FORECASTING FUTURE NATURAL GAS DEMAND IN ALGERIA USING BA YESIAN MODEL AVERAGING

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ABSTRACT

The purpose of this article is to forecast the Algerian natural gas consumption through a combinative method using the Bayesian moving average model (BMA).Four variables for forecasting the natural gas consumption have been chosen, including global domestic product (GDP), electricity demand (ELCD), urban population(UPOP)and industrial structure (INST). The study concludes that among the four variables that have been applied, ELCD is the first most important variable affecting natural gas consumption; the UPOP comes second and then the INST. This reflects the share of the gas use sectors in Algeria: first electricity production, then households, then industry. Based on some pertinent hypotheses and according to BMA estimations of future gas demand, the National demand would be between 62 B cm and 80 B cm by 2028 with an average annual growth rate between3% and 6%.

KEY WORDS

Natural gas consumption; Bayesian Model Averaging; Forecasting; combinative method, scenarios Algeria.

JELCLASSIFICATION : Q41 ; Q47 ; C11 ; C53.

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توقع الطلب على الغاز الطبيعي المستقبلي في الجزائر باستخدام نموذج بيزي متوسط

ملخص

الهدف من هذه المقالة هو توقع استهلاك الجزائر للغاز الطبيعي بطريقة اندماجية باستخدام نموذج بايزي متوسط (BMA). تم اختيار أربعة متغيرات مفسرة لاستهلاك الغاز الطبيعي: الناتج المحلي الخام (GDP)، الطلب على الكهرباء (ELCD)، سكان الحضر (UPOP) والهيكل الصناعي (INST). لخصت الدراسة إلى أنه من بين المتغيرات الأربعة التي تم تطبيقها ، يعتبر ELCD هو المتغير الأول الأكثر أهمية الذي يؤثر على استهلاك الغاز الطبيعي. يأتي UPOP في المرتبة الثانية، ثم INST. وهذا يعكس حصة قطاعات استخدام الغاز في الجزائر: أولاً إنتاج الكهرباء، ثم المنازل ثم الصناعة. بناء على بعض الفرضيات ذات الصلة ووفقًا لتقديرات BMA للطلب المستقبلي على الغاز، سيكون الطلب الوطني بين 62 و 80 مليار متر مكعب بحلول عام 2028 بمعدل نمو سنوي متوسط يتراوح بين 3٪ و 6٪.

كلمات مفتاحية:

نموذج بايزي متوسط، استهلاك الغاز الطبيعي، الجزائر، التنبؤ، الطريقة التوافقية، السيناريوهات

تصنيف جال: C53 ; C11 ; Q47 ; Q41 .

PRÉVISION DE LA DEMANDE FUTURE DE GAZ NATUREL EN ALGÉRIE EN UTILISANT LE MODÈLE DE MOYENNE MOBILE BAYESIENNE

RÉSUMÉ

Le but de cet article est de prévoir la consommation algérienne de gaz naturel par une méthode combinatoire utilisant le modèle bayésien de moyenne mobile (BMA). Quatre variables de prévision de la consommation de gaz naturel ont été choisies : le produit intérieur brut (PIB), la demande d'électricité (ELCD), la population urbaine (UPOP) et la structure industrielle (INST). L'étude conclut que parmi les quatre variables qui ont été appliquées, ELCD est la première variable la plus importante affectant la consommation de gaz naturel ; l'UPOP vient en second, puis l'INST. Cela reflète la part des secteurs d'utilisation du gaz en Algérie : d'abord la production d'électricité, puis les ménages, puis l'industrie. Sur la base d'hypothèses pertinentes et selon les estimations BMA de la demande future de gaz, la demande nationale se situerait entre 62 et 80 Gm^3 d'ici 2028 avec un taux de croissance annuel moyen entre 3% et 6%.

MOTS CLÉS :

Modèle bayésien de moyenne mobile, consommation de gaz naturel, Algérie, prévision, méthode combinatoire, scenarios

JEL CLASSIFICATION : Q41 ; Q47 ; C11 ; C53.

INTRODUCTION

Interest in natural gas increased in general after the 1973 oil crisis, and with the increasing of its importance as a clean source of energy, natural gas consumption in the word increases steadily from year to year until it almost represents a quarter of total primary energy consumption today (23% in 2019, British Petroleum 2019). Abundant natural gas resources and robust production contribute to the strong competitive position of natural gas among other resources. Natural gas remains a key fuel in the electric power sector and in the industrial sector. In the power sector, natural gas is an attractive choice for new generating plants because of its fuel efficiency. Natural gas also burns cleaner than coal or petroleum products, and as more governments begin implementing national or regional plans to reduce carbon dioxide (CO2) emissions, they may encourage the use of natural gas to displace more carbon-intensive coal and liquid fuels.

The Algerian economy is dominated by its oil and gas resources, which account for 93 percent of the country's exports (ministry of finance (Commercial balance 2018). The hydrocarbon sector represents about 23 percent of total GDP and about 60% of budget revenues(National Statistics Office, 2018) the ratio Reserves/Production (22 year for oil 46 year for gas (BP, 2019)) gives natural gas an extra priority, which is to cover the country's long-term energy need.

Nowadays, gas plays a dominant role in the country's energy balance. It represents 56% of primary energy production, 97% in electricity production, 38. 4% in total energetic consumption. If we include Liquefied Natural Gas (LNG), natural gas represents 56% of volume of hydrocarbon exports (Ministry of Energy and Mines, Assessment of achievements, 2018), and 30% of foreign currency earnings (Ministry of Finance, 2018).

Since 2004, Algeria's domestic natural gas consumption grew at an average annual rate of 5.2% from 22.6 Bcm in 2004 to 42.7 B cm in 2018, while natural gas production appears to have stagnated at best (grew at an average annual rate of 0.1%). The fast-growing domestic gas demand is dangerously reducing the country's gas export potential and resulting reduced gas export revenue, one of the main sources of external revenue. Thus, by wondering about the future development of domestic consumption and its impact on the volume of exports and therefore, the country's energy balance, we can ask the following central question: How is domestic consumption of natural gas changing in the long term? The object of our study is, therefore, to clarify and quantify the future profile of gas consumption in Algeria. The quantification of future scenarios allows decision makers to establish the measures and policies necessary to guarantee the country's energy security in the long term.

It should be noted that efficient use of energy resources requires accurate prediction of future energy demand. The various aspects of this problem have been the subject of some work in Algeria. In this context, we can distinguish two categories. The first, which is more or less abundant, brings together studies based on purely economic and institutional analyzes (Ouki, 2019, Khelif, 2005; Mekideche 2014,Aissaoui 2013 and 2016, Attar 2012). The second, which includes empirical work, is relatively less abundant. Most of this empirical work is carried out by public institutions such as the Electricity and Gas Regulation Commission (CREG), the Agency for the Promotion and Rationalization of the Use of Energy (APRUE), or large companies like Sonatrach and Sonelgaz. These works are mainly confidential.

At the academic level, little empirical work has been developed on these questions, and they focus, in particular, on gas and energy demand in a specific sector (Berrached, 2011, Bouznit & al, 2018, Benamirouche & Moussi, 2017; Bélaïd & Abderrahmani, 2013; Khraief et al, 2016).

At the international level, Numerous researchers have analysed various energy issues and focused on developing appropriate energy demand models to reduce forecasting errors. A large number of explanatory variables have been used in the literature as determinants of energy consumption. There are various different economic theories that are compatible with one another (Mehara & Rezaei, 2015). Some theories support the inclusion of particular variables while most techniques of including or excluding variables are arbitrary. Some theories include general variables without the method of measuring these variables like "human capital" which leads to a possible problem of uncertainty.

This paper attempts to build a long-term natural gas consumption outlook for Algeria using Bayesian model averaging approach (BMA). In the literature, different models were used to study the determinants of energy consumption. However, these models have the problem of uncertainty regarding the best choice of the variables and the model specification. Thus, the use of BMA will solve the model uncertainty, where it works on finding the best estimates of the model and not finding the best model!

The rest of this paper is organized as follows. In Section1, we present Algerian natural gas consumption context, in section 2, a literature review of gas consumption driven factors and the main energy consumption modelling approaches are presented. In Section 3, the BMA method is introduced. Section 4, first establishes the main results of the BMA model, and then analyses the natural gas consumption under the three scenarios according to three different development situations and provides some suggestions. In Section 5, conclusions are given.

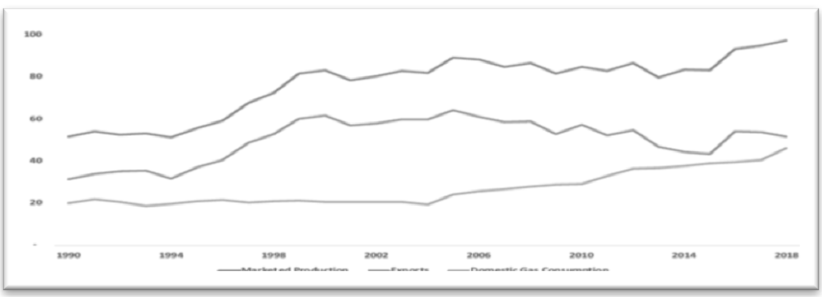
1- THE ALGERIAN NATURAL GAS CONSUMPTION CONTEXT

National consumption of natural gas started in 1961 following the start of production of the Hassi R'Mel deposit, with only 0.2 B cm to reach (17.7 B cm) in 1983, an annual increase over the period of 23%. During this period, the national gas industry experienced a new growth driven by the will of the public authorities to make available to the economy and also within the reach of citizens an energy at an affordable and widely available price. However, although gas consumption in Algeria increased sharply from 1960 to 1983, it only increased by 1% / year between 1984 and 2000 before being pulled up sharply by the residential sector and that of electricity production during the decade 2000-2010 (Ministry of Energy and Mines., "National energy balance 2010", Edition 2011, Algeria), a growth of 32%, and 2010-2018 (Ministry of Energy and Mines., "National energy balance 2018," Edition 2019, Algeria), a growth of 69%.

Since the early 1970s, Algeria has concentrated all its efforts on the development of natural gas as the main and alternative energy in the biggest uses of local consumption, which explains the large share of consumption in marketed production (61% in the period 1970-1983). However, from 1984, and following the entry into service of the first transcontinental gas pipeline "Transmed", the share of consumption fell to give way to exports, which recorded an annual share of 63% over the period 1984-2000 and 71% between 2000-2010. The high share of exports in these two decades reflects a certain disconnection from the energy sector compared to other sectors of the Algerian economy. Indeed, Algeria seeks during this period to honor its contracts with its partners and to preserve its place on the European natural gas market by fixing a ceiling of gas exports of 85 Bcm for 2010 (which has not been achieved) and 100 Bcm for 2020 (Le Leuch, 2009).

In the period 2010-2018, the share of exports in marketed production fell to represent 58%, this could be explained by the importance of domestic consumption, on the one hand, and the decline in marketed production, in the other hand.

Figure 1. Algerian gas production, domestic consumption and exports (1990-2018)[3]



Source: developed by the author from OPEC, Sonatrach[4], Ministry of Energy data.

We note that since 2004, Algeria's domestic natural gas consumption has increased at an average annual rate of 5.2%, from 22.6 bcm in 2004 to 42.7 Bcm in 2018, while natural gas production seems to have stagnated at best (grew at an average annual rate of 0.1%), Figure 1 shows how consumption exceeded production, causing the total volume of natural gas exports to contract by 2.2% /

[3] In data sets made available, domestic gas consumption plus exports do not always add up to marketed gas production. No explanation for this discrepancy is provided from the data sources.

[4] National society for research, production, transport, transformation, and marketing of hydrocarbons.

year, the internal market has indeed become the main and only growing component of the national gas balance sheet.

This trend is expected to continue, opening even bleak prospects in which Algeria's position as a producer and exporter of natural gas will become increasingly fragile.

The country, which has been producing, consuming and exporting natural gas for several decades, has reached a point in recent years where its gas balance sheet is facing multiple challenges. Declining or at best stagnating natural gas production and rapid growth in domestic gas consumption have combined to dangerously limit the country's gas export potential

2- LITERATURE REVIEW

In this section the main gas consumption driven factors and modelling approaches are described.

2.1- Gas consumption driven factors

Theoretical and empirical studies on gas consumption and its determinants are widespread; various studies have been carried out to examine the influence of different factors on gas consumption. In this part we will present the main influencing factors on natural gas consumption.

2.1.1. Economic growth

The literature applied to demonstrate the relationship between energy consumption and economic growth has been synthesized into four testable hypotheses which include growth, conservation, feedback and neutrality. (Apergis and Payne, 2009; Abbasian & al. 2010; Fulei, 2010; Ozturk, 2010).

The growth hypothesis claims that energy consumption has an important role in economic growth both as a direct input in the production process and indirectly as a complement to labor and capital inputs. Some of the studies that found evidence of the growth hypothesis include the following: Yu and Choi (1985) for Finland, Masih and Masih (1997) for Taiwan and Thoma (2004) for the U.S.

The conservation hypothesis asserts that energy consumption is dictated by economic growth. If there is a unidirectional Granger-causality running from economic growth to energy consumption, this hypothesis is confirmed. If this is the case, it may be implied that energy conservation policies may be implemented with few adverse or no effects on economic growth (Paul and Bhattacharya, 2004). Some of the studies that found evidence of the conservation hypothesis include the following: Kraft and Kraft (1978) for the U.S., Aqeel and Butt (2001) for Pakistan, Hatemi and Irandoust (2005) for Sweden, Zamani (2007) for Iran, Zhang and Cheng (2009) for China, Binh (2011) for Vietnam and Souhila Cherfi and Kourbali (2012) for Algeria.

The neutrality hypothesis means that energy does not affect economic growth. In other words, any decrease or increase in energy consumption has no effect on economic growth. Some of the studies that found evidence of neutrality hypothesis include the following: Akarca and Long (1980) for the U.S., Yu and Hwang (1984) for the U.S., Yu and Jin (1992) for the U.S. and Payne (2009) for the U.S.

The feedback hypothesis, in which bidirectional causality exists, proposes that energy consumption and economic growth affect each other simultaneously and may serve as complements .Some of the studies that found evidence of the feedback hypothesis include the following: Hwang and Gum (1991) for Taiwan, Paul and Bhattacharya (2004) for India, Ghali and El Sakka (2004) for Canada and Hou (2009) for China.

In our study the real GDP is taken as variable to examine the economic growth influence on gas consumption.

2.1.2. Electricity demand

Energy consumption can be influenced by population growth as with increasing population, demand for electricity is expected to increase and since Algeria still depends heavily on natural gas as a source of electricity production. Batliwala and Reddy (1993) in "Energy consumption and population" have shown that population growth increases the need for energy which is explained by various human activities.

Various studies have elucidated the relationship between electricity production and the demand for natural gas. Bhattacharyya and al (2008) examined the expansion of electric capacity in Thailand, an analysis of gas dependence and dependence on fuel imports. They found that the heavy reliance on gas in power generation makes the Thailand economy vulnerable over time.

Abiola and Babatola (2019) studied the excessive dependence on natural gas for electricity generation in Nigeria between 1999 and 2012. The study used the Gas Supply Security Index (GSSI) derived from four gas supply security indicators, a higher index indicating a higher gas supply which could lead to vulnerability in gas production. 'electricity. The results revealed that Nigeria was the least and the most vulnerable in 2000 and 2005 respectively. In 2012, the GSSI was0.83, making it the second most vulnerable among the years considered.

Urbanization

There is a small but growing literature looking at the impact of Urbanisation on energy consumption. Urbanization can affect energy use through different channels such as production, mobility, transportation and infrastructure channels (Sadorsky, 2013), the empirical evidence on the impact of urbanisation on energy consumption are mixed. Shahbaz et al. (2016) examine the effect of globalisation, urbanisation on energy consumption, found positive effect of urbanisation and negative impact of globalisation for Indian economy .Mishra and al. (2009) find that urbanisation has a negative impact on energy use in New Caledonia, but a positive impact in Fiji, French Polynesia. Mallick and Mahalik (2014) done a comparative analysis of India and China to explore the relationship between energy use, economic growth, and urbanisation. They found a positive impact of urbanisation and negative effect of financial development and economic growth on energy consumption for both India and China.

2.1.3. Industrialisation

Economic growth is known to have an indirect relationship with energy consumption through industrialisation .Jones (1991) and Samouilidis and Mitropoulos (1984), illustrate that industrialization contribute in increasing energy usage due to the high value-added as it needs more energy than other manufacturing. Moreover, they showed that particular industries that Algeria is specialized of like petroleum refining, primary metals and chemicals are tend to use more energy than other industries. Sadorsky (2014) studied The Effect of Urbanization and Industrialization on Energy Use in Emerging Economies and proved that the industrialization elasticity of energy intensity fluctuates between 0.07 and 0.12 for a long period. Liddle and Lung (2010), Zhou and Wang (2015), Wang and Zhang (2016), and Sereewatthanawut and al(2018) verified the above opinions through multiple types of data and empirical methods .Ding (2015)reported that energy intensity increases with industrialization. Zhang and Ding (2015) further confirmed that the positive effect of industrialization on energy intensity is stronger than the combined effects of income, industrialization, and ultimately energy intensity decreases

The study used industry value added as a % of GDP as an industrialization measure.

2.1.4. Prices

Some of the previous literature has focused directly on the relationship between absolute energy prices and energy consumption, which can reveal a visible relationship between energy prices and consumption. Many studies support the notion that rising energy prices lead to reduced energy consumption (IMF 2013; Fei and Rasiah 2014; Li and Lin 2015). Some of these studies focus primarily on the channels through which energy prices influence energy consumption. Zhanget al. (2014a, b) find that the stifling effect of rising energy prices on energy consumption is felt most in the transportation sector. However, Steinbuks and Neuhoff (2014) argue that improvements in energy efficiency and reductions in energy input resulting from rising energy prices are the main reasons for reduced energy consumption.

In practice, the own-price elasticity of energy in different industries (He et al. 2014), the purposes of energy consumption (Zheng and Wei 2014), and the sensitivity of energy prices in different areas (Moshiri 2015) all vary. Also, recent study of Osigwe and Arawomo (2015) concludes a significant relationship between energy consumption and energy prices in Nigeria .In summary, there is a consensus that increasing energy prices is an effective policy tool for reducing energy consumption.

2.1.5. IDE/ Financial Development/ Human capital

Different studies have indicated that foreign investment might have either negative or positive externalities. Sadorsky (2010) and Salah et al (2015) for Lebanon found the positive impact of financial development on energy consumption and a positive significant relationship between FDI and energy consumption. On the other hand, some studies show the negative impact of FDI on energy consumption see Bento (2011).

Some studies suggest that financial development can affect energy use. For example, Sadorsky (2011) for 22 emerging countries, Shahbaz and Lean (2012) for Indonesia, shows that financial development increases the use of energy,

Human capital might potentially influence energy consumption. At the micro level, households with higher human capital are more likely to select appliances which are energy efficient, hence consuming less energy (Broadstock et al., 2016; Li and Lin, 2016). At the macro level, human capital potentially influences energy consumption through the income effect, technology effect and complementarity between physical capital and human capital inputs in the production function (Salim et al. 2017a).

2.2- Gas Consumption modelling approaches

Natural gas consumption is a complicated system that is restricted and influenced by various factors and external environment. In the published papers, forecasting methods of natural gas consumption have been investigated by various tools and techniques, which can be divided into two types, including the single method and the combinative method.

The single method mainly included Hubbert curve model, Neural network model, Statistical models, Grey prediction model, Econometric model, Mathematical model, Expert system, Stochastic Gompertz innovation diffusion model, Dynamical system model and Simulated annealing. The Hubbert curve model is the primary tool to forecast the natural gas consumption. Several authors adopted this model or its expanded version to forecast the natural gas consumption (Maggio and Cacciola, 2009; Valero, 2010).

The first application of Artificial Neural Network for forecasting can be traced back to 1964, and now it has become a commonly tool in forecasting natural gas consumption (Szoplik, 2015; Ardakani and Ardehali, 2014; Demirel et al., 2012; Kaynar et al., 2011). Since the 1960s, Statistical models have been commonly used for forecasting natural gas consumption (Gorucu, 2010; Balestra and Nerlove, 1966; Brabec et al., 2009; Yoo et al., 2009). Several authors explored econometric modelling to forecast natural gas consumption (Nagy, 1996; Berndt andWatkins, 1997; Wan and Wang, 2013; Khan, 2015). Grey prediction model is based on first-order differential equations. Solutions of model coefficients are analyzed based on the least squares method of statistical regression analysis system (Boran, 2014; Ma and Li, 2010; Lee and Tong, 2011; Tuo, 2013). Besides, Mathematical model (Gil and Deferrari, 2004; Saboa & al., 2011), Stochastic Gompertz innovation diffusion model (Gutierrez & al., 2005), MARKAL economic optimization model (Jiang et al., 2008), Simulated annealing natural gas demand estimation model (Toksari, 2010) and System dynamics model (Li & al., 2011) were used to estimate natural gas consumption.

Compared with the single method, the combinative method can provide more accurate results and thus becomes more popular in forecasting natural gas consumption. The combinative method mainly includes Grey model and BP Neural Network combination model (Fu et al., 2006), Determinate and Stochastic time series combination model (Lu, 2006), as well as Polynomial Curve and Moving Average Combination Projection model (Xu and Wang, 2010). However, there are two common shortcomings for the current approaches to calculate the weight. One is that the subjective information has not been considered, and the other is that the correct predicted information from various prediction methods has not been adopted sufficiently. In view of these, this paper presents a combinative method for natural gas consumption prediction by using Bayesian Model Averaging (BMA). The Bayesian method can clearly show the information updated process, and meanwhile combine the subjective information and data with various kinds of interventions. Besides, BMA uses posterior probability as the weight to calculate the weighted average for all the possible single prediction models. Therefore, it can overcome the shortcomings of above methods and tackle the uncertainty problem of models.

The key of BMA is to estimate the weight of each single model, and many methods have been proposed to solve this problem (Gibbons et al., 2008), such as Laplace method, Bayesian Information Criterion (BIC) method, Akaike Information Criterion (AIC) method and Expectation Maximization (EM) method. The common advantage of Laplace method, BIC and AIC is that the weight can be easily calculated. For example, Laplace method can calculate the marginal likelihood function directly, requiring only the Hessian or covariance matrix. However, those methods are rough, and meanwhile the AIC method cannot explicitly specify a model in advance. As for the EM method, it can easily enumerate the algorithmic steps, and the results permanently satisfy the constraint that the BMA weights are positive with the sum up to one. However, EM method cannot guarantee the globally optimal weights. Besides, algorithmic modifications are required to adapt the EM method to predictive distributions other than the normal distribution (Vrugt & al., 2008). Considering the shortcomings of the above methods, this paper adopts Markov Chain Monte Carlo (MCMC) method to estimate BMA weights. This approach has three advantages. Firstly, ituses multiple different Markov chains for a random sampling; secondly ,it can handle a relatively high number of BMA parameters ;finally, it provides a full view of the posterior distribution of the BMA weights since it need not to assume that the predictive variable obeys normal distribution.

3- METHODOLOGY

3.1- Linear regression model for natural gas consumption

Bayesian Model Averaging method is based on Bayesian theory in which the uncertainty of the model itself can also be considered in the statistical analysis. In this paper, each considered model can be expressed as follows.

$$y = \alpha + \sum_{i=1}^{p} \beta_i x_i + \varepsilon \ (1)$$

Where, $y = (y_1, y_2, ..., y_r)'$ is the natural gas consumption, x_i is the explanatory variable, $\beta i = (\beta_1, \beta_2, ..., \beta_{pi})'$ is the vector parameter, and $\varepsilon \sim N(0, \delta^2)$ is the stochastic error.

3.2- Ensemble Bayesian Model Averaging (BMA)

Since Learner proposed the Bayesian model averaging framework in 1978, BMA has been widely used in econometric applications ,such as output growth forecasting, exchange rate forecasting,stock return prediction and inflation forecasting (Min and Zellner,1993;Fernández and al., 2001; Avramov , 2002; Wright, 2008;Beechey and Wright, 2009). In this paper, BMA is used for naturalgas consumption prediction as follows.

Let $F = \{f_1, f_2, ..., f_k\}$ be the set of forecasting models under consideration, and $D = (y_1, y_2, ..., y_t)^T$ be the observational data .We suppose that θ_k is the vector of parameters of model f_k, $p(\theta_k / f_k)$ is the prior density under model f_k, and that p(f_k) is the prior probability that f_k is the true model (given that one of the considered models is true). Then, the posterior distribution of y for the given data D is as follows.

$$p(y / f_1, f_2, \ldots, f_k, D) = \sum_{k=1}^{k} p(y / f_k, D) p(f_k / D) \tag{2}$$

Where $p(f_k / D)$ is the posterior model probability (PMP) and the fitting degree of single model describing the reality, and $p(y / f_k, D)$ isthe posterior distribution of y given model prediction f_k and observational data set D. In Eq. (2), the posterior probability of model f_k can be obtained by:

$$p(f_k / D) = \frac{p(f_k) p(D / f_k)}{\sum_{j=1}^{k} p(f_j) p(D / f_j)} \tag{3}$$

where $p(D / f_k) = \int p(D / \theta_k, f_k) p(\theta_k / f_k) d\theta_k$ is the Marginal likelihoodof model f_k

Using the posterior model probability (PMP) weights, BMA predictions can be calculated as a weighted average of these models:

$$E_{BMA}(y / D) = \sum_{k=1}^{k} p(f_k / D) E[p_k(y / f_k, D)] = \sum_{k=1}^{k} w_k f_k \tag{4}$$

$$\operatorname{var}[y / D] = \sum_{k=1}^{k} w_k (f_k - \sum_{i=1}^{k} w_i f_i)^2 + \sum_{k=1}^{k} w_k \delta_k^2 \tag{5}$$

Where δ_k^2 is the variance associated with model prediction f_k with respect to observational data set D. Obviously, the expected BMA prediction is essentially the average of individual predictions weighted by the likelihood that an individual model is correct under the given observational data. As illustrated in Eq. (3), the most important and difficult problem is to calculate the marginal likelihood function, which is generally a high-dimension and complex integral.

3.3- Calculation of marginal model likelihood

Recently, several Monte Carlo (MC) numerical methods have been developed for computing marginal likelihoods, such as Candidate's method, harmonic mean estimator, Laplace–Metropolis method and Bridge sampling.

MCMC is a special kind of Monte Carlo method in which a sampler is constructed to simulate a Markov chain converging to the posterior distribution. There are different MCMC algorithms, and one popular algorithm is the Gibbs sampling. Gibbs sampling can be described as follows.

Step 1. Determining the initial point $x^{(0)} = (x_1^{(0)}, x_2^{(0)}, .., x_n^{(0)})$ and $i = 0$.

Step 2. We draw sample $x_1^{(i+1)}, x_2^{(i+1)}, ..., x_n^{(i+1)}$ from full conditional distribution

$\pi(x_1 / x_2^{(i)}, x_3^{(i)}, ..., x_n^{(i)}), \pi(x_2 / x_1^{(i)}, x_3^{(i)}, ..., x_n^{(i)}), ...$

$\pi(x_n / x_1^{(i)}, x_2^{(i)}, ..., x_{n-1}^{(i)})$ respectively.

Step 3. Set $i = i + 1$. then implementing step 2.

When repeating Steps 1–3, we can obtain the MCMC value $x^{(0)}$, $x^{(1)}$, $x^{(2)}$, . . . , $x^{(t)}$. When the chain converges to the stationary, the samples can be used to calculate marginal model likelihood. At the same time, the samples of each model parameters can be drawn from the posterior distribution. Notably, the marginal likelihood can be calculated by various different methods, such as Candidate's method, the harmonic mean estimator, Laplace–Metropolis method, Importance sampling, Chib's method and Bridge sampling. Considering the natural consumption models are not very complicated, this paper adopts the following generalized harmonic means to calculate the marginal likelihood (Newton and Raftery, 1994).

$$p(D / f_k) = \{\frac{1}{T}\sum_{t=1}^{T} w^{(t)}\}^{-1}$$
$$= \{\frac{1}{T}\sum_{t=1}^{T} \frac{g(\theta_{f_k}^{(t)})}{f(D / \theta_{f_k}^{(t)}, f_k) f(\theta_{f_k}^{(t)} / f_k)}\}^{-1} \quad (6)$$

where, $f(D/\theta_{f_k}^{(t)}; f_k)$ is the likelihood of D given model prediction f_k,T is the total sample size of model parameters, and $g(\theta_{f_k}^{(t)})$ is thedensity function.

3.4- Evaluation of predictive accuracy

This paper adopts Mean Absolute Percentage Error (MAPE) to evaluate the predictive performance.

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{y_t - \hat{y}_t}{y_t}\right| \qquad (7)$$

Where y_t denotes the observational data, $\hat{y}_t$ is the predictive value, and n is the total number of samples.

Accuracy is assessed based on the estimated error. Thus, the smaller the value of the MAPE, the better the forecast. Lewis (1982) established the MAPE index for the evaluation of a model. The critical values of this index are shown in table 01.

Table 1. Critical values of MAPE.

MAPE%	Evaluation
MAPE ≤ 10%	High accuracy forecasting
10%< MAPE ≤ 20%	Good forecasting
20%< MAPE ≤ 50%	Reasonable forecasting
MAPE > 50%	Inaccurate forecasting

Source : Lewis (1982).

4- THE PREDICTION OF NATURAL GAS CONSUMPTION IN ALGERIA

4.1- Data

The data cover annual time series between 1984 and 2018, and the relevant data can be from the Electricity and Gas Regulation Committee (EGRC) and the National Statistics Office (NSO).The selection was based on data availability, the reliability of data sources, and the measurability of variables in the modelling process. This paper considers four predictive variables that are important for forecasting the natural gas consumption in the future, including (1) Global Domestic Product (GDP , the annual growth rate), (2) Urban Population (UPOP, the percentage of urban population to the total population, the annual growth rate), (3) Industrial Structure (INST, the percentage of value-added of industry to GDP, which is an indicator of industrial structure) and (4) Electricity Demand (ELCD, the annual growth rate). Here, natural gas price is not taken as an important factor in our consumption forecast, because the Algerian administration imposes a price control system on natural gas; thus, the price cannot significantly reflect the change of natural gas consumption. The following table illustrates the descriptive statistics of the variables used in the analysis.

Table 2: Descriptive statistics

Variable	Y	GDP	ELCD	UPOP	INST
Minimum	15,38075	85431257456	2953,3	10246073	1,052395
Maximum	42,735	20119545389	17509	29821745	14,32076
Mean	23,61813	12798710838	8332,798	19510972	7,107919
Std.Dev	7,309803	38502079572	4813,682	5868152	4,068608
Jark-Berra	9,982	4,858	3,806	1,879	1,435
Probability	0,007	0,088	0,149	0,391	0,488
Skewness	1,343	0,835	0,689	0,198	0,078
Kurtosis	0,763	-0,829	-0,888	-1,047	-0,944
Observations	35	35	35	35	35
Unit of mesure	bcm	Constant US $ of 2010	ktoe		

Source: developed by the author on Excel-Stat from EGRC's and ONS data.

4.2- Empirical Results

The subset of possible models, the model space Ω, to choose from, is $2^k = 16$ potential models. First, an adequate model that respects the body of evidence must be chosen. To this end, BMA is applied.

The following results are computed with R statistical software. The g prior is set to g =max (N; K^2), that is a mechanism such that posterior model probabilities (PMP) asymptotically either behave like the Bayesian information criterion (with g = N) or the risk inflation criterion (g = K^2)[5]. Generally, a small hyper parameter g reflects low prior coefficient variance and implies a strong initial belief that the coefficients are 0. In contrast, as $g \to \infty$, the coefficient estimator approaches the ordinary least squares OLS estimator.

In Table 3, the results are detailed, sorted by posterior inclusion probability (PIP) of the regressors . In the first column, the influences are named. In the second column, the posterior inclusion probability is displayed.

Table 3. Bayesian Model Averaging summary

	PIP	Post Mean	Post SD Cond.	Pos. sign	Idx
ELCD	1.0000000	0.702913255	0.06514826	1.0000000	4
UPOP	0.2424049	-0.163912527	0.42499623	0.0000000	2
INST	0.2162581	0.008008662	0.02408555	1.0000000	3
GDP	0.1534227	0.003253763	0.08635176	0.8212094	2

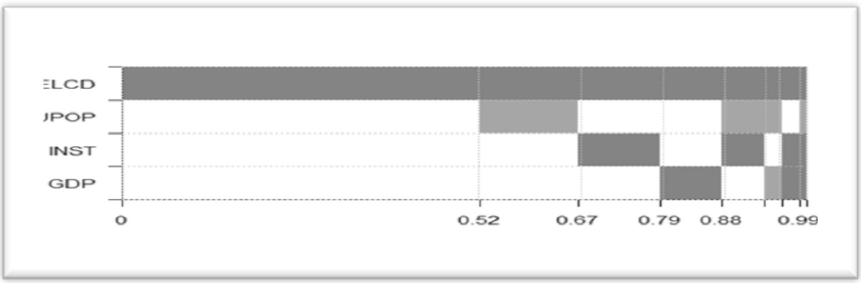
Source: Established by the author from BMA results.

The first corresponding statistic column represents the posterior inclusion probability (PIP) which shows the importance of the variables in explaining the data. It thus illustrates the “robustness” of the variables in BMA analysis, and a value of 0.5 and greater is recommended (Raftery,1997). We can see that with100%, all of posterior model mass rely on models that include ELCD, 24% on UPOP, 22% on INST and 15% on GDP. The second column represent the coefficient averaged over all models. It is obvious that ELCD has

[5] Munasinghe M, & Meier P., (1993) Energy policy analysis and modeling. Cambridge studies in energy and the environment. Cambridge University Press, Cambridge [England], New York, NY, USA.

positive coefficients over all models. The third column gives us the coefficients' posterior standard deviation (Post SD) gives further evidence of the coefficient so we can have an evident that ELCD, GDP and INST are positive. The fourth column shows the sign certainty of the 'posterior probability of a positive coefficient expected value conditional on inclusion' represented in"Cond. Pos.Sign". in the model we can see that ELCD and INST are having a corresponding 100% expected value with positive signs, while the expected value of the negative sign for UPOP is nearly zero.

Figure 2. Model inclusion of explanatory variables.

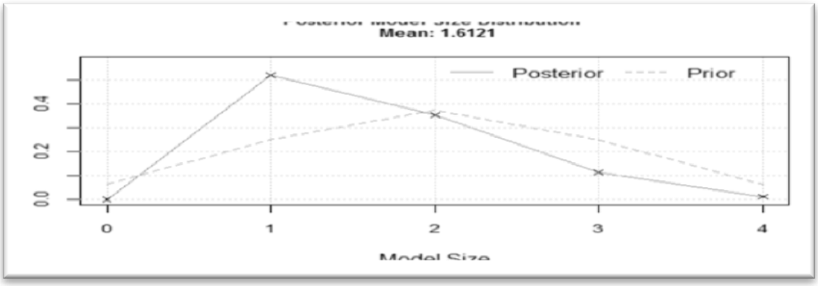


Red colour indicates a negative coefficient; blue colour indicates a positive coefficient and white colour indicates non-inclusion. The abscissa shows the 16 best models, scaled by their cumulated PMP. On the ordinate, the influences ranked by their inclusion are shown.

Source: Established by the author from BMA results.

This figure shows that among the best 16 models, the model which included the variables indicated in blue comprise 52 % of all models (the model mass). The abscissa shows the 16 best models, scaled by their cumulated PMP. The second section, roughly 15 % of model mass (between 0.52 and 0.67) on the abscissa shows a model which also includes one other influence, in Table 04, this model is named "Model 2". Alike one can retrieve all models of Table04 in this graph.

Figure 3. Posterior Model Size Distribution



Model size reflects the number of variables suggested by prior and posterior distribution of potential variables (mean1.6121).

Source: Established by the author from BMA results.

In this figure, model size distribution is shown. Model size distribution represents the number of adequate regressors depicted against the prior assumption, that was "uniform", i.e. the prior expected model size implicitly used in the model definition. With 2^K possible variable combinations, a uniform model prior means a common prior model probability of p(Model) = 2^{-K}. This implies a prior expected model size of 2.

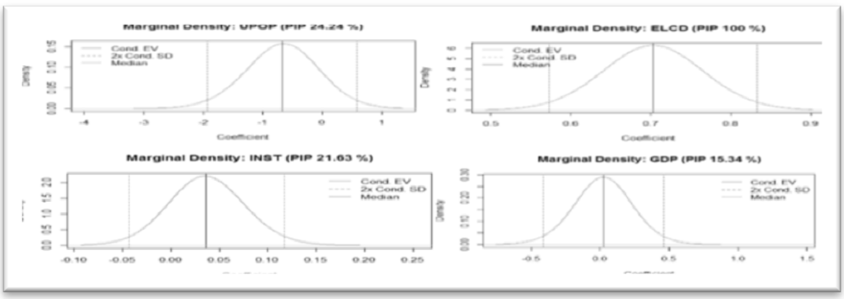
Table 4. Inclusion of variables (coefficient estimate) and posterior model probability for the best three models (rounded)

	Model 1	Model 2	Model 3
ELCD	0.71	0.69	0.7
INST	0.00	0.00	0.03
GDP	0.00	0.00	0.00
UPOP	0.00	-0.56	0.00
Pmp(exact)	0.52	0.14	0.12
Pmp(mcmc)	0.52	0.14	0.12

Source: Established by the author from BMA results.

In Table 04, the best three models in terms of PMP and the coefficient estimates are displayed. The exact PMP are analytical values, MCMC are simulated values. The PMP is proportional to the marginal likelihood of the respective model, i.e. the probability of the data given the model, times the prior model probability. The best model has a PMP of 52 %. In Fig.4, the marginal distribution density of the used variables coefficients is depicted. The numerical coefficient estimators correspond with the coefficient values in Table04. The integral of the densities sums up to the analytical PIP of the regressors, as reported in Table 03.

Figure 4: Marginal density distributions of coefficient estimates of the explanatory variables



The blue line represents the marginal density; conditional expected values (Cond.EV) are displayed in red solid line, the median in green solid line. The red dotted lines represent the double conditional standard deviation (2× Cond. SD)

Source: Established by the author from BMA results.

BMA densities can not only be applied for inference but also for a prediction based on historical data. Predictive quality can be used to investigate how well the model performs, given real data are available. For the present exercise, the same BMA parameters as described above are used.

The 31 observations of the dataset are split in order to predict the last three observations, i.e. the natural gas consumption in 2016, 2017 and 2018 (annual growth rate).

Table 5. Prediction of last three observations of the data set.

observation	32	33	34
Expected value	-0.87	6.96	5.12
Real value	-0.84	6.92	8.05
Standard error	0.03	0.04	2.02

Source: Established by the author from BMA results.

We see that the values estimated by the BMA model are not far from the real values, the standard error is relatively small. With an MAPE of 9.7 % which means a High accuracy forecasting of the model.

4.3- Scenario Analysis of Natural Gas Consumption in Algeria during 2019–2028

When the estimated model is validated, we can thus construct the scenarios for the evolution of gas demand. We are based on the evolution hypotheses of all the determining variables (ELCD, GDP, UPOP, INST).

To forecast the natural gas consumption in Algeria, and to reduce the uncertainty of forecasting, this paper forecasts natural gas consumption under different scenarios from 2019 to 2028.

A "Scenario Planning" type approach will be adopted in this work. The reference scenario will be constructed on the basis of the assumptions considered most likely for the evolution of the determining variables. For the "Strong" scenario and the "Weak" scenario, the variations of the determining variables will be chosen to make sensitive minimum and maximum forecasts of gas demand. Thus, the strong scenario will give the largest possible increase in gas demand, in our case it is a let-go scenario. Furthermore, the weak scenario is qualified as a proactive scenario, which mainly reflects efforts to control gas demand.

Hypotheses

For the GDP variable, we rely on the hypotheses described in the article: Algeria Vision 2035: Towards a Dynamic, Inclusive and Resilient Economy. Ministry of Finance (March 2019). In the reference scenario, we assume a GDP growth rate of 0.8% in 2019 and estimated rate at -2.6% in 2020, growth rates of 3.4% and 3.6% in the periods 2021-2024 and 2025-2028. In the strong scenario, the GDP growth rates are assumed to be 5.4% and 6.9% in the periods 2019-2024 and 2025-2028, reflecting an improvement in the country's financial situation following an increase in oil taxation and the revival of economic activity. In the weak scenario, the GDP grows annually by 1.5% by 2028, reflecting a revival of economic activity and a stagnation in oil taxation.

For the variable ELCD, we use the rates calculated by the CREG in its Indicative Program of Electricity Production Needs 2019-2028: (7% in the reference scenario, 9 % in the strong scenario and 5 % in the weak scenario), taking into account the appearance of new industrial projects and the application of the energy efficiency and development of renewable energies in the coming years.

For the variable UPOP, and on the basis of available data, it can be estimated that by 2028, average annual growth should fluctuate around 2.6%. This forecast has a relatively high level of reliability since the available values have a rather linear structure, despite notable variations (correlation coefficient = 0.89 and determination coefficient = 0.78). which means a growth rate of 2.6% would be assumed in the reference scenario (practically the same rate given by the WUP- World Urbanization Prospects 2018), for the strong scenario, a rate of 3% which reflects an accelerated urbanization level, for the weak scenario a rate of 2% is assumed.

In the reference scenario, we have assumed an average annual growth rate of the INST of 5.3% which represents the share of the manufacturing industry, in terms of value added displayed in the NMEG: New Model of Economic Growth, established in 2016, for the non-hydrocarbon industry .For the strong scenario, the average annual growth rate of INST is assumed to be 8%, which reflects a strong outlook in the NMEG and a new boom in industry in Algeria.

Finally, the weak scenario represents a slowdown in growth in gas demand for various reasons. Indeed, we assume a weak recovery (4%) of the non-hydrocarbon industry following the low attractiveness of FDI in this sector.

The following table summarizes the different hypotheses by scenario.

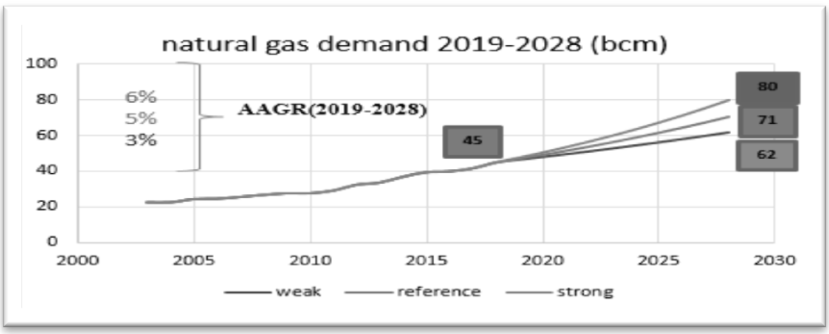
Table 6. Assumptions on the explanatory variables of gas demand

	Week scenario	Reference scenario	Strong scenario
ELCD	5 %	7 %	9 %
GDP	1.5 %	0.8 %/-2.6 % / 3.4 %/ 3.6%	5.4 % / 6.9%
UPOP	2 %	2.6 %	3 %
INST	4 %	5.3 %	8 %

Source : Established by the author.

Based on the assumptions in the table 06, our model provides three scenarios, which are illustrated in the following graph.

Figure 5 : Gas demand scenarios for 2028.



Source:Established by the author in Excel.

Based on the above three scenario settings, this study takes the four affecting factors and the natural gas consumption as the input and output of BMA forecasting model, respectively. Based on this proposed model, the natural gas consumption in Algeria from 2019 to 2028 has been analysed under low, reference and high scenarios, and the results are represented in Figure 5.

From Figure 5, the following three observations can be obtained.

First, and based on the results of scenario analysis, the Algeria's natural gas consumption is going to be 62, 71,80Bcm (billion cubic metres) in 2028 under the low, reference and high scenarios, respectively. Secondly, the natural gas consumption in the high, reference and low scenarios have a similar increasing trend, while, over time, the gap of natural gas consumption between high and low cases becomes larger and larger. Finally, in all three scenarios, natural gas consumption increases relatively rapid from 2019 to 2028, which may be interpreted as the four affecting factors have direct and important influences on the natural gas consumption.

We can also note that forecasted values of EGRC for the same period 2019-2029 (61, 67 and 76 bcm with average annual growth rates of 3.6%, 4.5% and 5.4% respectively in the weak, reference and strong scenarios) are close to ours. However, our values are a little higher, which can be explained by the updating of the assumptions made on the explanatory variables.

CONCLUSION

In summary, this paper adopts the BMA method to forecast the natural gas consumption in Algeria in the ten next years 2019-2028. The BMA method can calculate the posterior model probability and tackle the uncertainty problem of models, which overcomes the shortcomings of other existing methods. Therefore, it can be used as an effective tool to estimate natural gas consumption in different countries. According to this method, the natural gas consumption in Algeria would maintain a rapidly growing tendency, and the National demand would be between 62 Bcm and 80 Bcm by 2028 (71 Bcm in the reference scenario with an average annual growth rate of 5%). we see that the estimation results of the BMA model are close to those established by the CREG in the indicative program for supplying the national natural gas market 2019-2028 "national gas demand between 61 and 76 Bcm in 2018 with an average annual growth rate of 4.5%".

According to the contribution of each variable in our BMA model for estimating gas consumption in Algeria, the classification of the variables by order of importance is as follows: electricity demand (ELCD with PIP of 100%), pop (UPOP with PIP of 24%), industrial structure (INST with PIP of 22%). This reflects the share of the gas use sectors in Algeria: first electricity production, then households, then industry.

According to the analysis of Ali Aissaoui in his document (Algerian gas troubling trends troubled policies, May 2016), the decline in marked production in the last decade is an incontrovertible trend, marketed production is likely to plateau at best to reach a level of 85 bcm in 2028, Therefore, according to BMA results, gas exports will likely be reduced to a trickle of some16Bcm / year by 2028. Clearly, the drop-in exports would be even more dramatic if we consider a scenario of higher demand growth, which would put demand at the same level as production at 85 Bcm in 2028. In such a case, exports would be almost eliminated.

Based on the above analysis, the fragility of Algeria's natural gas balance continues to raise concerns locally and internationally about the country's ability to maintain its current gas export commitments and potentially develop new export opportunities.

The main factor fuelling this rapid gas consumption growth is the prevailing heavily subsidized domestic gas price. In the other hand, the very slow development of a renewable energy program to reduce the use of natural gas while, at the same time, a significant build-up of gas-fired power capacity is already under way. The tardy government policy response to curb such growth has been twofold: substituting in the long run renewables for natural gas in the dominant power generation sector: and, in the short to medium term, adjusting tariffs for gas and electricity to rationalize their consumption. This is unlikely to help renewable sources of energy quickly achieve a meaningful share of Algeria's future energy mix. Therefore, heavy reliance on natural gas to generate electricity may continue, at least until the end of next decade.

Finally, Algeria faces serious challenges in its natural gas sector. Confronting these challenges requires more aggressive policy responses to both supply and demand.

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