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Comparison of China's primary energy consumption forecasting by using ARIMA (the autoregressive integrated moving average) model and GM(1,1) model

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ABSTRACT

China's primary energy consumption increases rapidly, which is highly related to China's sustainable development and has great impact on global energy market. Two univariate models, ARIMA (the autoregressive integrated moving average) model and GM(1,1) model, are used to forecast China's primary energy consumption. The results of the two models are in line with requirements. Through comparing, it is found that the fitted values of ARIMA model respond less to the fluctuations because they are bounded by its long-term trend while those of GM(1,1) model respond more due to the usage of the latest four data. And the residues of the two models are opposite in a statistical sense, according to Wilcoxon signed rank test. So a hybrid model is constructed with these two models, and its MAPE (Mean Absolute Percent Error) is smaller than ARIMA model and GM(1,1) model. And then, China's primary energy consumption is forecasted by using the three models. And the results indicate that the growth rate of China's primary energy consumption from 2014 to 2020 will be rather big, but smaller than the first decade of the new century.

1. Introduction

China is the world's largest energy consumer. In 2014, China accounted for 23% of world's total primary energy demand; and China's energy consumption increased by 2.6% while the global rate is only 0.9% [1]. It means that China consumes lots of energy and will consume more. On the one hand, China's energy consumption not only takes huge pressure for the energy supply system [2], but also takes lots of environmental problems, and energy issue has become one of the key points of China's sustainable development [3]. On the other hand, the rapid growth of China's energy consumption will have a great impact on the international energy market [4]. Therefore, China's energy consumption forecasting, can not only provide some important references for China's economic and energy policy-making, but also some evidence for understanding the international energy market trends.

There are many researches on energy consumption forecasting. And many quantitative forecasting techniques are applied, which can be further segmented into two categories: univariate models and causal relationship models, as shown in Table 1.

A univariate model indicates that a system is a function of its own behavior. And the two univariate models, ARIMA (the autoregressive integrated moving average) model and GM(1,1) model, have been commonly used for energy consumption forecasting. The former is a time series model and the latter is a grey model. ARIMA model is used for energy consumption forecasting early. R.E. Abdel-Aal and A.Z. Al-Garni (1997) use time series analysis for modeling and forecasting monthly domestic electric energy consumption in the Eastern Province of Saudi Arabia [5]. S Gonzales Chavez, J Xiberta Bernat and H Llaneza Coalla (1999) use ARIMA model for modeling and forecasting future energy production and consumption in Asturias [6]. Samer Saab, Elie Badr and George Nasr (2001) use the autoregressive, ARIMA and a novel configuration combining an AR(1) with a highpass filter to forecast electrical energy consumption [7]. And recently, GM(1,1) model is increasingly used. Ujjwal Kumar and V.K. Jain (2010) apply Grey-Markov model, Grey-Model with rolling mechanism, and singular

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Table 1
Energy consumption forecasting models.

Category	Models	Cases
Univariate model	ARIMA	Abdel-Aal and A.Z. Al-Garni (1997); S Gonzales Chavez, J Xiberta Bernat and H Llaneza Coalla (1999); Samer Saab, Elie Badr and George Nasr (2001)
	GM(1,1)	Ujjwal Kumar and V.K. Jain (2010); Pingping Xiong et al. (2014); Weijun Xu et al. (2015)
Causal relationship model	Regression Model	Ahmed Z. Al-Garni, Syed M. Zubair and Javeed S. Nizami (1994); Keith J. Baker, R. Mark Rylatt (2008); Nelson Fumo and M.A. Rafe Biswas (2015)
	Artificial neural networks	H.T. Pao (2009); L. Ekonomou (2010); F.J. Ardakani and M.M. Ardehali (2014)
	The others	Hsiao-Tien Pao et al. (2012)

spectrum analysis (SSA) to forecast the consumption of conventional energy in India [8]. Pingping Xiong et al. (2014) propose a novel GM(1,1) model based on optimizing initial condition according to the principle of new information priority, and apply it in the modeling of China's energy consumption and production [9]. Weijun Xu et al. (2015) establish a new model with improved GM–ARMA based on HP Filter to forecast the final energy consumption of Guangdong Province in China [10].

A causal relationship model forecasts the dependent variables with one or more explanatory variables, which indicates that there exists the casual relationship between the dependent variables and explanatory variables. The most representative causal relationship methods used for energy consumption forecasting are regression model and artificial neural network. Certainly, regression models are used early. Ahmed Z. Al-Garni, Syed M. Zubair and Javeed S. Nizami (1994) build a model and treat electrical energy consumption in Eastern Saudi Arabia as a function of weather data, global solar radiation and population [11]. Keith J. Baker and R. Mark Rylatt (2008) use simple and multiple regression to identify the most statistically-significant indicators of differences in gas and electricity consumption [12]. Nelson Fumo and M.A. Rafe Biswas (2015) use simple and multiple linear regression analysis along with a quadratic regression analysis to research the residual energy consumption [13]. And artificial neural network is also frequently used in this field. H.T. Pao (2009) proposes two new hybrid nonlinear models that combine a linear model with an artificial neural network to forecast energy consumption in Taiwan, taking into account heteroscedasticity in the model's input [14]. L. Ekonomou (2010) addresses artificial neural networks in order to predict the Greek long-term energy consumption [15]. F.J. Ardakani and M.M. Ardehali (2014) develop optimized regression and artificial neural network models for electrical energy consumption forecasting based on several optimization methodologies [16].

Of course, a variety of methods mentioned above may be used simultaneously. And some other methods also used to predict energy consumption. For example, Hsiao-Tien Pao et al. (2012) employ the NGBM (nonlinear grey Bernoulli model) to predict carbon emissions, energy consumption and real outputs, and proposes a numerical iterative method to optimize the parameter of NGBM [17].

It is pointed out that the better accuracy can be achieved when the energy consumption is predicted with socio-economic indicators and DSM (demand side management) data [18]. But the univariate models are focused on in this paper. China is a developing country, and many socio-economic indicators and DSM Data are changing. The average economic growth rate is about 10% in the past 30 years, while the rate of 2014 is 7.4%, and whether China's economy can maintain a rate of 7% or not is in heated debate. All families are allowed to have a second child now, and the birth rate will increase. Improvement of living standards led to the rapid growth of residential energy consumption, but the growth will be slow, as the lagging car sales illustrate. DSM policy began about ten years ago, and has achieved positive effects. However, according to the experience of developed countries, the cost of energy saving will become increasingly high, and their effects may be attenuated. It is quite evident from every standpoint that predictions of these socio-economic and DSM indicators are as difficult as that of China's energy consumption. A rough estimate of these dependent variables will obviously reduce the accuracy of China's energy consumption forecasting. While the univariate methods are used in this paper, in which the dependent variables need not be predicted.

As to the two univariate models, there are some interesting issues should be in further explored:

(1) ARIMA and GM(1,1) model, which one is more suitable for energy consumption Forecasting? So the predictions by using the two methods should be compared.
(2) Although GM(1,1) model and ARIMA model are combined to be a hybrid model [10], it should be clarified why the hybrid model is better.

This paper is organized as follows: In Section 1, the background of the research is specified and the techniques for energy consumption forecasting are summarized; in Section 2, the methods used in this paper, ARIMA model and GM(1,1) model, are introduced; in Section 3, China's primary energy consumption is predicted with ARIMA model and GM(1,1) model, and the results of the two methods are compared, and then a hybrid model combined of ARIMA model and GM(1,1) model is proposed according to the analysis of the residuals of the two models; in Section 4, the conclusions of this study are made.

2. ARIMA Model and GM(1,1) Model

2.1. *ARIMA Model [19]*

The AR(p) model refers to the autoregressive model of order p. The AR(p) model is written:

$$y_t = c + a_1 y_{t-1} + \ldots + a_p y_{t-p} + u_t \tag{1}$$

Where $a_1, \cdots, a_p$ are parameters;
c is a constant;
and the random variable u_t is white noise.

The MA(q) model refers to the moving average model of order q, The MA(q) model is written:

$$y_t = \mu + u_t + m_1 u_{t-1} + \ldots + m_q u_{t-q} \tag{2}$$

Where: the $m_1, \ldots, m_q$ are the parameters of the model;
μ is the expectation of y_t (often assumed to equal 0);
$u_t, u_{t-1}, \ldots,$ and u_{t-q} are white noise error terms.

The ARMA(p, q) model refers to the model with p autoregressive terms and q moving-average terms. This model contains the AR(p) and MA(q) models, and is written:

$$y_t = c + a_1 y_{t-1} + \ldots + a_p y_{t-p} + u_t + m_1 u_{t-1} + \ldots + m_q u_{t-q} \tag{3}$$

When AR(P), MA(q) and ARMA(p,q) are applied in some cases where data show evidence of non-stationarity, an initial differencing step should be applied to reduce the non-stationarity, namely an ARIMA model. Non-seasonal ARIMA models are generally denoted ARIMA(p,q,d), where p is the order of the AR model, d is the degree of differencing, and q is the order of the MA model.

2.2. GM(1,1) model

GM(1,1) model can be defined as follows [20,21]:

Definition 1 For a sequence$X^{(0)} = (x^{(0)}(1), x^{(0)}(2), \cdots, x^{(0)}(n))$, if $x^{(0)}(k) \geq 0$, for $\forall k = 1, 2, \cdots n$, then $X^{(0)}$ is a non-negative sequence.

Definition 2 For a non-negative sequence $X^{(0)}$, its Accumulating Generation Operational Sequence (AGO Sequence) is:

$$X^{(1)} = \left(x^{(1)}(1), x^{(1)}(2), \cdots, x^{(1)}(n)\right)$$

where$x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i)$, $k = 1, 2, \cdots n$.

Definition 3 For an Accumulating Generation Operational Sequence, its sequence of consecutive neighbors is

$$Z^{(1)} = \left(z^{(1)}(2), z^{(1)}(3), \cdots, z^{(1)}(n)\right)$$

where $z^{(1)}(k) = \frac{1}{2}(x^{(1)}(k) + x^{(1)}(k-1))$, $k = 2, 3 \cdots, n$

Definition 4 GM(1,1) model can be defined as:

$$x^{(0)}(k) + az^{(1)}(k) = b \tag{4}$$

Where $x^{(0)}(k)$ and $z^{(1)}(k)$ are defined as definition 1 and definition 3.

And the parameters of GM(1,1) model, Equation (4), can be solved by least square estimate.

If$\hat{a} = (a, b)^T$ is the parameters of GM(1,1) model, and

$$Y = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{bmatrix}, \; B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \vdots & \vdots \\ -z^{(1)}(n) & 1 \end{bmatrix}$$

then the least square estimate of the parameters satisfies

$$\hat{a} = \left(B^T B\right)^{-1} B^T Y \tag{5}$$

Definition 5 the following equation

$$\frac{dx^{(1)}}{dt} + ax^{(1)} = b \tag{6}$$

is called the whitenization function of GM(1,1) model.

Definition 6 The solution of Equation (6),

$$x^{(1)}(t) = \left(x^{(1)}(1) - \frac{b}{a}\right)e^{-at} + \frac{b}{a} \tag{7}$$

is called a time response function.

Definition 7 the corresponding sequence,

$$\hat{x}^{(1)}(k+1) = \left(x^{(0)}(1) - \frac{b}{a}\right)e^{-ak} + \frac{b}{a}, \; k = 1, 2, \cdots n \tag{8}$$

is called time response sequence.

Then the restored values from the time response sequenced can be obtained as follows:

$$\begin{aligned} \hat{x}^{(0)}(k+1) &= \alpha^{(1)}\hat{x}^{(1)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k) \\ &= (1 - e^{a})\left(x^{(0)}(1) - \frac{b}{a}\right)e^{-ak} \end{aligned} \tag{9}$$

According to Equation (9), the fitted values and predicted values of the sequence $X^{(0)}$ can be calculated.

3. Forecasting of China's primary energy consumption

3.1. Forecasting with ARIMA(2,1,1) Model

The time series of China's primary energy consumption is shown as Fig. 1. It is not difficult to find that there is a turning point in 2001. After 2001, China's primary energy consumption rise at a larger growth rate. As it is known, China joined World Trade Organization (WTO) in 2001. The international market is more and more open to China. And China's exports have sharply grown since 2001 due to China's accession to WTO. In fact, China's development has entered a new stage since then. The sustained and rapid economic growth has stimulated rapid increase in energy consumption. In econometric time series analysis, a dummy variable may be used to indicate the occurrence of wars, major strikes or other incidents, and it takes the value 0 or 1. And a dummy variable F used to indicate China's accession to WTO. If China is a WTO member, F is assigned the value of 1; otherwise it would get the value of 0. The coefficient of F can be interpreted as the influence on energy consumption of China's WTO accession or not.

And it can also be found that there is a time trend in China's primary energy consumption in Fig. 1.

In order to verify the time trend and sudden change mentioned above, the following model is constructed:

$$E = c + b_1 t + b_2 F + u \tag{10}$$

Where: E is China's primary energy consumption;
c is a constant;
t is time;

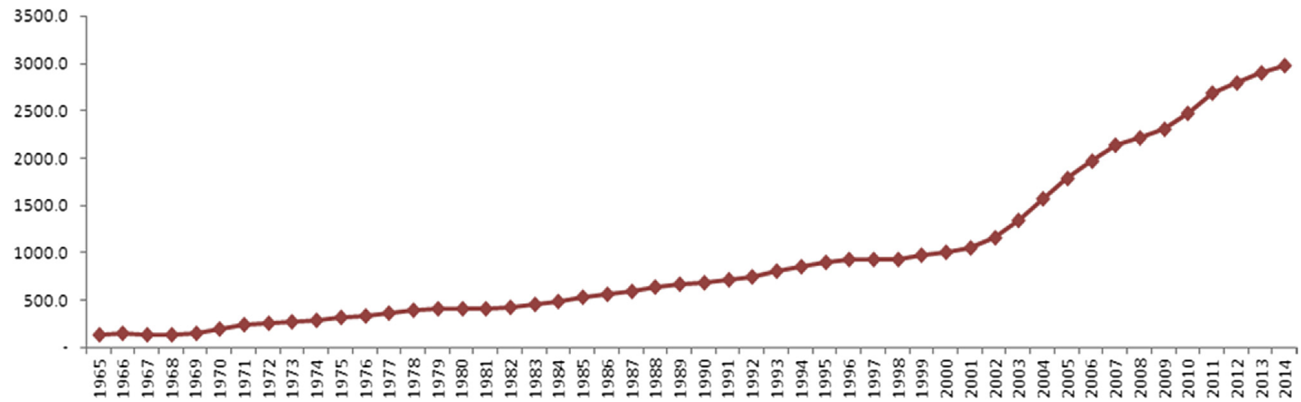

Fig. 1. China's primary energy consumption (million barrel barrels of oil equivalent).
Source: BP Statistical Review of World Energy 2015

u is white noise.

F is a dummy variable, and $F = \begin{cases} 0, t \leq 2000 \\ 1, t \geq 2001 \end{cases}$, represents China's accession to WTO which lead to a sudden change of China's primary energy consumption.

b_1, b_2 are the coefficients.

Equation (10) is estimated, and the results are shown in Table 2.

It is shown that the coefficients of the t and F are statistically significant at 1% significance level in Table 2. And the assumptions of time trend and sudden change of China's primary energy consumption is confirmed by this result.

Due to the time trend and sudden change, the times series of China's primary energy consumption will be detrended before the stationary test. And the following equation is obtained according to Equation (10) and Table 2:

$$\hat{u} = E + 101.0223 - 33.13844t - 756.1929F \tag{11}$$

Where $\hat{u}$ is the residual series of Equation (11), and it represents the detrended series of China's primary energy consumption. And the stationarity of $\hat{u}$ is tested by ADF, PP and KPSS methods, and the results are shown in Table 3.

Although KPSS tests show that $\hat{u}$ is stationary at 10% significance level and the first order difference is non-stationary, the ADF and PP tests indicate that $\hat{u}$ is non-stationary and the first order difference is stationary at 1% significance level. It is more reasonable that the first order difference of $\hat{u}$ is stationary according to these results, namely $\hat{u} \sim I(1)$. In further, the following equation is assumed:

$$D(E) = c + b_1 t + b_2 F + u \tag{12}$$

Table 2
The estimation of Equation (10).[a]

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	−101.0223	91.60366	−1.102820	0.2757
F	756.1929	137.7991	5.487649	0.0000
t	33.13844	4.287450	7.729174	0.0000
R-squared	0.893562	Mean dependent var.		955.7420
Adjusted R-squared	0.889033	S.D. dependent var.		825.3805
S.E. of regression	274.9489	Akaike info criterion		14.12917
Sum squared resid.	3553054.	Schwarz criterion		14.24389
Log likelihood	−350.2293	Hannan-Quinn criter.		14.17286
F-statistic	197.2855	Durbin–Watson stat.		0.213071
Prob (F-statistic)	0.000000			

[a] All the estimations related to ARIMA model are made with Eviews 6.0.

Table 3
Stationary tests.

		t-Statistic	Prob.
Level	ADF	−0.638553	0.9720
	PP	−0.843320	0.9541
	KPSS	0.133030[b]	
First difference	ADF	−5.875086[a]	0.0001
	PP	−5.872409[a]	0.0001
	KPSS	0.097434	

[a] Significant at 1% significance level.
[b] Significant at 10% significance level.

Where: $D(E)$ is the first order of China's primary energy consumption;

c, t, F, b_1, b_2,u are defined as Equation (10).

Then, Equation (12) is estimated, and the results are shown in Table 4.

The autocorrelation and partial correlation of the residuals (u) of Equation (12) are shown in Table 5. It is shown that AR (1), AR(2), MA(1) and MA(3) should be induced to Equation (12) by trailing or censored of the autocorrelation and partial correlation. But MA will be irreversible when AR(1), AR(2), MA(1) and MA(3) are included. And MA(3) is excluded. According to the form of ARIMA model in Equation (3), AR(1), AR(2) and MA(1) will be added to the right side of Equation (12). And then an ARIMA(2,1,1) is obtained as follows.

$$D(E) = c + b_1 t + b_2 F + a_1 AR(1) + a_2 AR(2) + mMA(1) \tag{13}$$

Then Equation (13) is estimated, and the results are shown in Table 6. The t tests show that all the coefficients are significant at 1%

Table 4
Estimation of Equation (12).

Variable	Coefficient	Std. error	t-Statistic	Prob.
c	17.80857	11.98227	1.486243	0.1440
F	106.7771	17.31149	6.167992	0.0000
t	0.371429	0.552995	0.671667	0.5052
R-squared	0.716184	Mean dependent var.		57.97347
Adjusted R-squared	0.703844	S.D. dependent var.		62.61961
S.E. of regression	34.07770	Akaike info criterion		9.954434
Sum squared resid.	53419.33	Schwarz criterion		10.07026
Log likelihood	−240.8836	Hannan-Quinn criter.		9.998378
F-statistic	58.03849	Durbin–Watson stat		1.040166
Prob (F-statistic)	0.000000			

Table 5
The autocorrelation and partial correlation.

<table>
<tr><th>Autocorrelation</th><th>Partial correlation</th><th></th><th>AC</th><th>PAC</th><th>Q-Stat</th><th>Prob</th></tr>
<tr><td>. |*** |</td><td>. |*** |</td><td>1</td><td>0.435</td><td>0.435</td><td>9.8367</td><td>0.002</td></tr>
<tr><td>.*| . |</td><td>***| . |</td><td>2</td><td>−0.143</td><td>−0.409</td><td>10.918</td><td>0.004</td></tr>
<tr><td>***| . |</td><td>.*| . |</td><td>3</td><td>−0.395</td><td>−0.192</td><td>19.374</td><td>0.000</td></tr>
<tr><td>.*| . |</td><td>.*| . |</td><td>4</td><td>−0.180</td><td>0.112</td><td>21.165</td><td>0.000</td></tr>
<tr><td>.*| . |</td><td>**| . |</td><td>5</td><td>−0.076</td><td>−0.254</td><td>21.494</td><td>0.001</td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>6</td><td>0.014</td><td>0.036</td><td>21.506</td><td>0.001</td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>7</td><td>0.050</td><td>0.018</td><td>21.653</td><td>0.003</td></tr>
<tr><td>.*| . |</td><td>**| . |</td><td>8</td><td>−0.085</td><td>−0.325</td><td>22.092</td><td>0.005</td></tr>
<tr><td>**| . |</td><td>.*| . |</td><td>9</td><td>−0.270</td><td>−0.181</td><td>26.630</td><td>0.002</td></tr>
<tr><td>.*| . |</td><td>. | . |</td><td>10</td><td>−0.175</td><td>0.039</td><td>28.589</td><td>0.001</td></tr>
<tr><td>. |*. |</td><td>. | . |</td><td>11</td><td>0.134</td><td>0.002</td><td>29.769</td><td>0.002</td></tr>
<tr><td>. |*. |</td><td>.*| . |</td><td>12</td><td>0.189</td><td>−0.194</td><td>32.191</td><td>0.001</td></tr>
</table>

significance level. And the adjusted R-squared is 0.823305, which also indicates that the model is good.

The related tests are shown in Table 7. All the tests except LJB, show that the model of Equation (13) is stable and in line with requirements. LJB test shows that the residuals are not normally distributed. And ARCH test shows no conditional heteroskedasticity. So the non-normal distribution of the residuals is probably caused by ignoring the nonlinear characteristics. In a word, the Equation (13) is acceptable.

And the fitted values of ARIMA(2,1,1) are shown in Fig. 2 by the green polyline. It is shown that it is a good fitting. The MAPE (Mean Absolute Percent Error) is defined to reflect the accuracy of the fittings:

$$\overline{\Delta} = \frac{1}{n}\sum_{t=1}^{n}\frac{|\widehat{y}_t - y_t|}{y_t} \tag{14}$$

Where: $\overline{\Delta}$ is MAPE;
$\widehat{y}_t$ is the fitted value at time t;
y_t is the actual value at time t.

Table 6
Estimation of ARIMA model.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	14.06834	5.673192	2.479793	0.0173
F	103.6168	8.526556	12.15225	0.0000
T	0.612647	0.264409	2.317042	0.0256
AR(1)	1.281217	0.128431	9.975931	0.0000
AR(2)	−0.695122	0.126146	−5.510462	0.0000
MA(1)	−0.950779	0.040622	−23.40576	0.0000
R-squared	0.842511	Mean dependent var.		60.50426
Adjusted R-squared	0.823305	S.D. dependent var.		62.64294
S.E. of regression	26.33200	Akaike info criterion		9.498191
Sum squared resid.	28428.34	Schwarz criterion		9.734380
Log likelihood	−217.2075	Hannan-Quinn criter.		9.587070
F-statistic	43.86721	Durbin−Watson stat.		1.766658
Prob (F-statistic)	0.000000			
Inverted AR Roots	0.64 − .53i	0.64 + .53i		
Inverted MA Roots	0.95			

And MAPE of ARIMA(2,1,1) calculated according to Equation (14) is 4.62%.

3.2. Forecasting with GM(1,1) model

GM(1,1) model in Section 2.2 can predict with four data. And the data of four consecutive year are used to forecast the next one by GM(1,1) to get the fitted value of the next year. The smooth ratio should be less than 0.5 [21], and the value of 1966 can not pass this test. Thus, the first fitted value of GM(1,1) model is that of 1971. Then, roll forward until the fitted value of 2014 is obtained. And all the fitted values are shown as the light blue polyline in Fig. 2. And the It is shown that it also is a good fitting. And MAPE of GM(1,1) model calculated according to Equation (14) is 3.75%.

3.3. Forecasting with GM-ARIMA model

It can be found that the residual of ARIMA model and GM(1,1) model have opposite signs in many points in Fig. 2. It is very interesting. The fitted values of ARIMA model, influenced by long-term trend, respond less to the fluctuations of the original data; while GM(1,1) model predicts with the latest four data, and the corresponding fitted values respond sensitively to the fluctuations. In further, this assumption will be tested with Wilcoxon signed rank test, because the residuals of ARIMA model are not normally distributed mentioned in Section 3.1.

A Wilcoxon signed rank test has a following null hypothesis and Alternative Hypothesis:

H0. Difference between the pairs follows a symmetric distribution around zero.

H1. Difference between the pairs does not follow a symmetric distribution around zero.

While we try to test that the residuals have opposite signs. Equivalently, we can test the relation between the residuals of ARIMA model and the opposite numbers of the residuals of GM(1,1) model. And they are paired for Wilcoxon signed rank test, and the results are shown in Table 8. It accepts the null hypothesis, which indicates that the residuals of the two models are opposite in the statistical sense.

So, the combination of these two models is a good idea to improve the accuracy of prediction. And the following GM-ARIMA hybrid model is defined to forecast China's primary energy consumption:

$$Hybrid = 0.5\, GM(1,1) + 0.5\, ARIMA\,(2,1,1) \tag{15}$$

Both the weights of the two univariate models are equal to 0.5, because their residuals are mutually opposite.

The fitted values of the hybrid model of GM-ARIMA are shown in Fig. 2 by the red polyline. It is shown that it is a better fitting. And MAPE of the hybrid model calculated according to Equation (14) is 2.30%.

The MAPEs of the three methods are shown in Table 9, and a smaller MAPE indicates that hybrid model is better than ARIMA and GM(1,1) model.

4. Results and conclusions

China's primary energy consumption is predicted by the three models, and the results are shown in Table 10. China's economic growth rate drops to about 7%, about two percentage less than the rates in previous years. It will lead to a slower growth of China's primary energy consumption, according to the casual relation between China's energy consumption and

Table 7
Tests for ARIMA model.

Tests	Q_{20}	Q^{*}_{20}	LM2	Heteroskedasticity test: ARCH	Ramsey RESET test:	LJB
Statistic	21.822	12.759	0.343401	0.578516	0.595640	35.64274
P value	0.192	0.752	0.7115	0.4510	0.6217	0.00000

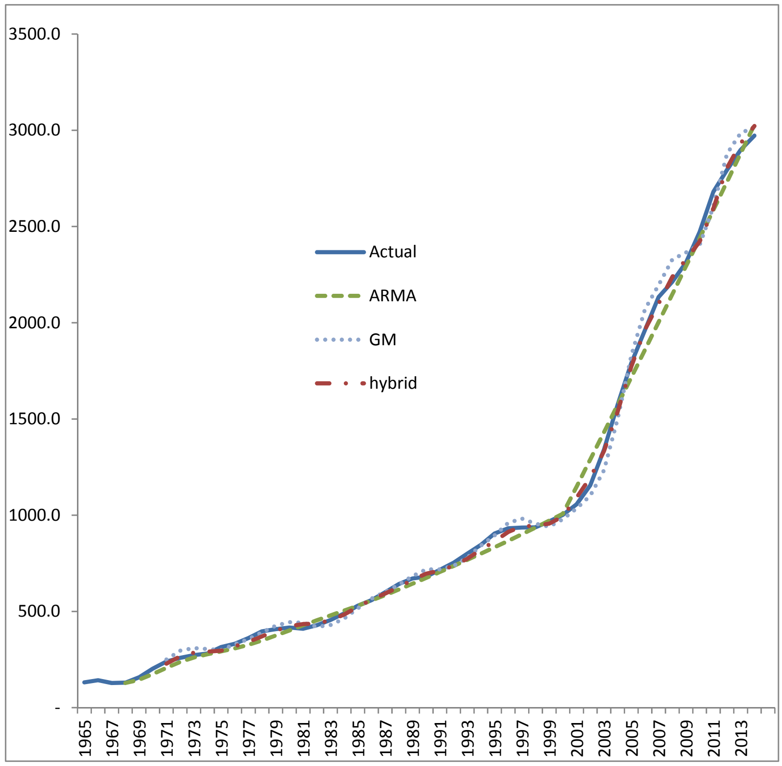

Fig. 2. The fittings of the three models.

Table 8
Wilcoxon signed rank test.

	-GM(1,1) residuals ARIMA residuals
Z	−1.435[a]
Asymp. Sig. (2-Tailed)	0.151

[a] Based on negative ranks

Table 9
MAPEs of the three methods.

	ARIMA	GM(1,1)	Hybrid
MAPE	4.62%	3.75%	2.30%

economic growth [22,23,24]. It is a real change. All the models reflect the newly trend. According to the Section 3, the results of ARIMA model will react less while those of GM(1,1) model will respond more. That is, GM(1,1) model will give a smaller prediction than the actual ones and the ARIMA model will give a bigger one. And the hybrid model will give a moderate and better one. It is worth noting that, the average annual growth rate of China's primary energy consumption reaches 8% since the new century, which induced the massive investment in the energy sector, while the slowdown of China's primary energy consumption in the next years could result in overcapacity of China's energy industry.

This paper uses ARIMA model, GM(1,1) model and the hybrid model to forecast China's primary energy consumption, and the following conclusions can be made:

(1) ARIMA, GM(1,1) and the hybrid model of GM-ARIMA are suitable for China's primary energy consumption forecasting. From the MAPEs, the hybrid model of GM-ARIMA is the best, GM(1,1) is the second best one, and ARIMA is the last best one.

Table 10
The prediction of China's primary energy consumption.

	2015	2016	2017	2018	2019	2020	Average annual growth rate
ARIMA	3177.448	3326.995	3477.154	3627.923	3779.304	3931.296	4.77%
GM	3069.8579	3165.5343	3264.1926	3365.9256	3470.8294	3579.0026	3.15%
Hybrid	3123.653	3246.265	3370.673	3496.924	3625.067	3755.149	3.97%

(2) As for the amount of calculation, GM(1,1) model is the most advantageous, although the three models are simple and easy to use.
(3) It is very interesting that the signs of the residuals of GM(1,1) model and ARIMA model are mutually opposite, resulting from the different modeling principles and data usage.
(4) For the future work, it is recommended to compare these models with the data of US or other developed countries, or compare these univariate models with the casual relationship models.

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