Forecasting day ahead spot price movements of natural gas – An analysis of potential influence factors on basis of a NARX neural network

Sebastian Busse
Patrick Helmholz
Markus Weinmann

Veröffentlicht in:
Multikonferenz Wirtschaftsinformatik 2012
Tagungsband der MKWI 2012
Hrsg.: Dirk Christian Mattfeld; Susanne Robra-Bissantz

Braunschweig: Institut für Wirtschaftsinformatik, 2012

Forecasting day ahead spot price movements of natural gas – An analysis of potential influence factors on basis of a NARX neural network

Sebastian Busse

Georg-August-University Göttingen, Institute of Information Systems
(Chair of Information Management), 37073 Göttingen,
E-Mail: sbusse@uni-goettingen.de

Patrick Helmholz

TU Braunschweig, Institute of Business Information Systems
(Chair of Information Management), 38106 Braunschweig,
E-Mail: p.helmholz@tu-bs.de

Markus Weinmann

TU Braunschweig, Institute of Business Information Systems
(Chair of Information Management), 38106 Braunschweig,
E-Mail: markus.weinmann@tu-bs.de

Abstract

Using a dynamic forecasting approach on basis of a NARX neural network, the possibility of forecasting the day ahead spot price movement of natural gas in the market area of NetConnect Germany is examined. For this purpose, several trader interviews brought together potential influence factors such as temperature, cross-border flows or storage withdrawal rates. To determine the optimal variable combination, those influence factors are used in a sensitivity analysis to estimate the individual impact. It could be shown, that a NARX net depending on only five factors (temperature, exchange rate and the settlements of three major gas hubs) produces the most accurate forecast. As the dominating influence factor the temperature forecast four days ahead (t+4) could be identified.

1 Introduction

For decades, the German natural gas market was characterized by a monopolistic structure which did not allow a competitive environment at all. It consisted out of a mosaic-like pattern of different little subnets for the transmission of natural gas. Therefore, a utility company which wanted to supply natural gas to a customer not situated in its own transmission networkk, had to agree with a large number of transmission operators to transport the gas from the origin to the specific customer. Against the background of a decrease in investments in the mid 80's, the European Commission (EC) started reacting with directives aiming at the liberalization of the energy sector to ensure compatible energy prices. In the middle of the ECs activities was the implementation of the "Entry-Exit-Model" in 2005. This model footed on the creation of large market areas (think of it as pools) in which one has to only agree on one entry- and one exit-agreement. By implementing this system, the barrier for supplying gas to customers nationwide was lowered significantly, enhancing competition.

The forecast of the future movement of the natural gas price becomes therefore more and more important. Accurate forecasts enable market participants to manage their portfolio optimally by placing bids and orders at the right point in time which again helps them to outperform their opponents. To determine this point in time, knowledge about potential input factors which have an impact on the future movement of natural gas spot prices is needed.

In the course of a research project between Braunschweiger Versorgungs-AG & Co. KG (BS Energy) and a German university, this problem was addressed and a model to forecast the day ahead movement of the natural gas spot market price was developed and tested to identify and analyze impact factors on the natural gas spot price movement.

During this research project, three questions had to be answered:

- Which external (fundamental) factors exist having an impact on the short-term natural gas spot price movement? Which impact do they have?
- Which variable combination is sufficient enough to calculate compatible forecasts?

Because BS Energy is already using tools to forecast electricity and natural gas load time series, which are based on Artificial Neural Networks (ANN), the third question to be answered was:

- Are ANN a good model architecture to forecast natural gas spot price movements?

This paper presents an overview of the research results and is structured as follows:

First, the motivation of this research is discussed and a short literature review is given revealing publications which deal with the forecasting of price time series in energy markets and the application of ANN for this purpose. Also, it is reasoned why ANN are used as the model architecture to forecast natural gas spot price movements. Second, the development of the used model, the used data and the methodology of the performed sensitivity analysis are explained. Afterwards the results of the sensitivity analysis used for variable selection are shown. Finally, the model is tested and compared to similar research results.

2 Literature review

Many papers exist implementing Artificial Neural Networks or other statistical methods, i.e. Box-Jenkins (BJ), autoregressive integrated moving average (ARIMA) or generalized autoregressive conditional heteroscedasticity (GARCH) for the purpose of forecasting electricity related time series (e.g. system load and hourly price forecasts) [12]. However, publications in the domain of natural gas market oriented forecasts are sparse.

Subject of most research in this domain is the analysis of general or specific applicability of those methods for energy specific time series (e.g. [13], [15], [17]). Another common approach is to compare them against each other (e.g. [1], [9], [18], [19], [20]). It could be shown, that ANN (or hybrid methods based on ANN) outperform rivaling methods forecasting electricity related time series in most cases (e.g. [3], [13], [18]). It is reasoned that ANN draw their strength in the underlying nonlinearity within the input data. There is no doubt that electricity related time series clearly show nonlinearities (e.g. [1], [15]).

For both, the electricity and the natural gas market, the air temperature is to be said (one of) the main variable(s) influencing the demand.[1] In addition, both resources are grid-bound. Furthermore, gas-fired power plants link both markets closely together. The current politically influenced switch in the German energy mix away from nuclear power towards renewables even intensifies this link because more flexible gas-fired plants are needed to level out the dynamic renewable energy supply.

It is because of that close relationship between the electricity market and the natural gas market, why ANN are guessed to be a good model architecture to forecast natural gas spot price movements.

Due to their complexity and their "black-box" nature, many people still do not trust ANN forecasting capabilities (e.g. [15], [20]). In [15] the authors identified two reasons for this behavior: First they mention that often overfitting leads to poor results. Additionally, non-systematic model tests and results not presented in an adequate manner contribute to that problem. Furthermore, the authors criticized common (linear) methods to determine the optimal lag like the autocorrelation function (ACF) or the partial autocorrelation function (PACF) having ANN as the model architecture. They state that using those methods, nonlinear relations within the model data cannot be detected.

In comparison to most publications in which the approach is to directly forecast the future price (e.g. [1], [3], [8], [9], [13], [17], [18]) the target variable represents the price movement in percent in relation to the settlement price of the day before. This is done for the reason that unlike the electricity price, natural gas prices show little volatility.[2]

As mentioned, publications regarding price forecasting in the natural gas market are sparse. One of the few is the early paper of Buchananan et al. (2001) [5]. They try to predict natural gas spot price movements for the US market analyzing trader positions which are published on a weekly basis for the American market in the U.S. Commodity Futures Trading Commission (CFTC) Commitment of Traders Report. A similar publication for the German market area is not available. Therefore this approach is not feasible for the local market, although they were able to present satisfactory results applying this method.

Another research paper dealing with natural gas price forecasts is published by Nguyen et al. (2010) [11]. However, the authors of that paper are not focusing spot market prices but monthly forward products (futures) instead. They were able to calculate the forecast with a mean absolute percentage error (MAPE) between 1.6 and 1.8 percent using linear regression (LR) and GARCH models. Using a multilayer perceptron (MLP), a special form of ANN, they achieved slightly worse results than using the GARCH approach.

[1] This is claimed in [15] for the electricity market.

[2] The spot market price for electricity (PHELIX) at the European Energy Exchange (EEX) fluctuates between 30 and 80 EUR per MWh, whereas the average volatility of the spot market price for natural gas at the EEX is about three percent.

3 Method and Data

3.1 Data

At the beginning of the research project in February 2011, several internal, i.e. BS Energy, and external (i.e. Centrica Energie GmbH, Stadtwerke Hannover AG) traders and portfolio managers were questioned to identify potential influence factors of natural gas prices. All questioned persons possess many years of experience in natural gas trading and can therefore be classified as experts regarding the natural gas market. They identified the following influence factors:

- Geopolitical events and political decisions
- Seasonality / Temperature
- Storage key figures
- Transport capacity / System load
- Substitutes (e.g. oil price)
- Clean Spreads
- Liquefied natural gas (LNG) availability

Most of those named factors are backed by literature (e.g. [2], [11]).

After the survey was completed (end of February 2011), time series data for available information reflecting the mentioned factors or derivations of it was gathered. Yet, the factor "geopolitical events and political decisions" could not be mapped in a time series due to its nature. Also, sufficient information regarding LNG availability was not obtainable.

On top of the named input variables, technical variables in form of the settlement spot prices of the major gas hubs National Balancing Point (NBP), Title Transfer Facility (TTF) and the target price time series of NetConnect Germany (NCG) were collected. The interval limiting factors were the storage key figures, like the storage withdrawal rate and the storage level in use. That information is available since January 2010 only. Therefore time series data from January 2010 to February 2011 is being used. Data for all fundamental variables can be found openly accessible in the internet.[3] Price time series were provided by Norwegian data aggregator Montel and the European Energy Exchange (EEX) via their online platforms.

Hence, the variable test set includes the following inputs:

- Natural gas price time series (NCG, NBP and TTF)
- Diff2FM
  (difference between current spot price and the future contract for delivery in 2 month)
- Exchange rate USD/EUR
- Gasoil (spot price)
- Net cross-border flows into Germany (for available border points)

[3] Fundamental variables like cross-border flows, storage withdrawal rate, storage level, etc. are openly accessible via the transparency platform of the European network of transmission system operators for gas (ENTSOG) under the URL *http://www.gas-roads.eu*

- Temperature forecasts (1 to 5 days ahead)
- Storage withdrawal rate (netWD), storage level (sfull) and self-designed weighted[4] net withdrawal rate (weighted netWD)
- Clean Spreads (spot and front month contracts for base- and peak-load)
- Temporal information (days to next trading day / national holidays)

To fit the task, the data is preprocessed. First, all but the time series for the temporal information are converted into the daily change in percent:

$$t_{perc} = \left\{ \frac{t_0 - t_{-1}}{t_{-1}} \right\} \tag{1}$$

Secondly, data sets containing outliers were removed, having outliers defined as values differing more than four times the standard deviation from the mean. Afterwards, using a map-min-max function, the values were transformed into the interval]-1:1[reflecting the most sensitive range of the activation function (hyperbolic tangent) of the ANN.

3.2 Model architecture and forecasting method

A Nonlinear Autoregressive Neural Network with eXogenous inputs (NARX) was used as model architecture to forecast the movement of the day ahead spot price for the market area NetConnect Germany (NCG) as the, at that time, largest market area in Germany. This type of network design belongs to the group of (time) recurrent networks meaning that it incorporates temporal information in its forecasting algorithm.[5] The choice to use a NARX topology is based on the conclusion, that NARX networks have been shown to perform better than many conventional recurrent networks [10].

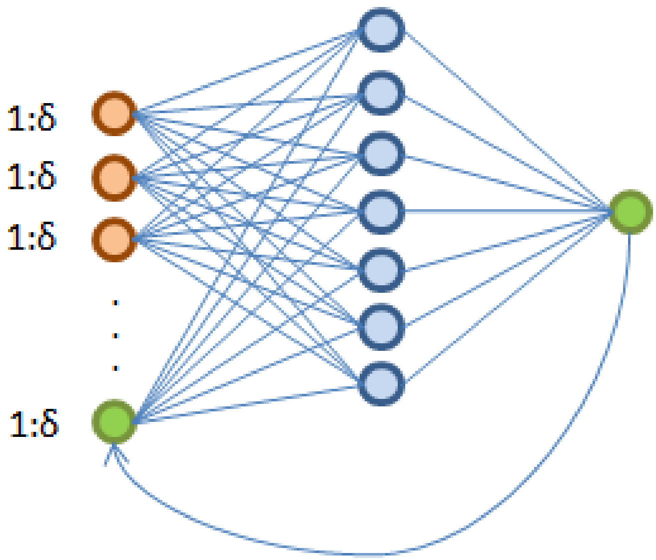


Figure 1: Schematic draft of a NARX Neural Network

---

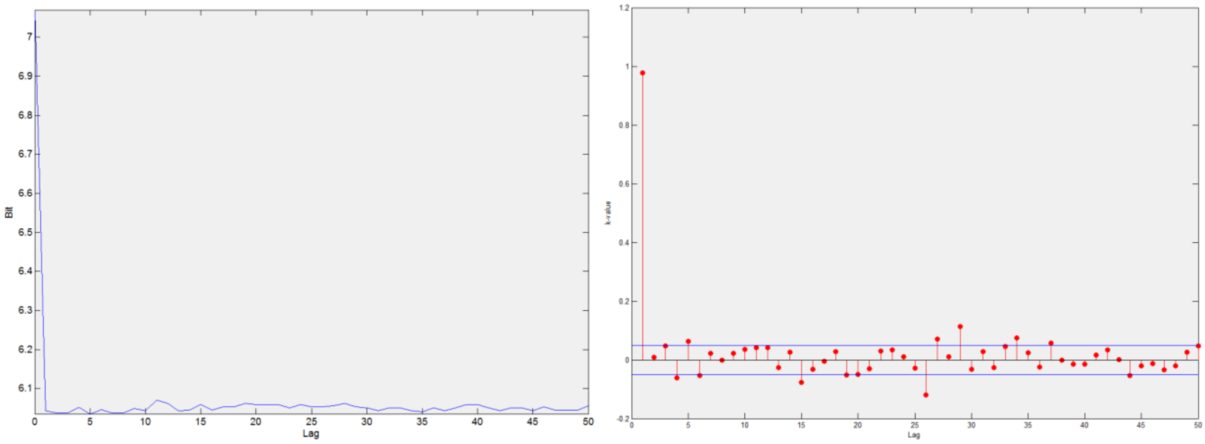
[4] The weight is a parabolic function of the storage level. This approach is based on the assumption that the impact of a storage withdrawal has more influence on market participant's behavior when the storage operates at its technical boundaries.

[5] See [4] for detailed information about recurrent neural networks.

For the optimal amount of hidden neurons a methodology introduced in [8] is being used which is based on the Geometric Pyramide Rule of Masters. Following this rule the optimal amount of hidden neurons is determined by the square root of the amount of input neurons multiplied by the number of output neurons. Therefore, the model architecture consists out of a NARX neural network with 40 neurons[6] on the input layer, one neuron on the output layer and one hidden layer containing seven hidden neurons.

Using a recurrent neural network (RNN) helps to map temporal information from passed periods onto the future development of the time series. However, this methodology creates the need of determining the optimal lag (δ) of each individual input stream. In this case, the optimal lag is selected using two different methods. First, with an auto mutual information function (AMIF) trying to analyze the nonlinear dependencies within the temporal data (see Figure 2(a)).[7] Second, for reasons of comparison, a partial autocorrelation function (PACF) as a linear method was used to calculate the, by definition linear, correlation within each input stream (see Figure 2(b)).

By finding the first local minimum of each time series AMIF, the optimal lag is being determined [3]. Applying this method to all time series the optimal lag is found to be at point t_{-1}. The PACF analysis produces the same outcome, having the level of significance set to 0.05.



(a) Auto Mutual Information Function (b) Partial Autocorrelation Function

Figure 2: AMF and PACF to determine optimal lag

Furthermore, due to a small data basis a jackknife method, as presented in [1], combined with a moving window testing method (see Figure 3), similar to the one presented in [8], is being used. By doing this, the latest data set within the interval is separated and the remaining sets are assigned to the training and validation sets by random. Only the separated set is being used as test set. To guarantee a sufficiently large testing interval, after the forecast is calculated using this configuration, the windows are moved one time step ahead and the model is newly initialized and trained to calculate the next forecast.

[6] 40 input neurons result out of 19 input variables each be considered with the current value and one lagged value. Additionally the calculated forecast is used as a input for the next calculation.

[7] See [16] for a detailed explanation of mutual information.

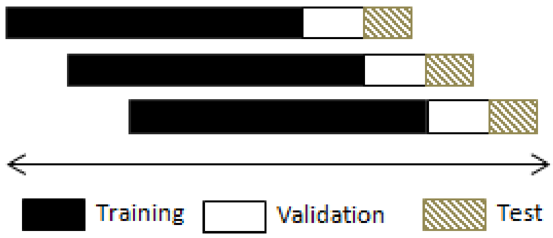


Figure 3: Moving window testing method based on [8]

To ensure automatic forecasting ability, meaning that the model is always using the latest information available, a dynamic forecasting approach is applied. This is especially important, because the natural gas market changes constantly due to the fact that it is still in a development phase. The dynamic forecasting method therefore does not initialize and train the ANN one time only but for every forecast again. Additionally, for every single forecast a number of iterative forecasts are calculated to average the output. That way, extreme forecasts can be reduced.

3.3 Evaluation criteria and sensitivity analysis

As main evaluation criteria a performance indicator called "hitratio" is being used. It reflects the proportion of successful forecasts and is calculated as follows:

$$\text{hitratio} = \left\{ \frac{forecasts - errorcount}{forecasts} \right\} \tag{2}$$

In the end a forecast is called successful if the algebraic sign of the forecast matches the true one. This kind of performance measure is not one of the popular measures but can be found in other publications, possibly under different names [7]. Mainly the decision to use this measure is based on the task provided by BS Energy, who wanted to develop a method forecasting the direction the spot price will change. The little volatility of natural gas spot price movements added to the problem that standard measures were not appropriate for the task assigned. However, to include at least one standard measure classifying ANN performance [20], the forecast's MAPE is calculated.

To analyze each input's impact on the movement of the natural gas spot price, two sensitivity analysis are conducted. First, as a benchmark, a feature selection method introduced in [14] by Peng et al. (2005) is applied. Their minimal-redundancy-maximal-relevance (mRMR) criterion is based on the calculation of the maximal relevance between the individual variables using mutual information trying to achieve minimal redundancy between the input factors. Mathematically it is defined by the following constraint:

$$\max_{x_j \in X - S_{m-1}} \left[I(x_j; c) - \frac{1}{m-1} \sum_{x_i \in S_{m-1}} I(x_j; x_i) \right] \tag{3}$$

In this case, *I* stands for the, on mutual information based, relevance and S_{m-1} for the feature set with m-1 features.[8]

[8] For detailed information about the mRMR-algorithm see [14]

The second sensitivity analysis is focusing on a sensitivity test of the model analyzing the influence of each fundamental variable on the set of technical input factors (i.e. all natural gas price time series). During the analysis, each fundamental variable was added to the set of technical input factors separately observing the impact on model performance in terms of hitratio and MAPE. In the aftermath, the results of the sensitivity analysis were used to select the features maximizing the model performance.

4 Results

4.1 Sensitivity analysis

As test interval, the period between mid January 2011 and mid February 2011 is selected representing the most current period within the available data. For each day of the test period six forecasts are calculated to select the median as benchmark. The results of the sensitivity analysis are shown in Table 1. In contrast to the mRMR-based sensitivity analysis the variables relevant for storage (*sfull*, *netWD*) were examined independently to be able to evaluate the designed variable *weighted netWD*. The results tend to show that the storage level does not have a significant impact on the price movement. Therefore, the designed withdrawal measure is influenced negatively by the storage level and does not have more impact than the withdrawal rate on its own.

			Hitratio			
Var Name	Sens Rank	mRMR Rank	Median	Min	Max	Spread
Tech Vars		2,3,4	0.4656	0.4138	0.5862	0.1724
Temp Progn t+4	1	1	0.6207	0.5172	0.6923	0.1751
Temp Progn t+2	2	17	0.5769	0.4615	0.7692	0.3077
Gasoil	3	7	0.5690	0.3793	0.6207	0.2414
Diff 2FM	3	14	0.5536	0.5000	0.6071	0.1071
t+1 holiday	5	12	0.5517	0.5172	0.5862	0.0690
USD/EUR	6	5	0.5517	0.4138	0.6207	0.2069
netWD	7	*	0.5400	0.4800	0.6000	0.1200
weighted netWD	8	15	0.5158	0.4815	0.6667	0.1852
CS DA Base	9	10	0.5000	0.4138	0.6552	0.2414
CS FM Base	10	8	0.4828	0.4138	0.6897	0.2759
Span t+1	11	13	0.4828	0.4138	0.6207	0.2069
Netflow	12	6	0.4815	0.4444	0.5158	0.0741
Temp progn t+3	13	18	0.4815	0.2963	0.6296	0.3333
Temp Progn t+5	14	16	0.4808	0.2692	0.5385	0.2692
Temp progn t+1	15	19	0.4808	0.2692	0.5769	0.3077
sfull	16	*	0.4483	0.3793	0.4828	0.1034
CS FM Peak	17	9	0.4483	0.2414	0.5862	0.3448
CS DA Peak	18	11	0.4138	0.3893	0.4828	0.1034

Table 1: Results of the sensitivity analysis

Another observation suggests that of all examined fundamental input factors the forecast of the temperature four days ahead has the most impact on the natural gas spot price movement. This could be due to the instance that close temperature forecasts are already included in today's prices. Because temperature forecasts for days far in the future (obviously more than four days ahead) are very uncertain, four days ahead could therefore be the point at which market participants start to believe in temperature forecasts and begin to include those information gains into their pricing estimates.

The variable *Temp Progn t+2* does probably not have a significant impact on the price movement although the sensitivity analysis suggests that at first sight. The large spread indicates that by adding this input factor no forecasting stability is being gained. In addition, the high mRMR-rank does tend to suggest that the high sens-rank is achieved randomly. In contrast to this variable, the two input factors *USD/EUR* and *gasoil* seem to have a significantly large impact on the natural gas spot price movement, because they show relatively good and equal performances in both rankings.

It is important to bear in mind that the mRMR-method does consider dependencies between the variables. Hence, most differences between both methods' rankings are explainable.

4.2 Maximizing model performance

Adding input factors iteratively based on the variable's mRMR-rank, the best model performance can be observed at step five, at which the model processes five input streams: the temperature forecast four days ahead, the natural gas prices of the three major hubs and the exchange rate USD/EUR (see Figure 4).

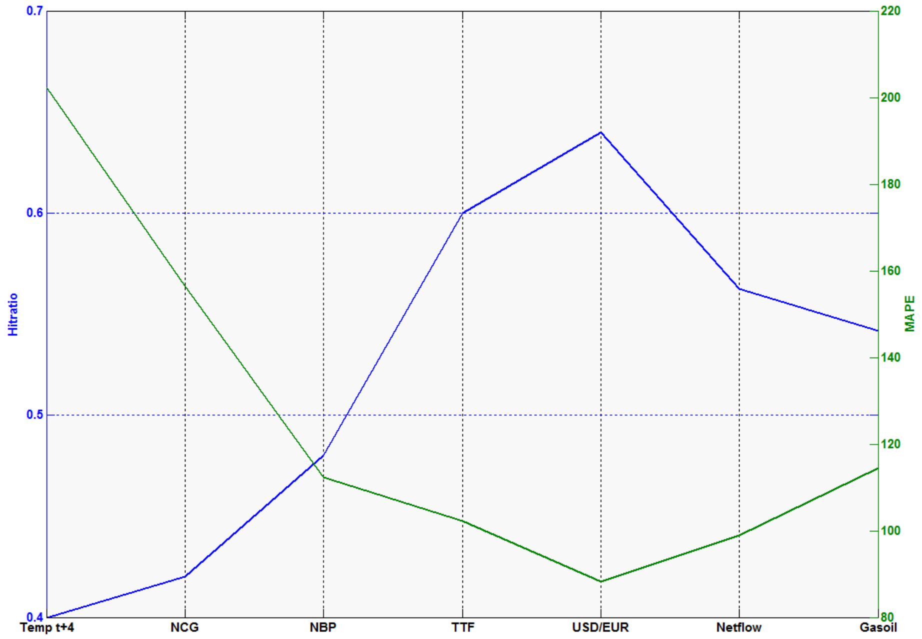


Figure 4: Model test results based on mRMR rank

At step five, the hitratio reaches a maximum at 0.64. At the same time the MAPE is at its minimum at 88.20. After step eight, the performance converges against a hitratio of 0.5490 and a MAPE of 125.

Compared to a naïve forecasting approach, defining today's price movement as the forecast, the model performs better. Over the same period, the naïve method achieves a hitratio of 0.6 and a MAPE of 317.

5 Discussion

It was not a surprise that the temperature does have the largest impact on the short term gas price development. Nevertheless, the observation, that the four day ahead forecast does have the most influence is interesting. This finding matches presumptions some traders mentioned in the interviews previous to the model development, that four days ahead marks the point in time from which on temperature forecasts are being trusted.

In addition, the result, that the exchange rate between the US dollar and the Euro is of importance for the natural gas spot price movement, leads to the question if the exchange rate between the British Pound and the Euro is of importance, too. This is based on the fact, that with the NBP, the most active (European) trading hub in terms of traded volume is located outside the Euro zone.

Also, the observation that both, nonlinear and linear methods to identify the optimal lag show the same results suggests, that the natural gas price (short-term) development is not dominated by nonlinear input factors. Therefore linear methods, like GARCH, may be favored before nonlinear ones like ANN to reduce forecasting complexity.

6 Conclusion and outlook

At the beginning of the research project three questions were addressed:

1. Which external (fundamental) factors exist having an impact on the short-term natural gas spot price movement? Which impact do they have?
2. Which variable combination is sufficient enough to calculate compatible forecasts?
3. Are ANN a good model architecture to forecast natural gas spot price movements?

Forecasting price movements instead of definite prices is not common in literature. The reasons why it was done for this research were laid down in section two.

During the project, a set of input factors having an impact on the short-term natural gas spot price movement was assembled questioning natural gas market experts. This variable set was then tested on each variable's individual impact on the spot price movement. The results are shown in Table 1.

To answer the second question, the feature selection algorithm of Peng et al. (2005) [14] was applied and the selected variables were fed to the model iteratively. The best performance could be achieved selecting only five input factors (the temperature forecast four days ahead, the natural gas spot prices of the three major hubs and the exchange rate USD/EUR). This variable combination led to a forecasting accuracy of 0.64 in terms of hitratio and of 88.20 in terms of MAPE.

It was mentioned that publications aiming at forecasting natural gas prices are sparse. Therefore it is difficult to evaluate the model performance. To get a feeling and to classify the model performance one may have a look at the recently published paper of Kara et al. (2011) [7]. They do not forecast natural gas prices but the development (movement) of the Istanbul Stock Exchange National 100 Index. Because the Turkish stock market is relatively small compared to major stock markets, it may be seen analogously to the market of natural gas which is a relatively small market, too. Applying an ANN-model, they were able to achieve hitratios, they call it prediction performance, between 68.29 and 79.67, depending on the interval observed. Thus, this model's results can be seen as satisfactory. The poorer results for the gas market forecasts may be due to even less market participants than there are on the Turkish stock market. Even Federal Minister of Economics and Technology Philipp Rösler just stated in an *Energate* newsletter that there is not enough structural competition in the German energy sector.[9]

For future research the data availability and quality should be much better, enhancing especially ANN forecasting performance, because ANN are said to perform better on a relatively large data set, compared to other forecasting methods [6]. During 2011 the liberalization process took a step forward and now forces transmission operators to publish relevant data immediately and openly accessible on the internet. Rising competition helps to additionally increase volumes traded at EEX. Between natural gas traders it is commonly agreed on, that in the near future even more volumes are traded at EEX.

As a conclusion of this research, linear models should be tested on their forecasting performance of natural gas spot price movements. Our model results could serve as a good benchmark for this purpose. Additionally, similar tests should be conducted in later periods to validate the hypothesis, that data availability and quality is improving continuously.

7 References

[1] Allred, LG (1991): Jackknife method for validating neural network models. In: IJCNN-91-Seattle International Joint Conference on Neural Networks.

[2] Amjady, N; Keynia, F (2008): Day ahead price forecasting of electricity markets by a mixed data model and hybrid forecast method. International Journal of Electrical Power & Energy Systems 30(9):533-546.

[3] Andalib, A; Atry, F (2009): Multi-step ahead forecasts for electricity prices using NARX: A new approach, a critical analysis of one-step ahead forecasts. Energy Conversion Management 50(3):739-747.

[4] Bodén, Mikael (2001): A guide to recurrent neural networks and backpropagation: Report from the NUTEK-supported project AIS-8, SICS.Holst: Application of Data Analysis with Learning Systems.

[5] Buchananan, WK; Hodges, P; Theis, J (2001): Which way the natural gas price: an attempt to predict the direction of the natural gas spot price movements using trader positions. Energy Economics (23):279-293.

[6] Foster, WR; Collopy F; Ungar LH (1992): Neural network forecasting of short, noisy time series. Computers & Chemical Engineering 16(4):293-297.

[7] Kara, Y; Acar Boyacioglu, M; Baykan, Ö (2011): Predicting direction of stock price index movement using artificial neural networks and support vector machines: The sample of the Istanbul Stock Exchange. Expert Systems with Applications 38(5):5311-5319.

[8] Kastra, I.; Boyd, M. (1996): Designing a neural network for forecasting financial and economic time series. Neurocomputing 10(3):215-236.

[9] He stated this in an interview printed in the *Energate Messenger* of 11/08/03

[9] Li, G; Liu, CC; Mattson, C; Lawarree, J (2007): Day-Ahead Electricity Price Forecasting in a Grid Environment. IEEE Transactions on Power Systems 22(1):266-274.

[10] Lin, T; Horne, GB; Giles CL; Kung, SY (1998): What to Remember: How Memory Order Affects The Performance Of NARX Neural Networks. In: IEEE World Congress on Computational Intelligence:1051-1056.

[11] Nguyen, HT; Nabney, IT (2010): Short-term electricity demand and gas price forecasts using wavelet transforms and adaptive models. Energy 35(9):3674-3685.

[12] Nogales, FJ; Contreras, J; Conejo, AJ; Espinola, R (2002): Forecasting Next-Day Electricity Prices by Time Series Models. IEEE Transactions on Power Systems 17(2):342-348.

[13] Pino, R; Parreno, J (2008): Forecasting next-day price of electricity in the Spanish energy market using artificial neural networks. Engineering Applications of Artificial Intelligence 21(1):53-62.

[14] Peng, H; Long, F; Ding, C (2005): Feature selection based on mutual information: criteria of max-dependency, max-relevance, and min-redundancy. IEEE Transactions on Pattern Analysis and Machine Intelligence 27(8):1226-1238.

[15] Steinherz Hippert, H; Pedreira, CE; Rainaldo Castro, S (2001): Neural networks short-term load forecasting. A review and Evaluation. IEEE Transactions on Power Systems 16(1):44-55.

[16] Steuer, R.; Kurths, J.; Daub, O.; Weise, J.; Selbig, J. (2002): The mutual information: Detecting and evaluating dependencies between variables. Bioinformatics 18(2): 231-240.

[17] Szkuta, BR; Sanabria, LA; Dillon, TS (1999): Electricity Price Short-Term Forecasting Using Artificial Neural Networks. IEEE Transactions on Power Systems 14(3):851-857.

[18] Vahidinasab, V; Jadid, S; Kazemi, A (2008): Day-ahead price forecasting in restructured power systems using artificial neural networks. Electric Power Systems Research 78(8):1332-1342.

[19] Weigend, AS; Gershenfeld, N (1993): Results of the time series prediction competition at the Santa Fe Institute. In: IEEE International Conference on Neural Networks.

[20] Zhang, G; Patuwo, BE; Hu, MY (1998): Forecasting with artificial neural networks. The state of the art. International Journal of Forecasting 14:35-62.