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# Forecasting natural gas consumption in China by Bayesian Model Averaging



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## ABSTRACT

With rapid growth of natural gas consumption in China, it is in urgent need of more accurate and reliable models to make a reasonable forecast. Considering the limitations of the single model and the model uncertainty, this paper presents a combinative method to forecast natural gas consumption by Bayesian Model Averaging (BMA). It can effectively handle the uncertainty associated with model structure and parameters, and thus improves the forecasting accuracy. This paper chooses six variables for forecasting the natural gas consumption, including GDP, urban population, energy consumption structure, industrial structure, energy efficiency and exports of goods and services. The results show that comparing to Gray prediction model, Linear regression model and Artificial neural networks, the BMA method provides a flexible tool to forecast natural gas consumption that will have a rapid growth in the future. This study can provide insightful information on natural gas consumption in the future.

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## 1. Introduction

Natural gas is the most efficient and clean-burning fossil fuel. The demand for natural gas has a significant impact on energy strategy, energy consumption, economic growth, and the daily life of people. In recent years, under the pressure of carbon dioxide reduction, China has been seeking for more efficient energy to maintain sustainable growth of the economy (Li et al., 2011). In China, the natural gas consumption is far lower than the average level of the world. Not only will this status have an influence on the energy security of China's future, but also threaten its economic security. Consequently, it is very important to make a scientific prediction of the dynamic characteristics of China's natural gas consumption in the future (Wang and Lin, 2014; Szoplik, 2015).

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. According to Hubbert's research, any complete life cycle curve of limited resource system was bell-shape, and the curve could be used to simulate the logistic function. Similarly, several authors adopted this model or its expanded version to forecast the natural gas consumption (Maggio and Cacciola, 2009; Valero, 2010). Artificial neural network (ANN) is a computing system formed by a plurality of very simple processing units connected to each other in some way. It possesses functions of learning, memory, association and calculation, and can simulate the structure and function of human brain's neural networks. By adaptive information processing, ANN can effectively deal with data with model uncertainty. The first application of ANN 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 modeling to forecast natural gas consumption (Nagy, 1996; Berndt and Watkins, 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

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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 et al., 2011), Stochastic Gompertz innovation diffusion model (Gutierrez et al., 2005), MARKAL economic optimization model (Jiang et al., 2008), Simulated annealing natural gas demand estimation model (Toksari, 2010) and System dynamics model (Li et 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 et 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, it uses 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 assume that the predictive variable obeys normal distribution.

This paper presents the BMA method to forecast natural gas consumption in China. The rest of this paper is organized as follows. In Section 2, the BMA method is briefly introduced. In Section 3, results are provided based on BMA and its analyses. In Section 4, conclusions are given.

## 2. Methodology

### 2.1. 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.

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

where,  $y = (y_1, y_2, \dots, y_T)'$  is the natural gas consumption,  $x_i$  is the explanatory variable,  $\beta_i = (\beta_{i1}, \beta_{i2}, \dots, \beta_{ip_i})'$  is the vector parameter, and  $\varepsilon \sim N(0, \sigma^2)$  is the stochastic error.

### 2.2. 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 et al., 2001; Avramov, 2002; Wright, 2008; Beechey and Wright, 2009). In this paper, BMA is used for natural gas consumption prediction as follows.

Let  $F = \{f_1, f_2, \dots, f_k\}$  be the set of forecasting models under consideration, and  $D = (y_1, y_2, \dots, y_T)'$  be the observational data. We suppose that  $\theta_k$  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.

$$p(y|f_1, f_2, \dots, f_k, D) = \sum_{k=1}^K p(y|f_k, D)p(f_k|D) \quad (2)$$

where  $p(f_k|D)$  is the posterior model probability (PMP) and the fitting degree of single model describing the reality, and  $p(y|f_k, D)$  is the 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:

$$p(f_k|D) = \frac{p(f_k)P(D|f_k)}{\sum_{j=1}^K p(f_j)P(D|f_j)} \quad (3)$$

where  $p(D|f_k) = \int p(D|\theta_k, f_k)p(\theta_k|f_k)d\theta_k$  is the Marginal likelihood of model  $f_k$ .

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

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

$$\text{Var}[y|D] = \sum_{k=1}^K w_k (f_k - \sum_{i=1}^K w_i f_i)^2 + \sum_{k=1}^K w_k \sigma_k^2 \quad (5)$$

where  $\sigma_k^2$  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.

### 2.3. 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.

**Table 1**  
Simulation results for the model parameters.

Parameter	Mean	sd	MC error	2.5%	Median	97.5%	Sample
$\beta_0$	-0.21652	0.00806	6.21E-4	-0.28132	-0.22132	-0.18321	5000
$\beta_1$	0.18132	0.00921	4.23E-4	0.15342	0.19932	0.20332	5000
$\beta_2$	6.32153	0.00512	6.25E-4	6.03421	6.22348	6.86562	5000
$\beta_3$	-0.46184	0.00212	1.79E-4	-0.63442	-0.47654	-0.39632	5000
$\beta_4$	0.14621	0.00633	2.86E-4	0.12653	0.13762	0.17998	5000
$\beta_5$	1.34768	0.00442	2.97E-4	1.32023	1.35654	1.58787	5000
$\beta_6$	2.10023	0.00197	1.53E-4	1.99032	2.09256	2.18265	5000

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  $x^{(0)} = (x_1^{(0)}, x_2^{(0)}, \dots, x_n^{(0)})$  and  $i = 0$ .
- Step 2. We draw sample  $x_1^{(i+1)}, x_2^{(i+1)}, \dots, x_n^{(i+1)}$  from full conditional distribution  $\pi(x_1 | x_2^{(i)}, x_3^{(i)}, \dots, x_n^{(i)})$ ,  $\pi(x_2 | x_1^{(i)}, x_3^{(i)}, \dots, x_n^{(i)})$ ,  $\dots$ ,  $\pi(x_n | x_1^{(i)}, x_2^{(i)}, \dots, x_{n-1}^{(i)})$ , respectively.
- Step 3. Set  $i = i + 1$ , then implementing step 2.

When repeating Steps 1–3, we can obtain the MCMC value  $x^{(0)}, x^{(1)}, x^{(2)}, \dots, x^{(t)}$ . 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).

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

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 the density function.

#### 2.4. Evaluation of predictive accuracy

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

$$RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^n (y_t - \hat{y}_t)^2} \quad (7)$$

$$MAPE = \frac{1}{n} \sum_{t=1}^n \left| \frac{y_t - \hat{y}_t}{y_t} \right| \quad (8)$$

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

### 3. The prediction of natural gas consumption in China

#### 3.1. The data

The data cover a time series between 1965 and 2012, and the relevant data can be from BP Statistical Review of World Energy 2013 and the World Bank. This paper considers six predictive variables that are important for forecasting the natural gas consumption in the future, including (1) GDP (the annual growth rate), (2) urban population (UPOP, the percentage of urban population to the total population which stands for the urbanization level), (3) energy consumption structure (ECST, the percentage of coal consumption to the total energy consumption), (4) industrial structure (INST, the percentage of value-added of heavy industry to GDP, which is an indicator of industrial structure), (5) energy efficiency (EEFF, the added production value divided by energy consumption of industry) and (6) exports of goods and services (EPGS, the annual growth rate). Here, natural gas price is not taken as an important factor in our consumption forecast, because the Chinese administration imposes a price control system on natural gas; thus, the price cannot significantly reflect the change of natural gas consumption.

#### 3.2. MCMC sampling

At the beginning, there is no prior information on which model performs better. Thus, the priority of each model is equal. This paper illustrates the convergence of simulation using regression model which includes 6 predictive variables. It can be observed that all models converge approximately after 10,000 iterations. However, the simulation still needs to be run for a further number of iterations to obtain samples that can be used for posterior inference. After the 10,000 “break-in” iterations, the simulation has converged and then another 5000 samples are drawn for each parameter from their posterior distributions. Generally speaking, the more the saved samples, the more accurate the posterior estimation. The Monte Carlo error of each parameter that is the difference between the estimated posterior mean of the sampled values and the true posterior mean; the Monte Carlo error can be used to assess the accuracy of the posterior estimation. In general, the simulation should be run until the Monte Carlo error of parameter is less than about 5% of the sample standard deviation. When 5000 samples are obtained for each model parameter, the above criterion can be satisfied.

In Table 1, the values of 2.5% and 97.5% mean the range of confidence intervals. For example, the 8th line of Table 1 means that confidence interval of 97.5% is 1.99032–2.18265. As illustrated in Table 1, the standard deviations of parameter estimation are smaller than absolute values of their mean. Besides, MC errors are less than about 5% of the sample standard deviation. That is to say, the parameter estimation has stabilized and the chains have converged.

#### 3.3. Posterior model probability

When the samples of parameter are drawn from their posterior distributions, they can be used to calculate the posterior

**Table 2**  
Posterior model probability.

Model	GDP	Urban population	Energy consumption structure	Industrial structure	Energy efficiency	Exports of goods and services	Posterior model probability
Model 1	✓	✓	✓	✓	✓	✓	0.235
Model 2		✓		✓	✓		0.142
Model 3	✓	✓				✓	0.122
Model 4	✓		✓		✓		0.098
Model 5		✓	✓	✓		✓	0.085

PMP denotes the posterior model probability. Only the 5 models with the highest PMP values are shown.

**Table 3**  
The evaluation of predictive performance.

Model	MAPE	RMSE
Grey prediction model	0.051	0.082
Linear regression model	0.057	0.068
Artificial neural networks	0.045	0.061
Bayesian model average	0.026	0.043

probability of the single model. Table 2 lists the BMA method of the posterior probability model for the top five models and the selected variables.

From Table 2, the posterior probability of the “best” model is 0.235, and the posterior probability sum of top five models is 0.682. Thus, the uncertainty of the model can be evaluated.

In order to verify the BMA method, this paper compares the predictive result of BMA with those of Grey prediction model, Linear regression model and Artificial neural networks (Li et al., 2014; Gao et al., 2013). The data covered a time series between 1985 and 2012.

As illustrated in Table 3, BMA has a better prediction effect than Grey prediction model, Linear regression model and Artificial neural networks. To sum up, theoretical analysis and applicative study both confirm the effectiveness of BMA.

### 3.4. Forecasting

The natural gas consumption of different industry can reflect the reality of economic structure in China. Natural gas consumption of industry depends on investment, while population can determine natural gas consumption of resident. Besides, investment will improve the energy consumption structure and energy efficiency. Therefore, GDP, urban population, energy consumption structure, industrial structure, energy efficiency and exports of goods and services have a close relationship that can influence the natural gas consumption. To forecast the natural gas consumption in China, this paper makes some assumptions for GDP, urban population, energy consumption structure, industrial structure, energy efficiency and exports of goods and services.

It can be known from National Population and Family Planning Commission of China, China would develop at a rapid growth rate, and the average growth rate would be about 8% in the next 5 years, 7%–8% in the 5 years from 2013 to 2015, and 6%–7% from 2016 to 2020. The urbanization rate in the year of 2015 and 2020 would be 56%, and 62%. According to the data from China Macro Economic Information Network, the percentage of the industry added value to GDP would be 51% and 50% in the year of 2015 and 2020. Based on historical data, it can be assumed that EF increases by 3% annually from 2013 to 2015, 2% from 2016 to 2020 and then declines by 0.5% every 10 years; the EPGs will be 12% and 10% in 2015 and 2020, respectively. In accordance with the predictive data from Dr. Ruhr, chief economist at British Petroleum, energy consumption structure in the year of 2015 and 2020 would be 68%, and 60%.

To reduce the uncertainty of forecasting, this paper forecasts natural gas consumption under different scenarios from 2015 to

**Table 4**  
Parameters assumptions of different scenarios.

Parameter	Scenarios	2015	2020
GDP	High level	8%	7.5%
	Reference level	7%	6%
	Low level	6%	5.5%
Urban population	High level	58%	67%
	Reference level	56%	62%
	Low level	54%	58%
Industrial structure	High level	52%	51%
	Reference level	51%	50%
	Low level	50%	49%
Energy efficiency	High level	4%	3.5%
	Reference level	3%	2.5%
	Low level	2.5%	2%
Energy consumption structure	High level	72%	65%
	Reference level	68%	60%
	Low level	62%	56%
Exports of goods and services	High level	20%	17%
	Reference level	12%	10%
	Low level	7%	6%

**Table 5**  
Forecasting natural gas consumption in different scenarios (billion cubic meters).

	Low level	Reference level	High level
2015	213.138	220.889	228.639
2016	232.321	249.604	267.508
2017	250.906	279.556	310.309
2018	270.979	310.308	356.855
2019	289.947	341.338	403.247
2020	307.344	375.473	451.636

2020. We assume the different value of parameters under different scenarios in Table 4.

Given the above assumptions, the natural gas consumption can be forecasted using BMA by Eq. (4), and the results are shown in Table 5.

## 4. Conclusions

In summary, this paper adopts the BMA method to forecast the natural gas consumption in China. The BMA method can calculate the posterior model probability and tackle the uncertainty problem of models, which overcomes the shortcomings of other existing methods. In terms of prediction accuracy, BMA has a better prediction effect than Grey prediction mode and Artificial neural networks. 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 China would maintain a rapidly growing tendency, and the consumption in the year of 2015, 2016, 2017, 2018, 2019 would be 220.889 billion cubic meters (bcm), 249.604 bcm, 279.556 bcm, 310.308 bcm, 341.338 bcm and 375.473 bcm, respectively.

Based on the above analysis, the natural gas consumption will have a rapid growth in the future. As clean energy, the exploitation of natural gas can bring economic and social benefits. So, China should take measures to guarantee the security of natural gas.

Firstly, China should formulate corresponding laws and regulations to regulate the market and provide good market environment for investment. Furthermore, China may cooperate with other countries to disperse investment risk. At the same time, China may attract social talents to promote the development of natural gas. Finally, China should build the market-oriented price mechanism of natural gas to conducive the healthy development of natural gas industry. Currently, China imposes 13% tax for onshore natural gas and 5% tax for offshore nature gas. However, China will mainly depend on the onshore natural gas in the next 20 years. Therefore, China should levy the uniform tax to promote the development of natural gas.

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