MATHEMATICAL MODELLING OF ENGINEERING PROBLEMS
Vol.2, No.1, 2015, pp.1-4
http://dx.doi.org/10.18280/mmep.020101

THE PROPORTION OF ENERGY CONSUMPTION STRUCTURE PREDICTION BASED ON MARKOV CHAIN

Ren Xiao-hang, Liu Qian and Zhang Yu-meng

University of Petroleum, Beijing, China.

Email: 632824435@163.com

ABSTRACT

This paper applies a Markov Chain approach based on quadratic programming model to forecast the trends of energy production and consumption structures. The proposed models are used to simulate China's energy consumption structure during 2003–2013 and forecast its trends from 2014 to 2020. The proposed models can effectively simulate and forecast the structures of energy production and consumption. Our study demonstrates that the growth rate of energy consumption in China will decrease, and the proportions of natural gas and other renewable energy will keep growing. However, the increasing rate is far from satisfactory; China may fail to achieve the 13th Five-Year Development Plan. Therefore the Chinese government should take more effort to achieve its energy plan.

Keywords: Energy, Energy structure, Markov Chain, Energy prediction, Energy policy.

1. INTRODUCTION

Energy has already become one of the most important guarantees for social activities, and it is the material basis of the national economy. Starting from the time of the two oil crises, energy has been a hot topic of the international community. In recent years, due to the requirements of economic development and dwindling energy resources in the world, China's energy security has emerged with many problems caused by the conflicts and the wars around world. So we need to find some methods to make sure energy security. In the meantime, the energy structure reform has played an increasingly important role to improve China's economy and the level of social development. Therefore the prediction and the adjustment of energy structure has been becoming very important. Because of the haze, the government pays more and more attention to low-carbon and clean energy to protect our environment. That also needs to change the energy structure. To save the energy and decrease the carbon dioxide emission, the target of the Twelfth Five-Year Development Plan was modified to 16% reduction in the 12th Five-Year (2011–2015), and the proportion of coal and crude oil should be decreased while the proportion of clean energies, such as natural gas and other new energies, should be increased. Thus the consumptions of gas and other clean energies increase fast in recent years. As the Thirteenth Five-Year Plan is coming, we need to know that according to the reality, how much the energy ratios will be in 2020. As the improvement at such speed, can we achieve the targets?

There have been many forecasting models applied in energy problems, such as regression analysis, time series analysis, artificial neural network, semi-parametric approach and non-parametric method [1–4]. Wu [5] applied the Bayesian vector autoregressive methodology to forecast China's energy consumption and to discuss potential implications. Zhu [6] introduced an endogenous economic growth model to demonstrate energy input and economic growth. However, these models typically require a large number of observations to make sensible predictions. The prediction objects involved in more simple, the shorter the time involved in the future, the accuracy of predictions may be higher; the more complex matters involved, the more influential factors involved, the poorer the accuracy of the prediction will be. But the developing trends of the energy system are changed significantly and the available observations are limited and cannot satisfy the requirements of those traditional methods. To forecast the developing trends with limited data sequence, a new model working with small data sets is necessary to overcome the limited data availability.

So we will use the Markov Chain to do the prediction. A Markov chain is a stochastic process with the Markov property. The term "Markov chain" refers to the sequence of random variables such a process moves through, with the Markov property defining serial dependence only between adjacent periods (as in a "chain"). It can thus be used for describing systems that follow a chain of linked events, where what happens next depends only on the current state of the system. Markov prediction uses the stochastic process change law to do prediction. Krogh A [7] applied the hidden Markov model in predicting transmembrane protein topology. Also some researchers used Markov model in different areas, such as futures, weather and medicines [8-12].

2. DATA

The annual data of total amounts and structures of energy production and consumption of China for the period 2003–2013 are provided by the National Bureau of Statistics of China [13], as shown in Figs 1 and 2. The variables are the total consumption, coal consumption, oil consumption, gas consumption and others energy consumption (wind energy, nuclear energy, hydro-energy and solar energy). The unit is million tons of coal equivalent. From 2003 to 2013 the total energy consumption changed from 183791.82 million tons of coal equivalent to 375000 million tons of coal equivalent, the consumption of coal changed from 128286.82 million tons to 247500 million tons, and the consumption of gas doubles five times. We can also find the consumption trend of different energies through Fig1. The main energy consumption is the coal. Although we have made efforts to reduce using coal. The structures of China's energy production and consumption were also unbalanced during 2003–2013. China is a country with abundant coal and scarce crude oil and natural gas, as shown in Fig. 2, and we can get that the percentage of gas and nuclear, wind, solar consumptions have been increasing and the percentage of coal and oil is decreasing.

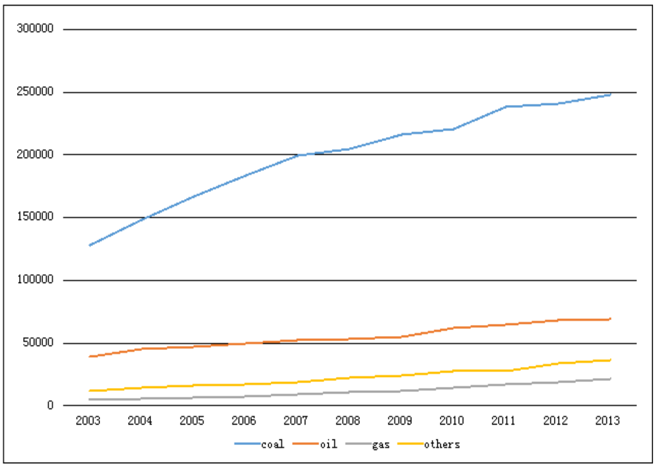

Figure 1. The trends of different energies

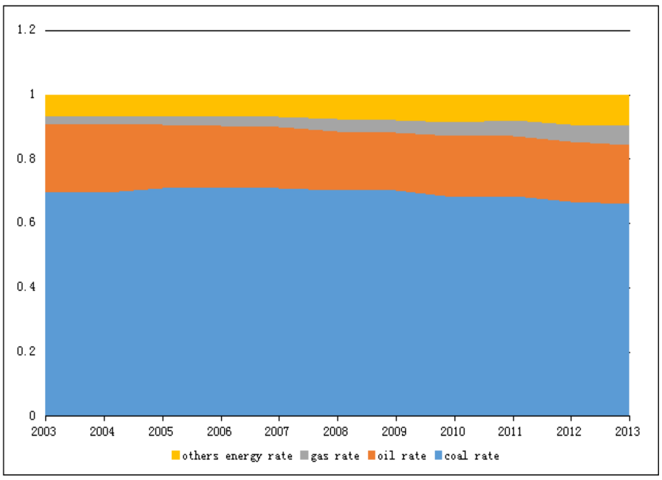

Figure 2. The percentage of different energies

3. MODEL

3.1 Develop model

A Markov chain is a sequence of random variables X_1, X_2, X_3, ... with the Markov property, namely that, given the present state, the future and past states are independent.

Formally, $\Pr(X\_(n+1) = x|X_1 = x_1, \ldots, X\_n = x\_n) = \Pr(〖X\_(n+1) = x|X〗\_n = x\_n$. If both conditional probabilities are well defined, i.e., if $\Pr(X_1 = x_1, \ldots X_n = x_n) > 0$, the possible values of X_i form a countable set S called the state space of the chain. Markov chains are often described by a sequence of directed graphs, where the edges of graph n are labeled by the probabilities of going from one state at time n to the other states at time $n+1$, $\Pr(X_{n+1} = x|X_n = x_n)$. The same information is represented by the transition matrix P from time n to time n+1. However, Markov chains are frequently assumed to be time-homogeneous (see variations below), in which case the graph and matrix are independent of n and so are not presented as sequences. And the Markov matrix is a matrix used to describe the transitions of a Markov chain. Each of its entries is a nonnegative real number representing a probability. From these theory, we use $S(0) = [S_1(0),\ S_2(0), \ldots, S_n(0)]$ to indicate the initial state probability vector and $S(k) = [S_1(k), S_2(k), \ldots, S_n(k)]$ is after k times transfer state probability vector. Then we can find

$$S(1) = S(0) \times P \tag{1}$$

$$S(k) = S(0) \times P^k \tag{2}$$

That is the Markov prediction model.

3.2 Probability matrix estimation

In the actual situation, it is generally difficult to directly find the probability transfer matrix. Therefore, in order to obtain precise transfer matrix, we can use the optimization ideas to solve. Minimize the sum of absolute value error between the actual value and observation value as the objective function. Assume that the transition matrix is $P = (p_{ij})_{n\times n}$.

Suppose $e_j(k) = S_j(k) - \widehat{S_j(k)} = S_j(k) - \sum_{i=1}^{n} S_i(k-1)P_{ij}$. $\widehat{S_j(k)}$ is the observation value after n times transfer. Then we can develop the model:

$$\begin{cases} \min Q = \sum_{j=1}^{n}\sum_{k=1}^{m} |S_j(k) - \sum_{i=1}^{n} S_i(k-1)P_{ij}| \\ s.t \sum_{j=1}^{n} P_{ij} = 1, i = 1,2,\ldots,n \\ P_{ij} \geq 0, i,j = 1,2,\ldots,n \end{cases} \tag{3}$$

This model is a nonlinear programming model with the absolute value. So it is difficult for us to solve. We can transform it into linear programming model through variable substitution. Suppose $u_j(k) = \frac{(|e_j(k)| - e_j(k)}{2}$ $v_j(k) = \frac{(|e_j(k)| + e_j(k)}{2}$, then

$$u_j(k) \geq 0, j = 1,2,\ldots,n \quad k = 1,2,\ldots,m$$

$$v_j(k) \geq 0, \quad j = 1,2,\ldots,n \quad k = 1,2,\ldots,m$$

$$u_j(k) \cdot v_j(k) = 0,\ j = 1,2,\dots,n\ \ k = 1,2,\dots,m$$

$$e_j(k) = v_j(k) - u_j(k)\ , j = 1,2,\dots,n\ \ k = 1,2,\dots,m$$

$$|\ \ e_j(k)| = v_j(k) + (k)\ , j = 1,2,\dots,n\ \ k = 1,2,\dots,m$$

So, we can get:

$$\begin{cases} \min Q = \sum_{j=1}^{n}\sum_{k=1}^{m}(u_j(k) - v_j(k)) \\ s.t\ \ S_j(k) - \sum_{i=1}^{n} S_i(k-1)P_{ij} + u_j(k) - v_j(k) = 0 \\ \sum_{j=1}^{n} P_{ij} = 1, i = 1,2,\dots,n \\ P_{ij} \geq 0, i,j = 1,2,\dots,n \\ u_j(k) \geq 0,\ v_j(k) \geq 0 \end{cases} \tag{4}$$

In this model, the constraints are achieved through the definition of step transition probability matrix. This optimization model is a quadratic programming model. We can use the softs such as MATLAB, GAMS, R or Lingo to solve it, here I use the Lingo to do this.

3.3 Example numerical analysis

Taking the 2003-2013 data into formula (4), we can get a new model:

$$\begin{cases} \min Q = \sum_{j=1}^{4}\sum_{k=1}^{10}(u_j(k) - v_j(k)) \\ s.t\ \ S_j(k) - \sum_{i=1}^{n} S_i(k-1)P_{ij} + u_j(k) - v_j(k) = 0 \\ \sum_{j=1}^{4} P_{ij} = 1, i = 1,2,3,4 \\ P_{ij} \geq 0, i,j = 1,2,3,4 \\ u_j(k) \geq 0,\ v_j(k) \geq 0, i,j = 1,2,3,4\ \ \ k = 1,2,\dots,10 \end{cases} \tag{5}$$

Using Lingo, we can the transition probability matrix P:

$$P = \begin{pmatrix} 0.8471600 & 0.1393094 & 0.0000000 & 0.0135000 \\ 0.5422596 & 0.4577404 & 0.0000000 & 0.0000000 \\ 0.0000000 & 0.0000000 & 0.8194175 & 0.1805825 \\ 0.0000000 & 0.0549000 & 0.1378641 & 0.8071921 \end{pmatrix} \tag{6}$$

Using $S^{[1]} = S^{[0]} \times P, S^{[n]} = S^{[0]} \times P^n$ *and matrix* P, we can predict the energy consumption structure in 2014-2020 (Table 1).

Table1. The prediction percentage of different energies

Year	Coal%	Oil%	Gas%	Others%
2014	0.6589014	0.1815486	0.06103690	0.09848861
2015	0.6566414	0.1803003	0.06359275	0.09941659
2015	0.6540499	0.1794650	0.06581499	0.10059668
2017	0.6514015	0.1787864	0.06779862	0.10191556
2018	0.6487900	0.1781793	0.06960588	0.10330260
2019	0.6462484	0.1776137	0.07127799	0.10471331
2020	0.6437885	0.1770782	0.07284264	0.10611967

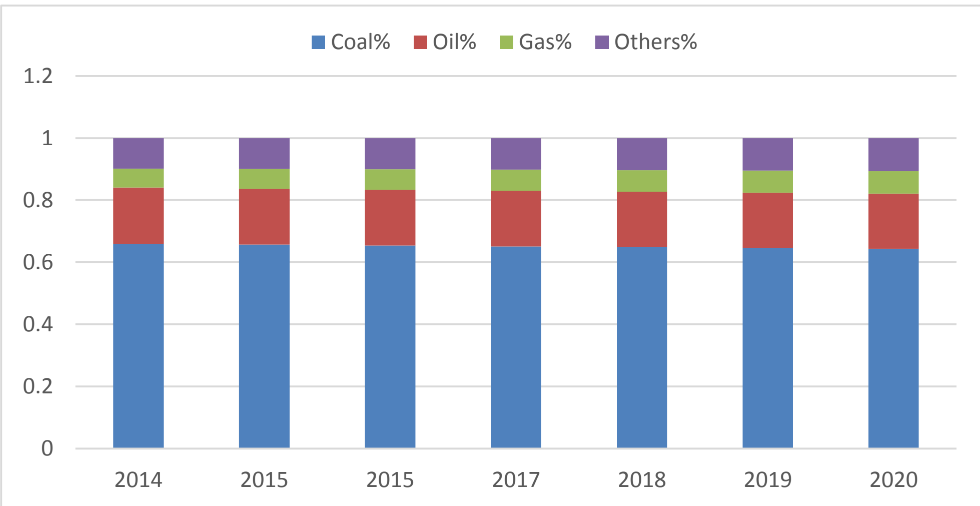

Figure 3. The prediction percentage of different energies

Forecasts suggest that proportions of coal and oil continue to fall, while ratios of gas, wind, nuclear and solar energy continue to rise. But if we want to achieve the low carbon target, we need to take a more strict policy measures. Otherwise, we cannot realize the goal of energy conservation and emissions reduction.

4. CONCLUSIONS

Forecasts are very important for the effective and creation implementation of energy policies. Considering the rapidly increasing energy consumptions and unbalanced energy production and consumption structures in China, accurate forecasting results of structures of energy production and consumption are essential to analyze the self-sufficiency rate and make new energy policies. The reform of energy structure is imperative, and the percentage is critical. In this paper, we use Markov chain to develop a quadratic programming model with constraints, and get the transition probability matrix. And we predict the China's energy consumption structure in the next few years. In 2020, according to the government`s climate planning, one unit of GDP of carbon dioxide emissions should be 40% to 50% lower than in 2005, non-fossil energy accounted for the proportion of primary energy consumption to 15%, taking a further optimization to the industrial structure and energy structure. The coal and oil percentage is lower than our prediction. So in order to achieve this target, we need to speed up the oil and gas exploration and exploitation of the resources, promote the exploration and exploitation of the shale gas and other unconventional oil and gas resources. We should take the development of hydropower orderly, the development of nuclear power safely and efficiently, and take the development of wind power, solar energy and biomass energy vigorously. It may be rough to reform energy structure, but it is significant for energy restructuring and contributes to pollution control and to China's economic upgrade. Because the tasks of reform is arduous, we need to continue efforts.

5. REFERENCES

1. Tso G. K. F., Yau K. K. W., Predicting Electricity Energy Consumption: A Comparison of Regression Analysis, Decision Tree and Neural Networks [J], *Energy*, 32(9): 1761-1768, 2007.
2. Kumar U., Jain V. K., Time Series Models (Grey-Markov, Grey Model with Rolling Mechanism and Singular Spectrum Analysis) to Forecast Energy Consumption in India [J], *Energy*, 35(4): 1709-1716, 2010. DOI: 10.1016/j.energy.2009.12.021.
3. Rumbayan M., Abudureyimu A., Nagasaka K., Mapping of Solar Energy Potential in Indonesia Using Artificial Neural Network and Geographical Information System [J], *Renewable and Sustainable Energy Reviews*, 16(3): 1437-1449, 2012.
4. Matallanas E., Castillo-Cagigal M., Gutiérrez A, et al., Neural Network Controller for Active Demand-Side Management with PV Energy in the Residential Sector [J], *Applied Energy*, 91(1): 90-97, 2012. DOI: 10.1016/j.apenergy.2011.09.004.
5. Crompton P., Wu Y., Energy consumption in China: Past Trends and Future Directions [J], *Energy Economics*, 27(1): 195-208, 2005. DOI: 10.1016/j.eneco.2004.10.006.
6. Zhu Y. B., Wang Z., Pang L., et al., Simulation on China's Economy and Prediction on Energy Consumption and Carbon Emission under Optimal Growth Path [J], *Acta Geographica Sinica*, 64(8): 935-944, 2009.
7. Krogh A., Larsson B. È., Von Heijne G., et al., Predicting Transmembrane Protein Topology with a Hidden Markov Model: Application to Complete Genomes [J], *Journal of Molecular Biology*, 305(3): 567-580, 2001. DOI: 10.1006/jmbi.2000.4315.
8. Logofet D. O., Lesnaya E. V., The Mathematics of Markov Models: What Markov Chains Can Really Predict in Forest Successions [J], *Ecological Modelling*, 126(2): 285-298, 2000. DOI: 10.1016/S0304-3800(00)00269-6.
9. Dueker M., Neely C. J., Can Markov Switching Models Predict Excess Foreign Exchange Returns? [J], *Journal of Banking & Finance*, 31(2): 279-296, 2007. DOI: 10.1016/j.jbankfin.2006.03.002.
10. Li G. D., Yamaguchi D., Nagai M. A., GM (1, 1)–Markov Chain Combined Model with an Application to Predict the Number of Chinese International Airlines [J], *Technological Forecasting and Social Change*, 74(8): 1465-1481, 2007. DOI: 10.1016/j.techfore.2006.07.010.
11. Tang J, Wang L, Yao Z., Spatio-Temporal Urban Landscape Change Analysis Using the Markov Chain Model and a Modified Genetic Algorithm [J], *International Journal of Remote Sensing*, 28(15): 3255-3271, 2007. DOI: 10.1016/j.techfore.2006.07.010.
12. Cruz-Monteagudo M., González-Díaz H., Unified Drug–Target Interaction Thermodynamic Markov Model Using Stochastic Entropies to Predict Multiple Drugs Side Effects [J], *European Journal of Medicinal Chemistry*, 40(10): 1030-1041, 2005.
13. National Bureau of Statistics of China (NBSC), China Statistical Yearbook, Beijing: China Statistics Press, 2013.