Predicting Natural Gas Consumption – A Literature Review

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Abstract*. Natural gas is considered to be one of the most important energy sources. Due to its many advantages, demand for this energy source has increased considerably. Many authors tried to develop models for predicting natural gas consumption. The aim of this paper is to present an overview and systematic analysis of the latest research papers that deal with predictions of natural gas consumption from the year 2002 to 2017. In this paper, prediction methods, input variables used for modelling, prediction area, as well as prediction horizon will be analysed. This research could be helpful for other researchers in order to create better and more accurate prediction models.*

Keywords. Natural gas, prediction models, energy, literature review

1 Introduction

Natural gas (NG) is one of the most important energy resources that is becoming more and more popular because of its environmental benefits (lower impact on environmental pollution). Therefore, demand for this source of energy has increased considerably in recent years. According to U.S. Energy Information Administration (U.S. Energy Information Administraton, 2016), natural gas has the largest increase in world primary energy consumption, so it is projected to increase from 120 trillion cubic feet (Tcf) in 2012 to 203 Tcf in 2040. Globally, natural gas accounted for 23.8% of primary energy consumption (BP Global, 2015). Natural gas remains the main fuel in the production of electricity and in industry sector.

Many authors have tried to develop models for predicting natural gas consumption on the hourly, daily, weekly, monthly or yearly basis. The accuracy of the model is important for decision making on gas nominations. Every natural gas distributor is obliged to make a nomination of natural gas by its supplier, which is the amount of gas needed for the following day (or other future period). There is a certain regulated tolerance that is allowed. In case the actual consumption exceeds the nominated amount, the distributor must pay a certain penalty. On the other hand, if nominated amount exceed actual consumption, different type of penalty will be charged as well. Since the incorrect nominations lead to high costs, an accurate predictions of natural gas consumption for the following day are very important due to financial reasons.

The purpose of this paper is to provide an overview of predictive models of natural gas consumption in several countries in the world. In the paper, the methods used for predicting NG consumption, the input variables used for modelling, as well as the prediction area and forecast horizon will be analysed. This paper is structured as follows: in Section 2 methodology is described, Section 3 gives an overview of prediction models, Section 4 describes input and output variables, Section 5 gives an overview of prediction area and Section 6 describes prediction horizons. The key findings of this research are given in Section 7.

2 Methodology

For the research purposes, literature overview analysis was conducted using the most relevant scientific database Web of Science Core Collection (WoSCC). The keywords "natural gas consumption (prediction OR demand)" were used for searching articles. The articles were searched within three indexes: Science Citation Index Expanded (SCI-Expanded), Social Science Citation Index (SCI), and Arts and Humanities Citation Index (A&HCI) for the period from 2002 to 2017.

This search resulted with 187 papers, including article (180), proceedings paper (8) and review (7). After reviewing the title, abstracts and keywords of all found articles, articles that are not related to models for prediction of natural gas consumption for residential or commercial use were eliminated. Thereafter, 27 articles remain that met posted criteria. Those papers were analysed according to several criteria: methods used for predictions of natural gas consumption, input variables used for modelling, prediction area and prediction horizon.

Similar literature review was conducted by Soldo (2012), who analysed natural gas consumption from the year 1949 to 2010.

As it can be seen in Table 1, in the last three years 13 papers considering natural gas prediction were published, which is more than 44% of all analysed papers.

Table 1. Number of published papers per year

Year of publication	Number of papers	%	Authors
2004	1	3.70%	Gil & Deferrari
2005	2	7.41%	Aras; Gutierrez et al.
2007	1	3.70%	Potočnik et al.
2008	1	3.70%	Brabec et al.
2009	1	3.70%	Tonković et al.
2010	3	11.12%	Azadeh et al.; Forouzanfar et al.; Ma & Li
2011	2	7.41%	Kaynar et al.; Sabo et al.
2012	2	7.41%	Demirel et al.; Olgun et al.
2013	1	3.70%	Taspinar et al.
2014	1	3.70%	Soldo et al.
2015	6	22.22%	Azadeh et al.; Boran; Izadyar et al.; Szoplik; Wu et al.; Zhu et al.
2016	4	14.82%	Akpinar & Yumusak; Bai & Li; Baldacci et al.; Zeng & Li
2017	2	7.41%	Akpinar & Yumusak; Panapakidis & Dagoumas
Total	**27**	**100.00%**	

3 Overview of prediction areas

Prediction of NG consumption can be conducted on different areas, for example on the country, region, city or individual customer area (Soldo, 2012).

NG consumption on country level was investigated by Gutierrez et al. (2005), Potočnik et al. (2007), Brabec et al. (2008), Azadeh et al. (2010), Forouzanfar et al. (2010), Ma & Li (2010), Kaynar et al. (2011), Olgun et al. (2012), Azadeh et al. (2015), Boran (2015), Wu et al. (2015), Zhu et al. (2015), Zeng & Li (2016) and Panapakidis & Dagoumas (2017). It can be seen that most of the papers dealt with the predictions on country area. Gutierrez and co-authors (2005) were predicting natural gas consumption in Spain, Potočnik and co-authors (2007) in Slovenia, while Brabec and co-authors (2008) made predictions using data about large commercial entities in Slovakia. Three papers dealt with predictions of NG consumption in Iran. Those are Azadeh et al. (2010), Forouzanfar et al. (2010) and Azadeh et al. (2015). Ma & Li (2010), Wu et al. (2015) and Zeng & Li (2016) conducted research about natural gas consumption predictions in China while the same number of papers investigated this problem in Turkey (Kaynar et al., 2011; Olgun et al., 2012; Boran, 2015). Zhu and co-authors (2015) were predicting demand of natural gas in United Kingdom. Natural gas consumption has been predicted by Panapakidis & Dagoumas (2017) in Greece.

There are only five papers that predicted natural gas consumption on regional level. Gil & Deferrari (2004) presented the results for the case of Greater Buenos Aires region in Argentina. The paper written by Tonković et al. (2009) investigated the prediction of NG consumption in the north-east region of Croatia. Several Turkish authors (Taspinar et al., 2013; Akpinar & Yumusak, 2016; Akpinar & Yumusak, 2017) tried to predict NG consumption in Marmara region (Sakarya province).

The following papers deal with predictions of natural gas consumption on city level. The predicting method based on genetic algorithms, developed by Aras (2005), has been applied by using data for Turkish city Eskisehir. Demirel et al. (2012) also made predictions of natural gas consumption in Turkish city, but in this case city of Istanbul. Sabo and co-authors (2011) proposed mathematical models of natural gas consumption for area of the city of Osijek. The residential heating demand of the Baharestan city in Iran was forecasted by Izadyar et al. (2015). Szoplik (2015) were predicting natural gas demand using NG consumption data for the Szczecin city in Poland. Bai & Li (2016) used the data of the NG consumption of Anqing city in China for modelling and forecasting. Baldacci et al. (2016) tried to predict gas consumption for a given gas network. First gas network services

Voltana, a small village, and the second gas network services Lugo, a small city. The aim of the study, conducted by Soldo et al. (2014), was to forecast residential natural gas consumption not only for the city level, but also for the house level. They used two datasets about past NG consumption. The first dataset was for two small cities with total of 4314 customers, and the second dataset was for the model house which has a heated space that covers 100 m2.

Overview of countries in which predictions of natural gas consumption were made, is shown in Table 2.

Table 2. Overview of the number of published papers by countries where predictions were made

Country	Number of published papers
Argentina	1
China	4
Croatia	3
Greece	1
Iran	4
Italy	1
Poland	1
Slovakia	1
Slovenia	1
Spain	1
Turkey	8
United Kingdom	1

4 Overview of prediction horizons

There are several prediction horizons that can be used for prediction of natural gas consumption. Large number of authors were predicting natural gas consumption on annual level. Gil & Deferrari (2004) presented a model intended to predict the annual natural gas consumption for the region in Argentina, Gutierrez et al. (2005) used the stochastic Gompertz innovation diffusion model for forecasting annual natural gas consumption in Spain, Forouzanfar et al. (2010) used a logistic based approach to predict the annual natural gas consumption in Iran, Ma & Li (2010) predicted China's gas consumption in 2009-2020, Olgun et al. (2012) presented a model in order to estimate the annual NG demand for Turkey until year 2030, Boran (2015), Wu et al. (2015) and Zeng & Li (2016) used grey prediction models to predict annual NG consumption in Turkey and China.

Forouzanfar et al. (2010) modelled seasonal NG consumption as well as Baldacci et al. (2016).

Predicting natural gas consumption on monthly level was reported by Aras (2005), who forecasted residential consumption using genetic algorithms, Azadeh et al. (2015), who proposed a hybrid method based on computer simulation and ANFIS, Izadyar et al. (2015), who predicted the residential heating demand in Iran, and Akpinar & Yumusak (2016), who forecasted NG consumption using time series methods.

There are two papers in which weekly prediction of natural gas consumption was reported. Those are papers written by Potočnik et al. (2007), who proposed a forecasting model in order to forecast risk estimation, and Kaynar et al. (2011), who used neural network and neuro fuzzy system for prediction of NG consumption on weekly basis.

Large number of authors predicted natural gas consumption on daily level. Gil & Deferrari (2004) proposed a daily prediction model in Argentina, and Potočnik and co-authors (2007) presented a risk model that is applicable to estimating the daily forecasting risk. In order to do that, they had to create a model for daily prediction of natural gas consumption. Brabec et al. (2008) forecasted a commercial NG consumption in Slovakia, Azadeh et al. (2010) predicted short-term NG demand, Demirel et al. (2012), Taspinar et al. (2013) and Akpinar & Yumusak (2017) predicted daily NG consumption in Turkey, Soldo et al. (2014) used solar radiation as an input variable in order to predict daily NG consumption, Zhu et al. (2015) tried to predict natural gas demand in United Kingdom, Bai & Li (2016) proposed a structure-calibrated support vector regression approach to forecast the daily NG consumption, Panapakidis & Dagoumas (2017) predicted daily natural gas demand.

Predicting natural gas consumption on hourly scale was reported by Tonković et al. (2009), who created a prediction model of natural gas consumption on a regional level by using neural networks, Sabo et al. (2011), who proposed mathematical models of natural gas consumption, and Szoplik (2015), who forecasted natural gas consumption in Poland using neural networks.

5 Overview of prediction methods

Natural gas consumption is predicted by using various predicting techniques and methods or even a combination of several methods. Soldo (2012) discovered that among the first tools for prediction of natural gas consumption was the Hubbert curve model used in 1950s. Since 1960s, when statistical models were developed, various statistical models have been used for predictions of NG consumption. From the late 1970s and 1980s, the artificial neural networks became very popular forecasting tool. Lately, there are new methods used in predictions of natural gas consumption such as Grey models or genetic algorithms.

In this research, the most often method used for prediction of natural gas consumption was neural network or techniques based on similar principles (like adaptive network-based fuzzy inference system). Neural networks are programs that, most often by the iterative process from the past data, try to find the connection between input and output variables of the model in order to obtain the output value for the new input variables (Zekić-Sušac et al., 2009). Adaptive network-based fuzzy inference system (ANFIS) was presented by Jang (1993), which is "a fuzzy inference system implemented in the framework of adaptive networks". According to Azadeh et al. (2010), "ANFIS possess both the learning capability of neural networks and the structured knowledge representation employed in fuzzy inference system which is appropriate for nonlinear modelling and time series prediction".

Authors who used neural networks were Tonković et al. (2009), Kaynar et al. (2011), Demirel et al. (2012), Olgun et al. (2012), Taspinar et al. (2013), Soldo et al. (2014) Izadyar et al (2015) and Szoplik (2015). Tonković et al. (2009), Taspinar et al. (2013) and Kaynar et al. (2011) trained and tested two neural network algorithms – the multilayer perceptron and the radial basis function network with different activation functions. The first mentioned algorithm produced the smallest mean absolute percentage error in all analysed paper. Taspinar et al. (2013) also compared neural networks algorithms and time series model. In their research, Demirel and co-authors (2012) used multilayer perceptron algorithm for neural network and compared this model with 2 time series models. Olgun et al. (2012) compared neural networks with support vector machines. Taspinar et al. (2013) and Szoplik (2015) also used a multilayer perceptron algorithm in order to predict natural gas consumption. Soldo et al. (2014) investigated the influence of solar radiation on residential NG consumption. Among several different methods, they used neural networks on two different data sets. The first data set is from a model house and the second one from the local distribution company. Extreme learning machine (ELM), as a learning algorithm for feedforward neural network, was used by Izadyar et al. (2015).

Panapakidis & Dagoumas (2017) proposed an interesting model that combines the wavelet transform, genetic algorithm, adaptive neuro-fuzzy inference system and feed-forward neural network. They tried to test the robustness of a novel hybrid computational intelligence model in day-ahead predictions of natural gas demand. There was one more paper that combined two different models. Azadeh et al. (2015) created a hybrid model of adaptive neuro fuzzy inference system and computer simulation for prediction of natural gas consumption. The same authors (Azadeh et al., 2010) presented an adaptive network-based fuzzy inference system in their earlier research. The ANFIS was used by Kaynar et al. (2011) as well, in order to predict weekly natural gas consumption in Turkey.

Ma & Li (2010) predicted natural gas consumption based on the Grey system model. The same approach was using Boran (2015) – grey prediction with rolling mechanism (GPRM), Wu et al. (2015), and Zeng & Li (2016). According to Kayacan et al. (2010), "Grey models predict the future values of a time series based only on a set of the most recent data depending on the window size of the predictor".

Another commonly used techniques for natural gas consumption prediction are support vector machine (SVM) and support vector regression (SVR). Olgun et al. (2012) compared neural networks with support vector machines and they concluded that support vector machines had less statistical error for demand estimation of natural gas consumption. Soldo et al. (2014) used several linear and nonlinear models for predictions. The testing errors obtained by nonlinear neural networks and SVR models are slightly higher compared to linear models. Zhu et al. (2015) presented the method that integrated the SVR algorithm with the reconstruction properties of a time series and optimises the original local predictor by removing false neighbours. A structure-calibrated SVR approach was used by Bai & Li (2016).

Aras (2008) tried to forecast short-term demand of natural gas in residences by using genetic algorithms. Genetic programming technique was used by Forouzanfar et al. (2010) and Izadyar et al. (2015) as well.

Some authors used mathematical models in order to predict natural gas consumption. Gil & Deferrari (2004) developed a model which is able to predict the NG consumption 1 to 5 days in advance with 10% of uncertainty. Gutierrez et al. (2005) presented a stochastic Gompertz innovation diffusion model while Potočnik et al. (2007) forecasted NG consumption by using their model that is already used in several gas distribution systems. Brabec et al. (2008) developed nonlinear mixed effects model (NLME), a parametric statistical model which is later compared with two classical time series approaches. Several advanced linear and nonlinear mathematical models, such as exponential, Gompertz and logistic model, were used by Sabo et al. (2011). Forouzanfar et al. (2010) used a method based on the concept of the nonlinear programming with earlier mentioned genetic programming technique. Soldo et al. (2014) compared several linear models such as auto-regressive model with exogenous inputs and stepwise regression. Akpinar & Yumusak (2017) used multiple linear regression (MLR) for prediction of NG consumption.

There are several time series methods used for predicting natural gas consumption. Kaynar (2011) and Demirel (2012) used autoregressive integrated moving average (ARIMA). Taspinar (2013) also used type of ARIMA model, called SARIMAX, which is seasonal autoregressive integrated moving average model with exogenous inputs. Akpinar & Yumusak (2016) presented time series decomposition, Holt-Winters exponential smoothing and ARIMA.

Among other methods used for NG consumption predictions can be highlighted Baldacci et al. (2016), who defined two predicting techniques, one based on a nearest neighbour approach and one employing local regression analysis.

Table 3 shows a systematic overview of prediction methods used in predicting natural gas consumption by prediction area and prediction horizon.

Table 3. Number of papers per prediction method by prediction area and prediction horizon

Prediction method	Prediction area				Prediction horizon*					
	Country	Region	City	House	Y	S	M	W	D	H
Neural network	2	2	4	1	1			1	3	2
ANFIS	2							1	1	
Grey model	4				4					
SVM/SVR	2		2	1	1				3	
Genetic algorithms	1		2		1	1	2			
Mathematical and statistical models	4	2	2	1	3	1		1	5	1
Time series	1	2	1				1	1	2	
Hybrid models	2						1		1	
Other			1							

*Y – yearly, S – seasonal, M – monthly, W – weekly, D – daily, H – hourly

6 Overview of variables used for modelling

Various data sets were used to produce prediction models of NG consumption. Accordingly, authors used different input variables in order to create a model but it can be noticed that the most commonly used variables were past natural gas consumption and meteorological data (especially temperature). Those two input variables were used by Gil & Deferrari (2004), Sabo et al. (2011), Izadyar et al. (2015) and Baldacci et al. (2016). Following papers also used past NG consumption, but some other meteorological data as well. Potočnik et al. (2007) developed a short-term energy consumption model. The predicting model is based on observations of past gas consumption, past weather data, weather forecast, seasonal information, days of week, holidays, industrial nominations etc. Tonković et al. (2009) used similar input variables, such as month, season detection, day type (working day, holiday, day after holiday), day of the week, temperature, wind direction, wind velocity at different time and past gas consumption. Zhu et al. (2015) used past gas consumption, together with temperature, wind speed, effective temperature and pseudo seasonal normal effective temperature. Input variables used by Akpinar & Yumusak (2017) were past gas consumption, minimum, maximum and 1-day lagged average temperature, minimum and maximum humidity, holidays, number of subscribers, building size. Panapakidis & Dagoumas (2017) used past gas consumption, temperature, months and days of week. There are several papers where only past gas consumption was used as input variable: Gutierrez et al. (2005), Forouzanfar et al. (2010), Kaynar et al. (2011), Boran (2015), Wu et al. (2015), Akpinar & Yumusak (2016), Zeng & Li (2016) and Bai & Li (2016). Those authors mostly used grey modelling and mathematical models. Aras (2005) used for predictions consumer price index and average daily temperatures. Brabec et al. (2008) used temperature and day of the week. Similar variables can be found in Szoplik's paper (Szoplik, 2015). He used temperature, hour of the day, day of the week, month and day of month. For the prediction of natural gas demand, Azadeh et al. (2010) used day of week, demand of the same day in previous year, demand of a day before, demand of 2 days before as input variables. Demirel et al. (2012) used daily average temperature, squared temperature, natural gas price, number of gas subscribers, 12 lags of consumption, while Taspinar et al. (2013) used humidity, atmospheric pressure, wind speed, ambient air temperature and average cloud cover. Some authors included Gross domestic product (GDP) in their models. Ma & Li (2010) used GDP and past consumption, Olgun et al. (2012) used GDP and population, while Azadeh et al. (2015) used GDP, population, NG price, inflation rate, unemployment rate, IT/IS index, human development index and CO2 emission. Soldo et al. (2014) conducted an interesting research in which the influence of solar radiation on predicting residential natural gas consumption was investigated. The input variables they used were weather data (on hourly basis) and solar radiation.

From this analysis, it can be seen that past gas consumption is the most important input variable for prediction of natural gas consumption. It was used in largest number of papers, especially in papers where mathematical and grey models were presented. The important variables were also various meteorological data.

Table 4 shows the overview of number of papers by input variables used most frequently according to prediction method, area and horizon.

Table 4. Number of papers by input variables used according to prediction method, area and horizon

Input variable	Prediction method*									Prediction area**				Prediction horizon***					
	A	**B**	**C**	**D**	**E**	**F**	**G**	**H**	**I**	**Co**	**R**	**Ci**	**H**	**Y**	**S**	**M**	**W**	**D**	**H**
Past gas consumption	3	2	3	1	2	6	2	1	1	10	4	3		6	2	2	2	6	2
Temperature	6	1		2	2	6	2	1	1	5	4	7	1	1	1	2	1	10	3
Days of week	2					2		1		3	1	1					1	3	2
Month	2							1		1	1	1						1	2
Seasonal information	1			1		1				2	1						1	2	1
Wind data	2			1			1			1	2							2	1
GDP	1		1	1				1		3				2		1			
Holidays						2				1	1						1	2	
Humidity	1					1	1				2							2	
No of gas subscribers	1					1	1				1	1						2	
Gas price	1	1					1			1		1						2	

*A – neural network, B – ANFIS, C – Grey model, D – SVM/SVR, E – Genetic algorithms, F – mathematical and statistical models, G – time series, H – hybrid models, I – other
**Co – country, R – region, Ci – city, H – house
***Y – yearly, S – seasonal, M – monthly, W – weekly, D – daily, H – hourly

7 Discussion and conclusion

The aim of this paper is to present an overview of the latest papers that deal with predictions of natural gas consumption. In order to achieve this goal, the search of relevant scientific articles was conducted using scientific database Web of Science Core Collection. There was total of 27 papers that met required conditions. Those papers were analysed and then compared according to several criteria, such as methods used for predictions, input variables used for modelling, prediction areas and prediction horizons. Natural gas prediction models are complex models with high interdependency between its structural components, e.g. choice of appropriate method will be dependent on chosen prediction horizon or the use of the appropriate input variables will depend on the method used. The results of this paper show that the most common method used for predictions of natural gas consumption is neural network. Other popular methods are neuro-fuzzy inference system, time series methods, genetic algorithms, support vector machines/ regression, Grey system models, mathematical and statistical models or hybrid models based on several methods. Some researches use two or more methods in the same paper. But analysis has shown that for modelling, authors often use past natural gas consumption data and weather data (mostly temperature) as input variables. Other variables include month, days of the week, wind speed, number of natural gas subscribers, GDP, inflation rate etc. Speaking of prediction areas, it can be seen that most of the papers deal with the predictions on country level. Predictions can be made as well as on regional, city, or even house level. The analysis also revealed that authors mostly predict natural gas consumption on daily and annual level. There are only few papers that predict natural gas consumption on seasonal, monthly, weekly or hourly level.

Limitation of this study is reflected in relatively small number of analysed papers. For further research, authors plan to search more relevant scientific databases, such as Scopus or Proquest in order to obtain larger number of relevant sources. This paper could be helpful for other researchers who deal with predictions of natural gas consumption in order to create better and more accurate models.

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References

Akpinar, M., & Yumusak, N. (2016). Year Ahead Demand Forecast of City Natural Gas Using Seasonal Time Series Methods. *Energies, 9*(9), 727.

Akpinar, M., & Yumusak, N. (2017). Naıve forecasting of household natural gas consumption with sliding window approach. *Turkish Journal of Electrical Engineering & Computer Sciences, 25*, 30-45.

Aras, N. (2008). Forecasting Residential Consumption of Natural Gas Using Genetic Algorithms. *Energy Exploration & Exploitation, 26*(4), 241-266.

Aydin, G. (2015). Forecasting Natural Gas Production Using Various Regression Models. *Petroleum Science and Technology, 33*(15-16), 1486-1492.

Azadeh, A., Asadzadeh, S., & Ghanbari, A. (2010). An adaptive network-based fuzzy inference system for short-term natural gas demand estimation: Uncertain and complex environments. *Energy Policy, 38*(3), 1529-1536.

Azadeh, A., Zarrin, M., Rahdar Beik, H., & Bioki, A. (2015). A neuro-fuzzy algorithm for improved gas consumption forecasting with economic, environmental and IT/IS indicators. *Journal of Petroleum Science and Engineering, 133,* 716-739.

Bai, Y., & Li, C. (2016). Daily natural gas consumption forecasting based on a structure-calibrated support vector regression approach. *Energy and Buildings, 127*(1), 571-579.

Baldacci, L., Golfarelli, M., Lombardi, D., & Sami, F. (2016). Natural gas consumption forecasting for anomaly detection. *Expert Systems With Applications, 62,* 190-201.

Boran, F. (2015). Forecasting Natural Gas Consumption in Turkey Using Grey Prediction. *Energy Sources, Part B: Economics, Planning, and Policy, 10*(2), 208-213.

BP Global. (2015). *Natural gas consumption*. Retrieved from http://www.bp.com/en/global/corporate/energy-economics/statistical-review-of-world-energy/natural-gas/natural-gas-consumption.html

Brabec, M., Konar, O., Pelikan, E., & Maly, M. (2008). A nonlinear mixed effects model for the prediction of natural gas consumption by individual customers. *International Journal of Forecasting, 24*(4), 659-678.

Demirel, O., Zaim, S., Caliskan, A., & Ozuyar, P. (2012). Forecasting natural gas consumption in Istanbul using neural networks and multivariate time series methods. *Turkish Journal of Electrical Engineering and Computer Sciences, 20*(5), 695-711.

Forouzanfar, M., Doustmohammadi, A., Menhaj, M., & Hasanzadeh, S. (2010). Modeling and estimation of the natural gas consumption for residential and commercial sectors in Iran. *Applied Energy, 87*(1), 268-274.

Gil, S., & Deferrari, J. (2004). Generalized Model of Prediction of Natural Gas Consumption. *Journal of Energy Resources Technology, 126*(2), 90-98.

Gutierrez, R., Nafidi, A., & Gutierrez Sanchez, R. (2005). Forecasting total natural-gas consumption in Spain by using the stochastic Gompertz innovation diffusion model. *Applied Energy, 80*(2), 115-124.

Izadyar, N., Ong, H., Shamshirband, S., Ghadamian, H., & Tong, C. (2015). Intelligent forecasting of residential heating demand for the District Heating System based on the monthly overall natural gas consumption. *Energy and Buildings, 104*(1), 208-214.

Jang, J. (1993). ANFIS: adaptive-network-based fuzzy inference system. *IEEE transactions on systems, man, and cybernetics, 23*(3), 665-685.

Kayacan, E., Ulutas, B., & Kaynak, O. (2010). Grey system theory-based models in time series prediction. *Expert Systems with Applications, 37*(2), 1784-1789.

Kaynar, O., Yilmaz, I., & Demirkoparan, F. (2011). Forecasting of natural gas consumption with neural network and neuro fuzzy system. *Energy Education Science and Technology Part A: Energy Science and Research, 26*(2), 221-238.

Ma, Y., & Li, Y. (2010). Analysis of the supply-demand status of China's natural gas to 2020. *Petroleum Science, 7*(1), 132-135.

Olgun, M., Ozdemir, G., & Aydemir, E. (2012). Forecasting of Turkey's natural gas demand using artifical neural networks and support vector machines. *Energy, Education, Science and Technology, 30*(1), 15-20.

Panapakidis, I., & Dagoumas, A. (2017). Day-ahead natural gas demand forecasting based on the combination of wavelet transform and ANFIS/genetic algorithm/neural network model. *Energy, 118*(1), 231-245.

Potočnik, P., Thaler, M., Govekar, E., Grabec , I., & Poredoš , A. (2007). Forecasting risks of natural gas consumption in Slovenia. *Energy Policy, 35*(8), 4271-4282.

Sabo, K., Scitovski, R., Vazler, I., & Zekić Sušac, M. (2011). Mathematical models of natural gas consumption. *Energy Conversion and Management, 52*(3), 1721-1727.

Soldo, B. (2012). Forecasting natural gas consumption. *Applied Energy, 92,* 26-37.

Soldo, B., Potočnik, P., Šimunović, G., Šarić, T., & Govekar, E. (2014). Improving the residential natural gas consumption forecasting models by using solar radiation. *Energy and Buildings, 69,* 498-506.

Szoplik, J. (2015). Forecasting of natural gas consumption with artificial neural networks. *Energy, 85*(1), 208-220.

Taspinar, F., Celebi, N., & Tutkun, N. (2013). Forecasting of daily natural gas consumption on regional basis in Turkey using various computational methods. *Energy and Buildings, 56,* 23-31.

Tonković, Z., Zekić Sušac, M., & Somolanji, M. (2009). Predicting natural gas consumption by neural networks. *Technical Gazette, 16*(3), 51-61.

U.S. Energy Information Administraton. (2016). *International Energy Outlook 2016.* Retrieved from https://www.eia.gov/outlooks/ieo/pdf/0484(2016).pdf

Wu, L., Liu, S., Chen, H., & Zhang, N. (2015). Using a Novel Grey System Model to Forecast Natural Gas Consumption in China. *Mathematical Problems in Engineering, 2015*, 1-7.

Zekić Sušac, M., Frajman Jakšić, A., & Drvenkar, N. (2009). Neuronske mreže i stabla odlučivanja za predviđanje uspješnosti studiranja. *Ekonomski vjesnik, 22*(2), 314-327.

Zeng, B., & Li, C. (2016). Forecasting the natural gas demand in China using a self-adapting intelligent grey model. *Energy, 112*(1), 810-825.

Zhu, L., Li, M., Wu, Q., & Jiang, L. (2015). Short-term natural gas demand prediction based on support vector regression with false neighbours filtered. *Energy, 80*, 428-436.