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Prediction of Natural Gas Price Using GMDH Type Neural Network:A Case Study of USA Market

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Abstract

In this paper, a model based on GMDH Type Neural Network, is used to predict gas price in the spot market while using oil spot market price, gas spot market price, gas future market price, oil future market price and average temperature of the weather. The results suggest that GMDH Neural Network model, according to the Root Mean Squared Error (RMSE) and Direction statistics (Dstat) statistics are more effective than OLS method. Also, first lag of gas price in the future market is the most efficient variable in predicting gas price in spot market.

Keywords: Prediction; Natural Gas Price; Neural Network; Natural Gas.

JEl Classification: Q4, Q47, C01, C53

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1. Introduction

Considering energy as a strategic material and its effect in the world's economy, recognizing energy market and presenting appropriate predictions of the situation of the variables in this market are one of the important scientific challenges of the world. In this regard, different studies are made to predict variables including supply and demand and its price. Although at the moment, the greatest share of the world's fossil energies market is being dedicated to the crude oil but during two recent decades, its share is decreased in international energy markets, and gas has earned the most rapid rate among primary energies in international market. Thus, precise and comprehensive assessment of global market for natural gas could be useful in the future decisions for reaching a unified method in pricing and cost analysis in developing countries, which have gas and oil resources. Gas and oil markets differ in many aspects. In most cases, gas markets are regional, while oil markets could penetrate in worldwide. The cause of this problem is rooted in the costs and the kind of oil and gas transmission, because gas is transmitted liquid and via pipelines but oil could transmit in different ways.

Also the study of price trends shows that there is a relation between gas and oil price in these markets. Gas trade in relation to the oil has three distinctive characteristics:

1. Gas transportation to the identified destinations in the long path by pipe or tanker.
2. Dependent, and close and intensified relation between importer and exporter, at least in the period of contract.
3. High risk of investment.

Study of Natural Gas Price, due to the increase in energy consumption and demand and tendency to the other energy carriers that can replace with crude oil is important Economic approaches in the world that is considered. According to statistics, America region is one of the most important and the largest consumer of natural gas in the world. Natural Gas in US market is exchanged freely among purchasers and sellers, and prices are derived from the balance of supply and demand.

According to what was said about the importance of gas price by considering different effective strategies on natural gas prices, this paper aims to predict the price of gas in US market by using GMDH Type Neural Network. It should be noted that Artificial Neural Network as one of the main tools predicting the price has some advantages compared with other methods of prediction Such faster computing power compared to statistical techniques, the ability to reform and improve the estimation and higher accuracy.

Rest of this paper is organized as following: Section 2 represents literature review. Section 3 represents GMDH Type Neural Network model. Section 4 reports the data and results and finally, Section 5 comes as conclusion.

2. Literature Review

Reiter and et al.(1999), beginning with the note that the gas price predictions concentrates on equilibrium price in long-term periods, moves toward the gas price momentum prediction and using econometrics and Neural network, tries to predict gas prices in short-term period. The results show that both of them have a good performance during the purposes period, though the neural network's results are better than the econometrics model.

Behradmehr (2009) predicts the oil price using wavelet-based smoothing and artificial Neural Network to have more accurate prediction with less error. The results show that decreasing noise and data smoothing will improve the prediction of the oil price.

Moeini and et al. (2009) uses synthetic intelligent GMDH Type Neural Network, and Genetic algorithm, and multi-sided optimization for price analysis of pre-purchase and pre-sale of oil (for calculating the extreme incomes of the prediction in different trends of the market, based on the principles of technical analysis). The results show that in the period of 5 to 10 days for different periods of the market, absolute income reaches to 97%.

Abrishami and et al. (2009), uses GMDH Neural Network based on Genetics Algorithm, to predict the price of gasoline through two ways, the inductive method and the principles of technical analysis. The results show that the accuracy of Neural Network predictions is more than the regression model, meaningfully.

Abrishami and et al. (2010) using this method for the prediction of gasoline price based on the technical analysis principles during different periods of the market. Neural Network predictions were being more accurate and less errors than the time-series method.

Mehrara and et al. (2010) predicts price volatility of oil. Sotoudeh & Farshad (2012) predict gas prices in America using artificial Neural Network and multi layer ANN model.

Panella and et al. (2012) in an article entitled "Forecasting Energy Commodity Prices Using Neural Networks" provides a new approach of using Neural Network models to predict prices of energy sources. In this study, data is time-series and because model was complex, this approach can be used by computer systems. Demirel and et al. (2012) predict natural gas consumption in Istanbul using neural networks and multivariable time series.

3. Methodology

In this section, first, in section 3-1, we introduce Neural Network model which used to predict the gas price and then in section 3-2, we introduce indexes of performance evaluation for prediction, RMSE and Dstat.

3.1.GMDH Type Neural Network

In this section, we introduce the GMDH Type Neural Network taken from Abrishami et al. (2008). GMDH type neural network is represented as a set of neurons in which different pairs of them are connected through a quadratic polynomial. This network with connecting these quadratic polynomials of neurons, defines a function, $\hat{f}\hat{f}$, in order to predict output $\hat{y}\hat{y}$ for a given input vector

$X = (x_1, x_2, x_3, \ldots, x_n)$

$X = (x_1, x_2, x_3, \ldots, x_n)$X as close as possible to its actual output y. Therefore, for M laboratory data, including n inputs and an output, the actual results are displayed in the form of equation 1:(1)

$$y_i = f(x_{i1}, x_{i2}, x_{i3}, \ldots, x_{in}) \quad (i = 1,2, \ldots, M)$$

Here, we are seeking to train a network to predict the output value $\hat{y}\hat{y}$ for any given input vector XX based on equation (2):

$$\hat{y}_i = \hat{f}(x_{i1}, x_{i2}, x_{i3}, \ldots, x_{in}) \quad (i = 1,2, \ldots, M)$$

That the mean square error between the actual output and the predicted one is minimized. In other words (3):

$$MSE = \frac{\sum_{i=1}^{M}(\hat{y}_i - y_i)^2}{M} \rightarrow \min$$

Using polynomial function, the general connection form between the input and the output variables can be expressed in the form of (4):

$$y = a_0 + \sum_{i=1}^{n} a_i x_i + \sum_{i=1}^{n}\sum_{j=1}^{n} a_i x_i x_j + \sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{k=1}^{n} a_i x_i x_j x_k + \ldots \qquad (4)$$

This is known as the Kolmogorov-Gabor polynomial (Ivakhnenko).

In most practical cases, the quadratic polynomials form consisting of only two variables is used in the form of (5):

$$\hat{y} = G(x_i, x_j) = a_0 + a_1x_i + a_2x_j + a_3x_i^2 + a_4x_j^2 + a_5x_ix_j \qquad (5)$$

The unknown coefficients $a_i a_i$ in equation (5) are calculated by the regression techniques such that the difference between the actual output yy and calculated $\hat{y}\ \hat{y}$ for each pair of input variables ($x_i x_i$ و $x_j)\ x_j)$ is minimized. A set of polynomials using equation (5) will be constructed such that their coefficients are calculated by the least squares method. The coefficients of each quadratic function $G_i G_i$ (each of constructed neurons) are obtained to fit optimally the output in the whole set of input–output data pairs

$$E = \frac{\sum_{i=1}^{M}(y_i - G_i)^2}{M} \rightarrow E = \frac{\sum_{i=1}^{M}(y_i - G_i)^2}{M} \rightarrow \qquad (6)$$

In the basic form of the GMDH algorithm, all the possibilities of two independent variables(neurons) are constructed out of the total *n* input variables, and The coefficients of all variables are calculated by least squares method.

Thus $\binom{n}{2} = \frac{n(n-1)}{2} \binom{n}{2} = \frac{n(n-1)}{2}$ Neuron will be constructed in the second layer that we could depict it in the form (7):

(7)

$$\{(y_i, x_{ip}, x_{iq}) | (i = 1,2, \dots, M)\ \&\ p,q \in (1,2, \dots, M)\}$$

We use the quadratic form of the function in equation (5) for each triple M row. These equations could be set in the following matrix:

$$Aa = Y \qquad Aa = Y \qquad (8)$$

That A is a coefficient vector of the quadratic equation in equation (5). It means:

$$a = \{a_0, a_1, \dots, a_5\} \qquad (9)$$

$$Y = \{y_1, y_2, y_3, \dots, y_M\}^T$$
$$Y = \{y_1, y_2, y_3, \dots, y_M\}^T \qquad (10)$$

And it is clear from the input vectors and the form of the function that:

(11)

$$A = \begin{bmatrix} 1 & x_{1p} & x_{1q} & x_{1p}^2 & x_{1q}^2 & x_{1p}x_{1q} \\ 1 & x_{2p} & x_{2q} & x_{2p}^2 & x_{2q}^2 & x_{2p}x_{2q} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & x_{Mp} & x_{Mq} & x_{Mp}^2 & x_{Mq}^2 & x_{Mp}x_{Mq} \end{bmatrix}$$

$$A = \begin{bmatrix} 1 & x_{1p} & x_{1q} & x_{1p}^2 & x_{1q}^2 & x_{1p}x_{1q} \\ 1 & x_{2p} & x_{2q} & x_{2p}^2 & x_{2q}^2 & x_{2p}x_{2q} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & x_{Mp} & x_{Mq} & x_{Mp}^2 & x_{Mq}^2 & x_{Mp}x_{Mq} \end{bmatrix}$$

The least squares method from the multiple-regression analysis gets the solution of equations:

$$a = (A^T A)^{-1} A^T Y$$

$$a = (A^T A)^{-1} A^T Y \qquad (12)$$

This equation establishes the coefficient vector of equation (5) for all M triple set.

The coefficients of neurons in hidden layers and the output in the modeling process (education) will be identified based on the primary definition of the program from the level of significance and the Confidence interval, which researcher sets and the optimization of coefficients and the equations of neurons and the mechanism of data screening, which means elimination of variables with low correlation, will be processed through Genetics Algorithm. Thus, high-volume computations are solvable practically and help to the normal equations system to set in an appropriate and solvable condition.

One of the important problems in multi-layers artificial neural networks (Perceptrons among others) is designing network structure. In this design, the number of layers and also, the internal structure such as the number of weights and their values and as well, stimulation function of each neuron will be selected appropriately to establish a suitable and ideal mapping between input and output data. (Abrishami and et al., 2009).

Designing GMDH Type Neural Network problem is distinct from the above discussions. In this type of design, the aim is avoiding from the developing network divergence growth and relating the form and the structure of the network to one or more numeral parameters, such that by changing this parameter, the structure of networks changes. The evolutionary methods such as Genetics Algorithm have large applications in different phases of Neural Network designs since their unique capabilities in finding optimized values and the possibility of search in unpredictable environments. (Nariman zadeh and et al., 2002) However, in this paper, we used Genetics Algorithm for designing the form of Neural Network and identification of the coefficients.

In Section 3-2, we represent indexes of performance evaluation of prediction.

3.1.Indexes of Performance valuation of

$$Dstat = \sum_{n=1}^{k} if((y_t - y_{t-1} > 0;1;0) \square (\hat{y}_t - \hat{y}_{t-1} > 0;1;0));1;0$$

Prediction

For performance evaluation of prediction, in addition to variance error of prediction, we could use Root Mean Squared Error (RMSE) and Direction statistics (Dstat) statistics.

3.1.1.Root Mean Squared Error (RMSE)

According to Gujarati (2004), suppose that our number of observation is n and $\hat{y}_t, y_t$ are predicted and actual values

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(\hat{y}_t - y_t)^2} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}e_i^2}$$

Such that e_i is the difference of $\hat{y}_t, y_t$ and n is the number of observations (Varhami, 2010).

3.1.2.Direction Statistics (Dstat)

According to Wang (2004), Dstat is an index for measuring the tracking power of prediction models. It could be calculated through: (14)

That k is the number of prediction. (Mehrara, 2010)

This statistic is such that if the dependent variable in relation to the last period, co-direct with the predicted value $\hat{y}$ to the last period, Dstat is one, otherwise Dstat will be zero. After adding Dstat value, we could compare prediction methods by comparing and accounting the prediction percentage. Dstat index is calculated:

$$Dstat = \frac{\sum_{i=1}^{n} |e_i|}{n} \quad (15)$$

Which following states exist for e_i;

$$e_i = 1 \quad (y_{i+1} - y_i)(\hat{y}_{i+1} - \hat{y}_i) \geq 0$$

$$e_i = 0$$

It is worth to notion that in price prediction for entrepreneurs, predicting the trend of changes is more important than values.

4. Data and Results

In this paper, future price of gas, and future and spot prices of oil and also, the average temperature of weather are considered as effective variable on spot price of natural gas. In most cases, gas contracts are long-term and the price will be balanced over definite periods of time. In this regards, for avoiding the effects of this issue on our model and preventing it from disturbance, we have used the trading data of gas price, which is defined daily in American energy markets. Therefore Dependent variable is Trading price of gas in the spot market for USA (spo). Data related to the gas and oil prices in the spot, and future price variables are elicited from U.S. Energy Information Administration site[1], and the data of temperature variable are from National Oceanic and Atmospheric Administration site[2]. Our data are daily (5working days in the week), and its period is between 2005 November to 2010

1. www.eia .doe.gov
2. www.noaa.gov (Since the pivotal and important role of New York in economic and trade of America, weather temperature of this city is selected.)

October (5years). The number of data is 1302data. 1102 primary observations are given to the model as a sample test to predict 200 final data. It may be possible to say that this period is as long as enough and we could estimate the relations among variables certainly.

In this study, acronyms intended for effective variables are:

- fpg: Trading price of gas in the future market for USA.
- spo: Trading price of oil in the spot market for USA.
- fpo: Trading price of oil in the future market for USA.
- tem: Daily average temperature of the weather in New York City.

Table 1. Statistical Characteristics of Data

	fpg	spo	fpo	tem	spg
max	15.38	145.31	145.29	82	15.39
min	2.51	30.28	33.87	-1	1.83
skewness	0.91	1.06	1.08	-0.29	0.86
Kurtosis	0.74	1.36	1.38	-0.85	0.81
Average(mean)	6.60	74.91	75.04	45.62	6.44
variance	5.75	428.91	424.42	329.75	5.62

Table 1 shows statistical characteristics of data. From the fourth row of the Table 1, kurtosis of gas price in the spot market variable (spg) is 0.81 that is more than normal distribution and skewed to the right. Kurtosis of temperature variable (tem) is -0.85 that is less than normal and skewed to the left. Frequency distributions of other variables are similar to gas price in the spot market variable (spg).

As maintained in previous sections GMDH Type Neural Network is used for predicting gas price based on which variables are chosen as effective variable and we designs 5 models and then predict the gas price for each model.

In first model, first lag of all variables is considered as Neural Network inputs (effective variables). Since One of the most important features of the GMDH algorithm is the ability to identify and eliminate redundant variables (Farlow, 1984 and Chen, 2006) Therefore, In constructing the second model while using the results of the first model, ineffective variables are eliminated and first lag of spot price of oil is eliminated and second lag of future price of gas besides other variables are considered as input variables (effective variables). In third model, according to the results of first and second model, first lag of average weather temperature is eliminated and first lag of future price of gas and oil and second lag of spot price of oil are considered as effective variables. In forth model, first lag of future price of oil and gas and second lag of spot price of oil and average temperature of the weather is considered as input variables (effective variables).

Finally, in fifth model, effective variables (input variables) are: first lag of future price of gas, first lag of spot price of oil, first lag of future price of gas, and also daily average temperature of the weather in New York city which in this model, fist lag of daily average temperature of the weather in New York city is eliminated and the variable of second lag of average weather temperature is added.

Table 2. Results of the prediction using OLS and GMDH

Models	Percentage of the Prediction Accuracy	RMSE	Dstat
OLS Method	95.13%	0.2116	44.5%
First Model of GMDH	95.98%	0.1745	84%
Second Model of GMDH	96.10%	0.1696	76.5%
Third Model of GMDH	95.65%	0.1888	82.5%
Fourth Model of GMDH	95.58%	0.1744	83%
Fifth Model of GMDH	97.57%	0.1056	82.5%

Source: Scholar

Table (2) reports the Performance evaluation criteria for presented models compared to benchmark OLS model.

First row of table (2) shows the results of benchmark OLS. In second raw, the results of the first model of GMDH are showed that the Prediction Accuracy percentage of this model is 95.98% and is more than Prediction Accuracy percentage of benchmark OLS. Also Dstat is improved but RMSE statistics is decreased respect to benchmark OLS. In third raw of the table, Second model's results show that the

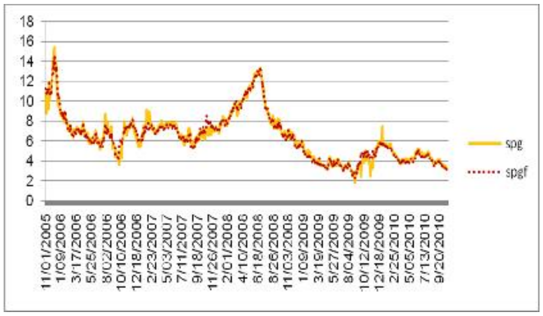

Fig 1 Comparing the Actual and Predicted Price of Natural Gas in Spot Market using GMDH Method

accuracy percentage of the prediction and RMSE statistics are improved but Dstat is decreased respect to the first model. The next raw show results of the third model of GMDH. The results show that just Dstat statistics is improved respect to the second model and other indexes is decreased. Forth model Results show that Dstat and RMSE are improved from the previous model. From bottom column of table (2) is observed that RMSE statistics of the fifth model is 0.1056 showed that these results are better than the previous models. Direction statistics (Dstat) of this model is 82.5% that it means 165 cases of 200 predicted samples are predicted in same direction and aligned with reality and finally, the Prediction Accuracy percentage of this model is more than 97 percentages.

After comparing statistics of prediction's performance evaluation (RMSE, Dstat and Prediction Accuracy percentage) in all models, fifth model of GMDH is selected as optimal appropriate model.

Since in all prediction of price in future, always, price in spot market and price in future market affect on each other, natural gas price changes in future market affect on natural gas price in spot market. However, according to the results, gas Price changes in future market does not affect on gas price in the spot market at the same period. But the effect appears in next period. Also oil price as substitution commodity is effective on gas price. Changes in oil price in spot and future markets, affect on gas price in spot market at next period. Temperature changes are effective on gas price in spot market at two periods later. Among the variables, natural gas price in futures market has the greatest effect on price of natural gas in the spot market. Therefore, considering the results of fifth model, like other models, first lag of future price of gas is introduced as the most influential variable or variable with multiplier effect[3] in this model.

As it is clear from the Figure (1), prediction is similar to the actual values of spot price of the gas.

Conclusion

Gas- as a newfound energy source that its consumption has increased dramatically and has the highest growth rate among the fossil fuels during last three decades- has found its place among other fossil fuels and today, is seen as the most important alternative of oil. According to the estimations of the various institutions, the share of natural gas in demand basket of world's primary energies will increase. In other words, natural gas will play a very important role in the future world's interactions. Considering the nature of this energy source and particular type of its contracts, That is usually long-run, and it is required a great investment for its production and extraction, its price prediction is One of the most important factors in Coalescence of Contracts And macroeconomic policy makings in this field. This study provides an appropriate method for predicting natural gas prices among different methods of prediction, considering effective specific variables on gas price (several factors affect on gas price in the spot market, which the most important of them are gas price in the future market, and oil price in

3. These variables with effects for inputs in GMDH-Type Neural Networks have a different meaning in Regression analysis. It is dedicated to the variables which its repetition is more than other variables in the outputs of the network's program, or could jump from a hidden layer.

the spot market, and oil price in the future market, and weather temperature).

In this study GMDH Neural Network models is used for prediction and the results of this prediction has been compared with OLS model as a basic model that according to the results, GMDH method according to the RMSE and Dstat statistics is more effective than OLS method and Also, first lag of gas price in the future market is the most effective variable in predicting gas price in the spot market.

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پیش بینی قیمت گاز طبیعی با استفاده از شبکه عصبی GMDH

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با توجه به بررسی‌های صورت گرفته، عوامل متعددی بر قیمت گاز طبیعی در بازار نقدی تأثیر دارند، که از مهمترین آنها می-توان قیمت گاز در بازار آتی، قیمت نفت در بازار نقدی، قیمت نفت در بازار آتی و دمای هوا، را نام برد. در این مقاله با استفاده از مدل شبکه عصبی GMDH، به پیش‌بینی قیمت گاز طبیعی در بازار نقد با استفاده از قیمت نفت در بازار نقدی، قیمت گاز در بازار نقد، قیمت گاز در بازار آتی، قیمت نفت در بازار آتی و میانگین دمای هوا، می پردازیم. نتایج تحقیق مشخص می که مدل شبکه عصبی GMDH با توجه به آماره-های جذر میانگین مربع خطا و همنوایی پیش بینی، به مراتب از کارایی بیشتری نسبت به روش حداقل مربعات معمولی برخوردار است. همچنین وقفه اول قیمت گاز در بازار آتی، مؤثرترین متغیر در پیش-بینی قیمت گاز در بازار نقد می‌باشد.

واژگان کلیدی: پیش بینی، قیمت گاز طبیعی، شبکه عصبی، گاز طبیعی.

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