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Can China Achieve the 2020 and 2030 Carbon Intensity Targets through Energy Structure Adjustment?

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Abstract: To mitigate global warming, the Chinese government has successively set carbon intensity targets for 2020 and 2030. Energy restructuring is critical for achieving these targets. In this paper, a combined forecasting model is utilized to predict primary energy consumption in China. Subsequently, the Markov model and non-linear programming model are used to forecast China's energy structure in 2020 and 2030 in three scenarios. Carbon intensities were forecasted by combining primary energy consumption, energy structure and economic forecasting. Finally, this paper analyzes the contribution potential of energy structure optimization in each scenario. Our main research conclusions are that in 2020, the optimal energy structure will enable China to achieve its carbon intensity target under the conditions of the unconstrained scenario, policy-constrained scenario and minimum external costs of carbon emissions scenario. Under the three scenarios, the carbon intensity will decrease by 42.39%, 43.74%, and 42.67%, respectively, relative to 2005 levels. However, in 2030, energy structure optimization cannot fully achieve China's carbon intensity target under any of the three scenarios. It is necessary to undertake other types of energy-saving emission reduction measures. Thus, our paper concludes with some policy suggestions to further mitigate China's carbon intensities.

Keywords: carbon intensity target; energy structure; gray model (GM (1, 1)); generalized regression neural network (GRNN); Markov forecasting model; non-linear programming

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1. Introduction

As the greenhouse effect continues to increase on a global scale, the warming climate has become a universal challenge facing modern human society [1]. In recent years, as China's economy has continued to develop, its energy consumption and carbon emissions have also risen. In 2007, China's total carbon emissions surpassed those of the United States, making China the world's largest carbon emitter [2]. At present, China's carbon emissions account for approximately one-quarter of the total global carbon emissions, and the country's participation in climate change mitigation actions is essential [3]. In 2009, the Chinese government made a commitment at the Copenhagen Global Climate Conference: by 2020, carbon dioxide emissions per unit of gross domestic product (GDP) in China will decrease by 40–45% compared to 2005 levels [4]. In 2015, China submitted a UN self-determination document on climate change. By 2030, the country intends to reduce carbon dioxide emissions per unit of GDP by 60–65% compared to 2005 [5]. These carbon intensity targets are not only voluntary actions for China to combat climate change but also a commitment to the international community. China's energy structure is lagging behind that of developed countries, and coal consumption has continued at a high level for many years. The slow development of renewable energy sources has led to high total carbon emissions, high carbon intensity and low energy efficiency in China. Simultaneously, the unreasonable structure of energy consumption has also put considerable pressure on China's ecological environment. As the largest developing country in the world, China remains in a stage of industrialization and rising urbanization with immense energy consumption. One of the great challenges China faces is how to coordinate economic growth with energy conservation and emission reduction. Optimization of the energy structure not only aids in reducing carbon emissions and carbon intensity, but it also addresses the current situation of China's energy demand. During the process of economic growth, the global community should prevent further deterioration of the ecological environment and promote sustainable economic development.

Forecasting energy consumption and carbon emissions will aid in setting reasonable energy saving and emission reduction policies. Recently, many experts have conducted research on China's carbon emissions. These studies can be classified into two main categories. The first is to factorize carbon emissions and to search for carbon emission factors to predict carbon emissions. The widely used methods include the logarithmic mean divisia index (LMDI) decomposition model [6,7], the divisia index decomposition model [8,9], the input–output analysis model [10], the Kaya model [11,12], stochastic impacts by regression on population, the affluence and technology (STIRPAT) model [13], and so on [14,15]. However, the prediction models do not usually have high accuracy due to the complexity of the selected factors and difficulty in predicting the influencing factors. The second category is based on timing trends, directly establishing mathematical models to predict carbon emissions. The most frequently used methods are the auto-regressive integrated moving average (ARIMA) model [16], gray prediction model [17], and the artificial neural network model [18]. Such models often have high requirements for data quality. In addition, some researchers have used other models to study carbon emissions. Gambhir et al. [19] used a combined model to forecast China's carbon emissions from 2005 to 2050. Choi et al. [20] used a data envelopment analysis (DEA) model to predict the carbon emission reduction potential and energy efficiency in China. When Du et al. [21] evaluated potential carbon emission reductions in China using a non-parametric metafrontier model, the results showed that China's annual carbon emission reduction potential during the 11th five-Year period reached up to 168.7 million tons of carbon dioxide.

Based on the forecasted carbon emissions, several researchers have conducted studies on whether the carbon intensity targets for China in 2020 and 2030 can be achieved [22–26]. Stern et al. [27] evaluated the difficulty of achieving the carbon intensity targets in China and India by decomposing the factors that influence carbon intensity, but the authors did not consider the economic factors in their model. Yi et al. [28] and Xiao et al. [29] used scenario analysis to conclude that the target for carbon intensity in China in 2020 will most likely be realized, while Yuan et al. [30] determined that if China's clean energy accounted for 17% of the total energy in 2020, the carbon intensity target could be achieved by 2020. Starting with a low-carbon policy, Wang et al. [31] conducted an inter-provincial emission reduction path analysis of China's carbon intensity in 2020. According to the principle of fairness and common but differentiated responsibility, Yi et al. [32] selected three indicators—per capita GDP, accumulated carbon emissions from fossil fuel and energy consumption per unit of industrial added value—to establish a provincial carbon intensity distribution model to achieve the 2020 carbon intensity target. Research by Xu et al. [33] showed that under China's existing policies, the carbon intensity targets for both 2020 and 2030 can be achieved, but the overall goals of 840 million tons of carbon dioxide emissions by 2020 and 710 million tons by 2030 cannot be met. Through Monte Carlo simulation and scenario analysis, Zhang et al. [34] observed that China can achieve the carbon intensity targets for 2020 and 2030 on the basis of the existing policies. However, it is not clear whether China can achieve its peak carbon emission goal by 2030. Most of the above studies focus mainly on the relationship between economic development and carbon emissions, and the generation of regional allocations of the carbon intensity targets. There are few studies on the energy consumption structure. In addition, existing research lacks a forecast for China's carbon emissions by 2030, and omits whether the carbon intensity targets can be achieved by 2030. The abovementioned papers are listed in Appendix A; Table A1. This paper also summarizes the above research methods and their advantages and disadvantages in Table 1. Based on these studies, we present research topics and methods.

According to our discussion, there are many ways to predict energy consumption and carbon emissions, but each method has some shortcomings. To overcome these shortcomings, this paper first uses the combined forecasting model to forecast the total primary energy consumption. Then, scenario analysis is utilized to predict the energy consumption structure. Finally, based on the predictions for energy consumption and energy structure, combined with the carbon emission factors, the total carbon emissions and carbon intensities under different scenarios are obtained, and the potential contribution of energy structure optimization to achieve the carbon emission intensity target is calculated.

Compared with the existing research, the innovations in this paper are reflected in the following three main aspects:

(1) First, this paper predicts the primary energy consumption based on a combined forecast model. A primary energy consumption forecast is the basis for a prediction of the energy structure. In this paper, to determine the characteristics of a time series of primary energy consumption that are affected by numerous factors, the gray prediction model and the generalized regression neural network (GRNN) model are combined to predict energy consumption. The gray prediction model predicts future energy consumption based on historical changes, and the exogenous variables considered by this model have less impact. To compensate for defects in the gray prediction model, the GRNN model is introduced. The influencing factors of primary energy consumption are selected as the input layer variables for the GRNN model, and the prediction results are achieved by predicting the input variables. Then, gray relational analysis is used to empower the gray prediction model and GRNN model, and finally, the combined forecasting result is obtained. Compared to the distinct forecasting model, the combined model synthesizes more factors that affect the dependent variable, the forecasting accuracy is higher, and the forecasting result is more closely aligned with reality.

(2) Second, this paper considers energy structure optimization in three scenarios: a natural evolution scenario, a policy planning scenario, and a cost perspective scenario. Firstly, according to the characteristics of China's energy consumption structure, the Markov model is used to predict the natural evolution of the energy consumption structure, and the forecast result is set as an unconstrained scenario. In addition, combined with the energy development plan formulated by the state, the energy structure should be adjusted accordingly to set the situation as a policy-constrained scenario. Finally, from the cost perspective, the minimum external cost of carbon emissions is used as the decision-making target, non-linear programming is performed, and the forecast result for the energy structure is obtained as the minimum cost scenario. Applying different scenarios is conducive to a more comprehensive understanding of future changes in China's energy structure.

(3) Third, this paper combines China's carbon intensity targets for 2020 and 2030 for analysis. The existing research focuses mainly on the target of a 40–45% reduction of carbon intensity by 2020 and less on the goal of a 60–65% reduction by 2030. This paper combines the carbon intensity targets for 2020 and 2030, and then analyzes the potential for optimizing the energy structure to contribute to achieving the carbon intensity targets in order to explore the possibility of reaching the targets in 2020 and 2030; finally, the paper presents several reference suggestions.

Table 1. Summary of each model's advantages and shortcomings.

Model	Purpose	Advantages	Shortcomings
ARIMA model	Forecast energy consumption and greenhouse gas (GHG) emissions for a pig iron manufacturing organization in India.	ARIMA is quite suitable for short-term forecasting.	The model requires a long data series.
Non-linear gray model	Forecast carbon emissions.	(1). Evaluates the non-linear effects of economic growth on carbon emissions in the model. (2). This model can analyze the effect of multiple influencing factor variables on the behavior of the system.	After the model is improved, the newly added power exponents are unknown. There are difficulties in estimating these parameters.
Artificial neural networks model	Forecast carbon emissions.	ANNs are adaptable for optimization and adaptive methods and are computationally efficient.	For some complex systems, artificial neural network prediction results may have considerable errors.
Hybrid model	Use the technology-rich integrated assessment (MESSAGE) model, and a combination of bottom-up models to forecast carbon emissions.	(1). The carbon emission index selected by this model is more concentrated. (2). The model can better describe the overall demand-side uncertainties owing to structural and methodological differences between top-down and bottom-up approaches.	The model does not consider feedback with respect to price-induced changes in energy supply from a detailed energy demand outlook.
Nonparametric metafrontier approach	Forecast carbon emissions.	The model takes into consideration the technology gap among China's regions.	This model does not consider any statistical noise.

Based on the above discussions, this paper first uses the GM (1, 1) model and GRNN model to predict China's primary energy consumption separately, and then a gray relational analysis is used to empower the GM (1, 1) model and GRNN model to obtain the forecasting results of the combined model. Secondly, the evolution of energy structure is divided into "Unconstrained scenario", "Policy-constrained scenario", and "Minimum external costs of carbon emissions scenario" to study the future changes in China's energy structure. Finally, according to the predicted results of energy consumption and structure, China's carbon emissions, and carbon intensity results for 2020 and 2030 are calculated for further analysis. The research process of this paper is shown in Figure 1.

The remainder of this paper is organized as follows. Section 2 discusses the model theory. Section 3 analyzes the forecast results for primary energy consumption. Section 4 analyzes the optimization results of the energy structure in different situations. Section 5 explores the potential contribution of optimizing the energy structure to achieving the carbon intensity targets under different scenarios. Section 6 presents the main conclusions and policy suggestions.

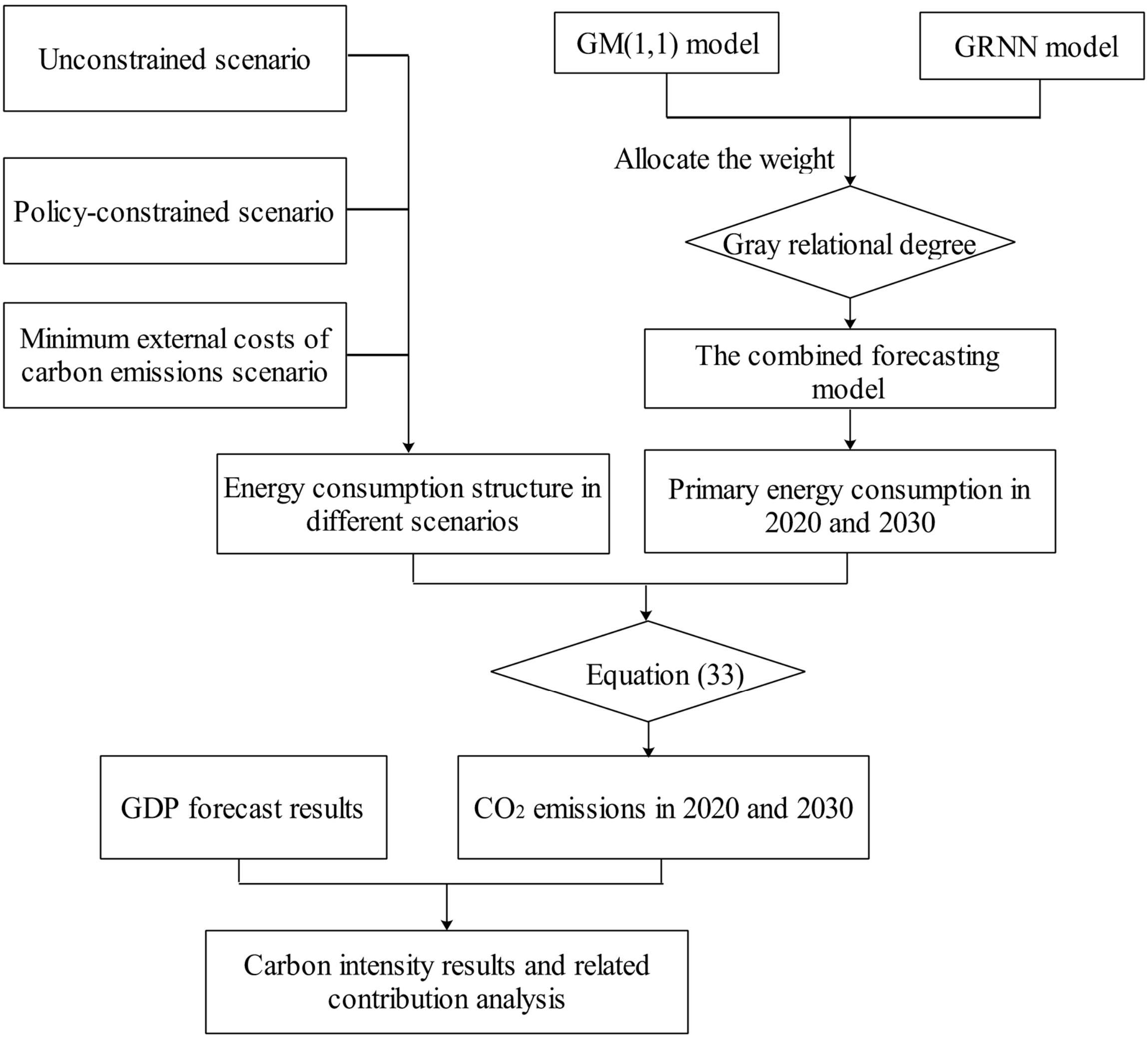

Figure 1. The general flowchart conducted in this paper.

2. Materials and Methods

2.1. Forecast Models for Energy Consumption in China

2.1.1. Model I: Gray Prediction Model

Since the advent of gray system theory, remarkable achievements have been accomplished in predictions regarding military systems, social systems, ecosystems, and commercial systems [35,36]. According to the gray system theory, useful information is extracted from the gray comprehensive sequence in the annual energy consumption time series to predict the future demand for energy consumption. Based on data availability, this paper selects primary energy consumption data [37] from 1953 to 2016 to predict the primary energy consumption in China for 2017 to 2030.

Step 1: Pre-process the primary energy consumption data. We assume that the sequence of primary energy consumption $Y^{(0)}$ from 1953 to 2016 is as follows, Equation (1):

$$Y^{(0)} = [Y^{(0)}(1), Y^{(0)}(2), \ldots Y^{(0)}(64)] \tag{1}$$

To weaken the randomness in the original sequence, prior to the establishment of the gray prediction model, the data for primary energy consumption sequences from 1953 to 2016 is processed, and the cumulative generation, Equation (2), is used to generate a cumulative generated column $Y^{(1)}$:

$$Y^{(1)}(k) = \sum_{i=1}^{k} Y^{(0)}(i) = Y^{(1)}(k-1) + Y^{(0)}(k) \tag{2}$$

$$Y^{(1)} = [Y^{(1)}(1), Y^{(1)}(2), \ldots Y^{(1)}(64)] \tag{3}$$

Step 2: Establish the gray differential, Equation (4):

$$\hat{Y}^{(1)}(k+1) = [Y^{(0)}(1) - \frac{b}{a}]e^{-ak} + \frac{b}{a} \tag{4}$$

Step 3: Determine the values of parameters a and b, according to Equation (5):

$$\begin{cases} \begin{bmatrix} a \\ b \end{bmatrix} = [B^T B]^{-1} B^T X_N \\ B = \begin{bmatrix} -\frac{1}{2}(Y^{(1)}(1) + Y^{(1)}(2)) & 1 \\ -\frac{1}{2}(Y^{(1)}(2) + Y^{(1)}(3)) & 1 \\ \ldots & \ldots \\ -\frac{1}{2}(Y^{(1)}(n-1) + Y^{(1)}(n)) & 1 \end{bmatrix} \\ X_N = [Y^{(0)}(2), Y^{(0)}(3), \ldots, Y^{(0)}(n)]^T \end{cases} \tag{5}$$

After obtaining the cumulative generated column $Y^{(1)}$, according to the available matrices B and X_N knowing that $B^T B$ is a symmetric matrix, the original time series $Y^{(0)}$ and cumulatively generated column $Y^{(1)}$ are entered into Equation (5) using the least squares method to obtain the values of parameter a and parameter b.

According to the above method, the primary energy consumption data from 1953 to 2016 are entered to obtain the gray differential Equation (6):

$$\hat{Y}^{(1)}(k+1) = 161324.24e^{0.0612k} - 155913.24 \tag{6}$$

Step 4: Predict the primary energy consumption for 2017–2030 according to Equation (7):

$$\hat{Y}^{(0)}(k+1) = \hat{Y}^{(1)}(k+1) - \hat{Y}^{(1)}(k) \tag{7}$$

Step 5: Test the residuals of the forecast data and examine the accuracy of the forecast data. The model fitting value $\hat{Y}^{(0)}$ for primary energy consumption in China from 1953 to 2016 is obtained based on the predictive value reduction formula. From the original sequence $Y(0)$ and predicted sequence $\hat{Y}^{(0)}$, the prediction data are tested for residuals and accuracy. The absolute error (AE), mean absolute error (MAE) and mean absolute percentage error (MAPE) of the prediction result are obtained from Equations (8), (9) and (10), respectively:

$$\delta(t) = Y^{(0)}(t) - \hat{Y}^{(0)}(t) \tag{8}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n} \delta_i(t) \tag{9}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n} |\delta_i(t)|/Y_i^0(t) \tag{10}$$

The standard deviation of the predicted value S_1 and standard deviation of sample S_2 are calculated in Equations (11) and (12), respectively. The posterior difference ratio C can be calculated as stated in Equation (13). According to the principle of the posterior difference test, as the posterior difference ratio decreases, the predicting effect improves:

$$S_1 = \sqrt{\frac{\sum_{i=1}^{n} [\delta(t) - \bar{\delta}]^2}{n}} \tag{11}$$

$$S_2 = \sqrt{\frac{\sum_{i=1}^{n} [Y^{(0)}(t) - \bar{Y}]^2}{n}} \tag{12}$$

$$C = S_1/S_2 \tag{13}$$

The correctness of using this model can be judged by observing the average relative error and posterior difference ratio.

2.1.2. Model II: Generalized Regression Neural Network

It is well-known that primary energy consumption is affected by many factors and that the system is complicated. A study of historical data shows that the sample is relatively small and presents a non-linear trend of development. GRNN is a general nonparametric regression model, which is a branch of the Radial Basis Function (RBF) neural network [38], and has a strong nonlinear mapping ability and flexible network structure, as well as a high degree of fault tolerance and robustness [39,40]. Therefore, in order to obtain a higher prediction accuracy, we apply GRNN to conduct the primary energy consumption forecasting.

Supposing the joint probability density functions of random variables x and y is $f(x, y)$, and the observed value of variable x is X, then the regression of y to x, that is, the conditional mean, is shown in Equation (14):

$$\hat{Y} = E[y|X] = \frac{\int_{-\infty}^{+\infty} y f(X, y) dy}{\int_{-\infty}^{+\infty} f(X, y) dy} \tag{14}$$

The unknown probability density function $f(x, y)$ can be estimated from the sample observations x and y, and the non-parametric estimation Equation (15) is as follows:

$$f(X,Y) = \frac{1}{(2\pi)^{(m+1)/2}\sigma^{m+1}n} \times \sum_{i=1}^{n} \exp[-\frac{(X-X_i)^T(X-X_i)}{2\sigma^2}] \exp[-\frac{(Y-Y_i)^2}{2\sigma^2}] \tag{15}$$

where X_i and Y_i are the sample observations of variables x_i and y_i, σ is the kernel width, n is the number of samples, and m is the dimension of variable x.

Substituting $\hat{f}(X,Y)$ with $f(x,y)$, exchange integrals and summation order, the estimated value is obtained from Equation (16):

$$\hat{Y}(X) = \frac{\sum_{i=1}^{n} \exp[-\frac{(X-X_i)^T(X-X_i)}{2\sigma^2}] \int_{-\infty}^{+\infty} y \exp[-\frac{(y-Y_i)^2}{2\sigma^2}] dy}{\sum_{i=1}^{n} \exp[-\frac{(X-X_i)^T(X-X_i)}{2\sigma^2}] \int_{-\infty}^{+\infty} \exp[-\frac{(y-Y_i)^2}{2\sigma^2}] dy} \tag{16}$$

where the estimated value $\hat{Y}(X)$ is the weighted average of all sample observations Y_i, and the weighting factor for each observation Y_i is the index of the Euclidean distance squared between the corresponding samples X_i and X.

The GRNN network structure consists of four layers: the input layer, pattern layer, summation layer, and output layer. The corresponding network input is $X = [x_1, x_2, \ldots, x_m]^T$, and the output is $Y = [y_1, y_2, \ldots, y_k]^T$.

(1) Input layer

The number of neurons in the input layer is equivalent to the dimensions of the input vector in the learning sample. Each neuron is a simple distribution unit that directly passes input variables to the pattern layer. For the analysis of the influencing factors of primary energy consumption, the energy price, population, GDP, household consumption level, industrial energy consumption, and industrial added value are selected as the input variables of the network; that is, the number of neurons in the input layer is six. Table 2 provides the detailed economic implications of these variables.

Table 2. The variables of the input layer.

Input	Economic Implications
Energy price	This variable is the most crucial factor for determining energy demand. Due to the lack of an energy price index, this paper uses the coal price to represent this index because coal is China's foremost consumer energy source, accounting for 60–70% of energy consumption, and the price of coal is more market-oriented.
Population	Energy is the fundamental material on which human beings depend for survival. Both energy production activities and energy consumption activities are intended to meet human needs. Studies such as those of Liu et al. [41] and Guo et al. [42] showed that population is a significant factor affecting energy demand.
GDP	This variable reflects a country's income level, which is a fundamental factor in determining energy demand. Lin et al. [43] and He et al. [44] showed that there is a significant positive correlation between energy demand and GDP.
Household consumption level	Household energy consumption includes two categories: direct and indirect consumption; that is, energy will be directly consumed during residential life and indirectly consumed by producing various goods and services. Residents' rising consumption level will increase not only the direct energy consumption but also the indirect energy consumption.
Energy consumption in the industrial sector	China's industrialization is in the mid-to-late stage. Studies have demonstrated that primary energy consumption in the industrial sector accounts for more than 70% of the total primary energy consumption in China [45].
Industrial added value	In the process of industrialization, the output values of the manufacturing industry and secondary industry have been continuously increasing, and the changes reflect the adjustment of the industrial structure, which is a basic factor affecting the energy demand.

The data for all the input layer variables proposed above come from the China Statistical Yearbook [46] and the China Economic Net Statistics Database [37]. Since the energy consumption data from the industrial sector date back to 1980 at the earliest, the historical data for the previous period is missing; thus, the above six variables range from 1980 to 2016.

(2) Pattern layer

The number of neurons in the pattern layer is equal to the number of learning samples. Here, the number of neurons in the pattern layer is six, and each neuron in the input layer corresponds to a different sample. The transfer function of the neurons $x_i\,(i = 1, \ldots, 6)$ is show in Equation (17):

$$p_i = \exp[-\frac{(X - X_i)^T(X - X_i)}{2\sigma^2}]\;(i = 1, \ldots, 6) \tag{17}$$

where the output of a neuron x_i is an exponential form of the square of the Euclidean distance between the input variable X and its corresponding sample X_i.

(3) Summation layer

The summation layer is divided into two types of neuron summing: one is $\sum\limits_{i=1}^{n} \exp[-\frac{(X-X_i)^T(X-X_i)}{2\sigma^2}]$; this expression is arithmetic summation of the output of all the pattern layer neurons, which has a connection weight of 1 with each pattern layer neuron, and the transfer function is $s_D = \sum\limits_{i=1}^{n} p_i$.

Another type is $\sum\limits_{i=1}^{n} Y_i \exp[-\frac{(X-X_i)^T(X-X_i)}{2\sigma^2}]$; this weighted expression sums the output of all the pattern layer neurons and the connection weight between the i-th neuron in the pattern layer. The j-th molecule summation neuron in the sum layer is y_{ij}, and the transfer function is $s_{Nj} = \sum\limits_{i=1}^{n} y_{ij}P_i$, $j = 1, 2, \ldots, k$.

(4) Output layer

The number of neurons in the output layer is equal to the number of dimensions of the output vector k in the learning sample; each neuron divides the output of the summation layer to obtain the output of the j-th neuron y_j through Equation (18):

$$y_j = \frac{S_{Nj}}{S_D}\;\; j = 1, 2, \ldots, k \tag{18}$$

2.1.3. Combined Forecasting Model of China's Energy Consumption Based on the Gray Relation Degree

Since the introduction of the combined forecasting model in 1969, it has been a popular topic in the field of forecasting both domestically and internationally [47]. The traditional single model prediction process has many shortcomings, such as the single structure of the forecast, limited information sources, incomplete factors, and the sensitive model setting. However, the combined forecasting model can comprehensively utilize the information provided by each individual model, collect the advantages of the individual models, enrich the model structure, and ultimately use the weighted average method to obtain the result of the combined forecasting model to improve the fitting accuracy and forecasting ability; therefore, the forecasting method is more effective.

Based on the predictions of primary energy consumption in China for 2017 to 2030 through the gray prediction model and the GRNN model, respectively, this paper uses the gray relational method to allocate the weights of the two models to construct the combined forecasting model.

Step 1: Preprocess the data. To eliminate the order of the magnitude difference between each set of dimension data and avoid the error of the order of magnitude being too large, according to

Equation (19), the real value sequence, the gray forecast value sequence and GRNN predictive value sequence are processed and converted into values between [0, 1]:

$$X_{\mathrm{i}}'(t) = \frac{X_i(t) - \min X_i(t)}{\max X_i(t) - \min X_i(t)} \tag{19}$$

Step 2: Calculate the gray relational degree between the reference sequence and the real value sequence.

Setting the actual value of primary energy consumption as $\{x_t, t = 1, 2, \ldots, N\}$, there is the gray prediction model and GRNN forecasting, which are two single forecasting models for predicting primary energy consumption, where x_{1t} is the forecast value corresponding to the gray prediction model at time t and x_{2t} is the forecast value corresponding to the GRNN forecast model at time t.

$$\xi_{0i} = \frac{1}{N}\sum_{i=1}^{N} \frac{\min\limits_{1 \le i \le 2}\min\limits_{1 \le t \le N}|e_{it}| + \rho \max\limits_{1 \le i \le 2}\max\limits_{1 \le t \le N}|e_{it}|}{|e_{it}| + \rho \min\limits_{1 \le i \le 2}\min\limits_{1 \le t \le N}|e_{it}|} \tag{20}$$

$$e_{it} = x_t - x_{it} \tag{21}$$

In Equation (20), ξ_{0i} represents the gray correlation degree between the predicted value sequence $\{x_{it}, t = 1, 2, \ldots, N\}$ of the i-th single-item prediction method and the real value sequence $\{x_t, t = 1, 2, \ldots, N\}$, as the gray correlation degree of the i-th single forecasting method. Here, e_{it} represents the prediction error of the i-th prediction model at time t. $\rho \in (0, 1)$ is the resolution coefficient, which usually takes the value $\rho = 0.5$. According to Equation (20), the gray relational degree between the gray prediction sequence and real value sequence ξ_{01} and the gray relational degree between the GRNN prediction sequence and real value sequence ξ_{02} can be calculated separately.

$$l_i = \xi_{0i} \Big/ \sum_{i=1}^{2} \xi_{0i} \tag{22}$$

Therefore, we can calculate the weight of the gray prediction model, and the weight of the GRNN prediction model according to Equation (22).

According to the definition of gray relational degree, $\xi_{0i} \in [0, 1]$. The accuracy of the prediction is accurate only when there is a gray correlation degree of 1 between them.

Step 3: Generate a combined forecast of primary energy consumption in China. The combined predicted value of primary energy consumption at time t is given by Equation (23):

$$\hat{x_t} = l_1 x_{1t} + l_2 x_{2t} \;\; t = 1, 2, \ldots, N \tag{23}$$

In Equation (23), l_1 is the weighted coefficient corresponding to the predicted value of the gray prediction model, l_2 is the weighting coefficient corresponding to the prediction value of the GRNN prediction model, which satisfies $l_1 + l_2 = 1$; Equation (23) shows that inequality (24) holds:

$$\min_{1 \le i \le 2} x_{it} \le \hat{x_t} \le \max_{1 \le i \le 2} x_{it} \;\; t = 1, 2, \ldots, N \tag{24}$$

Let e_t be the prediction error of the primary energy consumption at time t from the combined forecasting method, and according to $l_1 + l_2 = 1$, Equation (25) is as follows:

$$\begin{aligned} e_t &= x_t - \hat{x_t} = x_t - \sum_{i=1}^{2} l_i x_{it} \\ &= \sum_{i=1}^{2} l_i (x_t - x_{it}) = \sum_{i=1}^{2} l_i e_{it} \\ &t = 1, 2, \ldots N \end{aligned} \tag{25}$$

Letting ξ be the gray relational degree of the combined forecasting method, then the gray relational degree of the combined forecasting is given by Equation (26):

$$\xi = \frac{1}{N}\sum_{i=1}^{N} \frac{\min\limits_{1\le i\le 2}\min\limits_{1\le t\le N}|e_{it}| + \rho \max\limits_{1\le i\le 2}\max\limits_{1\le t\le N}|e_{it}|}{|\sum\limits_{i=1}^{2} l_i e_{it}| + \rho \min\limits_{1\le i\le 2}\min\limits_{1\le t\le N}|e_{it}|} \tag{26}$$

In Equation (26), the gray relational degree ξ of the combined forecasting method is a function of the weighting coefficient $L = (l_1, l_2)$ of each single forecasting model, so that ξ can be denoted as $\xi(L)$.

According to the gray relational theory, as the gray relational degree of the combined forecasting method increases, the combined forecasting model is more effective. If $\xi < \xi_{\min}$, the combined forecasting model is considered inferior forecasting; if $\xi_{\min} \le \xi \le \xi_{\max}$, the combined forecasting model is referred to as non-inferior combination forecasting; and if $\xi > \xi_{\max}$, the combined forecasting model is the optimal combined forecasting model.

2.2. Construction of the Forecast Model for Energy Consumption Structure in China

2.2.1. Energy Structure Prediction Based on the Markov Model

The evolution of primary energy consumption structure has its own changes and development laws. This evolutionary law provides the basis for our study of the future energy consumption structure. The main methods for predicting the energy consumption structure in existing research include the Markov forecasting model, and the energy and environment comprehensive policy evaluation model (Integrated Assessment Model, IAM model) [48]. Taking into account that the IAM model involves many factors, the data are not easy to obtain, the model is not generally suitable for cooperative research and development groups, and an individual research model is very difficult to establish. This paper uses the Markov forecasting model to predict the future energy consumption structure in China.

Step 1: Build a Markov model that predicts the primary energy consumption structure.

A represents the total primary energy consumption; for simplicity, it can be divided into four types of energy sources: coal, oil, natural gas and clean energy (water, nuclear, and wind electricity, etc.). At time n, the vector of the primary energy consumption structure is $S(n) = \{s_c(n), s_o(n), s_g(n), s_e(n)\}$, where $S_c(n)$, $S_o(n)$, $S_g(n)$, and $S_e(n)$ represent the shares of coal, oil, natural gas and clean energy, respectively, in the total primary energy consumption; the sum of their proportions is 1. We assume that the one-step transition probability matrix of the energy consumption structure from time n to time $n+1$ is:

$$P(n) = \begin{bmatrix} P_{c\to c}(n) & P_{c\to o}(n) & P_{c\to g}(n) & P_{c\to e}(n) \\ P_{o\to c}(n) & P_{o\to o}(n) & P_{o\to g}(n) & P_{o\to e}(n) \\ P_{g\to c}(n) & P_{g\to o}(n) & P_{g\to g}(n) & P_{g\to e}(n) \\ P_{e\to c}(n) & P_{e\to o}(n) & P_{e\to g}(n) & P_{e\to e}(n) \end{bmatrix} \tag{27}$$

In the probability matrix, every element is a positive number less than 1, and the sum of the probabilities in each row is always equal to 1. Here, the elements are classified according to the characteristics of the elements in the probability matrix.

First, the main diagonal elements of the matrix $P(n)$ are classified as the first category, referred to as the "retention probability elements." These elements represent the probability that various types of energy consumption continue to maintain the original ratio (for example:$P_{c\to c}(n)$ represents the probability that coal consumption will continue to maintain the original ratio from time n to time $n+1$). Second, the main diagonal line elements are classified as the second category, referred to as the "transition probability elements." These elements represent the proportion of such energy consumption to other types of energy consumption in terms of the transfer probability (for example:

$P_{c\to o}(n)$ represents the probability that the ratio of coal consumption to oil consumption transfers from time n to time $n+1$). Third, the column elements outside the main diagonal are classified as the third category, referred to as the "absorption probability elements." These elements represent the probable proportion of such energy consumption absorption of other types of energy consumption (for example, $P_{o\to c}(n)$ represents the probability that the percentage of coal consumption absorbs the oil consumption ratio from time n to time $n+1$).

Step 2: Determine the average transition probability matrix P.

To predict the future energy consumption structure, we must find the average transfer probability matrix based on the existing energy consumption structure. The specific procedure is as follows: first, calculate the primary transition probability matrix of the energy consumption structure in each year, and then average the transition matrix to obtain the average transition probability matrix.

Supposing that from the initial moment to moment m, the transition probability matrix for each step of the energy consumption structure is $P(1), P(2), \cdots, P(m)$, then the average transfer probability matrix is $P = [P(1) \cdot P(2) \cdots P(m)]^{1/m}$. According to the average transfer probability matrix P, the structure of primary energy consumption at the time $n+m$ can be predicted by Equation (28):

$$S(n+m) = S(n) \cdot P^m \quad (28)$$

Step 3: Determine the transition probability matrix for each step $P(n)$. To determine the average transition probability matrix P, the key lies in how to determine a transition probability matrix of the energy consumption structure $P(n)$. This paper uses the following four steps to calculate the value for each element in the matrix $P(n)$:

(I) Calculate the retention probability elements. If from time n to $n+1$, the proportion of energy consumption increases, the retention probability of this energy in the transition probability matrix is 1; if the proportion decreases, the retention probability is equal to the ratio of time $n+1$ to time n.

(II) Calculate the transition probability in the rows in which the element with a retention probability of 1 is located. If the retention probability of a row is 1, there is no possibility of transferring energy to other types of energy, and the sum of the elements in each row of the transition probability matrix has been set equal to 1; therefore, the probability of a row transition probability element is zero.

(III) Calculate the probability of absorption in the columns where the element with a retention probability of less than 1 is located. If the retention probability of a column is less than 1, the percentage of energy consumption represented by the column is reduced. There is no possibility for such energy consumption to absorb other types of energy. Therefore, the probability of absorption for this column is zero.

(IV) Calculate the nonzero transition probability in the rows in which the element with a retention probability of less than 1 is located. The retention probability of energy corresponding to a row of elements is less than 1, indicating the transfer of such energy consumption to other types of energy consumption from n to $n+1$. Using coal as an example, if $P_{c\to c}(n)$ is less than 1, the proportion of coal consumption decreases from n to $n+1$, and the transfer of coal consumption to the other three types of energy consumption occurs. The probability of coal consumption shifting to oil consumption, natural gas consumption, and clean energy consumption can be calculated according to Equations (29)–(31), respectively:

$$P_{c\to o}(n) = \frac{[1 - P_{c\to c}(n)] \times [s_o(n+1) - s_o(n)]}{[s_o(n+1) - s_o(n)] + [s_g(n+1) - s_g(n)] + [s_e(n+1) - s_e(n)]} \quad (29)$$

$$P_{c\to g}(n) = \frac{[1 - P_{c\to c}(n)] \times [s_g(n+1) - s_g(n)]}{[s_o(n+1) - s_o(n)] + [s_g(n+1) - s_g(n)] + [s_e(n+1) - s_e(n)]} \quad (30)$$

$$P_{c\to e}(n) = \frac{[1 - P_{c\to c}(n)] \times [s_e(n+1) - s_e(n)]}{[s_o(n+1) - s_o(n)] + [s_g(n+1) - s_g(n)] + [s_e(n+1) - s_e(n)]} \quad (31)$$

For other types of energy retention probabilities less than 1, based on the same principle, we can calculate the non-zero transition probabilities of such energy sources.

Based on the above steps, the transition probability matrix of the energy consumption structure from the initial moment to the moment m is obtained as $P(1), P(2), \cdots, P(m)$, the average transfer probability matrix P can be obtained, and then Equation (28) can be used to predict the future energy consumption structure.

2.2.2. Energy Structure Prediction Model Based on the External Cost Minimization of Carbon Emissions

In this section, we optimize the structure of energy consumption with the goal of minimizing the external costs of carbon emissions. Research has established that the factors of various types of energy carbon emissions are different, and the amount of carbon dioxide released by different types of energy combustion per unit mass is discrete, so that the external costs of carbon emissions consumed are not equal. Studies [49] have shown that external emissions of carbon dioxide cost approximately 20 dollars/ton, which, according to the current exchange rate, converts into 129.21 RMB/ton. Carbon emission factors of coal, oil and natural gas are 0.7476, 0.5825, and 0.4435, respectively. Burning a ton of carbon in oxygen releases five tons of carbon dioxide. Thus, the external CO_2 emission costs for various energy sources are shown in Table 3:

Table 3. CO_2 emission factors for various energy sources and external emission costs.

Specie	Coal	Oil	Natural Gas
CO_2 emission factor	2.744	2.138	1.628
External cost (RMB/tce)	354.81	276.46	210.49

We set the coal consumption x_1 at ten thousand tons, oil consumption x_2 at ten thousand tons, natural gas consumption x_3 at ten thousand tons, and the renewable energy consumption x_4 at ten thousand tons. According to the above analysis, the objective function $f(x)$ is set as follows:

$$f(x) = 354.81x_1 + 276.46x_2 + 210.49x_3 \quad (32)$$

$$\text{Total } CO_2 \text{ emission} = \sum Energy\ consumption \times Carbon\ emission\ factor\ \times \frac{44}{12} \quad (33)$$

$$\text{Carbon Intensity} = \frac{\text{Total } CO_2 \text{ emission}}{\text{GDP}} \quad (34)$$

According to China's energy long-term development strategy research and the 13th Five-Year Plan, the following constraints are set:

(1) Primary energy consumption is not greater than the predicted value:

$$x_1 + x_2 + x_3 + x_4 \leq C_1 \quad (35)$$

(2) The total amount of CO_2 emissions is within the forecast range, where μ_i represents the corresponding emission factor of different types of energy:

$$\sum_{i=1}^{4} \mu_i x_i \leq C_2 \quad (36)$$

(3) Various types of future energy structure changes in China are set in Table 4:

Table 4. The proportions of primary energy consumption for 2020 and 2030.

Year	Coal Ratio	Oil Ratio	Natural Gas Ratio	Clean Energy Ratio
2020	0.50–0.60	0.20–0.30	0.06–0.15	0.15–0.25
2030	0.40–0.50	0.25–0.30	0.10–0.20	0.20–0.25

(4) All types of energy are not less than zero:

$$x_i \geq 0 \tag{37}$$

(5) Of all types of energy, only coal, oil, and natural gas are considered to generate carbon dioxide during combustion, while clean energy releases very little carbon dioxide, which is not taken into account.

According to the above objective function and constraints, a non-linear programming model is constructed, and the relevant software is used to obtain the energy structure optimization results.

3. China's Energy Consumption Forecast Results

3.1. Result Analysis Based on the GM (1, 1) Model

This section uses MATLAB2017a (MathWorks, Natick, MA, USA) to realize the GM (1, 1) model, of which the MAPE is 0.0692, the residual standard deviation is 13971.35, actual standard deviation is 128779.08, and the posterior difference C calculated by Equation (15) is 0.1085, $C < 0.35$, which shows that the constructed gray forecasting model has a better forecasting effect. In addition, the probability of small residuals is calculated as P is 1, which shows that the model has a high goodness of fit and is suitable for predicting primary energy consumption in China.

Table 5 shows the forecasting results for the future energy consumption of China. The primary energy consumption forecast for 2017 will be 4815 million tons of standard coal, reaching 5786 million tons of standard coal in 2020 and 10,070 million tons of standard coal in 2030. This prediction shows that China's energy consumption for the future is high, but the prediction error of the gray prediction model is small and the accuracy is high, so the model itself is not a problem. The reason for the high forecast result is that the sample data predicted by this model are sourced from the primary energy consumption data for China from 1953 to 2016. This stage represents the process of China shifting from being a largely agricultural country to being a mature industrial country. The consumption of energy each year is considerable, with a high annual growth rate. This trend is further extended, resulting in a high growth rate of the predicted model values, which directly leads to a prediction of high energy consumption. The gray model is commonly used for short-term forecasting [50]. Therefore, it is reasonable to predict the economic variables through the gray model to supplement the later forecast data.

3.2. Result Analysis Based on the GRNN Model

In this paper, through cross-validation, the neural network is continuously trained and tested. When the radial basis function expansion speed is set to 0.56, the network error RMSE is the lowest and the function approximation is the best. Therefore, a smoothing factor of 0.56 was determined. The GRNN model was constructed, and the predicted values were inversely normalized to obtain the primary energy consumption forecast results. The MAPE for the forecast of primary energy consumption in the GRNN model from 1980 to 2016 is calculated as 0.0618. The goodness of fit of the model is high, so the model is suitable for the prediction of primary energy consumption in China.

In the following steps, the forecast variables of China are entered into the GRNN neural network by predicting the explanatory variables in turn, and the forecast is obtained for primary energy consumption in China from 2017 to 2030.

(1) The change in the energy price is a stochastic process. The mechanism of this change is complicated and affected by a combination of multiple factors. Therefore, for the trend forecast of energy price changes, we cannot simply assume that it changes at a fixed rate but rather use a measurement model for prediction. In this paper, we choose the ex-factory price index for coal as an alternative variable for energy price and predict the future price index through the ARIMA (2, 1, 2) model combined with the changing trend of the price index itself.

ARIMA (p, d, q) is a common and effective forecasting model that is widely used in time series forecasting [51]. In the model, p and q represent the order of autoregressive and moving average processes, respectively, and d is the degree of differencing. Through the Augmented Dickey-Fuller (ADF) test, the results showed that the original series is non-stationary (p-value = 0.1019). After taking the natural logarithm and performing a first-order difference, it becomes stationary (p-value = 0.000), so set d to 1. According to the autocorrelation graph (ACF) and the partial autocorrelation graph (PACF), there is no significant seasonal trend. To determine p and q, Akaike's information criteria (AIC) criterion was applied here. Through comparing the values of AIC, ARIMA (2, 1, 2) model is the best, with the smallest AIC of -2.7517, and the MAPE is 4.006%, which indicates the model's strong forecasting ability.

(2) The natural population growth rate in China has been declining since 1978. Building on recent literature regarding future population growth trends in China, this paper refers to the forecast results from the National Development Plan 2016–2030 [52] and predicts that in 2017, the total population will reach approximately 1.404 billion. By 2020, the total population will be 1.42 billion, and by 2030, it will reach 1.45 billion.

(3) With regard to the growth forecast for China's economy, combined with current researchers' studies [53–55], the commonly held view among experts is that from 1990 to 2010, China's economy will have grown at a very high rate, while it will grow at a medium rate from 2010 to 2030 and a low rate from 2030 to 2050. Therefore, China's future economic growth will occur at a 6.5% annual growth rate from 2011 to 2020 and at a 5.5% annual growth rate from 2021 to 2030, from which the total amount of China's GDP for 2017–2030 can be predicted.

(4) Residents' consumption levels are directly related to economic growth. Based on the research by Wang et al. [56], this paper predicts that there is a co-integration relationship between GDP and residents' consumption level; for every 1% increase in GDP, the consumer price index will increase by 0.679%. According to this co-integration relationship, the annual growth rate of consumer spending for 2011–2020 can be calculated as 4.41% and that for 2021–2030 as 3.735%.

(5) For the prediction of energy consumption in the industrial sector, this article refers to the method from the China Energy Economics Research Center at Xiamen University [57], and according to the historical trend for industrial energy efficiency, the industrial energy efficiency growth rate is set at 3% in 2010, decreasing by 0.5% every five years thereafter. Therefore, the industrial energy efficiency growth rate is 2% for 2016–2020, 1.5% for 2020–2025, and 1% for 2026–2030. From the ratio of industrial energy efficiency equal to the ratio of added value for the energy consumption of the industrial sector, the predicted value of the energy consumption for the industrial sector can be calculated.

(6) Chen's [58] research showed that the average annual growth rate of China's industrial added value as a portion of GDP was 0.4% beginning in the Ninth Five-Year Plan period. This article draws on this static calculation method, considering the recession of growth, which sets the annual average growth rate of industrial added value as a share of GDP for 2011–2020 as 0.3% and presents the annual average growth rate of 0.2% for 2021–2030.

From this process, we can calculate the forecast value for industrial added value from 2017 to 2030.

According to the above settings, the predicted values for the six explanatory variables are entered into the trained generalized regression neural network as the network input layer to predict the primary energy consumption for 2017–2030 in China. The results are shown in Table 5.

3.3. Result Analysis Based on the Combined Forecasting Model

The forecast processes for primary energy consumption in China in 2020 and 2030 are shown in Figure 2. China's primary energy consumption is predicted through the GM (1, 1) model and the GRNN model to obtain the predicted values x_{1t} and x_{2t}, and the gray relational method is used to calculate the corresponding weights l_{1t} and l_{2t} in the individual models. According to Equation (25), we can obtain the predicted value of a combined model for primary energy consumption at time t.

Due to the GRNN model, the data for the original variables in the input layer can be traced back to 1980 at the earliest. To improve the prediction accuracy of the model, the forecast values for primary energy consumption in the GM (1, 1) model and GRNN model from 1980 to 2016 are selected as the reference sequences and the gray relational degrees of the two reference sequences and original sequence are calculated, respectively. The gray relational degree of the GM (1, 1) model is calculated as $l_1 = 0.7165$, and the gray relational degree of the GRNN model is $l_2 = 0.7281$. Thus, the results of the combined forecasting are shown in Table 5.

The gray relational degree of the combined forecasting model ξ is 0.7368, and according to $\xi > \xi_{02} > \xi_{01}$, the combined forecasting model is considered the optimal combined forecasting model. Among the models, the MAPE of the GM (1, 1) model is 6.92%, and the MAPE of the GRNN model is 6.18%, while the MAPE of the combined forecasting model is 5.87%, the prediction accuracy is improved, and the combined forecasting method is superior to the single prediction method. Therefore, this paper uses the combined forecasting method to predict China's primary energy consumption from 2017 to 2030.

Table 5 shows the forecasting results of China's primary energy consumption in 2017–2030 under the GM (1, 1) model, the GRNN model and the combined model, respectively. It can be seen that the prediction results of GM (1, 1) model have a fast growth rate, while the prediction results of GRNN model are more robust. The forecasting results of the two models are relatively close in 2017. However, the differences between the predicted values of the two models become larger and larger. By 2030, the forecasting value of GM (1, 1) model is nearly two times more than that of GRNN model. The results are mainly determined by the characteristics of each model. The GM (1, 1) model has the advantages of small sample size, less parameter requirements, and simple calculation, etc. However, the GM (1, 1) model is more suitable for a smooth data sequence with exponential change, but for data with a jumping nature or a rapidly changing speed, the forecasting accuracy is not high [59]. The GRNN model has a strong nonlinear mapping ability and learning speed. The neural network usually converges to the optimal regression with large sample size aggregation, which is suitable for processing unstable data and lone-term prediction. However, the model often has high requirements on sample quantity and quality [60]. In view of the characteristics of the GM (1, 1) model and the GRNN model, this paper uses the combined model to forecast the energy consumption, so as to better make up for the defects of each model and to improve the prediction accuracy. According to Figure 2, the fitting of the original data shows that the MAPE under the combined model is smaller than that of the GM (1, 1) model and the GRNN model, which indicates that the prediction accuracy of the combined model proposed in this paper is improved compared with the traditional single forecasting model.

As shown in Table 5 and predicted with the combined forecasting model, China's primary energy consumption in 2020 will reach 5.06 billion tce, and the primary energy consumption in 2030 will reach 7.54 billion tce. Furthermore, the forecasting results of this study are compared with those of other studies, which are shown in Appendix B. In this paper, the forecasting result for 2020 is close to that of British Petroleum (BP), and the forecasting result for 2030 is close to the high economic growth scenario of the Energy Information Administration (EIA). The predictions of 2020 and 2030 are both less than that of the South Korea Scenario and the Baseline Scenario, which implies that the prediction results of those two scenarios may be high. The comparison further proves that our results are robust and reliable.

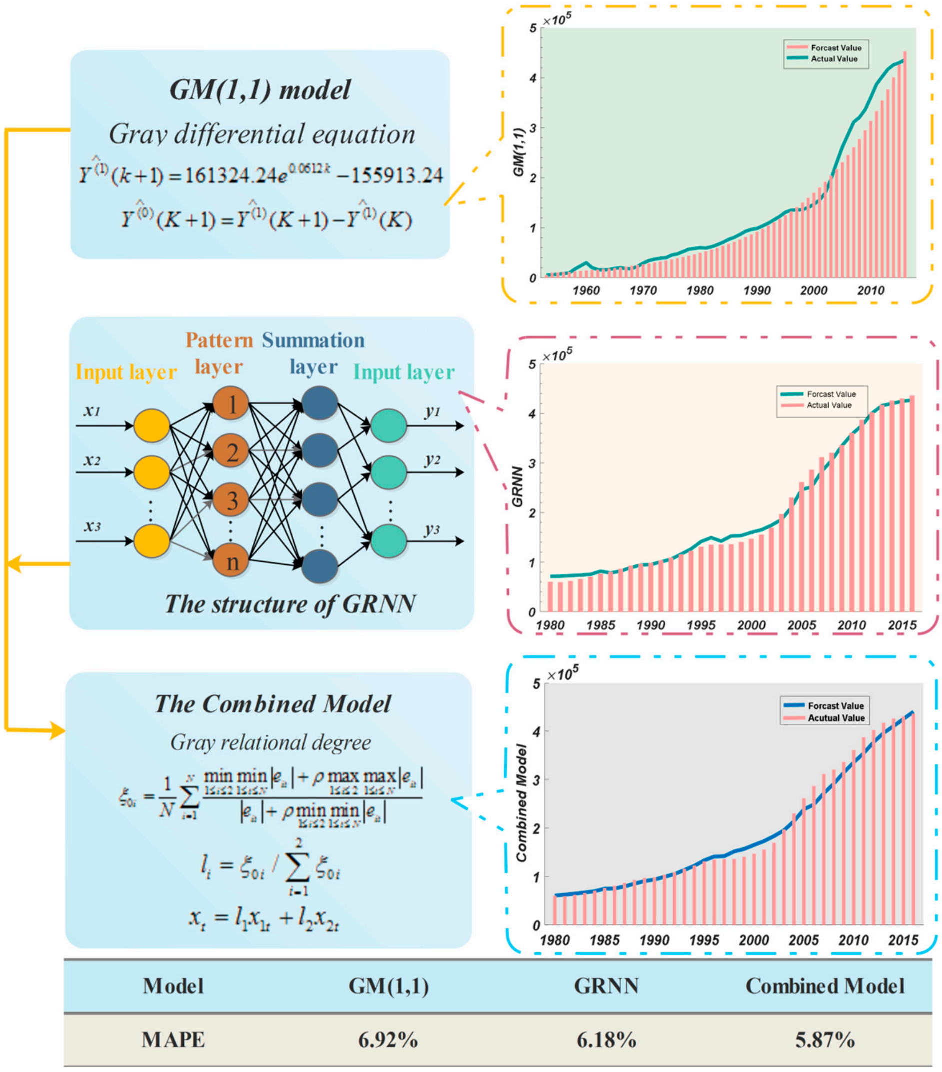

Figure 2. The forecasting process for the combined model.

Table 5. Prediction of primary energy consumption. (unit: 10^4 tce).

Year	GM (1, 1)	GRNN	The Combined Model
2017	481,509.07	428,574.45	455,252.80
2018	511,903.92	430,308.03	471,431.29
2019	544,217.41	431,775.91	488,444.95
2020	578,570.67	432,981.45	506,356.51
2021	615,092.45	433,770.76	525,154.52
2022	653,919.63	434,393.88	545,031.98
2023	695,197.75	434,867.40	566,070.49
2024	739,081.51	435,216.47	588,360.47
2025	785,735.40	435,467.43	611,997.90
2026	835,334.27	435,645.99	637,083.65
2027	888,064.03	435,768.62	663,719.59
2028	944,122.31	435,851.30	692,013.24
2029	1,003,719.22	435,906.06	722,076.46
2030	1,067,078.13	435,941.71	754,026.21

According to existing studies, China's primary energy consumption will continue to grow over the next 14 years. Adjusting the energy structure is a key factor in achieving the carbon intensity targets in 2020 and 2030.

4. China's Energy Consumption Structure Forecast Results

4.1. Different Scenario Settings

(1) Unconstrained Scenario (UCS)

The unconstrained scenario (UCS) is the scenario in which no specific measures are taken to reduce carbon intensity. At present, China is in the process of building a prosperous society in a comprehensive way. Industrialization is in a transition period, and it is heavily dependent on energy consumption. The coal-dominated energy consumption structure exerts tremendous ecological pressure on the environment. In recent years, due to the state's support and technological progress, the proportion of coal consumption has been gradually declining, the proportion of renewable energy consumption has been gradually rising, and the energy consumption structure has been gradually improving. This paper sets the unconstrained energy structure optimization scenario as a reference, which does not consider the national development plan and predicts the future development trend based on the natural evolution law, followed by the energy structure change.

(2) Policy-Constrained Scenario (PCS)

The policy-constrained scenario (PCS) is the scenario that optimizes the energy consumption structure according to energy policies. For a long time, China's primary energy consumption consisted of nearly 70% coal. To ease the pressure on carbon emissions, China launched the 13th Five-Year Plan in 2017 to clarify the guiding ideology, the basic principles, and the development goals for energy development. The plan proposes that non-fossil fuels account for 15% of primary energy consumption by 2020, the proportion of natural gas consumption reaches 10%, the proportion of coal is less than 62%, and that non-fossil fuels account for 20% of primary energy consumption by 2030. This paper sets this scenario, combined with the above energy development plan, as the policy-constrained scenario, and predicts the future energy consumption structure according to China's energy planning.

(3) Minimum external costs of carbon emissions scenario (MCS)

The minimum external costs of carbon emissions scenario (MCS) is a scenario that optimizes the energy structure with the objective of minimizing external costs. Given that carbon dioxide is the primary greenhouse gas, the external discharge of carbon dioxide has a negative impact on the environment and generates a certain cost. Therefore, from the cost perspective, this paper applies a minimum external cost of the carbon emissions scenario, which sets the minimum cost as the goal, determines the constraint conditions according to national energy policy planning, and constructs a non-linear programming model. By generating the non-linear programming model, we can obtain the results of energy structure optimization in this scenario.

4.2. Energy Structure Forecast Results

Based on the above three scenario settings, the energy structures in different scenarios are calculated separately.

(1) Energy structure prediction under the unconstrained scenario

In this paper, the energy structure is predicted with the Markov forecasting model. The energy structure variables from 2008 to 2015 are selected to calculate the average transfer probability matrix P (Appendix C).

Given the primary energy consumption structure and the average transition probability matrix P, we predict the energy consumption structure in the unconstrained scenario. Combined with the prediction for GDP and the total primary energy consumption (Table 5), we obtain the forecast results for the total energy consumption and the prediction of various types of energy in the future. The results are shown in Table 6.

In the unconstrained scenario, non-fossil energy will account for 14.1579% of the total energy consumption in 2020, natural gas will account for 7.57% in 2020, and non-fossil fuels will account for 17.4589% in 2030; these figures still lag behind the goals set in the 13th Five-Year Plan. Therefore, the energy structure under the policy-constrained scenario is adjusted as follows.

(2) Energy Structure Prediction under the Policy-Constrained Scenario

At present, coal accounts for the highest proportion of primary energy consumption in China. Compared to other energy sources, coal has low calorific value and high carbon emissions per unit. One of the principal ways to optimize energy structure is to reduce the proportion of coal and increase the proportion of renewable energy. Therefore, this paper assumes that in the future energy structure, the proportion of oil consumption will continue the same trend of adjustment. The increased ratio of clean energy and natural gas will be supplemented by a decrease in the coal proportion. Based on the above assumptions, the energy consumption structure optimization results can be calculated under the policy-constrained scenario. Table 6 shows that in this scenario, the primary energy consumption structure in 2020 will be 55.80% coal, 19.20% oil, 10% natural gas, and 15% clean energy; the primary energy consumption structure in 2030 will be 48.23% coal, 20.93% oil, 10.84% natural gas, and 20% clean energy.

(3) Energy Structure Prediction under the Minimum External Costs of a Carbon Emissions Scenario

From the cost perspective, this paper sets the minimum external cost of carbon emissions as a decision-making goal, and builds a non-linear programming model to predict the primary energy consumption structure. According to the analysis of the objective function and constraints in Section 2.2.2, we obtain the minimum scenario model of carbon emission costs in 2020 and the minimum scenario model of carbon emissions in 2030 (Appendix D).

Table 6 shows that the primary energy consumption structure in 2020 is 59% coal, 20% oil, 6% natural gas and 15% clean energy. The primary energy consumption structure in 2030 is 45% coal, 25% oil, 10% natural gas and 20% clean energy.

Table 6. China's primary energy consumption structure forecast results.

Year	2020			2030		
	UCS	PCS	MCS	UCS	PCS	MCS
Coal (10^4 tce)	299,115.43	282,541.36	298,750.34	382,843.23	363,683.43	339,311.79
Share (%)	59.07	55.80	59.00	50.77	48.23	45.00
Oil (10^4 tce)	97,226.02	97,226.02	101,271.30	157,828.24	157,828.24	188,506.55
Share (%)	19.20	19.20	20.00	20.93	20.93	25.00
Natural gas (10^4 tce)	38,325.11	50,635.65	30,381.39	81,709.30	81,709.30	75,402.62
Share (%)	7.57	10.00	6.00	10.84	10.84	10.00
Clean energy (10^4 tce)	71,689.45	75,953.48	75,953.48	131,644.68	150,805.24	150,805.24
Share (%)	14.16	15.00	15.00	17.46	20.00	20.00
Total (10^4 tce)	506,356.51	506,356.51	506,356.51	754,026.21	754,026.21	754,026.21

From the total primary energy consumption in China under different scenarios and their structures, the consumption levels of coal, oil, natural gas, and clean energy under various scenarios in 2020 and 2030 are calculated as shown in Figure 3. From Figure 3, we can observe the following. (1) In 2030, all types of primary energy consumption in China are higher than primary energy consumption in 2020, indicating that China's energy consumption will increase during this period. (2) In the same year, the coal consumption under the policy-constrained scenario is lower than that in the unconstrained scenario, indicating that at present, the energy consumption structure has a problem with an excessively high proportion of coal consumption. (3) From 2020 to 2030, under the unconstrained scenario, the proportion of coal consumption will decrease, and the proportions of oil, natural gas, and clean energy consumption will increase. Thus, China's energy structure has been optimized under natural evolution.

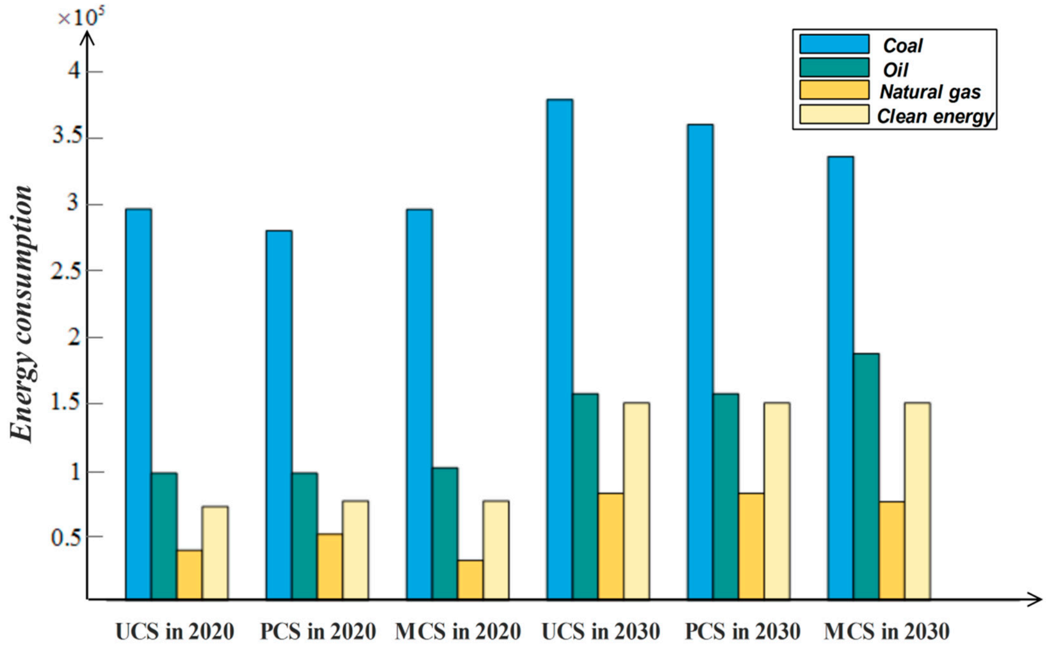

Figure 3. Energy consumption under different scenarios in China in 2020 and 2030.

5. Contribution Analysis of Energy Structure Optimization to Achieve the Carbon Intensity Targets

In 2005, China's GDP was 4,797.58 billion RMB (1980 constant price). By burning fossil fuel energy sources, the total amount of carbon dioxide emitted was 5.533 million tons, and the carbon intensity was 1.15 kg/RMB.

Based on the energy consumption in Table 6 and Equation (34), the total amount of carbon dioxide emitted from primary energy combustion in each scenario is estimated.

Given the prediction for China's national economy (GDP) in Section 3.2 of this paper and the carbon intensity in each scenario calculated with Equation (35), we can analyze the potential contribution of energy structure optimization to achieving the carbon intensity targets. The results are shown in Table 7 and Figure 4.

Table 7. Energy structure optimization results under various scenarios.

Year	2020			2030		
Scenario	**UCS**	**PCS**	**MCS**	**UCS**	**PCS**	**MCS**
GDP (billion)	164,048.47	164,048.47	164,048.47	280,218.49	280,218.49	280,218.49
Carbon emissions (10^4tce)	1,089,917	1,064,503	1,084,638.26	1,519,418	1,466,897	1,455,357.30
Carbon intensity (kg/RMB)	0.66	0.65	0.66	0.54	0.52	0.52
Degree of decline (%)	42.39	43.74	42.67	52.98	54.61	54.97

(1) Carbon Intensity Prediction Results in each Scenario

The carbon intensity prediction results in each scenario are shown in Table 7. Under natural evolution, the carbon intensity in 2017 is 0.74 kg/RMB. The carbon intensity will decline to 0.66 kg/RMB by 2020 under the unconstrained scenario, a total decrease of 10.81% from 2017, and the carbon intensity will decline to 0.54 kg/RMB by 2030, a total decrease of 27.03% from 2017. Under the policy-constrained scenario, the carbon intensity will decline to 0.65 kg/RMB by 2020, a total decrease of 12.16%, and the carbon intensity will decline to 0.52 kg/RMB in 2030, a total decrease of

29.07%. Additionally, under the minimum external cost scenario, the carbon intensity will decline to 0.66 kg/RMB by 2020, a total decrease of 11.63%. In 2030, the carbon intensity will decline to 0.52 kg/RMB, a total decrease of 29.63%.

(2) Contribution Analysis of Optimizing the Energy Structure to Realize the Carbon Intensity Targets

Based on the results, the contribution potential of optimizing the energy structure that drives the carbon intensity relative to the decrease in 2005, and the goal of achieving carbon intensity, are calculated. The contribution potential refers to the ratio of the decrease of carbon intensity in each energy structure optimization scenario relative to the target of the carbon intensity reduction. The carbon intensity target is deemed to be a range, so that the calculated contribution potential is also a range.

China set the target for carbon intensity to decline using 2005 as the base year, and the carbon intensity in 2005 was 1.15 kg/RMB. If the carbon intensity declines by 40–45% from 2005 to 2020, the carbon intensity must be reduced to 0.63–0.69 kg/RMB. If the carbon intensity in 2030 is 60–65% lower than that in 2005, the carbon intensity must decline to 0.40–0.46 kg/RMB.

Figure 4 comprehensively reflects the energy structure optimization results under various scenarios. The figure contains four graphs that reflect the predicted values of carbon intensity in each scenario for 2020 and 2030, and their potential contributions to achieving the carbon intensity targets. Among the graphs, Figure 4a,b provide the total amount of carbon dioxide emissions and carbon intensity results under the various scenarios in 2020 and 2030, respectively. Figure 4c shows the decrease in carbon intensity in each scenario between 2020 and 2030 compared to 2005. Figure 4d shows the potential contribution of the structure optimization of energy consumption to achieving the carbon intensity targets in the 2020 and 2030 scenarios.

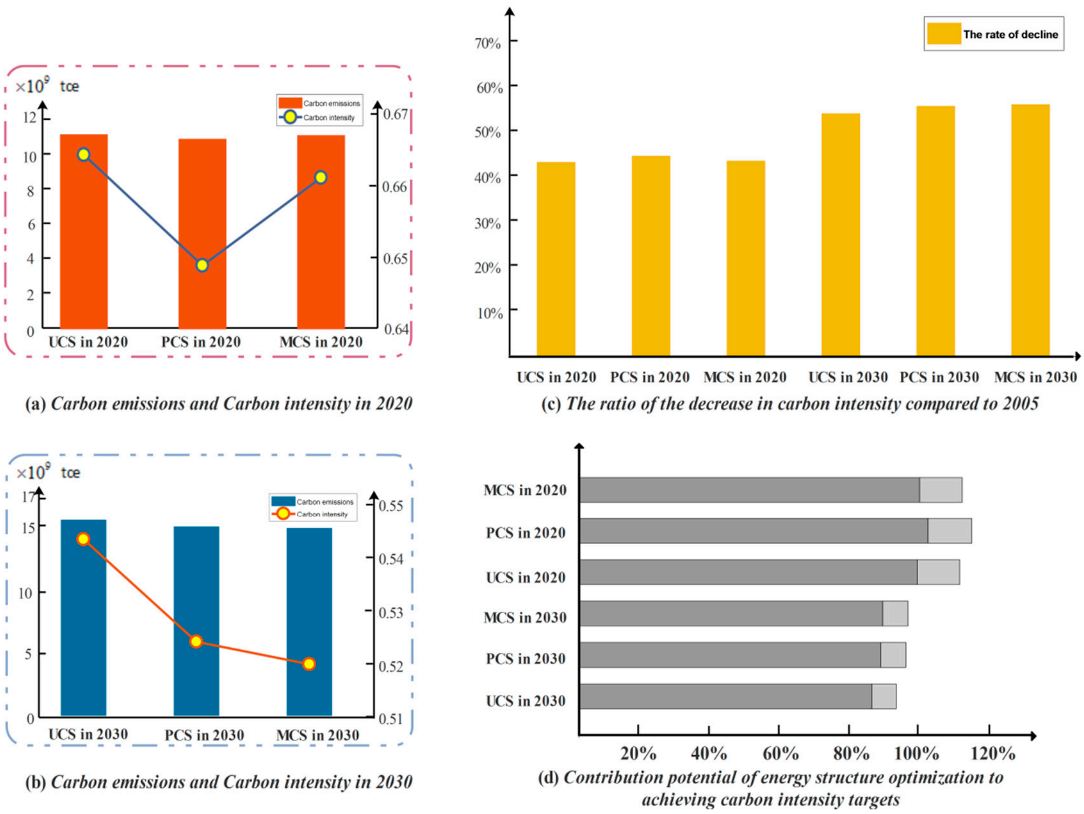

Figure 4. Energy structure optimization results under all scenarios.

Considering the results from Table 7, in 2020, the carbon intensity predicted by the unconstrained scenario is 0.66 kg/RMB, a decrease of 42.39% from 2005; the carbon intensity of the policy-constrained scenario is estimated to be 0.65 kg/RMB, a decrease of 43.74% from 2005; and the carbon intensity predicted by the minimum external costs scenario is 0.66 kg/RMB, a decrease of 42.67% from 2005. We can observe that the carbon intensity consequences predicted by the three scenarios are all within the target range; the energy structure optimization achieves 100% of the carbon intensity target in all scenarios, and the carbon intensity target for 2020 can be completely achieved.

In 2030, the carbon intensity predicted by the unconstrained scenario is 0.54 kg/RMB, which is a decrease of 52.98% from 2005, with a potential contribution of 81.51–88.31% to achieving the carbon intensity target. The carbon intensity of the policy-constrained scenario is 0.52 kg/RMB, which a decrease of 54.61% from 2005, with a potential contribution of 84.01–91.01%. The carbon intensity of the minimum external cost scenario is predicted to be 0.52 kg/RMB, which is 54.57% lower than that of 2005, with a potential contribution of 84.56–91.61%. To achieve the carbon intensity target for 2030, the carbon intensity must be reduced to 0.40–0.46 kg/RMB. We can observe that under the three scenarios, all failed to achieve the carbon intensity target of 2030 by relying on energy structure optimization; however, the contribution potential of energy structure optimization is greater than 80%. By further implementing other measures to save energy and reduce emissions, it is very possible to reach the goal of a 60–65% reduction in carbon intensity by 2030.

According to Table 6, the consumption proportion of natural gas is 10–11%, and that of oil is 20–25% in 2030. The proportion of oil is much higher than that of natural gas. It is known that natural gas is a relatively clean fossil energy. Under the same standard, the CO_2 produced by burning one ton of coal is 30% more than oil, and 70% more than natural gas. That is, natural gas emits the least amount of carbon dioxide when it generates the same amount of heat. According to the results of this paper, the predicted energy structure optimization fails to achieve the carbon intensity target by 2030. Therefore, as an efficient, clean, and high-quality fossil energy, increasing the proportion of natural gas consumption is one of the best choices to optimize the energy structure, improve energy efficiency, and achieve the carbon intensity target [61]. In addition, in the process of achieving energy-saving and emission reduction targets, natural gas has more cost advantages and technological advantages than new clean energy such as wind energy and nuclear energy. It is less restricted by natural conditions such as time and region. Natural gas has great potential in optimizing energy structure. At present, natural gas is a lagging energy in China, and the reason is that the price is on the high side. In the future, it will be necessary for the Chinese government to further strengthen the reform of natural gas price market, to change the situation in which resources such as natural gas exploration, to import channels and bargaining negotiations are highly concentrated in the three state-owned companies, to open up the natural gas market, and to encourage more market institutions to participate in. Higher market-oriented offshore LNG projects can also be used to increase the development and utilization of unconventional natural gas, in order to increase the consumption proportion of natural gas.

Through a comparison of the prediction results for the three energy structure optimization scenarios, the following conclusions are also obtained:

(1) The scenario with the lowest predicted carbon intensity in 2020 is the policy-constrained scenario. This scenario has the fewest total carbon emissions. Compared with the unconstrained scenario, CO_2 emissions will be reduced by 254.14 million tons in 2020 under the policy-constrained scenario, which is equivalent to 92.71 million tons of standard coal.

(2) The scenario with the lowest predicted carbon intensity in 2030 is the minimum external costs of the carbon emissions scenario. This scenario has the least total carbon emissions. Compared with the unconstrained scenario, CO_2 emissions will decrease by 640.607 million tons in 2030, which is equivalent to 233.7 million tons of standard coal.

(3) The comparison of different scenarios in the same year shows that the best energy structure optimization effect in 2020 occurs through the policy-constrained scenario. Coal consumption in this scenario accounts for 55.8%. The best energy structure optimization effect in 2030 occurs

through the minimum external costs of carbon emissions scenario, in which the coal consumption accounts for 45%. The above two scenarios are the scenarios with the lowest proportion of coal consumption in the same year. The reason for this result is perhaps that, compared with other types of energy, coal has low calorific value and high unit carbon emissions, and it is a poor-quality energy source. These characteristics indicate that reducing the proportion of coal consumption is critical to achieving the carbon intensity targets.

(4) The natural evolution of the energy consumption structure in 2020 will achieve the planned target of less than 62% of coal consumption, but it will not meet the target of 10% of natural gas consumption or 15% of non-fossil energy consumption. When the energy consumption structure evolves in 2030, the proportion of natural gas consumption will just reach the 2020 planning goal. Although non-fossil energy consumption accounts for more than 15% of total energy consumption, the target of 20% of consumption has not been achieved. All these scenarios show that China's current energy consumption transformation and upgrading process is slow, and that the goal is still arduous. It is necessary to further increase the energy conversion rate and upgrade energy technologies.

(5) Based on the results shown in Table 7, under the state of sustained economic growth, the carbon intensity in 2020 calculated under the three energy structure optimization scenarios will decrease by 42.39–43.74% compared with 2005, and the carbon intensity target of 2020 can be successfully realized. The calculated carbon intensity in 2030 will decrease by 52.98–54.97% compared with 2005, which is a gap of nearly 10% to achieve the carbon intensity target of 2030. An important reason for this result is that coal is still the most important source of energy consumption in the three scenarios, as shown in Figure 3. This indicates that the optimization of China's energy structure is not sufficient and needs to be further strengthened. To achieve the carbon intensity target by 2030, China needs to develop renewable energy vigorously, reduce the proportion of coal, replace fossil energy with non-fossil energy, and replace coal with natural gas in fossil energy, so as to promote low-carbon diversification of energy structure and to realize sustainable energy development.

6. Conclusions and Policy Suggestions

6.1. Conclusions

This paper studies China's primary energy consumption structure based on the carbon intensity targets for 2020 and 2030. First, primary energy consumption is predicted with a combined forecasting model. The single forecast is generated using the GM (1, 1) model and GRNN model, and the single model is weighted using the gray relational degree method to obtain the primary energy consumption for 2017–2030. Furthermore, we compare China's primary energy consumption predictions between this study and others, as shown in Appendix B. Second, from the perspectives of natural evolution, policy planning and cost, we set three scenarios to optimize the energy structure and obtain the prediction results. Finally, we analyze the energy structure and its contribution to achieving the carbon intensity targets in each scenario.

According to the above study, we can draw the following conclusions. (1) The estimated primary energy consumption is 5.06 and 7.54 billion tce in 2020 and 2030, respectively. Combined with the forecasting results of other studies, we can conclude that China's primary energy consumption will continue to grow over the next 14 years. (2) The carbon intensity target for 2020 can be achieved under the unconstrained scenario, policy-constrained scenario and minimum external costs of the carbon emissions scenario; among these scenarios, the predicted carbon intensity decreases the most and the carbon emissions are the lowest under the policy-constrained scenario. (3) The carbon intensity target will almost be attained in 2030 under the optimized energy structure in different scenarios, and so further emission reduction efforts are still required. In 2030, the predicted carbon intensity will decrease the most under the minimum external costs of the carbon emissions scenario, with a contribution potential of 84.56–91.61%. Under the unconstrained scenario, the predicted carbon intensity is 52.98% lower than that in 2005, with a potential contribution of 81.51–88.31%. Under the policy-constrained scenario, the predicted carbon intensity is 54.61% lower than that in 2005, with a contribution potential of 84.01–91.01%. (4) To achieve the carbon intensity targets, it is necessary to further develop clean energy and promote a change in the energy consumption structure from mainly coal in order to classify the consumption of coal, oil, natural gas, and clean energy.

6.2. Policy Suggestions

Based on the above conclusions, we propose the following policy suggestions:

(1) Control the primary energy consumption and reduce coal consumption.

According to the forecasting results of our study, China's primary energy consumption will continue to grow over the next 14 years. To achieve the carbon intensity targets in 2020 and 2030, controlling total energy consumption is a key measure. First, an overall national total primary energy consumption plan should be made, and the energy consumption targets should be assigned to each province according to equity principles and regional development strategies by taking full account of the economic development level and the industrial structure of each province. Second, the local government assessment systems should be improved, and the government and enterprises should be supervised to accomplish the established targets of energy conservation and emission reduction.

In addition, the forecasting results show that coal consumption will account for more than 45% of total energy consumption in 2030, which is still higher than the world average (30%). The excessive proportion of coal has put increasing pressure on the environment and contributed to climate change. To adjust the energy structure, total coal consumption should be controlled in key areas, such as the Pearl River Delta, Yangtze River Delta, and Beijing–Tianjin region, by gradually phasing out or upgrading coal-fired power stations, strictly limiting the growth of new heavy industries based on coal consumption, and promoting industrial equipment and technologies.

(2) Increase oil and natural gas consumption and develop renewable energy.

The proportion of oil and natural gas is relatively low in China's energy consumption structure. China has abundant oil resources, and given the monopoly of China's oil market and the pressure of large-scale oil imports to energy supply security, it is necessary to fully utilize the oil resources to meet basic demands. Meanwhile, the development of the natural gas industry must be accelerated, including the excavation of natural gas resources, introducing advanced technology and equipment, speeding up the construction of domestic natural gas pipelines, and strengthening the cooperation with neighboring countries regarding natural gas resources.

Based on the forecasting results of the energy consumption structure, it is clear that China's energy consumption is overly dependent on fossil fuels, which is not sustainable. Vigorously developing new types of clean energies, such as hydropower, wind, solar, and nuclear, is necessary in order to achieve a low-carbon economy. First, policy and financial support for renewable energies should be strengthened. Second, advanced foreign technologies should be introduced to the clean energy industry, and they should help clean energy enterprises to improve their technological level. Meanwhile, increasing the investment in Research and Development (R&D) in new energy fields is also significant to reduce the costs of renewable energy.

(3) Improve energy efficiency and develop carbon emissions reduction technology.

Given the conclusions of this study, energy structure optimization cannot fully achieve China's carbon intensity target by 2030. Thus, it is important to improve the energy efficiency and to develop corresponding technology. First, energy waste should be reduced, and the efficiency of energy deployment should be increased by further improving the reform of the energy price mechanism and linking domestic energy prices with international energy prices. Second, it is also important to learn from the advanced experience in emission reduction in developed countries, and to establish a sound legal system to supervise enterprises to reduce energy consumption and improve the efficiency of energy use. Third, the unified carbon trading market should be developed, and carbon taxes levied, in order to accelerate the green transformation of energy-intensive enterprises.

To develop carbon emissions reduction technology, financial support should be given to adopt environment-protecting technologies, and to formulate a sound low-carbon transition development evaluation system. Meanwhile, carbon capture, utilization, and storage (CCUS) is an important strategic choice for carbon reduction in China. Special funds and compensation mechanisms should be established for CCUS as soon as possible.

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Appendix A

Table A1. Summary of the aforementioned studies.

Author	Time	Research Topics	Methodologies	Main Results
Tan et al. [6]	1998–2008	Explore the driving forces for reducing China's CO_2 emission intensity	LMDI model	The decomposition results show that improvements in the energy intensity of power generation, electricity intensity of GDP, and energy intensity of GDP for other activities were mainly responsible for the success in reducing China's CO_2 emission intensity.
Huang et al. [7]	1996–2009	Carbon intensity factor decomposition	LMDI model	In the long run, optimizing the energy structure and the industrial structure is the fundamental way to reduce carbon intensity.
Xu et al. [8]	2001–2011	Decomposition analysis of factors affecting CO_2	PDA model and IDA model	Economic activity is the main cause of substantial increases in carbon dioxide emissions in China. Different driving factors affect carbon emissions in different provinces.
Su et al. [10]	1997–2000	China's regional emission embodiments	Input–output model	The paper combines the HEET approach and stepwise distribution analysis to allocate the carbon emission reduction targets.
Zhu et al. [11]	1980–2007	Decomposition of carbon emissions from energy consumption	Kaya model and the LMDI model	The economic output effect makes the greatest contribution to the carbon emissions from energy consumption in this stage in China. The population scale effect and the industrial structure effect are positive, and the energy intensity effect and energy structure effects are negative.
Raupach et al. [12]	2000–2004	The area and factor decomposition of carbon emissions	Kaya model	In 2000 to 2004, developing countries had a greater share of emissions growth than of emissions themselves.
Wang et al. [13]	1980–2010	Analyze the impact factors of CO_2 emissions in Guangdong province	STIPPRAT model	Population is the most important impact factor of CO_2 emissions. Industrialization level, urbanization level, energy consumption structure, service level, and GDP per capita are also significant impact factors.
Yue et al. [14]	2010–2020	Find the influencing factors and calculate CO_2 emissions	Expanded IPAT model and decomposition method	Rapid economic growth is the main determinant that results in increasing CO_2 emissions in Jiangsu province.
Liu et al. [15]	2008–2020	Investigate the energy consumption and CO_2 emissions trend	System dynamic analysis	The total energy consumption and CO_2 emissions in 2020 are 1.6 and 1.9 times higher than 2008 figures.
Parag Sen et al. [16]	2002–2013	Forecast energy consumption and GHG emission	ARIMA model	ARIMA (0,1,0) $\times$ (0,1,1) is the best model to forecast energy consumption.
Wang et al. [17]	2014–2020	Forecast Chinese carbon emissions	Non-linear grey model	Compared with other models, the TNGM (1, 2) has the smallest predicted error, and the prediction results can be obtained from this model.

Table A1. *Cont.*

Author	Time	Research Topics	Methodologies	Main Results
Nabavi-Pelesaraei et al. [18]	2013–2014	Forecast and sensitivity analysis of energy input and GHG emissions	Artificial neural networks model	The total energy consumption and energy output for kiwifruit production were 37.32 GJ ha^{-1} and 43.44 GJ ha^{-1}, respectively. The highest energy consumption among all energy sources was made by chemical fertilizers.
Ajay et al. [19]	2005–2050	Forecast China's carbon dioxide emission	The MESSAGE model and the Grantham Institute model	The total energy consumption and energy output for kiwifruit production were 37.32 GJ ha^{-1} and 43.44 GJ ha^{-1}, respectively. The highest energy consumption among all energy sources was by chemical fertilizers (mainly nitrogen, with 45.61%).
Yongrok et al. [20]	2001–2010	Estimate the energy efficiency, potential emission reductions and marginal abatement costs of energy related CO_2 emissions	DEA model	Most provinces in China are not performing energy efficiently, and Hebei and Shandong are the two provinces with the largest energy consumption and have profound energy use reduction potential.
Du et al. [21]	2006–2010	The estimation of the CO_2 emission efficiency and the potential emission reduction	Nonparametric metafrontier model	The potential CO_2 emission reduction is 1687 million tons, and over half of the potential emission reduction is caused by the technology gap.
Stern et al. [27]	2005–2020	Examine the carbon intensity targets of China and India in 2020	Stochastic frontier model	China is likely to need to adopt ambitious carbon mitigation policies in order to achieve its target; India's target is less ambitious.
Yi et al. [28]	2005–2020	Analyze the determining factors and diverse scenarios of CO_2 emissions intensity reduction	Extended Kaya model and scenario analysis	The carbon intensity target for 2020 is very likely to be achieved in China.
Xiao et al. [29]	2005–2020	Examine the carbon intensity targets of China in 2020	System dynamics model	The Chinese government can accomplish the target under carbon tax policy scenario and integrated policy scenario.
Yuan et al. [30]	2005–2020	Investigate clean energy targets	Scenario analysis	A 17% clean energy target can achieve the carbon intensity target of 2020 and exceed the IEA 450 ppm scenario.
Wang et al. [31]	2005–2020	Discuss low-carbon energy policies at the province level	Reactor model and scenario analysis	Due to their different energy structures, Chinese provinces should evaluate their own unique situations and how they relate to carbon emissions.
Yi et al. [32]	2005–2020	Allocate the CO_2 reduction target regionally	Index analysis and top-down model	Shanghai, Hebei, Shanxi, Shandong, Guangdong and Liaoning provinces may undertake greater burdens to achieve the 45% intensity reduction target by 2020.
Xu et al. [33]	2005–2030	Predict carbon emissions and carbon intensity	GM (1,1) model and STIPPRAT model	China's carbon intensity reduction targets in 2020 and 2030 can be met under current policies.
Zhang et al. [34]	1993–2035	Determine whether and how the carbon intensity targets will be realized from a sector-specific perspective	Dynamic Monte Carlo simulation and scenario analysis	It is very possible for the industrial sector to achieve the 2020 and 2030 intensity-reduction targets.

Appendix B

Table A2. Comparison of China's primary energy consumption predictions between this study and others. (unit: 10^4 tce).

Authors	Model	Scenarios	2020	2030
(Energy Information Administration) EIA [62]	World Energy Projections plus, WEPS+	High economic growth	619,384.40	738,768.70
		Low economic growth	605,657.20	679,284.50
		High oil price	609,401.00	731,281.20
		Low oil price	611,480.90	686,356.10
		Reference case	612,728.80	708,818.60
(British Petroleum) BP [63]	-	-	494,740.00	594,197.00
Shen et al. [64]	Exponential Smoothing (ES)	United States scenario	455,300.00	447,700.00
		United Kingdom scenario	419,100.00	432,800.00
		Germany scenario	454,200.00	429,400.00
		France scenario	518,900.00	564,300.00
		Japan scenario	458,300.00	577,300.00
		South Korea scenario	649,900.00	830,300.00
		Baseline scenario	617,100.00	892,500.00
Wang et al. [65]	Self-adaptive MVO-SVM	High economic growth	484,701.00	545,365.40
		Low economic growth	482,657.50	581,781.10
		High coal consumption	493,987.50	620,522.90
		Low coal consumption	467,364.20	553,733.10
		Reference case	483,929.90	565,624.80
Authors	Combined model	-	506,356.51	754,026.21

Appendix C

Under the unconstrained scenario, the average transfer probability matrix P is:

$$P = \begin{bmatrix} 0.9813 & 0.0055 & 0.0036 & 0.0095 \\ 0.0035 & 0.9934 & 0.0024 & 0.00075 \\ 0 & 0 & 1 & 0 \\ 0.0083 & 0 & 0.005 & 0.9867 \end{bmatrix}$$

Appendix D

I The non-linear programming model under the minimum external costs of carbon emissions scenario in 2020:

$$\min f(x) = 354.81x_1 + 276.46x_2 + 210.49x_3$$
$$s.t \begin{cases} x_1 + x_2 + x_3 + x_4 \leq 506356.51 \\ (0.7476x_1 + 0.5825x_2 + 0.4435x_3) \times \frac{44}{12} \leq 1089917 \\ 0.5 \leq x_1 / \sum\limits_{i=1}^{4} x_i \leq 0.6 \\ 0.2 \leq x_2 / \sum\limits_{i=1}^{4} x_i \leq 0.3 \\ 0.06 \leq x_3 / \sum\limits_{i=1}^{4} x_i \leq 0.15 \\ 0.15 \leq x_4 / \sum\limits_{i=1}^{4} x_i \leq 0.25 \end{cases}$$

II The non-linear programming model under the minimum external costs of carbon emissions scenario in 2030:

$$\min f(x) = 354.81x_1 + 276.46x_2 + 210.49x_3$$
$$s.t \begin{cases} x_1 + x_2 + x_3 + x_4 \leq 754026.21 \\ (0.7476x_1 + 0.5825x_2 + 0.4435x_3) \times \frac{44}{12} \leq 1519418 \\ 0.4 \leq x_1 / \sum\limits_{i=1}^{4} x_i \leq 0.5 \\ 0.25 \leq x_2 / \sum\limits_{i=1}^{4} x_i \leq 0.3 \\ 0.10 \leq x_3 / \sum\limits_{i=1}^{4} x_i \leq 0.20 \\ 0.2 \leq x_4 / \sum\limits_{i=1}^{4} x_i \leq 0.25 \end{cases}$$

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