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Prediction of Natural Gas Price in European Gas Hubs Using Artificial Neural Network

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ABSTRACT

The liberalization of natural gas markets and the emergence of gas hubs in recent decades have shifted the natural gas trade from the regional to the global trade. The growth and maturity of these hubs have weakened the previously established relationship between the natural gas price and the prices of crude oil and petroleum products. Therefore, predicting the price of gas as a strategic commodity has become more important for different countries. Using the neural network method, this paper attempts to develop a model of the monthly prediction of natural gas price. Based on the time series data from 2012 to April 2019 as the input to the neural network, this model predicts the prices in five hubs and natural gas exchange centers in Europe. Based on the R^2 performance evaluation index of 98% of the neural network model fitted based on the aforementioned data series, the neural network model has acceptable performance in predicting the natural gas price. The results of this study show that using the artificial neural network (ANN) method, the gas prices in the European gas hubs, which are located in European countries, can be predicted with a high degree of accuracy.

1. Introduction

There are raised concerns over climate change and air quality in the world, limited growth and development of renewable energies, and failure to achieve low-carbon energy. These issues have caused that the natural gas with the lowest environmental pollution index and potentially easy and accessible use to play a significant role in the fuel consumption of countries in recent years (Su et al., 2019). Currently, the natural gas accounts for about 24% in the global fuel basket and 67% in the Irnn's energy basket (BP, 2018).

Since natural gas is considered to be one of the important carriers of energy, it will also have a more important role in the future among the energy sources due to the environmental benefits. Therefore, it is very important to predict the price of natural gas. Predicting the natural gas prices as an essential and significant tool allows different stakeholders in the natural gas market to make better decisions when facing potential risks. On the other hand, predicting the price reduces the gap between supply and demand and optimizes the use of resources based on the accurate predictions (Su et al., 2019).

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In many studies, the price of crude oil has been predicted, but since the natural gas price still follows the price of crude oil and petroleum products in some places, the prediction of natural gas price has less been studied compared to the oil price. In general, the price of natural gas in some markets including the Asian markets remains at a high level, and for solving the problem of high price of this energy carrier, developing the gas market and establishing the gas hubs[2] in East Asia are suggested. The prediction of natural gas price and use of prediction tools improve the efficiency of the developed markets. The accurate prediction of the natural gas price is essential to support effective investment and negotiation decisions on the import and export contracts (Jin and Kim, 2015). In addition, predicting the natural gas price not only provides an important guide on the effective implementation of energy policy making and planning, but is also very effective in the economic planning, energy investment, and environmental protection (Su et al., 2019).

Due to the importance of the oil and gas market, there have been several studies on the predictions in these markets where each study has examined and predicted a market aspect using a specific method. The studies on the monthly gas price prediction can be divided into two groups: the studies using econometric methods and the studies predicting the natural gas price using the machine learning tools such as neural network methods[3], genetic algorithm[4], support vector machine[5], etc. In either of the methods, the price of natural gas is predicted using either a single variable or several variables. The results of the above studies show that the accuracy of neural network prediction is significantly higher than that of the regression models in terms of error criteria. In other words, based on the research, the nonlinear and combined models, especially the neural networks, have a higher capability and accuracy than other models to predict the gas price because they include more factors in the modeling[6]. This paper aims to predict the gas price in the European hubs using the artificial neural network model. In the second section of this paper, the experimental studies of this field are reviewed. In the third section, the theoretical foundations are provided, and, in the fourth section, the application of neural network in the prediction of natural gas price, data analysis and description, performance evaluation features of prediction, the validation technique, and model parameters are investigated. Section 5 also presents the results of the neural network model, and Section 6 draws the conclusions.

2. Literature Review

Today, the future price or quantity is predicted using the computational and statistical sciences in different fields. Therefore, many methods have been considered for the analysis and prediction, among which the use of machine learning-based methods has attracted more attention in recent years. One of the studies conducted in this context is the research of Su et al. (2019) which predicts the price of natural gas in the Henry Hub market based on the 2001–2017 data by utilizing four models, namely artificial neural network (ANN), support vector machine (SVM), gradient boosting machine (GBM), and Gaussian process regression (GPR) models; the neural network model is better than the other three models based on the results. In another work, Jin and Kim (2015) predicted the natural gas price in Henry Hub using three methods, namely wavelet, time series, and neural networks, based on the 2000–2013 data, and showed that using the neural networks alone is the best method for the two-step prediction and combining the wavelet method with the auto regressive integrated moving average (ARIMA) method is the best technique for the four-step prediction.

In a paper reviewing the literature on natural gas prediction, Tamba et al. (2018) examined the prediction

[2] Natural gas hubs tend to be at the heart of gas infrastructure networks such as pipelines and liquefied natural gas (LNG) terminals. The hub is used as a central pricing point for the networks natural gas. In some cases, a financial derivative contract is the priced-off gas delivered at this point as well. (Reuters)

[3] The artificial neural network is a computational model developed in 1943 by McCulloch and Pitts based on the mathematics and threshold logic algorithms (Su et al., 2019). A neural network (also called an artificial neural network) is an adaptive system that learns by using interconnected nodes or neurons in a layered structure that resembles a human brain. A neural network can learn from data, so it can be trained to recognize patterns, classify data, and forecast future events (mathworks.com).

[4] The genetic algorithm (GA) is a search technique used in computing to find exact or approximate solutions to search and optimization problems (Ganesh Bonde).

[5] The support vector machine (SVM) is machine learning algorithm that analyzes data for classification and regression analysis (techopedia.com).

[6] Price prediction can be performed through the economic and econometric methods such as time series methods, ARIMA, GARCH, machine learning methods (including genetic algorithm and support vector machine), and combined models.

models presented for the production, consumption, demand, price and income elasticity, market liquidity, and price changes. Busse et al. (2012) estimated the day ahead spot price movement of natural gas in market area of NetConnect Germany[7] using the neural networks model with five factors, including temperature, exchange rate, and the price in three national balancing point (NBP), Net Connect Germany (NCG), and Dutch Title Transfer Facility (TTF) hubs based on the data from January 2010 to February 2011. Based on the results, the temperature has the greatest impact on the short-term gas price. Also, the prices predicted for the next four days have the highest impact.

In a research, Fabini predicted the gas prices in three NBP, Zeebrugge Hub (ZEE) and TTF hubs using the generalized autoregressive conditional heteroskedasticity (GARCH), exponential general autoregressive conditional heteroscedastic (EGARCH), and threshold generalized autoregressive conditional heteroskedasticity (TGARCH) models based on the 2008–2012 price data. The fitted models showed a positive correlation between the fluctuations of the three markets. Hosseinpoor (2016) predicted the natural gas price in the United States based on the 1997–2016 data in his mrrrrr rs thesis at the University of Oklahoma using the stochastic differential equations, ARIMA, and neural network and showed that the neural network model outperforms other models in predicting the prices.

However, in the field of studies conducted in Iran, the study by Mohammadi et al. (2017) entitled "Natural Gas Price Prediction Using Combined Wavelet Transform and Neural Network" based on the US gas market survey and the daily price data from 1997 to 2015 can be noted. In this study, the combined model of wavelet transform and neural network had a better prediction than the neural network model. Pourkazemi and Asadi (2009) used the artificial neural network model to dynamically predict the West Texas Intermediate (WTI) crude oil price based on the 1998–2008 price data. In addition to the univariate neural network model, the oil storage data of organization for economic co-operation and development (OECD) countries were added to the input to the network, and the results indicated the better prediction of the neural network model than the ARIMA model and the more accuracy of the bivariate model than the univariate model. In another study, Pourkazemi et al. (2005) predicted the urban gas demand using the fuzzy neural networks and ARIMA model based on the demand data from April 2003 to December 2004 and finally concluded that the neural network model provides the predictions with less error based on different criteria. Mirsoltani and Akhavan (2013) used the neural network model and fuzzy system to predict the energy price and consumption in the industry sector in Iran based on the 1996–2010 data and stated that, based on the consumption data of oil products and prices, the results of fuzzy logic have a smaller rate of error than the neural network model. Using a combination of neural network technique and rule-based expert systems, Abrishami and Varahrami (2011) predicted the gas price based on the price data during 2006–2010. Moshiri and Forootan (2004) compared the performance of the neural network model with the nonlinear GARCH models and ARIMA linear model for predicting the daily crude oil price during 1983–2003. They showed the superiority of the neural network model with a lower error rate. In a paper entitled "Prediction of Crude Oil Price Using Wavelet Smoothing and Artificial Neural Network", Behradmehr (2008) predicted the oil price based on the price data from January 2000 to September 2004. The results showed that the used combined model leads to the better performance in the prediction of oil price through the data denoising and smoothing.

In a study on the modeling and prediction of natural gas price using the artificial neural networks, Abbasi and Varnamkhasti (2014) sought to present a high-accuracy and acceptable price prediction model and indicated the higher accuracy of the fuzzy neural network model after examining the multi-layer filtering (MLF) networks with one and two hidden layers, radial basis function network (RBF) neural network, and neural-fuzzy network model. In a study aimed at predicting the natural gas consumption in the domestic and commercial sectors of Isfahan, Iran using the neural network model, traditional regression model, and ARIMA based on the consumption data from 2002 to 2011, Honari et al. (2016) found that the neural network models have less error than the other two methods. Abrishami et al. (2008) in another work modeled and predicted the gasoline price using the GMDH neural network from 1998 to 2007 and reported that the accuracy of the neural network predictions is significantly higher than the regression model, which indicates the high capability of the neural network model to model the complex processes and

[7] NetConnect Germany GmbH and Co. KG (NCG) together with Gaspool, is one of the two market area managers on the German natural gas market.

predict the nonlinear dynamic paths. Sotoudeh and Farshad (2012) in a paper entitled "Neural Network Application for US Gas Price Prediction" predicted the price using the variables of consumption, production, import and export of gas, crude oil reserves, and prices during 1949–2010 and showed that the model has an acceptable prediction.

As stated in the studies reviewed above, the prediction accuracy of the neural network model is significantly higher than the regression models in terms of error criteria. In other words, based on the aforementioned research, the nonlinear and combined models, especially the neural networks, have the capability and accuracy to predict the gas price better than the other models since they include more factors in the modeling.

Therefore, studies reviewed above show that there are publications regarding gas international price forecasting in European gas hubs. Therefore, the contribution of this paper is the forecasting of the gas international price in European hubs by utilizing the ANN as an accurate forecasting technique.

3. Theoretical Foundations

The natural gas market was established since the 1950s when the large Groningen field was discovered in Norway and then other fields in the Black Sea. In 1962, the Dutch gas exports to France, Belgium, and Germany began, and the natural gas pricing formula was based on the market value analysis where the market price of competing domestic fuels of each market, i.e. coal and gasoil at that time, formed the basis for the pricing. In addition, the gas price was determined according to the distance from the market and the storage capacity of each country.

Currently, Europe, Asia, and the US each have their own pricing mechanism. In Europe and in the areas where the free and integrated markets of natural gas have not formed or are emerging, the natural gas price is partly related to alternative energy prices, particularly fuel oil and thermal oil; in other sectors, it is determined by the market mechanism and the quantity of supply and demand. However, in recent years, the growth of the gas hubs in Europe has also influenced the pricing of gas in the international contracts and led to the gradual integration of national markets in the EU and the evolution of gas pricing in the long-term contracts. In other words, the gas market is emerging as a new market independent of the oil market, and for this reason, the relationship between the price of gas and the price of oil or petroleum products is weakening in this market. Therefore, as a result of the effects of market liberalization, this relationship is likely to change in the future and will evolve as what has happened in the US market in the past.

Certainly, there is no single mechanism for pricing the natural gas on a global scale. The differences in the gas pricing mechanisms in different markets are also due to the existence of gas-on-gas competition pricing indices, oil price index, monopoly, recursive and replacement methods, and market regulation.

The gas market can be divided into the three regional markets of the United States of America, Asia-Pacific, and Europe. Even in the last few years, the European market has been different in various segments, and with the development of the gas market on the continent and the emergence of gas hubs, the market spot pricing is actually emerging (Zajdler, 2012).

The review of the world gas market shows that there are currently two main pricing mechanisms for natural gas in the three regional markets. In the early 1960s in Norway and its borders, the pricing method based on the price of oil and its products was developed by gas producers. This method is the pricing based on the natural gas alternative fuels, which was also used in the Asia and is still practiced in some parts of the world. However, the second pricing method which was initially established in the United States and later transferred to the UK and other parts of Europe was based on the market or hub price where the gas price varies from market to market.

Over time, with dividing the British Gas Company into multiple sectors, separating the distribution from the commercial sector, and providing the access for both sectors to the transmission network, a virtual gas balancing location, which was later introduced as the British National Balancing Point (NBP), was established to conclude the spot contracts; thus, natural gas was traded like other commodities and similar to crude oil.

This pricing model was then applied to the British NBP in 1998 for the Dutch and Belgian markets, and lastly, the European gas producers in the British market took action considering the NBP hub gas price as a reference price for the Belgian Zeebrugge (ZEE) and Dutch Title Transfer Facility (TTF) hubs that quickly became the two important natural gas hubs in Europe. Currently, other local hubs across Europe determine the gas price based on the supply and demand.

Since the mid-2000s, the natural gas in Europe and the US has been traded based on the hub price rather than oil price index. Since 2001, the European Commission has implemented three waves of reform, most notably the Third Energy Package in 2009, which aims to liberalize the European energy markets. In fact, Europe entered a period of reforms similar to Britain in the 1990s. One of the most important structural changes by Europe as an integral package was implemented in 2011 (Grandi, 2014), which has contributed to the development of the European energy and gas markets.

The development of gas infrastructure in the member states, including the pipelines, LNG terminals, and storage facilities, which has led to the flexibility of the gas supply chain, has made a significant change in the E'' s gas market pattern, leading the gas market development to be subject to the competition laws and liberalization principles, which were adopted by the EU member states and are gradually being implemented.

The greatest progress has been seen in the development of European gas hubs in the last decade, while few numbers of European countries had a traded gas hub 10 years ago. Nowadays, new trading hubs are gradually formed, and there are still seven countries without a traded gas hub. However, it is possible that all European countries have a single gas market by 2025 (Patrick Heather, 2019).

The managing long term gas contracts encountered increasing commercial difficulty in the late 2008 and reduced sales prices to customers, as oil-linked purchase prices rose significantly above the hub-based prices. Therefore, gas hub-based prices and oil-linked converged at the end of 2010, but this convergence was only temporary and partly due to the very cold weather in Europe. In the context of a surplus of European gas supply over demand during this period (2010–2014), this was a commercially untenable position for European gas buyers (Jonathan Stern and Howard Rogers, 2011). The transition from oil-linked prices into hub-based prices continued in the following years and became as a dominant price-setting mechanism (Jonathan Stern and Howard Rogers, 2014).

Hub-based pricing is supported to be able to better reflect the fundamental value of natural gas (Shi and Variam, 2016; Stern, 2014; Zhang et al., 2018a). In other words, the hub price of natural gas is determined by demand and supply in natural gas market (Zhang et al., 2018b).

Stern (2014) and Zhang et al. (2018a) argue that oil and natural gas cannot necessarily substitute each other and have different underlying fundamentals. Their idea is consistent with the efficient market hypothesis (EMH) introduced by Fama (1965). The main argument is very simple: the price should reflect the fundamental value of underlying asset, and in an efficient market it should respond to shocks accurately and quickly (Zhang et al., 2018b). Supporting arguments claim that hub pricing can better reflect fundamentals in natural gas and thus create better efficiency. By contrast, the opinions against hub pricing and in favor of oil indexation advises that oil indexation is the best remedy for gas market failure (Zhang et al., 2018b).

Obviously, the replacement of gas pricing mechanisms in different markets is performed by exclusive methods and oil-based or recursive pricing with the pricing method based on the price index and gas-on-gas competition, that is, the hub price index. Therefore, it is important to predict the gas price in the hubs for the producers and for the consumers. Given the enormous volume of Irnn's gas reserves of about 34 trillion cubic meters (BP, 2018), the analysis of the price and pricing indices is very important. Therefore, it is necessary to predict the gas prices in the European hubs as a potential market for Iran.

4. Methodology

4.1. Application of Neural Network to Prediction of Natural Gas Price

The neural network is a computational model developed in 1943 by McCulloch and Pitts based on the mathematics and threshold logic algorithms. The neural network is a framework to attract machine learning algorithms for the cooperative work, so it is not an algorithm. The neural network has become more important since the 1980s and has served as the focus of research in the field of artificial intelligence which has various applications in the data processing, classification, performance approximation, and numerical control (Su et al., 2019).

As one of the new approaches that has also been considered in the field of economics in Iran, artificial intelligence provides linear and nonlinear tools for the prediction. In other words, the artificial neural network, as an intelligent system, can detect linear and nonlinear relationships between inputs and outputs based on training data and identify their fundamental relationships and then generalize the detected relationships to other data. As such, by properly designing the neural network architecture and selecting the right training data, one can achieve a structure that can predict the time series (Pourkazemi and Asadi, 2009).

The neural network processes in the same way as the neural network of the human brain create different complex networks by connecting different units and nodes called artificial neurons. As shown in Figure 1, each node contains an activation function to generate output based on one or more inputs. The output signal of one node can be transmitted by a weight connection to another node (Su et al., 2019).

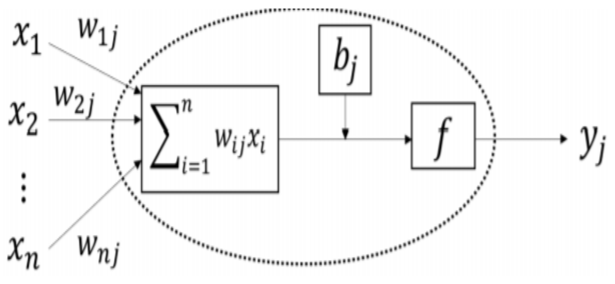

Figure 1. The structure of artificial neuron in ANN.

The relationship between the target variable (Y_j) and the independent variable (X_i) is obtained from Equation (1):

$$Y_j = f\left(\sum_{i=1}^{n} w_{ij}X_i + t_j\right) \tag{1}$$

where X_i (i = 1, 2, …, n) is the input data, and w_{ij} is the weight of the data. There are two basic units, namely summing and activating the input signals in the processing unit. Also, Y_j is the unit output which is defined as Equation (2):

$$Y_j = f\left(\sum_{i=1}^{n} w_{ij}X_i + t_j\right) \tag{2}$$

The error backpropagation training algorithm is also used to train the networks. The algorithm was developed in 1986 by David Rumel Hart and James McClelland. The error backpropagation is designated because the calculated error is returned from the output layer to the intermediate layer and finally to the input layer. The accuracy index of this algorithm is the mean square error. The activation function for the hidden and output layers is a standard sigmoid function, as expressed in Equation (3):

$$f(x) = \frac{1}{1+e^{-x}} \tag{3}$$

Output Yj is transmitted from the next layer as the input signal to the connected units. According to the designed model, all the units in the artificial neural network are interconnected in different layers. A simple example of a three-layer neural network is shown in Figure 2. In this network, the information flows through the input, hidden, and output layers, where the input layer or the first layer contains the same number of units as the input vector. Then, there is the hidden layer with the desired number of units, and finally, the output layer is the weighted output of the hidden layer unit.

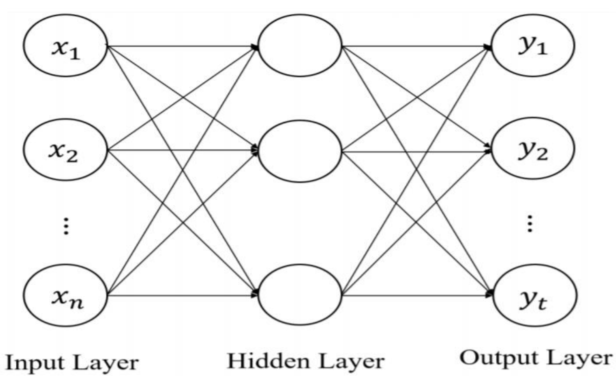

Figure 2. A simple structure of an artificial neural network comprised of three layers.

The neural network intelligence is derived from the learning process, which allows the network to be capable of automatic adaptation, communication, and memory for specific tasks. Although the gas price is primarily determined by factors such as supply and demand, it is also influenced by factors such as product inventory, stock market activities, exchange rate, and political issues (Abrishami and Varahrami, 2011).

Unlike traditional methods, neural networks are the self-adaptive and data-driven networks which have little assumptions about the models used for different problems. The neural network provides better analyses than the linear regression analysis when there are ambiguities in the independent variables. In addition, the network structure is trained using part of the data and then tested using the rest of the data (Abrishami and Varahrami, 2011).

In addition, the neural networks are easy to generalize, so after the learning using the sample data, they are able to correctly elicit and derive the unobserved parts of the population even with the possibility of disturbance in the sample data. In other words, these networks can be trained, that is, they can adjust network weights using the training data, and can be generalized; in fact, after training the network using the training data and adjusting the network weights, the network is able to accept an input and to provide an appropriate output (Menhaj, 2005). Also, the biggest advantage of the neural networks is the ability to model complex nonlinear relationships.

4.2. Data Preparation and Description

Many factors such as crude oil price, fuel oil and gas oil prices, drilling activities, temperature, supply and demand of natural gas, storage, and import of gas affect the price of natural gas. To predict the gas price as accurate as possible, these data should be taken into account (Su et al., 2019). However, it is somewhat impossible for the European Union to obtain the above data with respect to the gas transmission and distribution centers in the continent and to apply the data to the model. Therefore, the prediction of natural gas price in the European hubs is based on the published historical price data as a univariate model.

Currently, the active gas hubs and transmission centers in Europe include the National Balancing Point, Title Transfer Facility, Zeebrugge, Net Connect Germany, Punto di Scambio Virtuale (PSV), Central European Gas Hub (CEGH), Gaspool (GPL), and Points d'Échange de Gaz (PECG), and given the availability of the price data of the NBP, TTF, ZEE, NCG, and PECG hubs, the price was predicted for the five selected hubs.

The price predictions are based on the time series data from monthly hub prices available from 2012 to 2019. The comparison of gas prices in different hubs is shown in Figure 3.

Figure 3 shows that the natural gas prices do not have a regular upward or downward trend. In addition, the intensity of the fluctuations and their periods are not constant and identical. This indicates the existence of a nonlinear structure in the gas price data series.

During the study period, the average price in each hub, the maximum price, and the minimum price were determined. Table 2 lists the results from the description and analysis of the natural gas spot price data in each of the hubs and the related variables, including the maximum, the minimum, the median, the mean, and the standard deviation.

Table 1. List of variables used in this study.

Variable	Data	Unit
Natural gas price	Gas price in NBP hub	$ per thousand cubic meters
	Gas price in TTF hub	
	Gas price in NCG hub	
	Gas price in the ZEE hub	
	Gas price in PECG hub	

Source: Research findings

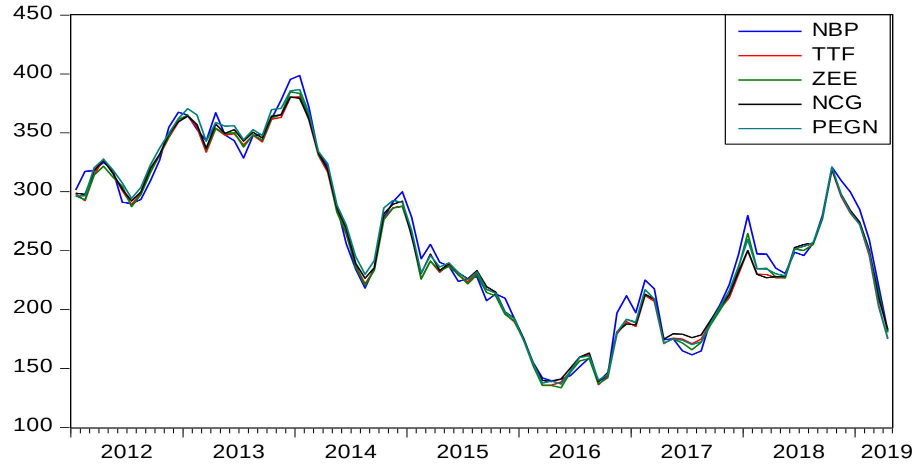

Figure 3. Historical trend of natural gas prices in European hubs (Data published by Platts and Argus.).

Table 2. Statistical summary of natural gas prices in selected European hubs from 2012 to 2019 ($ per thousand cubic meters).

Hub	Maximum	Minimum	Median	Mean	Standard Deviation
NBP	399	139	248	259	70.7
TTF	381	136	244	254	69.5
NCG	381	139	249	256	69.2
PEGC	387	137	247	258	71.2
ZEE	385	134	245	255	70.1

Source: Research findings

Table 3 tabulates the correlation between gas prices in different hubs. It is clear that there is a correlation between the gas prices in different hubs. The highest correlation is seen between the gas price of TTF and NCG hubs and the lowest correlation between the gas price of NBP and NCG hubs. The correlation between the prices of different hubs is positive, meaning that increasing or decreasing the price in one hub leads to the increased or decreased prices in other hubs respectively. The higher the correlation between the prices in the two hubs, the greater the changes in the price of the two hubs.

Table 3. The correlation between the gas prices of different hubs.

Hub	NBP	TTF	ZEE	NCG	PEGC
NBP	1.0	-	-	-	-
TTF	0.9920	1.0	-	-	-
ZEE	0.9945	0.9991	1.0	-	-
NCG	0.9914	0.9996	0.9988	1.0	-
PEGC	0.9922	0.9993	0.9990	0.9992	1.0

Source: Research findings

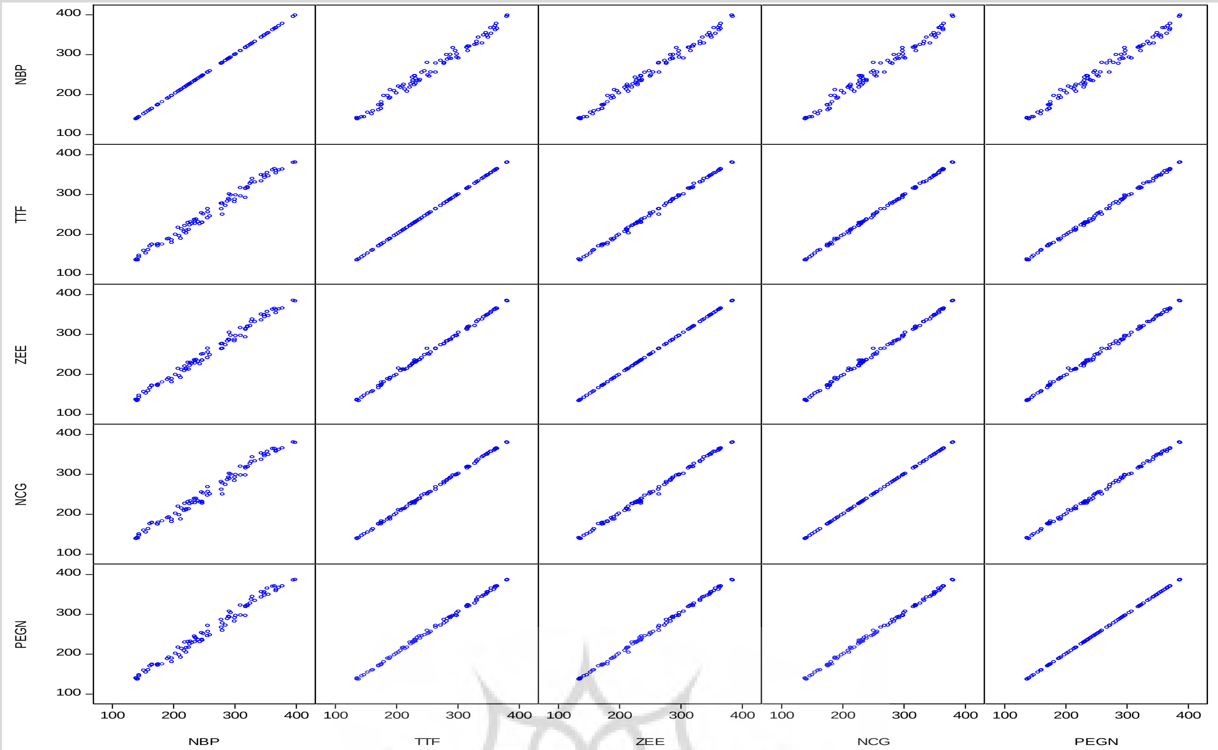

Figure 4. The correlation between the price highlight of gas hubs in Europe.

Source: Research findings

Figure 4 delineates the correlation between the European hubs in a graphical and pairwise manner. As it can be seen, the gas prices in all of the five hubs are nearly correlated and move together in one direction.

4.3. Evaluation Indicators of Prediction Performance

There are many evaluation criteria for measuring the performance of a prediction model. In fact, the criteria examine the validity of the prediction methods via the difference between the real and the predicted value of the dependent variable; some of the criteria are given in this section for measuring the performance of the model. The *R*-squared (R^2) index is used to measure how the prediction model matches the actual data and is obtained using Equation (4):

$$R^2 = \left[1 - \frac{\frac{1}{N}\sum_{t=1}^{N}(\tilde{y}t - yt)^2}{var(y)} \right] \quad (4)$$

where yt and $\tilde{y}t$ represent the real values and the predicted values at time t respectively; N stands for the number of data used, R^2 represents the conformity of the data with the estimated model and ranges from 0 to 1; the better the estimated model exhibits the changes, the closer to the unity R^2 will be. In other words, in a model with an R^2 of greater than 0.8, the estimates can sufficiently match the existing data.

Mean absolute error (MAE) is a performance evaluation tool for the prediction model which calculates the MAE based on Equation (5).

$$MAE = \frac{1}{N} \times \sum_{t=1}^{N} |\widetilde{yt} - yt| \quad (5)$$

Mean square error (MSE) represents the mean squared deviation of the predicted value from the real value and is used to measure the amount of variations. The prediction model performs better when the MSE is lower. In contrast to the MAE, the mean square error increases the prediction deviation. The mean square error is calculated by Equation (6):

$$MSE = \frac{1}{N} \times \sum_{t=1}^{N} (\tilde{y}t - yt)^2 \quad (6)$$

The root mean square error (RMSE), which is sensitive to very large or very small error values, can be directly obtained by calculating the square root of the mean square error (MSE); as a result, it is a good reflection of the prediction model; it is expressed by Equation (7):

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{N} \times \sum_{t=1}^{N} (\tilde{y}t - yt)^2} \qquad (7)$$

The less the error in the model results, the better the prediction capability of the model. In other words, the lower the RMSE, the higher the capability of the prediction model.

Mean absolute percentage error (MAPE) is often used as a loss function because it can intuitively describe the relative errors. It not only considers the deviation of the prediction value and the real value, but also takes their ratio into account. To calculate the mean absolute percentage error, Equation (8) is used:

$$MAPE = \frac{1}{N} \times \sum_{t=1}^{N} \left| \frac{\tilde{y}t - yt}{yt} \right| \qquad (8)$$

4.4. Selection of Model Parameters

The machine learning methods have many parameters, some of which are the key parameters that should be carefully selected. The model complexity often depends on these parameters, which are called the model selection parameters. In a neural network model, a nonlinear auto-regression model with the external input is selected (Su et al., 2019).

Selecting the number of the hidden layers is very important because a large number of the layers reduce the network performance. In theory, a neural network with two hidden layers is able to estimate any nonlinear function with an arbitrary degree of accuracy (Mohammadi et al., 2017).

4.5. Neural Network Validation and Verification

In model selection, cross-validation is an important technique to obtain the practical and stable models in the machine learning. In the cross-validation, the K validation is a common method to prevent excess connections in very complex models, and using the K validation requires less data. Due to the MSE value of the validation samples, the training stops automatically when it is not possible to improve the generalization.

The training data is divided into K parts, and K–1 parts are used for the model training; the rest is used for the validation. The training and validation operations are often performed by rotating the K folds. After performing this operation for K times, all the errors are collected to calculate the final error. K is often considered equal to 10.

In the neural model used to predict the gas prices in the European hubs, the number of hidden neurons and the number of layers are set at 10 and 2 respectively. In the training network, the selected training algorithm is the Levenberg-Marquardt algorithm which typically requires more memory and less time. In addition to building a neural network, a two-layer feedforward neural network with complete connection between the nodes is used, and the complete network information is presented in Table 4. The feedforward backpropagation algorithm of the artificial neural network was used in MATLAB R2017b software to design the prediction model.

Table 4. The parameters of the ANN used in the designed model in this study.

Input layer nodes	Hidden layer nodes	Output layer nodes	Transfer function: hidden layer and output layer	Training and test data size
16	10	5	Tansig	20% for training and 80% for testing

Source: Research findings

5. Neural Network Simulation Results

Using the designed neural network model, the applied data, the evaluation indicators of prediction performance, the model validation technique, and the model parameters, the performance indicators of the prediction model were extracted.

Figure 5 shows the model performance and the validation indicators based on the results.

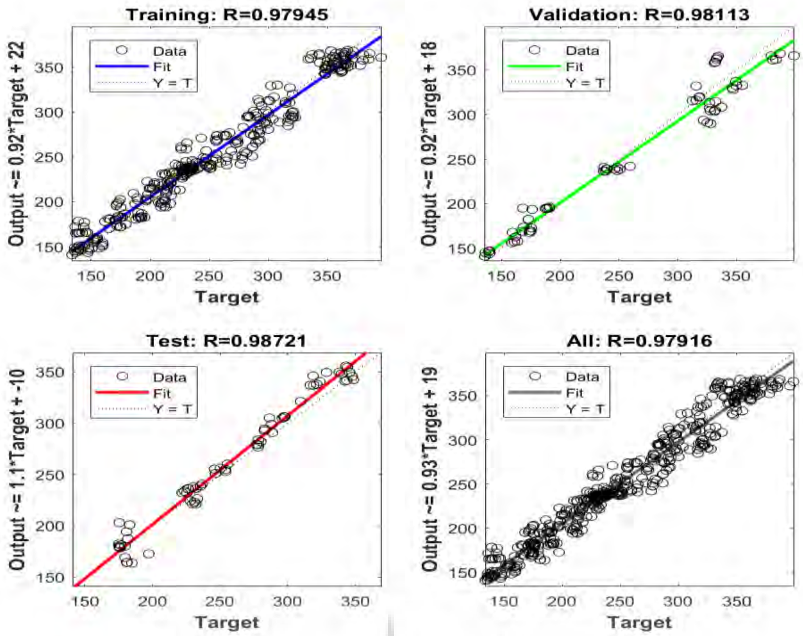

Figure 5. The performance and the validation indicators of the prediction model.

Source: Research findings

As shown in Figure 5, the R^2 index is estimated for the training data, the test data, the validation, and, generally, the overall model. The index is about 98%, which indicates the very good performance of the prediction model through the use of the artificial neural network method.

Figure 6 shows the projected values of natural gas prices in the five European hubs based on 88 gas price data from the beginning of 2012 to April 2019.

In Figure 6, the blue lines are the historical data (the real values) used to fit the prediction model, and the red lines are the predictions based on the model; the green lines are the model error rates fitted based on the real values. It is obvious that for each of the gas hubs, the predicted values of the fitted model are able to significantly cover the real values, and the R^2 value of the model is about 98%, which shows a significant match between the predicted and real values. Based on the results of the neural network model, it can be stated that the neural network is well capable of self-learning, self-adaptation, and self-organization, can analyze the patterns and rules of the observed data, can form complex nonlinear through the training, and can adapt to large-scale, multi-factor, incomplete, and inaccurate data processing.

Based on the above results, the used ANN model has better prediction performance and accuracy (98%) than machine learning methods such as SVM (84%), GBM (80%), and GPR (83%), as well as the ANN (89%) developed by Su et al. (2019). In another study conducted by Sebastian Busse et al. (2012), the ANN model was used for predicting the natural gas spot prices of the three major hubs, namely the NBP, TTF, and NCG. Their result revealed a forecasting accuracy of 64%.

Therefore, based on the historical data and using the ANN method in this study, the gas prices in the European gas hubs can be well predicted, and the predicted data can be widely used in the areas of investment, negotiating the import and export contracts, and, more generally, energy policy making and planning.

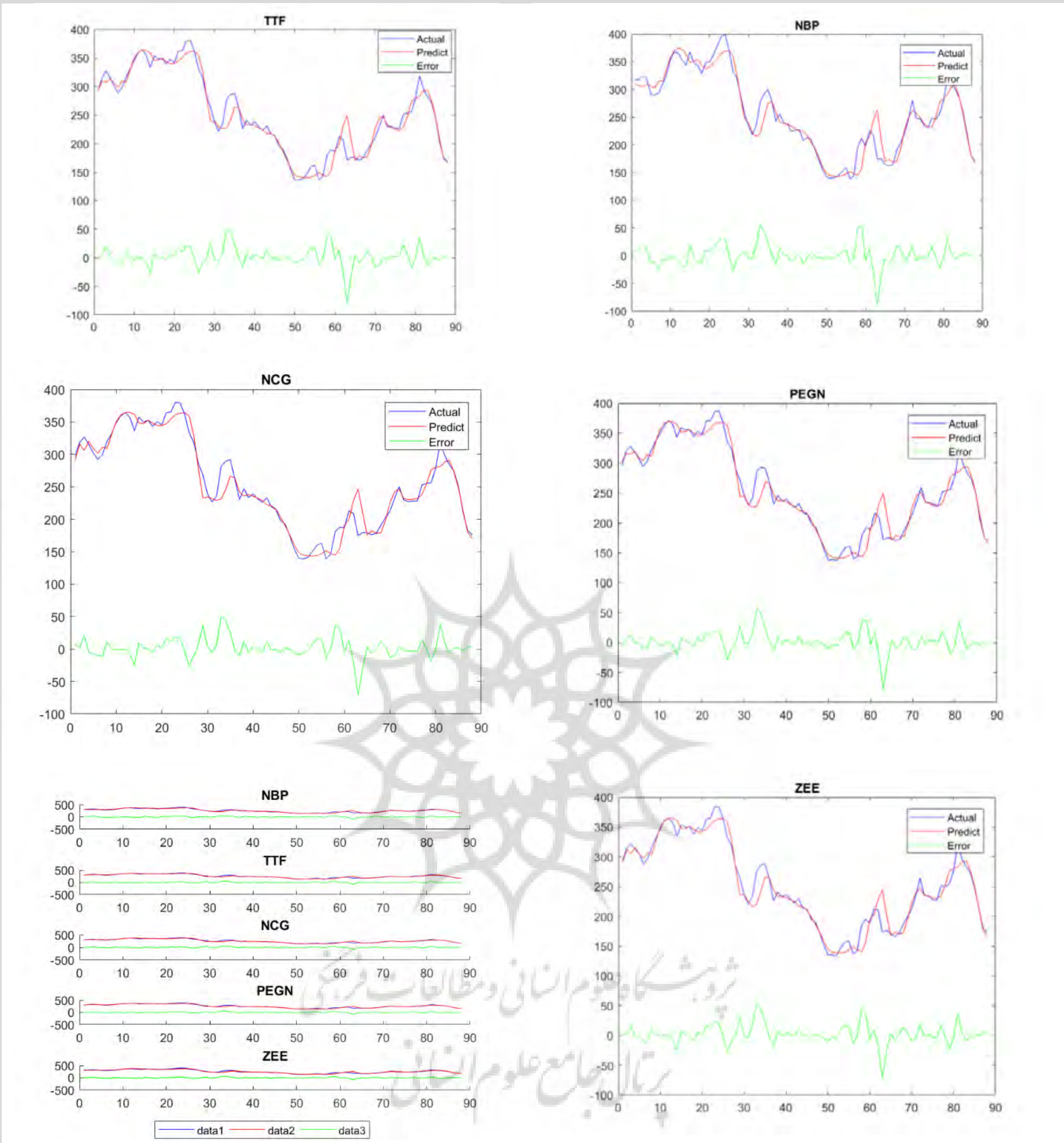

Figure 6. The comparison of the prediction prices with the real prices in the European hubs.

6. Conclusions

Due to its less pollution and easy access, natural gas has been able to make a significant contribution to the energy basket of countries in recent years. The importance of this fuel in recent years has caused the price prediction to be taken into account, and various models have been introduced for the price prediction; all these efforts have aimed to provide a prediction model with a lower error. Based on the conducted studies and according to the results of previous works, the neural network model can well predict the price values. The purpose of this study was to predict the prices of natural gas in the European gas hubs based on the machine learning method using the neural network model.

To this end, the monthly data on natural gas prices from the beginning of 2012 to May 2019 are used for the prediction. The prediction model inputs are the price data of the NBP, TTF, ZEE, NCG, and PEGC hubs, and the cross-validation method is used for the model learning. The performance evaluation indicators of the prediction model also include the R^2, MSE, RMSE, and MAPE; the

R^2 value of the fitted neural network model is 98% which shows very good performance in predicting the natural gas price.

To carry out further studies in this field, predicting the gas prices in the European gas hubs using the multivariate models is suggested. Obviously, increasing the number of price-related variables such as gas storage, demand and supply, and air temperature can improve the model output.

The prediction of natural gas prices in the European markets in the coming years can help to conclude the natural gas export contracts in Iran. Since new long-term contracts in the European markets are concluded based on the price index of gas sold in the hub, it is necessary to continuously examine the price trends in these markets, influencing variables, and the price prediction in the above markets to be included in the future contracts of Iran with the purchasing countries.

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