Prediction of the Impact of Increased Photovoltaics Power on the Swedish Daily Electricity Spot Price Pattern

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Abstract

As the demand for electricity increases throughout the globe while we want to reduce the use of fossil fuels, the need for renewable energy sources is bigger than ever. In countries where solar power makes up a large part of the total energy production, the overall electricity spot price level has become lower. This thesis investigates the underlying mechanism that drives the energy market, and in specific, how the solar power impacts the electricity spot price. We present results from studies made in other markets, and introduce a Regime Switching model for explaining the impact in Sweden. We show that an increase of photovoltaics power has a price lowering effect on the daily price pattern in price area SE3 and SE4.

Keywords:

Regime Switching, Photovoltaics, Electricity Spot Price, Cannibalization Effect, Merit Order Effect

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Nomenclature

Abbreviations

ADF	Augmented Dickey-Fuller
ARCH	Autoregressive Conditional Heteroscedasticity
CET	Central European Time
EM	Expectation–Maximization
IHS	Inverse Hyperbolic Sine
iid	Independent and Identically Distributed
KPSS	Kwiatkowski–Phillips–Schmidt–Shin
LCOE	Levelized cost of electricity
ML	Maximum Likelihood
PV	Photovoltaic
R1	Regime (state) 1
R2	Regime (state) 2
RCM	Regime Classification Measure
RES	Renewable Energy Sources
RS	Regime Switching
SD	Standard Deviation
TSO	Transmission System Operator

UTC Coordinated Universal Time

Functions

$L(\cdot)$ Likelihood function

$\mathrm{E}[\cdot]$ Expected Value

$\ln(\cdot)$ Natural logarithm

Variables

β Regression coefficient

$\boldsymbol{\theta}$ Estimable parameters vector

Δ Difference operator

γ Skewness

κ Kurtosis

λ Scale parameter (spread)

μ Mean

ϕ Auto-regressive coefficient

σ Standard deviation

τ Time difference

$\mathbf{Z}$ Vector with unobserved data

ξ Location parameter (shift)

K Number of regimes

$Load$ Consumed electricity

N Sample size adjusted for lags

n Sample size

Nuc Generated nuclear power

P Probability

$Prod$ Electricity production

R^2	R-squared
$Rprod$	Production except solar, nuclear and wind production
S	Regime state
$Solar$	Generated solar power
t	Time point
$Wind$	Generated wind power
$\mathbf{P}$	Probability transition matrix

Contents

Chapter 1

Introduction

We live in a world where the climate is changing faster than ever. According to the NOAA (2020), the years 2011–2020 was the warmest decade on earth. The use of fossil fuels has a large impact on temperature, making it crucial to find new ways to provide society with electricity. This has led to an increase in renewable energy sources (RES), such as wind and solar power.

As more RES are generated, the equilibrium electricity price tends to become lower. This is a result of the electricity bidding process of buyers and sellers, and the fact that RES have a low marginal cost. This makes it possible for sellers of RES electricity to offer a relatively low price (Lazard 2021). In Germany, RES have had a rapid growth rate. In 2020 solar generation made up for 10.5 % of the total public electricity generation (Burger 2021). As the generation has increased, the country has experienced a reduction of the electricity spot price (Sensfuß, Ragwitz and Genoese 2008), (Martin de Lagarde and Lantz 2018).

Several studies have been made on electricity markets around the world, investigating how the price is affected by an increased share of renewables. To be able to model the price and understand how it is influenced by different factors, time series econometrics is widely used. However, electricity prices are highly volatile and often show characteristics like heteroscedasticity, which makes it difficult to model. Engle (1982) introduced a way to handle this by modelling the variance of the errors so that it depends on the past values of the dependent variable. The process called autoregressive conditional heteroscedastic (ARCH) was further developed by Bollerslev (1986) to include the past conditional variance as well, to further capture the characteristics of electricity prices.

Another approach is to model prices using a regime switching model. Hamilton (1989) proposed a model that distinguishes periods of high and low growth to better capture the characteristics of the U.S. gross national product time series. The main idea for regime switching models is to allow for the time series characteristics to change across recurring states. This can be applied to periods of high and low electricity prices, which tend to coincide with periods of high and low volatility, respectively (Martin de Lagarde and Lantz 2018).

In Sweden, the installed capacity of grid-connected photovoltaic (PV) systems has increased from 140 megawatts in 2016 to 1090 megawatt in 2020 (Energimyndigheten 2020). However, due to the relatively low proportion of solar power, a limited amount of studies has been made on Sweden. Additionally, most studies examine the effect on a daily (or even more rarely) basis, missing important information on the hourly changes. In this study, the hourly impact from an increased PV capacity on the Swedish electricity market is investigated using a two-state regime-switching (RS) model.

1.1 Background

At the company Becquerel Sweden, a model is developed which aims to show how the revenue from electricity generated by PV depend on the orientation in which the modules are being placed. The project is a further development of the model by Campana et al. (2020) that optimizes the irradiance on the module surface for a span of orientations, given different locations and the local weather on these locations. In the study, it is shown that local weather affects the optimal tilt and azimuth in which the panel should be placed, meaning that it is possible to maximize production by choosing the tilt and azimuth of the panels (Campana et al. 2020).

Traditionally, modules are being placed towards the south to maximize production during sunny hours. The model by Campana et al. (2020) is a tool to investigate whether the standard placing enables more solar power, or if it would be preferable to change the orientation. The existing model does not consider that the electricity prices vary during the day, which could have an impact on the revenues. The price tends to be slightly lower around lunch time as compared to in the morning and evening, but still higher than in the night. Selling at that point in time will result in less revenue. The project by Becquerel

Sweden investigates whether it is instead preferable to produce more electricity before or after mid day, and thereby shift the orientation of the PV modules more to either the east or west.

This thesis aims to complement the results from the project to get an understanding of how the hourly electricity spot price, and thereby the hourly revenue, is affected as more solar power is deployed.

1.2 Purpose

The purpose of the study is to show how the daily pattern of the electricity spot price is affected as PV production is increased.

1.3 Delimitations

In the scope of the study, following delimitations are made:

- The study only focuses on the Swedish market and the four price regions SE1, SE2, SE3 and SE4.
- The data used is limited to the years 2018 - 2020.
- The official day-ahead price currency is euro, however in this study we use the prices converted by Nord Pool to Swedish krona (SEK).

Chapter 2

Electricity pricing

This chapter aims to provide a broader background of the electricity market. The pricing process is described to give the reader an understanding of what role different energy sources have on the overall price level. The chapter also introduces the merit order effect which is a result of renewables entering the market. Due to their low marginal cost, RES can reduce the price and affect how the price varies during the day.

2.1 Day-ahead market

Nord Pool is a European power exchange market where participants of the electricity market buy and sell electricity. It is owned by the Swedish transmission system operator (TSO) Svenska kraftnät, together with the company Euronext and other Nordic and Baltic TSOs. At Nord Pool, trading on the Nordic, Baltic, Central Western European and United Kingdom electricity markets is provided.

Every day, buyers and sellers of electricity submit their orders for the next 24 hours. There are several available options for ordering. The most common is the single hourly order, where desired or offered volume is entered along with the price range you are prepared to accept (Nord Pool 2020c). This exercise take place for all hours, and consequently the electricity spot price varies between different hours. A Nordic system price is calculated representing the market

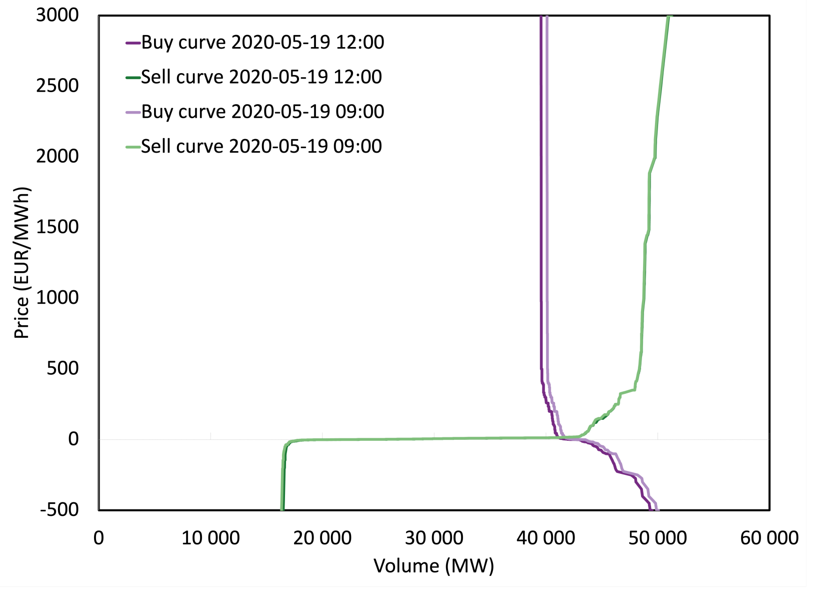


Figure 2.1: Illustration over the (Nordic) electricity pricing data on 2020-05-19 at CET 09:00 and 12:00. The sell-curves illustrates the power supply whereas the buy-curves show the power demand.

equilibrium price for the Nordic markets. The system price is used when trading different financial instruments, for example within futures trading (i.e. buying or selling at a set price on a specific future date). Nord Pool collects information from market participants about what volumes they want to sell or buy, and to which price range they are willing to trade. In the calculations the Nordics is considered as one region, meaning that the transmission capacities between the bidding zones are considered endless. Electricity that flows to and from bidding areas outside the Nordics have to be considered in the calculations as well. Therefore, imported and exported volumes are included when creating aggregated supply and demand curves for electricity in the Nordics (Nord Pool 2020a). Figure 2.1 shows an illustration of the Nordic curves on 2020-05-19 for two different hours, where the intersect of the curves gives the electricity price for the specific hour.

Looking at the relevant values, which are presented in figure 2.2, the equilibrium price for the Nordic electricity system at 09:00 and 12:00 was 16.42 EUR/MWh respective 14.77 EUR/MWh. Table 2.1 show the variation in the traded prices

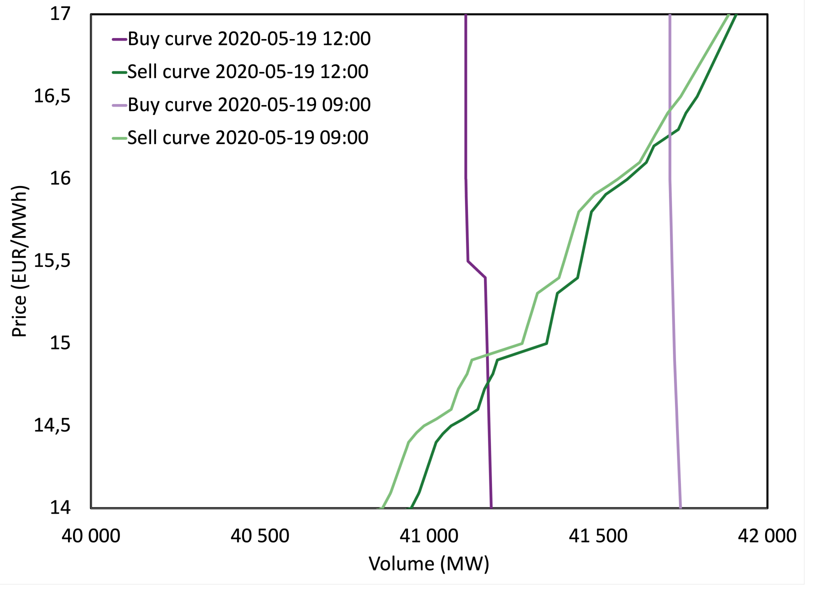


Figure 2.2: Illustration showing the supply- and demand intersections for the electricity pricing process on 2020-05-19 at CET 09:00 and 12:00.

throughout that day.

The system price is also used as an index market when hedging against price risk from differences between the Nordic electricity price and spot prices in specific areas within the Nordics. These futures are called Electricity Price Area Differentials. The electricity spot prices in different areas are calculated similar to the Nordic system price, although the transmission capacities between the specific areas are considered. Furthermore, the prices are expressed in euro and since it is possible to trade in different currencies, trades which are not in euro have to be converted. This is done using an exchange rate which is preliminary for the trading point (Nord Pool 2020b).

Some countries have one electricity price for the whole country, while Sweden is divided into four geographical price regions. The four bidding areas are called SE1, SE2, SE3 and SE4, see figure 2.3. SE3 is the only region generating electricity through nuclear power. It is possible to transfer electricity between the areas to reduce excess supply or demand, although it is not always possible to get a perfect match due to limitations on the grid. As the maximal transmission

2020-05-19	
Hour	**System price (EUR/MWh)**
00-01	12.79
01-02	12.64
02-03	12.50
03-04	12.50
04-05	12.63
05-06	13.02
06-07	13.84
07-08	17.49
08-09	17.96
09-10	16.42
10-11	15.65
11-12	14.44
12-13	14.77
13-14	14.54
14-15	14.62
15-16	13.62
16-17	13.18
17-18	13.68
18-19	13.92
19-20	14.88
20-21	14.91
21-22	14.81
22-23	13.57
23-00	12.53

Table 2.1: Nord Pool hourly day-ahead prices, 2020-05-19.

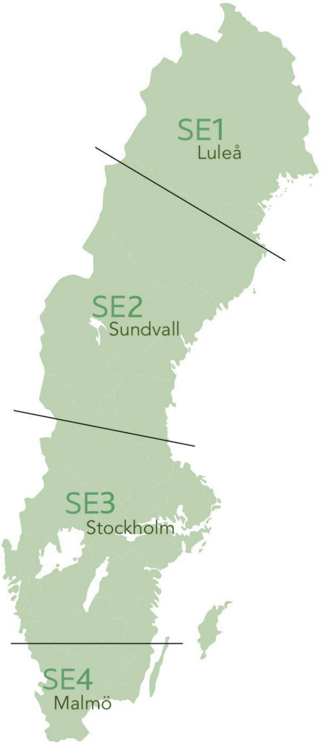


Figure 2.3: Price regions in Sweden.

capacity is reached, supply and demand are set for the regions (Svenska kraftnät 2021).

2.2 Merit order

The price is a result of how much electricity is produced, electricity consumption, and the possibility to transfer electricity between price areas and countries. In Sweden, the consumption pattern is predictable and rather constant. This also applies to the transmission limits. However, the supply varies a lot during the year. For example, during dry periods the possibility of extracting electricity from hydro power decreases. The weather also affects the amount of wind power,

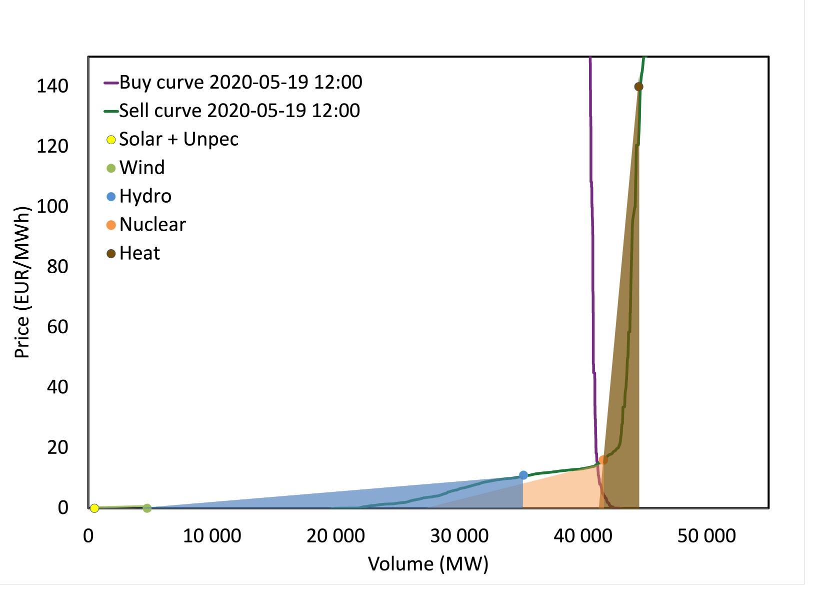


Figure 2.4: Illustration over the pricing process, including approximate production volumes of different energy sources.

windy periods provide more electricity. A decision on closing a nuclear plant can have big effects on the supply as well.

The hourly generated amount from each energy source affects the market price. Generators who can offer a low price will reduce the equilibrium price, while expensive energy sources will increase the market price. What price generators will offer depends on the marginal cost, how much it costs to produce one more unit. Since RES have a relatively low marginal cost, as there are no fuel costs associated to the production and low maintenance costs, they can offer a low price. Figure 2.4 shows an approximate figure over the merit order effect and how the price is connected to the different energy sources. The final production mix will consist of energy sources that can offer a competitive price.

In theory, as production from RES increases, the electricity market price will decrease. This is called the merit order effect: as RES generate the traditional power sources are pushed to the right, which lowers the total production cost those hours and consequently the overall price paid to all generators. This means that an increase of RES undermines their value, a phenomenon called the cannibalization effect. This phenomenon also applies to the other energy sources, although it is more prominent for RES. Lopéz Prol, Steininger and Zilberman (2020) show that an increase of solar and wind production in California undermines their own revenues, with cannibalization effect more prominent at high penetration levels.

2.3 Daily price pattern

On average, the electricity spot price in Sweden has its price peaks in the morning and evening. The price tends to be lower during the middle of the day, but is still higher than in the night. Figure 2.5 shows how the electricity price in price area SE4 depends on the hour of the day. This can partly be explained by the electricity consumption pattern, more electricity is used during the day and less at night. A similar pattern exists in the other Swedish price areas, presented in figure A.1- A.3 in appendix A

In Sweden, PV power still makes up a small proportion of the total electricity generation. Although, in countries with a larger share of solar, it is possible to see a price lowering effect. Martin de Lagarde and Lantz (2018) shows that in Germany, both wind and solar power helps to decrease the price as the production increases. They also show that the impact is greater during high price periods. Although, they do not investigate the hourly effect. Therefore, it is not possible to analyze the daily price pattern in their study. It is possible to imagine a price situation where it would be more profitable to produce PV power in the morning or later in the afternoon if the price is sufficiently low in the middle of the day. Therefore, it is interesting to investigate the impact of PV power on the price. In Sweden, solar panels are traditionally placed towards the south in order to maximize production during the middle of the day when the global radiation is the highest in the northern hemisphere. To enable maximal production in hours other than in the middle of the day, the panels have to be placed at a different azimuth.

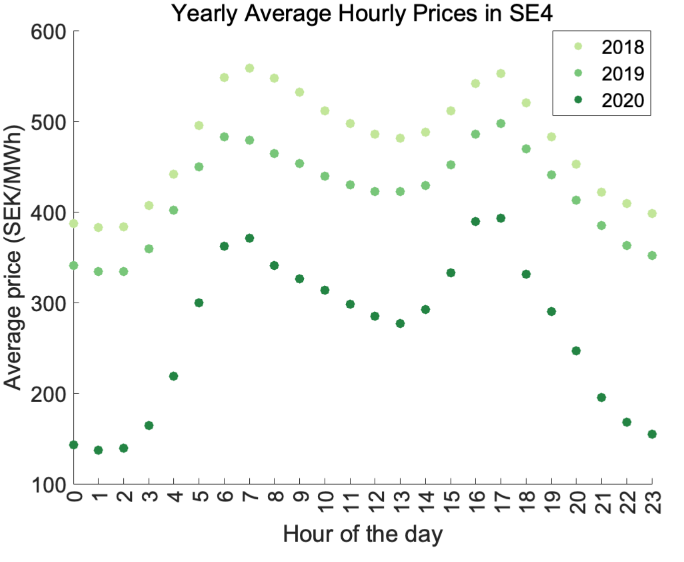


Figure 2.5: Average price in SE4 per hour.

Chapter 3

Theory

This chapter presents the theoretical framework needed to answer the purpose of the study. As we are interested in modelling electricity prices, data on historical prices needs to be analyzed. Therefore, we introduce the theory behind some tests relevant for time series. The chapter also describes the RS model used to answer the thesis problem, and methods used to evaluate the model.

3.1 Time series characteristics

Before implementing a model it is important to investigate whether the used time series are stationary or not. In reality we expect many time series to be time dependent, if we collect temperature data in Sweden we will most likely see a pattern of higher temperatures in the summer than the winter. In a stationary process, the probability density function $f_{X(t)}(x)$ does not depend on t. Yates and Goodman (2005) defines a stochastic process $X(t)$ to be stationary if, for all sets of $t_1, .., t_m$, and any time increment τ:

$$f_{X(t_1),...,X(t_m)}(x_1, ..., x_m) = f_{X(t_1+\tau),...,X(t_m+\tau)}(x_1, ..., x_m). \tag{3.1}$$

Time series that are stationary are easier to analyze and can be better suited for modelling, since the statistical properties do not change over time. Above that, many models for forecasting assume the data to be stationary. As a tool to investigate this, two stationary tests are described in the chapter. Two additional measures are introduced as well, which can be used to further analyze the price time series and its characteristics. To investigate the covariation of time series, correlation is introduced as well.

3.1.1 Augmented dickey fuller test

Stationarity is of importance in time series analysis and there are several tests that can be performed to detect it. Dickey and Fuller (1979) proposed a unit root test which was later further developed by Said and Dickey (1984), called the Augmented Dickey-Fuller (ADF) test. Let l be the number of lagged terms included and consider the model

$$y_t = c + \delta t + \phi y_{t-1} + \sum_{i=1}^{l} \beta_i \Delta y_{t-i} + \epsilon_t, \tag{3.2}$$

where the estimable terms c is the drift term, δ is the trend component, ϕ is the auto-regressive coefficient and β is the regression coefficient of the lagged change in y_t. Furthermore, Δ is the difference operator such as $\Delta y_{t-i} = y_{t-i} - y_{t-i-1}$, and $\epsilon_t = \sigma_t z_t$, where z_t are independent and identically distributed (iid) random variables with mean 0 and variance σ^2.

We want to test whether y, a time series of points at time t, is non-stationary and if it has a unit root. This can be expressed by setting the null hypothesis of a unit root as $H_0 : \phi = 1$ and the alternative hypothesis $H_1 : \phi < 1$.

The test statistic is given by

$$t_{ADF} = \frac{N\left(\hat{\phi} - 1\right)}{1 - \hat{\beta}_1 - ... - \hat{\beta}_l}, \tag{3.3}$$

where N is the size of observations in y, adjusted for lags. Rejecting H_0 means that no unit root is present and that the process is stationary. Not rejecting H_0 means that the test fails to reject the possibility of an existing unit root.

3.1.2 Kwiatkowski–Phillips–Schmidt–Shin test

Realizing that many time series fail to reject the hypothesis that a unit root exists, even though a unit root most likely does not exist, Kwiatkowski et al. (1992) introduced the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test. The test examines whether the time series is trend stationary, and can be used as a compliment to other unit root tests, as the ADF test.

Let u_t be a stationary process and r_t a random walk where z_t are iid with mean 0 and variance σ^2. The test model can then be expressed as

$$\begin{aligned} y_t &= r_t + \delta t + u_t \\ r_t &= r_{t-1} + z_t, \end{aligned} \tag{3.4}$$

where δ is a trend component. We want to test the null hypothesis $H_0 : \sigma^2 = 0$ against the alternative $H_1 : \sigma^2 > 0$. The test statistic is given by

$$t_{KPSS} = \frac{1}{n^2 \hat{\sigma}^2} \sum_{t=1}^{T} S_t^2, \tag{3.5}$$

where n is the sample size, $\hat{\sigma}$ is the Newey–West long run variance estimate, and $S_t = \sum_{i=1}^{t} e_i, t = 1, .., T$ where e are the errors. A test that rejects the null hypothesis, rejects that the data is trend stationary.

3.1.3 Kurtosis

Electricity price often show characteristics like price jumps which makes it more difficult to predict. Kurtosis is a measure of the expected value of extreme outcomes to occur. It was introduced by Pearson (1905) and is defined as the fourth central moment which can be expressed as

$$\kappa = E\left[\left(\frac{X - \mu_x}{\sigma}\right)^4\right], \tag{3.6}$$

where X is a real-valued random variable, μ_x is the mean, σ is the standard deviation and E the expectation operator. The standard normal distribution have kurtosis 3. For time series that show a kurtosis value above 3 the distribution is called leptokurtic and extreme outcomes have a higher probability to occur.

3.1.4 Skewness

Skewness is a measure of unevenness in the distribution and is defined as the third central moment (Hull 2018). A positive value indicates that the distribution is rightly skewed while a negative value indicates the values to be skewed to the left. This implies that a perfectly symmetric distribution will have a skewness of zero. Skewness is defined as

$$\gamma = E\left[\left(\frac{X-\mu_x}{\sigma}\right)^3\right], \tag{3.7}$$

where X is a random variable, μ_x is the mean, σ is the standard deviation and E the expectation operator.

3.1.5 Pearson's correlation coefficient

Correlation can be used to understand how variables move relative to each other. Pearson's correlation coefficient is a well known measure within statistics that indicates the relation between two variables. Let X be a time series with mean μ_x, and Y another time series with mean μ_y. A positive coefficient mean that as the values of X increase, Y will go in the same direction. A negative correlation, $\rho < 0$, indicates that the variables move in opposite directions.

$$\rho = \frac{E\left[(X-\mu_x)(Y-\mu_y)\right]}{\sqrt{E\left[(X-\mu_x)^2\right]E\left[(Y-\mu_y)^2\right]}} \tag{3.8}$$

3.2 Time series transformation

In some applications, data needs to be formatted before use. Removing outlier values, null values, or shifting a time series are three examples of transformations that can improve the quality of the data to make it easier to use and interpret.

Let $x_i \in \mathbb{R}$ be the value of data point i in a time series to be transformed and $f(\cdot)$ a function. Let y_i be the output of the transformed value of data point i, defined by

$$y_i = f\left(\frac{x_i - \xi}{\lambda}\right), \tag{3.9}$$

where ξ is the shift and λ is a scale factor.

In time series analysis a common way to reduce skewness and to normalize the data is by log transforming it, replacing $f(\cdot)$ in equation 3.9 with the natural logarithm

$$y_i = \ln\left(\frac{x_i - \xi}{\lambda}\right) \tag{3.10}$$

Another option is to use inverse hyperbolic sine (IHS) to transform a time series (Johnson 1949). The inverse hyperbolic sine transformation is defined as

$$y_i = \sinh^{-1}\left(\frac{x_i - \xi}{\lambda}\right) = \ln\left(\frac{x_i - \xi}{\lambda} + \sqrt{\left(\frac{x_i - \xi}{\lambda}\right)^2 + 1}\right). \tag{3.11}$$

3.3 Markov Regime Switching model

In this thesis a regime switching model is proposed for understanding the impact from solar power on the electricity price pattern. Markov RS models are widely used as they enable us to capture different characteristics in a time series, by dividing the data into two or more regimes. It was introduced by Hamilton (1989) and many scientists have used and improved the model since then. Electricity prices are highly volatile, which indicates that an RS model can be a suitable choice.

3.3.1 Markov chains

A (discrete-time) Markov chain $X_t, t = 0, 1, ...$ is a stochastic process where the state at a time t only depends on the previous state at time $t-1$. This is called the Markov Property:

$$P(X_t = x_t | X_{t-1} = x_{t-1}, ..., X_0 = x_0) = P(X_t = x_t | X_{t-1} = x_{t-1}) \tag{3.12}$$

The definition implies that by knowing X_t we have all information needed to be able to predict the next variable X_{t+1} (Yates and Goodman 2005).

3.3.2 Two state RS model

Let S_t be the unobserved state following a first order two state markov chain yielding the transition states:

$$\begin{aligned} P(S_t = 1 | S_{t-1} = 1) &= p_{1,1} \\ P(S_t = 2 | S_{t-1} = 1) &= p_{1,2} \\ P(S_t = 2 | S_{t-1} = 2) &= p_{2,2} \\ P(S_t = 1 | S_{t-1} = 2) &= p_{2,1} \end{aligned} \tag{3.13}$$

As $S_1, ..., S_t$ are random variables following a Markov chain, they hold the Markov property meaning that the probability of being in a state is only dependent on the most recent state. Equation 3.12 can then be written as:

$$P\left(S_t = s_t | S_{t-1} = s_{t-1}, ..., S_0 = s_0\right) = P\left(S_t = s_t | S_{t-1} = s_{t-1}\right) \tag{3.14}$$

Let the probability of going from state i to j in one time step be $P(j|i) = p_{i,j}$. Using the notation from equation 3.13, the transition matrix can be expressed as

$$\mathbf{P} = \begin{pmatrix} p_{1,1} & p_{1,2} \\ p_{2,1} & p_{2,2} \end{pmatrix}, \tag{3.15}$$

$\forall i \in \{1, 2\}$ it must hold that $p_{i,1} + p_{i,2} = 1$. The Markov chain and its states are illustrated in figure 3.1.

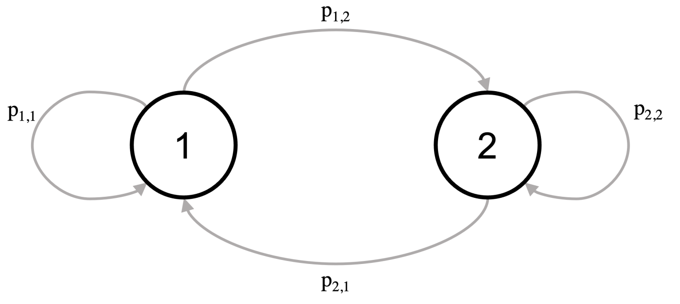


Figure 3.1: Markov chain and transition probabilities $p_{i,j}$ between state 1 and state 2.

The different regimes must be modelled by some process, which we allow to alternate between. In this thesis, linear regression is used to model the prices. The probabilities $p_{i,j}$ must be estimated together with the parameters from the regime models. Hamilton (1989) proposes the EM algorithm for doing the estimations.

3.3.3 Expectation–Maximization algorithm

The Expectation–Maximization (EM) algorithm was named by Dempster, Laird and Rubin (1977), although it had been mentioned by other authors before that. The algorithm is a method to compute maximum likelihood estimates of a vector $\boldsymbol{\theta}$ by dividing the problem into two smaller problems to maximize the marginal likelihood. First, by computing a distribution on $\mathbf{Z}$, a vector of unobserved or missing data, given some initial guess on $\boldsymbol{\theta}$. Then, using the probability values on $\mathbf{Z}$ to estimate new parameter values in $\boldsymbol{\theta}$, and repeating. The algorithm is considered done when the difference between $\boldsymbol{\theta}^{(t)}$ and $\boldsymbol{\theta}^{(t+1)}$ fulfills the convergence criterion, where $\boldsymbol{\theta}^{t+1}$ is considered the ML estimate $\hat{\boldsymbol{\theta}}$. The steps of computing the expected log likelihood value is known as the Expectation step, while the step of computing $\boldsymbol{\theta}^{(t+1)}$ is called the Maximization step.

Let X be a time series with observed data and $\mathbf{Z}$ a vector of unobserved data. The marginal likelihood function to be maximized is

$$L(\boldsymbol{\theta}; X) = p(X \mid \boldsymbol{\theta}) = \int_{\mathbf{Z}} p(X \mid \mathbf{Z}, \boldsymbol{\theta}) p(\mathbf{Z} \mid \boldsymbol{\theta}) \, d\mathbf{Z}. \tag{3.16}$$

As it can be difficult to find a solution to equation 3.16, following steps are given as a method for finding a solution:

E-step:

$$Q(\boldsymbol{\theta} \mid \boldsymbol{\theta}^{(t)}) = \mathrm{E}_{\mathbf{Z}|\mathbf{X},\boldsymbol{\theta}^{(t)}} [\log L(\boldsymbol{\theta}; X, \mathbf{Z})] \tag{3.17}$$

and as the E-step is done, the M-step begins:

$$\boldsymbol{\theta}^{(t+1)} = \underset{\boldsymbol{\theta}}{\arg\max}\ Q(\boldsymbol{\theta} \mid \boldsymbol{\theta}^{(t)}) \tag{3.18}$$

These iterative steps are then repeated until a solution, $\hat{\boldsymbol{\theta}}$, is found.

3.4 Model evaluation

To be able to evaluate the reliability of the models we use methods for measuring the quality. We introduce a measure for regime classification and also look into a measure on statistical significance.

3.4.1 Regime classification

Regime classification measure (RCM) can be used to evaluate the quality of the regime classification (Ang and Bekaert 2002). Let K be the number of regimes, then the statistic can be calculated as

$$\mathrm{RCM(K)} = 100K^2 \frac{1}{n} \sum_{t=1}^{T} \left(\prod_{i=1}^{K} p_{i,t} \right), \tag{3.19}$$

where n is the sample size, and $p_{i,t} = P(s_t = i | \{s_t\}_{t \in [1:T]})$ is the smoothed regime probability for regime i. It take values between 0 and 100, where an RCM statistic equaling 0 indicates that the model succeed to detect a perfect regime classification. A statistic of 100 implies that the model fail to make any classification.

3.4.2 Statistical significance

A probability value (p-value), is a measure of the probability of observing a test statistic equal or more extreme than the observed value, under the assumption that the null hypothesis is correct. It describes how likely it is that the data would have occurred randomly, meaning that the null hypothesis is true.

In hypothesis testing, the level of statistical significance is often expressed as the p-value taking a number between 0 and 1. A small p-value indicate that the probability of observing an extreme value would be very low.

Chapter 4

Method

This chapter aims to give the reader an understanding of the model implementation. First, we describe how the data was collected and analyzed. We then present the method for implementing the RS model, and the methods used to evaluate the results. The final model consists of code implemented in the programming platform MATLAB, together with Excel files containing all relevant data.

4.1 Data analysis

The data consists of 7 different time series for each price area in Sweden:

- Day-ahead electricity prices (SEK/MWh), retrieved from Europe's power market Nord Pool
- Wind electricity production, retrieved from the Swedish TSO
- Solar electricity production, retrieved from the Swedish TSO
- Nuclear electricity production, retrieved from the Swedish TSO
- Simulated solar electricity production, given by Becquerel Sweden
- Total electricity production, retrieved from Nord Pool

- Total electricity load, retrieved from Nord Pool

All data is given on hourly basis expressed in MWh, except for the simulated PV production which is given in kWh. Since the calculations throughout the project are made on hourly points in time, it is of high importance to make sure all data are expressed in the same time. The day-ahead prices retrieved from Nord Pool are given in Central European Time (CET), while the production and load time series retrieved from the Swedish TSO are expressed in Coordinated Universal Time (UTC)+0. CET is 1 hour ahead of UTC, which means CET equals UTC+1, so in order to make the data sets coincide all price data points are moved one hour back in time. The reason for choosing to use UTC+0 instead of CET is due to the transition from standard time to summer time which complicates the calculations. Therefore, only the data from Nord Pool was transitioned, to make all data sets expressed in UTC.

One reason for complementing the data with a set of simulated solar production is due to the fact that a lot of production is missing in the regular data for solar production, which is because households use the electricity for their own needs before injecting the excess into the public grid. The self-consumption is calculated by removing the solar generation acquired from the Swedish TSO from the simulated solar generation data. The load time series does not include self-consumption, so it has to be manually added to get the correct load. The simulated solar production data was provided by Becquerel, produced using the model developed by Lingfors and Widén (2016). During the project, we discovered that the simulated values for the dates 2018-06-29, 2018-06-30 and 2018-07-01 were missing. This was solved by filling in the missing values with the simulated solar production data from 2018-07-02. The date was chosen due to very similar levels of sun radiance on 2018-07-01, see figure 4.1. For simplicity, the same values were used for the two other dates as well, as the irradiance levels were rather similar.

Table 5.4 shows that the minimum of solar production is above zero in SE3 and SE4. This indicates that the measured values contains errors as the solar production should be zero at least for some hours during the night. These errors could be ejection of solar electricity from a battery or electricity from hybrid power plants, like a site that contain both PV and wind power.

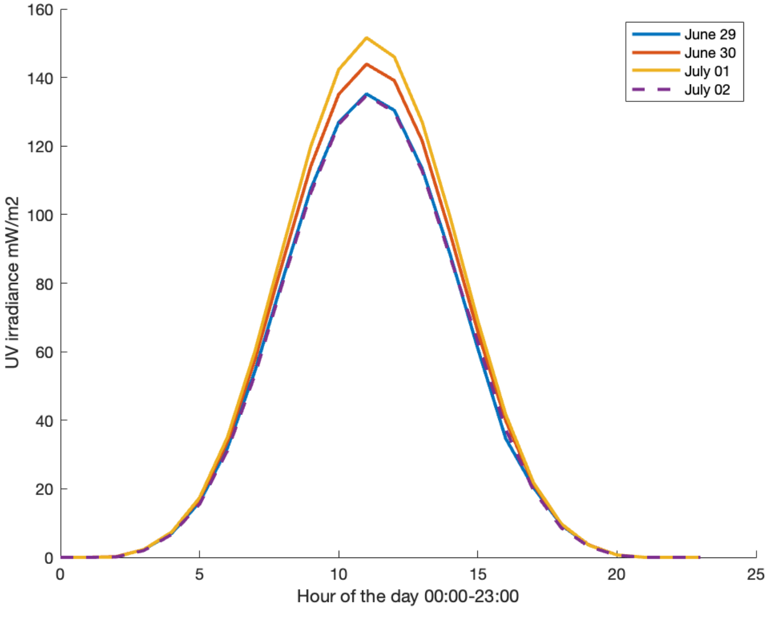


Figure 4.1: Hourly UV Irradiance data collected from SMHI STRÅNG Open Data

4.1.1 Time series analysis

To get an understanding of how the different parameters are affected relatively to each other, the Pearson's correlation coefficient is calculated. The correlation between all parameters are calculated using equation 4.1 rewritten for all observations to:

$$\rho = \frac{\sum_{t=1}^{T}(X - \mu_x)(Y - \mu_y)}{\sqrt{\sum_{t=1}^{T}(X - \mu_x)^2 \sum_{t=1}^{T}(Y - \mu_y)^2}} \tag{4.1}$$

As the electricity spot price plays a significant role in the project, the price time series is analyzed thoroughly. We perform two stationary tests, the ADF test for testing stationarity and the KPSS to complement the ADF test and test for trend stationarity. According to Kwiatkowski, Phillips and Schmidt (1991), the square root of the sample size is a suitable number of lags in the model. As all calculations are made on hourly data, meaning we have approximately 8760 data points in a year, we use $\sqrt{10000}$ as number of lags. In the KPSS test, the same number of lags are used for the autocovariance lags in the Newey-West estimator of the long-run variance. For the ADF test, we rewrite equation 3.2 to

$$Price_t = c + \delta t + \phi y_{t-1} + \sum_{i=1}^{100} \beta_i \Delta y_{t-i} + \epsilon_t, \tag{4.2}$$

where c is the drift term, δ is the trend component, Δ is the difference operator such as $\Delta y_{t-i} = y_{t-i} - y_{t-i-1}$, and $\epsilon_t = \sigma_t z_t$, where z_t are independent and identically distributed (iid) random variables with mean 0 and variance σ^2.

For each price area, the kurtosis (3.6) of the price time series is calculated as

$$\kappa = \frac{1}{n} \sum_{t=1}^{T} \left(\frac{Price_t - \mu}{\sigma} \right)^4, \tag{4.3}$$

where n is the sample size of the time series, μ is the mean and σ is the standard deviation of the prices in a specific region.

To examine whether the data is shifted, the skewness (3.7) is calculated by

$$\gamma = \frac{1}{n} \sum_{t=1}^{T} \left(\frac{Price_t - \mu}{\sigma} \right)^3, \tag{4.4}$$

4.2 The RS model

In this project we aim to investigate how the levels of solar generation affects the electricity spot price. To do so, we use an RS model in which we model the price with a linear regression model.

4.2.1 Price transformation

The price is transformed using the IHS transformation introduced in equation 3.11. We use the scale factor $\lambda = 10$ SEK/MWh and let the shift be the mean of the time series, $\xi = \mu$. For each price region the transformed price time series, $Price_t^*$, is generated by

$$Price_t^* = \ln\left(\frac{Price_t - \mu}{\lambda} + \sqrt{\left(\frac{Price_t - \mu}{\lambda}\right)^2 + 1}\right),\ t = 1, \ldots, T. \tag{4.5}$$

4.2.2 Regression model

Let $Prod_t$ be the total electricity production and $Wind_t$, $Solar_t$ and Nuc_t the electricity generated from wind, PV and nuclear power, at time t. Furthermore, let $Rprod_t$ be the residual production when removing wind, PV and nuclear, $Rprod_t = Prod_t - Wind_t - Solar_t - Nuc_t$. As we are interested in model two regimes, we let index (1) denote regime 1 and index (2) regime 2, which gives

$$\begin{aligned}\text{Price}_t^{*(1)} &= \beta_{0,t}^{(1)} + \beta_{1,t}^{(1)}\frac{Wind_t^{(1)}}{Prod_t^{(1)}} + \beta_{2,t}^{(1)}\frac{Solar_t^{(1)}}{Prod_t^{(1)}} + \beta_{3,t}^{(1)}\frac{Nuc_t^{(1)}}{Prod_t^{(1)}} + \beta_{4,t}^{(1)}Rprod_t^{(1)} + \epsilon_t \\ \text{Price}_t^{*(2)} &= \beta_{0,t}^{(2)} + \beta_{1,t}^{(2)}\frac{Wind_t^{(2)}}{Prod_t^{(2)}} + \beta_{2,t}^{(2)}\frac{Solar_t^{(2)}}{Prod_t^{(2)}} + \beta_{3,t}^{(2)}\frac{Nuc_t^{(2)}}{Prod_t^{(2)}} + \beta_{4,t}^{(2)}Rprod_t^{(2)} + \epsilon_t\end{aligned} \tag{4.6}$$

for SE3, and

$$\begin{aligned}\text{Price}_t^{*(1)} &= \beta_{0,t}^{(1)} + \beta_{1,t}^{(1)}\frac{Wind_t^{(1)}}{Prod_t^{(1)}} + \beta_{2,t}^{(1)}\frac{Solar_t^{(1)}}{Prod_t^{(1)}} + \beta_{3,t}^{(1)}Rprod_t^{(1)} + \epsilon_t \\ \text{Price}_t^{*(2)} &= \beta_{0,t}^{(2)} + \beta_{1,t}^{(2)}\frac{Wind_t^{(2)}}{Prod_t^{(2)}} + \beta_{2,t}^{(2)}\frac{Solar_t^{(2)}}{Prod_t^{(2)}} + \beta_{3,t}^{(2)}Rprod_t^{(2)} + \epsilon_t\end{aligned} \tag{4.7}$$

for SE1, SE2 and SE4, as the nuclear production is zero in these price regions. $Price_t^*$ is the transformed price and $\epsilon_t \sim \mathcal{N}(0, \sigma^2)$.

The estimation is made by first creating a discrete time Markov chain with an unknown transition matrix. We also create two initial regression models to be estimated, one for regime 1 (R1) and the other for regime 2 (R2), according to equation 4.6 and 4.7. As the regimes are unknown, the EM algorithm described in section 3.3.3 is used to estimate the probabilities as well as the regime model parameters. The parameters to be estimated in this study is $\boldsymbol{\theta_{SE3}} = [\beta_0, \beta_1, \beta_2, \beta_3, \beta_4, p_{i,j}]$ for SE3 and $\boldsymbol{\theta_{SE4}} = [\beta_0, \beta_1, \beta_2, \beta_3, p_{i,j}]$ for SE4, $\forall i, j \in \{1, 2\}$. Let the unobserved data be the state $\mathbf{S_t}$, then the EM algorithm procedure is:

Algorithm 1 The Expectation-Maximization Algorithm

Input: Initial guess $\boldsymbol{\theta}^{(0)}$

Initialize $\boldsymbol{\theta^{(t)}}$

while not converged **do**

Expectation step: $Q(\boldsymbol{\theta} \mid \boldsymbol{\theta}^{(t)}) = \mathrm{E}_{\mathbf{S}|Y,\boldsymbol{\theta}^{(t)}}\left[\log L(\boldsymbol{\theta}; Y, \mathbf{S_t})\right]$

Maximization step: $\boldsymbol{\theta}^{(t+1)} = \arg\max_{\boldsymbol{\theta}} Q(\boldsymbol{\theta} \mid \boldsymbol{\theta}^{(t)})$

end while

$\hat{\boldsymbol{\theta}} = \boldsymbol{\theta}^{(t+1)}$

Output: Maximum likelihood estimate $\hat{\boldsymbol{\theta}}$

4.2.3 Evaluating the coefficients

As the price time series is transformed, the beta coefficients can be difficult to interpret. As we are interested in analyzing the price effect of an increased PV power production we derive an expression for the hourly marginal effects. A decision to focus on SE3 and SE4 was made, as these price regions generate the most solar power. The derivative of the IHS is

$$\frac{d}{dx}\sinh^{-1}(x) = \frac{1}{\sqrt{x^2+1}}. \tag{4.8}$$

With all other variables held constant we end up with the marginal effect on price from wind, PV and nuclear by calculating the differentials from equation

4.9.

$$\begin{aligned}
\left(\frac{\partial Price_t}{\partial Wind_t}\right)^{(i)} &= \lambda\sqrt{\left(\frac{Price_t^{(i)}-\mu^{(i)}}{\lambda}\right)^2+1}\left(\frac{\beta_{1,t}^{(i)}}{Prod_t^{(i)}}-\beta_{4,t}^{(i)}\right)\\
\left(\frac{\partial Price_t}{\partial Solar_t}\right)^{(i)} &= \lambda\sqrt{\left(\frac{Price_t^{(i)}-\mu^{(i)}}{\lambda}\right)^2+1}\left(\frac{\beta_{2,t}^{(i)}}{Prod_t^{(i)}}-\beta_{4,t}^{(i)}\right), i=1,2 \qquad (4.9)\\
\left(\frac{\partial Price_t}{\partial Nuc_t}\right)^{(i)} &= \lambda\sqrt{\left(\frac{Price_t^{(i)}-\mu^{(i)}}{\lambda}\right)^2+1}\left(\frac{\beta_{3,t}^{(i)}}{Prod_t^{(i)}}-\beta_{4,t}^{(i)}\right)
\end{aligned}$$

where i indicates regime 1 or 2. To adjust for the fluctuation in production levels, the values are also multiplied by the production for the specific hour of the day.

4.2.4 Validation

We evaluate the model in several different ways. First, the p-value (introduced in section 3.4.2) and standard errors in the parameter estimation in the regression models are investigated. We also calculate the RCM statistic (3.19) measuring the quality of the regime classification. A low measure value is preferable, as high RCM value indicate difficulties for the model to detect regimes. For a two-regime model, equation 3.19 can be rewritten as

$$\mathrm{RCM}(2) = \frac{400}{n}\sum_{t=1}^{T} p_{1,t}p_{2,t} = \frac{400}{n}\sum_{t=1}^{T} p_t\left(1-p_t\right), \qquad (4.10)$$

where n is the sample size and $p_t = P(s_t = 1|\{s_t\}_{t\in[1:T]})$.

Chapter 5

Results

In this chapter all results are presented. We show all characteristics for the data used in the project, and the results that are obtained. We also show the impact from wind, PV and nuclear power on the daily electricity price pattern in Sweden.

5.1 Time series characteristics

Figure 5.1-5.4 shows the final time series used in the study for all four price areas, between the years 2018 and 2020. The figures aim to show an overall picture of how the time series evolve during the three years included in the study. In appendix A, figure A.4, A.5, A.6 and A.7 shows the time series for each year, making in possible to examine the time series more closely. Note that for 2018, the simulated solar production on 2018-06-29 to 2018-07-01 is replaced by the values for 2018-07-02 due to missing data in the delivered time series data. This is described thoroughly in section 4.1.

In all price areas the solar production show a seasonal pattern, during the winter month the production is close to zero while it peaks in June. A similar pattern can be seen for the simulated solar production, although the production is higher in spring and fall compared to the solar production. In SE3 the nuclear production level is rather constant, showing a decrease in 2020 which is

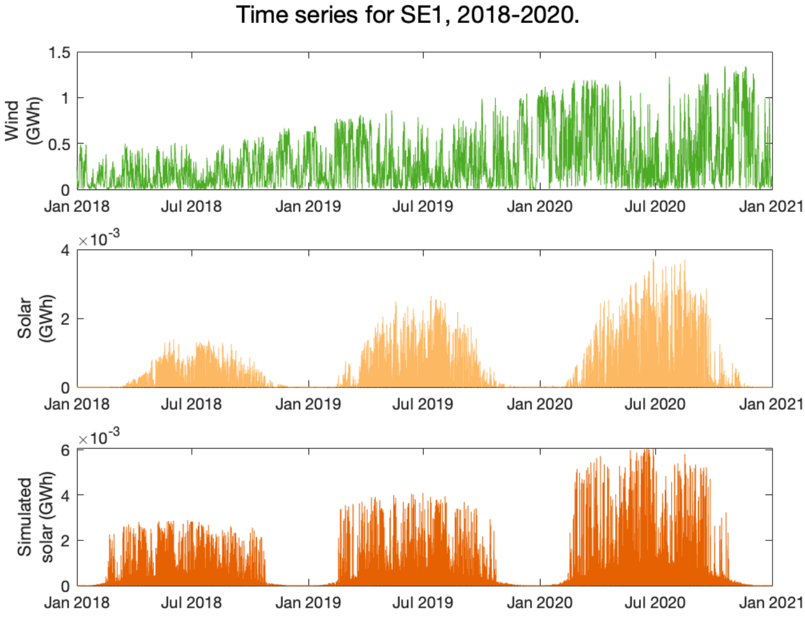
	Wind	Solar	Sim. solar	Load	Production	Price
SE1						
Wind	1.00	-0.14	-0.14	0.11	0.13	-0.37
Solar	-0.14	1.00	0.90	-0.25	-0.00	-0.12
Sim. solar	-0.14	0.90	1.00	-0.19	0.06	-0.08
Load	0.11	-0.25	-0.19	1.00	0.61	0.15
Production	0.13	-0.00	0.06	0.61	1.00	0.15
Price	-0.37	-0.12	-0.08	0.15	0.15	1.00
SE2						
Wind	1.00	-0.15	-0.15	0.10	0.38	-0.37
Solar	-0.15	1.00	0.92	-0.20	0.00	-0.18
Sim. solar	-0.15	0.92	1.00	-0.15	0.02	-0.13
Load	0.10	-0.20	-0.15	1.00	0.65	0.16
Production	0.38	0.00	0.02	0.65	1.00	-0.25
Price	-0.37	-0.18	-0.13	0.16	-0.25	1.00
SE4						
Wind	1.00	-0.11	-0.10	0.18	0.93	-0.30
Solar	-0.11	1.00	0.96	-0.09	-0.13	-0.07
Sim. solar	-0.10	0.96	1.00	-0.02	-0.10	-0.05
Load	0.18	-0.09	-0.02	1.00	0.45	0.26
Production	0.93	-0.13	-0.10	0.45	1.00	-0.26
Price	-0.30	-0.07	-0.05	0.26	-0.26	1.00

Table 5.1: Correlation between the parameters in SE1, SE2 and SE4 for 2018-2020.

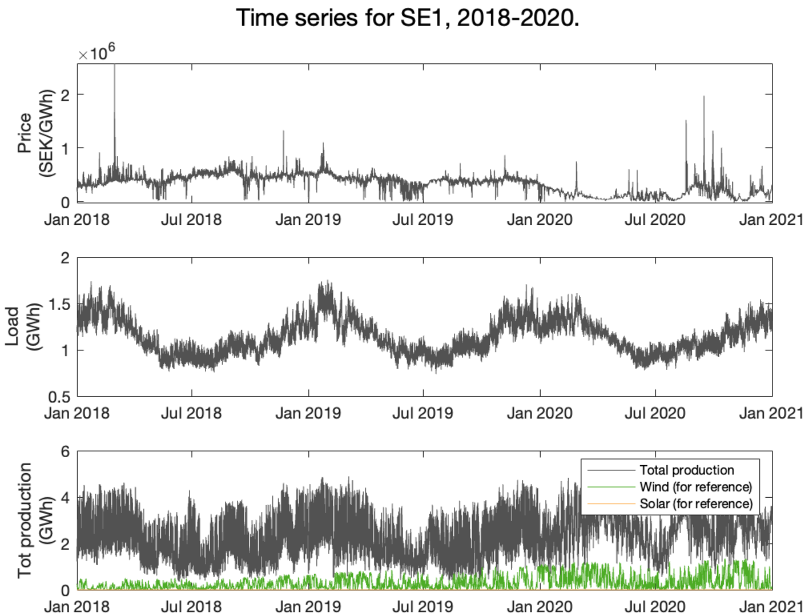
explained by the closing of reactor 2 in Ringhals on December 30, 2019. The wind production do not show any pattern over season, but it is clear that the wind production levels increased from 2018 to Dec 2021 in SE1, SE2 and SE3. For SE4, the levels are rather constant.

Load show a clear seasonal pattern in all price areas with a low electricity demand during summer and high in the winter. This is reasonable considering the Swedish climate. The total production show a similar pattern, although not as clear, with more production in the winter months and less in the summer. In SE4, wind generation makes up a large part of the total production.

Table 5.1 shows the Pearson's correlation coefficient for all parameters in price areas SE1, SE2 and SE4. The correlation coefficients in SE3 are shown in table 5.2, where nuclear is added.

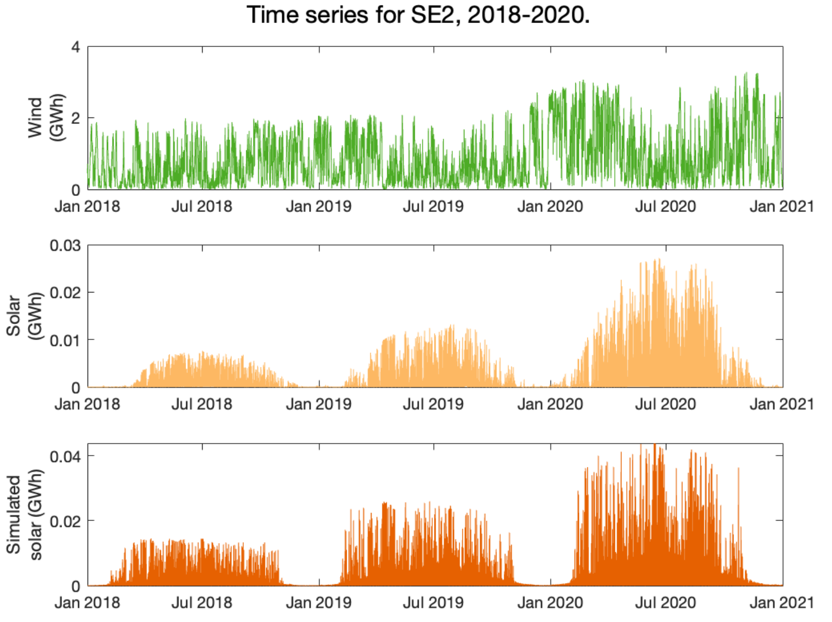


(a) Hourly wind and solar production in price area SE1.

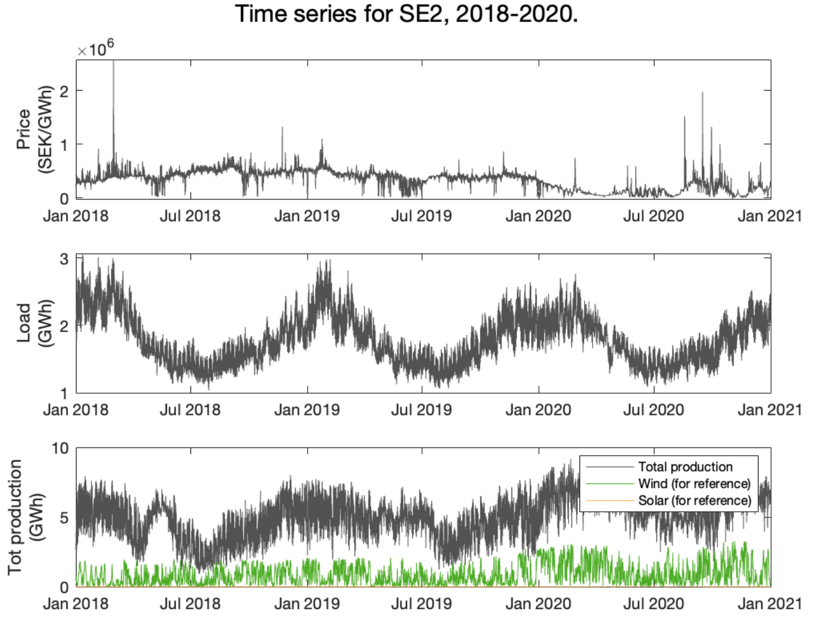


(b) Hourly electricity price, total load and total production in price area SE1.

Figure 5.1: Final time series 2018-2020 in price area SE1.

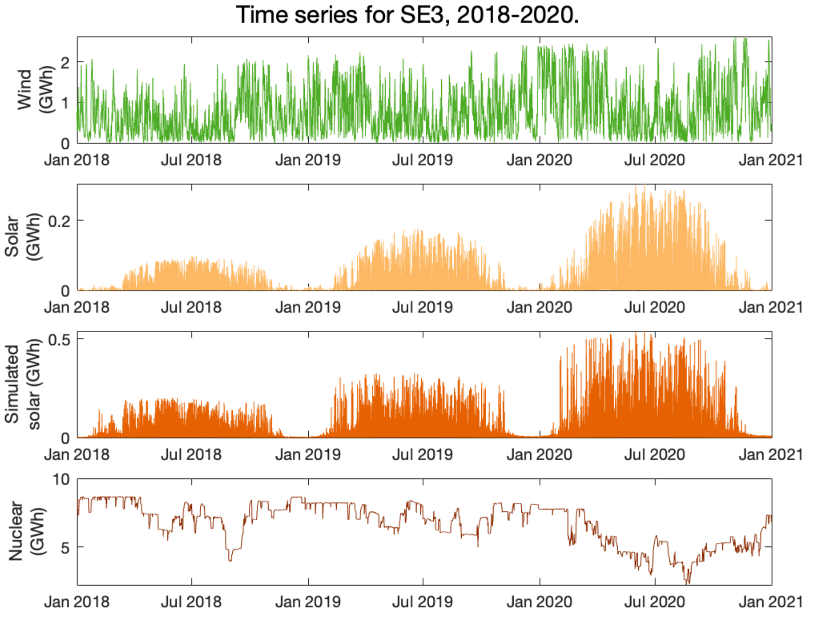


(a) Hourly wind and solar production in price area SE2.

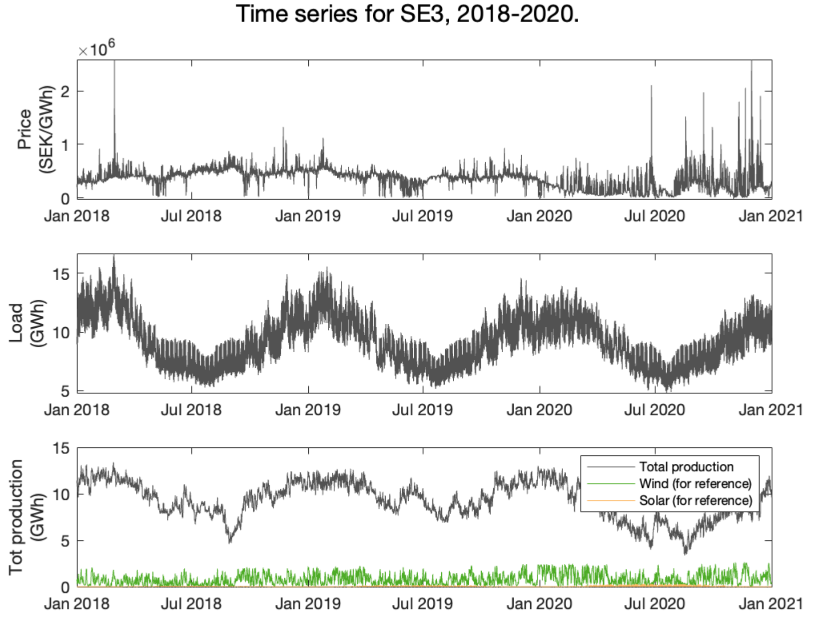


(b) Hourly electricity price, total load and total production in price area SE2.

Figure 5.2: Final time series 2018-2020 in price area SE2.

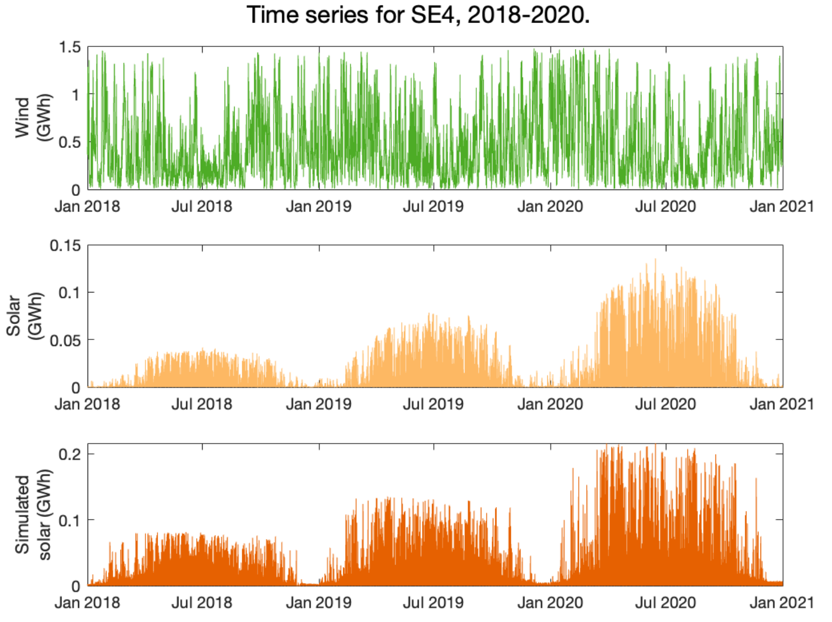


(a) Hourly wind, solar and nuclear production in price area SE3.

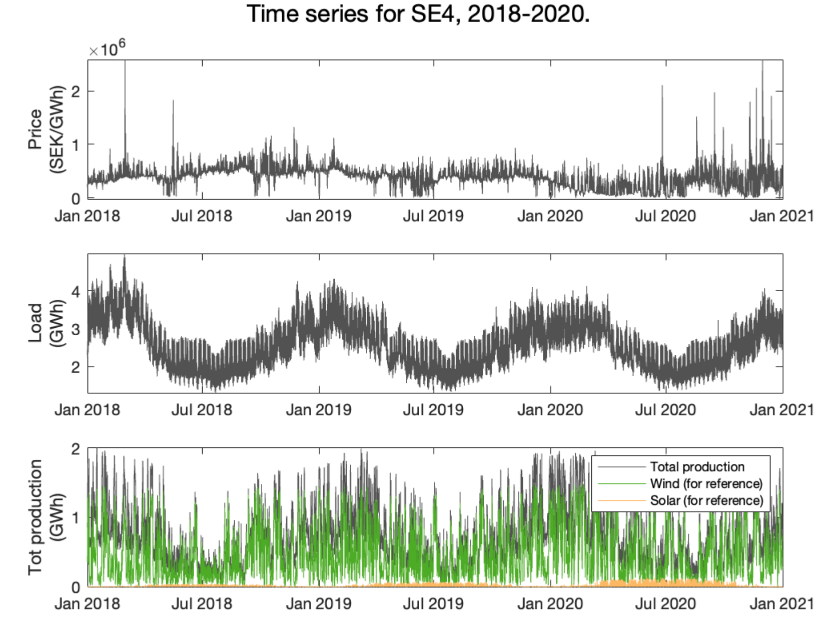


(b) Hourly electricity price, total load and total production in price area SE3.

Figure 5.3: Final time series 2018-2020 in price area SE3.



(a) Hourly wind and solar production in price area SE4.



(b) Hourly electricity price, total load and total production in price area SE4.

Figure 5.4: Final time series 2018-2020 in price area SE4.

	Wind	**Solar**	**Sim. solar**	**Nuclear**	**Load**	**Production**	**Price**
SE3							
Wind	1.00	-0.15	-0.14	0.01	0.13	0.33	-0.34
Solar	-0.15	1.00	0.96	-0.32	-0.16	-0.34	-0.08
Sim. solar	-0.14	0.96	1.00	-0.28	-0.10	-0.29	-0.06
Nuclear	0.01	-0.32	-0.28	1.00	0.48	0.89	0.28
Load	0.13	-0.16	-0.10	0.48	1.00	0.68	0.27
Production	0.33	-0.34	-0.29	0.89	0.68	1.00	0.14
Price	-0.34	-0.08	-0.06	0.28	0.27	0.14	1.00

Table 5.2: Correlation matrix for the parameters in SE3, 2018-2020.

	Load	**Production**	**Price**
SE1			
Residual Load	0.47	0.23	0.42
Residual Production	0.57	0.95	0.26
SE2			
Residual Load	0.38	-0.05	0.42
Residual Production	0.64	0.87	-0.07
SE3			
Residual Load	0.70	-0.02	0.19
Residual Production	0.85	0.71	0.09
SE4			
Residual Load	0.85	-0.08	0.41
Residual Production	0.80	0.54	0.02

Table 5.3: Correlation for residual load and residual production to total load, total production and price. For every price area, 2018-2020.

	Min (MWh)	Mean (MWh)	Max (MWh)	SD
SE1				
Wind	0.00	304.76	1341.61	294.64
Solar	0.00	0.22	3.72	0.50
Sim. solar	0.00	0.46	6.08	0.93
Load	738.89	1153.00	1754.18	187.85
Production	337.43	2480.70	4892.01	969.58
SE2				
Wind	0.27	864.98	3276.15	729.52
Solar	0.00	1.64	27.16	3.68
Sim. solar	0.00	3.06	43.84	6.21
Load	1036.27	1803.48	3065.97	368.48
Production	924.50	5122.07	9166.34	1454.55
SE3				
Wind	0.38	798.86	2630.67	595.63
Solar	0.01	21.61	305.67	45.26
Sim. solar	0.00	43.82	540.43	83.01
Nuclear	2255.88	6759.41	8671.27	1473.52
Load	4809.68	9443.67	16709.48	2133.15
Production	3360.02	9285.77	13385.94	1983.82
SE4				
Wind	0.53	471.37	1478.27	367.34
Solar	0.01	9.28	135.55	19.51
Sim. solar	0.00	19.22	216.13	35.50
Load	1311.05	2644.62	4988.43	638.35
Production	52.89	767.77	2006.47	425.48

Table 5.4: Characteristics for time series in SE1, SE2 and SE4, 2018-2020.

Comparing table 5.1 with table 5.3 we see that the residual load correlates more with the price than the load, meaning that removing solar and wind production from the load time series yields a parameter with higher correlation with price. Doing the same analysis on SE3 by comparing 5.3 with 5.2 we get the opposite result. Here, the correlation coefficient is 0.27 between load and price, while it is 0.19 for residual load and price. The same pattern goes for production, in SE3 the full production time series correlates more to the price while the rest of the price areas show a higher correlation for residual production. Note that for SE3, nuclear generation is included in the load and production but removed from the residual load and residual production.

	SE1	SE2	SE3	SE4
Wind/Production	0.12	0.17	0.09	0.61
Solar/Production	0.00	0.00	0.00	0.01
Nuc/Production	0.00	0.00	0.73	0.00
Total production (GWh)	65 252	134 730	244 250	20 195
Residual production (GWh)	57 230	111 940	44 872	7 552
Wind/Load	0.26	0.48	0.08	0.18
Sim solar/Load	0.00	0.00	0.00	0.01
Nuc/Load	0.00	0.00	0.72	0.00
Total Load (GWh)	30 329	47 439	248 406	69 564
Residual Load (GWh)	22 300	24 606	48 441	56 660

Table 5.5: Total share of production, with total production, residual production, load and residual load (all in GWh), 2018-2020.

Table 5.4 shows the minimum, mean and maximal value of the time series wind, solar, simulated solar, load and production. Characteristics of the price time series are presented in chapter 5.1.1. In general, we can see that SE3 and SE4 have a higher electricity demand than what is possible to generate in the areas, while SE1 and SE2 have a production surplus. Moreover, SE1 and SE2 both have low levels of solar. In SE3 the generation mix consist of 73 % nuclear on average, while wind power makes up the largest part of electricity production in SE4. What is common to all energy sources is that solar production constitutes a very small part of the total production, where SE4 have the largest share of solar relative to its total production. To confirm these values, table 5.5 show wind, solar and nuclear share out of total production and load during the time period 2018-2020. As previously stated, nuclear is the largest energy source in SE3 while there is no generation from nuclear power in the other regions. Solar production is low in all price regions.

5.1.1 Price characteristics

Figure 5.5 shows the distribution of prices in all price areas during 2018-2020. All time series are rightly skewed, with extreme values in the right tail. Table 5.6 show additional characteristics which confirms the skewness. Furthermore, the electricity price have a minimum below zero in all price areas. Overall, the

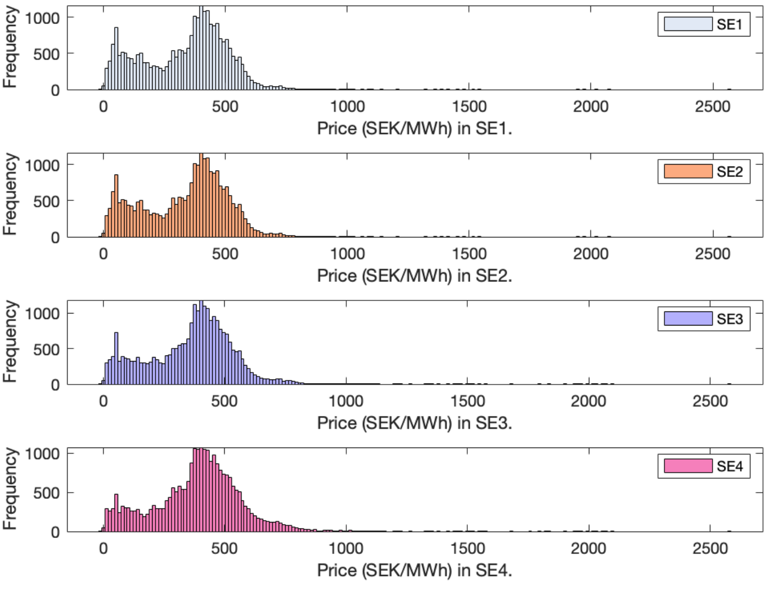


Figure 5.5: Histogram for prices, 2018-2020.

prices follow a similar pattern in all price areas. For SE1 and SE2, the prices are almost identical. This can be seen both by looking at the characteristics in table 5.6 and in figure 5.6 where SE1 and SE2 have a very similar plot line.

During 2018-2020 all price areas follow a similar pattern throughout the year. Figure 5.6 show that, on average, the prices are lower in April, May and June compared to the rest of the months. This is even more visible in figure 5.7 where it is clear that the price decreases as we get closer to July in all years, and that the price starts to increase from July. Although the price varies throughout the year, the daily pattern show the same characteristics all year. As shown in **??**, on average the prices are generally low during the nights, having its peaks before and after lunch and a bit lower during the middle of the day.

Table 5.7 show the results from testing the stationarity of the spot prices in all price areas using the ADF test. The test reject the unit-root null in favor of the alternative model in all price regions. Similar results were found doing the

	Min (SEK/MWh)	Average (SEK/MWh)	Max (SEK/MWh)	SD	Kurtosis	Skewness
SE1	-17.92	335.15	2573.41	175.35	5.14	0.13
SE2	-17.92	335.15	2573.41	175.35	5.14	0.13
SE3	-17.92	361.30	2584.07	180.85	9.01	0.61
SE4	-19.75	388.90	2584.07	184.64	8.71	0.65

Table 5.6: Price characteristics, 2018-2020.

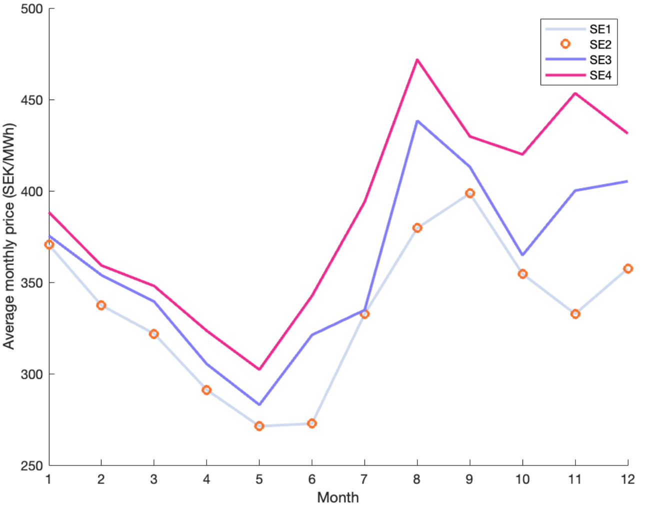


Figure 5.6: Average prices for Jan-Dec, 2018-2020.

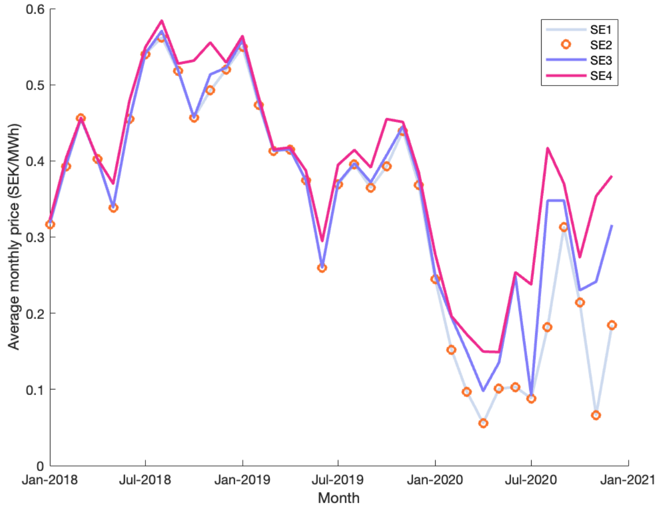


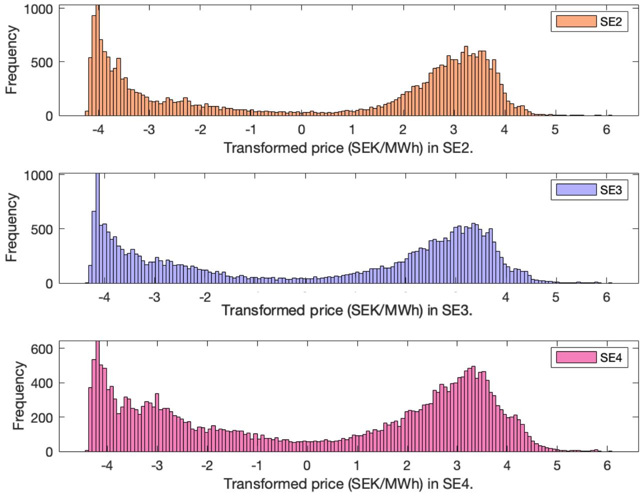
Figure 5.7: Average prices for Jan-Dec 2018, Jan-Dec 2019 and Jan-Dec 2020.

KPSS test, see table 5.8.

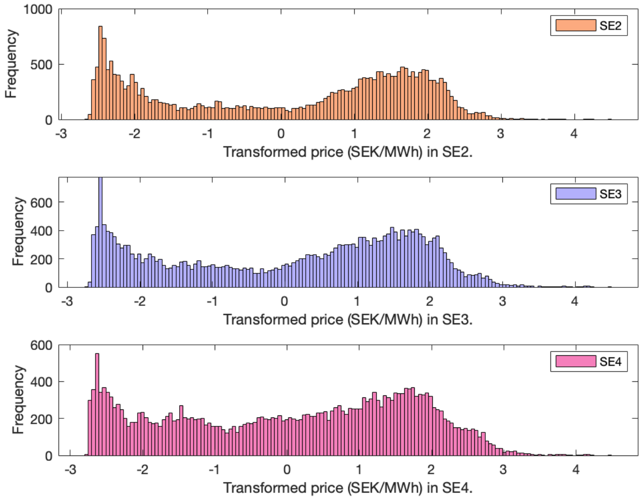
The transformed prices, $Price^*$, are less spread out than the original data and have two distinct peaks. Figure 5.8 show a histogram over the prices in SE2, SE3 and SE4. Price area SE1 is not included due to its similarities with SE2. For $\lambda = 50$ the prices are more evenly spread out, making the two peaks less clear to distinguish.

	SE1	**SE2**	**SE3**	**SE4**
ϕ (h)	1	1	1	1
N	26 203	26 203	26 203	26 203
t_{ADF}	-59.72	-59.72	-138.59	-172.95
P Value	0.00	0.00	0.00	0.00
Adjusted R^2	0.97	0.97	0.94	0.92

Table 5.7: Results ADF test.



(a) $\lambda = 10$ MWh.



(b) $\lambda = 50$ MWh.

Figure 5.8: Histogram showing transformed prices in SE2, SE3 and SE4 for different values on λ, during 2018-2020.

	SE1	SE2	SE3	SE4
ϕ (h)	1	1	1	1
n	26 304	26 304	26 304	26 304
t_{KPSS}	1.89	1.89	1.23	1.25
P Value	0.01	0.01	0.01	0.01
Adjusted R^2	0.42	0.42	0.21	0.14

Table 5.8: Results KPSS test.

5.2 Impact on electricity spot price

As we can see in table 5.9, the installed capacity have grown a lot during the last couple of years. It also clear that the levels are much higher in SE3 and SE4, why we chose to analyze the results from those two price areas.

	SE1	**SE2**	**SE3**	**SE4**	**Total** [MW]
2021-01-01	8.7	59.6	736.1	285.0	**1089.4**
2020-01-01	4.9	37.2	460.4	188.4	**690.9**
2019-01-01	4.2	21.6	275.8	110.0	**411.6**
2018-01-01	2.2	10.6	172.1	70.3	**255.2**

Table 5.9: Installed capacity (MW) solar power at the end of each year for all price regions (1 Jan 2021 is installed capacity at the end of 2020).

5.2.1 Regime distribution in SE3

In table 5.10 the RS model estimates are shown for SE3 (2018-2020), using the regression model in equation 4.6. The p-values are all very close to zero in both regimes, so the results are statistically significant. The β-value for *Solar* have the largest standard error relative to their beta-coefficient. Since the price time series is transformed, the betas can be difficult to interpret. Further analysis on the coefficients and what impact the different energy sources have on the price levels, can be found in section 5.2.3.

Equation 5.1 show the transition probabilities. The probability of changing from state 1 into state 2 is 4.46 % and 3.15 % the other way, which means that being in any state means you will stay there with a high probability. As an example,

	β-coefficient	Standard Error	P Value
Regime 1 (SE3)			
$\beta_0^{(1)}$ **Intercept**	-11.8783	0.1739	0.00e+0
$\beta_1^{(1)}$ **Wind/Production**	4.1218	0.1877	7.47e-107
$\beta_2^{(1)}$ **Solar/Production**	4.5241	0.7798	6.57e-9
$\beta_3^{(1)}$ **Nuc/Production**	9.9988	0.1913	0.00e+0
$\beta_4^{(1)}$ **Residual production**	0.7410	0.0144	0.00e+0
Regime 2 (SE3)			
$\beta_0^{(2)}$ **Intercept**	6.2846	0.2120	4.31e-193
$\beta_1^{(2)}$ **Wind/Production**	-6.0500	0.2337	8.52e-148
$\beta_2^{(2)}$ **Solar/Production**	-14.1889	1.3540	1.08e-25
$\beta_3^{(2)}$ **Nuc/Production**	-3.3514	0.2212	7.62e-52
$\beta_4^{(2)}$ **Residual Production**	-0.3249	0.0193	9.05e-64

Table 5.10: Estimates for SE3, 2018-2020.

figure 5.9 show the price level and the corresponding probability of being in R1 during the first week of September 2019 in SE3. Figure 5.10 show the sectioning of the prices into the two states, with R2 being the state including most of the high prices.

The results from evaluating the regime classification by the RCM test described in section 4.2.4 is $\text{RCM}(2)_{SE3} = 1.0823$ indicating an adequate model that manages to do a good regime classification.

$$\mathbf{P}_{SE3} = \begin{pmatrix} 0.9554 & 0.0446 \\ 0.0315 & 0.9685 \end{pmatrix} \tag{5.1}$$

5.2.2 Regime distribution in SE4

Figure 5.11 show the results from running the RS model on SE4, resulting in low p-values and errors. As in SE3, the standard errors are (relatively) high for *Solar/Production* compared to the other energy sources. Looking at the transition probabilities (equation 5.2), we see that there is a slightly lower probability of staying in a regime compared to in SE3, although it still much more likely than switching state into the other regime. Figure 5.11 show the

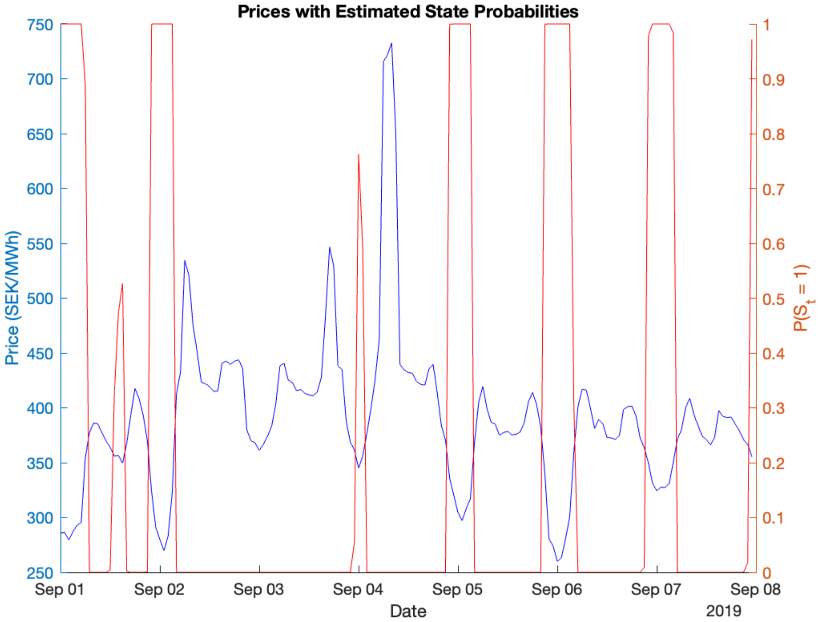


Figure 5.9: Prices (left axis) and the probability of being in R1 (right axis), during the first week of September 2019 in SE3.

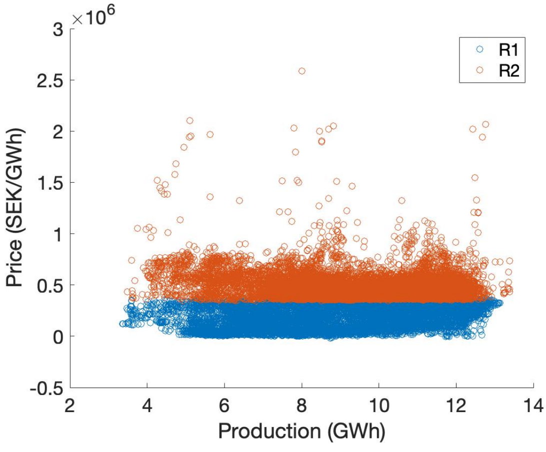


Figure 5.10: Prices per regime in SE3 (2018-2020)

	β-coefficient	Standard Error	P Value
Regime 1 (SE4)			
$\beta_0^{(1)}$ **Intercept**	-1.7606	0.0352	0
$\beta_1^{(1)}$ **Wind/Production**	-1.6542	0.0394	0
$\beta_2^{(1)}$ **Solar/Production**	-1.7089	0.1617	4.19e-26
$\beta_3^{(1)}$ **Residual production**	-0.3767	0.0521	4.79e-13
Regime 2 (SE4)			
$\beta_0^{(2)}$ **Intercept**	3.7463	0.0283	0
$\beta_1^{(2)}$ **Wind/Production**	-0.9942	0.0322	9.94e-210
$\beta_2^{(2)}$ **Solar/Production**	-1.2727	0.1547	1.93e-16
$\beta_3^{(2)}$ **Residual Production**	-1.2929	0.0461	4.13e-173

Table 5.11: Estimates for SE4, 2018-2020.

probability of being in $S_t = 1$ (R1) for one week in September 2019. For this period, we see that the probability of being in R1 equals 1 (100 %) when prices are low. Investigating the regimes for the whole time period, by viewing figure 5.12 we see that R1 includes lower prices while higher prices have a higher probability of belonging to R2. Evaluation the model show that $\text{RCM}(2)_{SE4} = 1.9205$, which indicates that the model has well classified regimes.

$$\mathbf{P}_{SE4} = \begin{pmatrix} 0.9423 & 0.0577 \\ 0.0498 & 0.9502 \end{pmatrix} \tag{5.2}$$

5.2.3 Energy sources impact on the electricity price

Since the prices are transformed according to equation 4.5, it is difficult to interpret the values of the coefficients. Therefore, differentials of the transformation is calculated as described in section 4.2.3.

For SE3 the graph in figure 5.13 show a rather constant pattern in R1 for all generators as well as for nuclear in R2. On the other hand, in R2 we see that the impact from solar and wind production is higher during daytime, with it peaks in the morning and around 16:00-17:00. This is also the time of the day when the prices are highest, as shown in figure **??**. The price effect is (in absolute terms) strongest from solar in R2, decreasing the price with an average of 96.44

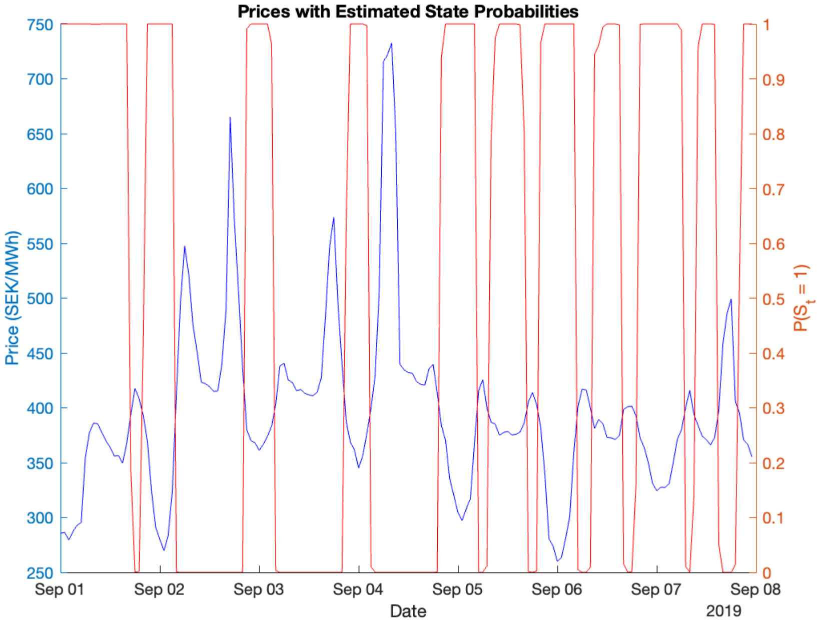


Figure 5.11: Prices (left axis) and the probability of being in R1 (right axis), during the first week of September 2019 in SE4.

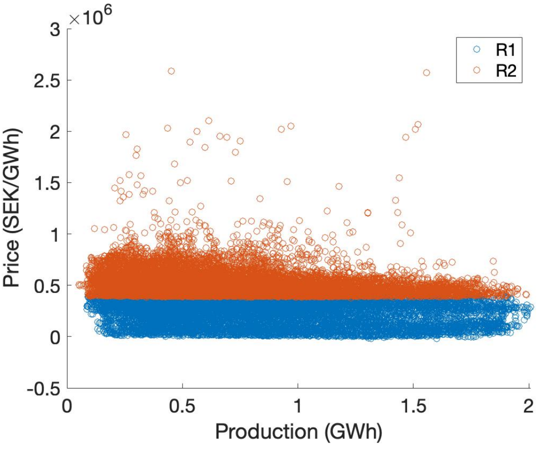


Figure 5.12: Prices per regime in SE4 (2018-2020).

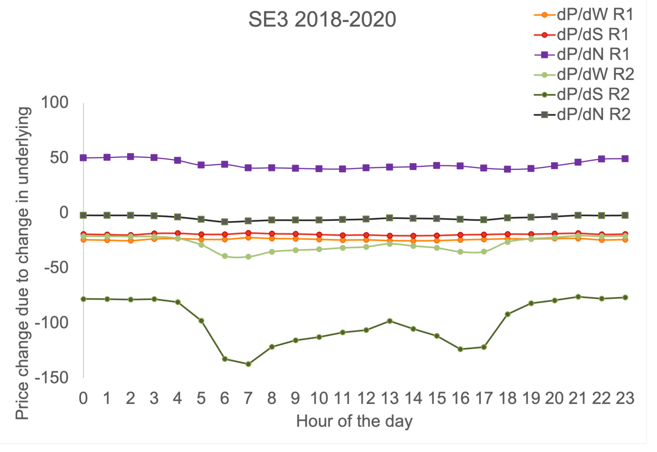


Figure 5.13: Differential pattern from wind ($\frac{\partial P}{\partial W}$), solar ($\frac{\partial P}{\partial S}$) and nuclear ($\frac{\partial P}{\partial N}$) power in SE3 for R1 and R2.

SEK/GWh. R2 is the state including most of the high prices. In periods of lower prices, which is regime 1 the effect is not as prominent. Exact numbers can be found in table A.1 in A.

As the production levels on average varies throughout the day, it is interesting to evaluate the results while considering the different production amounts. Figure 5.14 show the adjusted values. We see that all generators tend to lower the price, except from nuclear power in R1 (the purple graph and axis). In R2 (the green plots) solar have the largest impact in the middle of the day, while wind power show the lowest values, and thereby highest impact, during morning and evening. Furthermore, the derivatives for solar are more negative in R2 than in R1, which means seeing a larger impact in the high-price regime.

Figure 5.15 show the differentials pattern for SE4, and the results adjusted for the hourly production level can be found in figure 5.16. Exact numbers can be found in table A.2 in A. We see that for the data points in R1 wind production have a lowering but rather stable impact on the prices (see the orange plot and axis), while solar only have a lowering impact on daytime. This is reasonable since solar have a very limited production level during the night. In R2 wind production show a very volatile pattern, while solar decreases the prices during the day with its peak around CET 10:00.

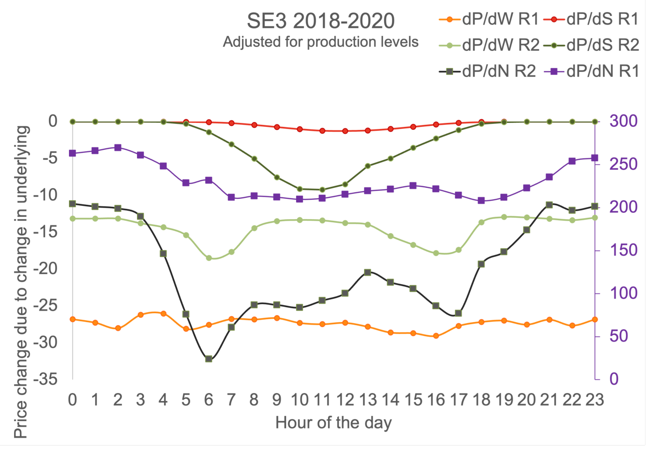


Figure 5.14: Effect in hourly price levels (SEK/GWh) from wind, solar and nuclear power in SE3 for R1 and R2, adjusted for production levels. All plots use the left y-axis except for Nuclear in R1 using the right y-axis.

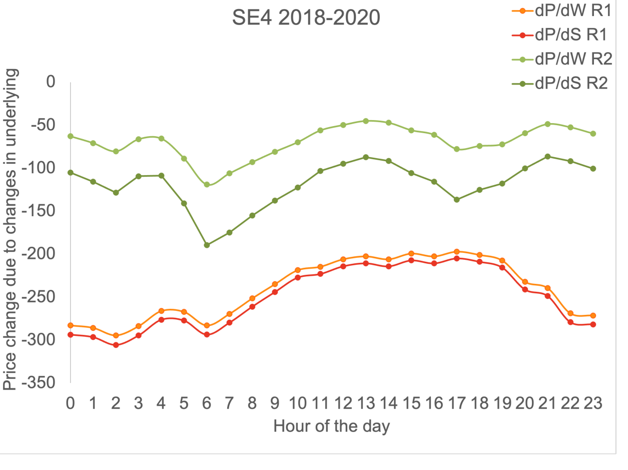


Figure 5.15: Differential pattern from wind and solar power in SE4 for R1 and R2.

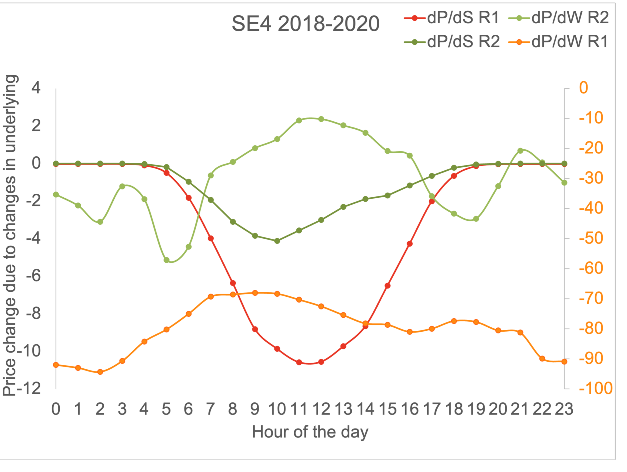


Figure 5.16: Effect in hourly price levels (SEK/GWh) from wind, and solar power in SE4 for R1 and R2, adjusted for production levels. All plots use the left y-axis except for Wind in R1 using the right y-axis (in orange).

Chapter 6

Discussion

The results from analyzing the price time series show that the price have a similar pattern in all price areas, although the production vary a lot. This can be explained by the pricing system in Sweden, where energy is transferred between the areas which makes prices reach towards an equilibrium price. Although, the prices are not always equal due to grid limitations. It is a situation that needs to be handled in the future, as renewable energy sources are taking a bigger part of the total production all over the world. One reason is the demand for more environmental friendly power, in combination with new technologies making it possible to produce more, in new ways and at a lower cost. Unfortunately the limitations on the grid decrease the transition pace towards a greener electricity production.

As the results show, solar power still make up a very small part of the total electricity consumption in Sweden, although it is growing at a fast pace. The data in this thesis was limited to the years 2018-2020 for mainly two reasons. First, a similar study was made in Germany using data from 2014-2015 and in order to be able to compare our results with theirs, we did not want to use too many years. Second, we were not certain that it would be better to extend the model by including more years, since the levels of solar are almost insignificant going only a few years back. Furthermore, the fact that solar power constitutes to a very small part of the total production, can also make the results uncertain. Especially in comparison to the German market.

In this project, we had some problem with selecting the value of λ in the price transformation. One of the reason why $\lambda = 10$ was chosen was due to the fact that 1 euro was used in the German article, the article that we wanted to be able to compare our results with. 10 SEK was assumed to equal 1 euro. The authors of that article did not motivate the reason for using $\lambda = 1$ euro other than "for simplicity reasons" and even after correspondence with the authors, the reason was still not clear. In the end, the results were not significantly affected by choice of λ in the price transformation. This was only investigated in a small scale, and could be further examined.

The fact that solar power is a relatively small energy type might also have affected the result. To reduce the impact from that, we decided to do the analysis on SE3 and SE4 being the two price areas with most installed capacity (MW) for solar power in Sweden. Still, the difference between SE3 and SE4 is not insignificant since the installed capacity is more than doubled in SE3 compared to SE4, which is seen in table 5.9. However, the impact on the results was not further investigated in this thesis. The same table also show that the total amount of installed capacity have had a lot of growth the last years, with very small levels in the beginning of the selected study period, especially in SE4 which also might have affected the results.

The result show a price lowering effect on the daily price pattern from increasing solar power in both SE3 and SE4. In SE3, the impact is larger in R2. In SE4, the impact is on the other hand larger in R1. As mentioned above, the level of solar production (capacity) is smaller in SE4 and regime 1 is the state with most of the low prices which occur mainly during the night. This means that the solar production and corresponding prices included in R1 in SE4 is not very interesting to investigate. As we are interested in investigating the electricity price changes from increasing solar power, it is naturally most important to investigate the hours when we actually have sunlight. In that sense, it is SE3 (and R2 where we have higher prices) that we can assume give us the most accurate results.

6.1 Further research

This is a project that could be extended in many ways. For example, researchers interested in understanding the impact of hydro power on the Swedish electricity prices could change the model to include a hydro power parameter. There are several ways to improve the model to gain greater understanding of the impact from solar production too. As earlier mentioned, a decision was made to perform the study on the years 2018-2020. As soon as new simulations on the solar production has been made, the year 2021 can be added to the model. In that way, it is possible to see whether the trends discovered in this thesis are still valid as the time series from 2021 are added to the model. Although, adding data from 2021 could cause some problems. It was a year with extremely high electricity prices caused mainly by high prices on natural gas in Europe. Limitations on the Swedish grid also caused large price differences between the price areas. The extreme values and the volatility in the data would then have to be considered. Other improvements could be to do new simulations on solar production for the dates in 2018 that were missing.

The main drawback in this study is that the derivatives showing the solar production impact on the electricity spot price is only valid for the time period that we used in this study. This means that, as the production continue to grow, there are no guarantee that the effect on prices will continue in the same pace further on. To solve this, a first step could be to investigate the pattern in countries who have a higher share of renewable energy, such as Germany or Spain. In theory, at a certain point in time the merit order effect will be lower. When the electricity generation mix consists mainly of RES, the impact of adding more RES will not affect the price on the same levels as today. Another approach would be to implement an RS Autoregressive model that make the price not only depend on factors such as load or production, but also linearly on its own previous values. It could also be good to have a model where it is possible to put weight on the different years, for example it might be good to put more weigh on years more recent in time than further back.

To further deepen the analysis of this thesis, it would be interesting to investigate future levelized cost of electricity (LCOE) for the price levels computed in this project. The results from this thesis tell us about the price levels today if we would have other levels of production, and therefore making a prediction of LCOE based on only this would not be a very robust way to go. Although the values could be used as one scenario together with other possible future outcomes.

Chapter 7

Conclusion

This study presents a model that can help to understand the impact from solar, wind and nuclear on the daily Swedish electricity spot price pattern. The result show that an increase of solar power have a price lowering effect on the daily price pattern in both SE3 and SE4. In SE3 wind production tend to lower the spot price even more.

One drawback with this project is the fact that solar power is still considered a small contributor to the total energy production in Sweden. This complicates the work of making good models and analyzes on the results. As a consequence of that, not all price areas were analyzed in this study. As more photovoltaics is being installed, this study can advantageously be performed again including all price areas.

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Appendix A

Results

A.1 Daily price pattern

Figure A.1: Average price in SE1 per hour.

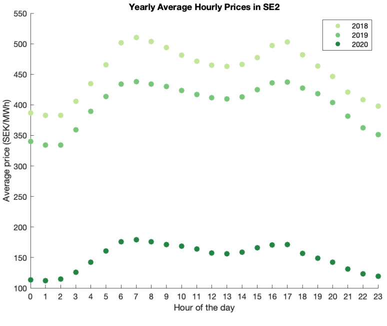


Figure A.2: Average price in SE2 per hour.

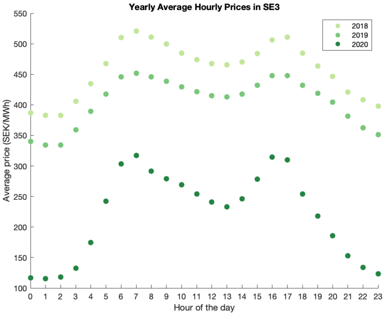
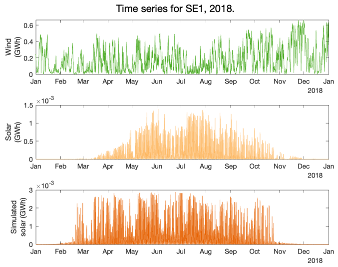
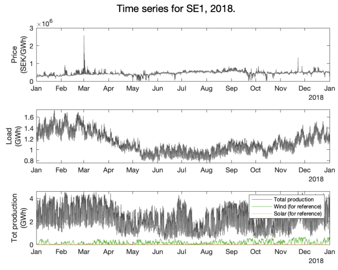


Figure A.3: Average price in SE3 per hour.

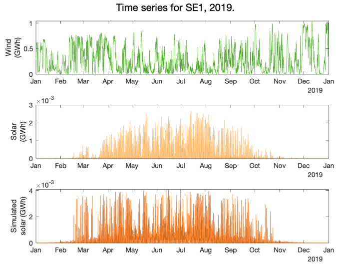
A.2 Time series per year and price area



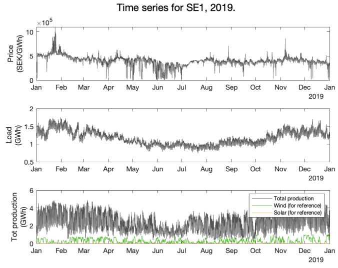
(a) **SE1 2018** Hourly wind, solar and nuclear production in price area SE1.



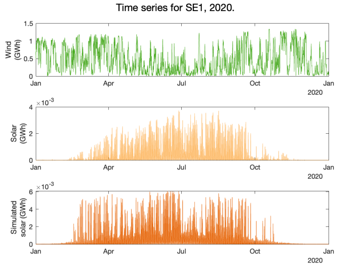
(b) **SE1 2018** Hourly electricity price, total load and total production in price area SE1.



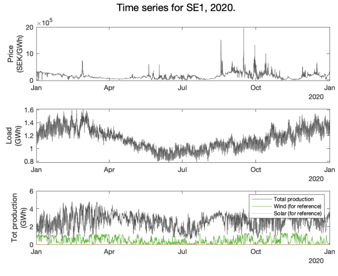
(c) **SE1 2019** Hourly wind, solar and nuclear production in price area SE1.



(d) **SE1 2019** Hourly electricity price, total load and total production in price area SE1.

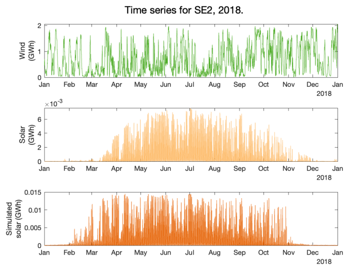


(e) **SE1 2020** Hourly wind, solar and nuclear production in price area SE1.

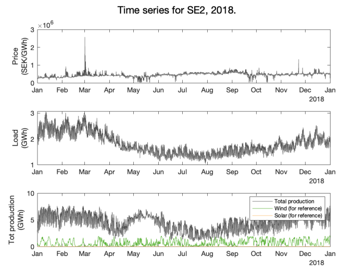


(f) **SE1 2020** Hourly electricity price, total load and total production in price area SE1.

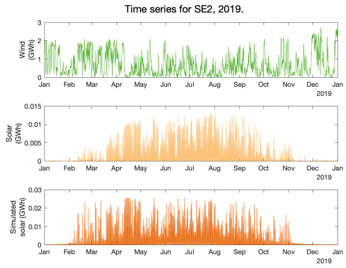
Figure A.4: Final time series for 2018, 2019 and 2020 in price area SE1.



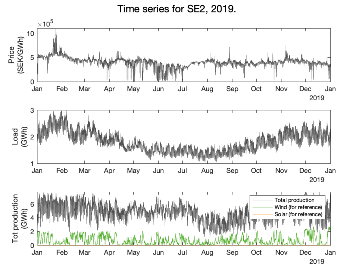
(a) **SE2 2018** Hourly wind, solar and nuclear production in price area SE2.



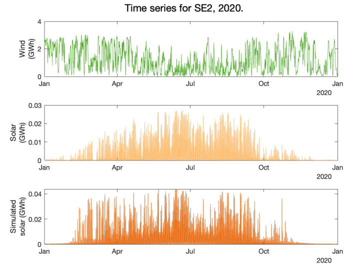
(b) **SE2 2018** Hourly electricity price, total load and total production in price area SE2.



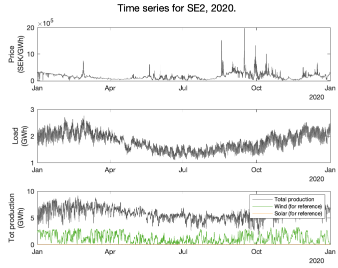
(c) **SE2 2019** Hourly wind, solar and nuclear production in price area SE2.



(d) **SE2 2019** Hourly electricity price, total load and total production in price area SE2.

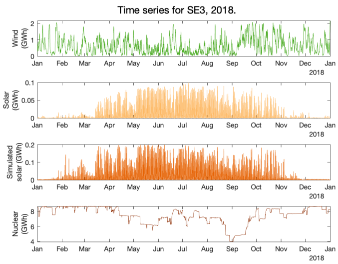


(e) **SE2 2020** Hourly wind, solar and nuclear production in price area SE2.

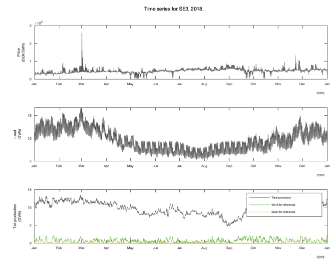


(f) **SE2 2020** Hourly electricity price, total load and total production in price area SE2.

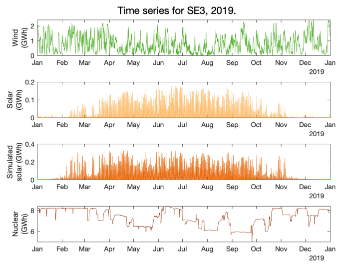
Figure A.5: Final time series for 2018, 2019 and 2020 in price area SE2.



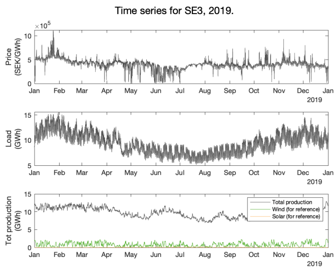
(a) **SE3 2018** Hourly wind, solar and nuclear production in price area SE3.



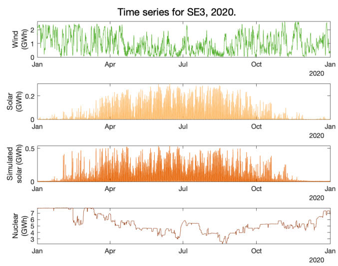
(b) **SE3 2018** Hourly electricity price, total load and total production in price area SE3.



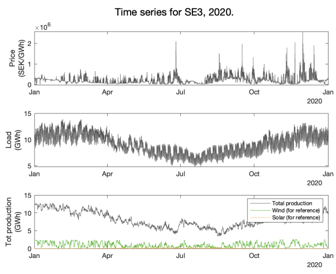
(c) **SE3 2019** Hourly wind, solar and nuclear production in price area SE3.



(d) **SE3 2019** Hourly electricity price, total load and total production in price area SE3.

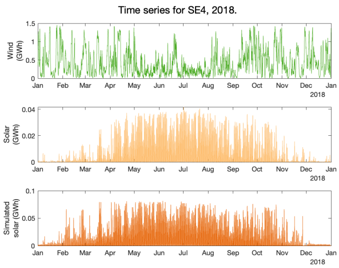


(e) **SE3 2020** Hourly wind, solar and nuclear production in price area SE3.

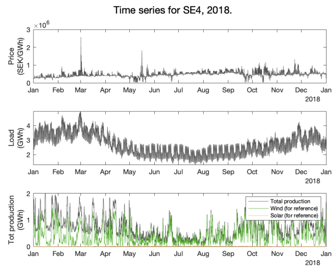


(f) **SE3 2020** Hourly electricity price, total load and total production in price area SE3.

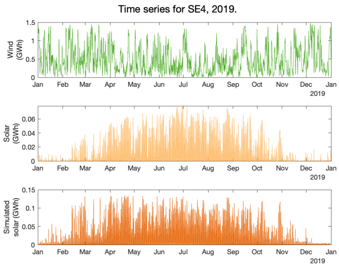
Figure A.6: Final time series for 2018, 2019 and 2020 in price area SE3.



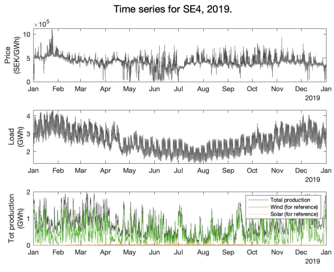
(a) **SE4 2018** Hourly wind, solar and nuclear production in price area SE4.



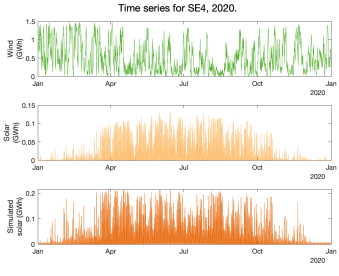
(b) **SE4 2018** Hourly electricity price, total load and total production in price area SE4.



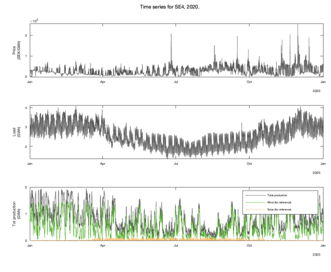
(c) **SE4 2019** Hourly wind, solar and nuclear production in price area SE4.



(d) **SE4 2019** Hourly electricity price, total load and total production in price area SE4.



(e) **SE4 2020** Hourly wind, solar and nuclear production in price area SE4.



(f) **SE4 2020** Hourly electricity price, total load and total production in price area SE4.

Figure A.7: Final time series for 2018, 2019 and 2020 in price area SE4.

A.3 Differentials

	Regime 1 (SE3)			*Regime 2 (SE3)*		
Hour	$\frac{\partial Price}{\partial Wind}$	$\frac{\partial Price}{\partial Solar}$	$\frac{\partial Price}{\partial Nuclear}$	$\frac{\partial Price}{\partial Wind}$	$\frac{\partial Price}{\partial Solar}$	$\frac{\partial Price}{\partial Nuclear}$
00	-24.25	-19.17	50.04	-21.08	-78.07	-2.18
01	-24.74	-19.60	50.40	-21.12	-78.12	-2.22
02	-25.16	-19.95	51.03	-21.26	-78.57	-2.25
03	-23.53	-18.49	50.17	-21.43	-78.21	-2.61
04	-23.20	-18.34	47.76	-23.00	-80.98	-3.77
05	-23.93	-19.32	43.44	-28.80	-97.94	-5.88
06	-23.96	-19.30	44.13	-39.07	-132.65	-8.04
07	-22.41	-18.07	40.97	-39.67	-137.27	-7.31
08	-23.15	-18.76	41.01	-35.14	-121.48	-6.51
09	-23.34	-18.96	40.63	-33.69	-115.73	-6.49
10	-23.94	-19.56	40.05	-32.99	-112.75	-6.54
11	-24.54	-20.13	39.96	-31.59	-108.47	-6.10
12	-24.43	-19.95	40.98	-30.70	-106.24	-5.65
13	-25.11	-20.55	41.60	-27.93	-98.15	-4.64
14	-25.29	-20.69	42.03	-29.88	-105.21	-4.90
15	-25.14	-20.47	43.07	-31.62	-111.52	-5.13
16	-24.38	-19.80	42.59	-35.17	-123.65	-5.83
17	-23.94	-19.52	40.65	-35.08	-121.85	-6.31
18	-23.37	-19.05	39.73	-26.31	-91.96	-4.55
19	-23.54	-19.17	40.27	-23.40	-82.00	-3.97
20	-23.21	-18.69	42.86	-22.21	-79.35	-3.27
21	-23.06	-18.33	45.95	-20.61	-75.97	-2.25
22	-24.43	-19.41	48.99	-21.14	-77.70	-2.39
23	-24.13	-19.10	49.31	-20.79	-76.71	-2.25

Table A.1: Derivatives SE3, 2018-2020.

	Regime 1 (SE4)		*Regime 2 (SE4)*	
Hour	$\frac{\partial Price}{\partial Wind}$	$\frac{\partial Price}{\partial Solar}$	$\frac{\partial Price}{\partial Wind}$	$\frac{\partial Price}{\partial Solar}$
00	-282.90	-293.62	-62.89	-105.06
01	-285.75	-296.56	-70.77	-115.60
02	-294.44	-305.56	-80.37	-128.44
03	-283.77	-294.51	-66.28	-109.30
04	-266.13	-276.23	-65.58	-108.75
05	-267.15	-277.28	-88.68	-140.86
06	-282.93	-293.56	-119.05	-189.43
07	-269.46	-279.61	-105.98	-174.85
08	-251.48	-261.06	-93.00	-154.98
09	-234.93	-243.96	-80.88	-137.74
10	-218.66	-227.16	-69.79	-122.38
11	-214.60	-222.99	-56.05	-103.29
12	-205.96	-214.07	-49.81	-94.68
13	-202.60	-210.61	-45.03	-87.08
14	-205.99	-214.13	-47.14	-91.64
15	-199.32	-207.22	-55.84	-105.68
16	-202.65	-210.66	-61.14	-115.80
17	-197.10	-204.89	-77.80	-136.57
18	-200.92	-208.80	-74.18	-125.08
19	-207.40	-215.52	-72.13	-117.74
20	-232.16	-241.12	-59.33	-100.32
21	-239.51	-248.69	-48.70	-86.47
22	-268.88	-279.13	-52.40	-91.67
23	-271.35	-281.66	-59.70	-100.41

Table A.2: Derivatives SE4, 2018-2020.

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