CONDITIONAL VALUE-AT-RISK OPTIMIZATION FOR MANAGING AREA PRICING RISK IN THE FINNISH ELECTRICITY MARKET

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ABSTRACT

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Abstract

Differences in area pricing in the Nordic electricity markets creates price risk for large electricity consuming industries. The thesis will present a method to determine the optimal amount of electricity price area differentials (EPAD) futures to purchase for hedging area price risk in the Finnish electricity market for a large electricity consumer. A hedging portfolio was constructed by minimizing total electricity costs subject to the constraint that the conditional value at risk (CVaR) stays below a given level. To illustrate how this method can be used in practice, three simple forecasting models were developed to predict the futures premium for the Finnish area price. These forecasting models are used to generate possible future scenarios of the future premium, which is then used in the hedging portfolio optimization to minimize CVaR. The performance of the CVaR hedging strategies using different forecasting methods is compared against the performance of minimum variance and two fixed hedge ratio strategies.

Key words
Conditional value-at-risk, hedging, electricity futures, EPAD

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NOMENCLATURE

Symbol	Definition
C	Cost (€)
S	Price on spot market (€/MWh)
F	Price of futures (€/MWh)
X	Electricity consumption, amount bought on spot market (MWh)
H	Hedge amount (MWh)
J	Set of all scenarios
τ	Set of all time intervals
N	Number of scenarios in set J
β	Confidence level
FP	Futures premium
R	Reservoir level
p	Probability of scenario occurring
a	Skew parameter
μ	Location parameter
σ	Shape parameter
$\boldsymbol{\phi}(\boldsymbol{L})$	Non-seasonal autoregressive lag polynomial
$\tilde{\boldsymbol{\phi}}(\boldsymbol{L})$	Seasonal autoregressive lag polynomial
$\boldsymbol{\Delta}$	Difference term
$\boldsymbol{A}(\boldsymbol{t})$	Trend polynomial
$\boldsymbol{\theta}(\boldsymbol{L})$	Non-seasonal moving average lag polynomial
$\tilde{\boldsymbol{\theta}}(\boldsymbol{L})$	Seasonal moving average lag polynomial
Subscripts and superscripts	
t	Time period t, $t \in \boldsymbol{\tau}$
T	The delivery time for a futures contract
sys	System (price)
a	Area (price)
APD	Area price difference
rl	Riskless
j	Scenario
ask	Ask price
bid	Bid price
p	Lag number for auto-regressive term
d	Differencing degree
q	Lag number for moving average term
s	Periodicity of the seasonality
P	Lag number for seasonal auto-regressive term
D	Differencing degree for the seasonal term
Q	Lag number for seasonal moving average term

1 INTRODUCTION

Starting in the 1990s a large number of countries began processes of deregulation and restructuring of their electricity markets. The exact reasons, actions taken and results of this process differ between the countries, but the general goal was the same: to introduce elements of competition into electricity generation and purchasing. For a detailed look at the history of electricity market deregulation and restructuring see, for example, Rothwell and Gómez (Rothwell and Gómez 2003).

The result of this process in the Nordic countries was the formation of the Nord Pool power market. Nord Pool offers a marketplace for intra-day and day-ahead electricity trading. Nord Pool is divided into 21 regions which are shown, along with the daily price quotation (€/MWh), in Figure 1. Nord Pool calculates a system price, which is the price that balances the supply and demand for the entire Nordic market assuming no physical capacity limitations. If there were no physical transmission capacity constraints between the bidding areas, the prices in all bidding areas would be equal to the system price. However, because there are in fact capacity constraints between the bidding regions, there will be differences in the electricity prices in bidding areas. As can be seen from Figure 1, the area price for Finland on 05.10.2020 was 31.12 €/MWh while in the NO1 bidding area the price was 6.16 €/MWh. The system price at that time was 10.25 €/MWh. For more information on the history and structure of the Nord Pool market, see Flatabø et al. (Flatabø et al. 2003).

In addition to the physical electricity market operated by the Nord Pool, financial derivatives for the Nordic power market can be traded on the NASDAQ OMX Commodities exchange. The types of financial instruments traded in the Nordic Power product offering include futures contracts based on the Nord Pool system price, options based on the Nord Pool system price, and Electricity Price Area Differential (EPAD) contracts. EPAD contracts are futures contracts, which are based on the price difference between the area price of a bidding area and the system price.

Electricity prices in modern electricity markets are known to be more volatile than the prices of other commodities (Souhir, Heni, and Lotfi 2019). This price volatility creates risks for businesses which are highly dependent on the electricity markets, such as electricity generators or industries which are large electricity consumers. In Finland in 2019, industry and construction accounted for 46.1% of total electricity consumption or 39 665 GWh (Statistics Finland 2020). At the 2019 average Finnish area price of 44.04 €/MWh (Nord Pool AS 2020), this implies that electricity-related costs accounted for approximately 1.7 billion € of the costs to these businesses. In addition, for electricity intensive manufacturing processes it is not always possible to pass increased electricity costs along to the final customer in terms of increased sales prices (Mulhall and Bryson 2014).

Because of the potentially high volatility and high costs, it is important that businesses have tools to maintain their electricity cost risk at an appropriate level. Conditional value-at-risk, a risk measure, is one such tool. In this thesis conditional value-at-risk measures will be used to create a hedging portfolio of EPAD futures to manage the monthly electricity price risk for a theoretical large electricity consumer.

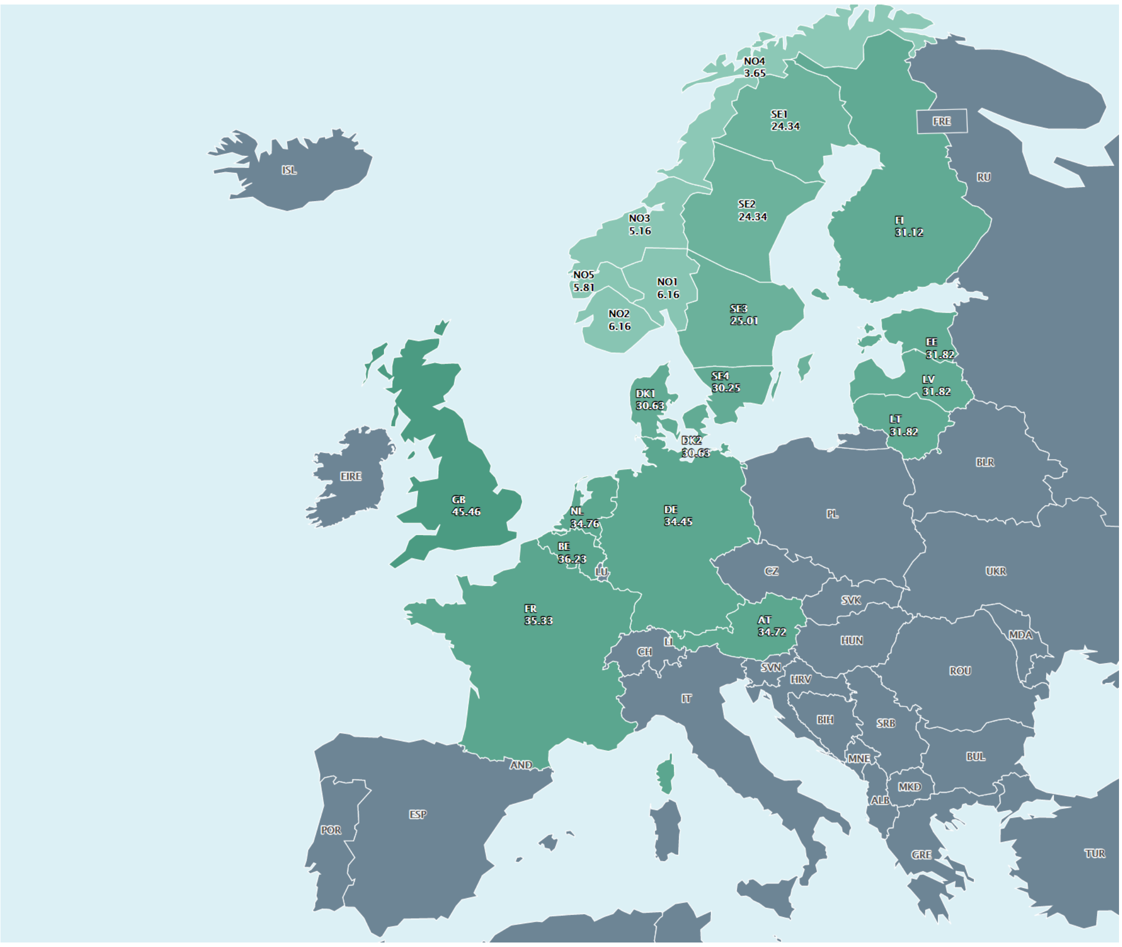

Figure 1 The Nord Pool market regions and the daily prices on 05.10.2020 (Nord Pool AS 2020).

This thesis consists of four main parts. Section 2 gives an overview of the field of financial risk management as it relates to pricing the risks in electricity markets. In Section 3 the Finnish area spot price and futures price data are presented. In Section 4 the methods used are shown. The main topic of this section is the portfolio optimization model shown in Section Portfolio optimization model. It can be seen in that section that to perform the portfolio optimization routines, future price scenarios must be generated. As such, Section Forecasting methods for scenario generation presents three methods, which can be used to generate these price scenarios. In Section 5 the results are presented and discussed. This consists primarily of the calculated optimal hedging amount using each of the three forecasting methods presented in Section Forecasting methods for scenario generation and a comparison of the results of conditional value-at-risk hedging strategies against more traditional hedging portfolios. In Section 6 the conclusions are given.

2 THEORETICAL FRAMEWORK

This work largely falls under the field of financial risk management. There is no universally agreed definition of risk, but Aven and Renn propose the definition "uncertainty about and severity of the consequences (or outcomes) of an activity with respect to something that humans value" (Aven and Renn 2009). In the context of financial risk management, the consequences of interest in this definition would be a potential financial loss for a business.

There are many ways to measure risk, and the understanding of the suitability of different risk measures has changed over time. In Modern Portfolio Theory (MPT) risk is measured using the variance of returns on a portfolio. It was realized, however, that there are some undesirable consequences of using the return variance as a risk measure, such as the fact that both upside and downside risk are penalized equally (Rom and Ferguson 1994; T. R. Rockafellar, Uryasev, and Zabarankin 2005). Artzener et al. attempted to formalize the desirable qualities of risk measures, and created the term 'coherent' risk measures to describe measures which possess these qualities (Artzner et al. 1999).

Value-at-risk (VaR) is a very widely used risk measure which does not satisfy the requirements of a coherent risk measure (Artzner et al. 1999). While the basic concepts of VaR were described as early as 1945, the method and modern naming was popularized in the 1990s by JP Morgan (Adamko, Spuchľáková, and Valášková 2015; Holton 2002). The basic definition of VaR is that it gives the value of loss which will not be exceeded with a given probability, β. An example is shown is Figure 2, where the threshold probability β is set to 95%, and so VaR is the value of loss which will not be exceeded in 95% of the cases or which will be exceeded in only 5%.

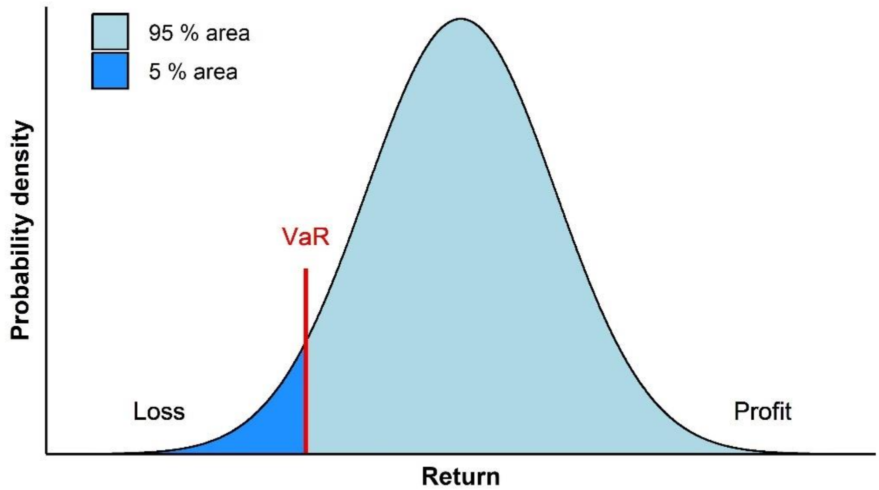

Figure 2 Value-at-risk (VaR) at the β = 95% level.

Conditional value-at-risk (CVaR) is a popular risk measure, which is defined as the expected loss in the (1- β)% worst cases. CVaR can be thought of in most cases as the expected loss conditional that the loss exceeds the VaR level. CVaR accounts for the shape of the loss tail beyond the VaR threshold. CVaR has additional advantages when compared to VaR as it is a coherent risk measure (Lim, Shanthikumar, and Vahn 2011) and it is better suitable for using in scenario based optimization (R. T. Rockafellar and Uryasev 2000). Figure 3 depicts the relationship between VaR and CVaR.

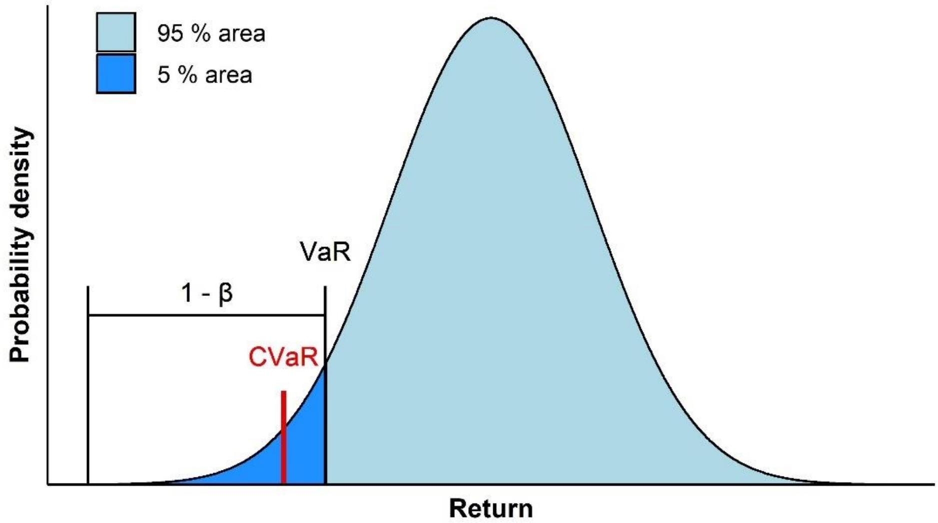

Figure 3 Conditional value-at-risk (CVaR) compared to value-at-risk (VaR) at the β = 95% level

After electricity markets were deregulated and restructured, financial risk management methods began to become more common among both the buy and sell side of the market. By the mid 2000's the basic principles of using energy derivatives to manage electricity price risk and the application of VaR in electricity markets were well established (Deng and Oren 2006; Liu, Wu, and Ni 2006). Many other works have looked at hedging strategies from the perspectives of either electricity produces, retailers, or consumers. From the electricity generator perspective, Conejo et al. (Antonio J. Conejo et al. 2008) developed a model to manage risk by optimizing purchases of forwards contracts. CVaR was used as the risk measure in this work. Similarly from the retailer perspective, Kettunen, Salo and Bunn (Kettunen, Salo, and Bunn 2010) studied hedging with forward contract by CVaR optimization approach. Zhang and Wang developed a model for hedging contract choices for a electricity consumer, and also used CVaR as a risk measure (Qin Zhang and Xifan Wang 2009).

Demand response is another method for managing electricity price risk exist, which does not necessitate hedging with financial derivatives. Demand response entails electricity consumers adjusting their consumption of electricity based on price signals, and so they consume more electricity when prices are low and less when prices are high (Kirschen 2003). Demand response has been shown to be effective in a wide range of cases, such as the pulp and paper industry (Helin et al. 2017) and by managing air-conditioning units (Marwan, Ledwich, and Ghosh 2014). Gómez-Villalva and Ramos also consider a large industrial customer and develop a model which can optimize both operational and contractual decisions to manage energy costs (Gómez-Villalva and Ramos 2003). While businesses should utilize all options available for managing electricity risk, including demand response, this work will focus only on risk management through financial hedging.

3 DATA

Monthly spot price data for the Finnish area price and the Nordic system price were retrieved from the Nordpool Historic Market Data webpage. The data was treated in the same way as done in Junttila et al. (Junttila, Myllymäki, and Raatikainen 2018), and so the area price difference (APD) for period t was calculated as the difference between the system price and the area price, that is,

$$S_{APD,t} = S_{sys,t} - S_{a,t}, \quad (1)$$

where $S_{APD,t}$ is the area price differential, $S_{sys,t}$ the system price, and $S_{a,t}$ the area price at time t.

The area price differences for monthly data for all the bidding areas in the Nordpool power market are shown in Figure 4 for the period of 2005-2017. In addition, the mean and standard deviations for the same time period are shown in Table 1. The Finnish area has the second highest mean area price differences and third highest standard deviation. This indicates that the Finnish area price is both relatively high and volatile.

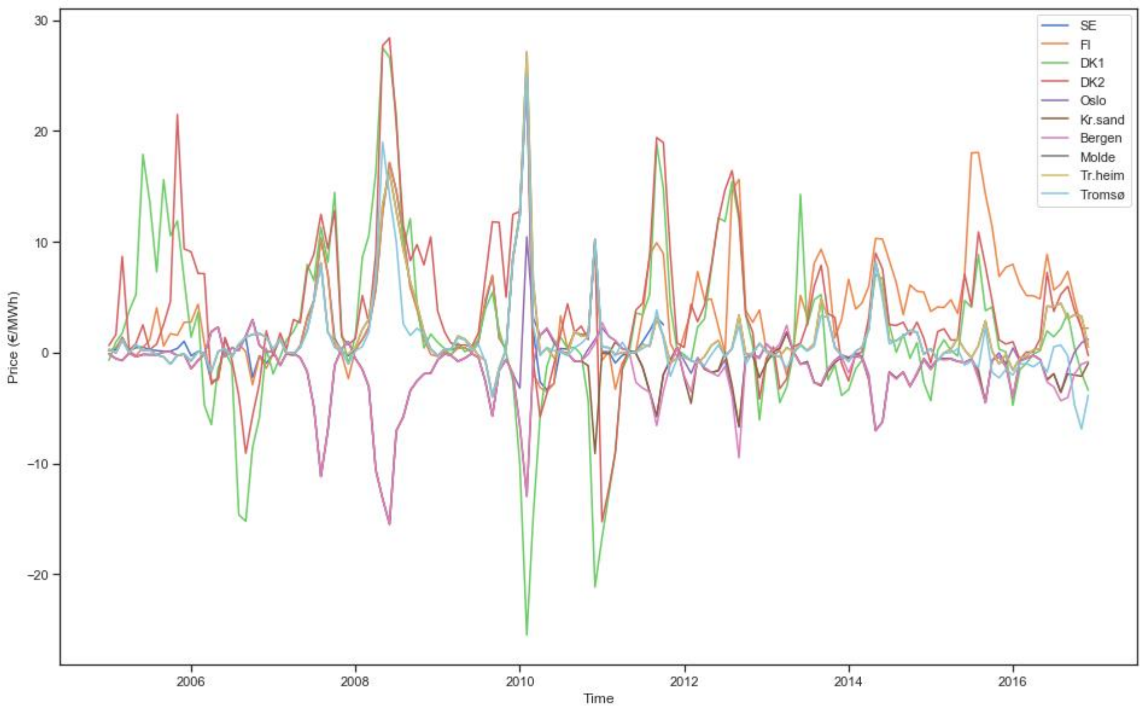

Figure 4 The area price differences for the bidding areas of the Nordpool power market.

Table 1 Mean and standard deviations for the area price differences of all the bidding areas in the Norpool power market for 2005-2016.

	SE	FI	DK1	DK2	Oslo	Kr.sand	Ber-gen	Molde	Tr.heim	Tromsø
Mean	2.219	3.808	1.886	3.877	-1.141	-1.594	-1.545	1.583	1.583	0.979
St.d.	4.690	4.792	7.572	6.491	2.800	2.820	2.885	3.603	3.603	3.582

The prices for Finnish EPAD contracts were obtained from Nasdaq. The data set included daily ask, bid and closing prices. The monthly averages for these were calculated using the last five business days of each month. The futures ask price at time t for delivery period T would then be

$$F_{t,ask}^{T} = \frac{1}{5}\sum_{n=-5}^{-1} F_{n,ask}^{T} \, . \qquad (2)$$

where $F_{n,ask}^{T}$ is the ask price on day n with delivery period T. Similarly, the bid price would be

$$F_{t,bid}^{T} = \frac{1}{5}\sum_{n=-5}^{-1} F_{n,bid}^{T} \, , \qquad (3)$$

where $F_{n,bid}^{T}$ is the bid price on day n with delivery period T. Finally, the closing price is given by

$$F_{t,c}^{T} = \frac{1}{5}\sum_{n=-5}^{-1} F_{n,c}^{T} \, . \qquad (4)$$

Figure 5 shows the Finnish monthly area price difference given by Eq. (1) along with the futures contract closing price in the preceding month given by Eq. (4), and the resulting futures premium. The data presented in this plot is identical to the plot shown in Junttila et al. (Junttila, Myllymäki, and Raatikainen 2018), which confirms that the data sources and processing are consistent with that work. The ask, bid, and closing prices are shown together in Figure 5.

In addition to the spot market and futures contract data, the historical Finnish hydro reservoir water levels were retrieved from the Finnish Environment Institute website (Environmental Institute of Finland 2017). The Finnish reservoir level can be seen in Figure 7 along with the Finnish area price difference for the same period.

As will be seen in Section 3 it is necessary to predict possible future area price differences in order to perform the CVaR portfolio optimization. To create these forecasts three models were developed and are presented in Section 3. In addition to the futures contract prices (closing, ask, and bid prices) and Finnish reservoir level, two other features were calculated from the data to use as possible model variables for prediction the future area price differences. The three-month rolling average area price difference was calculated and indicated by $\bar{S}_{apd,t3}$. In addition, the ex-post future premium from the previous month was included.

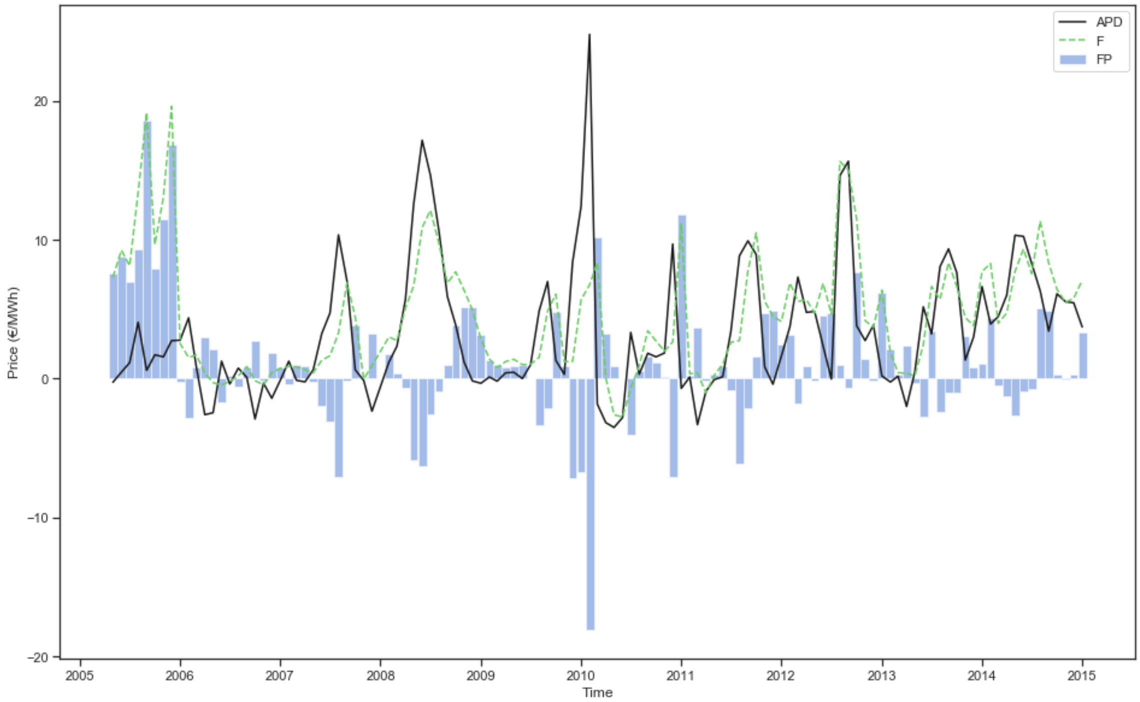

Figure 5 The monthly Finnish area price difference (APD), the corresponding closing price of the futures contract (F) and the resulting futures premium (FP).

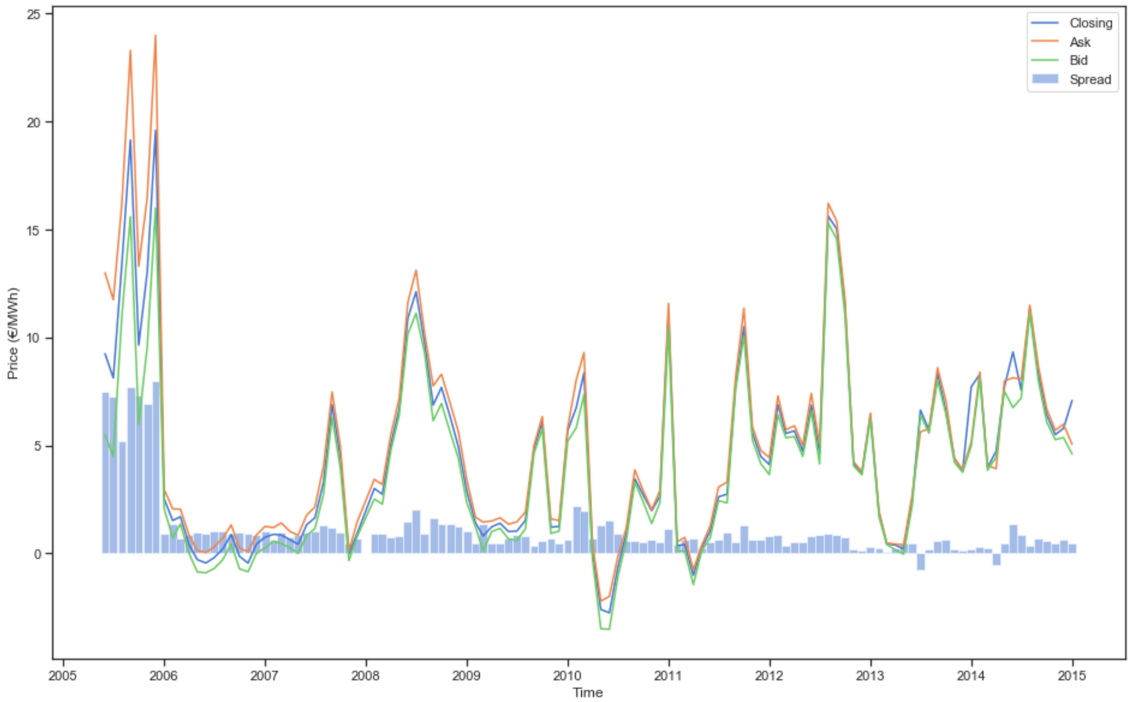

Figure 6 Closing, ask, and bid prices for Finnish EPAD futures ask calculated by Eqs. 2-4. The difference between the ask and bid prices is shown as the spread.

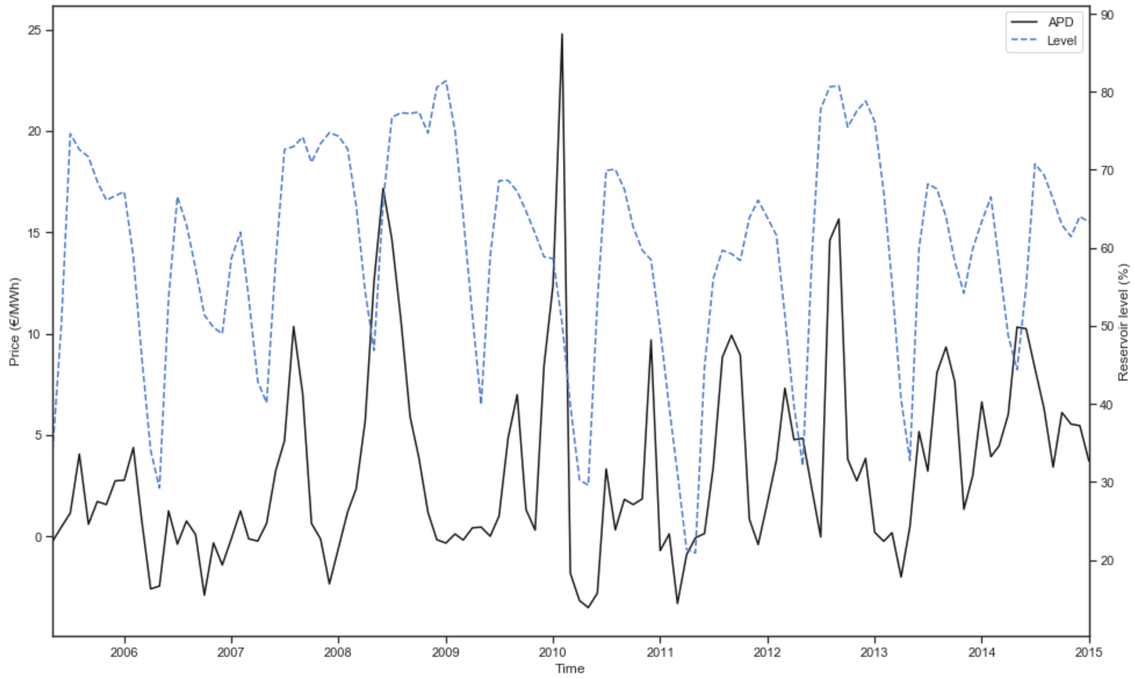

Figure 7 Finnish area price difference (APD, left axis) and the Finnish hydro reservoir level (Level, right axis).

The correlation matrix between these seven variables and the Finnish area price difference is shown in Table 1. As can be seen from the table, the previous month's spot price for the area price difference ($s_{apd,t-1}$) has the highest correlation with the current month's area price difference ($s_{apd,t}$). The closing, ask and bid prices for the futures contracts are also correlated the spot price and are highly correlated with each other. The correlation between the area price difference and the previous month's reservoir level and futures premium are also noteworthy.

Table 2 The correlation matrix between the seven variables used for predicting Finnish area price differences. The seven variables are: the previous period area price difference ($S_{APD,t-1}$); the closing price of the futures contract as given by Eq. 4 ($F^{t}_{t-1,c}$); the ask price of the futures contract as given by Eq. 3, ($F^{t}_{t-1,ask}$); the bid price of the futures contracts as given by Eq. 2, ($F^{t}_{t-1,bid}$); the rolling average of the previous three months' area price difference ($\bar{S}_{apd,t3}$); the difference between the previous month's spot price and the 3 month rolling average spot price ($s_{apd,t-1} - \bar{S}_{apd,t,3}$); the previous month's Finnish reservoir level (R_{t-1}); and the previous month ex-post futures premium (FP_{t-1}).

	$S_{APD,t}$	$S_{APD,t-1}$	$F^{t}_{t-1,c}$	$F^{t}_{t-1,ask}$	$F^{t}_{t-1,bid}$	$\bar{S}_{apd,t,3}$	$S_{apd,t-1} - \bar{S}_{apd,t,3}$	R_{t-1}	FP_{t-1}
$\mathbf{S_{APD,t}}$	1	0.573	0.507	0.447	0.555	0.083	0.483	0.269	-0.324
$\mathbf{S_{APD,t-1}}$	0.573	1	0.605	0.536	0.656	0.346	0.686	0.253	-0.566
$\mathbf{F^{t}_{t-1,c}}$	0.507	0.605	1	0.984	0.984	0.229	0.4	0.418	0.021
$\mathbf{F^{t}_{t-1,ask}}$	0.447	0.536	0.984	1	0.952	0.186	0.368	0.404	0.095
$\mathbf{F^{t}_{t-1,bid}}$	0.555	0.656	0.984	0.952	1	0.266	0.421	0.429	-0.051
$\mathbf{\bar{S}_{apd,t,3}}$	0.083	0.346	0.229	0.186	0.266	1	-0.444	0.175	0.05
$\mathbf{S_{apd,t-1} - \bar{S}_{apd,t,3}}$	0.483	0.686	0.4	0.368	0.421	-0.444	1	0.106	-0.579
$\mathbf{R_{t-1}}$	0.269	0.253	0.418	0.404	0.429	0.175	0.106	1	0.094
$\mathbf{FP_{t-1}}$	-0.324	-0.566	0.021	0.095	-0.051	0.05	-0.579	0.094	1

4 METHODS

In this section the necessary calculations for optimizing an EPAD hedging portfolio using CVaR are presented. First, it will be shown how to calculate the total cost to an electricity consumer which purchases electricity on the spot market and hedges some of its consumption using EPAD futures. Second, it will be shown how to calculate the risk of the portfolio. Third, the CVaR optimization is presented in general. Fourth, the EPAD portfolio optimization model, which is used to determine the optimal hedging portfolio, is presented. And finally, the forecasting models used to generate the price scenarios necessary for using the CVaR optimization model are shown.

The forecasting models presented here are not meant to be novel, as they are only necessary for performing the portfolio optimization and are not the focus of the thesis. There already exists significant work on forecasting electricity prices and, in particular, EPAD futures premiums for the Finnish market. In addition, many large industrial electricity customers will have in-house forecasting models using commercial software such as PLEXOS. The forecasting models presented in this thesis are only meant to generate plausible price scenarios for using the CVaR optimization, and to illustrate how the optimization can be used independently of how the forecasts are actually generated. The optimization model could be used by any electricity customer by simply replacing the forecasting methods presented here with their own price prediction models.

4.1 EPAD futures portfolio

A large industrial electricity consumer who has a constant electrical demand (or, at minimum, has future demand which is known with 100% certainty) will be considered. Having demand with no uncertainty is a common assumption in studies optimizing from a electricity consumer's perspective (A.J. Conejo, Fernandez-Gonzalez, and Alguacil 2005; Carrion et al. 2007). The consumer must purchase its electricity on the spot market but can use the futures market to reduce the risk of increased electricity costs due to higher spot prices in the future. If the spot price is equal to the Nordic system price, the customer uses system futures, and the electricity consumption is constant, the customer's total costs are:

$$C = \bar{S}_{sys} X_{sys} + \left(F_{sys} - \bar{S}_{sys}\right) H_{sys}, \tag{5}$$

where C is the total cost, $\bar{S}_{sys}$ is the average system spot price, X_{sys} the electricity consumption at the system price, F_{sys} the futures price, and H_{sys} the hedged amount.

If the customer's spot price differs from the system price and the customer uses EPAD futures (along with a corresponding systems futures), their total cost would be:

$$C = \bar{S}_a X_a + \left(F_{sys} - \bar{S}_{sys}\right) H_{sys} + (F_{APD} - \bar{S}_{APD}) H_{APD}, \tag{6}$$

where $\bar{S}_a$ is the average area price, X_a the electricity consumption at the area price, F_{APD} the EPAD price, $\bar{S}_{APD}$ the area price differential on the spot market, and H_{APD} the amount of EPAD hedging purchased.

If the customer's electricity demand is not constant, then the average spot price cannot be used and instead the hourly spot price and hourly consumption considered instead. Equation 5 will then become

$$C = \sum_{t \in T} S_t X_t + (F - \bar{S}) H \tag{7}$$

where S_t is the hourly spot price and X_t the hourly electricity consumption at time t, F is the future price used for hedging, $\bar{S}$ the average spot price for the hedging period, and H is the amount of electricity consumption which has been hedged.
Similarly, Equation 6 becomes

$$C = \sum_{t \in T} S_{t,a} X_{t,a} + \left(F_{sys} - \bar{S}_{sys}\right) H_{sys} + (F_{APD} - \bar{S}_{APD}) H_{APD} \tag{8}$$

4.2 Portfolio risk

If a corporation hedges fully its future electricity consumption, it faces only minor basis risk. If the portfolio is not fully hedged, it faces the risk that costs of consumption will increase, and it faces an opportunity to gain if electricity price goes down.

The electricity consumer's loss can be calculated as:

$$loss = cost - cost_{rl} \tag{9}$$

where $cost$ is the customers actual costs and $cost_{rl}$ is the cost of the fully hedged, or riskless, portfolio. In terms of spot and futures prices, the loss of a portfolio with system futures and EPAD futures can be written as:

$$loss = \left(F_{sys} - \bar{S}_{sys}\right) H_{sys} + (F_a - \bar{S}_a) H_a - \left(\left(F_{sys} - \bar{S}_{sys}\right) + (F_{APD} - \bar{S}_{APD})\right) X_a. \tag{10}$$

The definition for a futures premium is taken from Junttila et al. (Junttila, Myllymäki, and Raatikainen 2018)

$$FP = F_t^T - E_t(S_T). \quad (11)$$

where F_t^T is the futures price at time t which applies for the period starting at time T and $E_t(S_T)$ is the expected spot price at time T. The ex-post futures premium can be calculated by replacing $E_t(S_T)$, with the realized spot price at time T, S_T.

4.3 Conditional Value at Risk optimization

This work uses a scenario-based approach for determining CVaR. This method involves creating various scenarios, which describe the possible behavior of the uncertain variables. This allows standard linear programming methods to be used to solve the portfolio optimization problem. This method is described by Rockafellar & Uryasev (2000) (R. T. Rockafellar and Uryasev 2000) and in particular, this thesis uses the formulation presented in Yau et al, (2011) (Yau et al. 2011).

Conditional value at risk is calculated as:

$$CVaR = VaR + \frac{1}{N(1-\beta)} \sum_{j \in J} z_j \quad (12)$$

where

$$z_j \geq loss_j - VaR, z_j \geq 0 \text{ for } j \in J \quad (13)$$

Based on this formulation, CVaR and VaR are found simultaneously during the optimization. In the current work it is the future spot price which is not known, and a possible future spot price will be generated in each scenario.

4.4 Portfolio optimization model

The portfolio optimization attempts to minimize total electricity costs while maintaining a given level of CVaR. The overall optimization model can be summarized as:

$$\min C = \sum_{j \in J} p_j (\bar{S}_{a,T} X_a + (F_{sys,j,t}^T - \bar{S}_{sys,T}) H_{sys} + (F_{APD,j,t}^T - \bar{S}_{APD,T}) H_{APD}), \quad (14)$$

where p_j is the probability of scenario j occurring.

Using the definition of the futures premium Equation 14 can be rewritten as

$$\min C = \sum_{j \in J} p_j(\bar{S}_a X_a + FP_{sys,j} H_{sys} + FP_{APD,j} H_{APD}) \quad (15)$$

Initially only the area price risk will be considered, so removing the system price hedging from Equation 15 gives

$$\min C = \sum_{j \in J} p_j(\bar{S}_a X_a + FP_{APD,j} H_{APD}) \quad (16)$$

Subject to:

$$CVaR \leq CVaR_l \quad (17)$$

$$CVaR = VaR + \frac{1}{N(1-\beta)} \sum_{j \in J} z_j \quad (18)$$

$$loss = (F_{sys} - \bar{S}_{sys})H_{sys} + (F_{APD} - \bar{S}_{APD})H_{APD} - \left((F_{sys} - \bar{S}_{sys}) + (F_{APD} - \bar{S}_{APD})\right) X_{APD} \quad (19)$$

$$z_j \geq loss_j - VaR, j \in J \quad (20)$$

$$z_j \geq 0, j \in J \quad (21)$$

To summarize, Equations 16-21 present a portfolio optimization model which minimizes the total electricity procurement costs with a CVaR constraint on the portfolio loss compared to a fully hedged portfolio. More specifically, Eq. 16 presents the objective function of the model and Equations 17-21 are the CVaR constraints. This model construction reflects the decision-making process of industrial electricity consumers, where the primary goal is to minimize the total cost to purchase electricity but at the same time managing the risk of large, unexpected monthly costs driven by spiking spot prices.

4.5 Forecasting methods for scenario generation

As can be seen from Equation 14, in order to perform the portfolio optimization it is required to forecast at time *t* what the spot price will be at time *T*. The forecast should be done in a way that generates multiple price predictions for use in the different scenarios and that reflect the distribution of possible future prices. Equation 15 shows that this forecasting can also be done in terms of the futures premium rather than spot prices

For this thesis, three forecasting models were developed. Significant work already exists on forecasting electricity prices (see, for example, Aggarwal et al. (2009) (Aggarwal, Saini, and Kumar 2009) for a review), including the Nordpool market (Kristiansen 2014, 2012). Most large electrical-intensive industrial companies have built custom forecasting models on a structural understanding of the electricity market and demand-supply balance. As a result, forecasting is not the focus of this thesis and the models presented here are relatively simple and not intended to be novel. However, the models do represent different levels of complexity: the first model predicts future values simply by sampling from the distribution of past values; the second model is a linear regression; and the third is a seasonal ARIMAX model.

4.5.1 Sampling from historic distribution

The first model for generating scenarios of the possible futures premiums consisted of fitting a skew-normal distribution to the ex-post futures premiums for one-month futures EPAD contracts for the Finnish area price at the end of the month before the delivery period. Figure 8 shows a histogram of the ex-post futures premiums and the black line indicates the fitted distribution. This can be used to simulate possible future developments of the area price by sampling from the fitted distribution and adding it to the closing futures price from the previous month,

$$S_{t,j} = F_{t-1}^{t} + \varepsilon_j, \qquad \varepsilon \sim SN(\alpha, \mu, \sigma) \tag{22}$$

where $SN(\alpha, \mu, \sigma)$ is the distribution fit to the historic ex-post futures premiums.

This method assumes that there is no information available to improve the prediction of the area price difference at time T beyond the current futures contract price. The fitted distribution parameters are given in Table 3.

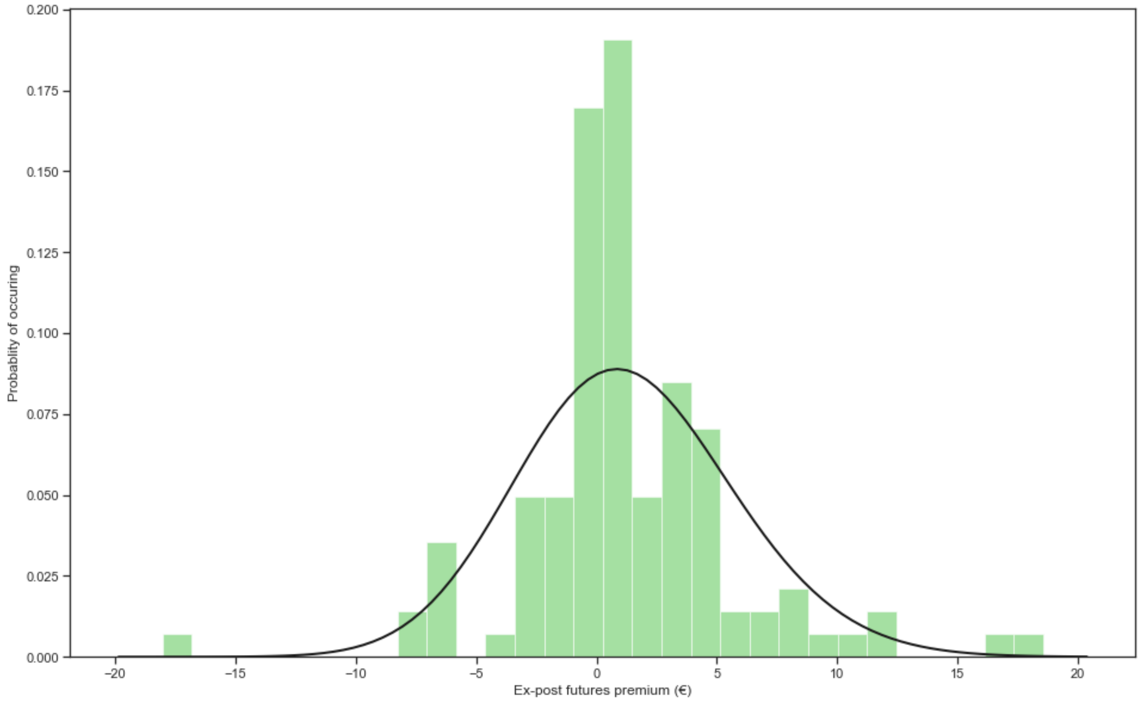

Figure 8 Histogram of ex-post futures premiums for monthly Finnish EPAD futures. Futures prices were taken at the end of the month before the delivery period. A skew-normal distribution was fit to the data.

Table 3 Fitting parameters for the skewnormal distribution fitted to the ex-post futures premiums shown in Figure 8.

Variable	Value
α	1.127
μ	-1.885
σ	5.252

4.5.2 Linear regression model

The second model is a linear regression model of the standard form

$$y_i = \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_p x_{ip} + \varepsilon_i. \quad (23)$$

In this case the dependent variable was the area price difference and the independent variables were chosen from Table 2 empirically, based on which variables minimized the out-of-sample prediction error while having all P values under 0.05. Out of sample prediction error was calculated using k-fold cross-validation, where k=10. The final independent variables used were: the ask price at the close of the previous month ($F^{T}_{T-1,ask}$); and the difference of the previous month spot price and the 3 month rolling average multiplied by the Finnish reservoir level ($\left(s_{apd,t-1} - \bar{s}_{apd,t,3}\right)R_{t-1}$). The resulting model, when fit to all the available monthly Finnish area price difference data, had an R^2 value of 0.67. The coefficient for the

$F_{T-1,ask}^{T}$ variable was 0.786 with a p-value of 0.000. The coefficient of the $\left(s_{apd,t-1} - \bar{s}_{apd,t,3}\right)R_{t-1}$ variable was 0.0037 with a p-value of 0.002.

The in-sample prediction results of the model are shown in Figure 9. The simple model clearly tends to lag the actual behavior of the area price difference which is particularly obvious when there are large monthly price swings, such as at the end of 2009 and beginning of 2010. Figure 10 shows the resulting predicted future premiums and the actual ex-post future premiums. The predicted future premium is nearly 0 (mean of 0.578 and standard deviation of 1.16) indicating that the predicted area price differences are very close to the closing price of the futures contracts.

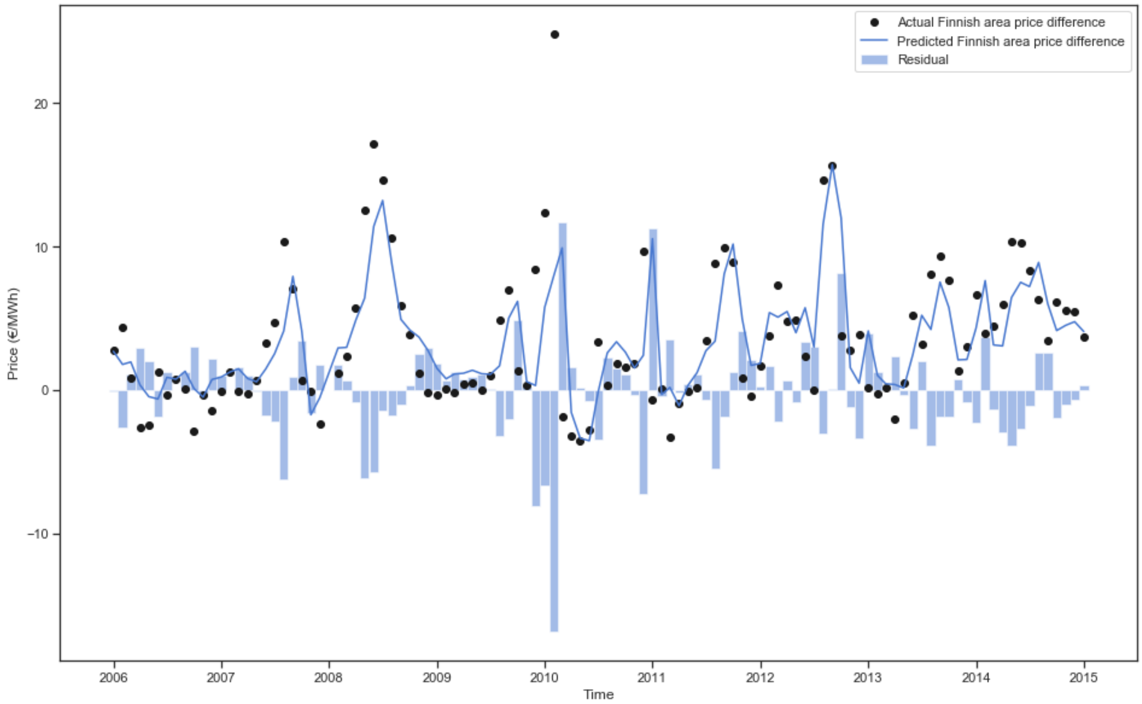

Figure 9 The in-sample results from the linear regression model for predicting Finnish area price differences. The black dots show the actual area price differences, the blue line shows the model predictions, and the blue bars show the model residuals.

To generate price scenarios using this linear regression model, the following equation was used

$$S_{t,j} = \widehat{S_t} + \varepsilon_j, \qquad \varepsilon \sim SN(\alpha, \mu, \sigma)\,, \tag{24}$$

where $\widehat{S_t}$ is the predicted area price difference from the model and $SN(\alpha, \mu, \sigma)$ is a skew-normal distribution fit to the residuals of the regression model. The distribution parameters are given in Table 4. The results of Equation 23 are shown in Figure 11, where three separate price scenarios are plotted, and Figure 12, where 1000 price scenarios are shown.

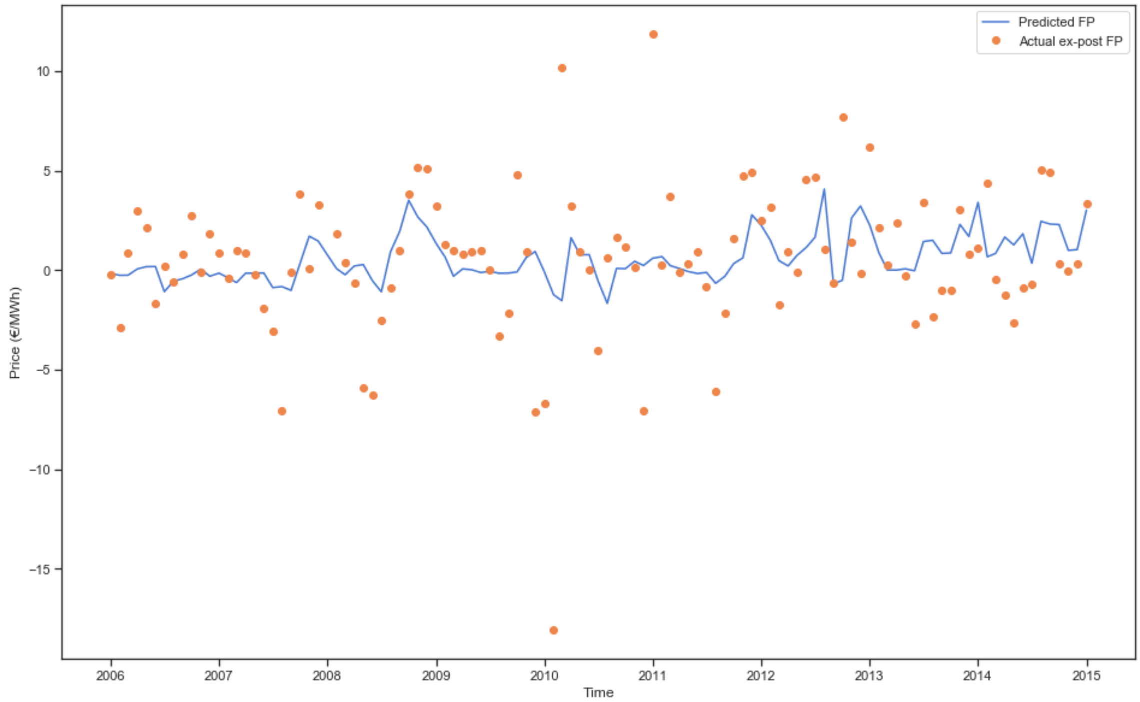

Figure 10 The predicted futures premium and actual ex-post futures premiums for the Finnish EPADs.

Table 4 Distribution parameters obtained by fitting a skew-normal distribution to the residuals of the linear regression model prediction Finnish area price differences.

Parameter	Value
α	1.887
μ	-2.542
σ	4.349

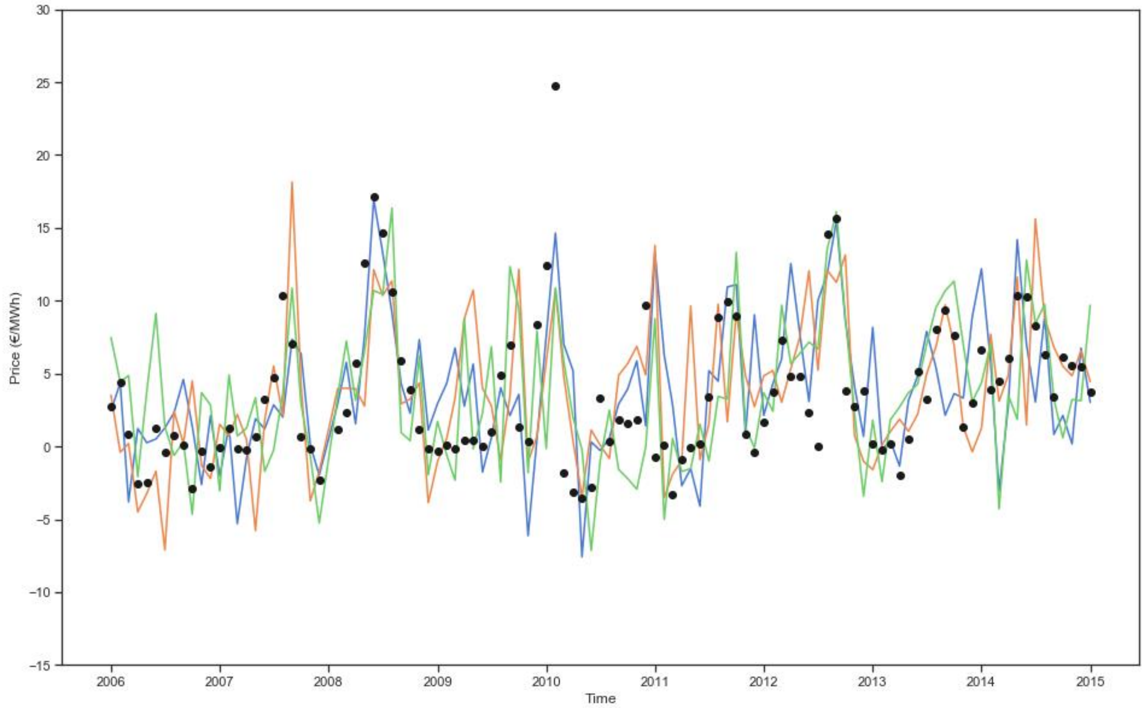

Figure 11 The colored lines show three different price scenarios generated from Equation 24 and the dots show the actual Finnish area price differences.

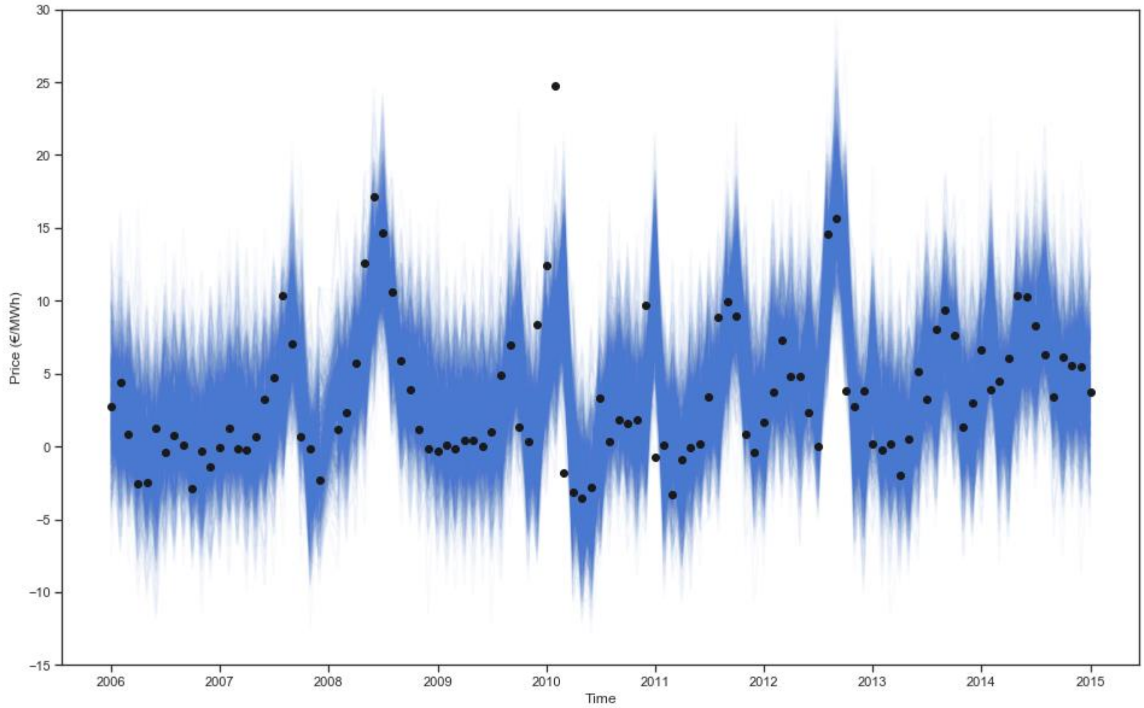

Figure 12 One thousand price scenarios generated by Equation 24 are shown by overlapping blue lines. The actual Finnish area price differences are shown by black dots.

4.5.3 SARIMAX model

The third forecasting model used was seasonal autoregressive integrated moving average with exogenous regressors (SARIMAX). ARIMA, ARIMAX and SARIMAX models have been used extensively in forecasting electricity prices (Aggarwal, Saini, and Kumar 2009) and loads (Tarsitano and Amerise 2017; Elamin and Fukushige 2018), including for generating electricity price scenarios when performing stochastic optimization for electricity procurement (Zhang et al. 2016; Carrion et al. 2007).

The SARIMAX model has the general form of (Perktold, Seabold, and Taylor 2020)

$$y_t = \beta x_t + u_t \tag{25}$$

$$\phi_p(L)\tilde{\phi}_p(L^s)\Delta^d\Delta_s^D u_t = A(t) + \theta_q(L)\tilde{\theta}_Q(L^s)\varepsilon_t \tag{26}$$

Equation 25 is a linear regression, similar to Equation 23, and describes the dependence on the exogenous variables. Equation 26 shows the SARIMA process model for the error component.

It has been established previously that the Finnish area price difference time series is stationary (Juntilla, Myllymäki, and Raatikainen 2017), and so it is assumed to be the case in this work as well. To determine possible autoregression and moving-average terms to include in the model, the autocorrelation (ACF) and partial autocorrelation (PACF) functions were plotted and examined. These are shown in Figure 13 and Figure 14 respectively. In both the ACF and PACF it can be seen the -1 lag term is significant. In the PACF plot it can be seen that also the -6 and -21 lag terms are significant, while no other terms besides -1 are significant in the ACF plot. These plots indicate that possible a AR(1) or MA(1) model would work best. Finally, a few different lag terms were tested and the model with the lowest AIC value was selected. Table 5 shows the AIC values for the various models that were tested. The model with AR lags of -1 and -6- and 12-month seasonality had the lowest AIC value and so was used for the time series modeling.

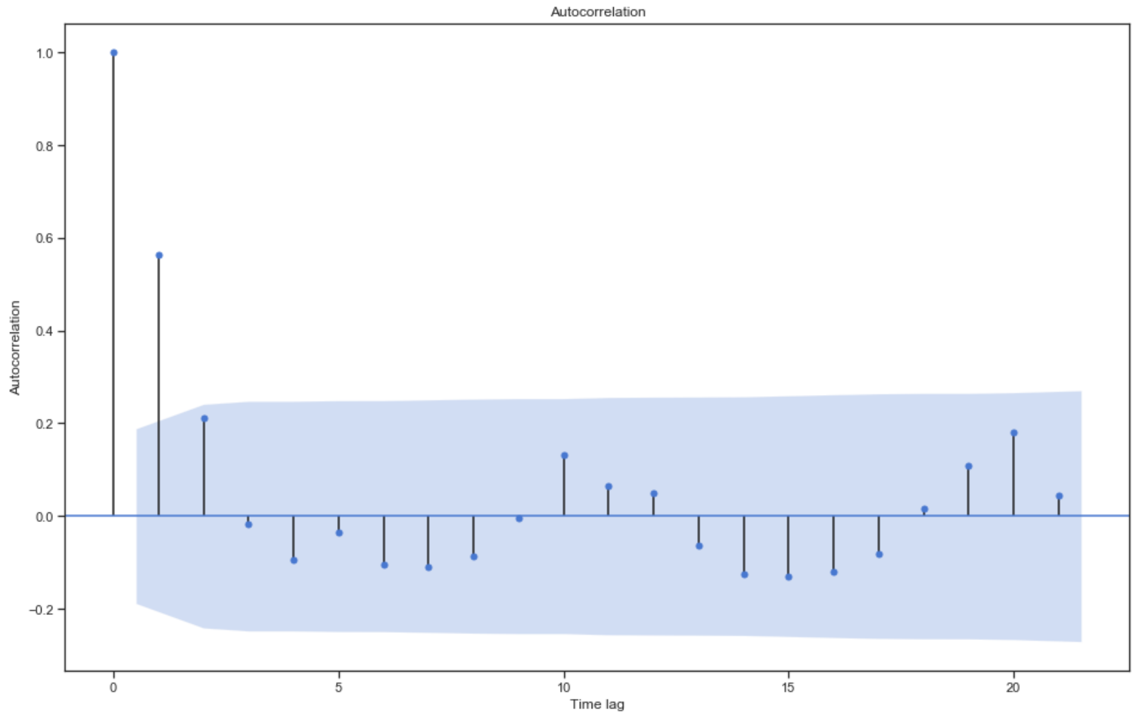

Figure 13 Autocorrelation function for the Finnish area price difference time series.

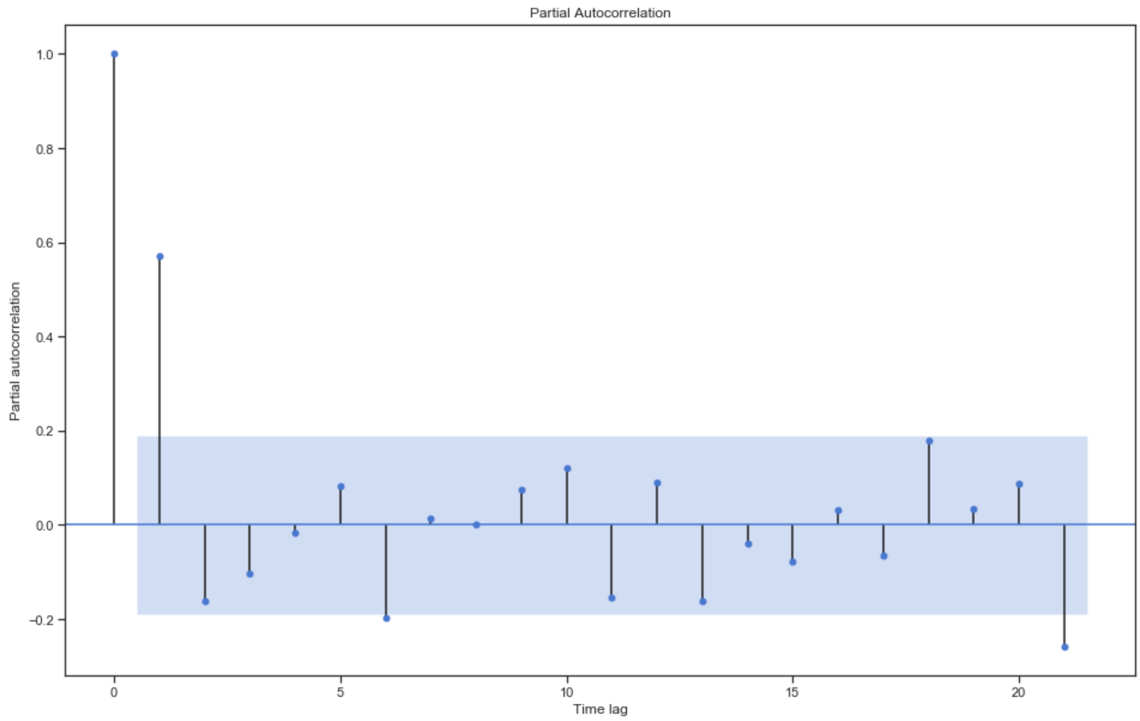

Figure 14 Partial autocorrelation function for the Finnish area price difference time series.

In addition to the ARIMA lag terms, the exogenous variables were evaluated as well. The variables in Table 2 were checked by adding them to the

AR(1,6)$AR_s(12)$ model and finding the combination which again gave the lowest AIC. It was determined that the previous month's futures closing price and the previous month's Finnish reservoir level were the best exogenous variables to include.

The resulting model was then used to create a rolling, 1 month ahead prediction for the last 18 months of the data set. This was done by first fitting the model to the period of January 2006 – June 2013, and then predicting the Finnish area price difference of July 2013. Next the model is fit to the period of January 2006 – July 2013 and the prediction is made for August 2013. This continues until the prediction is made for December 2014. These 18 one month ahead predictions give a root-mean-squared prediction error of 3.61. This can be compared to, for example, using just the closing futures price, $F^t_{APD,t-1}$, to predict the next month's spot price, $S_{APD,t}$. This would give a root-mean-squared error of 3.71, and so the time series model offers a small improvement in prediction accuracy. The results of this rolling forecast are shown in Figure 15.

Table 5 AIC values for models with different AR, MA and seasonality terms.

AR	MA	Seasonality	AIC
1	0	0	616
1	1	0	613
1	0	12	556
1	1	12	557
1,6	0	0	593
1,6	1	0	594
1,6	0	12	533
1,6	1	12	535

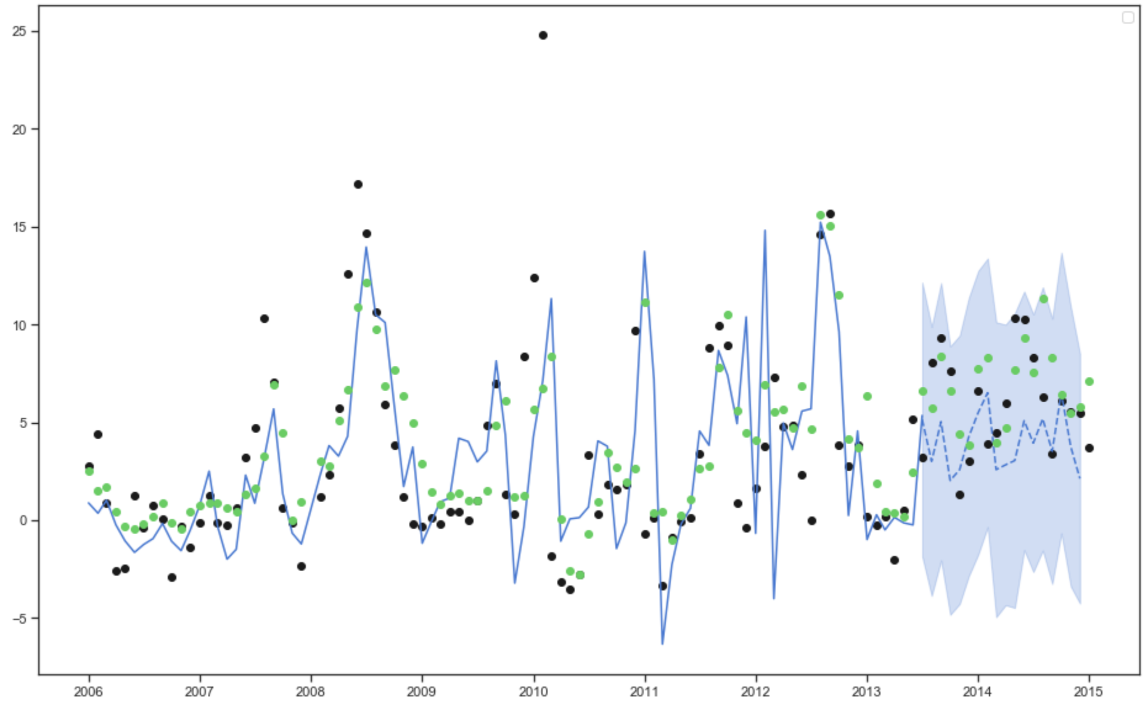

Figure 15 Prediction results for the SARIMAX model. The solid line indicates the in-sample prediction results and the dotted line shows the out-of-sample prediction results from a rolling, 1 month ahead prediction.

Price scenarios were generated from the time series model using the same process described in Section Linear regression model. First, a probability distribution was fit to the model's residuals. Then, using Equation 24 the price scenarios were creating by sampling from the residual distribution and adding this to the price predicted by the rolling, 1-month-ahead time series model. The result can be seen in Figure 16 where three price scenarios are shown for the final 18 months of data. The distribution parameters obtained from fitting a skew-normal distribution to the residuals is shown in Table 6.

Table 6 Distribution parameters obtained by fitting a skew-normal distribution to the residuals of the SARIMAX model given in Equations 25 and 26

Parameter	**Value**
α	0.7336
μ	-2.179
σ	4.956

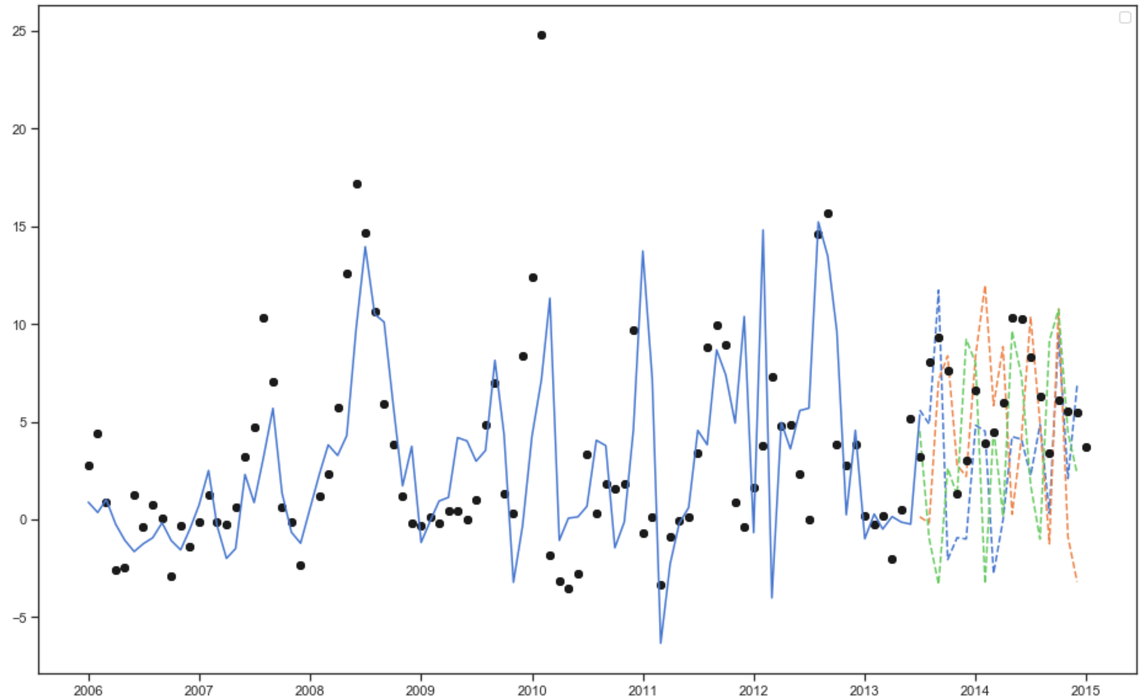

Figure 16 Price scenarios for July 2013-December 2014. The in-sample model predictions for January 2006-June 2013 are shown by the blue line, the actual Finnish area spot prices are shown by the black dots, and the three price scenarios shown by the dotted lines.

4.6 Minimum-variance hedging

The minimum-variance hedging ratio was also calculated to compare against the performance of the VaR hedging methods. The minimum variance (MV) hedge ratio is defined as (Wang, Wu, and Yang 2015; Chen, Lee, and Shrestha 2003)

$$h = \frac{Cov(S,F)}{Var(F)} = \rho \frac{\sigma_S}{\sigma_F}. \tag{27}$$

In order to apply this, this hedging ratio will be estimated using the ordinary least squares (OLS) method (Wang, Wu, and Yang 2015; Chen, Lee, and Shrestha 2003),

$$S_t = \alpha_1 + \beta_1 F_t + \epsilon_t , \tag{28}$$

where β_1 is the optimal hedging ratio given by Eq. 27.

4.7 Portfolio comparison

Hedging portfolios are compared against each using the following metrics:

- Total portfolio cost
- Savings vs the fully hedged portfolio
- Maximum monthly loss
- Reduction in variance (Cotter and Hanly 2006)
- Sharpe ratio

The total portfolio cost is given by Equation 6. The savings vs the fully hedged portfolio is calculated as

$$Savings_h = C_h - C_{fully\ hedged}\ . \tag{29}$$

The maximum monthly loss is calculated using the loss definition in Equation 19. This loss is calculated for each month and then maximum value is then reported for each hedging strategy. The reduction in variance is given by

$$RV = 1 - \frac{Var_{HedgedPortfolio}}{Var_{UnhedgedPortfolio}}\ . \tag{30}$$

Finally, the Sharpe ratio is calculated as

$$SR = \frac{E[R_h - R_f]}{\sigma_h}\ . \tag{31}$$

R_h is the return on the hedged portfolio, which in this case is the savings of the hedged portfolio vs the fully hedged portfolio. R_f is the return on the risk-free portfolio, which in this case is the fully hedged portfolio and so is zero. As a result, the Sharpe ratio for evaluating these hedging strategies can be reduced to

$$SR = \frac{Savings_h}{\sigma_h}\ . \tag{32}$$

5 RESULTS AND ANALYSIS

In this section the results of the portfolio optimization are presented. The portfolio optimization will be done separately using each of the forecasting methods presented in Section Forecasting methods for scenario generation

5.1 Portfolio optimization using historic distribution for scenario generation

Based on the method presented in Section Sampling from historic distributionthe future premium for the Finnish EPAD can be simulated based on the current futures price and distribution fitted to the historic price data. The price scenarios generated in this way can be used in the CVaR optimization shown in Section Portfolio optimization model

Here an example is constructed where the futures price is the price of the April 2013 Finnish EPAD future as observed at the end of March 2013. This closing price was 0.38 €/MWh. For the electricity consumption, a medium sized industrial consumer is considered which has a constant demand of 50 MW. The total electricity consumed, X_a, is then calculated assuming 30 days in a month. A summary of the data used in the calculation given in Table 7.

Table 7 The values used to calculate the hedging portfolio results shown in Figure 17. The distribution parameters α, μ, σ can be found in Table 3.

Variable	Value
$\boldsymbol{F_{a,t,T}}$	0.38 €/MWh
$\boldsymbol{S_{a,T}}$	$\boldsymbol{F_{a,t,T}} + SN(a, \mu, \sigma)$
$\boldsymbol{\beta}$	0.95
N	10000
$\boldsymbol{X_a}$	36000 MWh
CVaR	100,000 €

The values from Table 7 were used in Eqs. 12-17 With the CVaR set to 100,000 € the optimal hedging amount, H, is 24,977 MWh or 69% of the total electricity demand for the month. This hedging amount gives a VaR of 80687€ and the resulting losses from 10000 scenarios using this optimal hedging portfolio are shown in Figure 17.

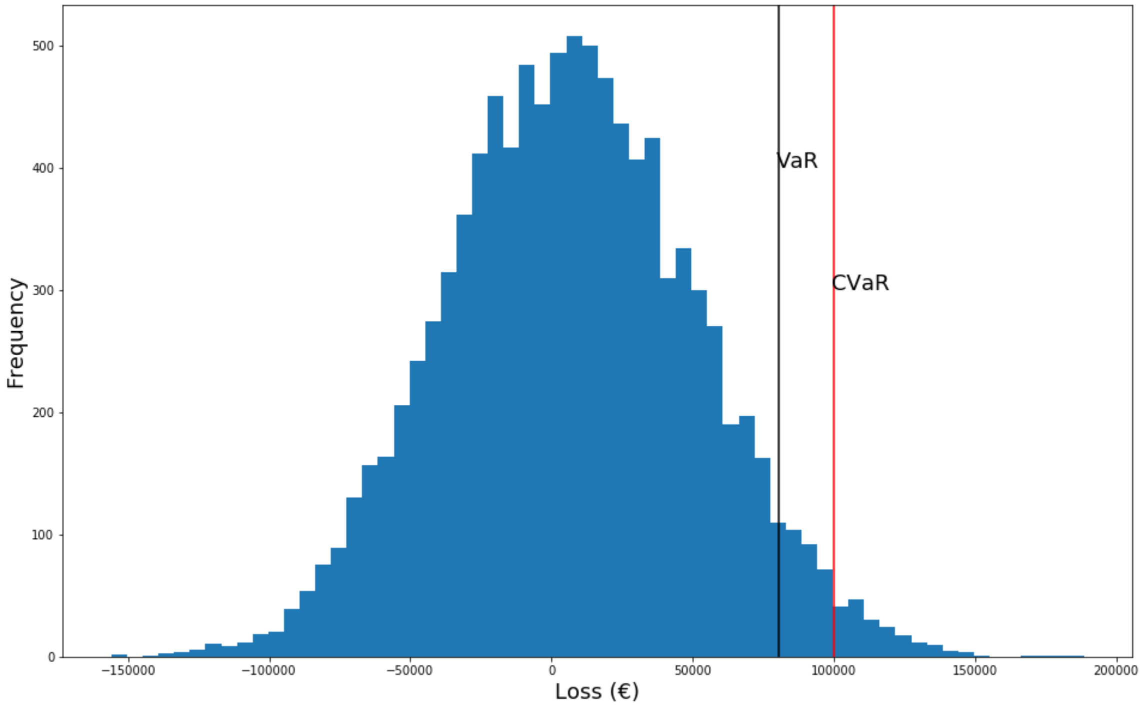

Figure 17 A loss function distribution from the portfolio optimization using the historic future premium distribution to predict future prices, including VaR and CVaR values at 5% level. Positive values indicate losses and negative values indicate negative losses (i.e. profits). This loss function is calculated using the values shown in Table 7 and Table 3 and a hedged amount of 24,977 MWh. The preselected CVaR value is shown by the vertical red line and the calculated VaR value by the black line.

Next the hedging optimization problem was solved using decreasing values of $CVaR_l$ in Equation 17. The resulting hedging amounts are shown as a function of $CVaR_l$ in Figure 18. As expected, if CVaR is limited to 0 then the entire electricity consumption must be hedged. As the value of CVaR increases the amount of hedging required decreases.

5.2 Portfolio optimization using linear regression model for scenario generation

The process performed Section 4.1 was repeated using the linear regression model developed in Section 3.5.2 for generating the price scenarios used in the portfolio optimization. First, the optimal hedging portfolio for April 2013 was calculated again, however now using the distribution parameters from Table 4 and the other values shown in Table 8.

Table 8 Input values used for calculating the optimal hedging portfolio using the linear regression model for generating future price scenarios.

Variable	Value
$\boldsymbol{F_{a,t,T}}$	0.383 €/MWh
$\boldsymbol{S_{a,T}}$	$\widehat{S_t} + SN(a, \mu, \sigma)$
$\boldsymbol{\widehat{S_t}}$	0.382
$\boldsymbol{\beta}$	0.95
N	10000
$\boldsymbol{X_a}$	36000 MWh
CVaR	100,000 €

The resulting optimal hedging amount was 22,778 MWh, which was 63% of the total monthly consumption. The resulting VaR was 78,305 €. The distribution of the loss function in the 10000 calculated scenarios is shown in Figure 19 and the VaR and CVaR values indicated by the black and red lines, respectively. The hedging amount required for various levels of CVaR is shown in Figure 20.

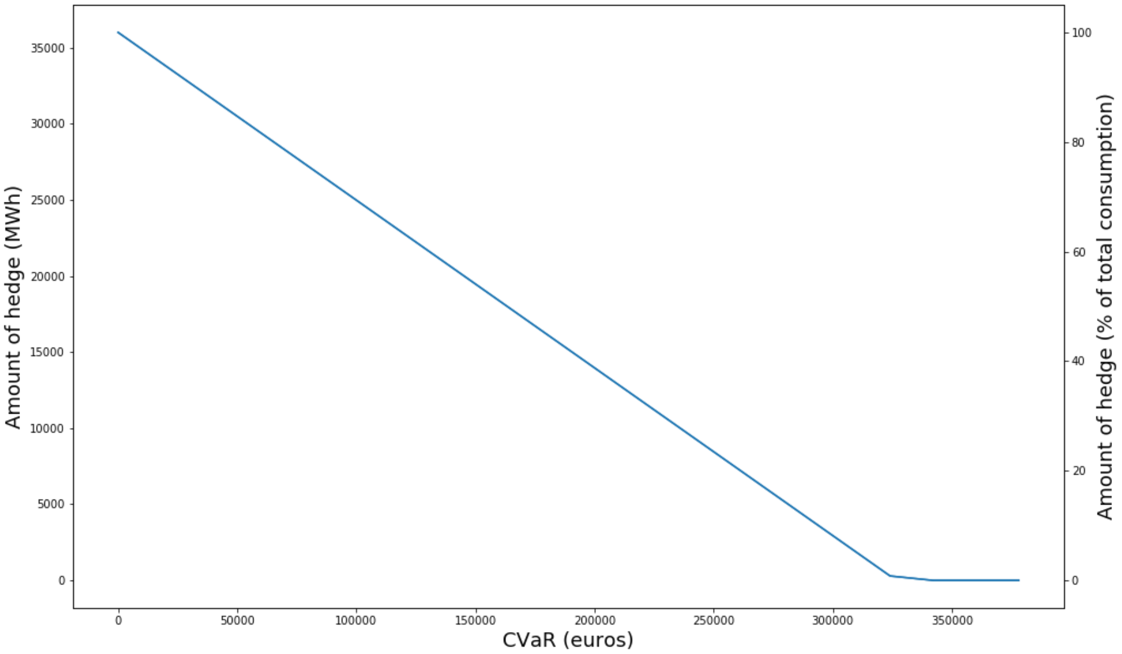

Figure 18 The hedging amount required for minimizing total portfolio cost with varying levels of CVaR calculated using the values from Table 7 The values used to calculate the hedging portfolio results shown in Figure 17. The distribution parameters α, μ, σ can be found in Table 3.and distribution parameters from Table 3.

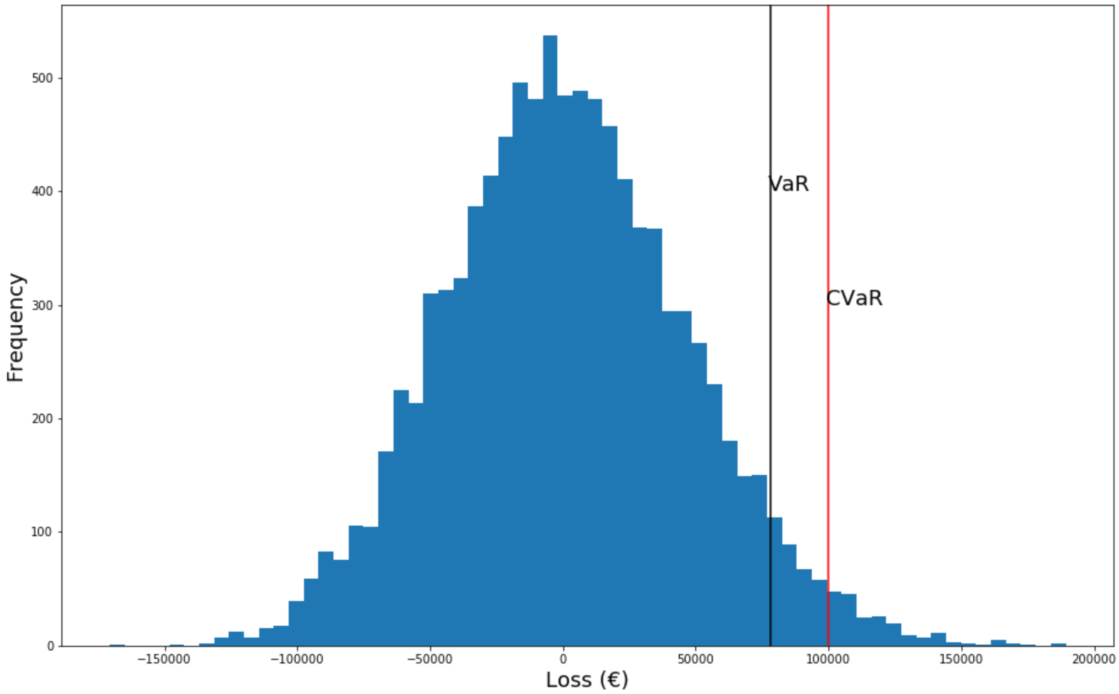

Figure 19 A loss function distribution from the portfolio optimization using the linear regression model for predicting future prices, including VaR and CVaR values at 5% level. Positive values indicate losses and negative values indicate negative losses (i.e. profits). This loss function is calculated using the values shown in Table 8 and Table 4 and a hedged amount of 22,778 MWh. The preselected CVaR value is shown by the vertical red line and the calculated VaR value by the black line.

Next, the size of the optimal hedge calculated for each of the months in the data set using the linear regression model to generate the price scenarios. These results are shown in Figure 21, where it can be seen that the optimal hedging amount is typically between 20,000 MWh and 25,000 MWh. In some cases, the hedging volume can be much lower when the model predicts that the spot price will be lower than the futures price. In other cases, it is optimal to hedge all the consumption if the model predicts the spot prices will be higher than the current futures price.

The total cost of this hedging portfolio over the entire period of 2006-2015 was 14,372,731 € compared with a total cost of a fully hedged portfolio of 15,513,792 €. This shows the optimal hedging portfolio saves 1,141,060 € in costs while still maintaining acceptable levels of risk. The maximum monthly loss of the optimal portfolio compared to the fully hedged portfolio was 202,255€. This is in comparison with the maximum monthly loss of a fully unhedged portfolio (i.e. buying all electricity on the spot market) against the fully hedged portfolio of 649,080€.

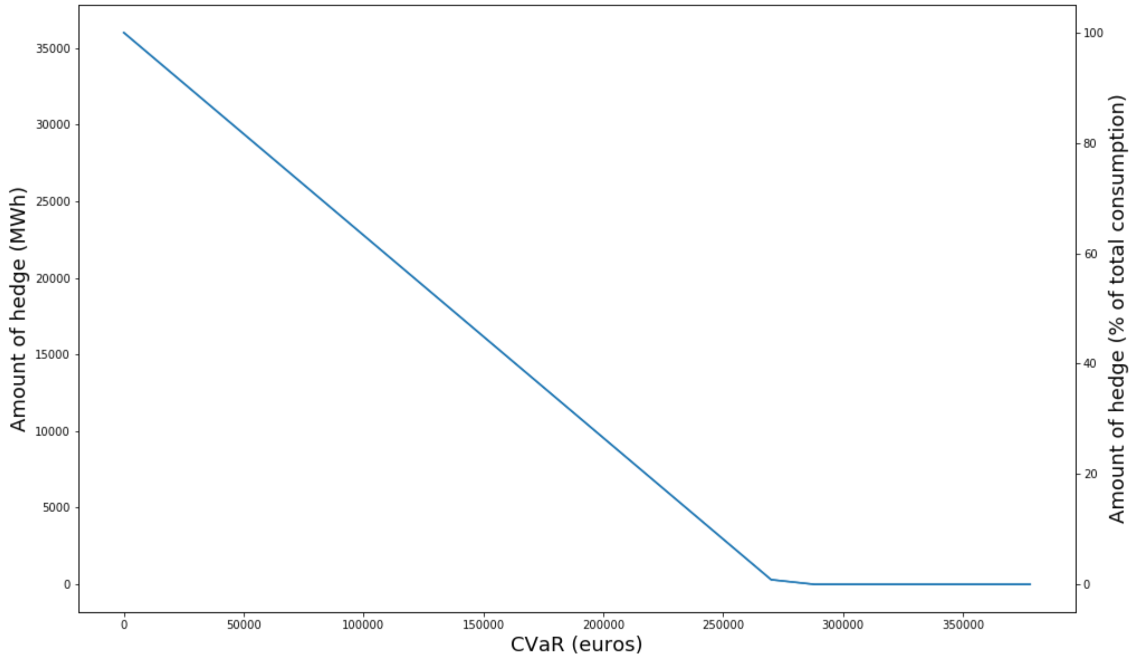

Figure 20 The hedging amount required for minimizing total portfolio cost using the values shown in Table 8 and Table 4 Table 3 with varying levels of CVaR.

5.3 Portfolio optimization using time series modeling for scenario generation

Finally, the portfolio optimization will be repeated using the time series model presented in Section SARIMAX model to generate the future price scenarios. The optimal hedging portfolio for April 2013 was again calculated and this time using the probability distribution parameters from Table 6 and the other values from Table 9.

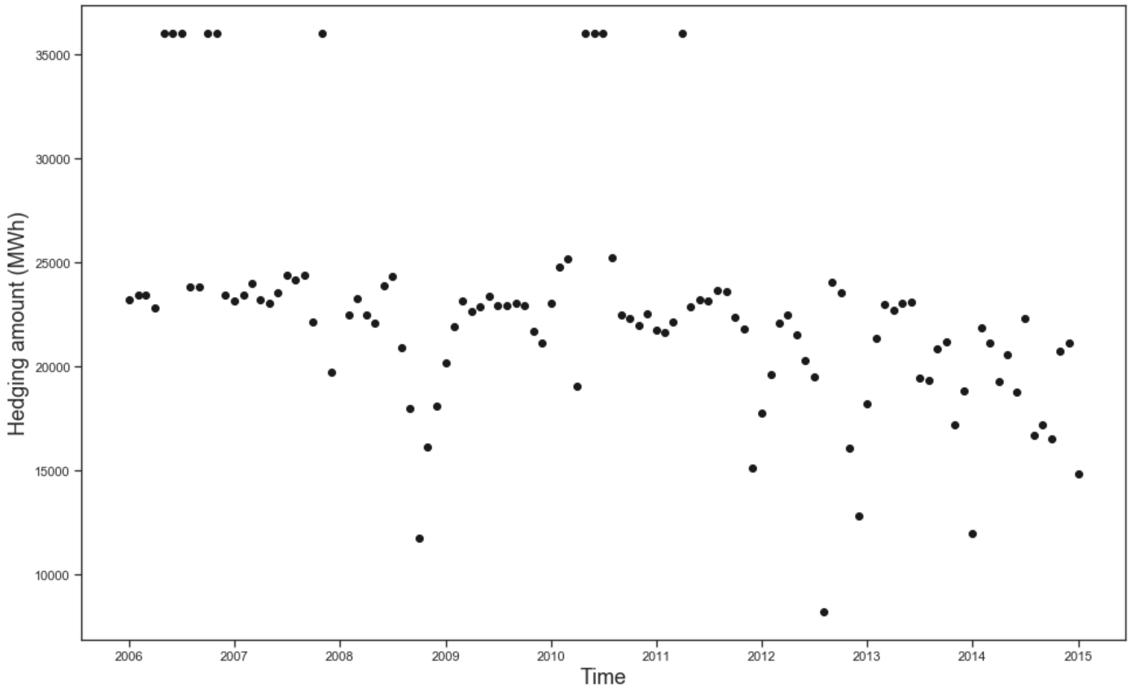

Figure 21 The optimal hedging amount for each month in the data calculated using the linear regression model to generate price scenarios.

Table 9 The input data used to calculate the optimal hedging portfolio using the time series model to predict future price scenarios.

Variable	Value
$\boldsymbol{F_{a,t,T}}$	0.383 €/MWh
$\boldsymbol{S_{a,T}}$	$\widehat{S_t} + SN(a, \mu, \sigma)$
$\boldsymbol{\widehat{S}_t}$	0.808
$\boldsymbol{\beta}$	0.95
N	10000
$\boldsymbol{X_a}$	36000 MWh
CVaR	100,000 €

The resulting optimal hedging amount in this case was 25,847 MWh, which was 72% of the total monthly consumption. The resulting VaR was 80,180 €. The distribution of the loss function in the 10000 calculated scenarios is shown in Figure 22 and the VaR and CVaR values indicated by the black and red lines, respectively. The hedging amount required for various levels of CVaR is shown in Figure 23.

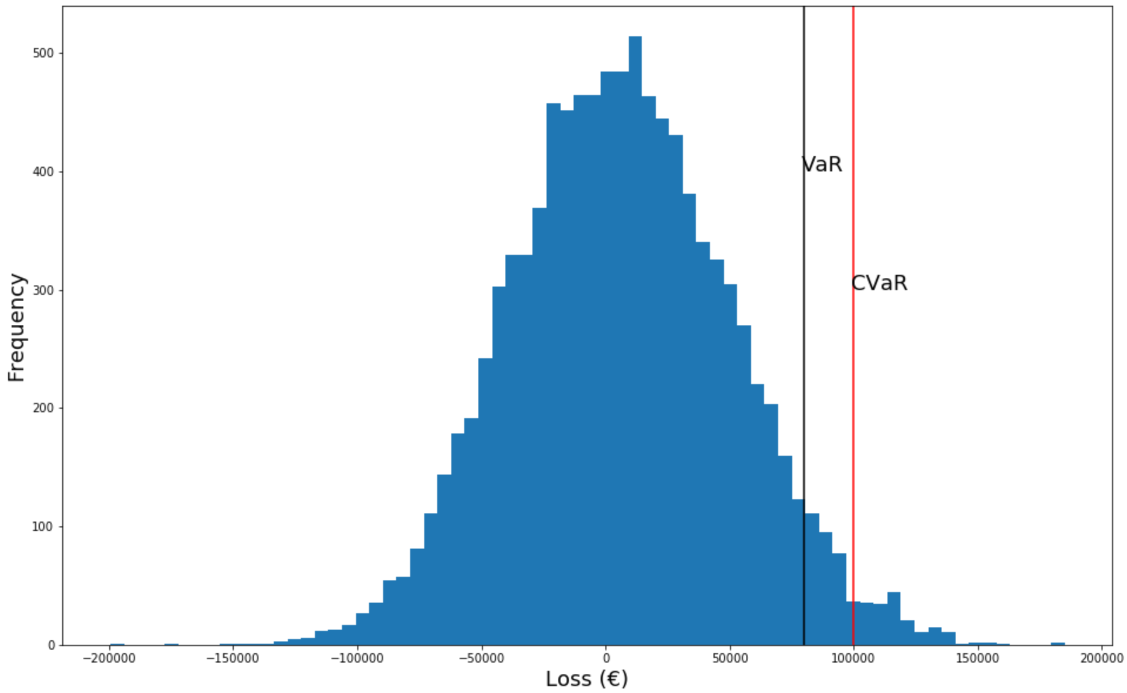

Figure 22 A loss function distribution resulting from the portfolio optimization using the time series model to predict future prices, including VaR and CVaR values at 5% level. Positive values indicate losses and negative values indicate negative losses (i.e. profits). This loss function is calculated using the values shown in Table 7 and Table 9 and a hedged amount of 25,847 MWh. The preselected CVaR value is shown by the vertical red line and the calculated VaR value by the black line

Finally, the optimal hedging amount was calculated for each month between July 2013 and December 2014. This was done using the rolling, one-month ahead forecast presented in Section SARIMAX modelAs these predictions are out of sample, they represent an accurate case for how the portfolio optimization would perform in a real-life situation. The results for the 18-month portfolio optimization are shown in Figure 24. The total cost of this hedged portfolio over the 18 months was 4,144,230 € while the cost of the fully hedged portfolio was 4,399,728 €. This means that the optimally hedged portfolio has a savings of 255,498 € compared to the fully hedged portfolio while maintaining acceptable levels of risk. The greatest monthly loss (compared to a fully hedged situation) during this period using the optimally hedged portfolio was 56,948 € while if not using any hedging and buying all electricity on the spot market the largest month loss would have been 94,103 €.

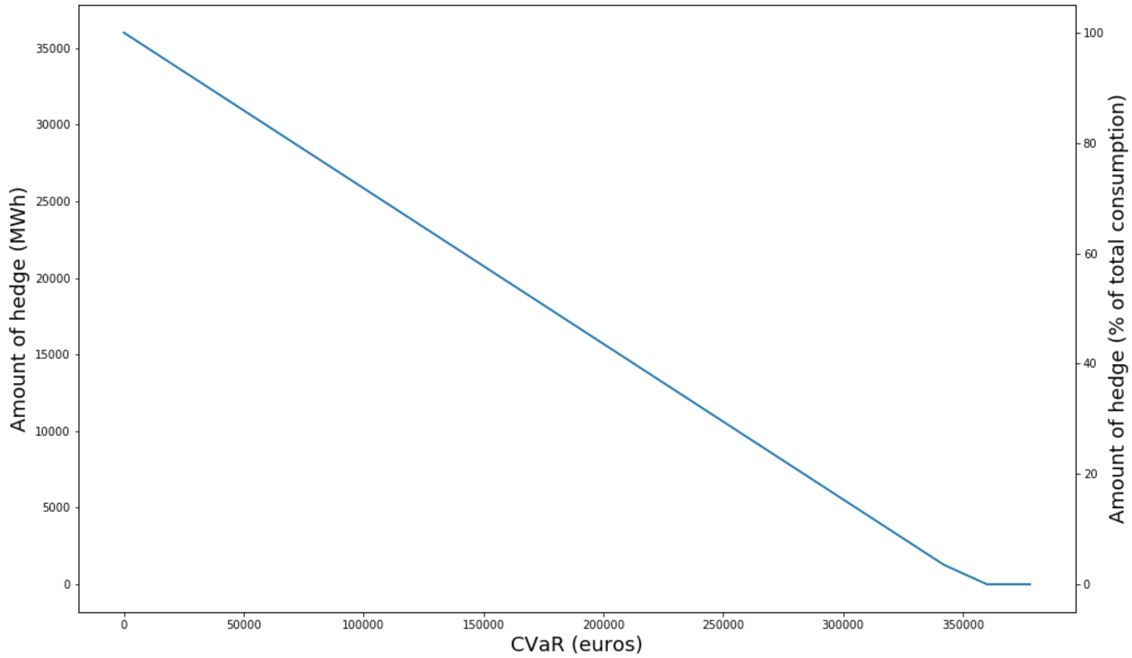

Figure 23 The hedging amount required for minimizing total portfolio cost using the values shown in Table 7 and Table 9 with varying levels of CVaR.

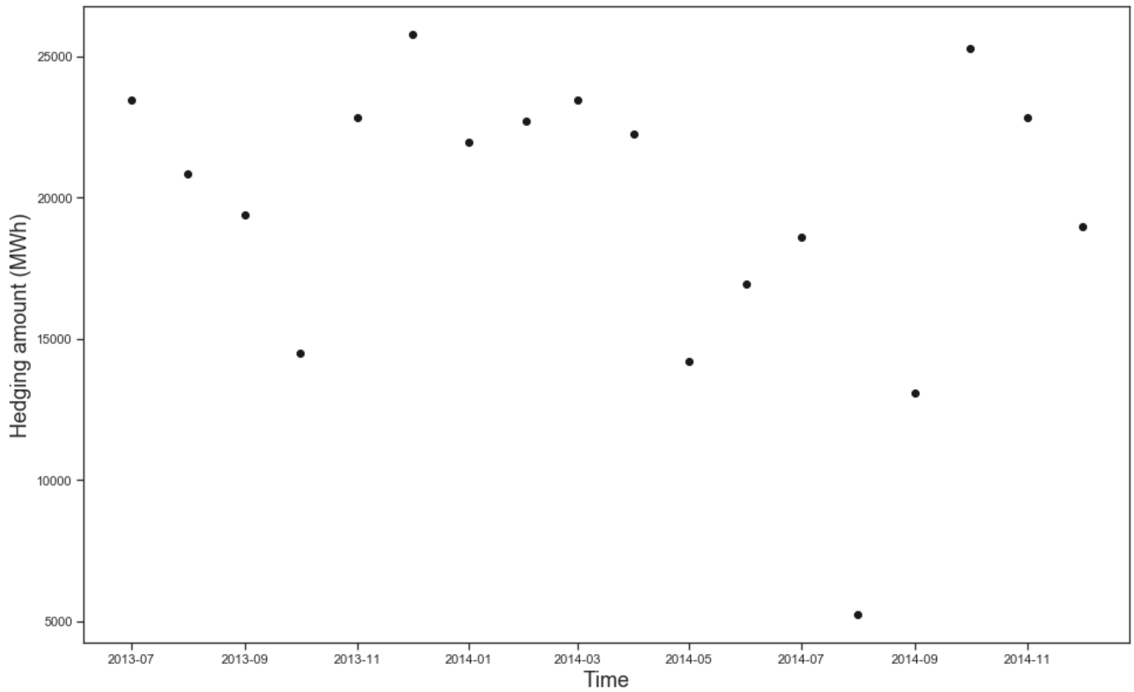

Figure 24 The optimal hedging amount for each month in the data calculated using the time series model to generate price scenarios.

5.4 Comparison of hedging strategies

The out-of-sample performance of five hedging strategies were compared using the metrics described in Section 4.7. The five strategies are:

- Fully hedged portfolio (i.e. naive hedging) where the hedge ratio is 1
- Fully unhedged portfolio where the hedge ratio is 0
- Fixed hedge ratio, with an arbitrarily chosen ratio of 0.75
- CVaR hedging using historic distribution for scenario generation (Section 4.5.1)
- CVaR hedging using linear regression for scenario generation (Section 4.5.2)
- CVaR hedging using time series modeling for scenario generation (Section 4.5.3)
- Minimum variance hedging using OLS (Section 4.6)

The out-of-sample performance was calculated for the period of July 2013 to December 2014 for each hedging strategy. A rolling, one month ahead prediction was used in each case. As an example, for predicting the spot prices for July 2013, the data of January 2006 – June 2013 was used to fit the prediction model. Then, to predict August 2013 the realized July 2013 data was included to the training data set. This rolling prediction was continued to December 2014, giving an accurate view of the real-world performance of these hedging strategies.

As shown in Table 10, the fully hedged portfolio has the highest total cost while the fully unhedged portfolio has the lowest total cost, saving 483 175 € over the 18-month time period compared to the fully hedged portfolio. However, the maximum monthly loss of the fully unhedged portfolio compared to the fully hedged portfolio is 94 103 €. The other hedging strategies offer some trade-off between cost and risk. Generally, the minimum variance portfolio has a higher hedging ratio resulting in higher costs but a lower maximum monthly loss while the CVaR based strategies have comparably lower hedging ratios and so lower costs but higher maximum monthly losses. The CVaR portfolio using the time series model for forecasting the future spot prices has the highest Sharpe ratio of the portfolio tested, indicating the best risk-return balance, at least by this metric.

When comparing the three CVaR portfolios in Table 10, the CVaR using the time series model has both lower total costs and lower maximum monthly loss than the CVaR using linear regression portfolio. The CVaR using historic distribution has a slightly lower maximum monthly loss when compared to the time series portfolio but has significantly higher costs. This shows how essential the forecasting process is to constructing a well performing hedging portfolio and companies without access to internal electricity price forecasts may struggle to use these hedging methods effectively.

Table 10 Out-of-sample comparison between hedging portfolios using a one month ahead rolling forecast for July 2013-December 2014. The portfolio costs have been calculated assuming an electricity consumer has a constant electricity demand of 50MW.

Hedging strategy	Total cost (€)	Savings vs fully hedged (€)	Maximum monthly loss (€)	Variance reduction	Sharpe ratio
Fully hedged	4 503 066	0	0	1	0
Fully unhedged	4 019 891	483 175	94 103	0	5.394
Fixed hedging, h=0.75	4 382 273	120 794	23 526	0.938	5.394
CVaR using historic distribution	4 362 350	140 717	30 515	0.909	5.205
CVaR using linear regression	4 270 215	232 852	42 744	0.788	5.651
CVaR using time series	4 247 667	255 401	32 668	0.783	6.125
Minimum variance	4 460 884	42 182	10 237	0.991	4.836

Byström (Byström 2003) also compares the hedging effectiveness of different portfolios of Nordic electricity futures contracts. However, Byström does not use CVaR and instead evaluates the portfolios based on how well they reduce variance compared to the spot market. In additional Byström does not consider EPAD contracts, only the system price. Byström found in this study that naïve (i.e. fully hedged) and OLS hedging strategies provided better variance reduction than more complex, time-dependent hedges. Garcia et al. (2017) used portfolio optimization to allocate electricity generating assets to mange profit and risk for a generation company (Garcia et al. 2017). A mean-variance portfolio was compared against a CVaR based portfolio to determine to which market company's generation assets should be allocated.

Other studies have compared the performance of CVaR hedging to other strategies, but typically not in the context of electricity markets. Krokhmal et al. (2001) compared CVaR portfolio to a minimum variance portfolio of S&P 100 stocks (Krokhmal, Palmquist, and Uryasev 2001). In this study it was found that for a given return the MV portfolio had a higher CVaR than the CVaR portfolio, while the CVaR portfolio had a higher variance than the MV portfolio. However, the two portfolios were extremely close to each other and the differences between them were not large.

It was observed by Krokhmal et al. (2001) that the results of the comparison between the CVaR based portfolio and the minimum-variance portfolio were data-set specific. As there have been no other works using this Finnish EPAD dataset for CVaR optimization, no direct comparisons can be made with the current results. However, the general observations from Table 10, that the minimum-variance portfolio offers the largest variance reduction and that a fixed hedge ratio performs relatively well, do match with previous findings. The results presented here show that the CVaR model from Section 4.4, when combined with a well validated forecasting model for scenario generation, allows for the management of risk due to spiking spot prices while maintaining low costs.

6 CONCLUSIONS

In this thesis a method for managing electricity area pricing risk for a large industrial customer was presented. An optimization model which determines the optimal amount of EPAD futures contracts to be purchased each month in order to minimize total costs while maintaining a given level of CVaR was developed. Three methods for forecasting the month ahead area price difference for the Finnish area price were constructed based on historic market data from the NASDAQ OMX Commodities exchange and the historic Nordpool spot prices. The optimization model was then used, in combination with each of the three different forecasting methods, to determine the optimal hedging portfolio in some simple example cases.

The out-of-sample results of the CVaR based hedging portfolios were then compared against a minimum-variance strategy, as well as a fixed hedge ratio strategy. The minimum-variance portfolio generally resulted in a higher hedge ratio than the CVaR portfolios, which meant higher variance reduction and higher overall costs. It can also be seen the importance of the forecasting model that is used to generate the price scenarios in the CVaR optimization, as the CVaR model using time series forecasting had a much lower overall cost and only a small increase in maximum monthly loss when compared to the CVaR portfolio which used the historic distribution sampling.

With this approach an electricity consumer can manage their area price risk by determining the level of loss they are willing to accept. This methodology for area pricing risk management could be used for any electricity consumer in the Nord Pool market, but especially those in bidding areas which tend to have volatility in the area price differential. In order for an electricity customer to take this approach into use, the forecasting methods presented in Section 4.4 could easily be replaced with an in-house forecasting model while the portfolio optimization would remain unchanged.

There are two main areas which could be the focus of future work. First, the hedging portfolio could be extended to include EPAD futures contracts of different lengths and at different purchase times. For example, monthly futures contracts could be purchase two or three months before the delivery period. This would require forecasting the electricity spot prices multiple months ahead, as well as forecasting the changing futures contract price. Daily, weekly, quarterly, or yearly futures contracts could also be considered, in addition to the monthly contracts studied in this work. The second major area of additional work would be to account of uncertainty in the electricity demand of the customer. In this work it was assumed that the customer could predict their electricity demand exactly for the next month and in reality, this will never be the case. This uncertainty in demand could be handled, for example, in the same way as the uncertainty in the spot price forecast, which is to generate additional scenarios which describe the possible realized demand levels.

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