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The game of the electricity market

A game theoretical approach to investigate trading strategies in the Nordic electricity futures market

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Abstract

With the background of the increasing volatility in the electricity market the recent years this thesis investigates the electricity futures market and the benefit for market participants to perform some trading strategy in order to increase profit or reduce risk. By modeling the market as a stochastic game the trader acts as a player in the game and with two simple models the player can predict the probability that the market moves up or down and take the appropriate position according to the prediction. This is simulated with Nasdaq closing prices for monthly electricity futures contracts for the years 2018-2022 and evaluated against a benchmark model.The result shows that a simple trading strategy can give a positive impact on the outcome and the stochastic game model leaves a good foundation for modeling with an almost endless number of machine learning algorithms.

Contents

1 Introduction

The European energy market has gained much attention during the recent year, which is no surprise given the challenges of rising energy costs that affects all energy consumers such as households, industries etc. every day. The increasing demand due to electrification has been met with a transition towards a more stochastic supply side, when intermittent energy sources like wind and solar energy get a larger and larger share of total production while the share of more predictable energy sources decreases. A vast majority of the European nuclear power plants has already been shut down or faces problems due to old age and power plants that use fossil fuel meet higher fuel cost due to rising prices and climate targets. This increasing complexity of energy markets affect the electricity prices making them much more volatile then we have ever seen before which in turn affects the financial market with larger risk of financial losses, higher collateral requirement and lower liquidity.

1.1 The characteristics of the Nordic electricity market

The history of the Nordic spot market began in 1996 after Sweden deregulated its electricity market and together with Norway, who deregulated the market already in 1991, established Nord Pool which today is the common Nordic physical energy market.[21] The electricity market is of interest for many and is well-described throughout the scientific world as well as in popular science. An example of a micro economist view is given by Mohammad Reza Hesamzadeh and Darryl R. Bigger in *The Economics of Electricity Markets*.[16] In their book they describe how the deregulation makes also the electricity market work like any other market where the supply and demand decide price and quantity. Unlike any other markets electricity has some characteristics that contribute to its volatile nature. In recent years the decarbonisation process has changed the supply side with less fossil fueled Combined Heat Power and increased renewable power sources such as wind and solar power. The nuclear question is seen differently between countries, where some countries like Poland and Finland have deemed it necessary to replace other sources and invested in this technology, while other countries like Germany decided to exit existing nuclear power plants. Since electricity cannot be stored in an efficient way but must be produced and consumed at the same time the volatility increases. This all combined led to more active power consumers, development in energy storage technology and increased the need to extend the transmission system. The interest and need of decarbonisation has also increased the future demand of (nonfossil fueled) electricity.

1.2 Forward and futures market

Forward and futures contracts are agreements between buyers and sellers of an underlying asset. The participants are obligated to execute the trade at a specified future time at a specified future price. In the forward case the payment, that is the difference between spot price and the forward price, will happen at the delivery date. The futures contracts work in a similar way but unlike forwards where payment is done once at delivery the participants have an ongoing cash-flow during the time period (Capinski and Zastawniak, 2003)[5]. Financial contracts in the electricity markets are usually futures contracts and the contracts specify the volume (typically in MW) and the period of delivery, which is usually yearly, quarterly or monthly but other products like e.g. weekly contracts or peak load contracts also exist. We introduce the notation $f(t, T)$ for the price of a future contract at time t with delivery time T which should represent the expected spot price at time T, $S(T)$, at time t i.e. $f(t, T) \approx \mathbb{E}[S(T)]$. If it does not, then the future should be considered as undervalued or overvalued. The sum of the daily cash-flows for futures contracts should equal the single payment in the forward case.

1.3 Aim and research question

The larger volatility on the spot market causes much more unpredicted costs for both electricity users and producers. In order to make this more predictable their interest for a financial hedge should increase. The aim of this thesis is to investigate the electricity futures market by modeling it as a stochastic game. We will consider two kinds of players who engage in the market, one of them will be a risk-averse player, which we refer to as hedger, who only takes buying position, and the other will be a more risk-neutral player purely interested in profit who takes both buying and selling positions, which we will refer to as speculator. In order to chose the best position from its feasible set the players wish to predict the most probable future outcome. We will suggest two different methods which will be illustrated by simulations together with a benchmark model. The success of the strategy will be measured by profit, standard deviation and how many times the correct position was selected.

1.4 Disposition

This thesis will be structured as follows: Chapter 1 gives the reader an introduction of the subject, motivation of its relevance and states the research question. In chapter 2 the theoretical framework is given, including a review of relevant research. Chapter 3 presents the methodological framework used in the thesis. Chapter 4 gives a description of the data, a motivation on how it was chosen and limited, and the simulations of the data. Chapter 5 contains the the results which are also further discussed in the chapter. The thesis is summarized and assessed in chapter 6.

2 Theoretical framework

This chapter will present the theoretical background with relevant literature.

2.1 The basis of Game Theory

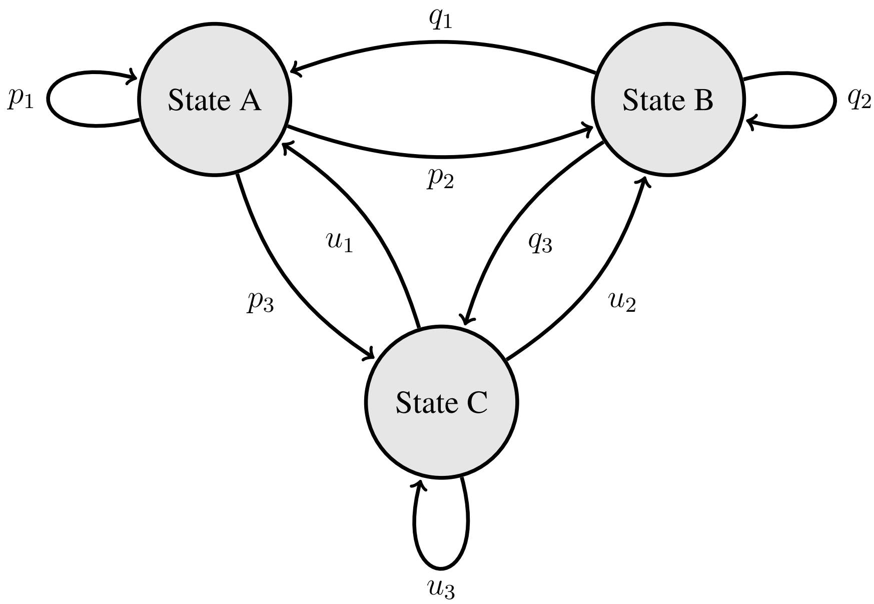
The concept of Game Theory was popularized by John von Neumann and Oskar Morgenstern in the 1940s and heavily contributed to by John Nash in the 1950s and their work can be considered as the foundation of Game Theory. The theory can be applied in many different situations and can be used to model and analyse a large number of economic behaviours and interactions. Some key elements in game theory are the players who wish to maximize a reward or minimize a cost. Each player has a set of possible actions and the chosen strategies lead to some payoff for each player. Each player will try to figure out what action to take and what actions the other players are expected to take. Formalized this can be expressed as a collection of pairs $(A_k, u_k)_{k \in K}$ where K is a set of at least one player. Each player $k \in K$ has a set of possible actions A_k and a utility function $u_k : A \to \mathbb{R}$, where A is defined as the set of Cartesian products $A := \times_{k \in K} A_k$ that represent all possible combinations of actions. [6] In a game with complete information each player has access to all information in the game including information about other players such as their cost functions. If it is a game with perfect information the player knows all previous actions chosen by the others when it is their time to choose. The Nash equilibrium in a game is the optimal choice for each player given the other players choice, or in other words when the other players choice is revealed one should not change the first choice. The Nash equilibrium in a game could be unique, but there could also be several equilibria or none.[8] The repeated game makes a learning process possible where wrong decisions are punished with a loss and good decisions are rewarded. One could learn and improve a strategy by analysing previous steps, since we do know the payoff of previous actions. [19] Even in the deregulated market one should remember that some bigger companies could have more impact than smaller companies which implies that such a market could work similar to an oligopoly. In game theory an oligopoly could be modeled in a simple case like a Cournout game, if the firms are assumed to chose the quantity, or opposite chose the price like in a Bertrand game. For a longer period of time the players will interact at several occasions and should be considered as a repeated game.[16]

2.2 Stochastic games

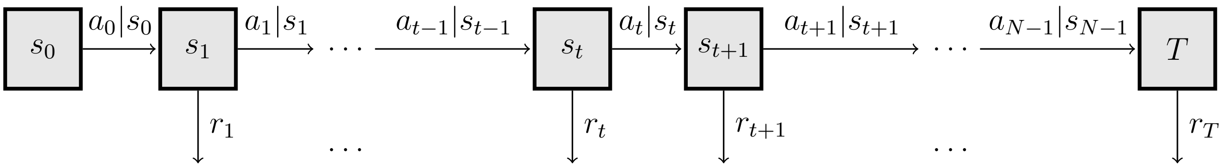
The concept of stochastic games was presented in the 1950s by Shapley [18] and is considered as a subset of Game Theory. This is a sequential game focused around one or more players and the set of possible states each player can move between according to some transition probabilities. To measure what step would be the best choice we use a *probability measure* $\mathbb{P}$ that maps all possible outcomes of a sample space Ω into the interval $[0, 1]$, $\mathbb{P}[\emptyset] = 0$ and $\mathbb{P}[\Omega] = 1$. If we consider the event A and measure the probability that A will occur as $\mathbb{P}[A]$ then a small value means that A is not likely to occur and of course the opposite will be a value close to 1 means that it is very likely to occur. If we want to measure the probability that A occurs given that the event B occurred, then we consider the *conditional probability* denoted $\mathbb{P}[A|B]$. For more details see for example the book by Gut (2005). [9]

If a player has the same transition probabilities for a certain state every time it is reached the game is said to have stationary strategies, denoted $x = (x^1, x^2, \ldots, x^N)$, where each $x^n = (x_1^n, x_2^n, \ldots, x_{m_n}^n)$ and N is the number of possible states and number of sequences can be of any length and not necessarily the same length every time it is played. Every action is connected with some reward.

Consider an example with three different states $\{A, B, C\}$ with probabilities $\mathbb{P}[s_{t+1} = A|s_t = A] = p_1$, $\mathbb{P}[s_{t+1} = B|s_t = A] = p_2$, $\mathbb{P}[s_{t+1} = C|s_t = A] = p_3$, $p_1 + p_2 + p_3 = 1$ and so on for state B and C, illustrated with a graph and a corresponding transition matrix, $\begin{pmatrix} p_1 & p_2 & p_3 \\ q_1 & q_2 & q_3 \\ u_1 & u_2 & u_3 \end{pmatrix}$.



For a game with length T the different steps will look like this: at initial step s_0 the player chooses an action a_0 and moves to step s_1, which gives the reward r_1 and continues this until the final step of the game, illustrated in the picture below.



2.3 Background and previous studies

With the growing complexity of the energy market more powerful tools are required to provide useful information to market participants and the use of game theory should be helpful also for financial trading. [11] Pang, Deng and Wang (2017) [15] investigated hog futures, i.e. price hedging for pork, in the Chinese market by considering it as a two player game with hedgers and speculators as players. In the game model the players should take a long position if the price is expected to rise and otherwise take a short position if the price is expected to fall. While the two different players trade in the same market they are however assumed to have different incentives for trading, since hedgers are expected to trade to avoid future losses and speculators trade to win high profits. In other words, they have different degrees of risk aversion which will influence their chosen strategies. The possible actions for a hedger in this model would be buy or not buy and for a speculator speculate or not speculate, $A_{\text{hedger}} = \{\text{buy}, \text{not buy}\}$

and $A_{\text{speculator}} = \{\text{speculate}, \text{not speculate}\}$, leaving four possible combinations of actions. If the aim of a futures market is to give stability, then the conclusion from the article is that the market should promote the $(\text{buy}, \text{not speculate})$ strategy combination. However the absence of speculators would have a negative impact on liquidity and thus the market should aim to find an optimal ratio of hedgers and speculators. The importance of speculators is also stressed by Sebastiao et al. (2020) [17]. In their article they describe the use of Machine Learning methods when creating a trading strategy by finding risk premium situations and applied this to the Nordic electricity market. Their models was built only on financial data and did not include fundamental factors, but both methods have been used by previous researchers.

A game theoretic model for energy commodities was developed by Funk (2017)[7] in his dissertation where he used Cournot differential games to model a futures market in continuous time. The benefit of the differential game is that it among other things allows us to take exhaustibility and storage possibilities into account, which suits the commodity market well. As an example of an extension Ludkovski and Yang (2015) [14] used a dynamic Cournot model to investigate a duopoly consisting of an exhaustible producer and a renewable competitor and their reaction to high and low demand, showing that the exhaustible producer is sensitive to changes in demand and may stop producing during low demand, which makes it a reasonable to think that it should also be an important property to include when hedging in the futures markets. Funk also argues for several different theories regarding futures market and risk aversion, which are important for our assumptions about the player's behaviour like how players can change strategy depending on their own or other player's risk aversion, and includes risk aversion in the model as a cost. Hanly et. al. (2017)[10] studied hedging in different electricity markets, among them the Nordic, as a risk management tool. They made a reference back to Bystrom(2003)[4] and his findings that Naive, OLS and GARCH models were successful in the Nordic market, methods that have been widely used for this type of markets. While Bystrom used weekly contracts and measured success as a reduction of variance, Hanly et al. extend this to two risk measures, besides variance they also used Value at Risk, and used both weekly and monthly contracts, but did not find the method as effective as Bystrom did for the weekly contracts. This can be explained with the larger period of time and increasing volatility in the market in the latter case. The result for monthly contracts was better than for weekly contracts and among the included markets best result was found in the Nordic market, but still worse than comparable studies in other, non-electricity, markets. This finding should not be surprising for the electricity market, whose volatility is considered as one of the hardest to handle, but made Hanly et al. question the utility of the financial market.

This thesis will contribute with new information in the area since it will focus on more recent years including two extreme years, the wet year 2020 which also included a global pandemic with exceptionally low prices and then 2022 with exceptionally high prices due to what is commonly known as the European energy crisis.

3 Method

In this chapter we will introduce some important concept and notations. Further on the different models used to predict future outcomes will be presented as they will provide the player with valuable information on which action to take and this will be illustrated as simulations in the next chapter.

Just as the case described by Pang et al. we will allow the two actions buy or not buy for the hedger while the speculator is also allowed short positions and can chose between buy or sell. The utility or reward for our player will be the profit from the position, i.e. the change of value of the contract from current step to next step. A positive value is equal to winning the round of play at this step, while a negative value is a loss. To help the player decide which step to take next it has time series with historical data from previous actions and corresponding rewards. This could be used to form models that provides the player with a suggestion on which action would be the most likely to give the desired best reward. First let us state some definitions that will be necessary in order to build the model.

Time series are defined as continuous stochastic processes measured at discrete time periods t in a time interval I, $\{X_t\} := \{X_t | t \in I \subset \mathbb{R}_+\}$. The stochastic process is defined as weakly stationary if the expected value function $\mathbb{E}[X_t]$ is independent of t and the covariance function $C[X_s, X_t]$ is only dependent on $t - s$. A simple example of a stationary process is the white noise $\{\epsilon_t\}$ which is a sequence of independent identically distributed random variables with mean 0 and variance σ^2. The white noise is very useful when modeling time series and can be used to define the moving average process. A process X_t is said to be a *moving average process* of order q, $MA(q)$-process, if

$$X_n := c_0\epsilon_n + c_1\epsilon_{n-1} + \cdots + c_q\epsilon_{n-q} = \sum_{k=0}^{q} c_k\epsilon_{n-k}$$

where ϵ_n is the white noise, $c_0 = 1$ and $c_1, \ldots c_k \neq 0$. A time series depending on its own previous outcomes is called an autoregressive process. A process X_t is said to be an *autoregressive process* of order p, $AR(p)$-process, if

$$X_n := b_1 X_{n-1} + \cdots + b_p X_{n-p} + \epsilon_n,$$

where ϵ_n is the white noise and $b_1, \ldots b_p \neq 0$.

It is reasonable to believe that sequential observations, such as financial time series, are dependent on previous values, but also that the values closer in time to be more important than older observations. It would also make sense to limit the number of values that we consider to be of importance or otherwise an algorithm used for simulations would be slower and slower. [2] For all possible choices the player can make it estimates the probability for that outcome, with for example the models presented below as a tool. The player then chooses the one with highest probability.

3.1 Naive hedge

For a naive hedge the position in the spot market should have a corresponding opposite position in the futures market. [4] For this case we let the trader take a long position every day during the trading period and the result will be used as a benchmark.

3.2 Markov chain

To observe the current state is often helpful information to predict future outcome in a sequential time series. For a sequence of random variables $x_1, \ldots, x_n$ the *first-order Markov chain* have the property

$$\mathbb{P}[x_n | x_1, \ldots, x_{n-1}] = \mathbb{P}[x_n | x_{n-1}].$$

This can be extended to any M^{th} order Markov chain $\mathbb{P}[x_n | x_{n-M}, \ldots, x_{n-1}]$ (Bishop, 2006) [2].

In this case a first simple step would be to only consider two states, the price goes up or the price goes down, but this could be extended to more steps, for example if we believe that a large rise would have a different impact than a small rise. We let x_t denote the price movement at step t and x_{t+1} denote the price movement in the next step. This can be represented as a probability transition matrix as below:

	Up	Down
Up	$\mathbb{P}[x_{t+1} = \text{Up} \| x_t = \text{Up}]$	$\mathbb{P}[x_{t+1} = \text{Down} \| x_t = \text{Up}]$
Down	$\mathbb{P}[x_{t+1} = \text{Up} \| x_t = \text{Down}]$	$\mathbb{P}[x_{t+1} = \text{Down} \| x_t = \text{Down}]$

3.3 Logistic regression model

A linear probability model is a suitable variant of linear regression for a binary variable [20] in order to predict the probability of event X with the help of explanatory variables $X_1, \ldots, X_k$. While a linear regression could be used there are some problems with using it for this type of problem, the most obvious being that it can range outside the interval $[0, 1]$ so in order to avoid this the logistic regression is used instead (James et al. 2021) [12]. In this case we instead use the logistic function to model the prediction as

$$p(X) = \frac{e^{\beta_0+\beta_1 X_1+\ldots+\beta_k X_k}}{1 + e^{\beta_0+\beta_1 X_1+\ldots+\beta_k X_k}}.$$

The coefficients β are estimated by the maximizing the likelihood function, or log-likelihood function with the observations $x_1, \ldots, x_n$

$$L(\beta; x_1, \ldots, x_n) = \prod_{i=1}^{n} \mathbb{P}[x_i; \beta]$$

$$\Leftrightarrow$$

$$\ln L(\beta; x_1, \ldots, x_n) = \sum_{i=1}^{n} \mathbb{P}[x_i; \beta]$$

by finding the zero of the gradient $\nabla L(\beta) = 0$. The more technical details are omitted since this can easily be calculated in any statistical software, such as using the **glm** function in R, see Bishop (2006) [2] for a deeper explanation.

Moving more straightforward to modeling the first step is to classify the data so that if it belongs to the category which we want to predict the probability of we assign this value 1 and otherwise 0. In this case we create an array with data that replaced all days with upward price movement with 1 and all downward price movement with 0. Next decide what explanatory variables to include. To compare this with the Markov chain model presented before today's price movement is included to predict the probability of tomorrows price being larger than today, but more explanatory variables could be added.

4 Data

The need for participants in the energy market to handle risks in the markets has made a financial market necessary. Such contracts, usually forward or futures contracts, can be traded at Nasdaq Commodities who offer energy derivatives and related products and also operate as a clearing house via Nasdaq Clearing. The contracts are an agreement between a buyer and a seller to pay the difference between the agreed price and the spot price. The data in this thesis consist of Nasdaq closing prices for monthly electricity futures contracts for the years 2018-2022, from the first trading day which is 6 months before delivery until the last trading day before delivery. Monthly contracts are considered to be the most liquid contracts and this thesis will be limited to only consider this type of contracts. The choice on the five year period is because it is long enough to experience both an exceptional low priced period and an exceptional high priced period and will give a trading result for 60 months, enough data points to be able to present a result which exemplifies the methods presented in chapter 3. The underlying asset for the Nordic electricity futures contracts is the Nordic system price from Nord Pool, which is a common theoretical price for the Nordic area. The closing prices for all 60 contracts are plotted in figure 1 together with the rolling front month which corresponds to the last months trading period for each contract. The rolling front month contracts are further illustrated in figure 2 together with the spot price to give a feeling on how the spot prices give a price driving influence on the futures contract and with the spot result for each contract. A total list of the contracts and relevant statistics is given in the appendix.

What the player wishes to predict is the profit or loss for the next trading day, PL_{t+1}, defined as $PL_{t+1} := (f(t+1,T) - f(t,T))$, where $f(T,T) = S(T)$. The profit and loss for the front month contracts are illustrated in 3. If a positive number of PL_t is more often followed by a positive number than a negative number and vice versa then the data points in a plot like figure 4 should be more clustered in quadrant I and III. For this example data there is also a lot of opposite findings, suggesting that such an approach would also fail several times and that a more refined method would be necessary to ensure more winnings.

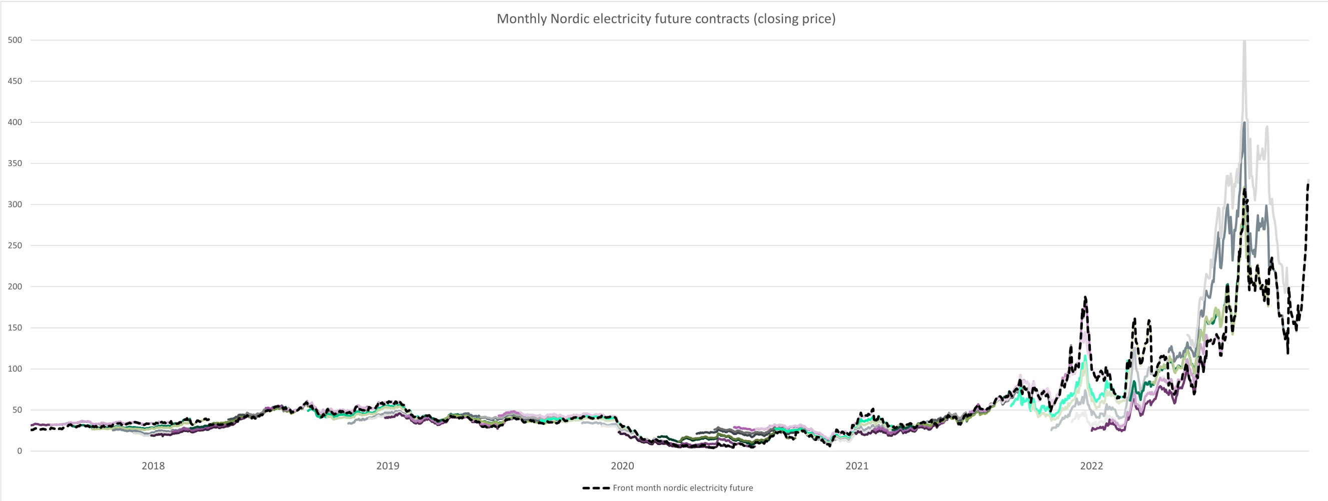


Figure 1: Monthly Nordic electricity futures contracts 2018-2022 with 6 months trading period, rolling front month in dashed line.

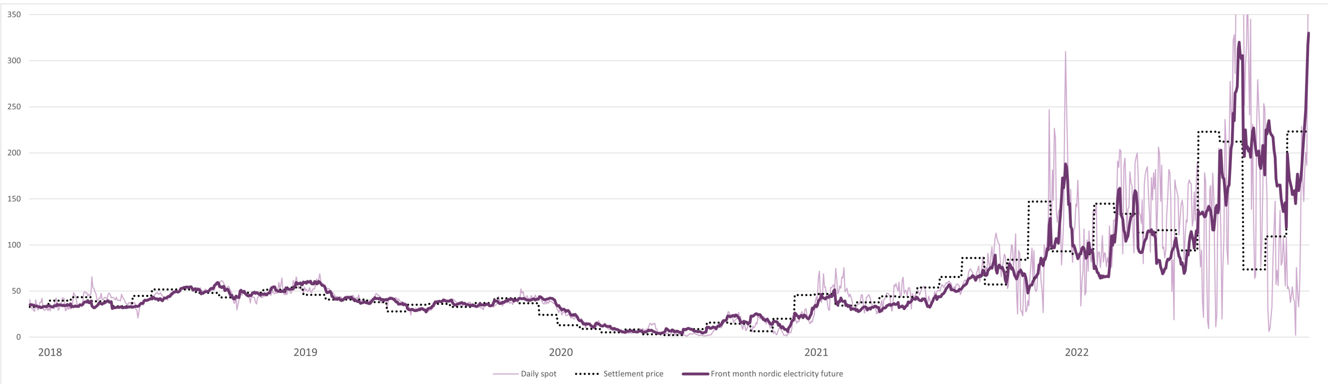


Figure 2: Nordic electricity futures contracts front month 2018-2022 with corresponding spot result and spot price at trading day.

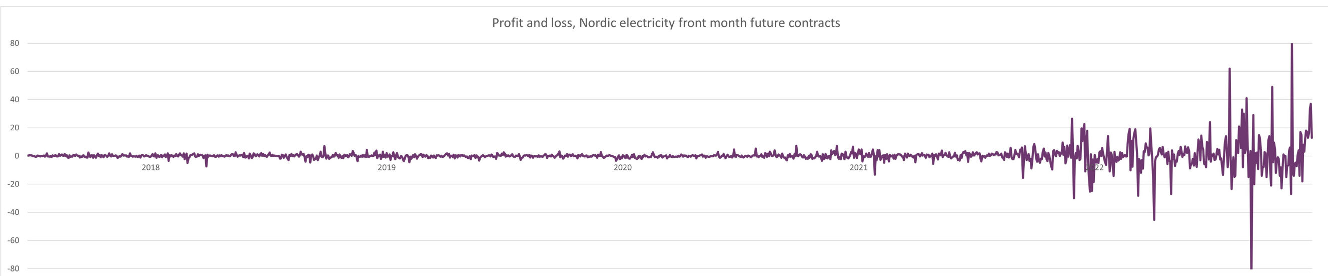


Figure 3: Profit and loss for front month.

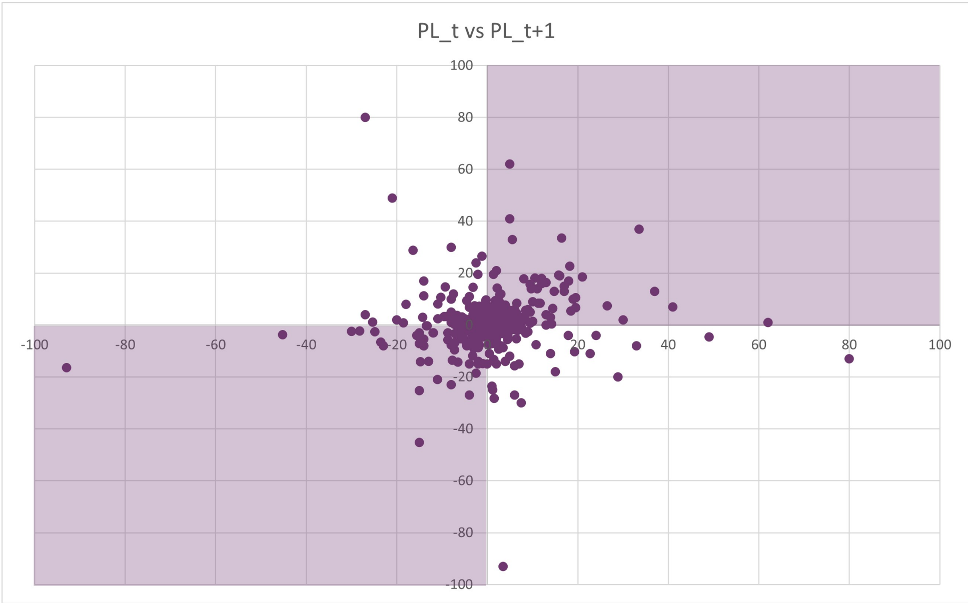


Figure 4: Profit and loss plotted against profit and loss for the next day, front month data.

4.1 Simulations

In this section we will use the methods presented in chapter 3 in order to perform some simulations.

For the benchmark model we chose to use a naive hedge that takes a buying position every trading day for every contract. The next day the player receives a profit if the price did go up or a loss if the price went down. The last trading day is settled against the corresponding spot result.

The next strategy is based on Markov chains and in this attempt we divide the data into three different states and calculates the probability transition matrix T with the conditional probabilities which shows that there is a little higher probability to guess right if we use todays price movement to predict the movement of the nexyt day. Buying after a non-negative profit is in this case successful 56% of the time.

	$PL_{t+1} > 0$	$PL_{t+1} = 0$	$PL_{t+1} < 0$
$PL_t > 0$	0.56	0.03	0.41
$PL_t = 0$	0.56	0.03	0.41
$PL_t < 0$	0.47	0.02	0.51

With only this information the hedger decides to buy if $PL_t \geq 0$ and otherwise not buy.

For the speculating player we allow both short and long positions so this player chose buy if $PL_t \geq 0$ and otherwise sell. From the probability transition matrix we can also get information about steps ahead. By performing matrix multiplication with itself we get a new matrix T^2 that tells us the probability of the states two steps forward. Repeating this n times until the probabilities stabilize will give the *steady state vector* for this probability transition matrix as $(0.519, 0.025, 0.456)$. This matrix stabilizes after only a few iterations which indicates that the current state will not have a great influence for the events a few steps ahead. This is interesting information also for the naive hedge, since it predicts that a naive hedger will take the right position in 52% during this time period. To capture more of the price trend one could instead of todays value consider the moving average of some different lengths and compared with current value perform the same strategy, if todays value is larger then the moving average the price trend seems to be upwards and one should take a buying position. A test performed on the front month contracts for MA(1)-MA(10) visualized in figure 5 showed that it gave the same number of wins or worse and this method was therefor not investigated further.

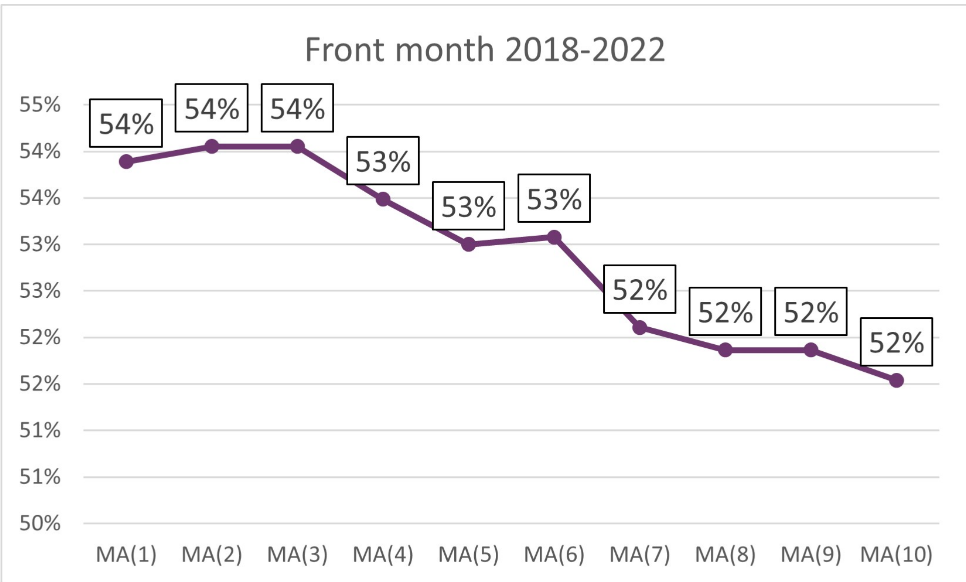


Figure 5: Number of wins for different moving averages compared with todays value, with front month contracts for 2018-2022 as data.

The same thought was also tested in the logistic regression case with the front month data. A first model included the lagged values from 1 to 5 previous steps as explanatory variables with the true direction as response variable. A positive coefficient suggests that an increased value of previous profit and loss gives higher probability that tomorrows value is positive, which corresponds to previous hypothesis. The z-statistic tests the null hypothesis $H_0 : \beta = 0$ and a larger (absolute) value of the z-statistic is associated with evidence against the null hypothesis. For β_1 we can reject the null hypothesis but the result suggest less impact from lag 2-5. In the next try these were excluded and only lag1 remained and the result of this model with the plotted predicting line is presented in the graph in figure 6.

```
Call:

glm(formula = Direction ~ Lag1 + Lag2 + Lag3 + Lag4 + Lag5,
family = binomial)

Deviance Residuals:
    Min        1Q    Median       3Q       Max
-2.1207  -1.1888   0.9519   1.1626   1.5571

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept)  0.030486   0.054586   0.559  0.57650
Lag1         0.027266   0.010007   2.725  0.00644 **
Lag2         0.005141   0.008770   0.586  0.55773
Lag3         0.005223   0.008638   0.605  0.54543
Lag4        -0.002748   0.008784  -0.313  0.75437
Lag5        -0.006498   0.008949  -0.726  0.46772
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

For the final logistic regression simulation the coefficients was re-estimated for each contract with the most recent 6 months data as observations, lag1 as explanatory variable and direction as response variable. Recall from previous chapter that this gives a model of the form

$$\mathbb{P}[PL_{t+1} \geq 0] = \frac{e^{\beta_0+\beta_1 PL_t}}{1 + e^{\beta_0+\beta_1 PL_t}} \qquad (1)$$

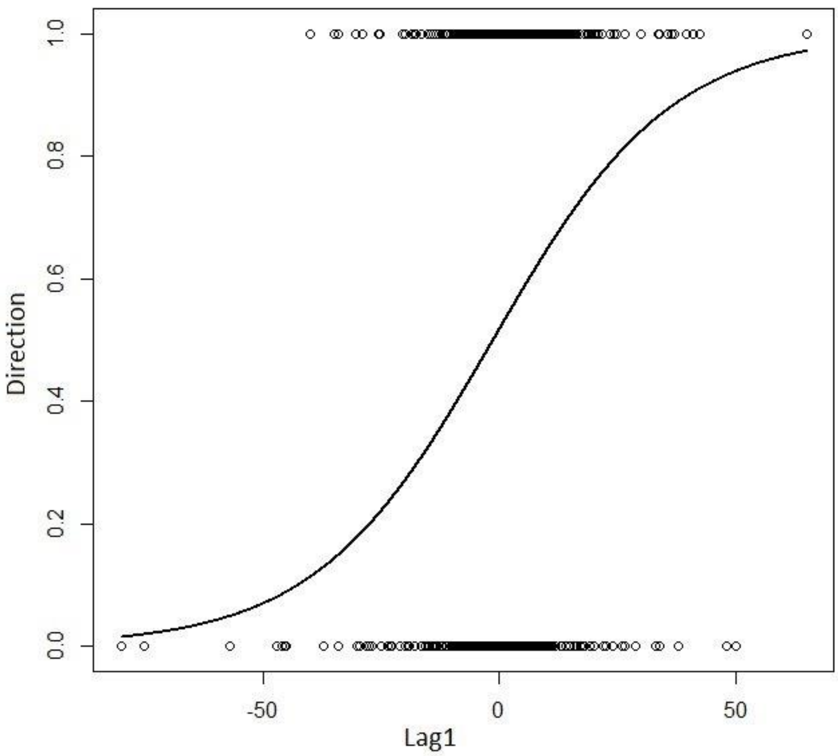


Figure 6: Plot with data points and corresponding logistic regression.

5 Result and discussion

A summary of the simulation result presented in the table below shows that just a simple first model did help to improve the trading profit. From previous research we know that a risk avert player is willing to pay a premium to avoid risk while others are willing to take the risk for the possibility of profit, and the strategy of choice would depend on the players utility function.

	Hedger			Speculator		
	profit/contract	σ	wins	profit/contract	σ	wins
Naive	20.42	4.91	51.8%			
Markov model	36.08	3.89	55.3%	51.73	4.90	55.3 %
Logistic regression	36.82	4.15	57.4 %	53.24	4.90	57.4 %

A small change for the hedger in just trying to predict what days to not buy decreased the volatility and improved profit and number of wins. The more risk taking speculator more than doubled the profit during the period compared to the inactive naive hedge, but in order to win higher profit the player has to accept larger volatility. An interesting result is that the largest differences are seen in the periods 2020 and 2022 when the price changes start to deviate more and the risk for both larger profits and larger losses increases.

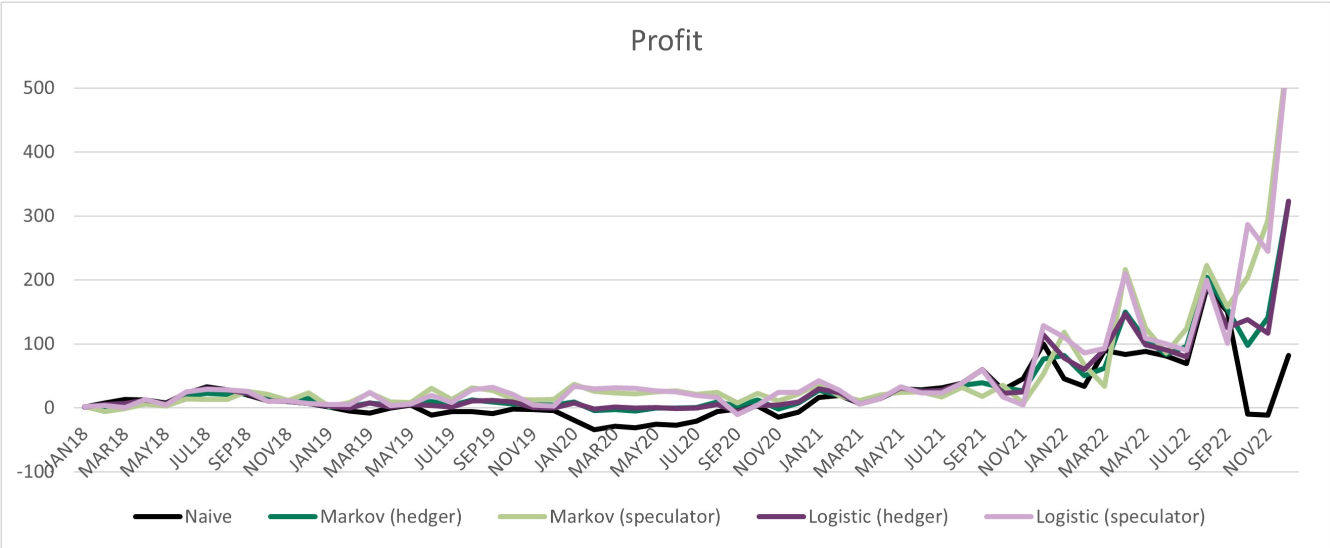


Figure 7: Profit for each contract and method.

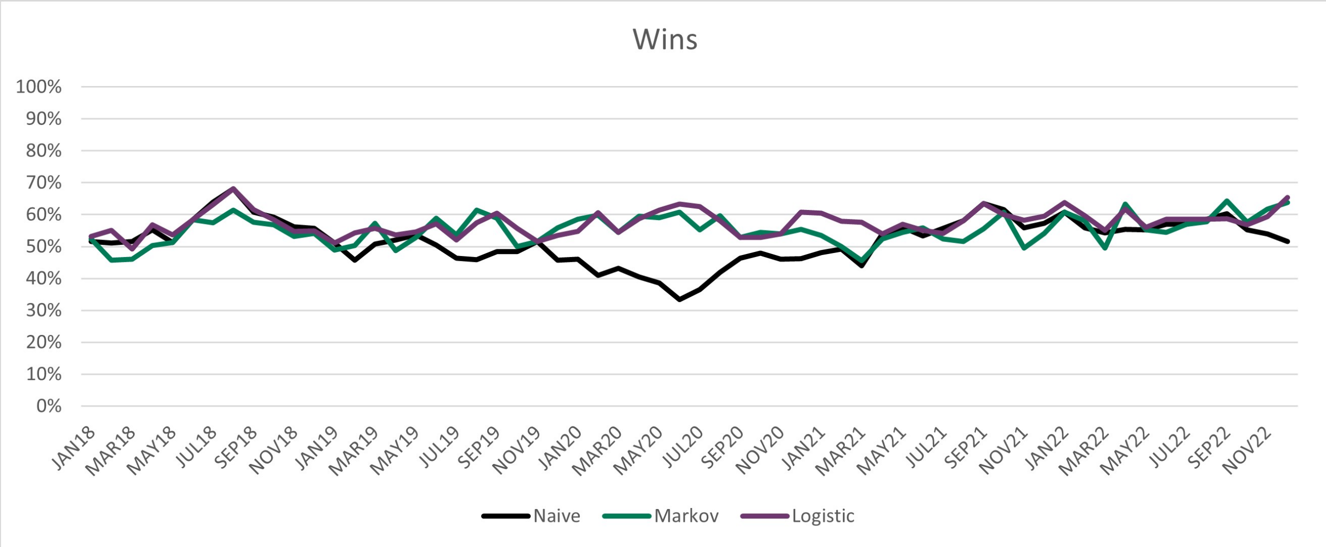


Figure 8: Wins for each contract and method.

6 Conclusion

In this thesis a stochastic game as a subarea of game theory was presented together with a suggestion on how to model transition probabilities as a tool for the player to choose the next step in a sequential game. This was applied on data from the Nordic electricity futures data with two different players. The data in this thesis was limited to only monthly contracts, but the strategies could be extended to also include yearly, quarterly and/or weekly contracts. The scenarios could also be extended to include more possible states. Instead of just considering the movements up or down, would we find a difference with four steps and divide up and down into large and small ups and downs or extend this to even more steps?

A game theoretical approach for trading strategies should give valuable insights for participants, but one should not focus only on a technical analysis but combine it also with fundamental analysis for the full picture. An example of this was presented in chapter 2.3 where the model of Ludkovski and Yang (2015) [14] also included high and low demand. Another factor that is reasonable to include if one wishes to extend the model to also include such factors could the hydrobalance in the area, the expected nuclear availability or expected windpower output. Interactions between the different players would be an interesting next step for further research, stochastic games gives a very good foundation for modeling with machine learning algorithms and this gives an almost endless number of variations one could use to perform simulations of this type. As a conclusion it should benefit market participants to invest in trading strategies as a tool to manage the increased price volatility in order to reduce risk. The result from this thesis shows that even simple strategies can improve the outcome.

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7 Appendix

Contract	# of obs.	Mean	Min	Max	Std. Dev	Spot result
NPENOMJAN18	128	33,55	31,4	36,45	1,29	32,93
NPENOMFEB18	129	34,03	31,7	36,63	1,16	39,58
NPENOMMAR18	126	30,35	27,2	39,8	2,70	43,43
NPENOMAPR18	125	29,70	25,65	39,5	3,56	39
NPENOMMAY18	123	26,49	20,85	32,98	3,30	33,45
NPENOMJUN18	120	26,91	18,6	42,25	5,84	44,8
NPENOMJUL18	122	29,06	18,25	47,25	8,19	51,7
NPENOMAUG18	122	36,32	23,4	54,6	9,67	51,73
NPENOMSEP18	125	42,29	27,7	59,4	9,03	47,98
NPENOMOCT18	125	44,58	31,95	58,65	6,87	43,04
NPENOMNOV18	128	48,18	38,5	59,15	4,57	48,37
NPENOMDEC18	131	49,43	43,6	59	3,47	51,56
NPENOMJAN19	127	52,10	46,45	61	3,21	53,78
NPENOMFEB19	127	53,06	46	60,75	4,10	45,86
NPENOMMAR19	124	47,23	39,65	56,3	4,79	40,86
NPENOMAPR19	125	44,47	36,7	54,65	5,12	40,82
NPENOMMAY19	121	40,71	33,5	48,85	4,12	38,07
NPENOMJUN19	119	40,05	33,55	47,55	3,43	27,96
NPENOMJUL19	121	37,11	27,35	45,9	4,57	35,15
NPENOMAUG19	122	37,50	29,5	43,48	3,71	36,11
NPENOMSEP19	124	38,92	33,6	45,45	3,35	32,92
NPENOMOCT19	124	37,79	33	44,28	3,32	37,1
NPENOMNOV19	128	40,24	35,9	45,88	2,54	42,15
NPENOMDEC19	129	41,09	38,15	46,15	1,65	36,79
NPENOMJAN20	128	43,68	34,45	48,5	2,01	24,1
NPENOMFEB20	127	40,67	18,05	47,15	6,68	13,08
NPENOMMAR20	125	33,14	10,65	42,35	9,96	9,01
NPENOMAPR20	126	26,91	5,7	40,2	11,76	5,26
NPENOMMAY20	122	19,83	5,2	35	10,80	8,34

Contract	# of obs.	Mean	Min	Max	Std. Dev	Spot result
NPENOMJUN20	120	13,99	3,9	31,55	8,73	3,15
NPENOMJUL20	123	9,02	4,18	23,55	5,10	2,35
NPENOMAUG20	124	9,68	4,55	15,25	2,53	8,79
NPENOMSEP20	125	14,22	7,65	22,75	3,02	15,73
NPENOMOCT20	125	16,39	10,35	25	3,23	14,63
NPENOMNOV20	128	22,16	13,75	28,15	2,74	6,32
NPENOMDEC20	130	22,69	6	29	5,03	20,09
NPENOMJAN21	129	26,03	12,1	32,65	4,59	45,81
NPENOMFEB21	126	28,75	14	51,4	7,55	46,84
NPENOMMAR21	125	25,42	9,65	42,65	8,43	34,21
NPENOMAPR21	126	24,49	8,7	38,13	8,18	37,86
NPENOMMAY21	123	23,87	7,95	37,6	8,00	44,28
NPENOMJUN21	120	25,81	11,2	43,55	7,10	43,54
NPENOMJUL21	122	28,03	18,7	45,05	7,17	53,99
NPENOMAUG21	124	34,60	21,75	57	9,36	65,39
NPENOMSEP21	126	41,55	25,7	72,75	12,34	86,01
NPENOMOCT21	125	48,51	29,15	89,13	15,18	57,1
NPENOMNOV21	127	55,61	36,88	88,78	13,41	84,05
NPENOMDEC21	131	62,28	38,98	129	15,26	147,18
NPENOMJAN22	130	78,91	46,8	188	29,66	93,25
NPENOMFEB22	129	83,08	55	145	20,32	90,25
NPENOMMAR22	127	66,51	40,1	116,1	15,62	144,79
NPENOMAPR22	128	72,87	37	161,5	31,71	133,8
NPENOMMAY22	125	64,40	25,5	125,65	26,83	113,61
NPENOMJUN22	123	57,31	30,13	107,5	21,58	116,12
NPENOMJUL22	123	58,72	24,33	115,5	25,14	94,02
NPENOMAUG22	123	84,78	29,25	143	33,53	222,86
NPENOMSEP22	126	133,05	61,5	320	57,48	212,27
NPENOMOCT22	125	154,93	81,75	322	53,06	73,54
NPENOMNOV22	128	209,96	108,88	400	71,81	109,26
NPENOMDEC22	130	265,65	126	530	86,52	223,17