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Article

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Forecasting Natural Gas: A Literature Survey

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ABSTRACT

This work presents a state-of-the-art survey of published papers that forecast natural gas production, consumption or demand, prices and income elasticity, market volatility and hike in prices. New models and techniques that have recently been applied in the field of natural gas forecasting have discussed with highlights on various methodologies, their specifics, data type, data size, data source, results and conclusions. Moreover, we undertook the difficult task of classifying existing models that have been applied in this field by giving their performance for instance. Our objective is to provide a synthesis of published papers in the field of natural gas forecasting, insights on modeling issues to achieve usable results, and the future research directions. This work will help future researchers in the area of forecasting no matter the methodological approach and nature of energy source used.

Keywords: Forecasting Natural Gas, Existing Forecasting Models, Models categorization
JEL Classifications: C53, Q4, Q47

1. INTRODUCTION

Energy in general is vital for sustainable development of any nation: Be it social, economic or environment. Consumption of clean energies like natural gas is also an important criterion to evaluate the performance of the economy of any nation, for it is a crucial factor of production in all aspects of every economy. Interest in forecasting natural gas has led to a tremendous surge of research activities in the last decade (Soldo, 2012; Aydin, 2014; Voudouris et al., 2014; Fagiani et al., 2015; Khan, 2015; Suganthi and Samuel, 2012). World energy demand has increased sharply as primary energy sources are required for sustainable development (Fan and Xia, 2012; Panella et al., 2012; Gracias et al., 2012; Aydin, 2015; Azadeh et al., 2015; Ozturk and Al-Mulali, 2015; Szoplik, 2015; Rafindadi and Ozturk, 2015; Zaman, 2016; Karacaer-Ulusoy and Kapusuzoglu, 2017). Energy is linked to industrial production, agricultural output, health, access to water, population, education, quality of life, cooking, transport (Xiong et al., 2014; Dilaver et al., 2014). Around one-fifth of the globe's primary energy is met from natural gas which is considered as the cleanest-burning fossil fuel (Selehnia et al., 2013; BP, 2009; Imam et al., 2004; Xu and Wang, 2010; Agbonifo, 2016; Solarin and Ozturk, 2016).

Aside from natural gas demand, the question of its availability quickly arises to know whether gas resources are large enough to support projected plans. For this, it is of crucial importance to be able to predict natural gas consumption with an acceptable degree of accuracy in order to improve operational efficiency, save energy, reduce costs at different levels, manage supply contracts, indigenous production and infrastructures planning. Failing one of these goals would certainly cause instabilities in a nation's energy system (Bianco et al., 2014).

Over the years, energy demand, particularly natural gas demand has attracted interest as much significance is attached to the issue

(Erdogdu, 2010; Gorucu, 2004; Gorucu and Gumrah, 2004). Many studies have forecasted natural gas production, consumption or demand, prices and income elasticity, market volatility and hike in prices in several different areas, on world level, regional level, national level, city level, industrial and residential sectors, and individual costumer level (Hubbert, 1949; 1956; Al-Jarri and Startzman, 1997; Sanchez-Ubeda and and Berzosa, 2007; Behrouznia et al., 2010; Tonkovic et al. (2009); Azadeh et al., 2010). These studies used various data which could be classified into three main categories: Meteorological data, historical data and economic data. The first experimental study on natural gas demand prediction was conducted in 1966 by Balestra and Nerlove (1966) while the first theoretical study was that of Hubbert (1949).

Just as forecasting natural gas consumption and its availability is important, forecasting natural gas production, price and income elasticity, hike in prices and market volatility are also inescapable in decision making at all levels of the economy. In energy sector, where decision environment is characterized by risks and uncertainty, decision makers need some information about possible future outcomes Dalfard et al. (2013a). The oil shocks of the 1970s are a clear example. Thus, developing models for accurate natural gas price forecasting is crucial because these forecasts are relevant in determining a whole range of regulatory decisions covering both supply and demand of natural gas or for market participants Selehnia et al. (2013).

An overview of various forecasting approaches from 1949 to 2010 in the field of natural gas consumption was published in Soldo (2012). At his time, Soldo (2012) presented a review of natural gas consumption and production forecasts from 1949 to the end of 2010. He provided analysis and synthesis of published researches with insights on applied area, forecasting horizons, data and tools. This paper is a revisited form of the works of Soldo (2012). In the present work, we include papers that also deal with price and income elasticity, market volatility and hike in prices of natural gas, and we extend his works up till 2015. We equally include data type, data size, data source, results of researches and corresponding conclusions. In particular, we compare various models whenever it is possible, giving their performance measure, their advantages and shortcomings.

The objective of this paper is to provide a synthesis of published papers in the field of natural gas, insights on modeling issues to achieve usable results, and the future research directions. The rest of this work is organized as follows: Section 2 presents an up-to-date overview of published papers. Section 3 describes the application areas and methodological approaches. Section 4 of this paper describes the various data, including data size and data sources encountered in published papers. In Section 5, we give the forecasting periods. Results and model performance are described in Section 6. Finally, major conclusions and directions for future researches are presented in Section 7.

2. UP-TO-DATE OVERVIEW OF PUBLISHED PAPERS

In this section, we present a historical overview of all published papers in the field of natural forecasting. Hubbert (1949; 1956) was probably the first to investigate on fossil fuels. With his model, he pointed out that the production curve of any fossil fuel will rise, pass through one or several maxima, before declining asymptotically to zero. Later, Hubbert presented the mathematical foundation for his model where a logistic curve was used to fit cumulative production versus time. His model later became a reference in the field of forecasting with ups and downs. In 1950, Verhulst (1950), considering price and income of natural gas for 46 firms in the French industry followed the move by constructing a set of equations: Demand equation, equation of production and equilibrium of production. It was not until 1966 that Balestra and Nerlove (1966) made use of econometrics parameters by applying an ordinary least square (OLS) model. In 1973 Tinic et al. (1973) forecasted natural gas demand as a tool for evaluating rural gasification. In 1977 Berndt and Watkins (1977), based on the works of Balestra and Nerlove (1966), studied natural gas demand in the residential and commercial sectors in British Columbia and Ontario. In 1981, Beierlein et al. (1981) estimated the demand for natural gas and electricity for the residential, commercial and industrial sectors in Northeastern USA. High resolution forecasting (very short term horizon forecasting) began in 1983 when Piggott (1983) forecasted daily and weekly natural gas demand. In the same year, Jager (1983) provided a discussion of the wintertime decrease in urban energy supply and demand resulting from a warmer climate whereas regression analysis was used in 1987 by Herbert et al. (1987) to evaluate monthly industrial natural gas demand in the USA. Still in 1987, Herbert (1987) went further to analyze monthly sales of natural gas to residential customers in the USA. In 1988 Werbos (1988) reported the use of artificial neural networks (ANNs) with generalization of back propagation (BP) to recurrent gas market model.

In 1991, Liu and Lin (1991) explored the dynamic relationships among several potentially relevant time series variables and developed appropriate models for forecasting natural gas consumption in Taiwan. In 1994, Lee and Singh (1994) used micro consumption data to analyze patterns in residential gas and electricity demand while Brown et al. (1994) developed feed-forward network models to predict daily gas consumption. In 1995, Li and Sailor (1995) presented an overview of a methodology for developing regional assessments of the climate's role in determining monthly energy consumption in the residential and commercial sectors. In 1996, Eltony (1996) explored the structure of the demand for natural gas in Kuwait using two econometric models. In the same year, Brown and Martin (1996) developed ANNs to predict gas consumption; Smith et al. (1996) forecasted short term regional gas demand using expert systems, Suykens et al. (1996) modeled the Belgian gas consumption using neural networks (NN) while Bartels et al. (1996) estimated regional end use gas in Australia. In 1997, Sailor and Munoz (1997) developed a methodology for assessing the sensitivity of electricity and natural gas consumption to climate at regional scales. Broad area and long-term natural gas forecasting started with Al-Jarri and Startzman (1997) in 1997. They forecasted worldwide petroleum liquid supply and demand including natural gas liquids (NGL) 50 years ahead. In 1998, Dahl and McDonald (1998) forecasted energy consumption for 28 developing countries and Hobbs et al. (1998) surveyed 19 gas utilities on their uses of forecast and the benefits they perceived from using ANNs and simulating how improved accuracy lowers expected power generation costs. In 1999, Khotanzad and Elragal (1999) forecasted natural gas loads by using a combination of adaptive NN.

In 2000, Khotanzad et al. (2000) focused on combination of ANN forecasters, applying their study in the prediction of daily natural gas consumption needed by gas utilities; Al-Fattah and Startzman (2000) presented the forecast for the world's supply of conventional natural gas by region and organization/group to the year 2050 using a "Multicyclic Hubbert" approach, and Durmayaz et al. (2000) applied the degree-hour method to estimate heating energy and fuel consumption needs in Istanbul. In 2001, Gumrah et al. (2001) developed a degree-day (DD) model for forecasting the amount of natural gas consumption for the city of Ankara in Turkey. In 2002, Tahat et al. (2002) designed and simulated a house model in Jordan aimed at reducing purchased-energy consumption during both the heating and cooling seasons, and Baltagi et al. (2002) compared forecasting performance for homogeneous, heterogeneous and shrinkage estimators with evidence from 49 states in the USA. Siemek et al. (2003) in 2003 used the logistic-curve interpretation to estimate natural gas consumption in Poland. Still in 2003, Sarak and Satman (2003) constructed predictive map to determine natural gas consumption by residential heating based on transmission lines and DD concept. The year 2004 marked the beginning of increased attention to the issue of natural gas forecasting as numerous papers have been published yearly since then. In 2004, Cavallo (2004) discussed the assumptions and limitations of the Hubbert model as this model usually has failed in predicting world and regional oil and natural gas peak, Gorucu (2004) examined the factors affecting the output and training the ANNs to decide optimum parameters to be used in forecasting daily gas consumption of the remaining days of 2002–2005, Cho et al. (2004) examined the effect of length of measurement of period on accuracy of predicted annual heating energy consumption of buildings, Gorucu and Gumrah (2004) used statistical analysis to evaluate and forecast gas consumption for the city of Ankara using optimistic and pessimistic scenarios, Aras and Aras (2004) described an approach to obtain appropriate models for forecasting residential monthly gas consumption and investigated the dynamic relationships between gas consumption with time and DDs measured by weather temperature variations, Elragal (2004) presented a novel two-stage system for gas demand prediction using ANNs in the first stage and a fuzzy-genetic model in the second stage, Gil and Deferrari (2004) proposed a generalized model for predicting short- and medium-term gas demand for the residential and commercial sectors, and Imam et al. (2004) just like Al-Fattah and Startzman (2000) equally used the "Multicyclic Hubbert" model to show the globe's future natural gas peak.

In 2005, Gutierrez et al. (2005) used the stochastic Gompertz innovation diffusion model to forecast total natural gas consumption in Spain, Viet and Mandziuk (2005) used neural and fuzzy neural systems for predicting natural gas consumption in two regions in Poland, Thaler et al. (2005) presented a new empirical modeling approach to predict and optimal control of energy distribution systems, while Pelikan and Simunek (2005) used genetic algorithm (GA) to deal with the possibility of obtaining minimum loss or maximum profit. In 2006, Musilek et al. (2006) introduced a new model to improve results of a statistical system for gas load forecasting and Gelo (2006) examined the average gas consumption for the Croatian city Zagreb through an econometric model. In 2007, based on a risk model Potocnik et al. (2007) proposed a method to improve knowledge about expected forecasting risk and to estimate the expected cash flow in advance. Potocnik et al. (2007) introduced a new model that analyses energy consumption cycles yielding short-term prediction, Sanchez-Ubeda and Berzosa (2007) provided a novel statistical decomposition model able to produce 3 year-ahead daily forecast of industrial end-use natural gas consumption, Timmer and Lamb (2007) quantified relations between temperature and residential natural gas consumption in central and eastern United States, Parikh et al. (2007) in their study projected the demand of fuels up to 2011–2012, end period for the 11th Indian Five Year Plan, under two scenarios of annual gross domestic product (GDP) growth of 6% and 8%, and Huntington (2007) addressed an empirical model for evaluating future industrial US natural gas consumption trends.

In 2008, Aras (2008) presented an application of GAs to forecast short-term demand of natural gas in residences, Ghose and Paul (2008) focused on energy requirements perspectives for India and demands for petroleum, natural gas, and coal bed methane in the foreseeable future, Vondracek et al. (2008) presented a nonlinear regression model for estimating natural gas consumption on small scales, Aydinalp-Koksal and Ugursal (2008) modeled the national residential end-use energy in Canada with the conditional demand analysis (CDA) method, Potocnik et al. (2008) discussed practical considerations on building forecasting applications due to economic perspective of forecasting natural gas consumption. Still in 2008, Brabec et al. (2008) described the daily consumption of natural gas at the level of individual customers, Simunek and Pelikan (2008) preprocessed temperature as input data for short-term natural gas forecasting, Jiang et al. (2008) investigated the important factors that might drive natural gas consumptions in three regions in China, and Kizilaslan and Karlic (2008) tried to find Istanbul's natural gas energy model by testing several different algorithms. In 2009, Reynolds and Kolodziej (2009) investigated the possible effects of oil and gas market institutions in North America on natural gas supply. They used the multi-cyclic Hubbert curve with inflection points similar to the Soviet Union's oil production curve to determine North American natural gas discoveries rates and to analyze how market specific institutions caused these inflection points. Brabec et al. (2009a) discussed a problem pertinent to many situations in which a statistical model is developed on a sample of individuals applied to a large population of interest with typical examples occurring in natural gas and energy consumption contexts. A few months later, Brabec et al. (2009b) went further with their works on the construction of standardized load profiles. Rui et al. (2009) put forward a method based on GAs to determine the weight which avoids the limits of the OLS method and meets the requirements of model projections through different directions, Kizilaslan and Karlic (2009) presented different types of NN algorithm for forecasting gas consumption for residential and commercial consumers in

Istanbul in Turkey, Yoo et al. (2009) attempted to estimate the natural gas demand function in the residential sector using data from a survey conducted in Seoul, South Korea. Ma and Wu (2009) applied Grey theory to forecast natural gas consumption and production in China from 2008 to 2015 using NNs, Tonkovic et al. (2009) developed a prediction model for natural gas forecasting on a regional level, Xie and Li (2009) constructed a model prediction of natural gas consumption based on Grey modeling optimized by GA, and Maggio and Cacciola (2009) presented a model based on a variant of the well-known Hubbert curve with the aim of forecasting future production trends in world oil NGL.

In 2010, Azadeh et al. (2010) estimated the daily natural gas demand of Iran by proposing an adaptive network-based fuzzy inference system (ANFIS), Ma and Li (2010) predicted the future production and consumption of China's natural gas using the generalized Weng model and the gray prediction model, Li et al. (2010) used a dynamic system to create a possible outlook of the future tendency of substituting coal by natural gas in some parts of the Chinese primary energy consumption, Xu and Wang (2010) developed a new polynomial curve and moving average combination projection (PCMACP) model to accurately predict China's natural gas consumption, Forouzanfar et al. (2010) in their paper used a logistic based approached to forecast natural gas consumption in Iran for the 11th, 12th, and 13th year based on data available for the previous 10 years, Erdogdu (2010) estimated short and long run price and income elasticities of sectoral natural gas in Turkey. He went further to forecast future growth in natural gas demand using ARIMA modeling. Still in 2010, Dombayci (2010) developed an ANN model based on economic indicators in order to predict hourly heating energy consumption of a model house designed in Denizli, Turkey. Toksari (2010) presented a heuristic approach to estimate Turkey's natural gas demand. Behrouznia et al. (2010) presented an ANFIS Fuzzy Data Envelopment Analysis (FDEA) for long-term natural gas consumption forecasting and analysis. They constructed and tested 104 ANFIS, and proposed 6 models to forecast annual natural gas consumption, Valero and Valero (2010) shed light on a more precise methodology that could improve the truth or falseness concerning limits to growth of the earth's mineral resources, while Kaynar et al. (2011) examined Turkey's natural gas consumption using statistical time series analysis, ANN and ANFIS methods on a weekly basis. In 2011, Li et al. (2011) studied the growth tendency of natural gas as an important substitute for coal in some parts of China and Wadud et al. (2011) improved natural gas demand models for Bangladesh and its different sectors of the economy by using dynamic econometric techniques to forecast national demand till 2025.

In 2012, Osgouei and Sorgun (2012) discussed the problems of the Iranian natural gas industry and propose possible solutions, Fan and Xia (2012) used a hybrid energy-output model to decompose driving factors to identify how these factors impact changes in energy intensity, Gracias et al. (2012) compared three mathematical models to analyze the possibilities of these models to describe the evolution of production, import and consumption of natural gas in Brazil. In the same year, Panella et al. (2012) proposed a new machine learning approach for price modeling, Derimel et al. (2012) developed a natural gas consumption forecasting methodology and implemented with state-of-the-art techniques, Lin and Wang (2012) figured out the natural gas production peak of China, predicted the import trends and studied the international and national impacts of China's increasing import of gas, Shekarchian et al. (2012) investigated five different scenarios, each of which proposed different combination of absorption and compression cooling systems for residential and commercial sectors in Malaysia, Economides et al. (2012) analyzed the U.S natural gas price environment in 2011 and beyond, Azadeh et al. (2012) presented a hybrid NN fuzzy mathematical programming approach for improvement of natural gas price estimation in industrial sector and Rahim and Liwan (2012) analyzed the trends of oil and gas reserves, production and consumption with the corresponding implications in Malaysia. In 2013, Logan et al. (2013) presented results from numerical modeling of different future US power sector. They assessed questions affecting today's natural gas and electric power markets. Kialashaki and Reisel (2013) described the development of energy-demand models which are able to predict the future energy demand in the residential sector of the United States, Taspinar et al. (2013) proposed a multilinear perceptron ANNs with time series approach to forecast short-term natural gas consumption, Selehnia et al. (2013) used the Gamma test analysis for the first time as a mathematical nonparametric nonlinear smooth modeling tool to calibrate three models: Local linear regression, dynamic local linear regression and ANNs. Leather et al. (2013) presented a review of Australia's natural gas resources. Dalfard et al. (2013a) proposed an integrated adaptive FIS to forecast long-term natural gas consumption when prices experience large increase, Dalfard et al. (2013b) went further with their previous works to propose an adaptive fuzzy expert system to concurrently estimate and forecast both long-term electricity and natural gas consumptions with hike in prices using a new procedure. Still in 2013, Melikoglu (2013) generated accurate forecasts for Turkey's natural gas demand between 2013 and 2030 by developing two semi-empirical models; Wang et al. (2013) analyzed China's natural gas resources and production. Lv and Shan (2013) forecasted spot and future price volatilities of natural gas using linear and nonlinear generalized autoregressive conditional heteroskedasticity (GARCH) class models. They showed that the availability of domestic resources is overestimated by China's authorities due to differences in classification and definitions of gas resources/reserves between China and those accepted internationally.

In 2014, Rodger (2014) addressed the problem of predicting demand for natural gas for the purpose of realizing energy cost savings. He created a decision support system to regulate the flow of natural gas from the wells to the heating, ventilation, and air conditioning (HVAC) systems of a group of buildings. In the same year, Chkili et al. (2014) explored the relevance of asymmetry and long memory in modeling and forecasting the conditional volatility and market risk of four widely traded commodities (crude oil, natural gas, gold, and silver) using GARCH-type models; Xiong et al. (2014) proposed a new GM(1,1) model based on optimizing initial condition according to the principle of "new information priority." They further utilized their model to predict China's energy consumption and production from 2013 to 2017;

Jiang (2014) proposed an improved BP algorithm with additional momentum item based on the sum of squares of relative error, Potocnik et al. (2014) investigated the performance of static and adaptive models for short-term natural gas load forecasting. For this, they constructed various models for 1 day ahead forecasting of residential natural gas consumption in Croatia; Soldo et al. (2014) presented a novel study of possibilities of improving natural gas consumption forecasting by including information about solar radiation as input parameter. To achieve their goals, the authors created a model house whose consumption highly depends on weather conditions. Kani et al. (2014) studied the natural gas demand pattern in Iran for the period 1971–2009 using the smooth transition regression (STR) model with GDP, real prize of natural gas and temperature as explanatory variables. Dilaver et al. (2014) attempted to investigate the impacts of income, real natural gas prices and the underlying energy demand trend on Organization for Economic Cooperation and Development (OECD)-Europe natural gas consumption by applying the structural time series techniques to annual data over the period 1978–2011. Voudouris et al. (2014) developed future scenarios for natural gas supply using the ACEGES computational laboratory, Aydin (2014) identified the trends in the world's oil and natural gas production during the period 1998–2010 and applied linear regression analysis with respect to the observed trends. Considering the influence of economic and climatic data, as well as the impact of regulatory changes, Bianco et al. (2014) developed a model for the long term forecasting of nonresidential gas consumption in Italy.

Kovacic and Sarler (2014) elaborated a successful approach of gas consumption prediction with the aim of minimizing associated costs, Yu et al. (2014) estimated the price and income elasticities of residential demand for natural gas in urban China, Yu and Xu (2014) proposed an appropriate combinational model which is based on improved BP NN for short-term gas load forecasting and optimized the network by the real-coded GA to avoid partial dinky and achieve the global minimum. Paltsev (2014) analyzed scenarios for Russia's natural gas exports to 2050. Azadeh et al. (2014) were the first to introduce an optimum training and forecasting approach for natural gas consumption forecasting and estimation in cognitive and noisy environments by an integrated approach. Shi et al. (2014) proposed a new deliverability equation of gas condensate wells with consideration of fluid phase behavior in both the reservoir and the wellbore. Their works provide a more accurate method of forecasting both gas and condensate production in gas reservoirs. Feng et al. (2014) proposed ARIMA modeling which can predict China's natural gas demand as an effective tool. Aramesh et al. (2014) presented an approach to predict the transmission of natural gas in city gate stations by neural and fuzzy NNs. Karimi and Dastranj (2014) developed an ANN-based GA model to predict the natural gas consumption in the city of Yasouj in Iran. Wang et al. (2014) built a mathematical model of combinatorial optimization based on the natural gas consumption data of China, and solved it with MATLAB; while Yu et al. (2014) proposed a combinational model based on wavelet BP NN optimized by GA.

In 2015, Izadya et al. (2015) carried out a systematic approach to create the extreme learning machine monthly overall natural gas consumption as a residential demand side of the district heating system predictive model, Gomez et al. (2015) elaborated a detailed model of the Uzbek energy system in other to analyze in a quantitative way the options in Uzbekistan. Khan (2015) developed a sectoral (industrial, transport, residential and commercial sectors) natural gas demand model and estimated short- and long-run income, price and cross price elasticities in Pakistan over the period 2012–2015. Using trend analysis, Aydin (2015) modeled the consumption of energy sources for Turkey and presented future planning. Still in Turkey, Boran (2015) proposed a grey prediction with rolling mechanism approach to predict natural gas consumption and assist policymakers. Azadeh et al. (2015) presented an integrated forecasting algorithm based on ANFIS and computer simulation (SC) for long-term gas forecasting with economic, environmental and IT/IS (number of computer users divided by population in each year) as standard indicators. Szoplik (2015) discussed and presented the results of forecasts of cumulative gas demand for residents of Szczecin; Fagiani et al. (2015) presented experiments concerning the prediction of water and natural gas consumption, focusing on how to exploit data heterogeneity to get a reliable outcome; Askari et al. (2015) predicted the behavior of an abstract-semi-dynamic natural gas distribution network and nodal gas consumption; Nai-ming et al. (2015) applied new models to forecast the developing trends of China's energy production and consumption under the influence of China's energy saving policy; Zhang et al. (2015) analyzed the impacts of gas supply costs on interregional gas flow and gas infrastructure development in China out to 2035, Zhu et al. (2015) also presented a novel approach, named support vector regression (SVR) machine based support vector regression local predictor (SVRLP) with false neighbors filtered-support vector regression local predictor (FNF-SVRLP), to predict short-term natural gas demand. Darda et al. (2015) investigated the natural gas production of four South Asian states: Bangladesh, India, Maynmar, and Pakistan. Using a comprehensive framework, Lin and Li (2015) explored the spillover effects between crude oil markets and natural gas markets, including price spillover and volatility spillover. Lebed'ko and Lebed'ko (2015) analyzed the key indicators of the provision of economically recoverable hydrocarbons of oil and gas industry in Russia, and Clarkson et al. (2015) demonstrated that analytical/semi-analytical methods, developed previously for single-phase flow analysis, can be extended to tight gas and shale cases that exhibit significant condensate production.

Table 1 shows an up-to-date overview of published papers in the field of natural gas forecasting.

3. MODELS AND APPLICATION AREA

Forecasting problems arise in so many disciplines and the existing literature on forecasting provides applications in so many diverse fields. In this section, we give an overview of different application areas in which forecasting natural gas activities has been applied. We will start by describing each models used in the literature. Then we will survey the areas in which natural gas forecasting find applications, highlighting the specifics of some of the methodologies.

Table 1: Up-to-date overview of published papers

Date	Researchers
1949	Hubbert (1949)
1950	Verhulst (1950)
1956	Hubbert (1956)
1966	Balestra and Nerlove (1966)
1973	Tinic et al. (1973)
1977	Berndt and Watkins (1977)
1981	Beierlein et al. (1981)
1983	Piggott (1983), Jager (1983)
1987	Herbert (1987), Herbert et al. (1887)
1988	Werbos (1988)
1991	Liu and Lin (1991)
1994	Lee and Singh (1994), Brown et al. (1994)
1995	Li and Sailor (1995)
1996	Suykens et al. (1996), Eltony (1996), Brown and Martin (1996), Smith et al. (1996), Bartels et al. (1996)
1997	Sailor and Munoz (1997), Al-Jarri and Startzman (1997)
1998	Dahl and McDonald (1998), Hobbs et al. (1998)
1999	Khotanzad and Elragal (1999)
2000	Khotanzad et al. (2000), Al-Fattah and Starzman (2000), Durmayaz et al. (2000)
2001	Gumrah et al. (2001)
2002	Tahat et al. (2002), Baltagi et al. (2002)
2003	Siemek et al. (2003), Sarak and Satman (2003)
2004	Imam et al. (2004), Gorucu (2004), Gorucu and Gumrah (2004), Cavallo (2004), Cho et al. (2004), Aras and Aras (2004), Elragal (2004), Gil and Deferrari (2004)
2005	Gutierrez et al. (2005), Viet and Mandziuk (2005), Thaler et al. (2005), Pelikan and Simunek (2005)
2006	Musilek et al. (2006), Gelo (2006)
2007	Sanchez-Ubeda and Berzosa (2007), Potocnik et al. (2007), Potocnik et al. (2007), Timmer and Lamb (2007), Parikh et al. (2007), Huntington (2007)
2008	Aras (2008), Ghose and Paul (2008), Vondracek et al. (2008), Aydinalp-Koksal and Ugursal (2008), Potocnik et al. (2008), Brabec et al. (2008), Simunek and Pelikan (2008), Jiang et al. (2008), Kizilaslan and Karlic (2008)
2009	Tonkovic et al. (2009), Kizilaslan and Karlic (2009), Reynolds and Kolodziej (2009), Brabec et al. (2009), Brabec et al. (2009), Rui et al. (2009), Yoo et al. (2009), Ma and Wu (2009), Xie and Li (2009), Maggio and Cacciola (2009)
2010	Xu and Wang (2010), Erdogdu (2010), Behrouznia et al. (2010), Azadeh et al. (2010), Ma and Li (2010), Li et al. (2010), Toksari (2010), Forouzanfar et al. (2010), Dombayci (2010), Valero and Valero (2010), Kaynar et al. (2011)
2011	Li et al. (2011), Wadud et al. (2011)
2012	Fan and Xian (2012), Panella et al. (2012), Gracias et al. (2012), Osgouei and Sorgun (2012), Derimel et al. (2012), Lin and Wang (2012), Shekarchian et al. (2012), Economides et al. (2012), Azadeh et al. (2012), Rahim and Liwan (2012)
2013	Selehnia et al. (2013), Dalfard et al. (2013a; 2013b), Logan et al. (2013), Kialashaki and Reisel (2013), Taspinar et al. (2013), Leather et al. (2013), Melikoglu (2013), Wang et al. (2013), Lv and Shan (2013)
2014	Aydin (2014), Voudouris et al. (2014), Xiong et al. (2014), Dilaver et al. (2014), Bianco et al. (2014), Rodger (2014), Chkili et al. (2014), Jiang (2014), Potocnik et al. (2014), Soldo et al. (2014), Kani et al. (2014), Kovacic and Sarler (2014), Yu et al. (2014), Yu and Xu (2014), Paltsev (2014), Azadeh et al. (2014), Shi et al. (2014)
2015	Fagiani et al. (2015), Khan (2015), Aydin (2015), Azadeh et al. (2015), Szoplik (2015), Izadya et al. (2015), Gomez et al. (2015), Boran (2015), Askari et al. (2015), Nai-ming et al. (2015), Zhang et al. (2015), Zhu et al. (2015), Darda et al. (2015), Lin and Li (2015), Lebed'ko and Lebed'ko (2015), Clarkson et al. (2015)

3.1. Hubbert Model

3.1.1. Original Hubbert model

Hubbert (1949; 1956) was the first to treat the issue of depletion quantitatively. He observed that cumulative production as a function of time of an exhaustible resource usually followed (but not always) a logistic growth curve. Production grows slowly, then increases exponentially, reaches a maximum before declining. Hubbert fitted bell-shape curves to cumulative production and discoveries for US lower 48 states and predicted that production would peak in 1970. Following Hubbert's successful prediction of the timing of US peak production, many researchers worldwide extensively used Hubbert model to forecast natural gas prediction on different areas.

3.1.2. Multicyclic Hubbert model

Al-Jarri and Startzman (1997) modified Hubbert model by adapting it to demand. With this adapted model, they predicted the world's future supply and demand for petroleum liquids (crude oil and NGLs) to the year 2050. Al-Fattah and Startzman (2000) presented an analysis of the world's conventional natural gas supply and showed that the original Hubbert model with one production cycle as used in their previous study has some limitations. To tackle these limitations, they used a multicyclic model as an effective approach for modeling production trends with more than one cycle and developed forecasting models for them. Models for all countries and some organizations (e.g. the Organization of Petroleum Exporting Countries [OPEC], the OECD, the European Union, and the International Energy Agency [IEA]) were then used to forecast future production of natural gas worldwide. Maggio and Cacciola (2009) took into consideration three possible scenarios and adopted a multicyclic Hubbert model with two cycles to forecast trends of world oil and NGLs production from historical data. Valero and Valero (2010) accomplished an analysis of the earth's mineral resources, thereby carrying an exergy accounting of 51 minerals (both non fuel and fossil fuel minerals) throughout the 20th century. This allowed estimating from Hubbert model when the peak of natural gas production could be reached. Imam et al. (2004) used the "multicyclic Hubbert" curve to forecast the world's natural gas production. Reynolds and Kolodziej (2009) used a "multicyclic Hubbert" curve with inflection points similar to the Soviet Union's oil production "multicyclic Hubbert" curve to determine North American natural gas discovery rates and to analyze how market specific institutions caused the inflection points.

3.1.3. Other adaptations of the Hubbert model

Wang et al. (2013) used another version of Hubbert model known as the Weng model (this model is widely used by Chinese researchers) to forecast China's annual gas. Unlike the Hubbert model, the shape of generalized Weng curve is not necessarily symmetrical. The generalized Weng curve produces a flatter peak, indicating a stronger peak plateau and a better fit with the reality of China's oil and gas exploitation. In Lin and Wang (2012) a logistic growth curve is used to fit the historical data of natural gas production and predict the future gas production. Siemek et al. (2003) adapted Hubbert model to forecast natural gas demand in Poland. Cavallo (2004) argued that one shortcoming of Hubbert model is that it assumes economic factors (such as price) to be irrelevant in the long term. It also neglects impacts on economic cycles, policy changes, and other factors, thus it is purely a theoretical production model. Cavallo underlined that Hubbert model should be considered an economic model with its applicability determined by how well the assumptions are satisfied.

3.2. Statistical Models

3.2.1. GARCH-class and ARIMA models

ARIMA models assume the existence of a linear relationship between serial data. Moreover, this relationship can be found, and applied to time series that is stationary or made stationary with various statistical methods. These models have been applied on different areas in the field of natural gas forecasting. To forecast natural gas demand at the world level, Chkili et al. (2014) used a broad set of the most popular linear and nonlinear GARCH-type class models. Lin and Li (2015) proposed a VEC-MGARCH framework for examining spillover effects in price and volatility, taking into consideration regional segmentation and different pricing mechanism of natural gas markets of the US, Europe and Japan. GARCH have found extensive application in the literature and the most popular volatility model is GARCH (1, 1). Lv and Shan (2013) modeled gas market volatility using GARCH-class models with long memory and fat-tail distributions. ARIMA modeling is equally used in Erdogdu (2010) to estimate a model of natural gas demand in Turkey with a view to obtaining short- and long-run estimates of price and income elasticities, and equally to forecast future natural gas demand. Feng et al. (2014) focused on the characteristic of natural gas consumption sequence, and put forward three different kinds of models.

3.2.2. Primitive variable and DD

On regional level, Sailor and Munoz (1997) demonstrated two approaches for relating energy consumption to climate for eight states in the USA: The primitive variable approach which uses data that are directly available from meteorological stations and the DD approach. They found that the primitive variable approach is best for modeling natural gas consumption.

3.2.3. Time series models

In Dilaver et al. (2014), a statistical time series model with an underlying energy demand concept is used to estimate an OECD-Europe natural gas demand relationship. For this, an aggregate natural gas demand for OECD-Europe is estimated rather than combining the estimates of natural gas demand for individual countries. Aras and Aras (2004) divided the months of the year into two seasons (heating and non-heating periods) and used estimated individual autoregressive time series models for each period instead of attempting to capture the seasonal patterns in a single model. Panella et al. (2012) used a new machine learning approach for modeling commodity prices such as crude oil, coal, natural gas, and electricity prices for both the European and US markets. Their model can be considered as a nonlinear generalization of GARCH models, for which volatility clustering can be pursued in a straightforward manner.

3.2.4. Decomposition models and trend analysis

On national level, Sanchez-Ubeda and Berzosa (2007) proposed a novel statistical decomposition model able to capture demand patterns in a very large number of different historical profiles of industrial end-use natural gas consumption. Rahim and Liwan (2012) analyzed the reserves, production and consumption trends of oil and gas in Malaysia. Aydin (2014) developed models according to the oil and gas production trends observed in Turkey. He then tested the models with the t-distribution, the F-distribution and the residual analysis. In Aydin (2015), he still applied trend analysis to predict the consumption of primary energy sources.

3.2.5. Regression models

In order to evaluate industrial and residential demand for natural gas in the USA, regression analysis and linear regression equation are respectively used in Herbert (1987) and Herbert et al. (1987), Gorucu and Gumrah (2004) used multivariate regression analysis to evaluate and forecast gas consumption for the capital city of Ankara in Turkey. Timmer and Lamb (2007) used a linear model to develop two temperature indices (days below percentiles and heating degree days [HDD]) using the Richman-Lamb fine resolution (~1° longitude-longitude) set of maximum and minimum temperatures to determine the relation between temperature and residential natural gas consumption in the central and eastern US. The demand for natural gas and electricity for the residential, commercial and industrial sectors in the North Eastern US were estimated in Beierlein et al. (1981) using a combination of the error components model and seemingly unrelated regressions. A few authors discussed prediction of natural gas on individual costumer level using statistical models like Lee and Singh (1994). They used modified multilinear regression techniques, generalized Tobit model and several tests (Chow test, Hausman test, White test and the nearest neighbor estimation). Vondracek et al. (2008) used nonlinear regression principles to present a statistical approach to estimate natural gas consumption of individual residential and small commercial customers.

3.2.6. Transfer functions Box-Jenkins and Parametric regression

On the city and gas distribution system levels, Piggott (1983) used Box–Jenkins modeling in time series analysis. Box-Jenkins models are the most comprehensive of all popular and widely known statistical methods used for time series forecasting. Yoo et al. (2009) applied a sample selection model to estimate the residential demand function for natural gas in Seoul with correction for sample selection bias. Wadud et al. (2011) applied the log-linear Cobb Douglas functional form for demand modeling. Brabec et al. (2008) applied nonlinear mixed effects model, then Brabec et al. (2009a) went further to use time varying statistical model of state-space nature, and finally Brabec et al. (2009b) used semi parametric regression model with multiplicative structure which allows convenient separation of individual-specific and common time varying parts. Huntington (2007) developed a statistical model for tracking then industrial US natural gas consumption based on historical data. Assuming natural gas is mainly used for heating in Turkey, In the paper published by Liu and Lin (1991), a transfer function model was employed to explore the dynamic relationships between natural gas consumption, the temperature of the service area, and the price of natural gas in Taiwan.

3.3. Econometric Models

Econometric models correlate natural gas demand with other macro-economic variables. Econometric models include among others time series models, which are the most simplest of models which uses time series trend analysis for extrapolating the future energy requirement. There are a variety of models created by using different methods for forecasting. Most regression models are econometric models. Other econometric models include unit roots and error correction models (ECM), probabilistic models and a wide range of multivariate models.

Bianco et al. (2014) first identified and discussed consumption drivers, and then presented a single demand model equation. The model takes the classical form of a standard dynamic constant elasticity function of consumption. Finally, a scenario analysis is developed by analyzing twelve different cases. Kani et al. (2014) used STR model with GDP, real price of natural gas and temperature as explanatory variables to study the demand function of natural gas in Iran. Yu et al. (2014) used feasible generalized least squares techniques in order to control for panel heteroskedasticity and panel correlation. Khan (2015) examined natural gas consumption in Pakistan through an econometric model. Sector specific income, price and price elasticities of natural gas demand are also estimated. Dahl and McDonald (1998) used multiple regressions. Eltony (1996) analysed the demand for natural gas in Kuwait using two multilinear regression models: Partial-flow adjustment model (PAM) and cointegration and ECM.

3.4. Artificial Intelligence-Expert Systems

3.4.1. ANN models

ANNs are analytic techniques modeled on the learning processes inspired by biological systems, particularly that of the human cognitive system and the neurological functions of the brain. NNs are distributed information processing systems composed of many simple computational elements interacting across weighted connections. Inspired by the architecture of the human brain, NNs exhibit certain features such as the ability to learn from examples and capture subtle functional relationships among the data even if the underlying relationships are unknown and hard to describe. An ANN is typically composed of several layers of many computing elements known as nodes. NNs are simply parameterized nonlinear functions that can be fitted to data for prediction purposes. They are therefore data-driven self adaptive methods. Recently, there has been a considerable interest in the development of ANNs for solving a wide range of problems in different fields. One major application of ANNs is forecasting (Zhang et al., 2015; Haykin, 1998; Kalogirou, 2000).

Suykens et al. (1996) proposed an accurate model to forecast the Belgian gas consumption using static nonlinear ANNs. Most studies using ANNs have been carried out on city level and gas distribution systems. Werbos (1988) generarilzed back-propagation to reccurent gas market. Szoplik (2015) used ANNs trained with multiple linear perceptron (MLP) models to forecast natural gas consumption for residents in Szczecin, Poland. Dombayci (2010) used feed-forward back-propagation NN to predict heating energy consumption in a model house in Denizli, Turkey. Feed-forward ANN models were developed and used in Brown and Martin (1995) to predict daily gas consumption in two regions in Wisconsin served by Wisconsin Gas Company. Khotanzad and Elragal (1999) used a two stage system with three different ANN forecasters in the first stage and non-linearly combined forecasters in the second stage. Khotanzad et al. (2000) then expanded their works on combination of ANN forecasters with application to the prediction of daily natural gas consumption needed by local distribution companies (LDC). In their work, they proposed a two-stage system with the first stage containing two ANN forecasters, a multilayer feed-forward ANN and a functional link ANN. In the second stage, the two individual forecasts are mixed together to arrive at the final forecast. Gorucu (2004) used ANN modeling to evaluate and forecast gas consumption for the city of Ankara, thereby examining the factors affecting the output and training the ANNs to decide the optimum parameters to be used in the forecasting process.

3.4.2. Fuzzy logic

Another soft computing technique which is a very powerful method for constructing complex and nonlinear relationship between input and output data is fuzzy rule based approach. A specific approach in neuro-fuzzy development is ANFIS which combines the learning capabilities of NN and reasoning capabilities of fuzzy logic in order to give enhanced forecasting capabilities as compared to using only one methodology (Jang, 1993).

Behrouznia et al. (2010) used ANFIS for forecasting gas consumption, with the case study of South America. Viet and Mandziuk (2005) used neural and fuzzy neural systems to predict natural gas consumption in two regions in Poland. Musilek et al. (2006) used recurrent neural network as a gate for a statistical mixture model, combining historical data along with climatic conditions and other auxiliary descriptors with expert delineation of heating season boundaries to provide training data. Kizilaslan and Karlik (2008; 2009) used different types of NNs algorithms for forecasting gas consumption for residential and commercial consumers in Istanbul. In order to forecast gas consumption in distribution system in Osijek, Croatia, Tonkovic et al. (2009) created a prediction model in which he used multi-layer perceptron and a radial basis function (a–logistic activation function, b–tanh activation function, c–Gaussian activation function). Rodger (2014) created a decision support system that regulates the flow of natural gas from the wells to the HVAC systems of a building. The system was modeled with ANNs and the predictive models were implemented by comparing with regression, fuzzy logic, nearest neighbor, and NNs models. Just like Khotanzad and Elragal (1999) and Khotanzad et al. (2000), Elragal (2004) proposed a new technique for improving ANN prediction using fuzzy-genetic model and applied his method to the prediction of natural gas consumption needed by gas utilities. He used a hybrid system consisting of two stages, with the first stage containing two ANN predictors. Both predictors are a multi-linear feed-forward network trained with back-propagation, but the first one is trained to predict daily natural gas consumption while the second one is trained to predict the change in the daily natural gas consumption from the previous day.

3.4.3. Neuro fuzzy models

Azadeh et al. (2010) proposed an ANFIS equipped with pre-processing and post-processing concepts for Iranian natural gas consumption. Their model is capable of handling non-linearity, complexity as well as uncertainty that may exist in some datasets due to erratic responses and measurement errors. Askari et al. (2015) used the Takagi-Sugeno-Kang fuzzy system for forecasting semi-dynamic response of natural gas networks and nodal gas consumption. Structure identification of the system is carried out using cluster validity indices and possibilistic fuzzy C-means algorithm to determine the number of rules such that testing error of the system does not exceed a predefined value. Azadeh et al. (2015) proposed an integrated forecasting algorithm based on ANFIS and CS using the concepts of post-processing and pre-processing. At first the best distribution function is identified for each year and then CS is used to create random variables for each year to predict the effects of probabilistic distribution on annual consumption. Then, data is fed into ANFIS model to find the network with the lowest mean absolute percentage error (MAPE). Jiang (2014) considered more about the relative error than the absolute and belt a prediction model of the natural gas load of the Sichuan Province with an improved BP algorithm with additional momentum item based on the sum of relative square errors, while Smith et al. (1996) used a forecasting system based on expert systems to predict gas demands by regional gas company. Aramesh et al. (2014) used both ANN and ANFIS to predict natural gas transmission in two stations in Qazvin in Iran. The ANN and ANFIS were optimized for minimum error.

3.5. Grey Prediction Models

Researchers have also used grey prediction in the field of natural gas forecasting. Grey prediction gained popularity in the past decade because of its simplicity and ability to characterize unknown system by using a few data points. A GM combines a partial theoretical structure with data to complete the model. The theoretical structure may vary from information on the smoothness of results, to models that need only parameter values from data or existing literature. Thus, almost all models are grey box models as opposed to black box where no model form is assumed or white box models that are purely theoretical. Some GMs assume a special form such as a linear regression or NN. These have special analysis methods. In particular linear regression techniques are much more efficient than most non-linear techniques. The model can be deterministic or stochastic (i.e., containing random components) depending on its planned use. Natural gas demand forecasting can be regarded as a grey system problem, because a few factors such as GDP, income, population are known to influence natural gas demand, but how exactly they affect natural gas demand is not clear. Grey forecasting consists of several forecasting models of which GM(1,1) is commonly used for forecasting (Suganthi and Samuel, 2012).

Xiong et al. (2014) used a novel GM(1,1) model based on optimizing initial condition according to the principle of new information priority. The optimized model and five other GM(1,1) models are applied in the modeling of China's energy consumption, and production. Nai-ming et al. (2015) adopted an optimized single variable discrete grey forecasting model to forecast the total amount of coal, natural gas, crude oil and others sources of primary energy production and consumption in China, while a novel Markov approach based on quadratic programming model is proposed to forecast the trends of energy production and consumption structures. The grey prediction model of natural gas is given, and an example is given to verify the model and contrast the actual consumption. Ma and Wu (2009) improved forecast accuracy for natural gas consumption in China by replacing the original GM(1,1) models of Grey theory by Markov-chains.

3.6. GA

"GAs are a family of adaptive search procedures that are loosely based on models of genetic changes in a population of individuals. The main advantage of GAs is their ability to use accumulating information about initially unknown search space in order to bias subsequent searches into useful subspaces. GAs differ from conventional nonlinear optimization techniques in that they search by maintaining a population (or data base) of solutions from which better solutions are created rather than making incremental changes to a single solution to the problem" (Gen and Cheng, 1997).

Aras (2008) used GAs to predict natural gas consumption in residences in Turkey. Rui et al. (2009) put forward a method based on GAs to determine the weight which avoids the limits of the OLS method and meets the requirements of model projections through different directions. Xie and Li (2009) introduced grey modeling method optimized by GA.

3.7. Mathematical Models

Gil and Deferrari (2004) created a mathematical model to predict residential and commercial gas consumption in Buenos Aires, in Argentina. Darda et al. (2015) used a number of diffusion models (the traditional bass model and the generalized bass model), with convenient extensions, to investigate natural production for Bangladesh, India, Myanmar and Pakistan, and checked the model validation in terms of prediction capability. In Gracias et al.

(2012), three mathematical models are compared, logistic model or model of Verhulst, exponential model or the model of Malthus, and the model of Von Bertalanffy to analyze the possibilities of these models to describe the evolution of production, import and consumption of natural gas in Brazil. Some parameters of the differential equations were linearized and others were obtained by least square fitting. Wang et al. (2014) built a mathematical model of combinatorial optimization based on the natural gas consumption data of China, and solved it by means of MATLAB. Shi et al. (2014) proposed a new equation for production forecasting of gas condensate well considering fluid phase behavior in the reservoir and wellbore. In order to forecast natural gas spot prices, Selehnia et al. (2013) used the Gamma test for the first time as a mathematically nonparametric nonlinear smooth modeling tool to choose the best input combination before calibrating and testing models. This helped reduced the inputs selection uncertainty. They then developed several nonlinear models efficiently with the aid of the Gamma test, including regression models and ANN models, while Simunek and Pelikan (2008) preprocessed temperature data in their mathematical model.

3.8. Integrated models-Bayesian Vector Autoregression, SVR, Particle Swarm Optimization (PSO) Models

Some of the latest techniques such as Bayesian vector autoregression, SVR, ant colony optimization (ACO) and PSO models are being used in energy demand analysis. An integrated model which is based on improved BP NN and optimized GA to avoid partial dinky and achieve the global minimum is proposed in Yu and Xu (2014). In Azadeh et al. (2014), an integrated approach based emotional learning based FIS (ELFIS), ANN, ANFIS, conventional regression, analysis of variance and MAPE is introduced for the selection of training models for forecasting long term natural gas demand. This approach is capable of modeling sharp drops or jumps in natural gas consumption with appropriate cognitive and emotional signals. Zhu et al. (2015) used the SVR based SVRLP with FNF-SVRLP. This method integrates the SVR algorithm with the reconstruction properties of time series, and optimizes the original local predictor by removing false neighbors. This model has been used to predict natural gas demand for the National Grid of the United Kingdom (UK). Zhang et al. (2015) analyzed the dynamic interregional gas flow, gas infrastructure deployment, and impacts of gas supply costs in China using a dynamic optimization model.

3.9. Hybrid Models

To cope with random uncertainties in small historical datasets, Dalfard et al. (2013a) used Monte Carlo simulation to generate training data for ANFIS. Dalfard et al. (2013b) went further to and suggested a novel procedure to incorporate the impact of price hike into modeling. For this, logarithmic linear regressions were used to construct a first order Takagi-Sugeno-type FIS. In the adaptation phase, expert knowledge was used to define new fuzzy rules. Furthermore, an ANFIS-Monte Carlo simulation was conducted to forecast natural gas consumption in power generation in Iran. Fan and Xia (2012) used a hybrid input-output model to decompose driving factors to identify how these factors impact changes in energy (coal, oil, natural gas and renewable energy) intensity in China. A modified RAS approach is then applied to project energy requirements in a BAU scenario and an alternative scenario. Azadeh et al. (2012) presented a hybrid NN fuzzy mathematical programming approach for improvement of natural gas price estimation in industrial sector. This model is composed of ANNs, fuzzy linear regression, and conventional regression. Karimi and Dastranj (2014) developed an ANN-based GA model to predict the natural gas consumption in the city of Yasouj in Iran. The GA is used to optimize the NN topology and its parameters.

3.10. Combination or Mixed Models

Apart from traditional models surveyed above, some researchers decided to forecast natural gas by using two or several models in their papers. The reason for this is either to compare the results yielded by chosen models, get good results or to validate a model.

Taspinar et al. (2013) modeled natural gas consumption on a regional basis by using SARIMAX model, OLS, ANN-MLP and ANN-RBF models. Kialashaki and Riesel (2013) used ANN and multiple linear regression techniques to forecast future household energy demand in the US considering different scenarios. Derimel et al. (2012) used multivariate time series methods and NNs to forecast natural gas consumption in Istanbul. In order to investigate the influence of solar radiation on forecasting residential natural gas consumption, Soldo et al. (2014) applied several models: The random-walk model, the temperature correlation model, stepwise regression, linear auto-regressive with exogenous inputs (ARX), NN models and SVR. The models were systematically tested with and without solar radiation in order to determine the predictive relevance of this particular input variable. Moreover, they tested solar radiation impacts on two datasets, namely on natural gas consumption data of a model house, and on natural gas consumption data of LDC. Potocnik et al. (2014) compared eight forecasting models for short term residential natural gas consumption. Their paper focuses on comparison of static and adaptive forecasting models. In order to minimize associate costs, Kovacic and Sarler (2014) used linear regression and genetic programming (GP) approach to model and predict the gas consumption in a steel plant and, accordingly, to minimize ordered and supplied gas quantity error. Fagiani et al. (2015) evaluated a collection of techniques (ANNs, deep belief networks [DBN], echo state networks [ESN], SVR, GP and Extended Kalman Filter-GP [EKF-GP]) using the few publicly available datasets. Each dataset was tested with each technique for different configurations and input variables. In order to examine Turkey's natural gas consumption, Kaynar et al. (2011) combined fuzzy system and NNs, the main idea being that this combination yields an architecture that uses fuzzy system to represent knowledge in interpretable manner. In addition, the learning ability of NNs optimizes its parameters. Clarkson et al. (2015) combined analytical, semi-analytical and empirical methods. A PCMACP model is developed in Xu and Wang (2010) to predict China's natural gas consumption. Forouzanfar et al. (2010) used nonlinear programming (NLP) and GA to forecast natural gas demand in residential and commercial sectors in Iran. Yu et al. (2014) proposed a combinational model based on wavelet BP NN optimized by GA. The problems that traditional BP algorithm converge slowly and easily fall into local minimum was overcome.

3.11. Other Models

A dynamic model system was used in Li et al. (2010), Gutierrez et al. (2005) used stochastic Gompertz innovation diffusion process as a stochastic growth model of natural gas consumption in Spain, Toksari (2010) used simulated annealing to estimate Turkey's natural gas demand, Bartels et al. (1996) used CDA to estimate the end-use of gas in Australia whereas Aydinalp-Koksal and Ugursal (2008) compared CDA model with engineering based models. Gumrah et al. (2001) used DD concept for modeling gas demand in Ankara, while Sarak and Satman (2003) used the same concept to estimate residential natural gas consumption in Turkey. Thaler et al. (2005) used an empirical model, just as Berndt and Watkins (1977) and Gelo (2006), and Potocnik et al. (2007). Melikoglu (2013) developed two semi-empirical models based on econometrics to generate accurate forecasts for Turkey's natural gas demand: The logistic equation and the linear equation for long-term and medium-term natural gas demand forecasting respectively.

4. DATA

In the different papers encountered, various data have been used. Moreover, the source of data and data size were equally different. This is because data required is directly influenced by the applied model.

4.1. Forecasting Data

Hubbert (1949; 1956) used fossil fuels annual statistics of their production and estimates of ultimate reserves. Some authors like Derimel et al. (2012), Azadeh et al. (2010), Kovacic and Sarler (2014), and Yu and Xu (2014) instead used daily consumption of natural gas. Brabec et al. (2008) used daily consumption data of 62 individual customers and in combination with daily average temperature and day of the week; they made the individual gas consumption model for each customer. Brabec et al. (2009a) used daily consumption data, temperature and calendar data for their research in statistical calibration of the natural gas consumption model. Khotanzad and Elragal (1999), Khotanzad et al. (2000) and Aramesh et al. (2014) used daily consumption, temperature, wind speed and day of the week in order to forecast one day ahead gas consumption. Timmer and Lamb (2007) used historical daily maximum and minimum temperatures datasets from 766 weather stations to forecast gas consumption in Central and Eastern US. Selehnia et al. (2013) combined daily, weekly and monthly spot prices of natural gas because the applied model is data driven. The data used in Chkili et al. (2014) included daily spot and 3-month future prices of four major commodities traded in at international exchanges. Yu et al. (2014) on their side made use of maximum, minimum and average temperatures, calendar data and previous load data.

Authors like Eltony (1996), Al-Jarri and Startzman (1997), Al-Fattah and Startzman (2000), Gorucu (2004), Gutierrez et al. (2005), Sanchez-Ubeda and Berzosa (2007), Huntington (2007), Rui et al. (2009), Forouzanfar et al. (2010), Valero and Valero (2010), Li et al. (2011), Logan et al. (2013), Wang et al. (2013), Dalfard et al. (2013a; 2013b), Kialashaki and Reisel (2013), Xiong et al. (2014), Dilaver et al. (2014), Azadeh et al. (2014), Feng et al. (2014), Karimi and Dastranj (2014), Wang et al. (2014), and Xu and Wang (2018) used either historical annual consumption or historical production data as the main input parameter, while Bianco et al. (2014), Wadud et al. (2011), Azadeh et al. (2012), Jiang (2014), Boran (2015), used historical consumption data alongside with other economic data. Lin and Wang (2012), Darda et al. (2015) and Paltsev (2014) used historical data of natural gas production. On the other hand, Xie and Li (2009), Zhang et al. (2015) and Zhu et al. (2015) used historical natural gas consumption only. Reynolds and Kolodziej (2009) used natural gas reserve data and historical productions for all US lower 48 states.

Kaynar et al. (2011) used weekly time series natural gas consumption, Aydinalp-Koksal and Ugursal (2008) used data from a survey of household energy heating and cooling degree days. Aras and Aras (2004) used monthly natural gas consumption data, while Liu and Lin (1991) and Erdogdu (2010) included quarterly time series data in their model. Lin and Li (2015) used monthly prices of natural gas from major natural gas consuming regions namely US, Continental Europe and Japan for two reasons: (1) Daily and weekly data of natural gas prices were not available; (2) monthly data had sufficient frequency to analyze the spillover effects across markets over time. Lee and Singh (1994) in their analysis used micro consumption data of electricity and gas by residents in the US. Yoo et al. (2009) used the data obtained from a survey of households conducted in Seoul and Rodger (2014) used natural gas consumption data for public buildings.

Aydin (2014) identified and used production trends for oil and natural gas. Osgouei and Sorgun (2012), Rahim and Liwan (2012), and Ma and Wu (2009) in addition to the production trend included the consumption trend. Voudouris et al. (2014) collected various data including the domestic demand of dry natural gas, the projected growth rates of natural gas demand, the volume of natural gas that originally existed before any extraction, the dry annual production of natural gas, the cumulative production of natural gas, estimates of natural gas remaining, the maximum allowable projected growth rates and assumed peak/decline point of natural gas production. Yu et al. (2014) used a set of unbalanced panel data for 62 cities in China. Their explanatory variables include among others natural gas usages, gas price, electricity price, LPG and coal price, wage of urban employees, dwelling area, family size, HDD and length of pipeline. Data used in the paper published by Shekarchian et al. (2012) are based on electricity generation in Malaysia, fossil fuel used to produce electricity in power plants, and electricity consumption in residential and commercial sectors. Sarak and Satman (2003) and Melikoglu (2013) used the same data as their predecessors. Lv and Shan (2013) used weekly closing price data of natural gas spot and future contracts in New York Mercantile Exchange with a maturity of 1 month. In his paper, Khan (2015) used real GDP, per capita real income, total population and different fuel prices. Nai-ming et al. (2015) decided to use annual data of total amounts and structures of energy production and consumption of China. Fan and Xia (2012) focused on eight final demand categories varying from rural household consumption through government consumption and changes in inventory to imports and exports. In Askari et al. (2015) nodal historical data is used as the unique parameter. Szoplik (2015) in his work used real weather and calendar data that he looked upon as actual gas consumption. Panella et al. (2012) collected coal, natural gas, crude oil and electricity prices for both the European and US markets. In Gracias et al. (2012) the study was conducted from data on production, import and consumption of natural gas in Brazil. Clarkson et al. (2015) in their model took into account the flow rates and pressure, volumetric data for reservoirs and fluid properties. Taspinar et al. (2013) used daily natural gas consumption as well as weather data (ambient air temperature, wind speed, atmospheric pressure, relative humidity and average cloud cover). Soldo et al. (2014) in their investigation of gas consumption of a model house and of LDC, used weather data including hourly temperatures and solar radiation, hourly gas meter readings of the model house, and hourly gas meter readings of the LDC. In order to reduce the purchased-energy consumption for a house experiencing a Mediterranean climate, Tahat et al. (2002) used daily temperature, daily relative humidity ratio and monthly average daily solar radiation. Dombayci (2010) also predicted heating energy consumption in a model house by using hourly consumption values and number of heating degree hour. Using the DD concept, Gumrah et al. (2001) considered historical consumption, number of customers and meteorological data as the basic inputs, whereas weather data and weather forecast according to the required forecasting horizon are used in Potocnik et al. (2007). Elragal (2004) considered a slightly different approach by considering data obtained from distribution companies and actual weather data. Musilek et al. (2006) also considered climatic conditions but took into account the lack of extensive and reliable historical data, while Sailor and Munoz (1997) used historical energy and climate data for assessing sensitivity of electricity and natural gas consumption at regional scales. Aydin (2015) identified trends in consumption of energy sources. Besides monthly gas consumption, Azadeh et al. (2015) decided to include inflation rate, gas price, unemployment rate, IT/IS, human development index and CO_2 emissions. Kani et al. (2014) instead combined macroeconomic data such as GDP and real price of natural gas, and temperature as explanatory variables, whereas Potocnik et al. (2014) combined hourly consumption data with meteorological data for two heating seasons. Vondracek et al. (2008) used mainly two real datasets ordinary (approximately annual) meter readings of almost all customers and additional (approximately monthly) meter readings designed and tested in the West Bohemian Gas Distribution Company (WBGDC). Dahl and McDonald (1998) used historical price, income and population changes in the developing world. In Thaler et al. (2005), known prototype patterns and given future values of environmental variables are used.

4.2. Data Source

Fagiani et al. (2015) used available datasets from researches responsible for each dataset creation and maintenance. Khan (2015) collected data from public institutions in Pakistan and from researches conducted by his predecessors. In Szoplik (2015) data was provided by a network operator and weather parameters were obtained from meteorological database, whereas Dahl and McDonald (1998) used data from their previous works. Timmer and Lamb (2007) used temperature data provided by their predecessors and residential consumption data provided by the US Energy Information Administration (EIA). Vondracek et al. (2008) collected data from costumers meters readings and from meter readings designed and operated within the frame of cooperation between the Institute of Computer Science of the Czech Academy of Sciences and the WBGDC. In the paper published by Aydinalp-Koksal and Ugursal (2008) two sources of data were used for the development of the input units of the CDA model: The data from the 1993 survey of household energy use database and the 1993 heating and cooling degree day data for the cities in which the households in the CDA dataset are located. A survey of households in Seoul was conducted in Yoo et al. (2009). In Dombayci (2010) hourly energy consumption values for the model house in Denizli were calculated using hourly temperature data obtained from the Turkish State Meteorological Service. Aramesh et al. (2014) obtained weather and consumption data from Qazvin meteorological office and Qazvin Natural gas Distribution Company respectively. Karimi and Dastranj (2014) obtained consumption from a LDC and weather data were collected from the meteorological organization of Yasouj.

The data in Fan and Xia (2012) are from input-output tables compiled by the National Bureau of Statistics of China and from the Chinese energy statistical yearbooks. Gracias et al. (2012) obtained data from the energy balance of the Ministry of Mines and Energy of Brazil. Beierlein et al. (1981) collected data for nine US states comprising the Census Bureau’s northeastern region. Data used in Wadud et al. (2011) were obtained from different sources: Prices of natural gas from PETROBANGLA annual report, GDP and GDP per capita from World Bank and population from Bangladesh Bureau Statistics. Shekarchian et al. (2012) used consumption data from the Ministry of Energy of Malaysia, whereas in Azadeh et al. (2012) natural gas prices were obtained from Central Bank of Iran. Zhu et al. (2015) recorded demand data from the national grid of UK. Hubbert (1949; 1956), Al-Fattah and Startzman (2000), Huntington (2007), Ma and Wu (2009), Rui et al. (2009), Li et al. (2010), Lin and Wang (2012), Wang et al. (2013), Dalfard et al. (2013a), Xiong et al. (2014), Bianco et al. (2014), Yu et al. (2014), Azadeh et al. (2014), Nai-ming et al. (2015), Lin and Li (2015) all obtained data from public institutions in the respective countries where these studies were conducted.

Some Authors used data from international organizations. Consumption of energy sources data in Aydin (2014, 2015) were taken from the British Petroleum Statistical Review of World Energy. Lebed’ko and Lebed’ko (2015) exploited data from Gazprom. Al-Jarri and Startzman (1997) used data obtained from British Petroleum, US EIA and OPEC. Eltony (1996) made use of the OAPEC annual report consumption profile. Voudouris et al. (2014) collected data from numerous sources: US Energy Information Administration (EIA), US Geological survey, and from the works of their predecessors. Darda et al. (2015) and Zhang et al. (2015) equally recorded data from British Petroleum. Selehnia et al. (2013) collected natural gas prices from CME Group website and EIA web page, Rahim and Liwan (2012) used data from EIA just as Economides et al. (2012), Reynolds and Kolodziej (2009), Lv and Shan (2013), Chkili et al. (2014), and Boran (2015), while Osgouei and Sorgun (2012) modified the natural gas production and consumption data obtained from EIA and British Petroleum. Sailor and Munoz (1997) also adjusted data obtained from EIA. Valero and Valero (2010) reconstructed historical statistics of world fuel minerals from different information sources, being the most important ones those from the British Geological Survey and its preceding organizations. Erdogdu (2010), Gutierrez et al. (2005) and Dilaver et al. (2014) used data from IEA.

In some studies, data were collected from gas distribution companies or from production companies. Lee and Singh (1994) obtained datasets from Pacific Gas and Electricity Company. Brabec et al. (2008; 2009a; 2009b) obtained datasets from two separate projects organized independently by the Czech Gas Union and the Slovak Gas industry company. Kaynar et al. (2011) obtained weekly consumption data from BOTAS. Taspinar et al. (2013) also collected data from a local meteorology office and consumption data from a regional gas distribution company. Potocnik et al. (2014) used weather data from a weather station and consumption data from gas meter readings in HEP-Plin Ltd. Soldo et al. (2014) obtained hourly consumption meter readings from HEP-Plin Ltd., a gas distribution company in Osijek-Croatia and weather data were obtained from a weather station in the same town. In Kovacic and Sarler (2014) data on natural gas consumption were obtained from Store Steel Company, a steel producing plant in Slovenia. Paltsev (2014) undertook his analysis on Russia's natural gas exports with production data from Gazprom. Derimel et al. (2012) in their model used natural gas consumption data from the Turkish IGDAS city gas distribution company, while monthly observations data in Aras and Aras (2004) have been provided by several city distribution companies in Turkey (EGO, IGDAS, BURSAGAZ, ESGAZ and IZGAZ). Azadeh et al. (2010) and Forouzanfar et al. (2010) gathered daily data set from National Iranian Gas Company Publications. Potocnik et al. (2007), Khotanzad and Elragal (1999), Khotanzad et al. (2000), Sarak and Satman (2003), Elragal (2004), and Ghose and Paul (2008) also collected data from gas distribution companies.

Brabec et al. (2009b), Logan et al. (2013), Kialashaki and Riesel (2013), Dalfard et al. (2013b), and Gomez et al. (2015) used data from numerous sources that are either governmental institutions, private institutions, international organizations, gas distribution companies or from other published researches. Table 2 provides other details.

4.3. Data size

Aydin (2014) observed 25 production trends. Voudouris et al. (2014) set the base year as 2008 and each of the 216 countries was modeled in the ACEGES model initialized with real-world data as of 2008. The data used in Fagiani et al. (2015) varied from 10 to 210 336 samples. Khan (2015) utilizes annual data covering the period from 1978 to 2011. Azadeh et al. (2015) employed monthly gas consumption from 2000 to 2006, a total of 42 observations. Szoplik (2015) divided the input dataset into three subsets: The first one sized 8760 included data for 2009, the second set sized 17520 included data for 2009 and 2010, and the third set sized 8760 included data for 2011 and was not used in the training of the MLP network. The Quarterly data used by Erdogdu (2010) covers the period 1988–2005, a total of 72 observations. Liu and Lin (1991) made a total of 168 observations for monthly natural gas consumption, temperature and natural gas price between January 1975 and December 1988. Lee and Singh (1994) used dataset with a size of 735. The dataset in Aras and Aras (2004) contains monthly amounts of natural gas consumption in residences and daily mean temperatures for a 61-month period December 1996 to December 2001 in Eskisehir, Turkey. Temperature dataset in Timmer and Lamb (2007) contains 766 stations across the US and southern Canada east of the Rocky Mountains for which complete records of daily maximum and minimum temperatures are available from January 1949 through December 2000, while monthly residential natural gas consumption data were obtained for January 1989–December 2000. Vondracek et al. (2008) collected a total of 205544 annual gas meter readings for the residential and commercial sectors. Brabec et al. (2008; 2009a; 2009b) conducted hourly gas consumption measurements with sample sizes of roughly 1000 and 550 costumers from datasets provided by two separate projects organized independently by the Czech gas union and the Slovak gas industry company respectively. In Yoo et al. (2009) a total of 380 households were surveyed among which 158 provided necessary information in the interviews while 216 households failed to answer the question on residential natural gas consumption, whereas Aydinalp-Koksal and Ugursal (2008) surveyed 8767 households in Canada to get information on electricity billing and natural gas billing data. Dombayci (2010) considered hourly heating energy consumption values for the years 2004-2007, representing a total of 35070 h temperature data. Taspinar et al. (2013) used dataset for approximately 1800 days between 2007 and 2011. In Lv and Shan (2013) the in-sample for modeling from January 10, 1997 to October 27, 2006 (500 data points) and the out-of-sample period for evaluating the model performance are from November 3, 2006 to December 2, 2011 (262 data points). For subsequent analysis, Soldo et al. (2014) collected and combined weather data, model house data and LDC data with 4314 customers into a data base. The measurements were resampled from hourly to a daily resolution throughout two heating seasons: Season 1 from 6/11/2011 to 27/4/2012, and season 2 from 8/11/2012 to 1/4/2013. Azadeh et al. (2014) used 34 set of data which are annual natural gas demand in Iran from 1973 to 2006. The sample period in Lin and Li (2015) is from January 1992 through December 2012, a total of 252 price observations.

Panella et al. (2012) collected commodity prices over the period 2001–2010. In Gracias et al. (2012) data on natural gas production, imports, and consumption were collected over the periods 1970–1989, 1999–2009 and 1970–2009 respectively. Aydin (2015) identified trends in consumption of energy sources during the period 1965–2010. Bianco et al. (2014) considered historical data for the explanatory variables from 1990 to 2011. For future projections, Xu and Wang (2010) used historical consumption from 1995 to 2008. Gorucu (2004) considered consumption trends for the period 1995–2008. Hubbert (1949; 1956) reviewed US production and annual average price from 1911 to 1961. Al-Jarri and Startzman (1997) collected production and demand data from 1918 to 1995 and 1985 to 1995, respectively. They later added more historical data from other sources; these data could not be combined because of data discrepancies, possibly the conversion from tons to barrels. Sanchez-Ubeda and Berzosa (2007) provided a forecasting model with 1–3 years ahead daily forecast based

Table 2: Summary of literature on forecasting methodologies

Model type	Applied Model	Researchers	Application area	Main Input Data	Data source	Data size	Forecasting horizon
Hubbert model	Original Hubbert model	Hubbert (1949)	World and national level (USA)	Annual statistics of production and estimates of ultimate reserves	US bureau of mines	1911–1961	Yearly
		Hubbert (1956)	World level	Annual statistics of production and estimates of ultimate reserves	US bureau of mines	1911–1961	Yearly
		Al-Jarri and Startzman (1997)	World regions and organizations	Historical production and demand data	British Petroleum, EIA and OPEC	1918–1995 (production data) 1985–1995 (demand data)	Yearly till 2050
		Valero and Valero (2010)	World level	Exergy loss and average degradation of mineral commodities	British Geological Survey	1900–2006	Yearly till 2150
		Wang et al. (2013)	National level (China)	Historical annual proved geological reserves, Historical annual gas consumption	Statistics handbook of Chinese oil and gas reserves and production, National Bureau of Statistics, Ministry of Land and Resources of China	1949–2000	Yearly
		Al-Fattah and Startzman (2000)	World regions	Historical annual production, gas discovery data and proved reserves	IEA Tulsa (1998a, 1998b) DeGolyer and MacNaughton (1996, 1998)	1900–1997 (US gas-discovery data) 1918–1997 (US marketed-gas production data) 1971–1997 (annual production data for all other countries)	Yearly till 2050
		Siemek et al. (2003)	National level (Poland)	Historical annual consumption data	Al-Fattah and Startzman (2000)	1970–2001	Yearly from 2002 till 2070
	Multicyclic Hubbert model	Maggio and Cacciola (2009)	World level	Annual statistics of production and estimates of ultimate reserves	British Petroleum, ENI, EIA	1960–2008	Yearly
		Imam et al. (2004)	World level	Historical production	Not available	Not available	Yearly

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Table 2: ***(Continued)***

Model type	Applied Model	Researchers	Application area	Main Input Data	Data source	Data size	Forecasting horizon
		Reynolds and Kolodziej (2009)	National level (US)	Natural gas reserve data and historical production	EIA	1950–2003	Yearly
Statistical models	GARCH-type	Chkili et al. (2014)		Daily spot and 3-month future prices	EIA	7/1/1997–31/3/2011	Yearly
	VEC-MGARCH framework	Lin and Li (2015)	Regional level (USA, Europe and Japan)	Monthly prices	Wind Database	Jan 1992–Dec 2012 (252 observations)	Yearly
	ARIMA	Erdogdu (2010)	National level (Turkey)	Quarterly consumption	IEA	1988–2005 (72 observations)	Yearly from 2008 till 2030
	Primitive variable and degree-day	Sailor and Munoz (1997)	Regional level (8 states in the US)	Historical energy consumption and climate data	EIA	1984–1993	Monthly
	Time series	Dilaver et al. (2014)	Regional level (Europe)	Historical consumption, GDP, price index	IEA	1978–2011	Yearly
		Aras and Aras (2004)	National level (Turkey)	Monthly consumption	EGO, IGDAS, BURSAGAZ, ESGAZ and IZGAZ	Dec 1996–Dec 2001 (61 observations)	Monthly
		Panella et al. (2012)	Regional level (US and European markets)	Prices of coal, natural gas, crude oil, electricity	Not available	Training data: 500 samples Test data: 500 samples	Daily
	Decomposition model	Sanchez-Ubeda and Berzosa (2007)	National level (Spain)	Historical profiles	Not available	1/1/1996–30/6/2005	Daily (1–3 years ahead)
	Trend analysis	Rahim and Liwan (2012)	National level (Malaysia)	Production and consumption trends	EIA	1980–2010	Yearly
		Aydin (2014)	World level	Production trends for oil and natural gas	British Petroleum	25 production trends	Yearly
		Aydin (2015)	World level	Consumption trends	British Petroleum	1965–2010	Yearly
	Regression model	Herbert (1987)	National level (USA)	HDD, gas price, residual fuel oil	Not available	Not available	Monthly
		Herbert et al. (1987)	National level (USA)	HDD, CDD (cooling degree-days), gas price, income index, price of residual fuel oil, temperature	EIA, Federal Energy Regulatory Commission	Jan 1980–Dec 1984	Monthly
		Gorucu and Gumrah (2004)	City area (Ankara)	Not available	Not available	Not available	Yearly

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Table 2: ***(Continued)***

Model type	Applied Model	Researchers	Application area	Main Input Data	Data source	Data size	Forecasting horizon
		Timmer and Lamb (2007)	City area level (Central and Eastern US)	Historical daily maximum and minimum temperature datasets; monthly residential consumption	Skinner et al. (1999) EIA	Jan 1949–Dec 2000 (daily maximum and minimum temperature) Jan 1989–Dec 2000 (monthly residential consumption)	Seasonally
		Beierlein et al. (1981)	Regional level (North Eastern US)	Natural gas price, income per capita, fuel consumption per capita	Census Bureau	1967–1977	Yearly
		Lee and Singh (1994)	Individual customers level	Micro consumption data of electricity and gas by residents	Pacific gas and electricity company	735 observations	Not available
		Vondracek et al. (2008)	Individual customers level	Annual meter readings for almost all customers and monthly meter readings designed by the WBGDC	From costumers meter readings	205 544 gas meter readings	Monthly basis with daily resolution from May 2005 to May 2006
		Brabec et al. (2009a; 2009b)	Individual customers level	Daily consumption, temperature and calendar data	Czech load profile construction project	Not available	Daily
	NLME	Brabec et al. (2008)	Individual customers level	Daily consumption, daily average temperature and day of week	Czech Gas Union, Slovak Gas industry company	1000 gas meter readings (Czech Gas Union) 550 gas meter readings (Slovak Gas industry company)	Hourly, daily and yearly
	Transfer function	Liu and Lin (1991)	National level (Taiwan)	Quarterly consumption, monthly temperature and monthly price	Energy Committee of the Republic of China, Central Weather Bureau of China	Jan 1975–Dec 1988 (168 observations)	Quarterly and yearly
	Box-Jenkins	Piggott (1983)	Gas distribution system	Not available	Not available	Not available	Daily and Weekly
	Sample selection	Yoo et al. (2009)	City area (Seoul)	Residential consumption	Survey of Households in Seoul	380 observations	Monthly

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Table 2: ***(Continued)***

Model type	Applied Model	Researchers	Application area	Main Input Data	Data source	Data size	Forecasting horizon
		Huntington (2007)	National level (US)	Historical data (gas consumption, gas price, GDP, petroleum price, price controls, HDD, CDD, manufacturing output and industrial capacity utilization)	US Federal Reserve Board US Bureau of Labor Statistics US Bureau of Economic Analysis EIA	1958–2003	Yearly from 2004 to 2030
Econometric models	GARCH class models	Lv and Shan (2013)	National level (USA)	Weekly closing price of natural gas and future contracts in NYMEX with a maturity of 1 month	EIA	In-sample: 500 data points Test sample: 262 data points	Daily
	Feasible generalized least squares (FGLS)	Yu et al. (2014)	National level (China)	Natural gas usages, gas price, electricity price, electricity price, LPG and coal price, wage of urban employees, dwelling area, family size, HDD and length of pipeline	China Urban Construction Statistical Yearbook Price Monitoring Center National Statistical Bureau China Meteorological Data Sharing Service System	2006–2009	Yearly
	Smooth transition regression	Kani et al. (2014)	National level (Iran)	GDP, real price of natural gas and temperature	Not available	1971–2009	Yearly
	log-linear Cobb Douglas functional form	Wadud et al. (2011)	National level (Bangladesh)	Historical consumption	PETROBANGLA, World Bank, Bangladesh Bureau Statistics	1981–2008	Yearly till 2025
	Multiple regressions	Dahl and McDonald (1998)	World level	Historical price, income, population changes	From their previous works	Observations made for 28 developing countries	Yearly
	PAM and ECM	Eltony (1996)	National level (Kuwait)	Reserves, production, consumption and prices	OAPEC	1980–1993	Yearly from 1975 till 1993
Artificial intelligence-Expert systems	ANN models	Szoplik (2015)	City area (Szczecin)	Real weather, calendar data	LDC, meteorological database	1st dataset: 8760 samples 2nd dataset: 17520samples 3rd dataset: 8760 samples	Hourly
		Suykens et al. (1996)	National level (Belgium)	Temperature, number of costumers, oil price,	Not available	1/7/1982–31/12/1082	Monthly

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Model type	Applied Model	Researchers	Application area	Main Input Data	Data source	Data size	Forecasting horizon
		Brown and Martin (1994)	Gas distribution system	Daily consumption, HDD, temperature, wind speed, day of the week, day of the year	Not available	21/12/1989–29/3/1994	Daily
		Khotanzad and Elragal (1999)	Gas distribution system	Daily consumption, temperature, wind speed, day of week	LDC	Not available	One day ahead
		Gorucu (2004)	City area (Ankara)	Consumption trend, gas price, number of costumers, degree-day, exchange rate	Not available	1991–2001	Yearly
		Dombayci (2010)	Individual costumer	Heating energy consumption	In situ measurements; Turkish State Meteorological Service	Training data: 26310 samples Test data: 8 760 samples	Hourly
	Fuzzy logic	Behrouznia et al. (2010)	Regional level (South America)	Historical annual consumption, GDP and Population	Not available	1980–2007	Yearly till 2015
		Viet and Mandziuk (2005)	City area	Daily average temperature, working days-weekend days	Not available	Training data: 1/1/2000–31/12/2001 Test data: 1/1/2002–31/12/2002	Daily, weekly and four weekly
		Musilek et al. (2006)	Gas distribution system	Actual weather data and daily consumption	Not available	Total data: 1461 patterns Approximately 75% for training and 25% for validation	One day ahead
		Kizilaslan and Karlik (2009)	City area (Istanbul)	Monthly consumption, temperature	Not available	Not available	Monthly
		Kizilaslan and Karlik (2008)	City area (Istanbul)	Daily consumption, Day of the week, day of the year, month of the year, daily minimum and maximum temperature, number of costumers	Not available	Not available	Daily and weekly
		Tonkovic et al. (2009)	City area (Osijek)	Hourly consumption , temperature, wind speed, day of the week	Not available	Not available	Hourly and daily

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Table 2: ***(Continued)***

Model type	Applied Model	Researchers	Application area	Main Input Data	Data source	Data size	Forecasting horizon
		Rodger (2014)	Individual costumer	Consumption data for public buildings	In situ measurements	111 observations	Daily
		Khotanzad et al. (2000)	Gas distribution system	Daily consumption, temperature, wind speed and day of week	LDC	Training data: varies from 94 to 96 samples Test data: Varies from 148 to 212 samples	One day ahead
		Elragal (2004)	Gas distribution system	Consumption data and actual weather data	LDC	Training data: 400 patterns Test data: 200 patterns	Daily (4 weeks ahead)
	Neuro fuzzy models	Azadeh et al. (2010)	National level (Iran)	Daily consumption	National Iranian Gas Company publications	Training data: 22/12/2007 to 20/6/2008 Test data: 21/6/2008 to 30/6/2008	Daily
		Askari et al. (2015)	Gas distribution system	Nodal historical data	Aramesh et al. (2014)	Consumption data: 1200 samples Box-Jenkins data: 294 samples TAIEX data: 226 samples	Daily (30 days ahead)
		Azadeh et al. (2015)	National level (Iran)	Inflation rate, gas price, unemployment rate, IT/IS, human development index and CO2 emissions	Not available	2000–2006 (42 observations)	Monthly
		Jiang (2014)	City area (Sichuan province)	GDP, GDP of industry, per capita GDP, consumption level, gas consumption	Not available	2000–2012	Yearly
		Smith et al. (1996)	Gas distribution system	The current day, the following day, consumer behavioral pattern	Not available	Not available	Not available
Grey prediction	GM(1,1)	Xiong et al. (2014)	National level (China)	Historical consumption and production	China Statistical Yearbook	1990–2012	Yearly
		Ma and Wu (2009)	National level (China)	Historical production and consumption trends	China Council for International Cooperation on Environment and Development	1990–2007 (18 observations)	Yearly from 2004 till 2007

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Table 2: ***(Continued)***

Model type	Applied Model	Researchers	Application area	Main Input Data	Data source	Data size	Forecasting horizon
		Nai-ming et al. (2015)	National level (China)	Historical production and consumption trends	National Bureau of Statistics of China	1990–2011	Yearly
Genetic algorithms		Aras (2008)	National level (Turkey)	Monthly consumption, Calendar data, HDD, consumer price index	ESGAZ, Turkish State Meteorological Service, Turkish Statistical Institute	Dec 1996 to July 2008 (140 observations)	Monthly
		Rui et al. (2009)	National level (China)	Historical consumption	China Statistical Yearbook	1994–2006 (13 observations)	Yearly from 2010 till 2015
	GM(1,1) optimized by GA	Xie and Li (2009)	National level (China)	Historical consumption	Not available	Not available	Yearly
Mathematical models		Gil and Deferrari (2004)	City area (Buenos Aires)	Daily mean temperature, day of the week, holiday or working day	Not available	Not available	Daily, monthly and yearly
	Bass model and generalized bass model	Darda et al. (2015)	Regional level (Bangladesh, India, Myanmar and Pakistan)	Historical production	British Petroleum	1971–2011	Yearly till 2030
	Logistic model, model of Verhust, exponential model and model of Von Bertalanffy	Gracias et al. (2012)	National level (Brazil)	Production, imports and consumption data	Ministry of Mines and Energy of Brazil	1970–1989 (production data); 1999–2009 (imports data); 1970–2009 (Consumption data)	Daily
	Gamma test analysis	Selehnia et al. (2013)	National level (USA)	Daily, weekly and monthly spot prices	CME and EIA	7/1/1997–20/3/2012	Daily, weekly and monthly
Integrated models	ELFIS, ANN, ANFIS, conventional regression	Azadeh et al. (2014)	National level (Iran)	Historical consumption, population, national income, consumer price index, GDP and gas demand for the previous year	Statistical Centre of Iran Energy Balance of Iran	1973–2006 (34 observations)	Yearly
	False neighbors filtered-support vector regression local predictor (FNF-SVRLP)	Zhu et al. (2015)	Regional level (UK)	Historical consumption	National grid of UK	Training data: 1095 samples Test data: 366 samples	Daily

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Table 2: ***(Continued)***

Model type	Applied Model	Researchers	Application area	Main Input Data	Data source	Data size	Forecasting horizon
	Dynamic optimization model	Zhang et al. (2015)	National level (China)	Historical consumption	British Petroleum	1949–2014	Yearly till 2035
Hybrid models	Monte Carlo simulation-ANFIS	Dalfard et al. (2013a)	National level (Iran)	Annual time series data	Statistic Center of Iran, IMF, Hydrocarbori Energy Balance	1997–2009 (13 observations)	Yearly
	Linear regressions-(TK-FIS) and Monte Carlo simulation-ANFIS	Dalfard et al. (2013b)	National level (Iran)	Natural gas prices, GDP, population data, Electricity from renewable sources, average efficiency of gas-fired electricity generation	Statistic Center of Iran, IMF, Hydrocarbori Energy Balance	1997–2009 (13 observations)	Yearly
	Hybrid Input-Output model	Fan et Xia (2012)	National level (China)	Household consumption	National Bureau of Statistics of China; Chinese energy statistical yearbooks	1978–2010	Yearly
	Neuro-fuzzy simulation	Azadeh et al. (2012)	National level (Iran)	Domestic and industrial prices, consumer price index, population, GDP gas domestic and industrial consumption	Central Bank of Iran	1968–2008 (40 observations)	Yearly
Combination models	SARIMAX, OLS, ANN-MLP and ANN-RBF	Taspinar et al. (2013)	City area (Sakarya)	Daily consumption and weather data (ambient air temperature, wind speed, atmospheric pressure, relative humidity and average cloud cover)	Local meteorological office and a regional gas distribution company	2007–2011 (1800 observations)	Daily
	ANN and Multivariate time series	Kialashaki and Riesel (2013)	National level (USA)	Population, GDP, Household size, household income, electricity cost, natural gas price, heating oil price	US Census Bureau, EIA	1984–2010	Yearly till 2040
	Multivariate time series method and Neural networks	Derimel et al. (2012)	City area (Istanbul)	Daily consumption	IGDAS city gas distribution company	1/1/2004–30/11/2009	Daily
	Random-walk model, temperature correlation model, stepwise regression, ARX, Neural networks, SVR	Soldo et al. (2014)	Gas distribution system	Weather data, hourly temperatures, solar radiation, hourly gas meter readings of the model house and LDC	Weather station, HEP-Plin Ltd	4314 observations	Daily

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Table 2: ***(Continued)***

Model type	Applied Model	Researchers	Application area	Main Input Data	Data source	Data size	Forecasting horizon
	Static and adaptive models	Potocnik et al. (2014)	Gas distribution system	Hourly consumption data and meteorological data for two heating seasons	Weather station, HEP-Plin Ltd	4314 observations	Daily
	Hybrid neural network fuzzy mathematical programming model	Potocnik et al. (2007)	Gas distribution system	Actual weather data and weather forecast	LDC	Training data: 1/6/2002–31/12/2003 Test data: 1/1/2004–31/12/2004	Yearly (with monthly resolution)
	Linear regression and genetic programming	Kovacic and Sarler (2014)	Industrial level	Daily consumption	Store Steel Company	1/1/2005–25/3/2005	Daily
	ANFIS, ARIMA and ANNs (MLP and RBF)	Kaynar et al. (2011)	National level (Turkey)	Weekly consumption	BOTAS	Jan 2002–April 2006	Weekly
	PCMACP	Xu and Wang (2010)	National level (China)	Historical consumption	China Statistics Yearbook	1995–2008	Yearly from 2009 till 2015
	NLP and GA	Forouzanfar et al. (2010)	National level (Iran)	Historical consumption	National Iranian Gas Company publications	1996–2005 (10 observations)	Yearly from 2006 till 2008
Other models	Gompertz diffusion	Gutierrez et al. (2005)	National level (Spain)	Annual consumption	IEA	1973–2000	Yearly
	Degree-day concept	Gumrah et al. (2001)	City area (Ankara)	Historical consumption, number of customers and meteorological data	The general directorate of meteorology of Turkey	1991–1997	Daily
		Sarak and Satman (2003)	National level (Turkey)	Historical consumption and number of residences per transmission line	BOTAS, Satman and Yalcinkaya (1999)	1997–2000	Yearly from 2005 till 2023
	Empirical models	Berndt and Watkins (1977)	Regional level (British Columbia and Ontario)	Not available	Not available	Not available	Yearly
		Gelo (2006)	Gas distribution system	Natural gas price, temperature, monthly average natural gas consumption per costumer, average salary,	Not available	Not available	Monthly

(Contd...)

Table 2: ***(Continued)***

Model type	Applied Model	Researchers	Application area	Main Input Data	Data source	Data size	Forecasting horizon
		Potocnik et al. (2007)	Gas distribution system	Daily consumption, daily temperature, season, day of the week, holidays	Not available	Training data: 1/6/2002–31/12.2003 Test data: 1/1/2004–31/12/2004	Daily
		Thaler et al. (2005)	Gas distribution system	Known prototype patterns and given future values of environmental variables	LDC	Not available	hourly
		Melikoglu (2013)	National level (Turkey)	Historical consumption of energy sources, natural gas imports and population	EGO, IGDAS, BURSAGAZ, ESGAZ, BOTAS and IZGAZ	1985–2011	Yearly from 2013 till 2030
		Tahat et al. (2002)	Model house	Daily temperature, daily relative humidity ratio and monthly average daily solar radiation	In situ measurements	1990–2000	Hourly
	CDA	Bartels et al. (1996)	Regional level (Australia)	Bottled gas consumption, number of rooms, annual household income	Not available	Not available	Yearly
		Aydinalp-Koksal and Ugursal (2008)	National level (Canada)	Energy used for heating and cooling degree days	From the 1993 survey of household energy	8767 observations	Yearly
	Dynamic model	Li et al. (2010)	National level (China)	Historical annual consumption	Not available	1997–2007	Yearly
		Li et al. (2011)	National level (China)	GDP, Urbanization and Investment proportions of different industries	Development Research Center of State Council; National Population and Family Planning Commission of China	1997–2007	Yearly till 2030

EIA: Energy Information Administration, IEA, International Energy Agency, GARCH: Generalized autoregressive conditional heteroskedasticity, HDD: Heating degree days, WBGDC: West Bohemian Gas Distribution Company, NYMEX: New York Mercantile Exchange, GDP: Gross domestic product, LDC: Local distribution companies, PAM: Partial-flow adjustment model, ECM: Error correction model, ANFIS: Adaptive network-based fuzzy inference system, ANNs: Artificial neural networks, MLP: Multiple linear perceptron, PCMACP: Polynomial curve and moving average combination projection, NLP: Nonlinear programming, GA: Genetic algorithm, ARX: Auto-regressive with exogenous, SVR: Support vector regression, OLS: Ordinary least square, TK-FIS: Takagi-Sugeno-type fuzzy inference system, ELFIS: Emotional learning based fuzzy inference system on historical profiles from 1/1/1996 to 30/6/2005. Al-Fattah and Startzman (2000) used US gas-discovery data for 1900–1997, US marketed-gas production data for 1918–1997 and data for annual production of natural gas for all other countries for 1971–1997 and for proved reserves of natural gas for all countries. Gumrah et al. (2001) collected data for the years from 1991 to 1997, Tahat et al. (2002) used daily data for the city of Sarih in Jordan for the period 1990–2000, while Gutierrez et al. (2005) considered annual consumption in Spain for the period 1973–2000. Data used in Reynolds and Kolodziej (2009) runs from 1950 to 2003 whereupon price expectations start to change. In order to forecast natural gas in China, Rui et al. (2009) used consumption data from 1994 to 2006. The two approaches proposed in Forouzanfar et al. (2010) along with the gas consumption data in Iran for the previous 10 years (1996–2005) are used to predict gas consumption for the following years. Valero and Valero (2010) considered the exergy loss of mineral commodities including natural gas, in the world and average degradation velocities from 1900 to 2006.

Li et al. (2011) instead considered GDP, population, urbanization and investment proportions of different industries for the period 1997–2007. Wadud et al. (2011) collected information on GDP, natural gas price, demand for natural gas and population for Bangladesh for the period 1981–2008. Data used in Kaynar et al. (2011) is weekly time series that show natural gas consumption for Turkey between January 2002 and April 2006, while data in Ma and Wu (2009) are annual time series that show historical production and consumption from 1990 to 2007. The analysis in Ghose and Paul (2008) focuses on India's natural gas reserve for the period 1990–2005. Rahim and Liwan (2012) forecasted Malaysia's reserves, based on the domestic consumption trend for the period 1980–2010. In Lin and Wang (2012) historical production data for the period 1949–2010 is used after pointing out that the key variable is also natural gas reserve. Derimel et al. (2012) collected daily price of natural gas and number of costumers from 1/1/2004 to 30/11/2009. Electricity generation data in Malaysia from 1990 to 2009 are used in Shekarchian et al. (2012). Azadeh et al. (2012) in their attempt to improve natural gas price estimation in Iran's industrial sector collected 40 years raw data for gas price from 1968 to 2008, Osgouei and Sorgun (2012) instead used data on Iranian natural gas production and consumption from 1970 to 2007, Fan and Xia (2012) used information on the changes in energy consumption and energy mix based on energy type in China from 1978 to 2010, Wang et al. (2013) used historical data from 1949 to 2000, Kialashaki and Reisel (2013) collected trends for independent variables and energy consumption estimates between 1984 and 2010, and Selehnia et al. (2013) used daily, weekly and monthly spot prices in Henry Hub from 7/1/1997 to 20/3/2012 for modeling and forecasting. Dalfard et al. (2013a; 2013b) gathered a history of 13 years actual data from 1997 to 2009. Data used in the works of Xiong et al. (2014) are data on China's energy consumption from 1990 to 2012.

Dilaver et al. (2014) gathered annual time series data from 1978 to 2011. Potocnik et al. (2014) with quite a different approach as Soldo et al. (2014), used the same dataset but modified the two heating seasons as follows: Season 1 from 5/11/2011 to 26/4/2012, and season 2 from 9/11/2012 to 31/3/2013. Due to unavailability of monthly and seasonal data on Iran economy, Kani et al. (2014) employed annual data belonging to the period from 1971 to 2009. Kovacic and Sarler (2014) collected weekly ordered natural gas quantities reported to the natural gas supplier for the week from1/1/2005 to 25/3/2005. Yu et al. (2014) used an unbalanced panel data of Chinese cities for the period of 2006–2009. Paltsev (2014) observed historical production volumes for Russia and the USA for 1990–2013. Yu and Xu (2014) recorded data from November 15, 2005 until October 18, 2008. In Darda et al. (2015) annual data of natural gas production in the four neighboring states in South Asia was collected from 1971 to 2011. Boran (2015) used historical consumption for Turkey from 1987 to 2012. The model proposed by Nai-ming et al. (2015) uses production and consumption trends during the period 2006–2011. Feng et al. (2014) considered annual consumption for the years from 1987 to 2011.

In order to train and test the ANFIS models used in Azadeh et al. (2010), daily natural gas consumption data from 22/12/2007 to 20/6/2008 was used for training and data from 21/6/2008 to 30/6/2008 was used for testing the short term models. The statistical model developed by Huntington (2007) for industrial US natural gas consumption is upon annual historical data for the period 1958–2003. In Musilek et al. (2006) data for training and testing of forecasting modules and gating modules were all obtained for the period of 4 years 2001–2004. Elragal (2004) used 400 patterns (i.e., days) and 200 patterns for training and testing periods respectively. Potocnik et al. (2007) also divided data into training (1/6/2002 to 31/12/2003) and validation (1/1/2004 to 31/12/2004) subsets. In Rodger (2014) data on consumption of the system were collected for 111 days beginning from September 21, 2012 and the input/output data were used to train the ANN. Jiang (2014) used historical consumption and its influencing factors from 2000 to 2012 and set the maximum training times to 10000. In Askari et al. (2015), three datasets were modeled and tested. Concerning daily gas consumption, there are 1200 data vectors available, 1000 of them are used for training and 200 data vectors are used for testing. Concerning Box-Jenkins data, there are 294 data vectors: 270 for training and 24 for testing. TAIEX data contains 226 data vectors: 208 for training and the remaining 18 data vectors are used for testing. Zhu et al. (2015) used data set recorded for 1095 days to train the prediction model, and data set recorded for the next 366 days to test the prediction performance. Yu et al. (2014) also divided their data into two sets; training data (15/01/05–31/12/08) and test data (1/01/09–7/01/09).

5. FORECASTING HORIZONS

Forecasting natural gas has been carried out on various periods. Some authors focused on high resolution forecasting such as hourly, daily and weekly forecasting while other authors choose medium and long term forecasting running from monthly through quarterly prediction to annual predictions.

5.1. Short Term Predictions - Hourly, Daily and Weekly Horizons

Thaler et al. (2005) used an empirical model to estimate hourly predictions and optimal control of energy distribution systems.

Dombayci (2010) predicted hourly energy consumption of a model house in Denizli, whereas Tahat et al. (2002) predicted hourly energy consumption for a house experiencing a Mediterranean climate. Fagiani et al. (2015) and Szoplik (2015) also predicted hourly natural gas consumption.

Panella et al. (2012) provided daily description of energy prices dynamics, allowing estimating daily energy commodities over a long period horizon. Gracias et al. (2012) estimated daily natural gas production, import and consumption in Brazil. Sanchez-Ubeda and Berzosa (2007) presented a novel prediction model that provides forecasting in the medium-term horizon (1–3 years) with a daily resolution, Azadeh et al. (2010) estimated daily natural gas consumption in Iran, Elragal (2004) predicted daily natural gas consumption needed by gas utilities for a period of 4 weeks, while Khotanzad and Elragal (1999) and Khotanzad et al. (2000) gave results of 1-day-ahead forecasts of natural gas demand by six different gas utilities. Brabec et al. (2009b) improved their works on time-varying predictions. Askari et al. (2015) predicted nodal pressure drop in network distributions for a period of 30 days. Brown et al. (1994), Brown and Martin (1995), Gumrah et al. (2001), Derimel et al. (2012), Taspinar et al. (2013), Potocnik et al. (2014), Soldo et al. (2014), Kovacic and Sarler (2014), Yu and Xu (2014), and Zhu et al. (2015) estimated daily natural gas consumption. In Kaynar et al. (2011) weekly natural gas consumption of Turkey is predicted by means of three different approaches.

5.2. Medium Term Predictions-Monthly and Quarterly Horizons

Timmer and Lamb (2007) forecasted seasonal gas consumption, Yoo et al. (2009) estimated households' monthly demand function for natural gas in Seoul, Sailor and Munoz (1997) forecasted monthly sensitivity of electricity and natural gas consumption to climate in the USA, Aras and Aras (2004) also forecasted monthly residential natural gas consumption and Vondracek et al. (2008) estimated monthly natural gas consumption (with daily resolution) for a locality in Western Bohemia for the period ranging from May 2005 to May 2006. Azadeh et al. (2015) and Aras (2008) also forecasted monthly natural gas consumption. Herbert (1987), Herbert et al. (1987), Suykens et al. (1996), Gelo (2006) and Kizilaslan and Karlik (2009) predicted monthly natural gas consumption.

5.3 Long Term Predictions-Annual Horizons

Erdogdu (2010) predicted annual natural gas demand in Turkey for the period from 2008 to 2030. Still in Turkey, Melikoglu (2013) equally predicted annual natural gas demand from 2013 to 2030. Al-Jarri and Startzman (1997) projected the world's future supply of and demand for NGLs to the year 2050, Al-Fattah and Startzman (2000) presented forecasts for the world supply of conventional natural gas to the year 2050, Siemek et al. (2003) forecasted the Polish gas demand 40 years ahead, Huntington (2007) generated the projections of industrial natural gas consumption in the US yearly from 2004 till 2030, Economides et al. (2012) analyzed US natural gas in 2011 and beyond, Logan et al. (2013) investigated natural gas scenarios in the US power sector to the year 2050, Kialashaki and Reisel (2013) forecasted energy demand in the US residential sector for the period 2010–2030, while Gomez et al. (2015) examined the future of energy in Uzbekistan up to 2040. Hubbert (1949; 1956) at his time investigated the life circle of fossil fuel fields and forecasted their life circle several decades ahead. Valero and Valero (2010) applied the Hubbert peak model to the world exergy consumption of coal, oil and natural gas, giving annual predictions till 2150. Xu and Wang (2010) projected natural gas consumption from 2009 to 2015, Forouzanfar et al. (2010) used gas consumption data for the previous 10 years to predict the consumption for the 11th, 12th and 13th years, Wadud et al. (2011) estimated natural gas demand till 2025, Zhang et al. (2015) analyzed the impacts of natural gas supply costs in China for a multi-period of 5 years span till 2035, Darda et al. (2015) investigated the natural gas production for four South Asian states till horizon 2030, Potocnik et al. (2007) estimated annual risks (with monthly resolution) in natural gas distribution markets, while Lin and Li (2015) projected annual spillover effects across natural gas and oil markets. Berndt and Watkins (1977), Durmayaz et al. (2000), Sarak and Satman (2003), Gorucu (2004), Imam et al. (2004), Gutierrez et al. (2005), Aydinalp-Koksal and Ugursal (2008), Reynolds and Kolodziej (2009), Rui et al. (2009), Ma and Wu (2009), Xie and Li (2009), Behrouznia et al. (2010), Toksari (2010), Li et al. (2011), Rahim and liwan (2012), Fan and Xia (2012), Lin and Wang (2012), Shekarchian et al. (2012), Wang et al. (2013), Dalfard et al. (2013a; 2013b), Chkili et al. (2014), Xiong et al. (2014), Dilaver et al. (2014), Bianco et al. (2014), Jiang (2014), Kani et al. (2014), Paltsev (2014), Azadeh et al. (2014), Voudouris et al. (2014), Aydin (2014, 2015), Boran (2015), Nai-ming et al. (2015), and Khan (2015), predicted annual natural gas consumption.

5.4. Mixed Horizon Forecasting

Selehnia et al. (2013) estimated daily, weekly and monthly natural gas spot prices. Liu and Lin (1991) predicted quarterly and yearly residential natural gas consumption and its related variables. Tonkovic et al. (2009) and Potocnik et al. (2007; 2008) both predicted natural gas consumption on hourly and daily basis. Piggott (1983) predicted daily and weekly gas consumptions. Gil and Deferrari (2004) combined daily, monthly and annual forecasting horizons. Viet and Mandziuk (2005) combined daily, weekly and four weekly horizons. Kizilaslan and Karlic (2008) forecasted Istanbul's natural gas energy model on a daily and weekly basis. Brabec et al. (2008; 2009a) formulated three consumption models in their works on standardized load profile: Annual individual consumption, daily trajectory and hourly decomposition of daily sums. Table 2 recaps the existing literature on forecasting methodologies.

6. RESULTS AND MODELS PERFORMANCE

The methods for forecasting natural gas as reported in the literature are diverse, so are the evaluation criteria. Researchers do not agree on what should be considered a good performance measure or not but prediction accuracy is the most important measure of performance. However, a suitable measure of accuracy for a given problem is not universally accepted by researchers. An accuracy measure is defined as the difference between the desired and the predicted value. There are a wide number of performance measures reported in the literature, each with its advantages and limitations (Makridakis et al., 1983). The most common include:

- The mean absolute percentage error (MAPE) = $\frac{1}{N}\sum_t \left|\frac{e_t}{y_t}\right|.100$
- The mean squared error (MSE) = $\frac{1}{N}\sum_t (e_t)^2$
- The root mean squared error (RMSE) = $\sqrt{MSE}$
- The sum of squared error (SSE) = $\sum_t (e_t)^2$
- The mean absolute deviation (MAD) = $\frac{1}{N}\sum_t |e_t|^2$
- The coefficient of multiple determination (R^2) = $1-\frac{MSE}{Var\ (y)}$

Where e_t is the individual forecast error; Y_t is the actual value; and N is the number of error terms. Some authors used one of the above performance measures whereas others decided to combine two or more because of the limitations associated with each performance measure. In this section, we underline the major conclusions found in the literature.

6.1. Relative Performance of Forecasting Models

Hubbert (1949; 1956) accurately predicted the US peak 13 years before it happened. Werbos (1988) formulated that ANNs trained with back-propagation outperform the traditional statistical methods such as regression and Box–Jenkins approaches. Huntington (2007) concluded that projections based upon the demand model studied indicate that industrial natural gas consumption may grow slowly over the next 20 years in contrast to projections made by the US EIA. Yoo et al. (2009) compared their work with other studies and pointed out that there exist a selection bias in the sample and that failure to correct for sample selection bias distorts the mean estimate. Beierlein et al. (1981) also compared their work with other studies and concluded that natural gas had negligible income elasticities in the residential and commercial sectors. Khotanzad et al. (2000) tested their model on six LDCs and calculated the average MAPE and average standard deviations. The results indicate that combination strategies based on a single ANN outperform the other approaches. Kaynar et al. (2011) pointed that both ANN and ANFIS models outperform ARIMA model when their MAPE values are compared. Aydinalp-Koksal and Ugursal (2008) compared the predictions of the models and concluded that these models were capable of accurately predicting energy consumption in the residential sector. The fuzzy-genetic combination approach employed by Elragal (2004) gives more accurate prediction compared with single predictor. The performance was tested on four gas utilities for a period of several months.

Liu and Lin (1991) used RMSEs and just like their predecessors, they found that it is easier to obtain appropriate models using quarterly data. Erdogdu (2010) used absolute deviation and validated his model with observed data. Azadeh et al. (2010) used MAPE as a criterion to show that ANFIS provides more accurate results than ANN. Derimel et al. (2012) found that the NN model with BP outperforms multiple regressions, NN Neuroshell, the NN with GA, and the ARIMAX model for natural gas forecasting. According to Azadeh et al. (2012), the preferred model for estimating natural gas price in the industrial sector in Iran is Fuzzy linear regression which has the minimum MAPE in comparison to the ANN and conventional regression models. Aras and Aras (2004) used mean absolute error, MAPE and MSE. The results strongly indicate that forecasting errors are significantly reduced when using separate models. Forouzanfar et al. (2010) observed that the overall results obtained using NLP and GA approaches are as well or even in some cases better than results obtained using some older approaches such as Cavallini's. In Ma and Wu (2009), the posterior check results show that the Grey-Markov forecasting models have higher forecast accuracy than original ones. Based on the probability distribution of prediction error, Thaler et al. (2005) could estimate the probability that actually observed consumption will surpass a certain prescribed value of maximal allowed consumption at each predicted value. Gutierrez et al. (2005) found that the Gomperzt model is more suitable than other stochastic diffusion growth models, namely the logistic and the lognormal models.

Panella et al. (2012) performed validation on historical data and showed that the NN approach generates prices that are able to replicate the daily data. Based on six performance measures, Lv and Shan (2013) pointed out that nonlinear models are more important in forecasting future price volatility than in forecasting spot price volatility. Kialashaki and Reisel (2013) concluded that ANNs are likely to give more realistic predictions than regression models. Using RMSE, MAPE and coefficient of correlation, Taspinar et al. (2013) arrive at the conclusion that SARIMAX model had much better forecasting performance than OLS, ANN-MLP and ANN-RBF. Selehnia et al. (2013) stated that unlike local linear regression and dynamic local linear regression models, ANN models present a close up view and high accuracy of natural gas spot price trend forecasting in different time scales but their ability in forecasting price shocks is not notable.

Potocnik et al. (2014) drew the following conclusion: The comparison of static and adaptive models for natural gas consumption forecasting reveals the superiority of adaptive models for LDC whereas individual house consumption can be sufficiently well estimated by static forecasting models. Soldo et al. (2014) compared linear and nonlinear models and showed that NN model and also SVR model yield smaller training errors but do not improve the generalization ability on test data. The in-sample and out-of-sample results in Chkili et al. (2014), show that volatility of commodity returns are better described by nonlinear volatility models accommodating the long memory and asymmetry features. Xiong et al. (2014) found that the optimized model has higher prediction accuracy than the other five GM(1,1) models used. Kovacic and Sarler (2014) compared the results yielded by linear regression and GP models and observed that the latter performs approximately two times more favorably. Azadeh et al. (2014) observed that ELFIS is capable of modeling more accurately sharp drops or jumps in consumption than ANFIS. Taking a look at the MAPE, Nai-ming et al. (2015) concluded that the grey forecasting model and Markov model used could effectively simulate and forecast the total amounts and structures of energy under the influence of the saving energy policy in China. Fagiani et al. (2015) found that SVR compared to ANN, DBN, ESN, GP and EKF-GP yielded best performance for 6 h and 12 h resolution. Table 3 presents the relative performance of some forecasting techniques.

6.2. Projected Results

Lee and Singh (1994) observed that electricity conservation could be reduced by 2 473.57KWh a year per household if a gas connection is available to nonusers. To achieve this, the utility company would need to supply 611,09 therms for each household. The results of Sarak and Satman (2003) indicate that the potential residential consumption in Turkey by 2023 could be as high as 14.92 Gm^3 if 100% of residencies use natural gas for space heating. The results in Fan and Xia (2012) show that energy demand in China will continue to increase at a rapid rate if the economy develops as in the past decades, and is projected to reach 4.7 billion tce in 2020. The works of Dahl and McDonald (1998) suggest an annual growth rate for energy of 5.5% or more for the next 30 years. This implies tripling the world's energy consumption if such rates were applied to the whole developing world. With regard to the growth tendency, Li et al. (2011) compared their results with that of IEA and indicated that natural gas will become an important substitute for coal in some parts of the Chinese primary energy consumption. Rahim and Liwan (2012) concluded that even without new discoveries the current reserves are sufficient to last for several years. At the current production rate, the reserves will last up to 2036. However, if the reserves are extracted based on the current slower rate of consumption, Malaysia's gas reserves can last up to the year 2053. Economides et al. (2012) from their analysis concluded that US natural gas prices will rise quickly and the world prices will coalesce around a modest premium to the US prices. Valero and Valero (2010) estimated the peak of world's natural gas production in 2023. Using RMSE, Al-Jarri and Startzman (1997) showed that world supply (and demand) for NGLs peaked in the late 90s and is currently declining.

Al-Fattah and Startzman (2000) argued that most industrialized countries are depleting their gas resources much faster than developing countries. However, the former Soviet Union and major Middle East gulf countries will be major sources of gas supply. Osgouei and Sorgun (2012) state that Iran natural gas resource will be indispensable in the supply of world natural gas demand if its natural gas fields are developed effectively. Melikoglu (2013) underlined that natural gas demand in Turkey will first increase for the next 20 to 30 years, then decelerate and might even experience a slight slow decrease like in other EU countries. Even in the high scenario, Wang et al. (2013) insist on that discovery of annual proved geological reserves will peak in 2019 and the gap between gas production and demand will reach 210.4 bcm by 2020. In Logan et al. (2013), results from numerical modeling shows strong growth in natural gas generation, leading to roughly 2.5-fold increase in gas demand by 2050. The results of the case study in Dalfard et al. (2013a) shows that in 2010–2016, high energy prices decrease considerably the consumption for natural gas and electricity.

Dilaver et al. (2014) projected Europe natural gas demand to be somewhere between 572 and 646 bcm by 2020. Paltsev (2014) pointed that natural gas can still play a substantial role in Russian exports over the next 20–40 years. A key finding in Lin and Li (2015) is that changes in oil price could still be transmitted to gas price in the US, even though the prices of oil and US gas in level are decoupled. Darda et al. (2015) found that 27% of natural gas reserves in the four South Asian states had been extracted by 2011 and estimated the peak production of these states to be between 2020 and 2025. Khan (2015) found that price and cross elasticities of natural gas demand in Pakistan are relatively low, indicating consumer's indifference towards price escalations.

6.3. Summary Results of Modeling Issues

Sanchez-Ubeda and Berzosa (2007) also evaluated their model using MAPE. Musilek et al. (2006) concluded that the gating module of the model is able to learn and predict time series that exhibit complex non-stationary behavior. Cavallo (2004) pointed out four economic and political factors necessary for Hubbert's model to be applicable: Affordable prices for consumers and good profitability for owners of the resource, stable markets, exponentially increasing consumption, availability of imports and reasonable estimates of the magnitude of the easily accessible resources. Reynolds and Kolodziej (2009) drew the same conclusion as Cavallo (2004).

Wadud et al. (2011) argued that their demand model shows large long run income elasticity for aggregate demand for natural gas, while the results from the PAM model in Eltony (1996) indicate that demand for natural gas is inelastic with respect to both price and income in both the short and long run. Sailor and Munoz (1997) considered the correlation coefficient as a performance measure. They concluded that natural gas consumption depends only on air temperature. Timmer and Lamb (2007) found that there exist a strong correlation between temperature and natural gas consumption while Gumrah et al. (2001) found that gas consumption in Ankara highly depends on weather conditions and number of costumers. Since the ratio of weather sensitive gas usage to annual gas usage is around 0.93, they concluded that Ankara is not an industrialized city. One of the findings of Kani et al. (2014) is that the mean temperature variable has no significant impact on natural gas demand in Iran.

Even though the risk model in Potocnik et al. (2007) is adapted to the regulation of the Slovenian natural gas market, it can however be adjusted to other economic incentive models with minor alterations. This probability thus describes the risk of excess energy demand by costumers. With regard to relative errors, Xie and Li (2009) pointed that the GM(1,1) model is an effective tool for natural gas consumption prediction. Dombayci (2010) observed that for the ANN model utilizing the Levenberg-Marquardt learning machine, the best result were obtained for 29 neurons in the hidden layer with a great accuracy. Tahat et al. (2002) came out with the feasibility and financial viability to design and build low energy-consumption houses in Jordan. According to the predictions made by Lin and Wang (2012), no matter in which scenario, the two models used give similar results and the production curves of natural gas are well shaped by Hubbert's peak theory. The results presented in Gracias et al. (2012) show that the three mathematical models used in the study of population

Table 3: Forecasting results and relative performance

Researchers	Performance measure	Results
Fagiani et al. (2015)	NMSE[a], R^2, MSE, MAPE, RMSE	SVR achieve best overall resolutions compared to ANN, DBN, ESN, GP and EKF-GP
Panella et al. (2012)	MSE, NMSE, NSR[b]	The Gaussian neural network approach generates accurate prices with respect to other well-known models
Xiong et al. (2014)	MAPE	The optimized GM(1,1) model has a higher prediction accuracy than the other five GM(1,1) models
Selehnia et al. (2013)	MSE, R^2	Unlike local linear regression and dynamic local linear regression models, ANN models present a close up view and high accuracy of natural gas spot price trend forecasting in different time scales in different time scales but their ability in forecasting price shocks is not notable
Erdogdu (2010)	Posterior check results	There is a substantial difference between official projections and forecasts based on ARIMA modeling
Azadeh et al. (2010)	MAPE	ANFIS provide more accurate results than ANN
Beierlein et al. (1981)	SSE, R^2	The estimated elasticities for natural gas are more elastic than those of Mount and Tyrrell (1977) or Balestra and Nerlove (1966)
Liu and Lin (1991)	RMSE	It is easier to obtain appropriate models using quarterly data
Khotanzad et al. (2000)	MAPE and average standard deviations	Combination strategies based on a single ANN outperform other approaches
Aras and Aras (2004)	MAE[c], MAPE, MSE	Forecasting errors are significantly reduced when using separate models
Elragal (2004)	MAPE	The fuzzy-genetic combination approach gives more accurate predictions compared with a single predictor
Gutierrez et al. (2005)	Comparison with similar models: Logistic and lognormal model	Gomperzt model is more suitable than other stochastic models
Thaler et al. (2005)	Probability distribution of predicting error	Actually observed consumption will surpass a certain prescribed value of maximal allowed consumption at each predicted value
Huntington (2007)	Adjusted R^2 Jarque-Bera test, Breusch-Godfrey test	Natural gas demand may grow more slowly over the next 20 years than is being projected by the US EIA
Aydinalp-Koksal and Ugursal (2008)	Comparison of each model's prediction	The applied models are capable of accurately predicting energy consumption in the residential sector
Yoo et al. (2009)	Comparison with other studies	There exist a sample bias in the sample and failure to correct the sample bias distorts the mean estimate
Ma and Wu (2009)	Posterior check results	Grey-Markov forecasting models have higher forecast accuracy than original models
Forouzanfar et al. (2010)	Posterior check results	Results obtained using NLP and GA approaches are as well or even in some cases better than results obtained using older approaches such as Cavallini's
Kaynar et al. (2011)	MAPE	ANN and ANFIS models outperform the ARIMA model
Derimel et al. (2012)	RMSE, MAD and MAPE	Neural network models with back propagation outperform multiple regressions, neural network Neuroshell, the neural network with GA, and the ARIMAX model for natural gas forecasting
Azadeh et al. (2012)	MAPE	Fuzzy linear regression model is the preferred model for estimating natural gas price in the industrial sector in comparison to the ANN and conventional regression models
Kialashaki and Reisel (2013)	R^2, MSE and C_p-statistics, adjusted R^2	ANNs are likely to give more realistic predictions than regression models
Taspinar et al. (2013)	RMSE, MAPE and R^2	SARIMAX model has much better forecasting performance than OLS, ANN-MLP and ANN-RBF
Lv and Shan (2013)	MAE, MSE, HMAE[d], HMSE[e], R^2LOG[f], QLIKE[g]	Nonlinear models are more important in forecasting future price volatility than in forecasting spot price volatility
Chkili et al. (2014)	MAE, MAPE	No single GARCH-type model absolutely outperforms the others over both the in-sample and out-of-sample periods
Potocnik et al. (2014)	Adjusted R^2 MARNE[h]	Comparison of static and adaptive models for natural gas consumption forecasting reveals the superiority of adaptive models for LDC whereas individual house consumption can be sufficiently well estimated by static forecasting models
Soldo et al. (2014)	Adjusted R^2, MARNE	Neural network model and also SVR model yield smaller training errors but do not improve the generalization ability on test data
Kovacic and Sarler (2014)	Consumption diviation	Genetic programming performs approximately two times more favorably than linear regression

(Contd...)

Table 3: ***(Continued)***

Researchers	Performance measure	Results
Azadeh et al. (2014)	MAPE, NMSE	Integrated approach is more suitable and accurate for estimating natural gas demand when data is of noisy nature and cognitive nature
Nai-ming et al. (2015)	Percentage error, MAPE, MAE	Grey forecasting model and the proposed QP-Markov model could effectively simulate and forecast the total amounts and structures of energy under the influence of energy saving policy

[a]NMSE (normalized mean squared error) = $\dfrac{\sum_t e_t^2}{\sum_t (y_t - \bar{y})^2}$

[b]NSR (noise-to-signal ratio) = $10log_{10}\dfrac{\sum_t e_t^2}{\sum_t y_t^2}$

[c]MAE (mean absolute error) = $\dfrac{1}{N}\sum_t \left|y_t^2 - \bar{y}_t^2\right|$

[d]HMAE = $\dfrac{1}{N}\sum_t \left|1 - y_t^2 / \bar{y}_t^2\right|$

[e]HMSE = $\dfrac{1}{N}\sum_t \left(1 - y_t^2 / \bar{y}_t^2\right)^2$

[f]R2LOG = $\dfrac{1}{N}\sum_t \ln[\left(y_t^2 / \bar{y}_t^2\right)]^2$

[g]QLIKE = $\dfrac{1}{N}\sum_t \left(ln\bar{y}^2 + y_t^2 / \bar{y}_t^2\right)$

[h]MARNE (mean absolute range normalized error) = $100\dfrac{|\bar{y} - y|}{\max(y)}$

NMSE: Normalized mean squared error, MSE: Mean squared error, MAPE: Mean absolute percentage error, RMSE: Root mean squared error, SVR: Support vector regression, ANN: Artificial neural network, DBN: Deep belief networks, ESN: Echo state networks, GP: Genetic programming, EKF-GP: Extended Kalman Filter-genetic programming, NSR: Noise-to-signal ratio, EIA: Energy Information Administration, NLP: Nonlinear programming, MAD: Mean absolute deviation, ANFIS: Adaptive network-based fuzzy inference system, GARCH: Generalized autoregressive conditional heteroskedasticity, OLS: Ordinary least square, MLP: Multiple linear perceptron, LDC: Local distribution companies, MAE: Mean absolute error, GA: Genetic algorithm

dynamics can be used to study the production, consumption and import of natural gas in Brazil.

7. CONCLUSION AND DIRECTIONS FOR FUTURE RESEARCHES

The present study has presented the current state of the literature in the field of natural gas forecasting. We do not pretend to have surveyed all existing models in this field, but to the best of our knowledge, we think we have extracted a great majority if not all applied models in this field.

Despite the growing technical sophistication of forecasting tools, researchers are still not certain about which models surpass the other. Furthermore, there is no clear criterion for selecting relevant variables and extracted features for the construction of forecasting models. Moreover, the information available about the prediction accuracy of models is in many aspects unsatisfactory to provide clear understanding of the achieved performance. In most cases, it is very difficult and even impossible to make an objective comparison of two or more contributions. This is because each paper presents a different set of evaluation criteria.

Overall, one should recognize that to predict the exact future evolution of natural gas consumption or demand, production, prices, spillover and market volatility is impossible. Various authors considered different parameters and approaches. A parameter that is neglected by one author is considered to be of core importance in another study. Anyway, the objectives are not always the same and moreover data are not always readily available as one may think, thus leading to diverging conclusive views. However, as time goes by, models are being developed and many more parameters are being taken into consideration so that the future trends can be predicted with a higher level of accuracy.

Nonetheless, we give the following suggestions:

- Instead of developing scenarios based on wishful thoughts or on too strong hypothesis, it would be realistic to provide continuous scenarios based upon available information and alternative opinions should be explored.
- The influence of the application of weather forecasts instead of weather measurements should be examined on the performance of natural gas forecasting models.
- The development of a model for another city, region, country, or organization should always be preceded by the analysis assessing the impact of various factors on gas demand in order to optimize the selection of variables in the model, depending on the intended purpose of forecasting and the accepted forecasting horizon.

- Instead of tirelessly applying the same forecasting tools which clearly lack accuracy and originality, researchers could generate new tools.
- Despite the multitude of studies in the field of natural gas forecasting, there are still many questions that need to be answered. For instance, what data size is required to make a prediction with a best possible accuracy? Which input data are relevant in making the prediction and which are irrelevant? This is because models have certain demands for data property and sample size.

Some models are still underused in the field of natural gas forecasting. They include Bayesian model, hybrid models, support vector regression, bottom up models (MARKAL [acronym for MARKet ALlocation], Long-range Energy Alternatives Planning Systemand TIMES G5 [the integrated MARKAL-EFOM system]), while Information-theoretic model averaging, gravitational search algorithm (GSA), ACO and PSO remain unused in the field of natural gas forecasting. GSA, PSO and ACO are emerging techniques in clean energy sources forecasting. It is expected that such models will be used by researchers for accurate natural gas demand prediction.

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