

Natural gas price forecasting using recurrent neural networks

Research Proposal for Master's Thesis

to be submitted to

Prof. Dr. Stefan Lessmann

Humboldt-Universität zu Berlin
School of Business and Economics
Chair of Information Systems

by

Christian Koopmann

(572485)

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I would like to thank

Abstract

This is the template for a thesis at the Chair of Econometrics of Humboldt–Universität zu Berlin. A popular approach to write a thesis or a paper is the IMRAD method (Introduction, Methods, Results and Discussion). This approach is not mandatory! You can find more information about formal requirements in the booklet ‘Hinweise zur Gestaltung der äußeren Form von Diplomarbeiten’ which is available in the office of studies.

The abstract should not be longer than a paragraph of around 10 to 15 lines (or about 150 words). The abstract should contain a concise description of the econometric/economic problem you analyse and of your results. This allows the busy reader to obtain quickly a clear idea of the thesis content.

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1 Introduction

1.1 Topic

1.2 Motivation

1.3 Structure

2 European Gas Market

In this section I will give a very brief overview of the history and current situation in the European natural gas market. A special emphasis will lie on the different ways natural gas is traded and how the current system evolved.

2.1 History

The first commercially used gas was in fact produced from coal and used as a lighting fuel beginning in the late 18th century in Britain and then spreading to the United States and Continental Europe in the 19th century. The first well extracting natural gas directly from the ground was dug 1821 in Fredonia, New York (Heather (2015)). At the beginning this gas could only be consumed at locations close to its source. The expansion of the application of natural gas into fields such as heating, chemical processing and power generation was connected with the building of effective long distance pipelines. In Europe the advent of large scale natural gas imports from the former Soviet Union and North Africa in the mid 20th century required especially large infrastructure investments. To recover this investment long term contracts with durations of 25 to 30 years were negotiated by the usually state owned entities that controlled the natural gas trade. These entities usually integrated many different areas of the value chain from exploration over pipeline transport to the sale of natural gas. During this time there were relatively few participants in the European natural gas market that often occupied a monopoly position in their respective national markets. For the sale of gas from the then newly developed Groningen field the Dutch producers developed an oil based pricing system, where the price for long term natural gas contracts was tied to the market price for crude oil. This pricing system spread to many other natural gas contracts and became the predominant pricing system in the European market. An alternative pricing regime has developed in the 1970s in the United States. This pricing regime is based on defining regional gas trading hubs and developing independent markets for gas traded at each of these hubs. In the US the Henry Hub in Louisiana has evolved as the main trading hub. Hub pricing spread from the US to the UK with the privatisation of the British gas industry in the 1980s and the establishment of the National Balancing Point (NBP) as the main trading hub for the UK market. Whereas the Henry Hub evolved from a physical hub connecting various long distance pipelines the NBP was established as a Virtual Trading Point (VTP) with the aim of developing a new price reference for natural gas trading. Regulatory reform and privatisation of the gas industry was a key requirement for the

establishment of these markets since it allowed for the separation of distribution networks from natural gas trading activities and thereby ensured that all market participants had equal access to the distribution infrastructure. Aiming to establish an integrated European energy market these regulatory changes have later been adopted by the European Union and spread to the other member countries. This has led to the establishment of Continental European virtual trading points with the Dutch Title Transfer Facility (TTF) emerging as the main hub. The establishment of these hubs has allowed natural gas to evolve into a commodity traded on spot and future markets just as crude oil. With the improvement of the technology and infrastructure for trading Liquefied Natural Gas a new alternative to pipelines has emerged and the gas market has become more globally integrated. Due to the recent boom in domestic shale gas production the United States has drastically reduced its LNG imports and is becoming a net exporter. This has led to an oversupply in LNG markets with a resulting downward pressure on gas prices. As a result of this the long term oil indexed contracts have become a lot less attractive for buyers, who have pushed for switching to hub pricing. The share of oil indexed pricing in the North West European market (including France, Germany, UK and Netherlands) has fallen from 70 percent in 2005 to just over 10 percent in 2014. Accordingly hub pricing accounted for 90 percent in 2014 (Heather (2015), p. 14). In the past years various new national trading hubs were created throughout Europe with the two German hubs NetConnect Germany (NCG) and Gaspool (GP) chief among them. However these new exchanges still lack far behind the established hubs (NBP, TTF) in terms of liquidity and trading volume.

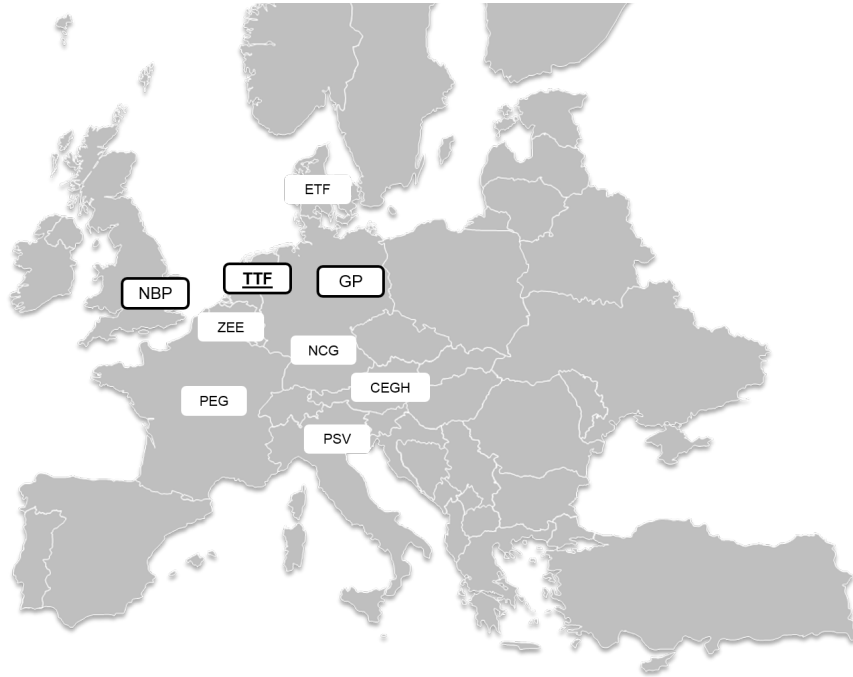


Figure 1: Selected European Gas Hubs. Primary Focus: TTF, Secondary Focus: NBP, GP

2.2 Types of natural gas trading

In the context of the above outlined history of natural gas three basic ways of trading have emerged, which are visualised in Figure 2.

Bilateral Negotiations The most classical way of trading natural gas are individually negotiated contracts between supplier and buyer. These are often very long term contracts aimed at ensuring a reliable physical supply of natural gas. Just as the other contract features pricing systems differ from contract to contract and are not transparent to other market participants. Prices are usually specified to follow a specific benchmark such as the oil price or the gas price at a certain trading hub.

Over the Counter Over the counter trading is a specific system of trading various financial assets. Although the contracts in this system are standardised the trading occurs individually between selling and buying party without the supervision of a financial exchange. This results in less transparency since both quotes and closed trades are not necessarily visible to other market participants. Also there is no clearing house involved in the trading which means that the trading parties are exposed to the credit risk of the opposite party defaulting on its obligations. The products available on natural gas OTC markets contain both spot trading

as well as forwards and options.

Exchange Trading Analogously to OTC trading, products traded at financial exchanges are standardised contracts such as futures or options. The key difference lies in the way trades between parties are conducted. At financial exchanges the market participants post sell or buy offers publicly to all other traders who then have an equal chance to trade on that offer. That way all offers and trades are visible to the whole market. Another difference is the existence of a clearing house which takes over the credit risk of both parties and pays out open debts in case of a default. Overall trading at exchanges is more tightly regulated and offers less risk with more transparency than OTC trading. The largest exchanges for trading natural gas derivatives of European hubs are the Intercontinental Exchange (ICE) and the European Energy Exchange (EEX). Both of these exchanges offer a variety of derivatives for TTF and NBP gas.

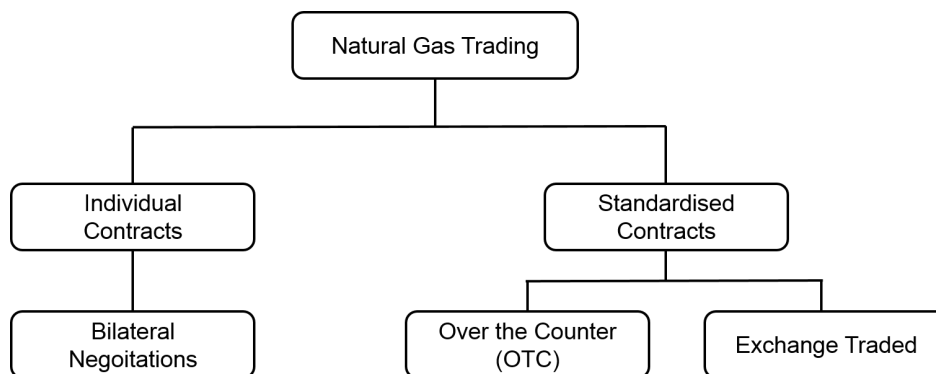


Figure 2: Types of Natural Gas Trading

2.3 Natural Gas Derivatives

The natural gas contracts to be analysed in the course of this thesis can be divided into spot and future contracts. Fundamentally these contracts work in the same way. They cover the delivery of a certain amount of gas at an equal rate over a certain time frame in the future. The difference between these markets lie in the length of the time frame as well as how far the delivery time lies in the future. In the context of this work the delivery of a spot contract lies at most one day in the future and the delivery time frame is at most one day long. This means that the spot market contains basically the day ahead and within day products. Day ahead markets trade gas to be delivered over the next day, whereas within day markets trade hourly products for the remaining hours of the current day. Future markets contain all

markets with delivery time frames longer than one day. These markets contain monthly as well as quarterly, seasonal and yearly products. The seasonal products are the winter season from October to March and the summer season. Usually the most intensively traded future of each kind is the one with the nearest delivery time, e.g. the next month or quarter. This future will be called the Front-Month, -Quarter etc. and will be the main focus of this study.

| Spot Markets | Future Markets |
|--------------|---------------------------|
| Within Day | Months |
| Day Ahead | Quarters |
| | Seasons (Winter / Summer) |
| | Calendar Year |

Table 1: Future vs. Spot Markets

3 Literature Overview

In the following I will give an overview over the current state of research regarding energy price predictions. Since the literature on gas price predictions is rather limited, this review is extended into the areas of electricity and oil prices. As explained above, natural gas shares characteristics with both of the other categories. The literature is categorised into three areas: Linear Models (LR), Feed Forward Neural Networks (FFNN) and Recurrent Neural Networks. The Linear category contains both classical Linear regression models as well as time series models such as AR-Type models and generalised linear models such as logistic regression. For each of the different energy products a table is included listing the reviewed sources with the energy market that was modelled in the respective study and the category of the models used. In the course of this overview the focus will be on the forecasting methods used as well as the choice of predictor variables. Deliberately excluded from this overview is literature that focuses on statistical modelling of energy prices for risk management or purposes other than the explicit prediction of future prices.

3.1 Electricity

With the rising importance and liberalisation of electricity markets the problem of predicting prices on these markets has received increasing attention by the research community. Apart from regulatory changes another factor that has led to an increasing price volatility in some electricity markets is the rising share of renewable producers. This has led to an increased volatility on the supply side of the market. Other factors that make electricity prices unique with respect to other commodities is the lack of storage, international integration of markets and different market regimes across countries. Regarding the different markets one can generally divide them into future markets, day ahead auctions and intra day spot markets. Whereas the first type works analogously to other commodity future markets the day ahead and intra day markets are unique to the electricity domain. While there is some deviation between different countries the day ahead auctions usually work in the way that suppliers place sell offers independently of each other. After the end of the bidding period the market operator clears the market by accepting the cheapest offers up until the estimated demand is met. All sellers whose offers were accepted then receive the price of the highest accepted offer. This price is called the market clearing price (MCP) or sometimes marginal price in the literature and is the focus of virtually all price forecasting research in this area. The intra day markets on the other hand offer continuous trading between market participants up to

around 30 minutes to delivery. Intra day markets are often used to correct for unexpected changes on the supply or demand side with respect to the expectations at the day ahead auction. The research referenced in this section is only a small subset of electricity price forecasting literature selected based on relevance and conceptual proximity to my modelling approach. For a comprehensive review on electricity price forecasting the reader is referred to *Weron (2014)* which illustrates the extend of research activity in this area with almost 500 publications from 1989 to 2013 and was the starting point for this overview.

Linear Models An early attempt to predict electricity prices using a regression purely based on exogenous variables was done by Schmutz and Elkuch (2004) who used natural gas prices and weather data as input variables. In an even earlier paper Kim et al. (2002) use multiple regression in combination with wavelet decomposition. The time series is decomposed into wavelets for different frequencies and these wavelets are then used as the target variable in the regression. Crespo Cuaresma et al. (2004) have applied various univariate time series models including $AR(1)$ as well as different $ARMA$ models to produce short term predictions of German day ahead electricity prices. Weron et al. (2005) applies a similar approach to Californian electricity prices with a focus on the time period of the power crash 2000/01. Despite these examples of models purely based on external regressors or purely based on past observations of the target variable, most linear models in the literature are models which include both types of input variables. One example of this is the extension of the above mentioned work on predicting Californian electricity prices in Misiorek et al. (2006). Here the authors include the system wide load or its forecast as additional input variable to predict the day ahead prices. Another explanatory variable that is often used in these kind of models is temperature data. Knittel and Roberts (2005) add a third order polynomial of the temperature to an ARIMA model in order to predict Californian electricity prices. The authors find the temperature variables to be highly significant in a model predicting power prices in the time period 1998-2000. A linear model combining a larger number of exogenous variable is presented in Zareipour et al. (2006). In this work the authors predict power prices in Ontario using supply and demand forecasts as well as simulation based price forecasts for the Ontario, New York and New England markets as input variables. They find that adding these variables increases model accuracy for forecasts both 3 and 24 hours ahead relative to a standard ARIMA model. Depending on the local market conditions production forecasts of electricity sources with a high local market share are also used as input variables. Following this approach water reservoir levels are used to predict prices in Columbia (Lira et al. (2009))

and wind power production forecasts are used for the Nordic electricity market (Kristiansen (2012)).

Feed Forward Neural Networks In one of the earlier works applying Artificial Neural Networks to electricity price prediction Yamin et al. (2004) generate forecasts for the day ahead price in the Californian power market. They use an architecture with a single hidden layer and one output node for each of the 24 hours. As input parameters they propose various variables describing the status of power lines, load patterns, power outages as well as different time factors such as the week day and conclude that this approach outperforms traditional methods. Gareta et al. (2006) applies a similarly simple feed forward architecture with just one hidden layer. However the authors do not train one model with 24 output dimensions but cluster the hours according to variable importances and train models with smaller output dimensions on each of these clusters. Although the authors report satisfactory accuracies on their test set, they do not include reference models for comparison. In Cruz et al. (2011) feed forward neural networks are evaluated in comparison to a variety of alternative models including ARIMA, exponential smoothing and dynamic regression. The authors fit one univariate model to the data for all hours and include the hour of the day as an input variable. Beyond this variable a further eight variables are chosen from a wider range consisting of demand forecasts and various past values of the electricity price. Based on the mean absolute percentage error for predictions on data from the Spanish electricity markets for the years 2007 / 2008 the neural network approach has only mixed success being ranked in the middle of the alternative approaches. In a more recent study Panapakidis and Dagoumas (2016) compare different neural networks that both vary in their architectures as well as input variables. In this study models solely based on past observations are compared with models incorporating demand, natural gas prices or market data from neighbouring countries. While these models are again of a simple single layer architecture, the authors also implement a stacked approach where they train a neural network to combine the predictions of these separate models into an improved price prediction. In fact this stacked model beats each of the base models on the test data.

Recurrent Neural Networks Recurrent neural networks have only more recently been used for electricity price prediction and there exists overall less literature based on this approach compared to feed forward neural networks. In Anbazhagan and Kumarappan (2013) the authors use an Elman architecture recurrent neural network to predict electricity prices

in both Spain and New York. The model in this work takes as sole input variables the prices for the respective hour of the last 16 days. This model is compared with time series methods such as AR, ARIMA and feed forward neural networks with past prices as inputs. While the RNN in their test scenario outperforms more traditional modelling approaches such as ARIMA it has a higher MAPE than hybrid approaches such as a combination of a neural network and wavelet transformation. In Mirikitani and Nikolaev (2011) the authors develop a new maximum likelihood based approach to train a fully connected recurrent neural network to predict electricity prices in Spain and Ontario. Using only past prices as input variables and 6 nodes in the hidden layer they achieve significant improvements over the reference methods (FFNN, ARIMA) regarding the mean absolute percentage error in both markets. The approach presented in Sharma and Srinivasan (2013) combines an RNN with a so called Fritz-Hugh Nagumo model to accommodate large price spikes and applies a feed forward neural network to predict the residuals from this model. The authors benchmark their model against the models of Mirikitani and Nikolaev (2011), Zareipour et al. (2006) on the respective datasets and find significant error reductions in the area of 10-30 percent of the original reported error. Overall RNNs are one of the most intensely researched modelling approaches for electricity price forecasting at the moment with some very promising results. Another observation one can take away from the literature is that many authors use RNN as a "pure time series" model, meaning they limit the input variables to past observations of the target variable and do not include exogenous variables.

| Source | Market | Category |
|----------------------------------|------------------|----------|
| Schmutz and Elkuch (2004) | Italy | LR |
| Crespo Cuaresma et al. (2004) | Germany | LR |
| Weron et al. (2005) | California | LR |
| Contreras et al. (2003) | Cal., Spain | LR |
| Misiorek et al. (2006) | California | LR |
| Nogales et al. (2002) | Cal., Spain | LR |
| Nogales and Conejo (2006) | Spain | LR |
| Knittel and Roberts (2005) | California | LR |
| Zareipour et al. (2006) | Ontario | LR |
| Weron and Misiorek (2008) | Cal., Nordic | LR |
| Lira et al. (2009) | Columbia, Nordic | LR |
| Kristiansen (2012) | Nordic | LR |
| Yamin et al. (2004) | California | FFNN |
| Gareta et al. (2006) | Spain | FFNN |
| Cruz et al. (2011) | Spain | FFNN |
| Shafie-khah et al. (2011) | Cal., Spain | FFNN |
| Panapakidis and Dagoumas (2016) | Italy | FFNN |
| Anbazhagan and Kumarappan (2013) | Spain, New York | RNN |
| Mirikitani and Nikolaev (2011) | Spain, Ontario | RNN |
| Sharma and Srinivasan (2013) | Spain, Ontario | RNN |

Table 2: Electricity Price Forecasting Literature

3.2 Oil

Being one of the most widely traded commodities and the leading primary source of energy it is not surprising that the problem of forecasting oil prices has received a lot of attention by the scientific community. Unlike electricity, the oil market is globally integrated and has been relatively lightly regulated for a long time. This has lead to the fact that research activity regarding forecasting of oil prices reaches further into the past compared to electricity prices which became interesting only with the liberalisation of the respective markets. Another difference is the fact that oil can be stored at relatively low costs and there is no need to constantly balance demand and supply. The target variables in oil price prediction can be

categorised according to two aspects: the type of oil (WTI, Brent) and the type of market or financial product (Spot, Future).

Linear Models The longer history of research in this area, coupled with the higher popularity of linear modelling techniques in earlier years leads to the fact that overall a higher share of literature on oil price forecasting focuses on linear models. In the studies Ye et al. (2002), Ye et al. (2005) and Ye et al. (2006) the same group of authors develop models to forecast the WTI spot price based on OPEC inventory levels. However instead of just taking absolute values of this variable as input they use various transformations such as deviations of the inventory level from average values for this time of the year as well as year on year changes. The authors reach good forecasting results for testing periods throughout the 1990s and early 2000s. They also point to the long history of studying the relationship between commodity prices and inventory levels which reaches back nearly a century (Ye et al. (2006), p.1). In a working paper for the European Central Bank Des et al. (2008) predict WTI spot prices using forward prices, inventories and OPEC capacity utilisation. Regarding test data from the period of 2004-2006 the authors find their model to outperform both a random walk benchmark as well as oil price expectations implied by the futures market. An example of using exogenous variables to explain changes in oil future prices is the work by Bu (2011) where the author uses reported trading positions of speculative traders as regressors and a GARCH model for the residuals. Moshiri and Foroutan (2006) forecasts the same target variable using an ARMA model purely based on past observations of the WTI future price, which is however outperformed by the other models in his study.

Feed Forward Neural Networks The model beating the ARMA approach in Moshiri and Foroutan (2006) is indeed a feed forward neural network trained on past prices. This network with five neurons in the hidden layer is found to significantly outperform ARMA and GARCH models for daily test data in the time period 2000-2003. In Haidar et al. (2008) the past future and spot prices are used in a neural network to predict the next days spot price and outperforms an alternative network trained with gold and stock prices as input. Alizadeh and Mafinezhad (2010) use a wide range of input variables for their network including the US Nominal Effective Exchange Rate, refinery capacity and historical prices. As is the case for electricity price prediction, many more recent papers that apply neural networks to oil price predictions focus on hybrid approaches. One approach that is especially popular is combining machine learning methods with a wavelet transformation of the price series. Two

examples of this trend are (Pang et al., 2011) and He et al. (2012) both of which manage to reduce model errors following this approach. An example of applying neural networks to the prediction of Oil Future prices is the work done in Shambora and Rossiter (2007).

Recurrent Neural Networks In Mingming and Jinliang (2012) the above mentioned work integrating neural networks with wavelet transformations is extended to recurrent neural networks. The authors find that the resulting model outperforms standard neural networks in forecasting WTI spot and Gold prices. A recent example of applying a recurrent neural network directly to oil price data without transformation is Wang and Wang (2016). In this work the authors use an Elman architecture to predict oil markets for the WTI Spot and Chinese markets as well as stock prices. They find that this architecture outperforms the reference feed forward neural network significantly regarding multiple metrics.

| Source | Market | Category |
|----------------------------------|------------|----------|
| Ye et al. (2002) | WTI Spot | LR |
| Ye et al. (2005) | WTI Spot | LR |
| Ye et al. (2006) | WTI Spot | LR |
| Des et al. (2008) | WTI Spot | LR |
| Bu (2011) | WTI Future | LR |
| Moshiri and Foroutan (2006) | WTI Future | LR, FFNN |
| Haidar et al. (2008) | WTI Spot | FFNN |
| Alizadeh and Mafinezhad (2010) | Brent Spot | FFNN |
| Shambora and Rossiter (2007) | WTI Future | FFNN |
| Amin-Naseri and Gharacheh (2007) | WTI Spot | FFNN |
| Pang et al. (2011) | WTI Spot | FFNN |
| He et al. (2012) | WTI Spot | FFNN |
| Wang and Wang (2016) | WTI Spot | RNN |
| Mingming and Jinliang (2012) | WTI Spot | RNN |

Table 3: Oil Price Forecasting Literature

3.3 Natural Gas

Compared to both electricity as well as oil prices there is a lot less research activity and literature in the field of natural gas price prediction. In fact a lot of the literature that

features statistical modelling of gas prices is focused more on explaining certain market characteristics rather than explicit price forecasting. Special attention of this kind of research has been focused on the connection between oil and natural gas prices (Villar and Joutz (2006), Hartley et al. (2008)) and how this connection has changed since the shale boom in the US market (Geng et al. (2016), Caporin and Fontini (2017)). Another research question, which has been intensively researched in most commodity markets, is the connection between future and spot prices of natural gas (Herbert (1993), Chinn and Coibion (2014)).

Linear Models The work done in Mishra and Smyth (2016) extends the question of the Spot-Future relationship and tries to derive trading strategies for the spot market based on the current future price and its relation to the spot price. Some of the models used in this work are equivalent to a linear regression of the spot price on its past value and the interaction with the logarithmic ratio between future and spot price. One of the earliest attempts at natural gas price forecasting has been implemented in Buchanan et al. (2001) where the authors implement a logistic regression based on trading positions to predict the direction of spot prices changes. In Woo et al. (2006) the authors use a linear regression to predict local natural gas spot prices in California based on prices observed for the Henry Hub trading point. An example of a linear model using the natural gas future price as target variable has been developed in Mu (2007) where the authors use a linear regression with weather data, oil price returns and treasury yields to model the return series of the front month Henry Hub future. One of the models presented in Malliaris and Malliaris (2008) uses a linear regression with price data from other energy commodities such as crude oil and heating oil as regressors to forecast natural gas spot prices.

Feed Forward Neural Networks In Nguyen and Nabney (2008) and Nguyen and Nabney (2010) the authors combine a wavelet transformation and several filters with various modelling techniques to predict natural gas forward prices on the UK market. While they included neural network models they found them performing worse than linear regression and GARCH models with wavelet transformation. A feed forward neural network on past price values is combined with a feature selection algorithm in Salehnia et al. (2013) to predict the Henry Hub spot price. In this study the neural network is found to be more efficient at short-term forecasting than the reference models. The authors of Panella et al. (2012) apply various different feed forward neural network architectures with past prices as input to predict spot prices and find that all those models outperform the reference GARCH model.

Recurrent Neural Network Judging from the examined literature research, the application of recurrent neural networks to natural gas price predictions seems to be extremely limited. In fact the only paper found to apply a recurrent architecture to this problem is Busse et al. (2012). In this study the authors use a recurrent architecture called *Nonlinear Autoregressive Neural Network with eXogenous inputs (NARX)* to predict gas spot prices at the NetConnect hub in Germany. They find that the optimal selection of input variables to the model are temperature forecasts, the USD/EUR exchange rate and the past prices at the NCG, NBP and TTF hubs. The proposed model significantly outperforms a naive prediction based on the last available price value.

| Source | Market | Category |
|--------------------------------|------------|----------|
| Woo et al. (2006) | Cal. Spot | LR |
| Mu (2007) | HH Future | LR |
| Malliaris and Malliaris (2008) | HH Spot | LR, FFNN |
| Nick and Thoenes (2014) | NCG Spot | LR |
| Nguyen and Nabney (2008) | NBP Future | FFNN |
| Nguyen and Nabney (2010) | NBP Future | FFNN |
| Abrishami and Varahrami (2011) | HH Spot | FFNN, LR |
| Panella et al. (2012) | HH Spot | FFNN |
| Salehnia et al. (2013) | HH Spot | FFNN |
| Busse et al. (2012) | NCG Spot | RNN |

Table 4: Gas Price Forecasting Literature

4 Method

In the following section I will give a brief overview over the theory behind Recurrent Neural Networks in General and Long Short-Term Memory (LSTM) network architecture in particular

4.1 RNN

Traditional feed-forward neural networks have shown to be successful in modelling a variety of non-linear input-output relations. However a major shortcoming when it comes to estimate variables that are part of a sequence is the fact that these models are limited to static input-output relations. This means that a set of values for the input variables produces the same output no matter where in the sequence it is located. Regarding many kinds of sequential data such as speech or financial time series, the input-output relation is presumed to change over the course of the sequence. A Recurrent Neural Network offers a method to model these kinds of dynamic relationships. The main idea is to use the output of the hidden layer of observation $t - 1$ in some way as input to the same layer in observation t . A simplified view of the general RNN architecture unfolded across time can be seen in Figure 3. Here we separated the structure of the model at each time step into the Hidden Layer which contains the recurrent structure and the Output Layer which has no connections across time and produces the final predictions \tilde{y} . In an RNN the prediction \tilde{y}_t depends on the inputs at all points in the sequence up to index t . The different types of single layer RNN architectures mainly differ in what the hidden layer H actually consists of and which part of its output is passed to the Output Layer and which to the Hidden Layer in the next time step. The simplest specification is to just use the output h_t of a single non-linearity f as input for both. This architecture is called Simple Recurrent Neural Network or Elman Network. In Figure 4 the architecture of the hidden layer of this network is visualised with the parameter matrices W and U for the weight of the past hidden layer output and current explanatory variables. This results in the following recursive formal definition of the hidden layer output:

$$h_t = f(W h_{t-1} + U x_t)$$

For this definition to be complete one needs to specify some initial state of the hidden layer output h_0 . This state can either be fixed to some reasonable level (e.g. 0) or can be treated as an additional set of parameter over which to train the model. Note that the dimension of the hidden output h can be chosen independently of the number of input variables. Be d_h

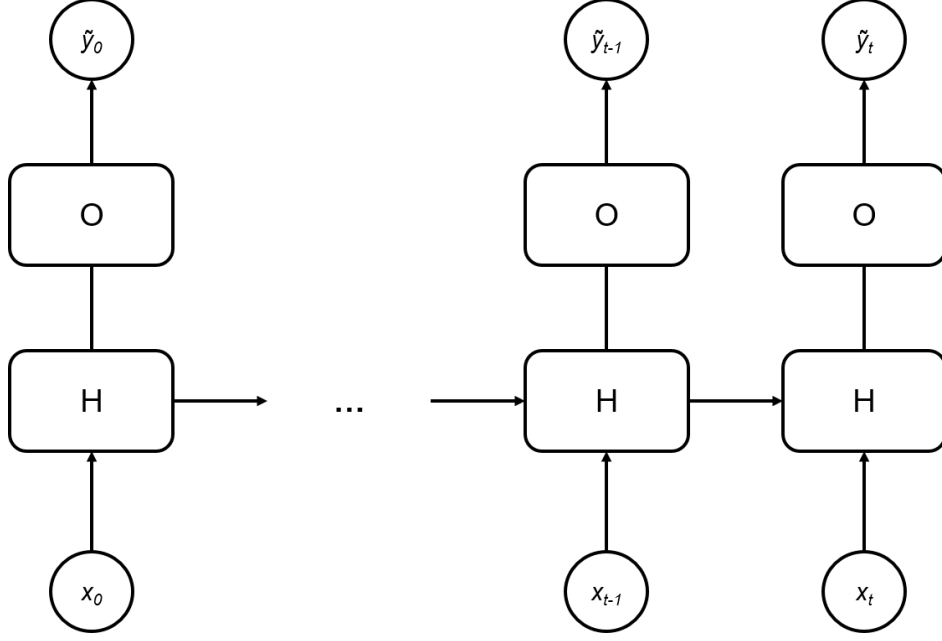


Figure 3: Simplified RNN Architecture

and d_x the number of hidden layer outputs and input variables respectively than the total number of trainable parameters is: $n_{par} = d_h * (d_h + d_x)$.

4.2 Vanishing Gradient Problem

Just as Feed Forward Neural Networks, an RNN is trained using the idea of Backpropagation. Therefore the weights are updated using the derivative of the loss function with respect to each weight. In the following I will assume an additive loss function. Therefore the analysis will be limited to the derivative of the loss function for one observation $l_t = l(y_t, \tilde{y}_t)$. From the previously defined general structure of an RNN network we now that the prediction \tilde{y}_t is a function (represented by the Output Layer in figure 3) of the hidden layer output h_t at that time point. Therefore the loss can be rewritten as:

$$l_t = l(y_t, \tilde{y}_t)$$

$$l_t = l(y_t, f_{output}(h_t))$$

To get the derivative of this loss with respect to one of the recurrent weights W_{ij} using the chain rule one gets:

$$\frac{dl_t}{dW_{ij}} = \frac{l(y_t, f_{output}(h_t))}{df_{output}(h_t)} \frac{df_{output}(h_t)}{dh_t} \frac{dh_t}{W_{ij}}$$

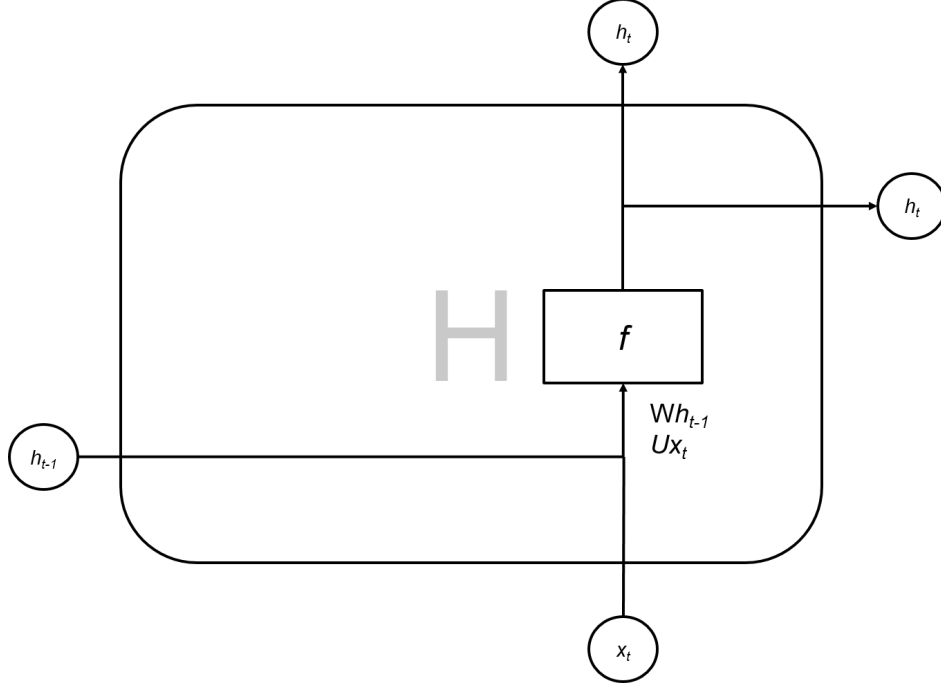


Figure 4: Hidden Layer of Elman Network

The first two terms on the right hand side are independent of the structure of the recurrent / hidden layer and in the following I will therefore concentrate on the derivative of the hidden layer output $\frac{dh_t}{dW_{ij}}$. Entering the definition of the hidden layer of a simple RNN architecture we get the following expression using the chain and product rule:

$$\begin{aligned}\frac{dh_t}{dW_{ij}} &= \frac{df(W h_{t-1} + U x_t)}{dW_{ij}} \\ \frac{dh_t}{dW_{ij}} &= \frac{df(W h_{t-1})}{dW h_{t-1}} \frac{dW}{dW_{ij}} h_{t-1} + \frac{df(W h_{t-1})}{dW h_{t-1}} W \frac{dh_{t-1}}{dW_{ij}}\end{aligned}$$

Due to the right hand term $\frac{dh_{t-1}}{dW_{ij}}$ this again is a recursive formula which we can expand up to $\frac{dh_0}{dW_{ij}} = 0$ and get:

$$\frac{dh_t}{dW_{ij}} = \sum_{k=1}^t \left(\prod_{l=1}^k \frac{df(W h_{t-l})}{dW h_{t-l}} W^{k-1} \frac{dW}{dW_{ij}} h_{t-k} \right)$$

This means that the effect of the hidden layer output k time steps in the past on the current loss gradient is multiplied by a factor of $(\prod_{l=1}^k \frac{df(W h_{t-l})}{dW h_{t-l}}) W^{k-1} \frac{dW}{dW_{ij}}$. Due to its exponential structure the absolute value of this term will either decay towards zero or exponentially rise, depending on the structure of the function f as well as the determinant of the matrix W . These cases are called the *vanishing* and *exploding gradient problem* respectively. While in practice the first problem could be solved relatively easily by clipping the gradient to a certain maxim value, the problem of a vanishing gradient cannot be solved within the framework of

this recurrent architecture. This problem severely limits the ability of simple RNNs to learn long term dependencies across time. While in theory simple RNNs could learn dependencies across arbitrarily large time lags in practise they are limited to influences across just a few time steps. Note that the derivative with regard to one of the parameters of the external variables U_{ij} would a very similar structure and learning these parameters would therefore suffer from the same problems.

4.3 LSTM

The LSTM architecture tries to overcome the vanishing gradient problem using a number of gates to control how the error gradient is passed through the network. This leads to a somewhat more complicated architecture of the hidden layer H which I visualised in Figure 5. This architecture is based on two main ideas. The first idea is to separate the Hidden layer output into two parts: The cell state c_t and the hidden layer output h_t . The second idea is to use logical gates to manipulate the input and output data. This manipulation can be separated into the *forget* (f_t), *input* (i_t) and *output* (o_t) modules. The forget and output gates consist of sigmoid layers which return values between 0 and 1. In the case of the forget gate the output values are multiplied by the previous cell state to "forget" certain parts by multiplying them with values close to 0. The output gate does the same to the hidden layer output of the current time step which is generated by applying some non-linear function f_o to the current cell state. The current cell state is determined by additively updating the past cell state after it has passed through the forget gate using the values returned by the input gate. The input gates values are the result of element wise multiplication of the output of a sigmoid layer and a non-linear layer f_i . This architecture avoids the vanishing gradient problem in two ways. Firstly the cell state is only updated multiplicatively and additively by the output of layers trained on h_{t-1} and x_t . This avoids updating the cell state by repeatedly passing it through a function. The second factor is the use of sigmoid gates which set different parts of the signal to zero at each time step. The combination of these factors avoids the kind of exponential decay observed in the previous section, which enables the network to learn longer dependencies. Since the cell state c_t has the same shape as the hidden layer output, an LSTM has four times as many trainable parameters as a simple RNN architecture with the same shape of h_t and x_t .

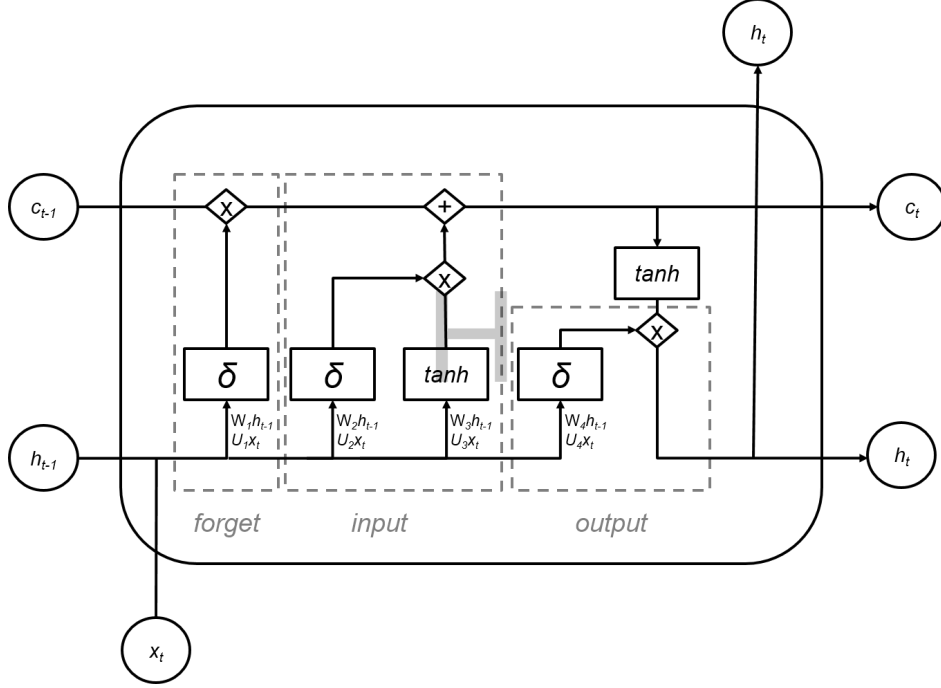


Figure 5: Hidden Layer of LSTM Network

5 Data

The data used for this analysis is downloaded from the *Thomson Reuters Eikon* database. For this purpose I have implemented a Python script that downloads all necessary time series through the *Eikon Web and Scripting APIs*. In the following I will give an overview over the structure and content of the data both on the target variable as well as the input variables used for the model.

5.1 Target Variable

5.1.1 Data Structure

The target variable to be predicted in this thesis is the closing price for the TTF gas future with delivery in the next month, referred to as front month. An advantage of this specification of the target variable is, that one gets one continuous time series for which data can be downloaded for a long period of time. However this definition also poses a significant challenge. The challenge lies in the fact that the product which is traded effectively changes at the change of the month as the delivery period changes. For example the Front Month price quoted on September 30 refers to natural gas delivered in the month of October, whereas on October 1 it refers to delivery in November. This leads to structural breaks and large price

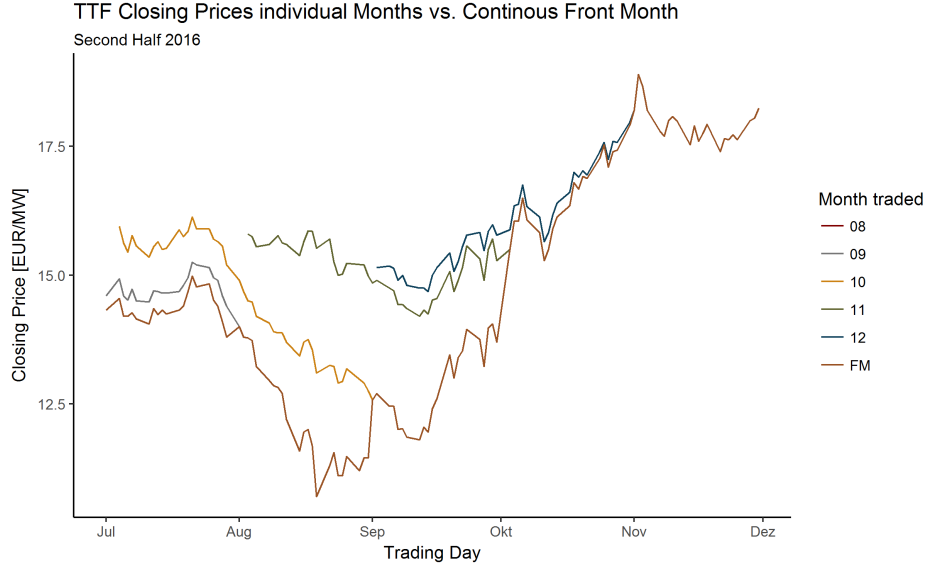


Figure 6: TTF Front Month vs. Individual Months

changes at the end of each month. To illustrate this I have plotted both the front month price as well as the price of each months future as traded before it becomes the Front Month for the second half of 2016 in Figure 6. As one can see the price of the front month jumps at the end of each month to the level at which the next month was traded previously. This means, that while in this thesis I refer to the front month as one continuous target variable, it might also be viewed as a collection of separate time series. To ensure adequate performance of the models this idea is implemented in the implementation of the model training. That means that, when generating predictions for observations at the beginning of each month past price values of the monthly future that is the current front month are used as inputs. This is done instead of choosing the price values of what was the front month before to prevent the structural breaks at the turn of the month to affect model performance.

To get a first overview of the inter temporal dependencies across time in the target variable as well as a hint on the performance of the autoregressive reference models both the autocorrelations as well as partial autocorrelations of the TTF front month are plotted in figures 8 and 9. The very high values of all auto correlations as well as the near zero partial autocorrelations for lags above 1 day suggest modelling the target variable using an AR(1) model, which will probably result in a parameter estimate very close to 1.



Figure 7: TTF Front Month Closing Prices

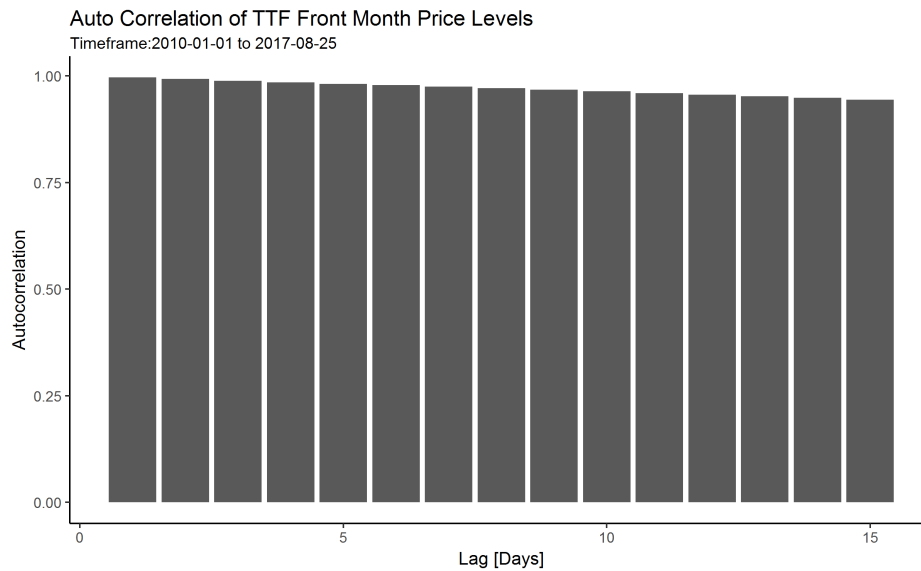


Figure 8: Auto Correlations TTF Front Month Closing Prices

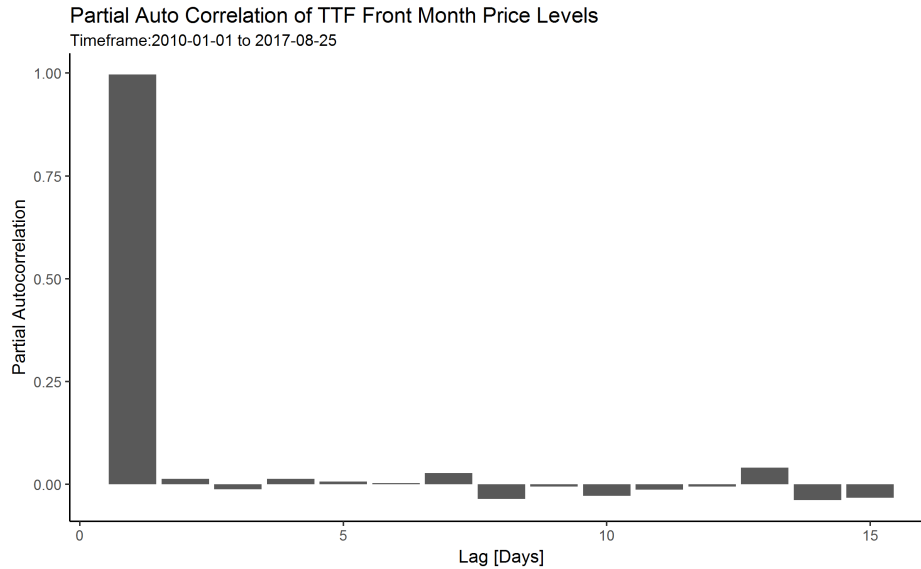


Figure 9: Partial Auto Correlations TTF Front Month Closing Prices

5.2 Input Variables

5.2.1 Other Energy Commodities

TTF Day Ahead /Spot:

NBP Front Month:

Oil Front Month:

Electricity Base Load Front Month:

Electricity Peak Load Front Month:

5.2.2 Gas Market Fundamentals

LDZ Gas Consumption:

Non-LDZ Gas Consumption:

Production:

Storage:

5.2.3 Exchange Rates

Euro - US Dollar:

Euro - Pound:

5.2.4 Correlation Analysis

5.2.5 Data Availability

6 Experimental Design

Designing an experiment to evaluate the performance of the LSTM model in comparison to reference models one has to solve several problems regarding the following topics:

1. Reference models
 - Selecting reference models
2. Parameter tuning
 - Defining parameter tuning process
 - Selecting hyper parameters to tune and choosing tuning grid
3. Variable selection
 - Defining variable selection process
 - Selecting candidate variables
4. Model evaluation
 - Selecting hold out data to exclude from parameter tuning and variable selection.
 - Defining testing scenario

A major challenge arising from this problem is the interdependence between the parameter tuning and the variable selection steps. To tune the parameters we have to have selected a certain set of input variables and vice versa. One way to solve this problem would be to view the subset of selected input variables as just another tuning parameter and integrate both steps. However in this process the number of training iterations that would have to be performed would increase significantly to the product of the iterations in both steps. To avoid excessive computational costs the following alternative approach was chosen:

1. Perform parameter tuning on *univariate* models
2. Perform variable selection using parameter values determined in step 1.
3. Tune parameters again for models using input variables determined in step 2.
4. Evaluate both the tuned univariate models from step 1 as well as multivariate models from step 3.

Each of these steps is executed both for the LSTM model as well as for each reference model for which it is applicable. A *univariate* model in this context is a model trained using only past observations of the front month price as input, whereas multivariate models use both the front month price as well as at least one additional input variable. In the following paragraphs the selected approach for each of the above mentioned decision problems is outlined.

6.1 Reference Models

The prediction results of the LSTM model are compared to each of the following reference models:

Simple Recurrent Neural Network (RNN): This model is the implementation of the above outlined simple RNN architecture where the hidden layer output of the past time step is used as another input variable.

Feed Forward Neural Network (FFNN): The FFNN model is an implementation of the classical Neural Network without any recurrent connection modelling a static input output mapping.

Regression Models: In the case of the price level prediction this reference model consists of a standard linear model. In the univariate case it is an AR(1) model whereas in the multivariate case it is a linear regression on the last available value for each variable. For the binary prediction problem a logistic regression on the same set of variables is applied. All regression models are implemented as special cases of a FFNN without hidden layer and a linear or logistic output layer. That means the solution in both cases is found using gradient descent, and the learning rate as well as dropout is trained in the same way as for the other models.

6.2 Parameter Tuning

The detailed structure of each model as well as the training process is controlled by a number of hyper parameters. The selection of parameters that are considered in this paragraph as well as the terminology is inspired by the *Tensorflow* and *Keras* Python packages, which were used to implement the neural network based models. Theoretically the models could be tuned on all of these parameters. However using the standard grid search used in this tuning approach the total number of parameter combinations would grow exponentially. Since each of the models have to be retrained on every parameter combination this would generate

excessive computational costs. To avoid these costs the parameters are separated into a set of fixed hyper-parameters which are set to constant values derived from experience and literature and a complimentary set of tuning parameters.

6.2.1 Fixed Hyper-Parameters

In the following I will give a brief description of each hyper-parameter that was excluded from the tuning process. This selection was done based on observations from literature as well as the online machine learning community. Except for the *length* parameter none of these parameters alter the actual structure of the respective model but are limited to the training process. The *length* and *batchsize* parameters can be considered features of the *Tensorflow* package and are not necessarily present in the theoretical work on neural networks or alternative implementations.

Length: From the definition of a recurrent neural network there is no theoretic limit on the length of inter temporal dependencies that the model can learn. This is due to the fact, that the gradient as well as the layer activations can flow infinitely far through the network. Regarding the implementation this would also mean that there is no limit on the amount of calculations that would have to be done to determine the gradient based updates to the network weights. Therefore the *Tensorflow* implementation of recurrent neural networks requires the user to pass a length argument which limits the number of time steps that are included in the calculation of the gradients for each observation. This length thereby also limits the maximum length of inter temporal dependencies that the model can learn.

Batchsize: The *Tensorflow* package processes the training data in batches. In practice that means that at a given training epoch the gradients are calculated for a certain subset of training observations. Then the weights are updated using the gradients calculated from this subset. The *batchsize* parameter controls the size of this subset. Therefore in each training step the weights are updated $\frac{n_{obs}}{batchsize}$ times (rounded up to the next integer). Given the same number of training steps a larger *batchsize* therefore means less frequent weight updates, slower learning and less computational complexity.

Epochs: The *epochs* parameter controls the number of training steps, which is the number of times the weight updates are repeated for each training batch. Therefore the total number of weight updates is $epochs * \frac{n_{obs}}{batchsize}$.

Loss: The *loss* parameter determines the loss-function that is minimized during the training of the model. In this work the *Mean Squared Error* (MSE) is used as loss for the price level prediction whereas *binary cross entropy* (BCE) is used for the binary prediction problem. These loss functions are defined in the following way:

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \tilde{y}_i)^2$$

$$BCE = -\frac{1}{n} \sum_{i=1}^n (y_i \log(\tilde{y}_i) + (1 - y_i) \log(1 - \tilde{y}_i))$$

Optimizer: The *optimizer* chooses an optimization algorithm to use when minimizing the loss function on the training set. Following practice and advice from the machine learning community the *Stochastic Gradient Descent* optimizer is used for the FFNN models. Following the advice in the *Keras* documentation the *RMSProp* optimizer is used for recurrent models.

6.2.2 Tuning Parameters

In the parameter tuning stage each model was tuned over the following parameters

Learning Rate: The learning rate is the value by which the gradient values in each iteration are multiplied to get the weight updates. This means that the weight value at epoch $n + 1$ ($W_{ij,n+1}$) is calculated as $W_{ij,n+1} = W_{ij,n} - learningrate * \frac{dl(W_{ij,n})}{dW_{ij,n}}$. A lower learning rate slows down the learning process and increases the number of training epochs necessary to converge on a local minimum of the loss function. If the learning rate is too high on the other hand the gradient descent algorithm might not converge at all, constantly "over-shooting" the minimum.

Dropout: One way to avoid the issue of over-fitting is to randomly drop different input variables at each time step. Using this approach the value of the dropout tuning parameter sets the probability with which any individual input variable is dropped. Dropout is only tuned in multivariate models whereas in the univariate cases it is set to zero.

Architecture: The architecture tuning parameter sets the number of neurons in the hidden layer. In the case of the LSTM network it sets the number of neurons for every trainable layer in all gates. Therefore the total number of neurons in the hidden layer of the LSTM is four times that number.

6.2.3 Tuning Process

For the parameter tuning a simple grid is expanded across the selected values for each tuning parameter. The model is then trained on all data up to December 2015 and evaluated using data from 2016 separately for each parameter combination. At the end the parameter combination with the best performance on the test set is selected.

6.3 Variable Selection

To select the most relevant input factor among all variables described above a forward selection method is used. This means that in each iteration of the process separate models are trained adding each of the remaining candidates to the model. Using the same train-test split as in the tuning process the most promising variable is selected and removed from the set of candidates for the next iteration. This is repeated until five variables have been added. Afterwards the model configuration with the best performance among all sets of selected variables of size one to five is chosen. Note that in all cases the training and testing data is limited to complete observations containing values for all candidate variables. This is done to ensure that differences in performance can be attributed to the model choice as opposed to differences in data availability.

6.4 Model Evaluation

In the model evaluation phase the performance of the LSTM is compared to each of the reference models listed above both in its univariate as well as multivariate version. For the univariate version the parameter configurations are used that were determined in the first tuning step, whereas the parameters and input variables of the multivariate models are set according to the results of the second tuning iteration and the variable selection steps. Evaluation is done in a month wise rolling prediction, meaning that for each month from January - July 2017 the model is retrained on all data previous to that month and then tested based on its prediction for that month. Afterwards the mean value of the evaluation metric is calculated across the testing months.

7 Conclusions

7.1 Results

7.2 Outlook

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A Figures

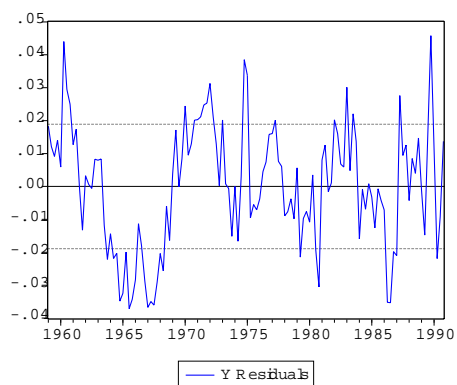


Figure 10: Estimated residuals (2) from model XXX. ...

B Tables

| | Year | Correlation |
|---|------|-------------|
| 1 | 2010 | 0.34 |
| 2 | 2011 | 0.10 |
| 3 | 2012 | 0.05 |
| 4 | 2013 | -0.06 |
| 5 | 2014 | -0.29 |
| 6 | 2015 | 0.78 |
| 7 | 2016 | 0.50 |
| 8 | 2017 | 0.74 |

Table 5: Annual Correlation of Oil and TTF price levels

| | Year | Correlation | Sign |
|---|------|-------------|------|
| 1 | 2010 | -0.07 | 0.49 |
| 2 | 2011 | 0.10 | 0.57 |
| 3 | 2012 | 0.09 | 0.58 |
| 4 | 2013 | 0.01 | 0.60 |
| 5 | 2014 | 0.18 | 0.61 |
| 6 | 2015 | 0.20 | 0.63 |
| 7 | 2016 | 0.20 | 0.61 |
| 8 | 2017 | 0.20 | 0.59 |

Table 6: Annual Correlation of Oil and TTF Daily Returns

| | Year | Correlation | Sign |
|---|------|-------------|------|
| 1 | 2010 | -0.07 | 0.49 |
| 2 | 2011 | 0.10 | 0.57 |
| 3 | 2012 | 0.09 | 0.58 |
| 4 | 2013 | 0.01 | 0.60 |
| 5 | 2014 | 0.18 | 0.61 |
| 6 | 2015 | 0.20 | 0.63 |
| 7 | 2016 | 0.20 | 0.61 |
| 8 | 2017 | 0.20 | 0.59 |

Table 7: Annual Correlation of Oil and TTF Daily Returns

Declaration of Authorship

I hereby confirm that I have authored this Bachelor's/Master's thesis independently and without use of others than the indicated sources. All passages which are literally or in general matter taken out of publications or other sources are marked as such.

Berlin, September 30, 2007

your name (and signature, of course)

| | Month | LaggedValue | LSTM | FFNN |
|----|------------|-------------|------|------|
| 1 | 2016-01-01 | 1.85 | 1.96 | 1.76 |
| 2 | 2016-02-01 | 2.55 | 2.62 | 2.55 |
| 3 | 2016-03-01 | 1.44 | 1.45 | 2.18 |
| 4 | 2016-04-01 | 0.67 | 0.83 | 1.52 |
| 5 | 2016-05-01 | 2.17 | 2.24 | 2.51 |
| 6 | 2016-06-01 | 1.22 | 1.99 | 1.45 |
| 7 | 2016-07-01 | 2.05 | 2.29 | 2.05 |
| 8 | 2016-08-01 | 1.18 | 1.55 | 1.32 |
| 9 | 2016-09-01 | 2.48 | 2.17 | 2.63 |
| 10 | 2016-10-01 | 2.22 | 2.18 | 2.31 |
| 11 | 2016-11-01 | 1.82 | 2.09 | 1.82 |
| 12 | 2016-12-01 | 1.43 | 1.45 | 1.52 |
| 13 | 2017-01-01 | 1.60 | 1.55 | 1.65 |
| 14 | 2017-02-01 | 2.71 | 2.72 | 2.70 |
| 15 | 2017-03-01 | 2.04 | 2.50 | 1.87 |
| 16 | 2017-04-01 | 1.26 | 1.22 | 1.54 |
| 17 | 2017-05-01 | 1.13 | 1.09 | 1.55 |
| 18 | 2017-06-01 | 1.15 | 1.23 | 1.33 |
| 19 | 2017-07-01 | 1.03 | 2.34 | 1.04 |

Table 8: MAPE of models by target month (delivery)

| | Month | LaggedValue | LSTM | FFNN |
|----|------------|-------------|------|------|
| 1 | 2016-01-01 | 0.29 | 0.31 | 0.28 |
| 2 | 2016-02-01 | 0.35 | 0.36 | 0.35 |
| 3 | 2016-03-01 | 0.18 | 0.18 | 0.27 |
| 4 | 2016-04-01 | 0.08 | 0.10 | 0.18 |
| 5 | 2016-05-01 | 0.27 | 0.28 | 0.31 |
| 6 | 2016-06-01 | 0.16 | 0.26 | 0.19 |
| 7 | 2016-07-01 | 0.30 | 0.33 | 0.30 |
| 8 | 2016-08-01 | 0.17 | 0.22 | 0.19 |
| 9 | 2016-09-01 | 0.29 | 0.26 | 0.31 |
| 10 | 2016-10-01 | 0.29 | 0.28 | 0.30 |
| 11 | 2016-11-01 | 0.30 | 0.35 | 0.30 |
| 12 | 2016-12-01 | 0.26 | 0.26 | 0.27 |
| 13 | 2017-01-01 | 0.28 | 0.27 | 0.29 |
| 14 | 2017-02-01 | 0.54 | 0.53 | 0.53 |
| 15 | 2017-03-01 | 0.40 | 0.48 | 0.37 |
| 16 | 2017-04-01 | 0.20 | 0.20 | 0.24 |
| 17 | 2017-05-01 | 0.18 | 0.17 | 0.25 |
| 18 | 2017-06-01 | 0.18 | 0.19 | 0.21 |
| 19 | 2017-07-01 | 0.15 | 0.35 | 0.16 |

Table 9: MAE of models by target month (delivery)

| | Month | LaggedValue | LSTM | FFNN |
|----|------------|-------------|------|------|
| 1 | 2016-01-01 | 0.14 | 0.15 | 0.13 |
| 2 | 2016-02-01 | 0.18 | 0.18 | 0.17 |
| 3 | 2016-03-01 | 0.06 | 0.05 | 0.11 |
| 4 | 2016-04-01 | 0.01 | 0.01 | 0.05 |
| 5 | 2016-05-01 | 0.18 | 0.17 | 0.20 |
| 6 | 2016-06-01 | 0.04 | 0.10 | 0.05 |
| 7 | 2016-07-01 | 0.13 | 0.15 | 0.13 |
| 8 | 2016-08-01 | 0.04 | 0.08 | 0.05 |
| 9 | 2016-09-01 | 0.14 | 0.11 | 0.16 |
| 10 | 2016-10-01 | 0.13 | 0.13 | 0.14 |
| 11 | 2016-11-01 | 0.12 | 0.15 | 0.12 |
| 12 | 2016-12-01 | 0.10 | 0.11 | 0.11 |
| 13 | 2017-01-01 | 0.13 | 0.12 | 0.14 |
| 14 | 2017-02-01 | 0.37 | 0.37 | 0.36 |
| 15 | 2017-03-01 | 0.24 | 0.31 | 0.25 |
| 16 | 2017-04-01 | 0.05 | 0.07 | 0.08 |
| 17 | 2017-05-01 | 0.05 | 0.05 | 0.08 |
| 18 | 2017-06-01 | 0.05 | 0.06 | 0.06 |
| 19 | 2017-07-01 | 0.03 | 0.16 | 0.04 |

Table 10: MSE of models by target month (delivery)

| | Model | CE | AUC | MAE | MeanPrices |
|----|---|------|------|------|------------|
| 1 | Reference | 0.54 | 0.81 | 0.27 | 15.07 |
| 2 | lstm_min_sep_l20_b10_e100_n32 | 0.50 | 0.80 | 0.31 | 15.04 |
| 3 | lstm_min_sep_l20_b10_e200_n16-8_univar | 0.54 | 0.81 | 0.34 | 15.08 |
| 4 | lstm_min_sep_l20_b10_e200_n16_TTFDA | 0.52 | 0.81 | 0.33 | 15.08 |
| 5 | lstm_min_sep_l20_b10_e200_n16_univar | 0.52 | 0.78 | 0.33 | 15.12 |
| 6 | lstm_min_sep_l20_b10_e200_n32_TTFDA | 0.52 | 0.77 | 0.32 | 15.02 |
| 7 | lstm_min_sep_l20_b10_e200_n32_univar | 0.52 | 0.80 | 0.31 | 15.05 |
| 8 | lstm_min_sep_l20_b10_e200_n8_TTFDA | 0.52 | 0.81 | 0.34 | 15.15 |
| 9 | lstm_min_sep_l20_b10_e200_n8_univar | 0.50 | 0.81 | 0.32 | 15.06 |
| 10 | lstm_min_sep_l20_e200_b10_CO2FM | 0.54 | 0.80 | 0.34 | 15.06 |
| 11 | lstm_min_sep_l20_e200_b10_CoalFM | 0.52 | 0.81 | 0.33 | 15.08 |
| 12 | lstm_min_sep_l20_e200_b10_EURGBPFX | 0.51 | 0.81 | 0.33 | 15.08 |
| 13 | lstm_min_sep_l20_e200_b10_EURUSDFX | 0.51 | 0.80 | 0.32 | 15.08 |
| 14 | lstm_min_sep_l20_e200_b10_ElectricityBaseFM | 0.51 | 0.80 | 0.32 | 15.17 |
| 15 | lstm_min_sep_l20_e200_b10_ElectricityPeakFM | 0.52 | 0.78 | 0.33 | 15.15 |
| 16 | lstm_min_sep_l20_e200_b10_NBPDA | 0.60 | 0.58 | 0.35 | 15.23 |
| 17 | lstm_min_sep_l20_e200_b10_NBPFM | 0.57 | 0.79 | 0.34 | 15.13 |
| 18 | lstm_min_sep_l20_e200_b10_OilFM | 0.55 | 0.78 | 0.32 | 15.08 |
| 19 | lstm_min_sep_l20_e200_b10_StorageNL | 0.56 | 0.80 | 0.35 | 15.18 |
| 20 | lstm_min_sep_l20_e200_b10_TTFDA | 0.51 | 0.81 | 0.32 | 15.08 |
| 21 | mlp_min_sep_l1_b10_e100_n32 | 0.52 | 0.81 | 0.33 | 15.12 |
| 22 | mlp_min_sep_l20_b10_e100_n32 | 0.53 | 0.81 | 0.34 | 15.17 |
| 23 | mlp_min_sep_l20_b10_e200_n16-8_ttfda | 0.59 | 0.78 | 0.33 | 17.18 |

Table 11: Results of univariate minimum models 2016-2017