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Modeling And Forecasting Energy Structure Using Dynamical System

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***Abstract*—Reasonable energy structure can promote the realization of carbon emission reduction targets. Integrating all energy types into an energy structure vector, this paper proposes a vector dynamical system model to analyze the evolution of energy structure and then make a short-term prediction. The dynamical system model is presented in the form of a first order linear differential equation with piecewise continuous source term. To evaluate the efficiency of our method, we carry out experiments on energy structure data from 1990 to 2015 in China and compare the model with dimension-reduction model through a hyperspherical transformation (DRHT). With a 4.3343% mean absolute percentage error, the dynamical system model is proved to be highly accurate. The results of the dynamical system model are better than those of the DRHT model by comparing indictors of both the vector and its component. Prediction results show that the portion of coal in the energy consumption structure would decrease to 56.5% in 2020, and the portion of non-fossil energy would go up to 15.9%. It is inferred from the dynamical model that China would have achieved its goal of energy structure adjustment at that time.**

Keywords—energy structure; dynamical system model; energy structure vector; energy consumption; energy sources

I. INTRODUCTION

China, the world's biggest emitter of greenhouse gases, has made great efforts to slow climate change caused by CO_2 and other greenhouse gases from burning fossil fuels. CO_2 emission is also directly linked with use of energy which plays a focal role both for production and consumption in the world economy [1]. Great pressure from the international community and its increased need for energy have forced China to make an “energy saving and emission reduction” plan, which has become a basic national policy and a guideline for its energy and environmental issues during the 11th Five-Years Plan (2006-2010) [2]. Followed this policy, industrial structure adjustment, technology improvement and effective management shift Chinese economy from growth-at-all-cost to a more “balanced and sustainable” output model. Environmental protection has become a favor awareness for both the administrative system and the public. Furthermore, in the 2016 Paris Agreement, the country promised to reduce its carbon intensity to 60-65 percent below 2005 levels and to reach its peak by 2030. In addition, the world's second-largest economy also aims to increase the share of non-fossil fuels in its primary energy consumption to about 20 per cent by 2030 [3].

The adjustment and optimization of the primary energy structure play a key role for China to complete its 2030 carbon emissions reduction targets. China has a wealth of energy resources, a large number of coal, oil, natural gas and hydropower, as well as huge solar, wind and biomass energy potential. It even has its own uranium. To date, coal are always relied to generate its electricity and oil are used to power its vehicles.

It is said that the high carbon energy structure is the main cause of the deterioration of the ecological environment in China. China gets most of the energy from the most polluting fossil fuel of coal, because the coal produced and consumed in the country is almost the same as that in other parts of the world. At present, there have been a large number of studies on China's carbon emission reduction targets and the optimization of the primary energy structure. Many researchers have studied the target of China's emission reduction and the optimization of the primary energy structure [4-10].

Research on primary energy structure can be roughly divided into four categories. First research focuses on the relationship energy structure and carbon emission. Many researchers have studied China's emission reduction targets, and different views are in progress. Ren et al. believed that in the case of energy structure optimization, China's emission reduction targets will be difficult to achieve by 2030. Wang et al. discussed that China's carbon emission peak technology can be realized in 2025, but there will be some economic losses [11]. Another school of thought argues that the adjustment of energy structure is effective in achieving the goal of reducing carbon emissions. Xu et al. believed that it is effective to adjust energy structure to achieve Chinese plan on a low carbon economy [12]. Xie et al. found that the most direct and effective means of achieving carbon dioxide emission control is to optimize the energy structure [13]. Zhang et al. concluded that development of China's energy structure in a low-carbon scenario can achieve the goal of reducing carbon dioxide emissions [14]. All the authors provide evidence that unreasonable energy structure is the major cause of environmental degradation.

An extensive literature has been discussed on the energy structure optimization and adjustment. The adjustment of energy structure is carried out under the constraints of economic system, population, economy, industrial structure, energy efficiency, total energy, energy saving and carbon emissions.

Gao et al. established the optimization model of China's energy structure [15]. Combining with the learning curve effect of renewable energy cost and the growth of fossil energy cost over time, the researchers replied the portfolio theory to the model. The results concluded that the investment portfolio theory can reasonably optimize the energy structure of China. Sun et al. applied the minimum energy cost and the minimum carbon transaction cost as the objective function, built the multi-objective optimization model. The results show that the model can effectively solve the problem of energy structure optimization in Hebei province. Su et al. proposed a multi-objective optimization model of urban scale, the sustainable development of energy, economy and environmental systems were achieved by integrating the goals of the least energy consumption, the energy cost and the environmental impact [16]. It concluded that the multi-objective optimization model which considers the environmental impact comprehensively is helpful to the rational allocation of energy resources in the urban sector. The adjustment and optimization of a reasonable and scientific energy structure will help to provide guidance to the goal of the energy strategy and the energy security of China.

Previous researches have also concentrated on the relationship between energy structure and economy. Han et al. studied the influences of China's energy structure on energy efficiency from 1978 to 2003 [17]. The result showed that the shift of energy structure can effectively increase its aggregate energy efficiency. San et al. showed that the economic cost of rural families in Kampuchea is too large at present, which is mainly due to the fact that the current energy consumption in Kampuchea is using unclean energy and irrational energy structure [18].

The relationship between energy structure and economy has been a long-standing issue, and researches on the forecasting of energy consumption has been focused in recent years. Traditional methods such as time series [19,20], regression [21], econometric [22], ARIMA [23] and soft computing techniques like fuzzy logic [24,25], genetic algorithm [26], and neural networks [27,28] are widely used in demand-side management. Support vector regression [29], ant colony [30] and particle swarm optimization [31] are new techniques used to predict energy demand Bottom-up models such as MARKAL [32] and LEAP [33] are also applied to the regional and national regional level about energy demand management. Other researches adopted some new methods to build a clear forecasting model. For example, GM (1, 1), improved GM-APMA, Bayesian vector auto regression (BVAR), ADE-BPNN methods were used to estimate the energy consumption in the future. It is expected that the composition of China's energy consumption structure will also change. As time goes on, the growth of coal consumption will slow, and oil, gas and water and electricity will occupy a greater market share.

From the point of view about energy consumption, the literature usually focuses on the energy consumption data rather than energy structure data. It is not convenient for us to directly observe the proportion of various energy varieties, and to make the corresponding adjustment measures. From the model taken by forecasting, models in the above-mentioned researches are mainly based on traditional statistical methods. These models ignore continuity although they improve the overall forecasting accuracy. The composition of energy consumption is also forecast to change in China. Oil, gas, and hydroelectricity are expected to take on larger market shares as growth in coal consumption slows over time.

This paper aims to make a short-term prediction of energy structure using a dynamical system model in a clear continuous expression. We want to deal with the energy structure date itself rather than energy consumption data. Furthermore, we want to treat all energy sources as an integral variable and represent the variable in a continuous function of time. This paper utilizes dynamic system method to study the evolutionary rule of energy consumption structure. A first order linear differential vector equation is proposed. The source term reflects the external influence of energy consumption structure in the form of piecewise continuous functions. Using the dynamical model, short-term prediction can be made.

There are possibly three contributions of this study. First, this study bridges the gap between energy consumption and energy structure by modeling structure data itself. The evolution and trend of each energy source can be obtained directly from the solution of the dynamical model. Second, this study also creates a new aspect of model evaluation. Integrating all energy sources into a variable, one can evaluate directly the whole performance of the model. Third, the dynamical model is an enhanced model in that one can get the adjustment rate of the energy structure except for its evolution. Representing the variable in a continuous function of time, this paper can explore the advance rate of energy consumption structure, which reflects instant variation and variation trend of energy consumption structure more clearly.

The remainder of the paper is structure as follows. Section 2 introduces a continuous dynamical model. Section 3 describes the data source in the paper and analyzes the experiment result. Section 4 shows the compared results with DRHT model. The last section devotes to the overall conclusions and policy implications.

II. Method

A. Dynamical system model

We integrate all energy forms into an energy structure vector. Considering the time-varying property of each element of energy structure, this section proposes a continuous dynamical system model to reflect the evolution of energy structure. Let

$$X(t) = (x_1(t), \cdots x_N(t))', x_i(t) \geq 0,$$

be the energy structure vector, where the prime" ' " means transpose, $x_i(t), i = 1, \cdots N$, is the time-varying variable at time t of the i th energy element and N represents the number of energy elements.

The element of energy structure may take a different form in given a time period T but has a unique property in any open subintervals. Assume that the segmentation point is T^*. Then T be the union of such subintervals and segmentation points, that is, $T = \bigcup \{I_D, T^*\}$, where I_D is a subinterval.

The dynamic system model of energy structure is proposed as

$$\dot{X}(t) + X(t) = F(t), t \in \bigcup I_D \tag{1}$$

where $F(t) = (f_1(t), \cdots, f_N(t))'$, $f_i(t)$ is continuous or piecewise continuous on the whole time period but differentiable in each subinterval and "$\bigcup$" is the union of every subinterval.

Evolution of energy structure can be represented by the solution of Eq. (1):

$$X(t) = (C + \int F(t) e^t dt) e^{-t}, \tag{2}$$

where C is a constant to be determined to ensure the continuity of $x(t)$ on the whole time period.

B. Evaluation indices

We evaluate the modeling accuracy using three measurements: mean absolute error (MAE), root mean square error ($RMSE$), and mean absolute percentage error ($MAPE$). These measurements are respectively calculated as follows:

$$MAE = (\sum_{i=1}^{n} \left\| \hat{X} - X \right\|) / \mathrm{n} \tag{3}$$

$$RMSE = \sqrt{(\sum_{i=1}^{n} \left\| \hat{X} - X \right\|^2) / \mathrm{n}}$$

(4)

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} (\left\| \hat{X} - X \right\|) / \left\| X \right\| \tag{5}$$

where $\hat{X}$ and X are fitted and actual value at t and n is the number of observations. $\|\cdot\|$ be the Euclidean norm.

The smaller the MAE and $RMSE$ are, the better the fitted agrees with the actual data. Fitting is highly accurate when $MAPE$ is less than 10%, good when the $MAPE$ falls in the range 10%-20%, reasonable when $MAPE$ ranges between 20% and 50%, and inaccurate when MAPE is greater than 50% [34].

III. Data and Experiment Result

A. Data

China has an energy rich source, such as a large amount of coal, oil, natural gas and hydropower, as well as huge solar, wind and potential biomass energy. So far, coal and hydropower are relied to generate electricity and oil are used to power its vehicles. However, with the sea level climate change and the consequent rise in the incidence of drought, increasing fierce storm and so on, China has become the world's largest emitter of carbon dioxide, is facing intense international pressure to re-examine its energy strategy and try to reduce its emissions of carbon emissions. Therefore, the government plans to significantly increase the use of gas in power generation. Gas emissions are less than half of the CO_2 of coal emissions. Some people believe that in the next 20 years, large quantities of natural gas can be imported through pipelines and LNG dispensers, and the development of unconventional gas reserves in the country may partially replace large quantities of coal that is currently used for power generation, but they cannot be completely replaced by them. As for transport fuels, like other countries, China has no choice but to continue to rely on oil, whether importing or developing its own large shale oil business.

There is no alternative fuel of the same density at the same or better price. In the near future, the use of biofuels and hybrid vehicles will not replace the use of gasoline or diesel. As a result, the role of oil and gas in China's energy strategy will remain very significant in the next 20 years.

We use consumption structure as the energy structure of China. Energy structure data comes from “China Statistical Yearbook” (2016). In the statistical yearbook, four types of energy are listed: coal, oil, natural gas, hydroelectricity. The data are given in the structure form of energy consumption directly. Sample period covers from 1990 to 2015 due to the availability date.

Fig. 1 shows an overview of the energy structure. Coal plays a leading role in China's primary energy structure. In the past twenty years, coal accounts for about 70% of the total energy consumption. This situation is unlikely to change in the next few years. Oil is the next most important energy, accounting for about 20%. Coal and oil account for about 90% of total energy structure. Natural gas and hydroelectricity account for a small proportion. It should be pointed out that the proportion of coal has been changing from falling to rising since 2002. The proportion of natural gas and other energies is increasing these years.

The variation of the energy structure is closely related to energy policy reform. China has carried out three reforms in energy policy. In the first stage, focusing on energy supply shortages and rigid pricing mechanism and other issues, the implementation of coal prices was a “two-track system” to promote a variety of price reform. Encouraging local development of small coal mines. Coal consumption increased significantly. In the second stage, with initial reform in energy management system, the large-scale restructuring was carried out the oil industry. China's oil accounted for the proportion began to rise. In the third stage, China is implemented energy-saving emission reduction policies to promote the development of renewable energy. Coal consumption decreased and non-fossil energy accounted increased.

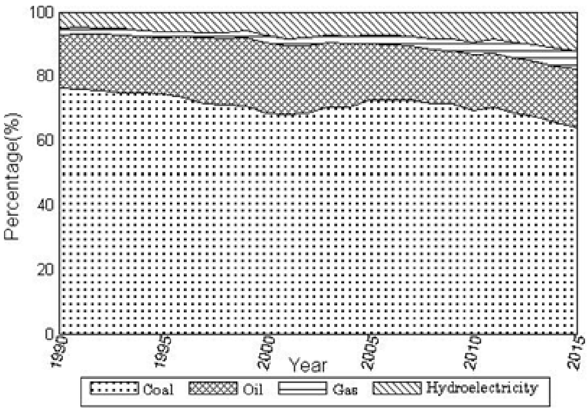

Fig. 1. The energy structure in China

B. *Evolution of energy structure*

This subsection reports the experimental results of energy structure element according to the Eq. (1). We first determined the possible segmentation points of each element according to energy market performance, implementation of energy policies, adjustment of energy price. Then the control function was obtained from the statistic data by the least-square method. Finally, the element of energy structure and its rate were derived from Eq. (1).

We found one turning point of the trend of actual data about coal. On the one hand, in 2005, as the macro-control and production capacity release, the development speed of electricity, iron and other downstream industries decreased significantly, resulting that the coal demand stabilized gradually. To achieve a basic balance between supply and demand, the domestic coal market has entered a new adjustment period. On the other hand, in 2006, analyzing from the international market point of view, the international energy prices rose continually, resulting increase in coal prices and the decline in coal consumption. Hence, we took 2006 (t=17) as the turning time of coal variable.

To oil consumption, there is also a clear turning point. Since 1990, China's oil consumption has shown an upward trend. In 2000, affected by high oil prices about international market, oil consumption declined. Therefore, we took 2000 (t=11) as the turning time of oil. There are no turning points for the last two types.

The control function for coal element is obtained as

$$\mathrm{f}_1(t)=\begin{cases}1.248*10^{-4}t^3-2.436*10^{-3}\mathrm{t}^2+\\ 5.632*10^{-3}\mathrm{t}+0.756, 1\le t<17\\ 1.842t^{-0.319}, 17\le t\le 26.\end{cases} \tag{6}$$

The evolution of coal element is presented by the first element of the solution of the dynamic function Eq. (1) as

$$x_1(t)=\begin{cases}1.248*10^{-4}t^3-2.810*10^{-3}\mathrm{t}^2+\\ 1.125*10^{-2}\mathrm{t}+0.745, 1\le t<17\\ 1.638t^{-0.282}, 17\le t\le 26.\end{cases} \tag{7}$$

whose graph is shown in Fig. 2.

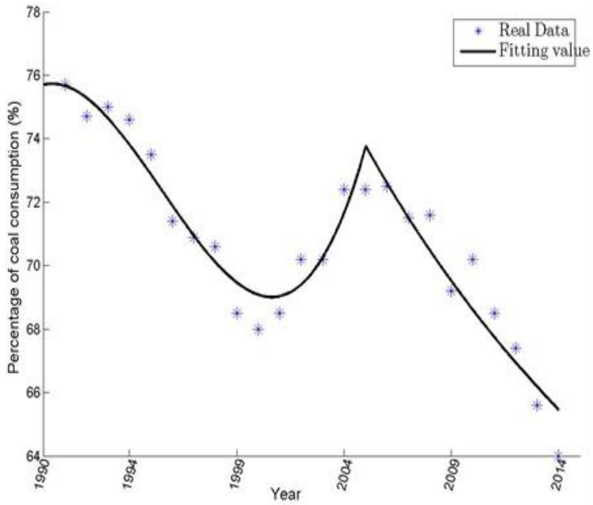

Fig. 2. Real data and fitting value of coal

To analyze the adjustment process of the coal, we calculated the adjustment rate of the coal and showed its graph in Fig.3. From Fig.2 and 3, one can see that coal mainly present a down-trend with two small short-period increases. It is a steadily increasing phase about coal consumption structure as its rate is positive from 1990 to 1992. The critical times are 1992, 2002 and 2006 with zero or non-existent derivatives.

From 1992 to 2002, the adjustment rate of coal structure is negative, reaching its local minima at 1997. The coal structure decreases faster year by year from 1992 to 1997, then deceases slower till 2002. The coal structure increases from 2002 to 2006 as the rate of coal structure is positive. After the segmentation point of 2007, there appears a rapid decline of coal structure. The adjustment strength is larger than that in the first decreasing period as the value of the absolute rate is greater.

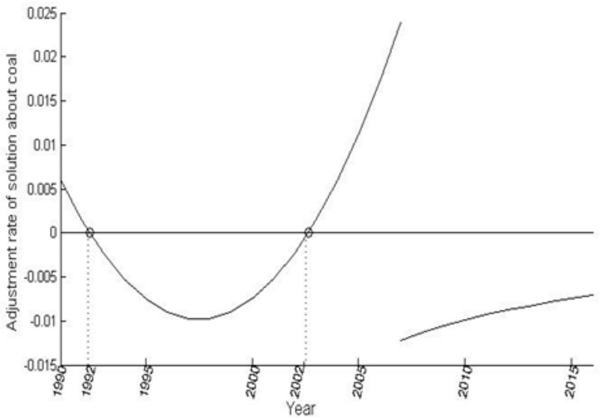

Fig. 3. Adjustment rate of coal

The evolution of oil element is presented by the second element of the solution of the dynamic function Eq. (1) as

$$x_1(t)=\begin{cases}5.833*10^{-4}t^2-1.808*10^{-3}\mathrm{t}^2+0.174, 1\le t<11\\ 5.424*10^{-4}t^2-2.310*10^{-2}\mathrm{t}\ +0.414, 11\le t\le 26\end{cases} \quad (8)$$

whose graph is shown in Fig.4. A graphical display of the adjustment rate for oil element is given by Fig.5.

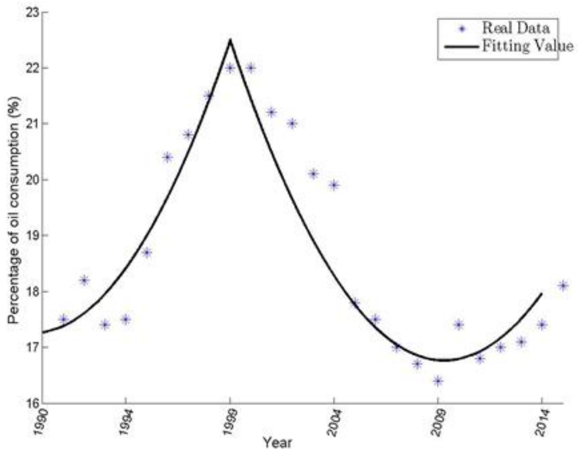

Fig. 4. Real data and fitting value of oil

The oil structure appears two increasing periods interrupted by a decreasing segment. Ignoring a decrease in less than one year at the beginning of the fitting function, we observe that the adjustment rate of oil structure is positive before 2000 and after 2011. Between 1990 and 2000, the oil structure shows an accelerating increase year by year. Then after the turning point of 2000, there appears a slower decrease till 2011. There is a steadily increasing phase of oil structure after 2011.

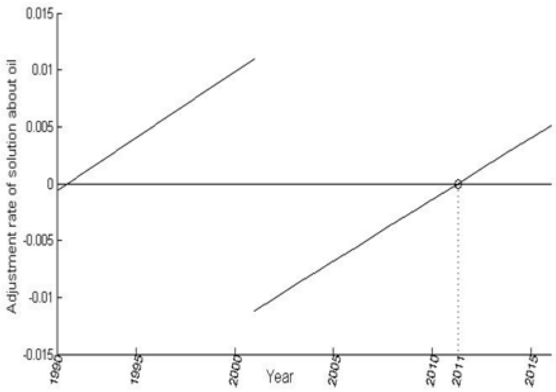

Fig. 5. Adjustment rate of the oil

(9)

whose graph is shown in Fig. 6. A graphical display of the adjustment rate for the natural gas element is given by Fig. 7.

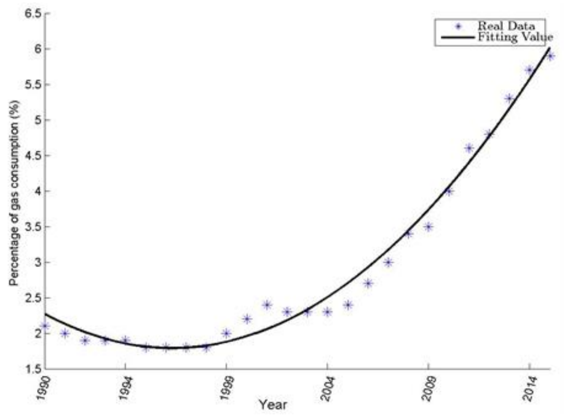

Fig. 6. Real data and fitting value of natural gas

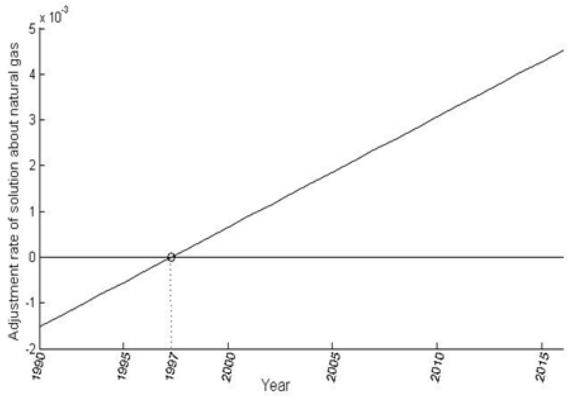

Fig. 7. Adjustment rate of natural gas

Different from the coal and oil, the natural gas structure evolves in a smooth way, decreasing slightly at the first eight years then increasing continuously. This phenomenon is explained by the sign of the adjustment rate which is negative before 1997 and changes to be positive after that year.

The evolution of hydroelectricity element is presented by the last element of the solution of the dynamic function Eq. (1) as

$$x_4(t) = 1.380*10^{-5}t^3 - 5.289*10^{-4}t^2 + 7.842*10^{-3}\mathrm{t} + 0.030, 1 \le t \le 26, \quad (10)$$

whose graph is shown in Fig.8. A graphical display of the rate for hydroelectricity element is given by Fig.9.

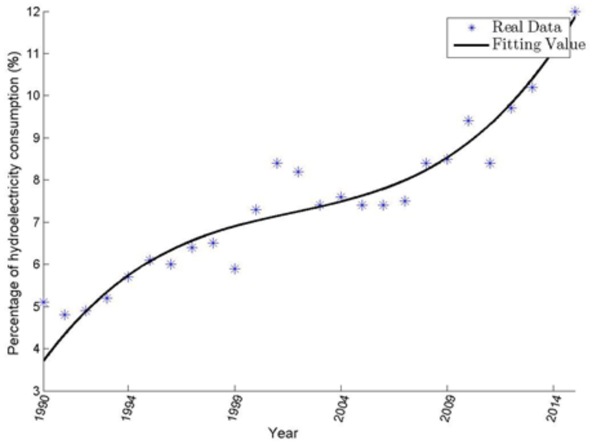

Fig. 8. Real data and fitting value of hydroelectricity

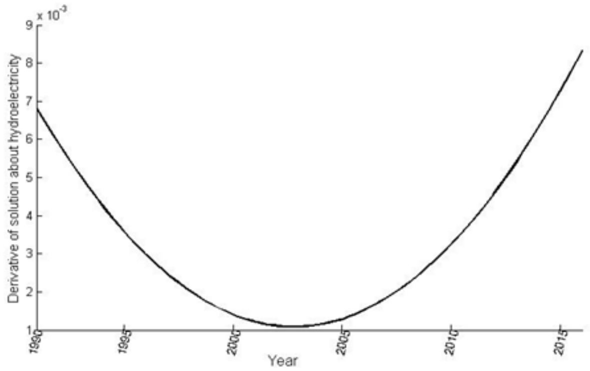

Fig. 9. Adjustment rate of hydroelectricity

The hydroelectricity show a unique characteristic in that it increases in the whole study period as the adjustment rate of hydroelectricity is always positive. The adjustment rate shows a tendency that decreases first and then increases. Before 1998, there is a steadily increasing phase, while between 1998 and 2006, it is a slightly increasing phase. After 2003, the hydroelectricity structure shows an accelerating-increasing trend.

C. Prediction results

We made a short-term prediction using the obtained expressions. Fig.10 shows the prediction results. It is predicted that the proportion of coal would decrease gradually while those of none-coal variables would increase. The share of coal structure would drop from 64% in 2015 to 56.5% in 2020, with an annual rate of 0.015%. The order of the shares is coal, oil, natural gas, and hydroelectricity. Coal remains the predominant role in energy structure in the new future. Those predicted values fall in the requirement of energy reform targets. In the "13th Five-Year Plan", China promised that the percentage of coal consumption is expected a decrease to below 60% in 2020 [35], the share of non-fossil in total primary energy consumption is up to 15% by 2020 [36]. It is obvious that China would have achieved those goals according to the dynamical model.

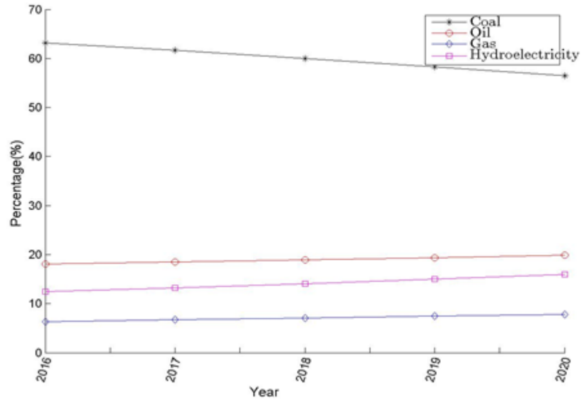

Fig. 10. Predicting value of energy elements

IV. COMPARING WITH DRHT MODEL

A. The DRHT method

Being proportions of energy consumptions, energy structure is actually a kind of compositional data. Compositional data, proposed by Aitchison [37] is quantitative descriptions of the parts of some whole, conveying exclusively relative information. The component data must satisfy the constraint that the sum of all components is one [38].

Wang et al. developed the dimension-reduction approach through a hyperspherical transformation (DRHT) method to forecast compositional data [39]. A detailed description about the DRHT method is presented in Appendix A of this paper.

B. Experiment results with the DRHT model

In words of the DRHT method, energy structure data $X(t)$ is represented as a time sequence

$$X(t) = \{(x_1(t), \cdots, x_4(t))' \in R^4 \,\Big|\, \sum_{i=1}^{4} x_i(t) = 1, 0 \le x_i(t) < 1\}, t = 1, \cdots, 26. \quad (11)$$

According to the DRHT method, we performed first a square root transformation and then a hyperspherical transformation on the elements of the energy structure data. By a reverse transformation, we calculated the fitting and forecasting results. Fig.11 shows those results.

Fig.11 shows a declined trend of coal and oil consumption. The proportion of coal goes down to 60.3% at the end of 2020. Nature gas and hydroelectricity consumption are rising and the consumption of hydroelectricity goes up to 19.4% in 2020.

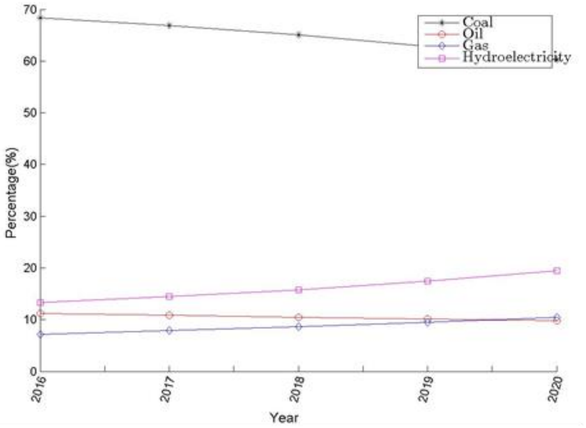

Fig. 11. Predicting value of energy elements

C. Performance comparison

Comparison between the dynamical system and the DRHT model were made from two aspects: the element point of view and the energy structure vector view. Three measurements mentioned in section 2.2 are used to evaluate the models. Figs.12 and 13 show the results.

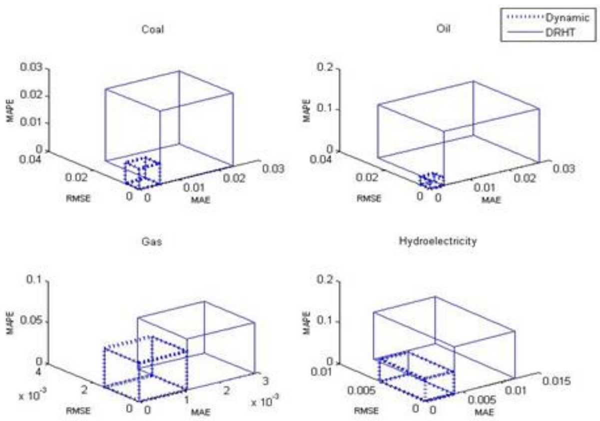

Fig. 12. Element performance comparison between the dynamical model and the DRHT model

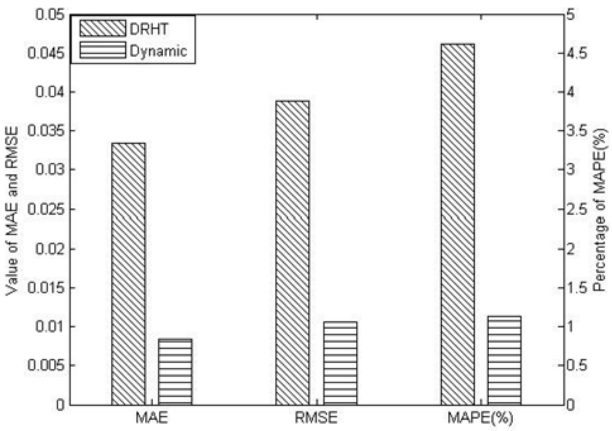

Fig. 13. Vector comparison between the dynamic model and the DRHT model

Fig.12 shows the elemental comparison between the dynamical system and the DRHT model. We visualize the model performance by cuboids in a coordinate space. Three performance measurements, namely, the MAE, RMSE, MAPE, are taken to be the $x-$, $y-$, $z-$ axis to build the space coordinate system. Values of the MAE, RMSE, MAPE represents the length, width, and height of the cuboids. The volume of the cuboid represents the fitting effect of the energy element.

From Fig.12, we can see that the volumes of cuboids about the dynamical system are less than those of the DRHT model for all energy elements. Large difference exists between the volumes of the cuboids in each subfigure except for natural gas, implying that the dynamical model performs better than the DRHT model. From the perspective of four energy structure elements, the volume of the cube of coal about the dynamical system is the smallest, followed by that of oil, natural gas, and hydroelectricity, indicating that the fitting results of the coal are the best.

The vector comparison is made in a $2-D$ plane. We established a plane rectangular coordinates. The horizontal axis represents the evaluation indices: MAE, RMSE, MAPE. The vertical axis represents the proportions of every evaluation indices. We made six histograms, whose height show the value of measurements. Fig.13 shows the comparison of energy structure vector between the dynamical system and the DRHT model, the height of MAE, RMSE are less than 0.05 while that of MAPE is less than 10%. The height of histogram about evaluation indices of dynamical system is about one-third of DRHT model. Forecasting performance measurement about two methods shows accuracy about dynamical system.

V. CONCLUSIONS AND POLICY IMPLICATIONS

A. Conclusions

This paper introduces a dynamic model of energy structure and makes short-term prediction. The model can be used to make continuous predictions for the future energy structure, either in China or other countries and regions.

The results of measurements show a high fitting accuracy of the dynamical model. A comparison between the dynamic model and the DRHT model shows the advantage of the dynamic model. Predicting result show that the percentage of coal would decrease to 56.5% in 2020, and the portion of non-fossil energy would go up to 15.9%. China would have achieved the reduction goals.

Further researches in energy structure should be conducted. It is worth noting that the current energy market in China is not perfect. So by no means, the government cannot ignore the impact of energy structure when formulating energy policies.

B. Policy implications

Energy consumption structure is directly related to a country's energy production structure as well as energy strategy for import and export. From 1990 to 2015, energy consumption structure of China were improved. As for the proportion of coal, there was a decline tendency. This trend will continue. Based on the above fact, if the government establish the logical energy strategies and policies, the goals of the percentage of coal decrease to 60% and 15% share of non-fossil in 2020 in the 13th Five-Year Plan will be achieved. Energy structure reasonable is an important index to measure the status of a national and regional economic development. In the meantime, it is an important index to evaluate a country's economic development sustainable.

Therefore, policy makers are suggested to focus on adjusting energy structure and developing new technologies.

China should accelerate energy structure adjustment, decline the proportion of coal in energy structure and increase the proportion of non-fossil energy consumption. The government should improve the utilization efficiency of coal and reduce the proportion of coal in energy structure because of the large percentage of coal in primary energy structure. Technology innovation should be strength, production technologies should be exploited. China should accelerate the development of non-fossil energy technologies. The green low-carbon should be implemented to accelerate the pace of development of low-carbon energy, to expand the proportion of natural gas utilization, and to increase continuously the proportion of non-fossil energy consumption. In addition, development of new energy resources and renewable energy resources should be emphasized. Nuclear and biomass sources will be the main alternatives.

The Chinese government should reasonably adjust energy price. Low prices prompt more coal consumption. The government should focus on the rational pricing of coal and the improvement of coal production and processing technology. As for some problems such as environmental damage, serious pollution and low resource utilization with the exploitation and using of coal. The future energy structure may be influenced by oil prices fluctuation. Reducing the oil prices will contribute to increase oil consumption and play an important role in replacing coal resources and reducing the coal consumption.

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APPENDIX A. Dimensionality reduction through hyperspherical transformation

The DRHT refers to dimensionality reduction through hyperspherical transformation, and map the compositional data vector to the spherical coordinates so as to achieve the goal of reducing the dimension.

We consider a set of compositional data $X(t)=(x_1(t),x_2(t),\cdots,x_q(t))'$ in the time series of $t=1,2,\cdots,T$. represents proportions of some whole subjected to both non-negativity and unit-sum constraints, and it satisfies

$$\sum_{i=1}^{p} x_i = 1, 0 \le x_i < 1.$$
(A.1)

First, we perform a square root transformation about $X(t)$,

$$y_i(t) = \sqrt{x_i(t)}, i = 1, \cdots, q, t = 1, \cdots, T.$$
(A.2)

It is obvious that

$$\|y(t)\|^2 = \sum_{i=1}^{q} (y_i(t))^2 = 1.$$
(A.3)

The vector

$y(t) = (y_1(t), \cdots, y_p(t))' \in R^q (t = 1, \cdots, T)$ is on the surface of a q-dimensional hypersphere with radius one at any time t.

Second, the mapping about the vector $Y(t)$ from the Cartesian coordinate system onto a hyperspherical coordinate system are finished. It is satisfied that, and the mapping equations are as follows:

$$\begin{cases} y_1(t) = \sin\theta_2(t)\sin\theta_3(t)\sin\theta_4(t)\cdots\sin\theta_q(t) \\ y_2(t) = \cos\theta_2(t)\sin\theta_3(t)\sin\theta_4(t)\cdots\sin\theta_q(t) \\ y_3(t) = \cos\theta_3(t)\sin\theta_4(t)\cdots\sin\theta_q(t) \\ \vdots \\ y_{q-2}(t) = \cos\theta_{q-2}(t)\sin\theta_{q-1}(t)\cdots\sin\theta_q(t) \\ y_{q-1}(t) = \cos\theta_{q-1}(t)\sin\theta_q(t) \\ y_{q-1}(t) = \cos\theta_q(t), \end{cases}$$
(A.4)

The dimension of the vector $X(t)$ is reduced from q to $q-1$. In Eq. (A.5), a recursive algorithm is applied to compute $\theta_i(t), i = 2, 3, \cdots, q.$

$$\begin{cases} \theta_q(t) = \arccos y_q(t) \\ \theta_{q\text{-}1}(t) = \arccos(\dfrac{y_{q-1}(t)}{\sin\theta_q(t)}) \\ \theta_{q\text{-}1}(t) = \arccos(\dfrac{y_{q-2}(t)}{\sin\theta_q(t)\sin\theta_{q\text{-}1}(t)}), t = 1, 2, \cdots, T. \\ \vdots \\ \theta_2(t) = \arccos(\dfrac{y_2(t)}{\sin\theta_q(t)\sin\theta_{q\text{-}1}(t)\cdots\sin\theta_3(t)}) \end{cases}$$
(A.5)

We build $q-1$ models for each angle data series $\theta_i(t)$, for example

$$\hat{\theta}_i(t) = f_i(t) + \varepsilon_i(t), i = 2, 3, \cdots, q. \quad \text{(A.6)}$$

Then, we predict the angle at time $T+l$ for different i using the angle models.

$$\hat{\theta}_i(T+1) = f_i(T+l), i = 2, 3, \cdots, q. \quad \text{(A.7)}$$

The predicted value

$\hat{y}(T+l) = (\hat{y}_1(T+l), \cdots, \hat{y}_Q(T+l))$ is computed. We have

$$\sum_{i=1}^{q} (y_i(T+l))^2 = 1.$$
(A.8)

Finally, we obtain the predicted value at time $T+l$:

$$\hat{x}_i(T+1) = (\hat{y}_i(T+l))^2, i = 2, 3, \cdots, q.$$
(A.9)