running. Note that they will need those power plants running again during the afternoon peak hours. In this case, many players are more likely not to change the selling offer after the morning peak hours that will result in a more inelastic $x_{cap}$ between the two peaks. Remember that the closer the demand to the $x_{cap}$ the more expensive the system price is. For this reason, the camel hump shape is also visible in the system price graph to some extent.

Supply Function

This subsection examines the hourly pattern of the supply function component based on the following categories of days:
The definition of a holiday in this case is a weekend day or a national holiday day, while the rest of the days are working days. The definition of summer is the time when the daylight saving hour is activated, while the rest of the time is winter.

Figure 3.4 and 3.5 show the hourly average value of $x_{zero}$ and $x_{cap}$ respectively in the working day and holiday. It is clearly visible that the working day and holiday categories have different patterns. It can also be seen that the $x$ value at the $6^{th}$ hour of the day is the lowest in the working day and one of the lowest in the holiday. The $x$ value starts to increase significantly after that hour, especially in the working day. It can be concluded that the time before $6^{th}$ hour of the day could be categorized as off-peak hours and the time after could be categorized as peak hours.

In order to see the pattern more clearly, the value in each hour is divided by the value at the $6^{th}$ hour of the day which later will be referred as the reference hour value. The ratio of $x_{zero}$ and $x_{cap}$ to the reference hour value for working day and holiday category is shown in Figure 3.6.

It can be seen that there is a slight difference between $x_{zero}$ and $x_{cap}$ ratios especially in the holiday peak-hours. It shows that the motivation mentioned earlier behind capturing the hourly pattern of both $x_{zero}$ and $x_{cap}$ turned out to be the right decision.
Figure 3.4. Hourly Average Value of $x_{\text{zero}}$ in working day and holiday.

Figure 3.5. Hourly Average Value of $x_{\text{cap}}$ in working day and holiday.

Figure 3.6. Ratio of $x$ to the $x_{\text{ref}}$ in working day-holiday categorization.

Figure 3.7 shows how the $x_{\text{zero}}$ and $x_{\text{cap}}$ value differ in summer and winter time. While the volume differences are obvious from Figure 3.7, the pattern difference is hardly captured. As done in the holiday and working day categorization, the $x$ value in each hour is divided by the value at the reference hour in order to see the pattern difference which is shown in Figure 3.8. From Figure 3.8, it can be observed that the patterns for each category are actually similar to each other.
From Figure 3.4-3.8 the market behaviour on an hourly basis can be concluded. Only working day and holiday categories have significant variation relative to the $x$ at the reference hour as shown in Figure 3.6, while Figure 3.8 shows that summer and winter categories are pretty much similar. Thus, that makes it unnecessary to differentiate between summer and winter in the model.

In the next subsections where the supply function is modeled, the important physical parameters will be examined against the $x$ values only at the reference hour due to peak and off-peak behaviour.

Figure 3.7. Hourly average value of (a) $x_{zero}$ and (b) $x_{cap}$.

Figure 3.8. Ratio of $x$ to the $x_{ref}$ in summer-winter categorization.
Demand Function

This subsection examines the hourly pattern of the demand function based on the electricity consumption. As explained in Section 3.32, the demand function is much more inelastic than the supply function. Since negative system prices never occurred in the last 5 years, the agreed buying volumes or the turnovers are always in the range between $x_{Dfloor}$ and $x_{Dzero}$.

Section 2.2.2 mentioned that the reason to why there can be a mismatch between total consumption and buying bid volumes. However, according to what has been observed in this thesis, the correlation between real consumption and the buying bid volume is pretty straightforward. The shape of both data in a day is very similar as shown in Figure 3.9 where each sample in a working day and a holiday are compared. Thus, the dynamics of the buying bids can be captured simply by scaling the available real consumption data by a factor.

![Figure 3.9. Sample of electricity market demand and consumption in two different days.](image1)

Figure 3.10 shows the ratio of buying bid volumes to the real consumption which later will be used as demand-per-consumption coefficient. As can be seen from Figure 3.10, the demand per consumption value varies mostly between 0.8 and 0.95 with a mean value of 0.867 and a standard deviation of 0.037.

![Figure 3.10. Electricity market demand divided by real consumption.](image2)

It is true that real consumption data actually cannot be obtained to forecast future system price as real consumption data is measured directly on real-time basis. The real consumption data can be replaced by consumption prognosis data when it comes to forecasting future system price. Nevertheless, this thesis relies on the existing consumption data and does not cover a novel modeling of load prognosis.
3.4.2 Temperature

Since there is peak and off-peak pattern as shown in subsection 3.4.1, it is necessary to examine the temperature to the $x$ value only at specific identical hours of the days. As described in subsection 3.4.1, the 6th hour of the day is ideal to be set as reference hour. The load at 6th hour of the day is considered as off-peak load, which means the load is basically a baseload power that is strongly defined by temperature. This specific condition might only apply for cold areas like Nordic-Baltic region and the other areas of the world might have different correlations.

Figure 3.11 shows the $x_{zero}$ and $x_{cap}$ dispersions against temperature and linear and table 3.2 presents the correlation of $x_{zero}$ and $x_{cap}$ to the temperature.

![Figure 3.11](image)

*Figure 3.11. (a) $x_{zero}$ and (b) $x_{cap}$ dispersions against temperature at the reference hour.*

<table>
<thead>
<tr>
<th>Correlation coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T$ vs $x_{zero}$</td>
</tr>
<tr>
<td>$T$ vs $x_{cap}$</td>
</tr>
</tbody>
</table>

As can be seen from Figure 3.11, the linear correlation between temperature and $x$ can be captured. Both $x_{zero}$ and $x_{cap}$ has a very strong correlation with absolute coefficient higher than 0.8. It can be concluded that the temperature influence on the market bids is solidly strong.

3.4.3 Nuclear Power Generation

As mentioned in Section 2.5, nuclear power has the most inelastic generation pattern due to its inflexibility. The available data categorized coal, biofuel and other heat-based power plants into thermal power. Since each type of thermal power plant has a different ramp-rate, it is hard to separate which ones are baseload thermal power plants such as coal, and which ones are intermediate or peaking thermal power plants. While IRE generation forecasting data is essentially needed as it has a unique
variability, the other non-IRE patterns such as thermal power generation seem to follow more or less the consumption load shape. It makes the explicit inclusion of non-IRE in the model unnecessary. Thus, among the available non-IRE power generation data, only nuclear power generation data is used as input to the model.

Figure 3.12 shows the $x_{\text{zero}}$ and $x_{\text{cap}}$ dispersions against nuclear power generation and linear correlations can be identified from there. Statistically, both $x_{\text{zero}}$ and $x_{\text{cap}}$ have strong correlations as shown in table 3.3. It can be concluded that nuclear power generation has a strong influence on the current market.

![Figure 3.12](image)

(a) $x_{\text{zero}}$ and (b) $x_{\text{cap}}$ dispersions against nuclear generation at the reference hour.

Table 3.3 nuclear generation against $x$ value correlation coefficient

<table>
<thead>
<tr>
<th>Correlation coefficient</th>
<th>0.765</th>
</tr>
</thead>
<tbody>
<tr>
<td>nuclear vs $x_{\text{zero}}$</td>
<td></td>
</tr>
<tr>
<td>nuclear vs $x_{\text{cap}}$</td>
<td>0.773</td>
</tr>
</tbody>
</table>

### 3.4.4 Hydropower Reserves

Figure 3.13 shows the hydro reserves level and $y_{\text{steady}}$ within a year from 2015 to 2017. From Figure 3.13, the correlation of $y_{\text{steady}}$ with the hydro reserves level can be observed. The $y_{\text{steady}}$ level does not correlate with the hydro reservoir directly in an inversely proportional way. For example, the $y_{\text{steady}}$ in March 2016 is lower than in November 2016 even though the hydro reserve is higher in November 2016. Instead, $y_{\text{steady}}$ is inversely proportional to the seasonal regular level of the hydro reservoir.

Within the period of January to April, the $y_{\text{steady}}$ is lower in 2016 while the hydro reserves level is higher compared to the values in the same period in the other years. The same pattern can be seen within the period of July to October, when the $y_{\text{steady}}$ is lower and the hydro reserves level is higher in 2015. Within the period of October to December, the $y_{\text{steady}}$ in 2016 is higher compared to the value in the other years due to lower hydro reserves level.
In order to see the correlation more clearly, the seasonal reference of hydro reserve level should be defined. Among hydro reserves and available $y_{steady}$ data in 3 years, the data in 2017 are chosen to be the reference data as it has more stable $y_{steady}$ through the year even though it is not perfectly stable.

Figure 3.13 shows the inversely proportional correlation between $y_{steady}$ and $y_{steady,ref}$ differences and $r$ and $r_{ref}$ differences, where $r$ stands for hydro reserve level, $r_{ref}$ and $y_{steady,ref}$ stand for reference data for hydro reserve and $y_{steady}$ respectively. The correlation coefficient between $y_{steady}$ difference and $r$ difference is -0.6 which means the data in 2017 is a fair choice for a reference.

Figure 3.14 shows $\Delta y_{steady}$ dispersions against $\Delta r$ with data from 2017 as a reference. $\Delta y_{steady}(t) = y_{steady,ref}(t) - y_{steady}(t)$, $\Delta r = r_{ref}(t) - r(t)$. 

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure3.13}
\caption{(a) Hydro reserves level and (b) $y_{steady}$ in 2015 to 2017.}
\end{figure}

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure3.14}
\caption{$\Delta y_{steady}$ dispersions against $\Delta r$ with data from 2017 as a reference. $\Delta y_{steady}(t) = y_{steady,ref}(t) - y_{steady}(t)$, $\Delta r = r_{ref}(t) - r(t)$.}
\end{figure}
As can be seen in the Figure 3.13, during early spring when ices throughout NordPool market area start to melt, the hydro reserve level does not seem to follow the reference hydro reserve level rule. It is assumed that water storage in ice and snow which later becomes snowmelt runoff to stream is the major factor which defines $y_{\text{steady}}$. However, this thesis considers that the hydro reserves level represents the hydropower-system price correlation well enough and does not cover a deeper investigation on more complex hydrology and system price correlations.

### 3.4.5 Intermittent Renewable Energy

Wind power generation accounts for most of the IRE generation in the Nordic Baltic region. Solar power has not reached 1% in the total generation while wind has contributed to almost 10% of the total generation in Nordic Baltic region. Nonetheless, the impact of wind generation on the market has not been clearly obvious due to its relatively small share in the market, but still a linear correlation between $x$ and wind power is slightly visible as shown in Figure 3.15. With correlation coefficients around 0.5 as shown in table 3.4, IRE influence cannot be ignored in the current market. A higher influence is expected when IRE penetration is increased.

![Figure 3.15](image.png)

**Figure 3.15.** (a) $x_{\text{zero}}$ and (b) $x_{\text{cap}}$ dispersions against wind generation at the reference hour.

<table>
<thead>
<tr>
<th>Wind generation against $x$ value correlation coefficient</th>
<th>Correlation coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>wind vs $x_{\text{zero}}$</td>
<td>0.517</td>
</tr>
<tr>
<td>wind vs $x_{\text{cap}}$</td>
<td>0.560</td>
</tr>
</tbody>
</table>

### 3.5 Model Construction

In this section, both supply and demand model construction will be conducted using fitting methods based on the statistical analysis from Section 3.4. The Matlab function `fitlm` was used to estimate the constants when the function has more than one independent parameter. While the `fitlm` is useful for such cases as it can have more
than two independent variables as the input, the fitlm function is only able to provide an accurate estimation only if each independent variable is strongly linear to the dependent variable. The Matlab function nlinfit was used if the function has only one dependent parameter. The nlinfit function can estimate the fitting coefficient in any form of equation. However it requires initial guess for the estimated constants as inputs and it can only have one independent variable to be fitted. An initial guess too far from the true value most likely will lead to inaccurate result.

3.5.1 Supply Model

The proposed supply model is constructed as a function of temperature, nuclear power generation, hydro reserves level and wind power generation. The supply model construction was done in the following order:

1. Fit the parameters at the reference hour of the day into the constructed functions of \( x_{\text{zero}} \) and \( x_{\text{cap}} \). The reference hour refers to the 6th hour of the day as stated earlier.
2. Multiply by scaling factor to estimate the \( x_{\text{zero}} \) and \( x_{\text{cap}} \) at other hours in the day
3. Estimate the other \( x \) values
4. Construct the complete supply model as a function of time

Parameters fitting for variables at the reference hour

The functions for \( x_{\text{zero}} \) and \( x_{\text{cap}} \) at the reference hour are defined as

\[
x_{\text{zero,ref}} = c_{\text{zero}} + k_{T-\text{zero}}T + k_{n-\text{zero}}n
\]

\[
x_{\text{cap,ref}} = c_{\text{cap}} + k_{T-\text{cap}}T + k_{r-\text{cap}}r + k_{n-\text{cap}}n
\]

where:
\( T \) is the temperature in °C
\( n \) is the nuclear generation in MWh
\( r \) is the hydropower reserves level in GWh

Coefficients and constants, which are obtained with the Matlab function fitlm, are described below:

\( c_{\text{zero}} \) is the constant for \( x_{\text{zero}} \) at the reference hour , it can be assumed logically that this constant refers to must-run power generations with nuclear generation subtracted at the reference hour.

\( k_{T-\text{zero}} \) is the coefficient for temperature correlation with \( x_{\text{zero}} \).

\( k_{n-\text{zero}} \) is the constant for correlation between nuclear generation and \( x_{\text{zero}} \).

\( c_{\text{cap}} \) is the constant for \( x_{\text{cap}} \) at the reference hours.

\( k_{T-\text{cap}} \) is the coefficient for correlation between temperature and \( x_{\text{cap}} \).

\( k_{r-\text{cap}} \) is the coefficient for correlation between hydro reservoir level and \( x_{\text{cap}} \).

\( k_{n-\text{cap}} \) is the coefficient for correlation between nuclear generation and \( x_{\text{cap}} \).

Values of these coefficients and constants can be found in table 3.5 and 3.6 as follows
Table 3.5. Fitted constant and coefficient values in the $x_{zero}$ function

<table>
<thead>
<tr>
<th>Parameter</th>
<th>$c_{zero}$</th>
<th>$k_{T-zero}$</th>
<th>$k_{n-zero}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Value</td>
<td>15781</td>
<td>-260</td>
<td>0.96</td>
</tr>
</tbody>
</table>

Table 3.6. Fitted constant and coefficient values in the $x_{cap}$ function

<table>
<thead>
<tr>
<th>Parameter</th>
<th>$c_{cap}$</th>
<th>$k_{T-cap}$</th>
<th>$k_{r-cap}$</th>
<th>$k_{n-cap}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Value</td>
<td>37200</td>
<td>-424</td>
<td>0.05</td>
<td>1</td>
</tr>
</tbody>
</table>

All the independent parameters in the $x_{zero}$ function are also used in the $x_{cap}$ function since the values of lower $x$ affects the value of higher $x$. The $x_{cap}$ function includes hydropower reserve parameter but the $x_{zero}$ function does not. The reason behind that is that the maximum power selling bid is assumed to be also influenced by the level of hydropower reserves, but the hydropower plant owners would not want to sell their power for 0 €/MWh since they can turn on and off their plants quickly without costly procedures unlike nuclear plants.

The result of the $x_{zero}$ parameter estimation is fairly correlated to the real $x_{zero}$ with 7% root-mean-square error (RMSE) as all the dependent parameters are strongly linear to $x_{zero}$ while the $x_{cap}$ estimation is not as smooth due to the nonlinear dependence on hydro reserve to $x_{cap}$ which is not suitable for Matlab command fitlm. Thus, the coefficients for the hydro reserves and wind parameters in $x_{cap}$ function obtained using the fitlm function are discarded and replaced with values obtained through a classical trial and error approach as shown in table 3.6 with the red color. The RMSE of the estimated $x_{cap}$ and real $x_{cap}$ is decreased from 15% to just 5% with the trial and error $k_{r-cap}$ inclusion.

Figure 3.16 shows the $x_{zero}$ and $x_{cap}$ model against the real values at the reference hour.
Hourly Scaling Factor Application

As stated earlier, hourly scaling factors is needed to distinguish the different trend within a day.

The hourly scaling factors are defined for

- each hour of the day (24)
- working day or holiday (2)

The hourly scaling factors are represented by \( h_{\text{zero}} \) for \( x_{\text{zero}} \) and \( h_{\text{cap}} \) for \( x_{\text{cap}} \).

\( h_{\text{zero}}(t) \) and \( h_{\text{cap}}(t) \) denote the hourly scaling factors for the \( x_{\text{zero}} \) and \( x_{\text{cap}} \) models for hour \( t \), which are obtained from

\[
\begin{align*}
h_{\text{zero}}(t) &= \frac{x_{\text{zero.avg}}(t)}{x_{\text{zero.avg.ref}}} & (3) \\
h_{\text{cap}}(t) &= \frac{x_{\text{cap.avg}}(t)}{x_{\text{cap.avg.ref}}} & (4)
\end{align*}
\]

where:
- \( x_{\text{zero.avg}}(t) \) is mean value of \( x_{\text{zero}} \) for hour \( t \) obtained from the available raw data,
- \( x_{\text{zero.avg.ref}} \) is mean value of \( x_{\text{zero}} \) for the 6\(^{th} \) hour of the day obtained from the available raw data,
- \( x_{\text{cap.avg}}(t) \) is mean value of \( x_{\text{cap}} \) for hour \( t \) obtained from the available raw data, and
- \( x_{\text{cap.avg.ref}} \) is mean value of \( x_{\text{cap}} \) for the 6\(^{th} \) hour of the day obtained from the available raw data.

The \( h_{\text{zero}} \) and \( h_{\text{cap}} \) value are the ones shown in Figure 3.6 in Section 3.4.1 and the exact values are presented in the appendix.

Equation (5) and (6) show \( x_{\text{zero}} \) and \( x_{\text{cap}} \) at hour \( t \) as functions of \( h_{\text{zero}} \) and \( h_{\text{cap}} \):

\[
\begin{align*}
x_{\text{zero}}(t) &= h_{\text{zero}}(t) \times x_{\text{zero.ref}} & (5) \\
x_{\text{cap}}(t) &= h_{\text{cap}}(t) \times x_{\text{cap.ref}} + w(t) & (6)
\end{align*}
\]

A new variable \( w(t) \) is introduced in the \( x_{\text{cap}} \) model which denotes for wind power generation at hour \( t \). A more detailed motivation for the placement of wind generation is described in the next subsection.

Estimation of Other \( x \) Parameters

As stated in the objective Section, the aim of this thesis is to forecast the long term system price, which means that some adjustments of the supply and demand function model will be needed to obtain a more accurate result.

The negative price volumes are not as essential as the other \( x \) parameter for the current Nordic-Baltic system as the negative system price has never occurred in the last 5 years. Thus, the modeling of \( x_{\text{floor}} \) and \( x_{\text{min20}} \) are simplified. For the IRE
electricity volume, it will be placed in between $x_{zero}$ and $x_{shift}$ as it is assumed in the real market the IRE will be sold for any price as long as the price is positive.

Since the traded volume is most likely to be in the range between $x_{steady}$ and $x_{extreme}$, overestimating this range will give more accurate forecast for long term simulation. This can be done by minimizing the range between $x_{shift}$ and $x_{steady}$ and the range between $x_{extreme}$ and $x_{cap}$.

With such assumptions, the other $x$ parameters at hour $t$ are defined as

$$x_{floor}(t) = x_{zero}(t) - c_{zf}$$

(7)

$$x_{min20}(t) = x_{zero}(t) - \frac{1}{2} c_{zf}$$

(8)

$$x_{shift}(t) = x_{zero}(t) + w(t)$$

(9)

$$x_{steady}(t) = x_{shift}(t) + c_{ss}$$

(10)

$$x_{extreme}(t) = x_{cap}(t) - c_{ce}$$

(11)

where:

$c_{zf}$ denotes a constant which is obtained from the mean of the $x_{zero}$ and $x_{floor}$ difference,

$c_{ss}$ denotes a constant which is adjusted around the mean of the $x_{steady}$ and $x_{shift}$ difference, and

$c_{ce}$ denotes a constant which is adjusted around the mean of the $x_{cap}$ and $x_{extreme}$ difference.

Table 3.7 shows the values of the constants used in the supply modeling.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>$c_{zf}$</th>
<th>$c_{ss}$</th>
<th>$c_{ce}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Value</td>
<td>3000</td>
<td>2800</td>
<td>2500</td>
</tr>
</tbody>
</table>

**Estimation of y Parameters**

Among $y$ parameters used in the supply modeling, only $y_{steady}$ has a non-negligible varying behaviour. However, the $y_{steady}$ values vary only on a daily basis following hydro reserves level variations instead of an hourly basis like $x$ values. Since $y_{extreme}$ is higher than the $y_{steady}$, the $y_{steady}$ variation also affects $y_{extreme}$. Thus, both $y_{steady}$ and $y_{extreme}$ should be defined as functions of some independent parameters:

$$y_{steady}(t) = y_{steady, ref}(t) + k_{r-y}(r(t) - r_{ref}(t))$$

(12)

$$y_{extreme}(t) = y_{steady}(t) + 10$$

(13)

where:

$y_{steady}(t)$ stands for $y_{steady}$ at time $t$,
$y_{\text{steady,ref}}(t)$ stands for the reference data for $y_{\text{steady}}$ at time $t$ obtained from the data in 2017.

$r(t)$ stands for hydro reserve level at time $t$,

$r_{\text{ref}}(t)$ stands for the reference data for hydro reserve at time $t$ obtained from the data in 2017.

$k_{r,y}$ stands for the coefficient for correlation between hydro reserves and $y_{\text{steady}}$ obtained with the Matlab fitlm function.

The other $y$ parameters can be set constant. $k_{r,y}$ and the other assumed $y$ values are listed in table 3.8.

**Table 3.8. Constant $y$ values and $k_{r,y}$**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>$k_{r,y}$</th>
<th>$y_{\text{floor}}$</th>
<th>$y_{\text{min20}}$</th>
<th>$y_{\text{zero}}$</th>
<th>$y_{\text{shift}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Value</td>
<td>-4.513 x 10^-4</td>
<td>-100</td>
<td>-20</td>
<td>0</td>
<td>3</td>
</tr>
</tbody>
</table>

While the values of $y_{\text{min20}}$ and $y_{\text{zero}}$ are clear based on their definitions, $y_{\text{shift}}$ is obtained from the mean value of the real $y_{\text{shift}}$ from the available NordPool raw data. Even though the negative price estimation is not that essential for the current market model, $y_{\text{floor}}$ still needs to be defined. The minimum selling bid price is limited to -100 in the model compared to -500 in the real raw data. The maximum selling bid price is not set as it will be auto-generated from the model due to the objective to avoid false spikes.

**Supply Function Construction**

The supply function modeled is constructed with 6 different linear functions with different slopes depending on in which range the electricity volume is. The whole supply function in function of time $t$ is defined as

$$S_{y}(t) = \begin{cases} 
  y_{\text{floor}} + m_{\text{floor}}(t) \left( x - x_{\text{floor}}(t) \right) & \text{if } x_{\text{floor}}(t) \leq x < x_{\text{min20}}(t) \\
  -20 + m_{\text{zero}}(t) \left( x - x_{\text{min20}}(t) \right) & \text{if } x_{\text{min20}}(t) \leq x < x_{\text{zero}}(t) \\
  0 + m_{\text{shift}}(t) \left( x - x_{\text{zero}}(t) \right) & \text{if } x_{\text{zero}}(t) \leq x < x_{\text{shift}}(t) \\
  y_{\text{shift}} + m_{\text{steady}}(t) \left( x - x_{\text{shift}}(t) \right) & \text{if } x_{\text{shift}}(t) \leq x < x_{\text{steady}}(t) \\
  y_{\text{steady}}(t) + m_{\text{linear}}(t) \left( x - x_{\text{steady}}(t) \right) & \text{if } x_{\text{steady}}(t) \leq x < x_{\text{extreme}}(t) \\
  y_{\text{extreme}}(t) + m_{\text{cap}} \left( x - x_{\text{extreme}}(t) \right) & \text{if } x_{\text{extreme}}(t) \leq x < x_{\text{cap}}(t) 
\end{cases}$$

(14)

where:

$x$ is the electricity volume between $x_{\text{floor}}(t)$ and $x_{\text{cap}}(t)$, and $m_{\text{floor}}(t)$, $m_{\text{zero}}(t)$, $m_{\text{shift}}(t)$, $m_{\text{steady}}(t)$, $m_{\text{linear}}(t)$ are the slope coefficients in each range at time $t$. The latter are defined as
where \( y_{\text{upper}} \) and \( x_{\text{upper}} \) are respectively the price and volume upper limits in each range, and \( y_{\text{lower}} \) and \( x_{\text{lower}} \) are the lower limits. For example

\[
m_{\text{floor}}(t) = \frac{y_{\text{min}_2}(t) - y_{\text{floor}}(t)}{x_{\text{min}_2}(t) - x_{\text{floor}}(t)} = \frac{-20 - (-100)}{x_{\text{min}_2}(t) - x_{\text{floor}}(t)}
\]

In order to avoid false spikes, \( m_{\text{cap}} \) is manually adjusted and set to 0.01.

Figure 3.17 shows a sample of supply curves with the constructor parameters

\[
D_x(t) = h_D(t) \left( k_{\text{DPC}} C(t) + k_D \frac{(c_{\text{avg}} - c(t))}{c_{\text{avg}}} \right)
\]

where:

\( D_x \) is the modeled electricity demand volume,

\[3.5.2 \text{ Demand Model}\]

The proposed demand model is constructed as a function of electricity consumption. Instead of making a full demand curve, the demand modeling is simplified with just picking one single value of electricity volume in each hour.

Even though the demand modeling can be done more simply due to the demand inelasticity, some adjustments will make the whole model obtain a value close to the real system prices. In this thesis, demand estimation adjustment is done with two simultaneous approaches, based on hourly pattern and electricity volume.
\( h_D(t) \) is the hourly demand scaling factor at hour \( t \),
\( k_{Dpc} \) is a fixed constant obtained from the average value of buying bid volume per consumption,
\( k_D \) is a fixed constant adjusted from the average of the \( x_{Dfloor} \) and \( x_{Dzero} \) difference,
\( C(t) \) is the electricity consumption at hour \( t \), and
\( C_{avg} \) is a fixed constant obtained from the electricity consumption average in 2015-2017.

The demand per consumption ratio \( k_{Dpc} \) is defined as

\[
k_{Dpc} = \frac{\sum_{i} D_{\text{turnover}, i}}{C_{i}}
\]

where \( D_{\text{turnover}} \) is the agreed buying volumes from the raw data, and \( C \) is the real electricity consumption, and \( n \) is total number of the available data.

It is assumed that the ratio of demand to real electricity consumption will be lower in the peak hour because many players use their own generation facilities at that time. Thus, hourly coefficients will be added to the model. The hourly coefficient for the demand is the inverse of \( x_{\text{cap}} \); hourly coefficients \( h_{\text{cap}} \). However the reference hour is changed from the 6\(^{th} \) hour to the 18\(^{th} \) hour:

\[
h_D(t) = \frac{1}{h_{\text{cap}}(t)} \frac{1}{h_{\text{cap}, 18}}
\]

where \( h_{\text{cap}, 18} \) is the hourly \( x_{\text{cap}} \) coefficient at the 18\(^{th} \) hour of the day. The exact values of \( h_D \) are presented in the appendix. The motivation behind the selection of the 18\(^{th} \) hour of the day as the reference is because the electricity consumption average at that time within a day is the highest. Making the 18\(^{th} \) hour of the day as the reference hour will set the \( h_D \) to 1 at the 18\(^{th} \) hour of the day and to a value bigger than 1 at the other hour. If the reference hour remains at the 6\(^{th} \) of the day, the \( h_D \) at the peak hours will be lower than 1. Having the scaling factor \( h_D \) lower than 1 for the peak hours is considered not good as it will underestimate the peak hours demand too much since in fact the peak hours has been underestimated by the main function already.

Even though the hourly classification in the demand modeling is not assessed as thoroughly as like in the supply modeling, applying this hourly classification approach will reduce the probability of getting a false spike as the demand is pulled away from the \( x_{\text{cap}} \).

The same reason motivates the electricity volume classification. The mean consumption value over 3 years is taken as a reference. If the consumption at a certain hour is higher than the reference, then the demand is expected to be lower than the estimated value from the demand per consumption \( k_{Dpc} \) function, and vice versa if the consumption is lower than the reference, then the demand is expected to be higher than the estimated value from the demand per consumption \( k_{Dpc} \) function.

The \( k_D \) is adjusted from the average of the \( x_{Dfloor} \) and \( x_{Dzero} \) difference. The mean difference of \( x_{Dfloor} \) and \( x_{Dzero} \) from the available data is around 3300 MWh with a
standard deviation around 700 MWh. If the approximated demand is presumed in the exact middle of \( x_{D_{floor}} \) and \( x_{D_{zero}} \), the mean of the largest potential error between real and approximated demand is around 1650 MWh with a standard deviation around 350 MWh. In that case, taking 1650 as \( k_D \) will be a reasonable choice. However, 1000 is taken as \( k_D \) in the model in order not to overestimate the price variation since in fact the real \( k_{DpC} \) does not have a high level variation.

The constant values which are used in the demand modeling are shown in table 3.9.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>( k_{DpC} )</th>
<th>( k_D )</th>
<th>( c_{avg} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Value</td>
<td>0.867</td>
<td>1000</td>
<td>46647</td>
</tr>
</tbody>
</table>

### 3.5.3 Supply-Demand Intersection Point

After the supply and demand curves are modeled, the modeled system price can be obtained from the intersection of the modeled supply and demand curves. Figure 3.18 shows the sample of the modeled supply and demand curves and the real supply and demand curves as well as their intersections which are defining the system prices. The complete model validation is done and presented in section 4.1.

![Figure 3.18. Sample of real and modeled supply and demand curves (data for 25/11/16 at 16.00-17.00).](image)

### 3.6 Future Scenario

After the model has been constructed, some future scenarios will be simulated. There are 6 future scenarios simulated which can be divided into two categories: IRE capacity addition without nuclear plants removal and electricity from IRE substituting electricity from nuclear plants. All these future scenarios will be compared to the base
scenario where no IRE is added and no nuclear is removed. All the scenarios simulated in this section are described in table 3.10.

<table>
<thead>
<tr>
<th>Scenario number</th>
<th>Scenario</th>
<th>Solar addition (TWh)</th>
<th>Wind addition (TWh)</th>
<th>Nuclear phase out (TWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Base</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>Low IRE</td>
<td>5</td>
<td>15</td>
<td>0</td>
</tr>
<tr>
<td>3</td>
<td>High IRE</td>
<td>10</td>
<td>60</td>
<td>0</td>
</tr>
<tr>
<td>4</td>
<td>High solar</td>
<td>50</td>
<td>20</td>
<td>0</td>
</tr>
<tr>
<td>5</td>
<td>Low IRE substitutes nuclear</td>
<td>5</td>
<td>15</td>
<td>20</td>
</tr>
<tr>
<td>6</td>
<td>High IRE substitutes nuclear</td>
<td>10</td>
<td>60</td>
<td>70</td>
</tr>
<tr>
<td>7</td>
<td>High solar substitutes nuclear</td>
<td>50</td>
<td>20</td>
<td>70</td>
</tr>
</tbody>
</table>

The studies [14] and [15] concluded that the electricity spot market price has a stronger correlation to the residual load than to the total load. In that case, residual load is the total load minus solar and wind generation. This thesis uses a different approach in including wind and solar power into the market model.

Since wind power plants are mostly connected into MV or HV transmission lines, it is assumed that almost all wind power plants are owned by power producers, not by end-users except for very few industries. In that case the wind power volume is added into the supply curve and placed just after \( x_{zero} \) meaning that the wind power will be sold to the market as long as the price is not negative. The considerations for not adding wind power volume into negative volume price is that the wind power is not a must-run power plant. When the wind is blowing, turning on and off the wind power systems is not very costly, as it is for, e.g., nuclear power plants. Thus, the wind power producers can disconnect their power plants from the system when the elspot price is negative.

It is a different case with solar power. Solar power plants are mostly connected to the distribution grid, except for centralized solar power systems. That is due to an increasing trend of building-applied PV systems which are most probably owned by the end-users. In that case the solar power volume is used as a direct subtraction from the demand, creating a new so-called residual-demand curve. This residual-demand curve will be used to define the system prices instead of the total-demand curve in the future scenarios. The residual-demand function involving the total demand formulated in section 3.5.3 which is used for scenario 2, 3, 5 and 6 is shown as follows

\[
D_{res-x}(t) = D_x(t) - s(t)
\]  (19)

where:
- \( D_{res-x}(t) \) is the residual-demand at time \( t \)
- \( s(t) \) is the solar power production at time \( t \)

However, for the high solar power scenarios (scenario 4 and 7), it is unlikely that all the solar power comes from the end-users or distribution grids. The residual-demand
function and the components in the supply function which are used for scenario 4 and 7 when the solar power share is much higher are shown as follows

\[ D_{res-x}(t) = D_x(t) - \frac{1}{2}s(t) \]  \hspace{1cm} (20)

\[ x_{cap}(t) = h_{cap}(t) \times x_{cap,ref} + w(t) + \frac{1}{2}s(t) \]  \hspace{1cm} (21)

\[ x_{shift}(t) = x_{zero}(t) + w(t) + \frac{1}{2}s(t) \]  \hspace{1cm} (22)

In these scenarios, half of the solar power is added into the supply curves just like wind power, and the other half goes to the demand curves. The solar inclusion in the supply curves will affect the \( x \) values larger than \( x_{zero} \). However, it is only the equations of \( x_{cap} \) and \( x_{shift} \) that change as the other affected \( x \) values are dependent to the values of \( x_{cap} \) or \( x_{shift} \). Since the potential of a negative system price is higher in this scenario, the negative price in the model is limited to -20 € in order to avoid extreme minus that will mess up the average and the standard deviation of the system price.
4. Results and Discussion

This section presents the model validation of the modeled system price against the real system price. The future market simulations with higher IRE and nuclear phase out are also presented and discussed.

4.1 Model Validation

The proposed model is simulated and validated with the real data from 2013 to 2017. Table 4.1 shows the average and standard deviation of real and model system price as well as correlation coefficient and mean absolute error between real and model price. Figure 4.1 illustrates the comparison between the modeled and real prices. In Figure 4.2, the price throughout the years and some dynamic highlights can be observed.

From table 4.1, it can be seen that the correlation coefficient between real and modeled price is mostly around 0.7 with the exception for 2013. The mean absolute error (MAE) value is used instead of the root mean squared error (RMSE) value to assess the errors in the model. The RMSE approach is used when an occurrence of a high level of error has a bigger impact than two or more occurrences of lower level of error. For example, an occurrence of 10% voltage drop will have greater damage to the power systems than two occurrences of 5% voltage drop. In that case, the RMSE will penalize more a 10% error than two 5% errors. That is not the case in this model validation, which is why MAE is used. The lowest MAE from the simulated year is the simulation for 2017 with only 1.49 €/MWh MAE. This is because the hydro reserve level data for 2017 is used as the model reference meaning that the simulation for 2017 uses the exact $y_{steady}$ data. The MAE for 2014 and 2016 is considered low as it is below 4 €/MWh while MAE for 2013 and 2015 is considered high with error higher than 6 €/MWh. One reason why MAE is high and correlation coefficient is so low for 2013 could be a factor that this thesis does not cover such as SEK-NOK-DKK-EUR currency, or global policies on fossil fuel etc, especially before summer. However, after June 2013, the modeled prices seem to follow the real price more smoothly as shown in Figure 4.1.

According to the study from report [8], 2015 was considered as a wet year making the selling bids after spring very low beyond what the model could estimate. That is why its MAE is bigger than MAE in 2014, 2016 and 2017 even though it has the best correlation coefficient among the simulated years. This shows that the modeling of the hydro reserve – selling bid correlation needs to be conducted in a more complex way if one wants to get better price forecasting in extreme conditions in different years.

The highest spike occurred in 2016 with 200 €/MWh system price. The model does not capture this spike as the model can only estimate spikes no higher than 70€/MWh. As mentioned in the model construction Section, the reason behind that is avoiding false spikes and drops is more prioritized in this thesis as it will give better correlation coefficient and lower mean absolute errors.
### Table 4.1. Model validation statistics

<table>
<thead>
<tr>
<th>Year</th>
<th>Real Mean (€/MWh)</th>
<th>Real Std (€/MWh)</th>
<th>Model Mean (€/MWh)</th>
<th>Model Std (€/MWh)</th>
<th>Correlation coefficient</th>
<th>MAE (€/MWh)</th>
</tr>
</thead>
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<tr>
<td>2013</td>
<td>38.10</td>
<td>6.95</td>
<td>32.05</td>
<td>6.62</td>
<td>0.54</td>
<td>6.74</td>
</tr>
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<td>2014</td>
<td>29.60</td>
<td>5.35</td>
<td>27.57</td>
<td>5.36</td>
<td>0.67</td>
<td>3.41</td>
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<tr>
<td>2015</td>
<td>20.96</td>
<td>7.92</td>
<td>26.4</td>
<td>4.48</td>
<td>0.72</td>
<td>6.09</td>
</tr>
<tr>
<td>2016</td>
<td>26.47</td>
<td>8.89</td>
<td>27.76</td>
<td>6.29</td>
<td>0.70</td>
<td>3.71</td>
</tr>
<tr>
<td>2017*</td>
<td>29.22</td>
<td>2.88</td>
<td>28.89</td>
<td>3.81</td>
<td>0.70</td>
<td>1.49</td>
</tr>
</tbody>
</table>

*Figure 4.1. Modeled against real system price in (a) 2013, (b) 2014, (c) 2015, (d) 2016, (e) 2017.*
Figure 4.2. Real and model system prices for (a) 2013, (b) 2014, (c) 2015, (d) 2016, (e) 2017. Whole data (-1) and dynamic highlights (-2).
4.2 Future Scenario

As stated in Section 3.6, there are 6 future scenarios and 1 base scenario simulated in this thesis. Section 4.2.1 presents the scenario where solar and wind power capacity is added without removing the nuclear plants and Section 4.2.2 presents the scenario where the electricity from IRE substitutes the electricity from nuclear plants.

The result in Section 4.1 shows that the lowest mean absolute error among the simulated years is the simulation for 2017 since it uses the exact \( y_{\text{steady}} \). However, since the nuclear and wind generation data for 2017 in a full year has not been available at the time of writing, the nuclear and existing wind generation data for 2016 are used instead in simulations of future solar and wind deployment. Other than that, the data for 2017 is used considering stable \( y_{\text{steady}} \) and fewer spikes occurrences.

The existing wind and nuclear power generation in 2016 accounts for around 40 TWh and 80 TWh respectively. The added IRE production data is obtained from an IRE production model for Nordic-Baltic region developed by the Built Environment Energy Systems Group (BEESG) at Uppsala University which is presented in paper [21].

Figure 4.3 shows solar, wind and nuclear generation throughout the year from the scenarios. It can be seen in terms of power that the maximum power generated by wind and solar is higher than nuclear in the substitution scenarios. If one wants to replace the electricity generated by one type of power plant with the other type of power plant, then the capacity factor (CF) of the plants need to be assessed. The capacity factor of power plant is the ratio of the electricity generated by a unit of power plant for a period of time to the maximum electricity the unit can generate if it is operated non-stop at its rated power [10]. Nuclear power plants have a capacity factor around 90%, while that of wind power plants is around 20-40 % and that of solar power plants varies between 10-30% depending on geographical conditions. For example, if electricity (TWh) throughout the year from nuclear power plant with 90% CF is to be replaced with electricity from a solar PV power plant with 15% CF, then the rated power (MW) of the solar PV power plant needs to be six times higher. With these conditions, some major price changes are expected in the market. From the technical point of view, a baseload nuclear power plant cannot be replaced by an IRE power plant since baseload power plant can generate power when it is needed while an IRE power plant cannot. However, considering the huge hydropower reserves, these scenarios are more feasible to be applied in the Nordic-Baltic region. Besides, the IRE power productions can be forecasted accurately one day-ahead, making these scenarios more relevant to be applied to a day-ahead market like elspot market. The mismatch between the load and the production prognosis will be solved in a different market, i.e., the regulating power market. The simulation results and more detailed discussions are presented in Section 4.2.1 and 4.2.2.
Figure 4.3. Solar, wind and nuclear generation for scenario (a) 1, (b) 2, (c) 3, (d) 4, (e) 5, (f) 6 and (g) 7.
4.2.1 Solar and Wind Power Capacity Addition

This section presents the base scenario (scenario 1) simulation and the future simulation of solar and wind power capacity addition into the market without nuclear phase out scenarios (scenario 2, 3 and 4).

Figure 4.4 shows the system prices for scenario 1, 2, 3 and 4 over the year while Figure 4.5 shows their price dynamics in 4 different period of the year. System price statistics in those scenarios are shown in table 4.3. The market trend differences can be observed by looking at the duration curves and monthly moving mean prices which are shown in Figure 4.6 and 4.7 respectively.

![Figure 4.4](image1)

**(a)**

![Figure 4.5](image2)

**(b)**

**Figure 4.4. System prices over the year for scenario (a) 1, (b) 2, (c) 3 and (d) 4.**

![Figure 4.6](image3)

**Figure 4.5. System price dynamics in 4 highlighted periods for the IRE power capacity addition scenarios.**
Table 4.2. System price statistics in scenario 1-4

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Mean (€/MWh)</th>
<th>Std (€/MWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>28.44</td>
<td>4.14</td>
</tr>
<tr>
<td>2</td>
<td>26.93</td>
<td>3.58</td>
</tr>
<tr>
<td>3</td>
<td>20.44</td>
<td>8.81</td>
</tr>
<tr>
<td>4</td>
<td>20.60</td>
<td>11.40</td>
</tr>
</tbody>
</table>

Figure 4.6. Duration curves of system prices in the IRE power capacity addition scenarios

Figure 4.7. Monthly moving mean of system prices in the IRE power capacity addition scenarios.

Overall, the capacity addition of solar and wind power in the current market will make the system price go down. Scenario 2 implementation will only decrease the mean system price from 28.44 €/MWh to 26.93 €/MWh. Other than that, scenario 2 gives more stable system prices with 3.58 €/MWh standard deviation compared to 4.14 €/MWh in the base scenario.
Both scenario 3 and 4 decreases mean system price down to below 21 €/MWh and creates high price variations. The system price variability in scenario 1 – 4 within a day and within a year can be observed from Figure 4.5 and 4.6 respectively. It can be seen that high solar penetration in scenario 4 creates stronger fluctuation in the system price within a day compared to scenario 3. Even negative system prices occur on some occasions. It is also visible that the mean system price in summer is much lower than in winter for scenario 4 with a ratio around 1 to 2. This is due to more prominent day-night and summer-winter variability of the solar power production compared to the wind power production.

### 4.2.2 Nuclear-IRE Substitution

This section presents the base scenario (scenario 1) simulation and the future simulation of solar and wind electricity replacing nuclear power scenarios (scenario 5, 6 and 7).

Figure 4.8 shows the system prices for scenario 1, 5, 6 and 7 over the year while Figure 4.9 shows their price dynamics in 4 different period of the year. System price statistics in those scenarios are shown in table 4.4. The market trend differences can be observed by looking at the duration curves and monthly moving mean prices which are shown in Figure 4.10 and 4.11 respectively.

---

*Figure 4.8. System prices over the year for scenario (a) 1, (b) 5, (c) 6 and (d) 7.*
Figure 4.9. System price dynamics in 4 highlighted periods for the nuclear-IRE substitution scenarios.

Table 4.3. System price statistics in nuclear-IRE substitutions.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Mean (€/MWh)</th>
<th>Std (€/MWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>28.44</td>
<td>4.14</td>
</tr>
<tr>
<td>5</td>
<td>28.60</td>
<td>4.32</td>
</tr>
<tr>
<td>6</td>
<td>29.06</td>
<td>5.67</td>
</tr>
<tr>
<td>7</td>
<td>28.52</td>
<td>13.34</td>
</tr>
</tbody>
</table>

Figure 4.10. Duration curves of system prices in the Nuclear-IRE electricity substitution scenarios.
The simulation results show that the nuclear-IRE substitution scenarios do not change the mean system price much. In general, the system prices in winter will be higher when these scenarios are implemented. The scenario 5 and 6 implementations have very small effect to the existing market condition as both system price average and variations only change to very small degrees. That means the electricity from IRE with realistic shares (much larger share of wind compared to solar) can substitute the electricity from nuclear plants without creating dramatic changes in the market, thanks to the wind power production behaviour which is less intermittent than the solar power production.

The only notable difference will be seen if scenario 7 is implemented as it will change the market quite dramatically. Scenario 7 has the highest level of variation among all the simulated scenarios. As explained in Section 4.2.1, the variability of solar power production is the reason behind the system price strong fluctuations in scenario 7 which also happened to scenario 4. However, unlike scenario 4, scenario 7 has fewer negative prices. The rarity of negative price will prevent the players from quitting the market. Thus, removing the nuclear plants will maintain the market equilibrium when solar power share is higher in the systems.
5. Conclusions and Future Works

In this thesis, the author investigated the dependency of the elspot system price to several physical parameters. The scenarios of future wind and solar capacity addition as well as a nuclear phase out have also been simulated.

Some conclusions that can be drawn from the statistical analysis, market modeling and future simulations, are the following:

- The model proposed has relatively small errors and has a fairly strong correlation to the real data. The model captures most of the hourly dynamics and estimates the price quite well. Thus, it can be used as a tool to model realistic future prices.
- The system price dependency with hydro reservoir level is strong. The correlations between system prices and nuclear generation, temperature, load and IRE have also been captured.
- The introduction of high level of intermittent renewable energy in the future will decrease the mean system price and give more variations throughout the year.
- The substitution of nuclear power generation with realistic shares of IRE (much larger share of wind compared to solar) will not give any significant change to both the system price average and variation throughout the year, which means that these scenarios do not lead to dramatic change in the market.
- The high solar scenario leads to high price gaps in day and night and summer and winter time. Negative prices are more likely to occur in summer. The price variation is much higher compared to the existing market condition. This scenario changes the market quite dramatically.

There is a lot for room of improvements for the existing model and it can be used for other purposes and scenarios. Some future works that the author suggests are listed as follows:

- To study deeper the hydrology and $y_{steady}$ correlation in order to get a more accurate model for $y_{steady}$ as it will make the modeled system price get even closer to the real spot price,
- To improve the spike catching method by implementing more advanced statistical machine learning approaches such as ANN, Monte Carlo, Markov chain, etc.
- To propose a model for estimating spot prices per area by taking into account transmission capacity, losses, power exchange with neighbouring markets, etc.
Acknowledgements

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Bibliography


## Appendix

**Coefficient of $h_{zero}$, $h_{cap}$ and $h_D$**

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<thead>
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<th>hour</th>
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