Acta Montanistica Slovaca
ISSN 1335-1788
actamont.tuke.sk

Driving Forces Behind Gas Price in Global Markets

Marek VOCHOZKA[1*], *Andrea NOVOTNÁ*[2] and *Blanka BOROVKOVÁ*[3]

Author, author´s address:
[1]Institute of Technology and Business in České Budějovice, School of Expertness and Valuation, Okružní 517/10, 37001 České Budějovice, Czech Republic
e-mail: vochozka@mail.vstecb.cz

[2]Institute of Technology and Business in České Budějovice, School of Expertness and Valuation, Okružní 517/10, 37001 České Budějovice, Czech Republic
e-mail: 27509@mail.vstecb.cz

[3]Pan-European University, Bratislava, Faculty of Economics and Business, Department Management and Marketing, Tematínská 10, 851 05 Bratislava, Slovakia
e-mial: 22725@mail.vstecb.cz

***Correspondence:**
Marek Vochozka, Institute of Technology and Business in České Budějovice, Research department of Economics and natural resources management, Okružní 517/10, 37001 České Budějovice, Czech Republic
Tel.:+420725007337
e-mail: vochozka@mail.vstecb.cz

How to cite this article:
Vochozka, M., Novotna, A., and Borovkova, B. (2022), Driving Forces Behind Gas Price in Global Markets, *Acta Montanistica Slovaca*, Volume 28 (1), 141-156.

DOI:
https://doi.org/10.46544/AMS.v28i1.12

Abstract
Gas is a fossil fuel belonging to non-renewable and essential energy sources. Although its reserves are, contrary to oil, sufficient, we expect the gas extraction to peak and gradually dwindle to nothing soon. The figures on natural gas prices gave us a breeding ground for research based on correlation analysis and time series regression using multilayer perceptron networks. The outcomes proved no measurable effect of government decisions on the global gas trends. The study foresaw that natural gas value will be highly variable through 2023 since gas rates go through regular cycles lasting several years. First, the course sends the price soaring and then lets it fall to its original value. Other contributory factors involve adopted legislation, prices of related commodities, weather changes, the Czech Crown exchange rate and the situation abroad. The war between Russia and Ukraine is one example of inflation.

Key words
Neural networks, correlation analysis, natural gas trends, government decisions, forecasting natural gas price

Introduction

Gas is a fossil fuel belonging to non-renewable and essential energy sources. Although its reserves are, contrary to oil, sufficient, we soon expect the gas extraction to peak and gradually dwindle to nothing. Virglerova (2013) argues that declining demand will probably reflect rising gas prices. The natural gas price depends on multiple factors, including local supplies, requests for goods or political situations and government decisions. Rocketing natural gas rates pose an enormous political and economic problem, incurring extra household and industry costs and affecting global firms' competitiveness. Europe must ensure that consumers receive sufficient sustainable and available energy supplies and that the industry maintains competitiveness (Giziene and Zalgiryte, 2016).

The European liberalization of the gas industry resulted in multiple trade hubs. Although these focal points seem liquid and support gas-to-gas competition, gas market efficiency remains at the centre of attention. A fair gas share always comes through long-term agreements and negotiated oil prices. Because of limited gas supplies in the European market, the growing demand for natural gas makes consumers careful about storing the fuel to ensure energy security (Hulshof van der Maat and Mulder, 2016; Qin et al., 2022). Europe has recently seen accelerating trends in building new and extending existing Union gas tanks, using depleted reserves or salt caves (Osieczko and Gazda and Malindžák, 2019). Heavy gas consumption in The European Union makes its member states dependent on imports, constructing the Nord Stream pipeline to secure sufficient supplies. Nord Stream 2 (NS 2) project along the shores of the Baltic Sea aims to increase gas supplies from Russia to Germany and other EU countries, championing mutual interests: to meet the growing demand for gas in the EU markets and strengthen the energy security in the EU (Zhiznin and Timokhov, 2019).

Trans Anatolian Natural Gas Pipeline Project (TANAP) contracted between Azerbaijan and Turkey is another essential gas supply for Europe, transporting natural gas from Sahdeniz 2 to Europe through Turkey (Kaya, 2017). The Turkish production sector became the backbone of the economy, kick-started by imported natural gas. On the flip side, the country's dependence on imported energy made the state highly vulnerable to unexpected "dreadful" supply shocks, threatening long-term industrialization sustainability (Hasheminasab et al., 20202; Skare and Porada-Rochon, 2022). Owing to long-term contracts ensuring cheap natural gas import, Turkey still has time to develop alternative energy sources and adopt a coherent pricing policy for imported gas to get generous fund allocation (Yorucu, 2016).

The eastern China-Russia pipeline guaranteeing the import of natural gas to China is the third global gas supply, reinforcing the natural gas infrastructure in North-Eastern China, including gas storage and connecting pipes. The pipeline network covering 14% of the total area of China observes the optimum layout of the gas storage and carbon emissions to comply with Chinese emission limits and neutrality objectives (Gedit, 2018).

Natural gas contributes to mitigating climate change (Zhu et al. 2016), replacing other fossil sources to improve the environment. This commodity ensures the safety of energy supplies, limiting global pollution. The parties involved welcome the possibility of forecasting natural gas prices, wielding an effective instrument in cut-throat competition markets (Su et al. 2019). Natural gas is a fossil fuel used as an energy source for cooking, heating, electricity, fuel for vehicles etc. At the current level of consumption, the remaining estimated depletable natural gas reserves would last 250 years, making it a primary commodity. The great need for this source serves as a powerful weapon in political negotiations (Stehel and Suler, 2016).

The global use of gas also impacts its price movement that depends on adopted legislations of individual countries, geopolitical situations and relations between the world's leading powers with the hugest gas reserves or its consumption. Given their political and geopolitical positions, the Middle-East states producing increased amounts of gas could become the future leading players in supply and demand scenarios, including Turkey as an outstanding gas supplier to European countries. Thanks to its strategic geography, the state is instrumental in the energy security of the European Union, building and designing pipelines through Anatolia (Ozturk, Yuksel and Ozek, 2012). In a bid to secure oil supplies and reduce geopolitical threats, China has recently diversified its oil import sources, weakening its dependence on the reserve from the Middle East. Geopolitical energy attributes and situations in Central Asia disrupt the energetic development and the countries' cooperation by domestic and foreign factors. Complicated energy development and geopolitical intrigues fit into a complex geopolitical pattern in Central Asia (Zhou and He and Yang, 2020).

Today's world is utterly dependent on energy sources, using gas as a strategic commodity. The energy spreads among all economic and military activities, constituting an invaluable and strategic resource in the international market (Gokce, Hatipoglu and Soytas, 2021; Masood et al. 2017). Upon a long-term adaptation of the energetic structure, the prominence of natural gas involves five factors: politics, resources, technologies, facilities and markets. Using natural gas as a primary source requires expanding gas reserves, allowing easy access, creating flexible trade systems, boosting investments in the infrastructure and reinforcing security systems (Huan et al. 2019).

Given the current gas deficiency, countries with vast resources can manipulate the lacking ones into serving their interest and meddle in foreign and in-house politics of importers. The enormous consumption of natural gas and reduced production capacities leaves Europe strongly dependent on Russia. More than half of Russian gas goes through Ukraine, causing violent transport upheavals given the war conflict (Roman and Stanculescu, 2021).

The article aims to measure the impact of the Russian government on the price movement of natural gas in Europe, including two hypotheses.

H1: Can we quantify the impact of government decisions on the global price movement of natural gas?

Answering this hypothesis, we will find or deny a link between specific government decisions and the global price movement of natural gas.

H2: What will the price movement of natural gas mean for European consumers in 2023?

This hypothesis will help us estimate the price movement of natural gas in terms of government decisions within the specified period.

Literary research

Correlation analysis comprises a standard, informative, descriptive and statistical tool for exploring relations between variables among two-dimensional and multi-dimensional data. Contamination with outliers causes the standard Pearson’s correlation to be misleading and yields incorrect results (Rodriques and Mahmouzdvand, 2016). Although the sample correlation coefficient reliably gauges the linear movement between variables, the bias caused by random outliers is enormous. Scientists avoid this scenario by suggesting an alternative robust correlation measurement with the lowest dispersion, calling it the bootstrap method (Tsagkanos, 2021). Faulty correlations occur upon two-time series correlating via a traditional statistic approach for the zero-hypothesis testing of the zero-correlation in the population (Agiakloglou, 2012). Gavrila and Gruia (2018) analysed the strength of the relationship between available statistical data, inspecting the correlation of polarisation levels for two H-2-Ne mixtures. Using the intensity of the monochromatic line (lambda=585.23 nm), the authors applied multiple values of discharge current I (mA) at 25kHz for various ratios. Andrzejewski, Dunal and Poplawski (2019) focused on the effects of changes in coal prices and CO_2 emission limits, revealing that electricity costs in the Polish market correlate with the coal price and CO_2 emission limits, indicating a stronger dependence on the latter.

Two-dimensional correlation analysis involves visualising relationships between variables among multi-dimensional data and assessing their temporal behaviour by applying cross-correlation. The function measures correlations of the same speed or frequency of occurrence regarding the time of the data collection. The cross-correlation function produces real and imaginary elements containing information on the phase behaviour of the variables. The former informs about dependent variations, while the latter concerns variations outside the phase (time delays or going astray) (Harrington, Urbas and Tandler, 2000). The 2D analysis involves simple operations multiplying matrices with the best application in hetero-spectral and hetero-modal correlations (Noda, 2010).

The asymmetric correlation analysis of time shift encompasses stock markets with multiple, yet not overlapping, trading hours to assess the global integration rate and interrelationship of foreign stock markets. The technique works with the next-day correlation (NDC) and same-day correlation (SDC) coefficients, exploring a link between main American and Asia-Pacific stock indexes. While SDCs have little significance, most NDCs grow in time and present an essential tool for American stock markets to dictate the pace for the Asia-Pacific region (Aityan and Inanov-Schitz and Izotov, 2010). Regarding the contribution of continuously analysing the stock market integration in the cited studies, their research employs the moving average method on top of the Detrended Cross-Correlation Analysis Coefficient to estimate the movement of the stock integration in Central and Eastern Europe. The approach allows dynamically examining the stock market integration, indicating increased integration in the Czech Republic, Hungary, Croatia, Poland and Romania. Bosna, Monte Negro, Serbia and Slovenia showed a lesser extent of unification (Tilfani and Ferreira, 2020). Yeh and Chiu (2021) compared two empirical outcomes based on waves, disclosing two strong positive correlations between three leading government bonds synchronised by time frequencies and American bonds governing the bonds of all developing countries. The US securities play a vital role in all developed stock markets, issuing new state guarantees. Yet, the method is not suitable for testing our hypotheses.

Fang, Lu and Li (2018) used Multifractal Detrended Cross-Correlation Analysis (MF-DCCA), examining correlations between carbon emission limits and stock series and their dynamics for European and Chinese markets. The results showed highly multifractal correlations between carbon emission limits and stock series in European and Chinese markets, indicating permanent correlations between subtle variations and anti-persistent equivalence between enormous fluctuations. The topic extensively covers the identification of parallels between time series in multi-dimensional systems. The presented article extends the Detrended Cross-Correlation Analysis (DCCA) by multi-dimensional structures, supplemented by the Detrended Cross-Correlation Analysis Between Multivariate Time Series (MVDCCA). Numeric simulations of synthetic multi-spatial time series generated by two-component mixed exponential distribution ARFIMA processes proved the efficiency of the proposed MVDCCA. The results show that the external-bond parameter governs the mutual correlation. This criterion is independent of interrelationships between trajectories in a specific multi-dimensional time series (Mao, Xeugeng and Pengjian, 2018). To achieve results, we can also use: quantitative and qualitive methods, analytical and comparative methods of processing, analysis and synthesis of statistical information, economic and mathematical modelling, etc. The mechanism of transforming global environmental challenges into environmental responsibility management in practice is substantiated (Kasych et al. 2020; Can et al. 2022). We find multi-criteria decision-making approaches when dealing with the sustainability and health of regions and cities (Kelemen et al., 2022), or smart city concepts that also consider alternative sources of energy (Gavurová et al., 2022).

Another study presents a method of generating a business strategy using value chain analysis. The analysis was carried out using mathematical-statistical methods (dimensional reduction, logit regression and its transformation in order to objectify the opinion level of the managers) and with a neural network in terms of validation of the results of the mathematical-statistical methods. The aim was to determine the significance of different parts of the value chain in terms of their impact on the profitability of an enterprise and to demonstrate its important role in the process of generating business strategy. The significance for the profitability of the enterprises was statistically proven in the area of scientific and technological development, input logistics and human resource management (Straková et al. 2020; Turisová et al. 2021; Petruf et al. 2015; Melnikova et al. 2016). Other researchers have examined the interdependence between financial development, fiscal instruments, and environmental degradation in developed and converging EU countries (Ziolo et al., 2020; Simionescu et al. 2022a,b), which are also reflected in the security management of the state (Kelemen et al., 2018).

Time Series Classification (TSC) poses a big problem in various fields of science, making many scientists think about its solution. Most methods only classify specific time series (TS), incurring huge calculation costs even in small datasets. The article suggests a new approach to multilayer perceptrons (MLP) for TSC, introducing hyperparameters related to the batch size and the number of neurons in hidden layers, adaptable to various TS natures. The experimental evaluation proved the high competitiveness of the design, comparing its accuracy with 14 up-to-date methods (del Campo FA and Neri and Villegas and Sanchez and Dominguez and Jimenez, 2021).

Tan, Bergmeir, Petitjean and Webb (2021) studied Time Series Extrinsic Regression (TSER), a regression task to learn the relationship between a time series and a continuous scalar variable. The function deals with generalising time series forecasts, reducing the need for the predicted value to be the input time series variable or depending on new quantities. The authors explore and compare existing solutions and adaptations of TSC algorithms by introducing a new archive containing 19 TSER datasets. The results showed that the up-to-date TSC Rocket algorithm, if modified for regression, is exceptionally accurate compared to other TSC algorithms and other modern machine-learning methods (ML), including XGBoost (Ilic, Georgulu and Cevik and Baydogon, 2021). Kučera, Vochozka and Rowland (2021) proposed new methodology for determining the optimal credit absorption capacity of an enterprise while maintaining the positive function of financial leverage, i.e., the maximum possible loan that would continuously bring benefit to the enterprise. Based on a theoretical analysis of the both indicators, the possibility of applying the proposed methodology.

Partial linear regression smoothing is an effective method for modelling time series. The study explores partial linear regression models of time series with correlated errors using polynomial splines and techniques of weighted least squares. N-consistency of parametric estimators and convergence rates in non-parametric estimations occur only in favourable conditions. Performed simulations reveal higher applicability of the proposed approach than ignoring correlated errors, proving its great utility in predicting Australian data in aviation several steps in advance (Liu and Yin, 2021). Datamining techniques involve algorithm sets for finding hidden knowledge from databases, including prediction, sequential pattern mining, association, classification, clustering, and decision tree. Forecasting uses classification and regression, whose algorithms reflect various regression models, including linear, non-linear, multiple, logistic and probabilistic regression. The suggested methodology discusses the prognosis of time series datasets with improved parameters. The pre-elaboration of the database involves moving averages or classification algorithms and adjusting coefficient values to the regression model (Sagae, Gupta and Kashyap, 2019).

Vochozka, Horák and Šuleř (2019) devised a methodology for estimating seasonal variations when smoothing time series using artificial neural networks on the example of the Euro and Chinese Yuan. At first, the study did not include categoric variables in the calculation, revealing that other quantities, including year, month, day, and a week would make the result more accurate when smoothing the time series. Since the Backpropagation algorithm trains multilayer neural networks too slowly, the authors suggest the CUDA programming model using the computing performance of graphic processing units (GPU) to speed up Backpropagation. The experiments show that the method can be seven times faster than the CPU (Liu and Guo, 2013). Glushchenko, Petrov and Lastochkin (2021) aimed to derive new effective formulae for adjusting neural network parameters that would outsmart backpropagation patterns. The authors modified the objective training function of neural structures by extending the abstract ideal output of all network layers to the Taylor series. The decay occurs near the current performance of the layer concerned. Adapted gradients of purpose functions respect the difference between ideal and actual network parameter values, making the obtained equations of weight modifications and bias (in all layers) dependent on the output and derivatives of the previous layer. Compared to the Backpropagation approach, this technique allows shorter training of the offline neural network. Vochozka, Kalinová, Gao and Smolíková (2021) focused on predicting the price movement of copper using neural networks. These structures readily forecast this time series, indicating low or near-to-zero copper price volatility (Wang et al., 2022; Chen et al., 2022).

Natural gas is a global commodity traded between regions. International trade with high volumes of gas as well as the complexity of transport alternatives generate new difficulties in market modelling and price forecasting. Therefore, it is necessary to define and analyze the future of newly emerging gas markets. Turkey has an important geopolitical position, with short distances to the areas with the largest deposits of natural gas. Although largely dependent on the import of gas from Russia, Iran, and Azerbaijan via pipelines, Turkey is also very close to high-demand countries. This is the reason why Turkey can play an important role when determining the prices of gas among international market players and become a market maker (Nalbant and Kayalica and Kayakutlu and Kaya, 2020). The affordability of natural gas reflects the willingness of natural gas consumers to pay for natural gas, and its price form is characterized by reasonable prices of natural gas. Unlike market prices, affordable prices of natural gas cannot be quantified by means of market relationship between supply and demand, and they reflect the highest price a consumer can afford to pay for natural gas. Chinese scientists have established a theory of natural gas price affordability system for analysing the affordability of natural gas. In their study, Rui and Feng (2018) summarize the Chinese literature on natural gas price and affordability and systematically sort out the theoretical system of natural gas affordability, proposing the main direction of further research (Rui and Feng, 2018).

The possibility to predict the price of natural gas is a benefit for various stakeholders and has become a valuable tool for all market players on competitive natural gas markets. In this paper, the authors examine data-driven predictive models for forecasting the prices of natural gas based on common tools of machine learning, ie. Artificial neural networks (ANN), support vector machines (SVM), gradient boosting machines (GBM), and Gaussian process regression (GPR). For evaluation, the authors use the method of cross validation for model training and monthly spot prices of natural gas Henry Hub from January 2001 to October 2018. According to the results, these four methods show different accuracy in predicting the prices of natural gas. Overall, however, ANN shows better prediction accuracy compared to SVM, GBM, and GPR (Su and Zhang and Zhu and Zha and Wen, 2019). The consumption of natural gas is growing rapidly. Accurate prediction of spot prices of natural gas would bring significant benefits to the energy management, economic development, and environmental protection. In this study, the spot prices of natural gas were predicted using the algorithm of least squares regression boosting (LSBoost). There were examined the spot prices of natural gas Henry Hub and a wide range of time series from January 2001 to December 2017 was selected. The LSBoost method is used to analyse daily, weekly and monthly data series. Using an empirical study, it was verified that the proposed predictive model shows a high degree of fit. In comparison with some of the existing approaches, such as linear regression, linear support vector machine (SVM), quadratic SVM and cubic SVM, the proposed model based on LSBoost showed better performance, such as higher R-squared and lower mean absolute error, mean squared error (Su and Zhang and Zhu and Zha, 2019).

The first research question will be answered using the correlation analysis and time series regression using multilayer perceptron networks. For the second research question, time series regression will be selected again using multilayer perceptron networks.

Data and methods

The data on natural gas prices were taken from the official websites of the US Energy Information Administration (EIA, 2022). The data are available for the period from 3 January 2020 to 25 February 2022. The data used contain the Friday figures only.

The formulated research questions assume the research using correlation analysis and time series regression using multilayer perceptron networks. From the data, spot prices of gas will be selected and arranged in the ascending order, from the oldest to the latest figures. Furthermore, the news taken from the official Twitter websites of the Financial Times will be sorted so that given news is assigned to the date of its release (Twitter/financialtimes, 2022). Subsequently, each piece of news will be valued by news sentiment on a scale from 1 to 5, where 3 is neutral and 1 very negative. Finally, each date that is not assigned any news is assigned the neutral value 3.

Figure 1 comprises dates and spot prices of natura gas, to which specific news are assigned on the basis of an identification number. The overall overview of the news is presented in the appendix along with the evaluation of the sentiment. The graph shows the development of spot prices of natural gas supported by the changes in the price depending on the sentiment.

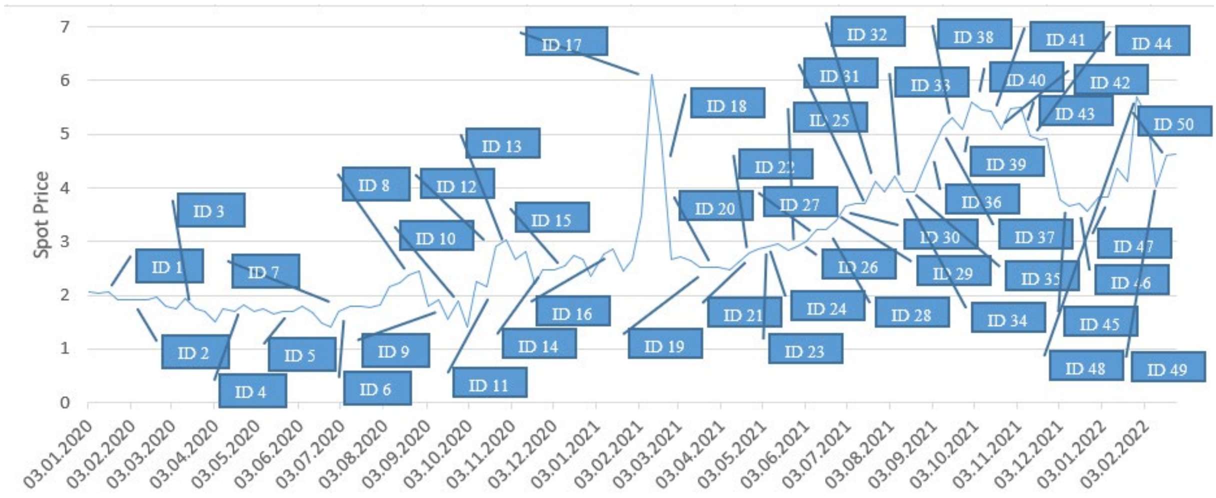

Figure 1: The value of sentiment of individual pieces of news

Moreover, the method of neural networks will be used. The data will be evaluated using the TIBCO´s software Statistica Version 13.5.0.17. For the analysis of the processed data, the method of neural networks will be used. Specifically, time series analysis (regression) will be selected. The price will be used as a variable in the first column; the date, year, day in month, and day in week will be selected as continuous inputs. The categorical input is news. The time series will be divided into three datasets. The first dataset, referred to as the training dataset, will contain 85 % of the input data. 15 % of the input data will be used in the training dataset, and 0 % in the validation dataset. These two datasets are used to verify the correctness of the neural network.

Table 1 shows the basic characteristics of the real time series. The data on spot prices of natural gas were taken from the official websites of the US Energy Information Administration (EIA, 2022).

Table 1. Dataset characteristics

Samples	Date	Year	Day in month	Day in week	Price
Minimum (Train)	43833.00	2020.000	1.00000	3.000000	1.410000
Maximum (Train)	44617.00	2022.000	31.00000	5.000000	6.120000
Mean (Train)	44215.97	2020.567	16.11340	4.917526	2.975876
Standard deviation (Train)	228.84	0.593	8.80563	0.343696	1.231614
Minimum (Test)	43889.00	2020.000	1.00000	3.000000	1.690000
Maximum (Test)	44603.00	2022.000	28.00000	5.000000	5.690000
Mean (Test)	44279.00	2020.813	15.12500	4.750000	3.271875
Standard deviation (Test)	232.31	0.750	9.08387	0.683130	1.365773
Minimum (Overall)	43833.00	2020.000	1.00000	3.000000	1.410000
Maximum (Overall)	44617.00	2022.000	31.00000	5.000000	6.120000
Mean (Overall)	44224.89	2020.602	15.97345	4.893805	3.017788
Standard deviation (Overall)	229.35	0.620	8.81097	0.408893	1.249297

Source: Author

The selected activation functions of the hidden and the input layer of MLP will be:

- Identity: $Id(x)=x$,
- Logistic function: $f(t, a, m, n, \tau) = a\,\frac{1+me^{-t/\tau}}{1+ne^{-t/\tau}}$,
- Hyperbolic tangent: $\tanh(x) = \frac{\boldsymbol{sinh}(\boldsymbol{x})}{\boldsymbol{cosh}(\boldsymbol{x})}$
- Exponential function: $f(x)=a^x$,
- Sine: $f(x)=sin(x)$.

Next, we will proceed to weight decomposition, where none of the offered options will be selected. In the case of the MLP network, the minimum number of hidden neurons is 3 and maximum 9. In the case of the RBF network, it will be 17 hidden neurons as the minimum and 24 hidden neurons as the maximum. A total of 10,000 networks will be generated for training, out of which 5 will be retained. “Training” will be selected.

Mathematically, the architecture of the MLP network can be expresses as follows:

$$\boldsymbol{y} = \sum_{j=1}^{M} \boldsymbol{w_j}\, \phi_j\left(\boldsymbol{u_j^T x} + \boldsymbol{u_{j0}}\right) + \boldsymbol{w_0}$$

The parameters u_j and u_{j0} define the projection of the input vector x in the set of planes marked $j = 1, \ldots, M$, as in multilayer perceptron. These projections are transformed by non-linear “activation functions” ϕ_j, which are linearly combined in the output variable y. The parameters of the model are determined by means of the minimization of the error function of the sum of squares. The process is repeated for each hidden unit until a sufficiently low value of error function is achieved, or until some other stopping criterion is met (Bishop, 1995).

Mathematically, the architecture of the RBF network can be expressed as follows:

$$y_k(x) = \sum_{j=1}^{M} w_{kj}\, \phi_j(x) + w_{k0}$$

where x is a d-dimensional input vector with elements x_1 and μ_j determining the centre of the basis function ϕ_j with elements $\mu_{ji.}$ The mapping function can be represented as a diagram of the neural network, as shown in Figure 2 (Bishop, 1995).

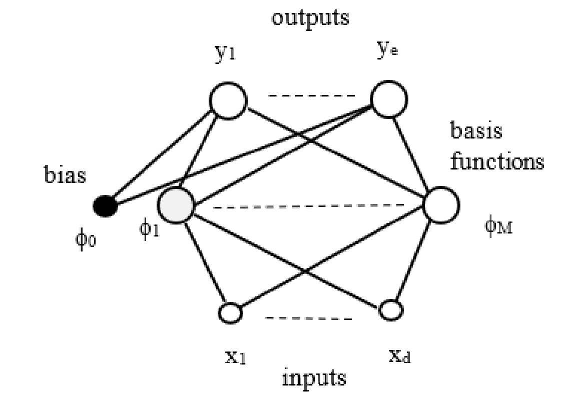

Figure 2: Radial basis function networks

The architecture of the radial basis function corresponds to the mathematical expression of the RBF network architecture. Each basis function works as a hidden unit. The lines of the basis function ϕ_j connecting at the inputs represent the corresponding elements μ_{ji} of vector μ_j. The weights w_{kj} are represented as rows from the basis functions to the output units; deviations are displayed as weights of the extra “basis function” $\phi_{0,}$, whose output is fixed at 1 (Bishop, 1995).

We will examine which of the results will show the best performance. The first criterion is the output of the test, training, and validation datasets. In ideal case, the output is as close to 1 as possible and is approximately the same in all three datasets. The second criterion is the error rate. The value 1 means death there, while 0 indicates an arranged system. Therefore, the smallest possible value is required.

Mathematically, least squares method can be expressed as follows:

$$\boldsymbol{E} = \frac{1}{2} \sum_n \| \boldsymbol{y}(\boldsymbol{x^n}; \boldsymbol{w}) - \boldsymbol{t^n} \|^{2}$$

The method of least squares is a sum of square roots of the real variable distance from the regression curve. In this case, the lowest possible value is required.

Results

The qualification of the effect of government decisions on the global development of natural gas prices.

In accordance with the established procedure, 1,000 neural networks were generated, out of which five showing the best values were retained. Table 2 shows the overview of these networks together with the parameters for individual networks. All retained networks are MLP networks.

Table 1. Overview of networks

Index	Net. Name	Training perf.	Test perf.	Training error	Test error	Training algorithm
1	MLP 9-10-1	0.967073	0.961246	0.048579	0.083458	BFGS 116
2	MLP 9-6-1	0.952711	0.963408	0.068919	0,063692	BFGS 114
3	MLP 9-10-1	0.957360	0.957191	0.062251	0.073290	BFGS 111
4	MLP 9-7-1	0.947524	0.951074	0.076276	0.084055	BFGS 113
5	MLP 9-9-1	0.953829	0.968519	0.067325	0.054629	BFGS 113

Source: Author

The network performance is evaluated in individual datasets, i.e., training, test, and validation datasets. The validation dataset will not be taken into account because it does not contain any data. The neural networks are RBF networks only. The input layer contains four variables, specifically date, year, day I month, and day in week. Neural networks in the hidden layer contain 3-9 hidden neurons.

In most cases, a network model is selected which shows high values but no significantly different fluctuations in individual datasets. Table 2 shows that the best network is 5. MLP 9-9-1.

Figure 3 provides a graphical representation of five networks with the best values.

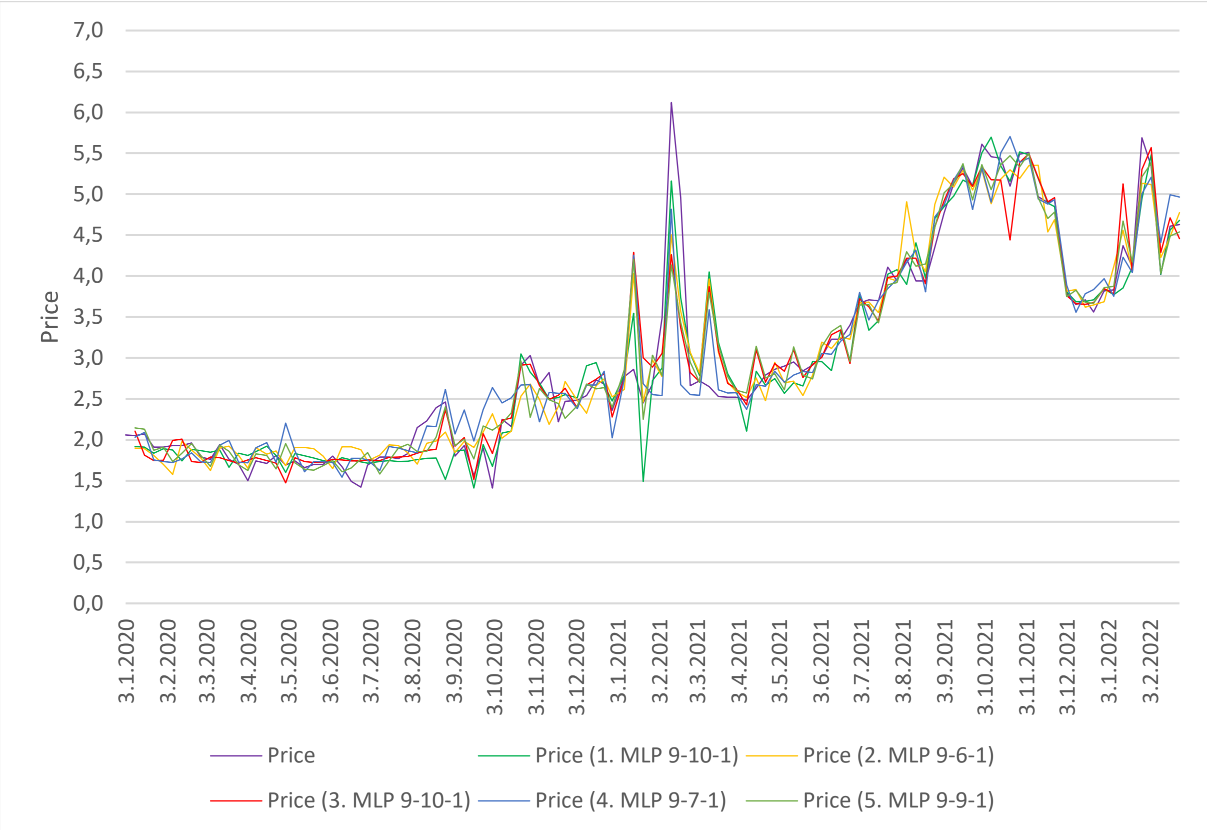

Figure 3: Overview of networks

The differences in the time series of the neural networks used are not significant. Therefore, it cannot be clearly determined which of the neural networks shows the best results. It can be seen from the figure that all networks more or less copied the real movements of prices in the past periods. For the whole monitored period, a frequent fluctuation can be seen. As at 3 January 2020, the network reached the value of 2 points. A more significant change was recorded on 3 January 2021, where the value of the network achieved slightly over 4 points, which was followed by a fall to 2.5 – 3 points. The most significant growth was recorded on 3 March 2021, where the value of the network reached 6 points.

Development of natural gas price for European customers until the year 2023

Figure 4 shows the predicted price time series of network 5. MLP 9-9-1, which was evaluated as the best neural network.

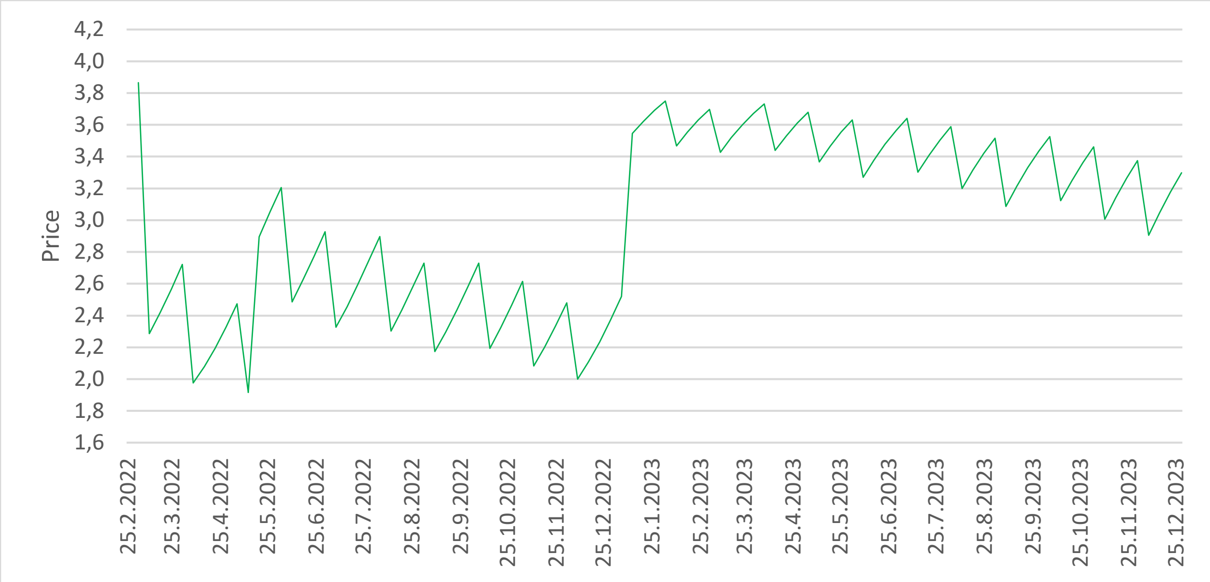

Figure 4: Prediction of price time series

It can be seen from Graph 4 that the price often fluctuates. The price of gas moves in cycles of several years, when it grows first and then falls back to its initial value. The fluctuations of natural gas prices at the beginning of 2022 are mainly caused by uncertainty concerning the flow of supplies from Russia. In this period, the price fluctuates between 3.6 – 2.9. Network 5. MLP 9-9-1 was selected because its performance is high but the fluctuations in individual datasets are not significantly different.

The best neural structure turns out to be network 5. MLP 9-9-1, whose course is captured in Figure 5.

Figure 5: Graph of residuals

As at 3 January 2020, the network reaches 2 points. For the whole monitored period, there are frequent fluctuations. A more significant growth is recorded on 3 August 2021, which lasts until 3 November 2021, when the value is 5 points. This network was selected because it contains the smallest sum of residuals of all networks.

There is also shown the course of absolute residuals of the given network. Residuals indicate the deviation of the time series models. This network is the most suitable one since it shows the smallest extremes of the selected networks and the sum of their residuals is closest to zero.

Discussion of results

Based on the results obtained, it is possible to answer the formulated research questions:

RQ1: Is it possible to quantify the impact of government decisions on the global development of natural gas prices?

A high correlation between the change and impact means that the impact of government decisions on the global development of natural gas prices can be quantified. In our case, the value of correlation was 0.13. This means that there is no correlation and the value is almost indifferent. Based on this, it can be concluded that the impact of government decisions on the global development of natural gas price cannot be quantified because there is no correlation between the variables.

The prices of natural gas are 13 % influenced by government decisions. This implies that 87 % of the price is influenced by other factors, such as the price of the related commodities, weather changes, supply and demand, the exchange rate of koruna, or the situation abroad. As an example, there can be mentioned the current war conflict between Russia and Ukraine, which resulted in the fluctuations of natural gas prices.

The prices of natural gas are a huge political and economic problem. They create additional costs for households and industry and affect the global competitiveness of companies (Giziene and Zalgiryte, 2015). The price of gas is affected also by newly adopted legislation that regulates the operation of oil and natural gas extraction sites. An important role is also palyed by regulations on the closure of coal power plants that could replace natural gas in the production of electricity, which would result in higher demand and thus prices (Epet, 2022).

RQ2: What is the predicted development of natural gas price for European customers until the year 2023?

It follows from Graph 4 that the price of natural gas will fluctuate in the next years. Gas price moves in cycles of several years, where the gas price grows and then falls to the initial value. An important factor are also government decisions that also have an impact on the price of natural gas. The market shows some uncertainty regarding the further development of prices because the European Union has decided to reduce its dependence on Russian gas in relation to the war conflict between Russia and Ukraine. The reduction of prices could be helped by ensuring import of natural gas from other states, e.g. Great Britain, Italy, or France. Also, it is suitable to focus on other, cheaper substitutes that are plentiful in the market. The price of natural gas is expected to grow at the end of 2022, which will be followed by a very slow decrease. However, it will not reach its original value by the end of 2023.

Purchase prices of electricity and gas are already very high. Electricity is currently bought at three times higher prices than last year. If energy prices remain this high, all suppliers will have to regulate the prices. Further evelopment also depends on the measures adopted by the European Union and the steps Russia will take (CSO, 2022).

The affordability of natural gas reflects the willingness of its consumers to pay for it and its natural gas and its price form is characterized by affordable natural gas prices. Unlike market prices, affordable price of gas cannot be quantified by means of market relationship between supply and demand (Rui and Feng, 2018). The possibility of predicting the price of natural gas is a benefit for various stakeholders, and has become a valuable tool for all market players in competitive natural gas markets (Su and Zhang and Zhu and Zha and Wen, 2019).

In Europe, the current high prices of natural gas reflect the specific situation in Europe. Europe´s gas reservoirs are currently largely empty. Low output of German wind farms in summer required the increased use of gas-fired backup plants, which along with the increased gas prices and a recovery of industrial activities during the COVID-19 pandemic showed down gas replenishment. According to market expectations, the price of this commodity should remain at this higher level for a longer period. The EU´s efforts to make individual countries buy more gas on stock markets also contributes to higher prices and their fluctuations (CNB, 2022).

Conclusion

The goal of the research was to determine whether it is possible to quantify the impact of government decisions on the global development of natural gas price. The authors further focused on the development of natural gas price for the European customers until the year 2023.

Based on the study conducted, it was found that the impact of government decisions on the global development of natural gas prices cannot be quantified. This conclusion was based on the research conducted using the correlation analysis with the resulting value of 0.13. This figure indicates a very slight correlation as the value is nearly indifferent. No statistically significant dependence of both variables was identified. The impact of government decisions on the global development of natural gas prices could be quantified if there was a high correlation between a change and the impact.

By means of time series regression using multilayer perceptron networks, it was found that the price of natural gas for the European customers will fluctuate in the next year. Gas price moves in cycles of several years, where the gas price grows and then falls to the initial value. An important factor are also government decisions that also have an impact on the price of natural gas. The market shows some uncertainty regarding the further development of prices because the European Union has decided to reduce its dependence on Russian gas in relation to the war conflict between Russia and Ukraine. The reduction of prices could be helped by ensuring import of natural gas from other states, e.g. Great Britain, Italy, or France. Also, it is suitable to focus on other, cheaper substitutes that are plentiful in the market. The price of natural gas is expected to grow at the end of 2022, which will be followed by a very slow decrease. However, it will not reach its original value by the end of 2023.

References

Agiakloglou, C., & Tsimpanos, A. (2012). An alternative approach for testing for linear association for two independent stationary AR(1) processes. *Applied Economics*, *44*(36), 4799–4803. https://doi.org/10.1080/00036846.2011.595695.

Andrzejewski, M., Dunal, P., & Popławski, Ł. (2019). Impact of changes in coal prices and CO2 allowances on power prices in selected European Union countries – correlation analysis in the short-term perspective. *Acta Montanistica Slovaca*, 24(1), 53-62.

Aityan, S. K., Ivanov-Schitz, A. K., & Izotov, S. S. (2010). Time-shift asymmetric correlation analysis of global stock markets. *Journal of International Financial Markets, Institutions and Money*, *20*(5), 590–605. https://doi.org/10.1016/j.intfin.2010.07.006.

Arias del Campo, F., Guevara Neri, M. C., Vergara Villegas, O. O., Cruz Sánchez, V. G., Ochoa Domínguez, H. de J., & García Jiménez, V. (2021). Auto-adaptive multilayer perceptron for univariate time series classification. *Expert Systems with Applications*, *181*, 115147. https://doi.org/10.1016/j.eswa.2021.115147.

Bishop, C. M. (1995). *Neural networks for pattern recognition. Clarendon Press ; Oxford University Press.*

Cnb.cz: What is the reason of the record-breaking prices of gas and electricity increasing in Europe? [online]. 4.2.2022 [cit. 2022-05-10]. https://www.cnb.cz/cs/menova-politika/zpravy-o-menove-politice/boxy-a-clanky/Co-stoji-za-rekordnim-zdrazenim-plynu-a-elektriny-v-Evrope/

Can, M., Oluc, I., Sturm, B., Guzel, I., Gavurova, B., & Popp, J. (2022). Nexus Between Trading Non-Green Products and Environment: Introducing Non-Green Trade Openness Index. *Frontiers in Environmental Science*, 915. https://doi.org/10.3389/fenvs.2022.950453

Chen, S., Xu, Z., & Skare, M. (2022). The impact of COVID-19 on the service business industry: insights from a bibliometric review. *Total Quality Management & Business Excellence*, 1-35. *https://doi.org/10.1080/14783363.2022.2078188*

Epet.cz: What influences the price of gas? They are weather, policy and price of crude oil. [online]. 2.7.2019 [cit. 2022-05-10]. https://www.epet.cz/co-ovlivnuje-cenu-zemniho-plynu-roli-hraje-pocasi-politika-i-cena-ropy/.

Fang, S., Lu, X., Li, J., & Qu, L. (2018). Multifractal detrended cross-correlation analysis of carbon emission allowance and stock returns. *Physica A: Statistical Mechanics and Its Applications*, *509*, 551–566. https://doi.org/10.1016/j.physa.2018.05.136.

Financial Times [online]. London, New York, Hong Kong, 2007 [cit. 2022-04-20]. https://twitter.com/financialtimes?lang=cs.

Gavurová, B., Kelemen, M., & Polishchuk, V. (2022). Expert model of risk assessment for the selected components of smart city concept: From safe time to pandemics as COVID-19. *Socio-Economic Planning Sciences*, Volume 82, Part B, 2022, 101253. https://doi.org/10.1016/j.seps.2022.101253

Gedich*, T. (2018). *Gas Market Of China: Barriers And Prospects For Russian Pipeline Gas*. 419–429. https://doi.org/10.15405/epsbs.2018.12.51.

Giziene, V., & Zalgiryte, L. (2015). The Assessment of Natural Gas Pricing. *Procedia - Social and Behavioral Sciences*, *213*, 111–116. https://doi.org/10.1016/j.sbspro.2015.11.412.

Glushchenko, A., Petrov, V., & Lastochkin, K. (2021). Backpropagation method modification using Taylor series to improve accuracy of offline neural network training. *Procedia Computer Science*, *186*, 202–209. https://doi.org/10.1016/j.procs.2021.04.139.

Gökçe, O. Z., Hatipoglu, E., & Soytas, M. A. (2021). The pacifying effect of energy dependence on interstate conflict: A Large-N analysis. *Energy Research & Social Science*, *78*, 102133. https://doi.org/10.1016/j.erss.2021.102133.

Gruia, I., & Gavrila, C. (2018). Correlation analysis of the polarization degree in H2-Ne gas mixture. In I. Cristea, M. Vladescu, & R. D. Tamas (Ed.), *Advanced Topics in Optoelectronics, Microelectronics, and Nanotechnologies IX* (s. 105). SPIE. https://doi.org/10.1117/12.2324672.

Harrington, P. de B., Urbas, A., & Tandler, P. J. (2000). Two-dimensional correlation analysis. *Chemometrics and Intelligent Laboratory Systems*, *50*(2), 149–174. https://doi.org/10.1016/S0169-7439(99)00062-3.

Hasheminasab, H., Hashemkhani Zolfani, S., Kazimieras Zavadskas, E., Kharrazi, M., & Skare, M. (2022). A circular economy model for fossil fuel sustainable decisions based on MADM techniques. *Economic Research-Ekonomska Istraživanja*, 35(1), 564-582. *https://doi.org/10.1080/1331677X.2021.1926305*

Huang, W., Chen, J., Fu, C., & Huang, Y. (2019). Approach for natural gas to be a primary energy source in China. *Frontiers of Engineering Management*, *6*(4), 467–476. https://doi.org/10.1007/s42524-019-0068-6.

Hulshof, D., van der Maat, J.-P., & Mulder, M. (2016). Market fundamentals, competition and natural-gas prices. *Energy Policy*, *94*, 480–491. https://doi.org/10.1016/j.enpol.2015.12.016.

Ilic, I., Görgülü, B., Cevik, M., & Baydoğan, M. G. (2021). Explainable boosted linear regression for time series forecasting. *Pattern Recognition*, *120*, 108144. https://doi.org/10.1016/j.patcog.2021.108144.

Kasych, A., Suler, P., & Rowland, Z. (2020). Corporate Environmental Responsibility through the Prism of Strategic Management. Sustainability, 12(22), 9589. https://doi.org/10.3390/su12229589

Kaya, I.,(2017). Evaluation of Tanap Agreements in Terms of International Law and Expropriation Law [online]. 2017, 99-119 [cit. 2022-02-10]. http://bilig.yesevi.edu.tr/yonetim/icerik/makaleler/2089-published.pdf.

Kelemen, M., Gavurová, B., & Polishchuk, V. (2022). A Complex Hybrid Model for Evaluating Projects to Improve the Sustainability and Health of Regions and Cities. *Int. J. Environ. Res. Public Health* 2022, *19*, 8217. https://doi.org/10.3390/ijerph19138217

Kelemen, M., Szabo, S., & Vajdová, I. (2018). Security Management in the Air Transport: Example of an Interdisciplinary Investigation of Special Security Questions, Challenges to national defence in contemporary geopolitical situation 2018 (2018), no. 1, 105-108, https://doi.org/10.47459/cndcgs.2018.15

Kučera, J., Vochozka, M., & Rowland, Z. (2021). The Ideal Debt Ratio of an Agricultural Enterprise. Sustainability, 13(9), 4613. https://doi.org/10.3390/su13094613

Liu, J., & Guo, L. (2013). Implementation of Neural Network Backpropagation in CUDA. In Z. Du (Ed.), *Intelligence Computation and Evolutionary Computation* (Roč. 180, s. 1021–1027). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-31656-2_140.

Liu, Y., & Yin, J. (2021). Spline estimation of partially linear regression models for time series with correlated errors. *Communications in Statistics - Simulation and Computation*, 1–15. https://doi.org/10.1080/03610918.2021.1990328.

Mao, X., & Shang, P. (2018). DETRENDED CROSS-CORRELATION ANALYSIS BETWEEN MULTIVARIATE TIME SERIES. *Fractals*, *26*(04), 1850058. https://doi.org/10.1142/S0218348X18500585.

Masood, O., Aktan, B., Gavurova, B., Fakhry, B., Tvaronaviciene, M., & Marinkute-Kauliene, R. (2017). The impact of regime-switching behaviour of price volatility on efficiency of the US sovereign debt market. *Economic Research-Ekonomska Istrazivanja,* 30(1), 1865–1881. https://doi.org/10.1080/1331677X.2017.1394896

Melnikova, L., Cibereova, J., Korba, P. (2016). Building a training airport for pilots. Informatics, geoinformatics and remote sensing conference proceedings, SGEM 2016. 16th International Multidisciplinary Scientific Geoconference (SGEM 2016), 109–116.

Nalbant, H., Kayalica, M. Ö., Kayakutlu, G., & Kaya, G. (2020). An analysis of the natural gas pricing in natural gas hubs: An evaluation for Turkey. *Energy Systems*. https://doi.org/10.1007/s12667-020-00395-8

Noda, I. (2010). Double two-dimensional correlation analysis – 2D correlation of 2D spectra. *Journal of Molecular Structure*, *974*(1–3), 108–115. https://doi.org/10.1016/j.molstruc.2009.11.048

Osieczko, K., Gazda, A. & Malindzak, D. (2019). Factors determining the construction and location of underground gas storage facilities. Acta Montanistica Slovaca, 24(3), 234–244.

Ozturk, M., Yuksel, Y. E., & Ozek, N. (2011). A Bridge between East and West: Turkey's natural gas policy. *Renewable and Sustainable Energy Reviews*, *15*(9), 4286–4294. https://doi.org/10.1016/j.rser.2011.07.122.

Petruf, M., Korba, P., & Kolesár, J. (2015). Roles of logistics in air transportation. NAŠE MORE: znanstveni časopis za more i pomorstvo, 62(3 Special Issue), 215–218. doi:10.17818/NM/2015/SI23

Qin, Y., Xu, Z., Wang, X., & Škare, M. (2022). Green energy adoption and its determinants: A bibliometric analysis. *Renewable and Sustainable Energy Reviews*, 153, 111780. https://doi.org/10.1016/j.rser.2021.111780

Rodrigues, P. C., & Mahmoudvand, R. (2016). Correlation Analysis in Contaminated Data by Singular Spectrum Analysis: P. C. Rodrigues and R. Mahmoudvand. *Quality and Reliability Engineering International*, *32*(6), 2127–2137. https://doi.org/10.1002/qre.2027

Roman, M. D., & Stanculescu, D. M. (2021). An Analysis of Countries' Bargaining Power Derived from the Natural Gas Transportation System Using a Cooperative Game Theory Model. *Energies*, *14*(12), 3595. https://doi.org/10.3390/en14123595.

Rui, X., & Feng, L. (2018). The Affordability of Natural Gas Price in China: A Literature Review. *Proceedings of the Third International Conference on Economic and Business Management (FEBM 2018)*. Proceedings of the Third International Conference on Economic and Business Management (FEBM 2018), Hohhot, China. https://doi.org/10.2991/febm-18.2018.9.

Sagar, P., Gupta, P., & Kashyap, I. (2019). Prediction Technique for Time Series Data Sets Using Regression Models. In A. K. Luhach, D. Singh, P.-A. Hsiung, K. B. G. Hawari, P. Lingras, & P. K. Singh (Ed.), *Advanced Informatics for Computing Research,* 955*,* 480–488. Springer Singapore. https://doi.org/10.1007/978-981-13-3140-4_43.

Simionescu, M., Strielkowski, W., & Gavurova, B. (2022). Could quality of governance influence pollution? Evidence from the revised Environmental Kuznets Curve in Central and Eastern European countries. *Energy Reports*, 8, 809-819. https://doi.org/10.1016/j.egyr.2021.12.031

Simionescu, M., Neagu, O. & Gavurova, B. (2022). The Role of Quality of Governance in Reducing Pollution in Romania: An ARDL and Nonparametric Bayesian Approach. *Front. Environ. Sci*. 10:892243. https://doi.org/10.3389/fenvs.2022.892243

Skare, M., & Porada-Rochon, M. (2022). The role of innovation in sustainable growth: A dynamic panel study on micro and macro levels 1990–2019. *Technological Forecasting and Social Chang*e, 175, 121337. *https://doi.org/10.1016/j.techfore.2021.121337*

Stehel, V., & Suler, P. (2016). The Game Theory and Shale Gas in a Global Economy. In: Globalization and its socio-economic consequences. Žilina: University of Žilina. p. 2108-2117. ISBN 978-80-8154-191-9. ISSN 2454-0943.

Straková, J., Rajiani, I., Pártlová, P., Váchal, J., & Dobrovič, J. (2020). Use of the Value Chain in the Process of Generating a Sustainable Business Strategy on the Example of Manufacturing and Industrial Enterprises in the Czech Republic. Sustainability, 12(4), 1520. https://doi.org/10.3390/su12041520

Su, M., Zhang, Z., Zhu, Y., & Zha, D. (2019). Data-Driven Natural Gas Spot Price Forecasting with Least Squares Regression Boosting Algorithm. *Energies*, *12*(6), 1094. https://doi.org/10.3390/en12061094.

Su, M., Zhang, Z., Zhu, Y., Zha, D., & Wen, W. (2019). Data Driven Natural Gas Spot Price Prediction Models Using Machine Learning Methods. *Energies,* 12(9), 1680. *https://doi.org/10.3390/en12091680.*

Tilfani, O., Ferreira, P., & El Boukfaoui, M. Y. (2020). Revisiting stock market integration in Central and Eastern European stock markets with a dynamic analysis. *Post-Communist Economies*, *32*(5), 643–674. https://doi.org/10.1080/14631377.2019.1678099.

Tsagkanos, A. (2018). Minimisation of bias of Pearson correlation coefficient in presence of coincidental outliers. *International Journal of Computational Economics and Econometrics*, *8*(1), 121. https://doi.org/10.1504/IJCEE.2018.088308.

Turisová, R., Pačaiová, H., Kotianová, Z., Nagyová, A., Hovanec, M., & Korba, P. (2021). Evaluation of eMaintenance Application Based on the New Version of the EFQM Model. *Sustainability*, 2021, 13, 3682. https:// doi.org/10.3390/su13073682

US Energy Information Administration: Natural Gas [online]. Washington DC, 2022 [cit. 2022-04-20]. Dostupné z: https://www.eia.gov/dnav/ng/hist/rngwhhdd.htm.

Virglerova, Z. (2012). Natural gas prices and its dependence on natural gas reserves. In: Innovation and Sustainable Competitive Advantage: From Regional Development to World Economies, Vols 1-5 [online]. Istanbul.

Vochozka, M., Horák, J., & Šuleř, P. (2019). Equalizing Seasonal Time Series Using Artificial Neural Networks in Predicting the Euro–Yuan Exchange Rate. *Journal of Risk and Financial Management*, *12*(2), 76. https://doi.org/10.3390/jrfm12020076.

Vochozka, M., Kalinova, E., Gao, P., & Smolikova, L. (2021). Development of copper price from July 1959 and predicted development till the end of year 2022. *ACTA MONTANISTICA SLOVACA*, *26*(2), 262–280. https://doi.org/10.46544/AMS.v26i2.07.

Yeh, C.-C., Chiu, C.-L., & Chang, T. (2021). Dynamic correlations in bond markets between US and emerging countries. *Applied Economics Letters*, *28*(16), 1371–1376. https://doi.org/10.1080/13504851.2020.1817303.

Yorucu, V. (2016). Price modeling of imported natural gas in Turkey. *Journal of Renewable and Sustainable Energy*, *8*(1), 013111. https://doi.org/10.1063/1.4942408.
Wang, X., Xu, Z., Wang, X., & Skare, M. (2022). A review of inflation from 1906 to 2022: a comprehensive analysis of inflation studies from a global perspective. *Oeconomia Copernicana,* 13(3), 595-631. https://doi.org/10.24136/oc.2022.018
Zioło, M., Kluza, K., Kozuba, J., Kelemen, M., Niedzielski, P., & Zinczak, P. (2020). Patterns of Interdependence between Financial Development, Fiscal Instruments, and Environmental Degradation in Developed and Converging EU Countries. *Int. J. Environ. Res. Public Health* 2020, *17*, 4425. https://doi.org/10.3390/ijerph17124425
Zhang, E., Chen, X., & Wang, L. (2020). Consistent Discriminant Correlation Analysis. *Neural Processing Letters*, *52*(1), 891–904. https://doi.org/10.1007/s11063-020-10285-w.
Zhiznin, S. Z. (2019). Economic and geopolitical aspects of the Nord Stream 2 gas pipeline. *Baltic Region*, *11*(3), 25–42. https://doi.org/10.5922/2079-8555-2019-3-2.
Zhou, Q., He, Z., & Yang, Y. (2020). Energy geopolitics in Central Asia: China's involvement and responses. *Journal of Geographical Sciences*, *30*(11), 1871–1895. https://doi.org/10.1007/s11442-020-1816-6.
Zhu, Z., Zhang, H., Tao, G., & Yu, F. (2016). Effects of gas pricing reform on China's price level and total output. *Natural Hazards*, *84*(S1), 167–178. https://doi.org/10.1007/s11069-015-1884-6.

Appendices

Date	ID	News	Sentiment
17 January 2020	1	Israel starts exporting natural gas to Egypt.	4
07 February 2020	2	Touchstone confirms gas discovery onshore Trinidad and Tobago.	4
13 March 2020	3	Ukraine ramps up gas imports by 47 % in February.	4
24 April 2020	4	Ukraine cuts domestic gas prices.	4
29 May 2020	5	Ukraine has agreed most interconnection agreements with EU neighbours and is the only EC member to comply with them accordingly.	3
01 July 2020	6	Germany´s gas imports show 13.3% y/y increase in April	3
24 July 2020	7	World Bank figures show that global gas flaring rose to the level last recorded in 2009 – 150 bn $m^{3.}$	3
21 August 2020	8	Europe needs more gas to make up for declining domestic gas production and Fortum is behind Uniper´s decision to invest in Nord Stream 2, said Fortum CEO Markus Rauramo to analysts during August 19 conference call on the second-quarter results.	4
11 September 2020	9	Eastern Mediterranean countries have reached such a tense moment over offshore gas discoveries that many experts are now talking about a possible war.	2
25 September 2020	10	U.S. industrial sector consumption of natural gas falls amid January and June by nearly 21 % this year.	4
16 October 2020	11	Turkey announces its major natural gas discovery in August 2020.	4
23 October 2020	12	Russia is increasing gas supplies to China.	
30 October 2020	13	Canadian natural gas exports to U.S. Midwest fall by 20%.	2
25 November 2020	14	Russia is increasing gas supplies to China.	4
18 December 2020	15	China´s gas production rose by 12 % in November 2020.	4
15 January 2021	16	LNG demand to rise by 2030.	5
12 February 2021	17	Russian ship Fortuna renewed Nord Stream 2 pipeline in Danish waters.	3
19 February 2021	18	Gazprom Neft sees 2020 bump in gas supply.	3
19 March 2021	19	Gazrom and Shell sign an agreement of strategic cooperation.	3
01 April 2021	20	German Eugal pipeline fully operational	4
16 April 2021	21	Gazprom planning new gas transit pipeline to China.	3
23 April 2021	22	BHP´s gas output up 2 % in January-March	4
30 April 2021	23	Indonesia´s Q1 oil, gas lifting below target.	3
07 May 2021	24	China´s oil imports rose by 22 % in January – April.	3
21 May 2021	25	U.S. natural gas production is to decline in June.	2
28 May 2021	26	Gazprom Q1 sales rise, prices recover.	4
11 June 2021	27	Nord Stream 2 ready for pre-commissioning.	4
18 June 2021	28	Nordic oil and gas increases Permian oil production.	3
25 June 2021	29	Natural gas exports via pipeline from Russia´s state-controlled monopoly Gazprom to continental Europe fell by about a fifth in 2021 from pre-pandemic level despite a sharp demand recovery and low stock of this vital fuel. The imbalance has helped European price rise to the highest level since 2008 and increase energy costs for households and businesses.	1
02 July 2021	30	Australian Victoria´s parliament lifted the moratorium on conventional onshore gas exploration.	3
16 July 2021	31	China´s gas imports grew by 24 % in the first half.	4
23 July 2021	32	Canada´s CGL pipeline sees workforce double.	4
06 August 2021	33	Continental Resources Inc. increases gas production guidance.	3
13 August 2021	34	High natural gas prices increase U.S. coal demand.	2
20 August 2021	35	Norwegian satellite lands gas in UK.	3
03 September 2021	36	China´s gas demand grew by 17 % in January-July.	4
10 September 2021	37	Nord Stream 2 is complete.	5
17 September 2021	38	U.K. gas prices show an 18% increase in news.	2
24 September 2021	39	Agency is the first major international body to address claims by traders and foreign officials on Moscow´s reduction of supplies.	3
08 October 2021	40	The latest price gains mean that gas in U.K and Europe is traded at more than $ 200 per barrel of oil equivalent – more than double the price of oil.	1
15 October 2021	41	If you live in continental Europe or the UK the natural gas that heats your home this October is costing at least five times more than it did a year ago.	2
22 October 2021	42	Russian president says that Russia could increase gas flows "the day after tomorrow" if regulators approved that "tomorrow".	3

05 November 2021	43	Europe is in the grip of gas crisis. Prices have soared to almost five times the level they were a year ago, threatening the economic recovery from the pandemic in the UK and EU alike. Stocks are so low that a winter even slightly colder than normal could cut supplies to industry, with households already paying the price.	1
19 November 2021	44	President Vladimir Putin denied last week he was playing politics with gas deliveries to the EU	3
03 December 2021	45	Which companies are benefiting from the rise in gas prices in Europe? One to consider is Gazprom, which has a monopoly on gas export via Russian gas pipeline and has just reported record profits.	3
23 December 2021	46	Russian pipeline gas exports by Russian state-controlled monopoly Gazprom to continental Europe in 2021 fell by about a fifth to pre-pandemic level despite a sharp recovery in demand and low stock of the vital fuel.	4
14 January 2022	47	Latest news: The head of the International Energy Agency has accused Russia of cutting gas supplies to Europe at the time of "increased geopolitical tensions", suggesting Moscow has created an energy crisis for political purposes.	2
28 January 2022	48	The EU plans to ask Azerbaijan for potential emergency gas supplies, as it rushes to draw up contingency plans, if Russian invasion of Ukraine starts.	3
11 February 2022	49	Russia´s invasion to Ukraine could lead to rising gas prices, a migration crisis, and cyber security threats.	2
25 February 2022	50	European gas prices soar and by nearly 70 % and oil tops $ 105 after Russia attacks Ukraine.	1

Source: Author