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The Optimal Path for China to Achieve the "Dual Carbon" Target from the Perspective of Energy Structure Optimization

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Abstract: Exploring the path of energy structure optimization to reduce carbon emissions and achieve a carbon peak has important policy implications for achieving the "Dual Carbon" target. To this end, this paper explores the optimal path for China to achieve the "dual carbon" target from the perspective of energy structure optimization in three steps: (1) we forecast China's carbon emissions and carbon intensity during 2024–2035 based on a combined forecasting model; (2) we simulate the development of energy consumption and carbon emissions under the "economic development scenario-energy structure scenario" with the help of Markov chain forecasting model; (3) we construct a multi-attribute decision model to account for the above elements as variables to calculate a composite index to analyze the optimal path for China to achieve "Dual Carbon" target under different decision preferences. It is found that (1) potential negative effects caused by COVID-19 are not as serious as reported; (2) only the scenario with low-speed economic growth and effective policies guiding, which doesn't follow laws of social development, can contribute to reaching carbon peaking by 2030 while maintaining a high-quality carbon intensity; (3) the optimal path that scenario with middle-speed economic growth and strict cost control is a sub-optimal choice subject to realities; (4) technologies innovations in green or low-carbon fields are needed to accelerate energy consumption structure optimization.

Keywords: energy structure optimization; "dual carbon" target; optimal path; multi-attribute decision making

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1. Introduction

In 2020, at the 75th UN General Assembly General Debate, China announced its "Dual Carbon" target, specifically to realize carbon peaking by 2030 and carbon neutrality by 2060. Inspired by the "Dual Carbon" target, countries around the world have proposed successively specific requirements and timelines for achieving carbon neutrality, which is regarded as the first-step and crucial solution to address increasingly serious issues from climate change, environment degradation and resource depletion.

The global climate and environment have been suffering negative changes. For about 200 years, human activities have increased carbon emissions rapidly. The record, which remained for nearly 2.5 million years with a carbon dioxide concentration of 280 ppm (parts per million), was broken by a level of 400 ppm in 2015. Research from the World Bank shows that the average annual growth rate of carbon dioxide concentration reached 0.2 ppm at the end of the 1950s. Then, the value raises to 2.2 ppm from 2005 to 2019. Unfortunately, this rapid growth may continue, and the carbon dioxide concentration could reach more than twice as high as the current situation if no measures are adopted. Affected by the rapid growth of carbon emissions, global surface temperatures show a fluctuating upward trend. Data from the Goddard Institute for Space Studies of the National Aeronautics and Space Administration (NASA) point out that average annual surface temperatures rise unstably, and this phenomenon becomes worse and more obvious over time. The average surface temperature added 1.2 ± 0.1 °C in 2020 compared with 1980.

The World Meteorological Organization (WMO) reports that not only did the quantity and concentration of greenhouse gas achieve a new all-time high in 2020, but also 2020 became one of the three warmest years on record. A "Dual Carbon" target is necessary to solve this dilemma. After decades of continuous follow-up and systematic evaluation, the Intergovernmental Panel on Climate Change (IPCC) finds that human activities represented by the large-scale exploitation of fossil fuels are the main reason leading to global warming. A wealth of data further supports this view. Fossil fuels such as oil, natural gas and coal are the most crucial energy consumption products current human activities rely on, and they are also the main contributors of greenhouse gas (such as carbon dioxide and PM2.5) emissions. The Statistical Review of World Energy 2021 reports that the situation is still not optimistic (fossil fuels account for 84.3% of primary energy consumption and carbon emissions because of fossil fuels burning account for 74.67%) except only negative growth caused by COVID-19 in 2020. Therefore, optimizing energy structures seems like a priority in achieving carbon neutrality.

The questions above are worse if turning perspective from worldwide to China. As the world's largest carbon emitter, China has been suffering serious carbon emissions related to fossil fuel consumption. Also shown in the Statistical Review of World Energy 2021, the growth rate of primary energy consumption in China is not only faster than the worldwide average but also remained positive in 2020 (2.41%) compared with global −4.28%. Not affected by strong shocks from COVID-19, China's total primary energy consumption accounted for a percentage of global consumption that changed from 20.64% in 2010 to 36.13% in 2020. Under huge regulatory pressure on energy consumption, China's carbon emissions related to energy account for 30.66% of the world's total. This is contrary to China's current development approach. China's economy is experiencing a transitionary stage from high-speed to high-quality, and promoting the "Dual Carbon" target by optimizing the energy consumption structure strives from three requirements: firstly, strategic needs of national energy security. In 2020, the external dependencies on oil and natural gas of China were 73.5% and 41.3%, respectively, and the structural contradiction between the supply and demand of energy was prominent; Secondly, the environmental carrying capacity of energy resources is facing harm. The limited per capita share of energy resources and relatively fragile ecological environment prove a long-standing, simple and crude development approach that is no longer sustainable; Thirdly, the public has a pressing need. Realizing the "Dual Carbon" target would help address problems such as recent extreme and severe weather and lift the quality of social life. Overall, the "Dual Carbon" target is an essential initiative to solve climate change and accelerate high-quality economic growth in China, and the first priority is to adjust China's energy consumption structure.

Realizing the "Dual Carbon" target is China's focus in future work, the government launched the "1 + N" policy system for the "Dual Carbon" target. The aims of "1" in the "1 + N" policy system, which are respectively known as Opinions on the Complete and Accurate Implementation of the New Development Concept to Realize Carbon Peaking and Carbon Neutrality on 24 October 2021, and Carbon Peaking Action Program by 2030 on 26 October 2021, are that: by 2025, the proportion of non-fossil energy consumption will reach around 20%, energy consumption per unit of GDP will fall by 13.5% compared to 2020, and CO_2 emissions per unit of GDP will fall by 18% compared to 2020; by 2030, the proportion of non-fossil energy consumption will reach around 25%, and CO_2 emissions per unit of GDP will fall by more than 65% compared to 2005, so as to successfully achieve the carbon peak target by 2030. It's not difficult to find that the "Dual Carbon" target is closely associated with energy structure optimization in general planning. Specially studying "N" in "1 + N" policy system, energy structure optimization is repeatedly mentioned: in two, 2021, Guidance on Accelerating the Establishment of Sound Economic System for Green, Low-carbon and Circular Development points out that " ... energy resources need to be allocated more rationally and utilized more efficiently, total emissions of major pollutants should continue to be reduced, and carbon emissions intensity aims to be significantly reduced ... "; in three, 2021, the 14th 5 Year Plan aimed to strictly control the growth of coal consumption and gradually reduce it during the 15th 5 Year Plan; what is more, " ... in 2030, the installed capacity of wind power and solar photovoltaic power generation should reach 1.2 billion kilowatts, build a new power system with new energy as the mainstay, promote industrial electric transportation and improve energy use efficiency . . . ”; on 28 October 2021, China updated its National Determined Contributions (NDCs) before Glasgow Climate Pact on 2 November 2021, and in 11 November 2022, China announced Progress on the Implementation of China’s Nationally Determined Contributions (2022), and the measures of carbon reduction also mainly concentrate on energy structure, for example, “ . . . under the requirements of achieving ‘Dual Carbon’ target, the development and utilization of low-carbon renewable energy industries need to be vigorously developed in order to increase non-fossil energy consumption and promote the sustainable development of the energy industry, and a revolution in energy production and consumption must be promoted . . . ”, and “ . . . in order to reduce the level of carbon dioxide emissions, it’s necessary to reduce greenhouse gases in human production activities, such as burning less coal or improving the efficiency of coal use, and using more green energy, such as solar, wind, water and nuclear energy . . . ”.

To achieve the “Dual Carbon” target, the energy structure urgently needs optimization, which leads us to wonder what is the optimal path to achieve the “Dual Carbon” target from the perspective of optimizing the energy consumption structure. Based on the doubt above, a research framework is established as follows: firstly, this paper aims to narrow the research scope for better accuracy. As announced by The State Council of China, the “Dual Carbon” target is divided into two sections: one is to achieve carbon peaking by 2030, and then is to reach carbon neutrality by 2060. Carbon peaking is the basis and prerequisite of carbon neutrality. Therefore, details that are currently available will focus on improving the accuracy for forecasting situation changes from 2024 to 2035, i.e., exploring whether or how carbon peaking can be achieved under existing policies; Secondly, based on the scenario settings of high-speed, middle-speed and low-speed economic growth, a combination of the GM (1,1) Model and the Multiple Linear Regression Model is used to forecast the proportion of secondary industries, the total of the resident population, social fixed-asset investment, and most importantly, the total emissions of carbon dioxide and total consumption of primary energy from 2024 to 2035. Thirdly, for scenarios of nature evolution and lowest carbon emissions, a combination of the Markov Chain Model and Multi-Objective-Programming Model is used to forecast energy consumption structure and resulting carbon emissions from 2024 to 2035 under different scenarios. Finally, the Multiple Attribute Decision-Making Model is used to analyze the feasibility of the “Dual Carbon“ target and the optimal path to achieve carbon peaking considering different decision-preference. The reasons why this paper chooses those model combinations will be further mentioned below.

Compared with previous research, this paper makes the following contributions: (1) in previous research, discussions about the influence of results focusing on the optimization of the energy consumption structure for carbon emissions and carbon intensity are lacking, and this paper will contribute to filling this gap. As mentioned above, a close connection exists between carbon emissions and energy consumption. For the “Dual Carbon” target, finding a suitable path to optimize the energy structure means “half the work, twice the effort”. (2) few previous research consider integrating carbon peaking and carbon intensity as a framework, and this paper fixes this deficiency. Although achieving a high-quality economy could sacrifice some economic growth rate, talking about carbon reduction with ignoring economic growth is not proper. Therefore, this paper uses carbon intensity instead of carbon quantity to portray carbon emissions. The reasons are that: on the one hand, carbon intensity can indicate how efficiently an entity is using resources and whether the change of emissions is due to positive or negative economic growth; on the other hand, carbon intensity, which depends on the carbon emission factor of fossil fuels, the structure of fossil fuels, and the proportion of fossil fuels in the total energy consumption, are more effective in demonstrating the link between energy consumption and carbon emission. (3) The scenario setting and factors considered depend on the related policies of China’s latest NDCs. Almost all parameter settings of the previous related research follow old

NDCs, which are the most comprehensive demonstration of the direction and process of the country's development. However, measures to achieve the "Dual Carbon" target are actually built on China's latest NDCs announced on 28 October 2021. Predictions with old NDCs cannot accurately represent real development situations, so this paper tries to eliminate this error with the latest NDCs.

The remainder of this publication is organized as follows. In Section 2, there is a literature review. In Section 3, primary energy consumption and related carbon emissions considering high-speed, middle-speed and low-speed economic growth are forecasted. In Section 4, changes in energy consumption structure and related carbon emissions under the lowest carbon emissions are forecasted. In Section 5, the feasibility of achieving the "Dual Carbon" target and the analysis of the optimal path is studied. In Section 6, there are discussions. In Section 7, conclusions and policy implications are provided.

2. Literature Review

With the gradual completion of industrialization, as a world power responsible for carbon emission reduction, China's carbon emission reduction pressure is increasing day by day, and the problems of inefficient energy use and low investment efficiency in China's secondary industry are gradually coming to the fore [1–3]. At present, few previous studies have been conducted in the primary industry, and most of them focus on the decomposition of carbon emission factors and carbon emission estimation, while relatively few previous research have been conducted on the peak path and peak value [4–7]. Among the tertiary industries, transportation is the main source of carbon emissions [8]. Improving the efficiency of fossil energy use, developing clean energy and improving transportation efficiency can effectively reduce carbon emissions from the transportation industry, thus effectively shortening the time to peak [9–11]. Most of China's regional carbon emissions show a significant growth momentum, and provinces such as Shandong, Shanxi and Hebei have a large volume of carbon emissions and a fast-growth trend of carbon emissions [12–15]. There are obvious regional characteristics that carbon emissions in China are higher in developed eastern provinces than in western provinces and higher in northern industrial provinces than in southern provinces [16–19]. Previous regional research focused on the more economically developed provinces (regions and cities) such as Beijing, Shanghai and Jiangsu and constructed regional carbon peaking models from factors such as population size, energy structure, investment efficiency and technological innovation [20–24]. The national peak carbon target is not a simple summation of the peak carbon target of each province (region and city) [25–28] but a reasonable prediction of the national peak carbon time and peak value [29–31] and on this basis, the total energy consumption and carbon growth constraint target should be proposed, and the total carbon emission and intensity characteristics of different provinces (regions and cities) should be considered according to local conditions, and the coordinated and integrated development of the whole country should be adhered to [6,9,10,25,28,31–35].

Specifically, previous research related to carbon peaking can be divided into four categories: (1) research industry features. Among the primary industries, China's total carbon emissions from agriculture are on an obvious upward trend [36,37]. Leaving policy guidance, it is difficult for agriculture to achieve the spontaneous transformation of decreasing carbon emissions [35,38]. Policy guidance is needed to further increase the share of renewable energy in its total energy consumption, reduce the total fossil energy consumption and optimize the energy structure to achieve better and faster carbon peaking in the primary industry [20,39,40]. The secondary industry is the main source of carbon emissions in China, and industry and construction occupy a major position in it [41,42]. Research shows that industry and construction can achieve the carbon peak target as scheduled, but the implementation of green policies will lead to longer-term economic losses in related industries [43–45]. The cost increase caused by green production and the output loss caused by restricted production are inevitable, and decoupling economic growth from carbon emissions and achieving a win-win situation between green production and economic growth are urgent issues to be solved [2,46,47]. Carbon emissions from transportation are the main source of carbon emissions in the tertiary sector, and the high proportion of fossil energy consumption and large greenhouse gas emissions are long-standing problems in the transportation industry [17,24,48]. Reasonable control of carbon emissions from the transportation industry will strongly promote the process of carbon peaking in China [49]. Combining the characteristics of various modes of transportation to design an efficient multimodal transport structure, reduce the carbon emission intensity of transportation, improve transportation efficiency, and vigorously develop new energy vehicles to adjust the energy consumption structure will promote the process of carbon peaking [3,13,50];

(2) Research regions. Previous research on China's carbon peaking is mainly divided into national peaking research and regional peaking research. From a macro perspective, the national carbon peaking study takes the whole country as a whole to study the factors influencing carbon emissions, peak carbon levels, and carbon peaking pathways [51–53]. China's energy consumption level and carbon emissions are mainly influenced by endogenous factors such as GDP, energy structure, energy intensity, population size, industrial structure, and technology level [10,38,42]. Most of the sample literature suggests that through green and low-carbon policy guidance, reducing the proportion of fossil energy consumption, promoting the rationalization and advanced development of industrial structure, actively building green cities, and accelerating the completion of the carbon emission trading market, China's total carbon emissions will slowly rise and reach the inflection point and decline in the short term, and the inflection point will appear earlier than 2030 [4,5,54]. Regional carbon peaking research is conducted for regional and local communities to achieve national carbon peaking [55–57]. By reasonably decomposing carbon dioxide emission factors in a specific province and analyzing specific scenarios based on local resource endowment, industrial structure, and humanities, regional carbon peaking research can provide a clear picture of energy consumption, carbon emissions, carbon peaking time, and peak value in different development scenarios [22,24,49,58]. It can effectively identify the potential factors to promote "carbon emission reduction" in the province [12,59];

(3) Research methods. The main research methods in the sample literature are qualitative research, quantitative research, "qualitative + scenario analysis", "quantitative + scenario analysis", and "mixed + scenario analysis". The Japanese scholar Yoichi Kaya established the Kaya constant equation by linking human social activities to carbon emissions and decomposed the factors influencing carbon emissions by the Kaya decomposition method [35,36,49,60]. These methods have been widely used in research related to carbon peaking. Some papers use the Monte Carlo simulation method to simulate scenario analysis, which effectively solves the problem that traditional scenario analysis methods cannot break through static analysis [16,32,36,61]. The environmental Kuznets curve shows that CO_2 emissions will rise and then fall in an inverted "U" shape with economic growth [18,43,44,62]. Some papers use the environmental Kuznets curve model to estimate the time of inflection point of carbon emission changes so as to predict the time of carbon peak in a certain region [10,47]; some papers use the LEAP (Long-range Energy Alternatives Planning System) model to evaluate the future total carbon emissions, so as to predict the future peak carbon level in China [8,63]. The IPAT (Stochastic Impacts by Regression on Population, Affluence, and Technology) model has the advantage of visualizing the relationship between the environment and various types of human activities [64,65], and the STIRPAT (Stochastic Impacts by Regression on Population, Affluence, and Technology) model is improved on this basis [13,49]. STIRPAT model can effectively solve the drawback of the same driving elasticity factors of the IPAT model. By decomposing the regional or industrial carbon emission impact factors using quantitative analysis, the main drivers of carbon emission can be identified, and then the path of carbon peaking can be simulated by using scenario design, which can effectively study the problems related to carbon peaking [6,15,25,29,50,63];

(4) Research topic. Analyzing previous research, this paper finds that China's carbon peak research is conducted according to the following three aspects: firstly, carbon emission reduction analysis, carbon peak time prediction, carbon peak level and peak path prediction for regions or industries with the theme of "carbon peaking" [41,49,62]. In the analysis of carbon emission reduction, researchers decompose the factors influencing carbon emission in the study area or industry through quantitative analysis and find out the drivers with a strong influence on carbon emission through comparative analysis [25,47,54]. The existing literature on peak time, peak value and peak path uses scenario analysis to build a green model or a technology breakthrough model based on the realistic situation to simulate the carbon emission reduction scenarios, predict the possible peak time and peak value, and find the optimal peak path [6,31,40,43]. The second is the research on the theme of "energy". Fossil energy consumption, new energy development, and energy structure optimization are the focus of energy research in the context of carbon peaking [22,30,64]. Rapid economic development has put forward higher requirements for the development of the energy industry, and in the context of carbon peaking, ecological and environmental protection and resource conservation, new energy technologies have gained wide attention and gradually become an important way to solve environmental problems [1,25,35,57]. Thirdly, the research is carried out on the theme of "climate change". Climate change is the inevitable product of rapid economic development and excessive use of energy [33,52,63]. Since different countries have different resource endowments, economic development models and social development stages, there are many differences in greenhouse gas emissions, energy consumption and energy structures, and only high-quality economic development can solve the resulting carbon emission problems [5,15,40,48].

In summary, many previous studies have been conducted to predict and analyze whether China's carbon emission reduction targets can be achieved. The previous research on China's carbon emission attainment target is broadly classified into three categories from the methodological perspective: the index decomposition method, the scenario analysis method and the system optimization method [9,47,57,66]. Among them, the Kaya and STIRPAT models are used to predict peak carbon emissions based on the exponential decomposition method [35,38]. The LEAP model is widely used in the scenario analysis method. The models based on system optimization models include the MARKAL-MACRO, IPAC and IMAC models [7]. In addition, the Environmental Kuznets Curve (EKC) is also widely used to predict the peak of carbon emissions in China [20,24]. Most of the results suggest that China is well-positioned to achieve peak carbon emissions around 2030 [46,60]. Green et al. constructed an IPAT-based Kaya decomposition model to predict China's future carbon emissions using 2014 and 2015 base data and showed that carbon emissions from energy consumption will peak by 2025 [67]. However, the results obtained by Elzen et al. suggest that it is difficult to reach the peak of carbon emissions by 2030 under the current policies, and the implementation of energy conservation and emission reduction policies must be further strengthened [68]. In addition, some previous research has taken into account economic growth, energy intensity, industrial structure, and urbanization rate to predict that China will reach the peak of carbon emissions between 2030 and 2035 [12,55]. The impact of changes in energy mix on carbon emission peaking has not yet been studied in depth.

Although many results have been achieved in previous research on China's carbon emission reduction targets, the previous research has the following limitations: (1) the impact of energy structure on carbon emission targets has not been fully considered; (2) the previous research has paid less attention to whether China can achieve the carbon intensity target by 2030; (3) the peak carbon emission target and carbon intensity target have rarely been studied under the same framework, and most of the previous research have only studied the single carbon intensity or peak carbon target. Most of the previous research only studied the single target of carbon intensity or carbon peak. Therefore, this study attempts to explore the possibility of achieving the carbon emission peak and carbon intensity targets through energy restructuring, and to find the optimal path to achieve the

"Dual Carbon" target, so as to provide a reference for the subsequent policy formulation of energy structure optimization and how to achieve low-carbon economic development.

3. Forecasting Energy Consumption in China

3.1. Scenario-Setting of China's Economic Growth Rate

For the setting of China's economic growth rate, this paper draws on the idea of Hu et al. (2021) [25] to apply the scenario forecasting method, combining China's economic situation since the 21st century and the economic growth projected in the Medium- and Long-term Development Strategic Plan for Energy in China, this paper sets China's future economic growth rate into three scenarios: high, medium and low. Each scenario is divided into two time periods: 2024–2029 and 2030–2035. In the first stage, the economic growth rate is 8%, 6.5% and 5.5%, respectively. In the second stage, it is 7%, 5.5% and 4%, respectively.

3.2. Other Variable Settings Based on GM (1, 1)

The three factors of the total population, social fixed asset investment, and industrial output value share are more influenced by the historical data of each year, which are the results of the interaction and constraints of many social and economic factors, and the cause-effect relationship is complex and has gray characteristics and certain regularity. Gray forecasting is often used to solve the data with a small amount of data and cannot find the pattern directly. For the series containing uncertain information, the gray prediction method transforms the original data into a gray series by processing it and modeling the differential equations. The GM (1, 1) model is the basic model of gray prediction theory and the most widely used dynamic prediction model in gray system theory, which consists of a univariate first-order differential equation. The construction steps are as follows.

Accumulation processing of the sequence. The original sequence is cumulated once to generate a 1 AGO sequence of $x^{(0)}$ (cumulatively generated sequence) as in Equation (1).

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

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

Calculate the sequence of immediately adjacent means as in Equation (2).

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

where $z^{(1)}(k) = \frac{1}{2}\left(x^{(1)}(k) + x^{(1)}(k-1)\right)$.

Establish the first-order differential linear equation, i.e., the gray differential equation, to obtain the mean value form of the GM (1, 1) model as in Equation (3).

$$x^{(0)}(k) + az^{(1)}(k) = b \tag{3}$$

The corresponding whitening differential equation is derived from the GM (1, 1) model as in Equation (4).

$$\frac{dx^{(1)}}{dt} + ax^{(1)} = b \tag{4}$$

where a represents the development coefficient while b represents the amount of gray effect.

Let $\hat{a}$ be the parameter vector to be estimated, let $\hat{a} = \begin{bmatrix} a \\ b \end{bmatrix}$, and use the least squares method to solve for Equation (5).

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

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

Establish the GM (1, 1) time response equation as Equation (6).

$$\begin{cases} \hat{x}^{(1)}(k+1) = \left(x^{(0)}(1) - \frac{b}{a}\right)e^{-ak} + \frac{b}{a},\ k = 1,\ 2,\ \cdots,\ n \\ \hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k) \end{cases} \tag{6}$$

According to the calculation, $a = 0.023$ and $b = 61.19$, the average relative error is 0.023, and the modeling accuracy is 97.12%, based on which the predicted values of each variable for 2024–2035 are shown in Table 1.

Table 1. Forecast values for each variable 2024–2035.

Year	Permanent Residents) (Growth Rate of Each Year Compared with Pre-Year, Unit: %)	Industrial Structure (%)	Social Fixed-Asset Investment (Growth Rate of Each Year Compared with Pre-Year, Unit: %)
2024	10.89	37.99	5.36
2025	0.60	36.87	5.83
2026	0.59	35.74	5.51
2027	0.59	34.62	5.22
2028	0.58	33.50	4.96
2029	0.58	32.38	4.73
2030	0.58	31.25	4.52
2031	0.57	30.13	4.32
2032	0.57	29.01	4.14
2033	0.57	27.88	3.98
2034	0.56	26.76	3.83
2035	0.56	25.64	5.36

3.3. Multiple Regression-Based Energy Consumption Forecast for China

In the multiple regression analysis of multiple variables, there is often serious multi-collinearity among the variables, and the variance of the obtained regression coefficients will be large; thus, the error of the predicted primary energy consumption demand will also increase and become less stable. Therefore, in this paper, the correlation analysis is first conducted for four variables: population size, regional gross product, social fixed asset investment, and industrial output ratio, based on which the principal components are extracted, and multiple regressions are conducted with the principal components of each variable so as to eliminate the effects of multi-collinearity.

As can be seen in Table 2, there is only one eigenvalue greater than one for the data correlation array, so the first principal component value is extracted, and the original variable represented by it is used as the independent variable affecting energy consumption for multiple regression. Then the principal component expression is Equation (7).

$$Z = 0.252zx_1 + 0.249zx_2 - 0.249zx_3 + 0.252zx_4 \tag{7}$$

where zx_1, zx_2, zx_3, zx_4 are the standardized regional GDP, total population, industrial output value share, and fixed social investment, respectively. Z denotes the first principal component value. The four factors' data from 2005 to 2022 were standardized, and the standardized data for each year were substituted into the principal component expression to derive the principal component values for 2005–2022. In turn, when multiple regression analysis was performed on the principal component values, the nonlinear regression, logarithmic function and power function all required the independent variable to be non-negative, so the coordinate transformation was performed on the principal component values Z. After the principal component analysis, the original four indicators of GDP, industrial output value share, population size, and social fixed investment amount in the model are dimensioned down, so the multiple regression problem is transformed into a one-dimensional regression problem. The regression equation is fitted by the predicted values of the principal components after the coordinate transformation process, as in Equation (8).

$$\begin{cases} linear: \ y = 25799.965 + 4384.076 \cdot z' \\ ln: \ y = 30219.601 + 7929.722 \cdot lnz' \\ Quadratic: \ y = 18565.775 + 13647.128 \cdot z' - 2287.602 \cdot z'^2 \\ Ternary: \ y = 12995.9 + 24924.423 \cdot z' - 8562.941 z'^3 \\ power\ function: \ y = 29902.534 \cdot z'^{0.245} \\ index: \ y = 26161.933 \cdot e^{0.134z'} \end{cases} \tag{8}$$

Table 2. Total variance explained.

Components	Total	Initial Eigenvalue Variance Percentage (%)	Cumulative (%)	Total	Extracted Load Squared and Percentage of Variance (%)	Cumulative (%)
1	3.978	99.455	99.455	3.978	99.455	99.455
2	0.018	0.461	99.916			
3	0.002	0.060	99.977			
4	0.001	0.023	100.000			

The predicted values of the line six functions from 2005 to 2022 were compared to the actual values, and their relative errors and average relative errors were calculated, and their results are shown in Table 3.

Table 3. Error table for different functions.

Year	Linear	Ln	Quadratic	Ternary	Power Function	Index
2005	0.175	0.079	0.070	0.034	0.089	0.172
2006	0.078	0.021	0.006	−0.010	0.022	0.073
2007	0.009	−0.014	−0.028	−0.026	−0.020	0.003
2008	−0.017	−0.019	−0.030	−0.017	−0.029	0.025
2009	−0.051	−0.037	−0.041	−0.021	−0.049	0.061
2010	0.058	0.090	0.101	0.125	0.076	0.046
2011	−0.111	−0.080	−0.062	−0.047	−0.090	0.122
2012	−0.128	−0.097	−0.074	−0.067	−0.106	0.138
2013	−0.010	0.021	0.050	0.048	0.014	0.020
2014	−0.015	0.011	0.039	0.028	0.007	0.022
2015	−0.022	−0.006	0.016	−0.002	−0.006	0.026
2016	−0.012	−0.006	0.004	−0.014	−0.003	0.011
2017	0.008	0.007	0.006	−0.008	0.012	0.012
2018	0.028	0.020	0.007	−0.001	0.027	0.036
2019	0.042	0.024	−0.005	0.001	0.035	0.054
2020	0.055	0.029	−0.021	0.005	0.041	0.073
2021	0.047	0.022	0.031	0.011	0.044	0.069
2022	0.059	0.019	0.027	0.007	0.038	0.061
2023	0.061	0.016	0.024	0.009	0.031	0.057
Average relative error	5.118%	3.502%	3.503%	2.833%	2.915%	5.582%

From Table 3, it can be inferred that a power function is chosen to forecast energy consumption for 2024–2035. The predicted values of the four influencing factors of China's GDP, population size, industrial output ratio and social fixed investment for 2024–2035 are substituted into the standardized formula derived from the actual data of the four factors from 2005 to 2022 for standardization, and the predicted results of the four factors after standardization are substituted into the principal component expression to obtain the predicted values of the principal components, which are predicted according to the previous correlation analysis. Coordinate transformation is performed. After that, the results obtained were brought into the regression equation, and the predicted values of energy consumption for 2024–2035 from the multiple regression model with different economic growth rates were obtained, as shown in Table 4. From Table 4, it can be seen that the energy consumption from 2024 to 2035 has been showing an upward trend, and different economic growth rates have a greater impact on energy consumption, and the growth rate of energy consumption under the high GDP growth scenario is higher than the medium speed scenarios in different years, and the medium speed scenario is higher than the low-speed scenario. By 2035, the growth rate of energy consumption in the high growth scenario still remains at 1.66%, while in the low growth scenario, it will be 0.35%. However, different types of fuels have different carbon emission factors when burned, so in order to project carbon emissions based on energy consumption, the energy consumption structure must be projected for 2024–2035.

Table 4. Projected growth rates of energy consumption under different economic growth rates (unit: %).

Year	High	Medium	Low
2024	6.38	9.46	5.27
2025	2.57	2.26	2.25
2026	1.99	1.85	1.54
2027	1.92	1.70	1.32
2028	1.87	1.44	1.07
2029	1.81	1.44	1.02
2030	1.55	1.42	0.91
2031	1.31	0.97	0.77
2032	1.36	1.15	0.92
2033	0.95	0.85	0.54
2034	1.05	0.94	0.43
2035	1.66	0.86	0.35

4. Energy Consumption Structure Forecast

4.1. Natural Evolutionary Scenarios

4.1.1. Initial Construction of Markov Chain Prediction Model

Markov process is a kind of past state for predicting the future Markov process is a stochastic process in which the past state is irrelevant ("no posteriority"), based on the theory of stochastic processes of the Russian mathematician Markov's theory of stochastic processes. The Markov chain-based energy The Markov chain-based energy structure prediction model assumes that the energy structure is a time-simultaneous The Markov chain-based energy structure prediction model is based on the assumption that the energy structure is a time-coincident Markov chain by predicting the one-step transfer matrix in each period of the sample. The average transfer probability matrix P is estimated by predicting the one-step transfer matrix in each period of the sample, and the initial state of the energy structure is determined. The model is used to predict the energy structure after determining the initial state of the energy structure. Based on the evolution of primary energy, the Markov chain prediction model is used to predict the future primary energy consumption structure of China. In this paper, a Markov chain prediction model is used to predict the future primary energy consumption structure of China. Let the system have n mutually incompatible states, and the initial state vector of the system is as Equation (9).

$$S(0) = \left[S_1(0), S_2(0), \cdots, S_j(0), \cdots, S_n(0)\right] \tag{9}$$

where $S_j(0)$ is the initial probability that the system is in state *j*. Since the probability of the system being in state *j* after *k*-step transfer is $S_j(k)$, the state vector after step transfer is as Equation (10).

$$S(k) = [S_1(k), S_2(k), \cdots, S_j(k), \cdots, S_n(k)] \tag{10}$$

where $S_j(k)$ is the probability of the system being in state *j* at moment *k*. This leads to a Markov chain prediction model, as in Equation (11).

$$S(k) = S(k-1)\cdot P = S(k-1)\begin{bmatrix} P_{11} & P_{12} & \cdots & P_{1n} \\ P_{21} & P_{22} & \cdots & P_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ P_{n1} & P_{n2} & \cdots & P_{nn} \end{bmatrix} = S(0)\cdot P^k = S(0)\begin{bmatrix} P_{11} & P_{12} & \cdots & P_{1n} \\ P_{21} & P_{22} & \cdots & P_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ P_{n1} & P_{n2} & \cdots & P_{nn} \end{bmatrix}^k \tag{11}$$

where the state transfer probability matrix P has the property as $\begin{cases} \sum_{j=1}^{n} P_{ij} = 1 \\ P_{ij} \geq 0 \\ i, j = 1, 2, \cdots, n \end{cases}$.

When the state transfer probability P is known and the initial state vector $S(0)$ is known, the conditions for using the formula are met, and the state of the system at moment k can be predicted. The initial state vector $S(0)$ is known in the real problem, so the estimation of the state transfer probability matrix P is the main step of the prediction using this model. Regarding the estimation of P, there are three main methods, namely, the statistical method, the linear system of equations method, and the quadratic programming method. Among them, when applying the quadratic programming method, conditions such as non-negative state transfer probability P_{ij} and a row sum of one can be introduced into the model to avoid the problem of non-negative conditions that cannot be guaranteed in the linear system of equations. At the same time, the minimum absolute value of the error between the predicted and actual values in n stages can be used as the objective function to minimize the prediction error. Therefore, this part will use the quadratic programming method to construct a quadratic programming model with the minimum sum of absolute values of errors as the objective function, solve the optimal state transfer matrix, and predict the energy consumption structure of China from 2024 to 2035 based on this.

4.1.2. State Transfer Probability Matrix Determination

Construct a quadratic programming model based on the minimization of the sum of differences. The transfer probability P_{ij} is the probability that the process is in state *j* after *k* stages when it is in state *i* at a certain moment. Let the estimated value $\hat{P}$ of the one-step state transfer the probability matrix P as in Equation (12).

$$\hat{P} = \begin{bmatrix} \hat{P}_{11} & \hat{P}_{12} & \cdots & \hat{P}_{1n} \\ \hat{P}_{21} & \hat{P}_{22} & \cdots & \hat{P}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \hat{P}_{n1} & \hat{P}_{n2} & \cdots & \hat{P}_{nn} \end{bmatrix} \tag{12}$$

Then the estimate $\hat{S}(k)$ of $S(k)$ is

$$\hat{S}(k) = S(k-1)\cdot\hat{P} = S(0)\cdot\hat{P}^k = S(0)\begin{bmatrix} \hat{P}_{11} & \hat{P}_{12} & \cdots & \hat{P}_{1n} \\ \hat{P}_{21} & \hat{P}_{22} & \cdots & \hat{P}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \hat{P}_{n1} & \hat{P}_{n2} & \cdots & \hat{P}_{nn} \end{bmatrix}^k \tag{13}$$

Further, let $e_j(k)$ be the error between $\hat{S}(k)$ and $S(k)$, then

$$e_j(k) = S_j(k) - \hat{S}_j(k) = S_j(k) - \sum_{i=1}^{n} S_j(k-1)\cdot\hat{P}_{ij} \tag{14}$$

Then in m stages, the sum of $|e_j(k)|$ in state j is $\sum_{k=1}^{m}|S_j(k) - \sum_{i=1}^{n} S_j(k-1)\cdot\hat{P}_{ij}|$. So in m stages, the sum of $|e_j(k)|$ in n states is $\sum_{j=1}^{n}\sum_{k=1}^{m}|S_j(k) - \sum_{i=1}^{n} S_j(k-1)\cdot\hat{P}_{ij}|$. Then, constructing the planning model as shown in Equation (15):

$$minQ = \sum_{j=1}^{n}\sum_{k=1}^{m}\left|S_j(k) - \sum_{i=1}^{n} S_j(k-1)\cdot\hat{P}_{ij}\right| \\ \begin{cases} \sum_{j=1}^{n}\hat{P}_{ij} = 1 \\ \hat{P}_{ij} \geq 0 \\ i,\ j = 1,\ 2,\ \cdots,\ n \end{cases} \tag{15}$$

Linear transformation of the quadratic programming model based on the minimization of the sum of differences. Since the model established in the above equation is a non-linear model with absolute values, which is tedious to solve, it needs to be transformed into a linear model by variable substitution for calculation.

Let $u_j(k) = \frac{|e_j(k)| - e_j(k)}{2}$, $v_j(k) = \frac{|e_j(k)| + e_j(k)}{2}$, then $u_j(k) \geq 0$, $v_j(k) \geq 0$, $u_j(k)\cdot v_j(k) = 0$, $e_j(k) = v_j(k) - u_j(k)$, $|e_j(k)| = v_j(k) + u_j(k)$, $j = 1,\ 2,\ \cdots,\ n$; $k = 1,\ 2,\ \cdots,\ m$.

Therefore, Equation (15) turns to Equation (16).

$$minQ = \sum_{j=1}^{n}\sum_{k=1}^{m} v_j(k) + u_j(k) \\ \begin{cases} \sum_{j=1}^{n}\hat{P}_{ij} = 1 \\ \hat{P}_{ij} \geq 0 \\ u_j(k) \geq 0,\ v_j(k) \geq 0 \\ i,\ j = 1,\ 2,\ \cdots,\ n \end{cases} \tag{16}$$

4.1.3. Solution of the Optimal State Transfer Probability Matrix

The International Energy Agency (IEA) released the World Energy Outlook 2013, in which it concluded that the center of gravity of energy demand is gradually shifting to China, the Middle East and other emerging economies and that energy importers are beginning to become exporters, which means that China officially became one of the centers of growth in global energy demand in 2013. Meanwhile, since the consumption of fossil fuel-coal, which accounts for the largest proportion of energy consumption in China from 2008 to 2013, fluctuates, this paper selects the changes in China's energy consumption structure (coal, oil, natural gas, and non-fossil fuels) from 2013 to 2022, estimates the Markov state shift probability matrix as Equation (17) based on Equation (16), and uses it to predict China's energy consumption structure from 2024 to 2035 under the natural evolution scenario.

$$P = \begin{bmatrix} 0.9449 & 0.0551 & 0 & 0 \\ 0.1733 & 0.7648 & 0.0493 & 0.0126 \\ 0 & 0 & 0.2013 & 0.7987 \\ 0 & 0 & 0.6659 & 0.3341 \end{bmatrix} \tag{17}$$

Taking the energy consumption structure of China in 2023 as the initial state, the energy consumption structure from 2024 to 2035 is predicted by using the state shift probability matrix obtained by solving the above linear programming model, as shown in Table 5. The proportion of oil decreases from 17.67% to 14.43%, with a smaller and slower decline, and basically remains stable; natural gas and non-fossil energy sources both increase significantly, and the proportion of consumption almost doubles by 2035, which is generally in line with the development pattern of China's energy consumption structure.

4.2. Policy Constraint Scenarios

Based on the prediction results of the energy structure under the unconstrained scenario, the energy structure is adjusted accordingly by combining the existing energy policy planning objectives to obtain the energy structure under the policy-constrained scenario. According to the prediction results, in the unconstrained scenario, non-fossil energy accounts for 14.16% of total energy consumption and natural gas accounts for 7.57%

in 2030; in 2035, non-fossil energy accounts for 17.46% and natural gas accounts for 10.84%, which is still a bit short of the relevant energy structure planning target. The above values are still far from the relevant planning targets for the energy structure. Here, the following methods are used to adjust the energy structure under the unconstrained scenario, taking into account the optimization methods of the energy structure in the relevant research and the energy policy planning values, to obtain the energy structure under the policy constraint: (1) since there is no specific planning target for the proportion of oil consumption, the proportion of oil consumption is kept fixed; (2) since the proportions of natural gas and non-fossil energy in 2030 and 2035 are both smaller than the target values, the proportion of natural gas and non-fossil energy in 2030 and 2035 are used to adjust the energy structure. Since the proportion of natural gas and non-fossil energy in 2030 and 2035 is less than the target value, the proportion of coal consumption is reduced to replace the increase of natural gas and non-fossil energy consumption, so that the proportion of natural gas and non-fossil energy is adjusted to the corresponding policy target value, and the degree of reduction of coal proportion is equal to the degree of increase of natural gas and non-fossil energy proportion to meet the sum of the proportion of each type of energy to 1.

Table 5. Projected energy consumption structure under natural evolution scenario (unit: %).

Year	Coal	Oil	Natural Gas	Non-Fossil Energy
2024	66.67	16.72	7.80	8.80
2025	65.89	16.47	8.26	9.38
2026	65.11	16.23	8.72	9.93
2027	64.33	16.00	9.17	10.49
2028	63.56	15.78	9.62	11.03
2029	62.79	15.58	10.06	11.57
2030	62.02	15.37	10.50	12.09
2031	61.27	15.18	10.93	12.62
2032	60.52	14.99	11.35	13.13
2033	59.78	14.80	11.77	13.64
2034	59.04	14.61	12.18	14.14
2035	58.32	14.43	12.59	14.64

This paper draws on Energy Outlook 2017 of the U.S. Energy Information Administration (EIA); by setting three scenarios of high-speed, medium-speed and low-speed economic development, we obtain the predicted values of China's total energy consumption under different economic development goals. On the basis of the total energy consumption meeting the economic development demand, a policy constraint scenario is set up to adjust the energy structure in conjunction with the national energy policy planning. This scenario not only achieves the economic development goals but also further explores whether the optimization and upgrading of the energy structure under the guidance of the national energy policy can achieve carbon peaking of the "Dual Carbon" target in China. Based on the prediction results of the energy structure under the natural evolution scenario, the energy structure is adjusted to obtain the energy consumption structure of China under the policy constraint scenario by combining it with the existing energy policy planning objectives of China. On 22 March 2022, the National Development and Reform Commission and the Energy Bureau released the 14th 5 Year Plan for Modern Energy System. In the energy consumption structure goals, it is clear that, by 2025, the proportion of coal consumption will fall to 60% or less, and the proportion of non-fossil energy consumption will increase to about 13%. It is also clearly pointed out that, by 2030, non-fossil energy (such as new energy and renewable energy) will account for 18% of energy consumption by 2030, the proportion of natural gas in energy consumption will rise 12–14% by 2030, while the proportion of coal consumption compared to 2020 will fall 15 percentage points to about 55%, while the proportion of oil consumption will remain stable. In this paper, drawing on the ideas of Zhang et al. (2022) [16] on the optimization of energy structure and combining the values of China's energy policy planning with the principle of keeping the share of oil consumption stable and increasing the share of natural gas consumption as much as possible, the following adjustments are made to the projected energy consumption structure of China under the natural evolution scenario in order to obtain the energy consumption structure under the policy constraints from 2024 to 2035. (1) The shares of coal, oil, natural gas and non-fossil energy consumption in 2025 are set at 60%, 16%, 11% and 13%, respectively. (2) The shares of coal, oil, natural gas and non-fossil energy consumption in 2030 are set at 55%, 14%, 13% and 18%, respectively. (3) The shares of coal, oil, natural gas and non-fossil energy consumption in 2035 are set to 50%, 14%, 15% and 21%, respectively. Based on this, the energy consumption structure of China under policy constraints in 2024–2035 is obtained by the mean-share method. More details can be found in the studies of Zhang et al. (2022) [16], Energy Policy Solutions in EI and Scenarios Construction of Carbon Emissions in Zhejiang.

4.3. Cost Constraint Scenarios

Based on the prediction results of energy structure under the policy constraint scenario and the data of gross regional product and total energy consumption obtained from the combined prediction of China's high, medium and low economic development, a multi-objective planning model is constructed to predict the energy consumption structure and obtain the energy consumption structure of China under the cost constraint scenario, taking into account the existing energy policy planning objectives of China.

4.3.1. Basic Assumptions

The objective of the model is to achieve the coordinated development of energy, the economy and the environment based on China's policy constraints, and to predict the energy consumption structure of China under the constraints of total carbon emissions, total energy consumption and total economic conditions with the objective of minimizing the external cost of carbon emissions and the cost of environmental pollution control. Therefore, it is assumed that China's economy will continue to grow as projected in the previous scenarios and that energy consumption will increase accordingly, ignoring the impact of industrial restructuring, technological innovation and other enhancements on the energy consumption structure. The design of the constraints on the consumption of different types of energy in different years is carried out with a variation interval of 10% above and below the consumption of a certain type of energy in that year. Assuming that non-fossil fuels do not produce CO_2 emissions, the carbon emission coefficients for each type of energy are fixed over time, and the coefficients used in the calculations are taken from the China Energy Study-Regional Chapter and the previous analysis. The calculations are performed without considering the impact of different economic growth rates on the structure of energy consumption under cost constraints, and the state of medium economic growth is used.

4.3.2. Objective Function Design

The sustainable development of the economy cannot be achieved without energy consumption, and controlling the cost of environmental pollution in energy consumption can lay a favorable foundation for the sustainable development of energy consumption. It is easy to see from the plans that have been continuously updated and released in China over the years that one of the objectives of continuously optimizing the energy consumption structure to reduce carbon emissions and carbon intensity is to reduce the external environmental cost of carbon dioxide emissions and the cost of environmental pollution control, so the objective function of minimizing the external environmental cost of carbon dioxide emissions and the cost of environmental pollution control is set to predict the energy consumption structure based on the policy constraint and further imposing the cost constraints on top of the policy constraints. Taking the share of coal, oil, natural gas and other non-fossil energy consumption as decision variables, denoted by x_1, x_2, x_3 and

x_4, respectively, and applying weighting coefficients to them when considering the two cost targets, the total formula of the weighted objective function is as Equation (18).

$$minF(x) = w_1 f_1(x) + w_2 f_2(x) \tag{18}$$

w_1 is the weight of the external environmental cost $f_1(x)$. From an economic point of view, it is understood that the carbon dioxide, carbon monoxide, sulfur dioxide and other substances emitted by fossil fuel combustion cause negative externalities by harming living things and the natural environment, and therefore generate the environmental cost of energy consumption. Over time pollutants can have substantial impacts on the natural environment and human society if they are not treated in a timely manner. The external environmental cost is used as one of the objective functions in the projection of energy consumption structure under the cost constraint, and its expression is as Equation (19).

$$f_1(x) = \sum_{i=1}^{4} \alpha_i x_i \tag{19}$$

where x_i denotes the proportion of different types of energy consumption and α_i is the external cost of CO_2 emissions. Since the amount of CO_2 emitted from non-fossil energy sources is negligible, only three types of energy sources are required for the calculation of external environmental costs: coal, oil and natural gas. Meanwhile, based on the conversion factor of carbon emissions and carbon dioxide emissions analyzed in the previous section, which is $44/12 \approx 3.667$, the carbon dioxide emission factors of the three fossil energy sources are calculated as 2.678, 2.051 and 1.567, respectively, and the units are all "tons of carbon dioxide/ton of standard coal." The final external emission cost coefficients per unit of carbon emission for coal, oil and natural gas are obtained in Table 6.

Table 6. Emission factors for various types of fossil energy (unit: tons/per ton of standard coal).

Unit Factor	Coal	Oil	Natural Gas
Unit carbon emission factor	0.7295	0.5589	1.565
Carbon dioxide emission factor	2.675	2.409	1.565
External cost of CO_2 emissions	875.53	670.64	512.22

This leads to the external environmental cost as in Equation (20).

$$f_1(x) = 875.53x_1 + 670.64x_2 + 512.22x_3 \tag{20}$$

w_2 is the weight of the environmental pollution control cost $f_2(x)$. The cost of environmental pollution control refers to the cost of controlling and removing the large amount of toxic and harmful substances such as carbon dioxide, sulfur dioxide, and soot that are generated by fossil energy consumption. The excessive emission of pollutants can seriously harm human society and the natural environment, and in order to reduce this impact, it is necessary to pay the environmental pollution control costs, so the environmental pollution control costs are set as an objective function, aiming to optimize the energy consumption structure by minimizing this cost. Referring to the National Bureau of Statistics, the China Energy Report-Regional Chapter and the China Energy Statistics Report, it is known that the range of sulfur dioxide emission pollution treatment cost is 474 dollars/ton–1149 dollars/ton and the soot emission treatment cost is 53.63 dollars/ton. After statistics and unit conversion, the emission coefficients of sulfur dioxide and soot in unit energy are shown in Table 7, and the treatment costs of sulfur dioxide and soot in unit energy are shown in Table 8.

4.3.3. Constraint Design

For example, according to the 14th 5 Year Plan for Modern Energy System and the current situation of energy development, the total energy consumption constraint, different types of energy consumption constraint and total carbon dioxide emission constraint are set respectively.

Table 7. Emission factor of sulfur dioxide and soot per unit of energy (tons/per ton of standard coal).

Energy Type	Sulfur Dioxide	Soot
Unit coal	0.02	0.13
Unit oil	0.0061	0.00105
Unit natural gas	0.00045	0.00021

Table 8. Treatment cost of sulfur dioxide and soot in unit energy (dollar/ton standard coal).

Pollution Treatment Cost Interval	Treatment Cost	Middle Value
Coal	70.89~164.89	117.89
Oil	20.51~49.18	34.85
Natural gas	1.56~3.84	2.7

This gives the cost of environmental pollution treatment as in Equation (21).

$$f_2(x) = 117.89x_1 + 34.86x_2 + 2.7x_3 \quad (21)$$

Total energy consumption constraint. The forecast results of the aforementioned research portfolio show that the total energy consumption from 2024 to 2035 will rise year by year. However, China has set the total energy consumption target in many documents and plans in the past, including the 14th 5 Year Plan, which states that China's total energy consumption should be controlled at 454 million tons of standard coal by 2025, with coal consumption at 350 million tons. Since the proportion of different types of energy consumption is chosen as the decision variable in this paper, and the total energy consumption under the policy constraint is in line with the total requirement mentioned above, the constraint becomes $\sum_{i=1}^{4} x_i = 1$.

Total carbon emission constraint. The country is actively promoting the transformation of old and new dynamics and controlling carbon emissions through a series of initiatives such as increasing green technology innovation and adjusting green credit policies, which ultimately lead to the regulation of energy consumption structure. At the same time, China has been implementing an energy conservation development plan, and it is pointed out that the high carbon emissions caused by fossil fuel combustion should be further reduced through energy substitution. Therefore, the total carbon emissions are taken into account as a constraint, and the total carbon emissions are capped according to the total carbon emissions obtained under the policy constraint scenario. The range of carbon emissions is as shown in Equation (22).

$$\sum_{i=1}^{4} \varepsilon_i x_i T_j \leq \textit{Carbon emissions under the policy constraint of the medium economic scenario in } 2025 \quad (22)$$

where ε_i denotes the carbon emission coefficients of different types of energy, and T_j denotes the total energy consumption under the medium economic growth scenario in a certain year.

Control the change interval of different types of energy consumption. In order to ensure the stability of the energy structure and avoid the unconventional change of different types of energy consumption, the energy consumption structure under the policy constraint scenario is combined with the total energy consumption under the medium-speed economic development scenario and a fluctuation interval of 5% is set as the upper and lower limits to obtain the interval constraint of change of different types of energy consumption.

4.3.4. Multi-Objective Optimization Model Construction and Solution

According to the planning related to energy consumption structure, the two objective functions of environmental pollution control cost and external environmental cost of carbon dioxide emission are specifically analyzed, and the control range values of total carbon emission and the interval constraints of different types of energy are set, and the multi-objective optimization model of energy consumption structure under cost constraints in China in 2025 is obtained as shown in Equation (23).

$$minF(x) = w_1[875.53x_1 + 670.64x_2 + 512.22x_3] + w_2[117.89x_1 + 34.86x_2 + 2.7x_3]$$
$$\begin{cases} (0.7295x_1 + 0.5589x_2 + 0.4269x_3) \times T_j \leq 25813.503 \\ 25627.233 \leq x_1 T_j \leq 28324.837 \\ 6833.929 \leq x_2 T_j \leq 7553.280 \\ 4698.326 \leq x_3 T_j \leq 5192.887 \\ 5552.567 \leq x_4 T_j \leq 6137.048 \\ \sum_{i=1}^{4} x_i = 1 \\ x_i \geq 0,\ i = 1,\ 2,\ 3,\ 4 \end{cases} \tag{23}$$

In this paper, it is considered that the control of the external cost of carbon emission is as important as the control of environmental pollution treatment cost. Therefore, the weight value in the objective function is assigned as (0.5, 0.5) and solved to obtain the energy consumption structure under the cost constraint scenario in China in 2025, in which the shares of coal, oil, natural gas and non-fossil energy are 58.3%, 16.8%, 11.45% and 13.45%, respectively. Similarly, the energy consumption structure under the cost constraint scenario from 2024 to 2035 can be predicted, as shown in Table 9; the proportion of coal consumption in China under this scenario shows a decreasing trend year by year from 67.4% in 2024 to 47.5% in 2035, with an average annual decrease of 1.23% in the proportion of coal consumption, which is in line with the various energy development plans issued by China. The proportion of oil consumption decreases slightly from 2024 to 2030 and fluctuates up and down from 2030 to 2035, with a fluctuation range of 13.4% to 14.7%, which is also in line with the 14th 5 Year Plan of the modern energy system: "Oil consumption will remain stable." The proportion of natural gas and non-fossil energy consumption shows a continuous upward trend, from 6.59% and 7.46% to 15.75% and 22.05%, respectively, and in the previous years, the increase is larger, with the growth of the year rising less and less, in general, slightly beyond the planning range but also within a reasonable range. Through the analysis of China's energy consumption structure in 2024–2035 under the cost constraint scenario, we can learn that the proportion of different types of energy consumption is generally in line with the various planning requirements issued by China. Meanwhile, since the scenario is based on the energy consumption structure under the policy constraint scenario and the relevant data under the medium-speed economic development, the energy consumption structure of natural gas and non-fossil energy is more adjusted but still within a reasonable range and in line with the future development trend.

Table 9. China's Energy Consumption Structure Forecast for 2024–2035 under Cost Constraint Scenario (unit: %).

Year	Coal	Oil	Natural Gas	Non-Fossil Energy
2024	60.63	17.22	9.98	12.17
2025	58.30	16.80	11.45	13.45
2026	56.84	16.38	12.18	14.60
2027	55.48	15.96	12.81	15.75
2028	54.22	15.54	13.44	16.80
2029	53.20	14.88	14.07	17.85
2030	52.25	14.15	14.70	18.90
2031	51.30	14.26	14.91	19.53
2032	50.93	13.45	15.22	20.39
2033	49.40	14.48	15.33	20.79
2034	48.91	13.78	15.69	21.62
2035	47.50	14.70	15.75	22.05

5. Analysis of the Feasibility and Optimal Path to Achieve the "Dual Carbon" Target

5.1. Feasibility Analysis of Achieving Carbon Peaking in China under Scenario Interaction

5.1.1. Analysis of Carbon Peaking by Scenario under Low Economic Development

The total energy consumption and carbon emissions of each scenario under the low economic development are shown in Figure 1, from which it can be seen that the total energy consumption under the low economic development shows a continuous upward trend from 2024–2035, and the growth rate of energy consumption at the three key nodes of 2025, 2030 and 2035 are 2.45%, 1.89%, and 0.27% respectively, the level of economic development has a greater impact on energy consumption. Compared with the medium- and high-speed economic development scenarios, the low-speed development scenario has the lowest energy consumption in different years, while under the high-speed economic development scenario, China's growth rate of energy consumption is expected to reach 5.19% in 2030, which is higher than the target value set by the National Development and Reform Commission in the 14th 5 Year Plan for Modern Energy Systems. Other conditions are unchanged; if China's economy continues to grow at a high rate, it will not be conducive to achieving the total energy target. From the above analysis, it is clear that the level of economic development and energy consumption are positively correlated, while energy consumption and energy consumption structure jointly determine carbon emissions, so the lower the level of economic development, the lower the carbon emissions for the same energy structure scenario.

As can be seen in Figure 1, both the policy constraint scenario and the cost constraint scenario can reach the peak of carbon emissions when the economy is developing at a low rate, in which the "low economic development-cost constraint" scenario reaches the peak around 2024 before the "low economic development-policy constraint" scenario, and the peak of the growth rate of carbon emissions is predicted to be 4.28%, and then start to decline year by year to 2030 at a more moderate and stable rate until 2035, when value will drop to 2.09%. In this scenario, the lower economic growth rate determines the lower total energy consumption, and the cost constraint leads to the most significant adjustment of the energy consumption structure, in which the two energy sources with high carbon emission coefficients, coal and oil, have a significant and small decrease in the total energy consumption, which makes the carbon emissions in this scenario reach a peak after a small increase and start to decline slowly in phases.

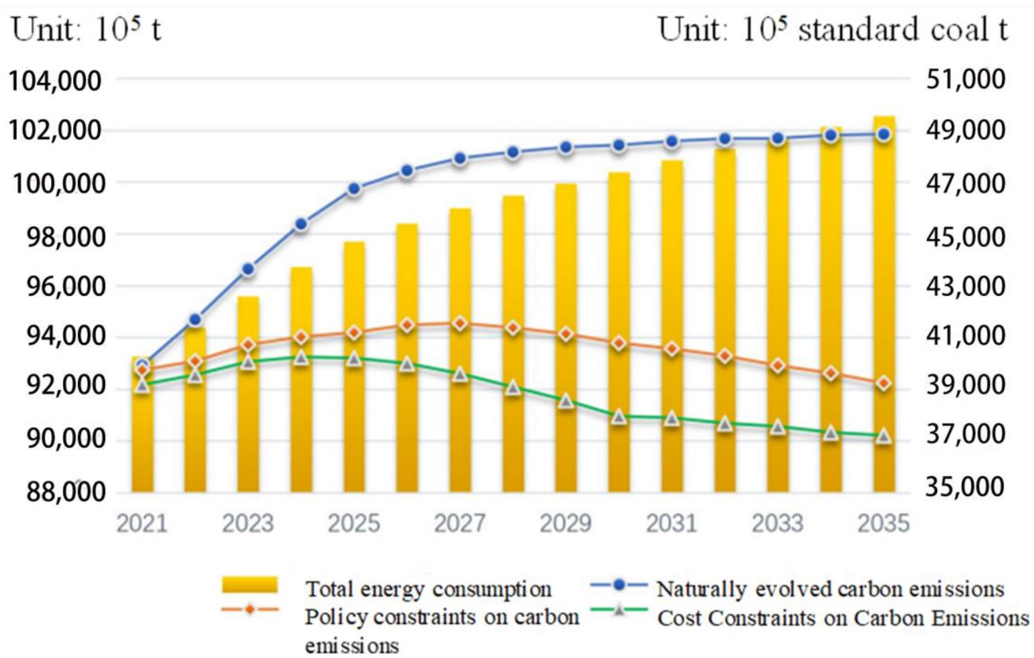

Figure 1. Energy consumption and carbon emissions under low economic development.

The "low growth-policy constraint" scenario also achieves the carbon peak target, but slightly later than the cost constraint scenario, in which the growth rate of CO_2 emissions shows an upward trend from 2024–2027, rising from 1.87% to 4.61% and peaking at and then starts to decline slowly. The energy mix adjustment under the policy constraint scenario depends on the energy-related plans issued by China, which shows that if China can strictly follow the energy-related plans and stabilize the regional GDP growth rate at around 5%, it can achieve the goal of peaking carbon emissions around 2027, all else being equal.

In the "low economic development-natural evolution" scenario, China's growth rate of carbon emissions will continue to rise and increase at a fast rate from 2024 to 2026, increase slightly from 2027 to 2031, and fluctuate slightly from 3.27% to 4.05% from 2031 to 2035, but basically remain stable, and it can be expected that in 2035, there is a trend of carbon peak but no peak of carbon emission. The magnitude of energy structure adjustment under natural evolution is small, especially in the first period when energy consumption is large and continues to rise, with coal and oil consumption accounting for a larger share and natural gas and non-fossil energy accounting for a smaller share, carbon emissions will continue to rise year by year, and in the later period, as the share of coal and oil gradually declines, and the share of natural gas and non-fossil energy rises slightly, the effect of energy structure change offsets the impact of continuous rise in energy consumption, making carbon emissions remain stable.

5.1.2. Analysis of Carbon Peaking by Scenario under Medium Economic Development

When the economy is developing at a medium speed, both the policy constraint scenario and the cost constraint scenario can reach the peak of carbon emissions, as shown in Figure 2, in which the growth rate of carbon dioxide emissions under the policy constraint scenario will peak in 2032 at 4.20%, and the overall trend will rise first and then fall, and the value will fall to 1.07% in 2035, basically returning to the 2025 level. Although the "medium economic development-policy constraint" scenario is able to achieve the carbon peak, there is still a certain distance to reach the carbon peak around 2030, as set by China. The "medium-speed economic development-cost constraint" scenario is in the rising stage of carbon emissions from 2024 to 2024, with the growth rate of carbon emissions rising from 2.19% to 3.08%, peaking in 2024, and then steadily declining to reach 1.74% in 2035, with carbon emissions basically falling back to the 2022 level. Compared with the policy-constrained scenario, this scenario can reach the peak of carbon emissions about 6 years earlier under medium-speed economic development. It is similar to the peak year in the "low growth-cost constraint" scenario but is slightly higher than the latter due to the impact of faster economic growth. The "medium growth-natural evolution" scenario is similar to the low growth scenario in that both scenarios have carbon peaking trends but are unable to reach peak carbon emissions by 2035 due to smaller energy mix adjustments. At the same time, the increase in the share of coal and the increase in energy consumption due to rapid economic development lead to higher carbon emissions in all years in this scenario than in the low growth scenario.

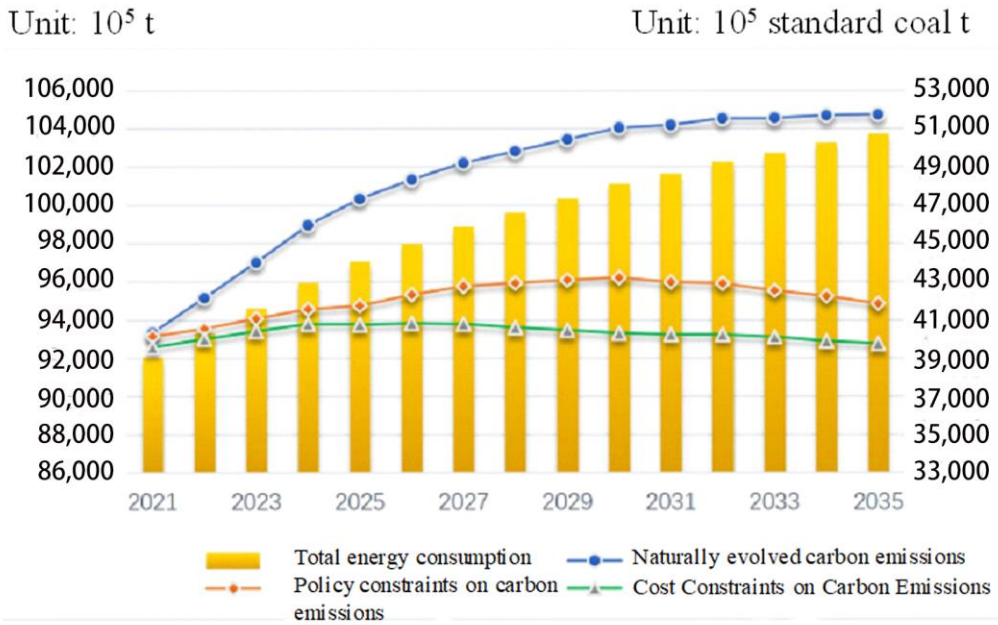

Figure 2. Energy consumption and carbon emissions under medium economic development.

5.1.3. Analysis of Carbon Peaking by Scenario under High Economic Development

The rapid economic development is accompanied by a sharp increase in energy consumption. Compared with the low and medium economic development in Figure 3, we can see that the annual growth rate of energy consumption under the rapid development is greater, and in 2030, significantly exceeds the target of standard coal set in the 14th 5 Year Plan Modern Energy System, and this will inevitably cause the delay of carbon peak time. In the policy constraint scenario, the growth rate of carbon emissions rises from 3.13% in 2024 to 3.49% in 2031 and reaches the peak, which is delayed compared to the policy constraint scenario under low and medium speed development and fails to meet China's peak target around 2030. The cost constraint scenario also fails to meet the carbon peak target, with carbon emissions rising from 4.08% in 2024 to 5.01% in 2029, then declining slightly but not reaching the peak, and remaining steadily up and peaking at 5.14% from 2030 to 2032. The natural evolution scenario is consistent with the low and medium development scenarios, and there is no obvious sign of carbon peaking, with carbon emissions fluctuating between 3.33% and 3.41% between 2030 and 2035. This shows that if we let the economy continue to develop at a high rate without formulating relevant plans and policies to control energy development, it will generate excessive carbon emissions, cause environmental pollution, delay the carbon peak time, and make it more difficult to achieve the "Dual Carbon" target.

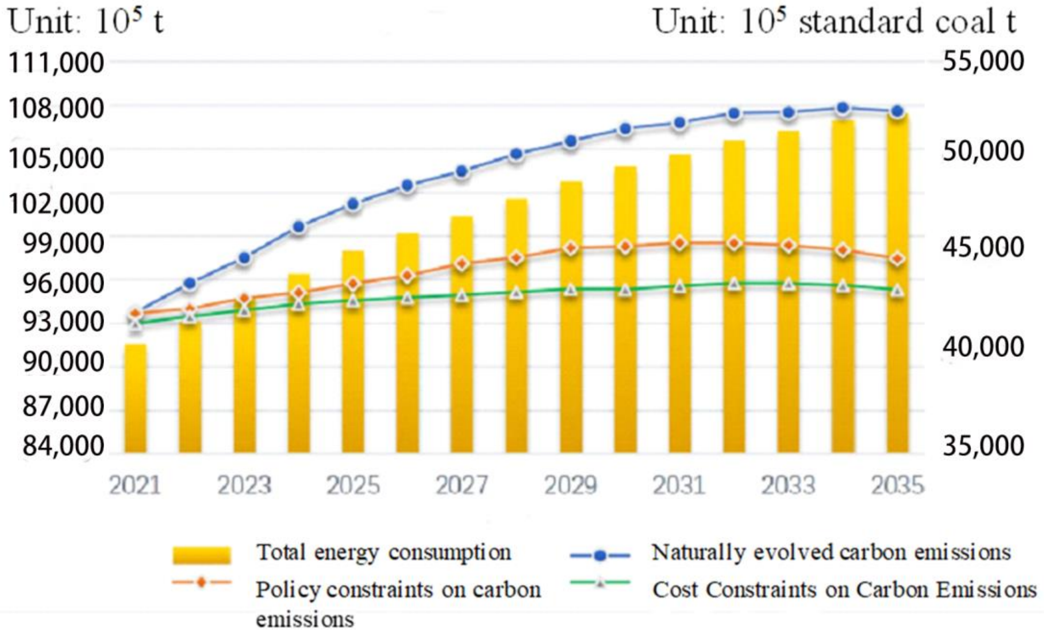

Figure 3. Energy consumption and carbon emissions under high economic development.

The analysis shows that, except for the three scenarios of natural evolution, China's carbon emission peaks in six scenarios of low, medium and high economic development with policy and cost constraints, with policy and cost constraints peaking in 2027 and 2024, respectively, with peaks of 4.79% and 4.86%, both of which are in line with China's carbon peak target around 2030. The policy constraint and cost constraint under medium economic development will peak in 2032 and 2024, respectively, with a peak of 5.00% and 5.23%, which is basically in line with China's carbon peak target. None of the scenarios under high economic development reaches the peak target around 2030 set by China. At the same time, the three scenarios of natural evolution do not show any obvious signs of carbon peaking, and there is a huge difference in carbon emissions compared to the policy-constrained and cost-constrained scenarios at the same economic development rate, which will further affect the subsequent carbon neutral management. The above results show that China's energy mix under the cost constraint scenario is most conducive to achieving the carbon peaking target and has the greatest effect on carbon emissions and carbon peaking by year, followed by the policy constraint, and the natural evolution scenario has the weakest effect on the target.

5.2. Feasibility Analysis of Carbon Intensity Targets

Based on the government's commitment to reduce carbon intensity by 40~45% in 2020 compared to 2005 and 60~65% in 2030 compared to 2005, this paper sets China's carbon intensity target at 5% up from the original target, i.e., 45~50% in 2020 compared to 2005, and 65~70% in 2030 compared to 2005, and calculates and analyses China's carbon intensity under nine scenarios from 2024–2035.

China's carbon intensity projections for each scenario from 2024 to 2035 are shown in Table 10, from which the following analyses can be made: (1) in all nine scenarios, China's carbon intensity decreases gradually with the growth of the year, which indicates that the economic development is rapid with the growth of the year, and the regional GDP is significantly increased along with the increase of energy consumption, but the carbon emissions are effectively controlled by the energy structure adjustment, so the carbon intensity decreases year by year. At the same time, the carbon intensity value of the scenario corresponding to the higher economic development rate in the same year is smaller, while the carbon intensity value of the cost-constrained scenario is the smallest at the same level of economic development due to the smallest carbon emissions. (2) Under high economic development, the highest carbon intensity is 1.187 t/million for the natural evolution scenario in the initial year, followed by 1.186 t/million for the policy constraint scenario, which decreases year by year until 2035 when the natural evolution scenario decreases to 0.511 t/million, while the smallest cost constraint decreases to 0.453 t/million. (3) The situation is similar under medium-speed economic development and low-speed development, but the value of carbon intensity of both of them is affected by the lower regional GDP and smaller than that of high-speed economic development.

Table 10. Carbon intensity projections by scenario for China 2024–2035.

Carbon Intensity	High Economic Growth			Medium Economic Growth			Low Economic Growth		
	N.E	P.C	C.C	N.E	P.C	C.C	N.E	P.C	C.C
2024	1.002	0.953	0.948	1.080	1.029	1.023	1.141	1.088	1.082
2025	0.942	0.891	0.880	1.035	0.977	0.967	1.110	1.048	1.038
2026	0.883	0.830	0.817	0.988	0.929	0.915	1.073	1.009	0.993
2027	0.825	0.775	0.757	0.942	0.882	0.864	1.035	0.969	0.949
2028	0.773	0.720	0.703	0.896	0.835	0.815	0.995	0.929	0.906
2029	0.732	0.681	0.661	0.860	0.798	0.777	0.966	0.898	0.873
2030	0.693	0.640	0.621	0.825	0.763	0.740	0.937	0.866	0.840
2031	0.653	0.603	0.584	0.788	0.726	0.705	0.909	0.838	0.814
2032	0.617	0.566	0.550	0.755	0.692	0.673	0.882	0.809	0.787
2033	0.580	0.530	0.516	0.720	0.658	0.641	0.855	0.781	0.761
2034	0.546	0.496	0.484	0.688	0.626	0.611	0.829	0.754	0.736
2035	0.511	0.463	0.453	0.657	0.595	0.582	0.804	0.728	0.712

5.3. Analysis of the Optimal Path to Achieve the "Dual Carbon" Target

In order to explore the optimal path for China to achieve the "Dual Carbon" target, a multi-attribute decision model will be constructed to assign weight coefficients to each indicator according to different decision preferences, and then each indicator will be weighted to obtain the composite index under different preference scenarios. Multiple attribute decision-making (MAD) refers to the integration and ranking of the criterion values of multiple scenarios under multiple criteria. Multi-attribute decision-making theory and methods are widely used in many fields, such as engineering, technology, economics, management and the military. Multi-attribute decision-making usually has the following characteristics: (1) multiple options: Before making a group decision, the decision maker has to weigh feasible option books as options to be evaluated; (2) multiple evaluation attributes: Before making a group decision, the decision maker must first measure the number of feasible attributes and propose several relevant attributes that affect the solution, which can be independent of each other or related; (3) weight assignment of attributes: For different attributes, decision-makers will have different preference tendencies and assign different weights to different attributes, and in general the weight assignment of attributes is usually formalized.

5.3.1. Selection of Model Indicators

Considering China's energy-related regulations and the research content of this paper, the indicators are selected as follows: (1) total energy consumption. The total energy consumption target is included in all kinds of plans promulgated by China, and the change in total energy consumption greatly affects the change in carbon emission and carbon intensity. Therefore, the total energy consumption is chosen as the model indicator, and the years 2025, 2030 and 2035, which are more representative, are chosen for the calculation of the weighting. (2) Total carbon emissions. The total amount of carbon emissions in China is the focus of this paper, and it is also an important measure of "peak carbon emissions around 2030 and carbon neutrality around 2060", so the total amount of carbon emissions in China is chosen as the model indicator, and the years 2025, 2030 and 2035 are chosen for the calculation. (3) Energy intensity. The Central Finance and Economics

Commission has emphasized the improvement of the energy intensity control system in several meetings. As an important indicator of energy use efficiency, energy intensity reflects the level of green technology development of a country or region and is also a measure of low carbon development, and the years 2025, 2030 and 2035 are selected for the assignment of values. (4) Gross national product. In the process of decision-making, we should not only consider energy consumption, carbon emissions, energy intensity and other targets but also ensure that China's economic development is in a stable state; only considering energy targets and ignoring economic development will result in overkill, low carbon development requires economic development and carbon emission reduction in parallel, so as to achieve high-quality development. Therefore, China's future GDP is used as one of the decision indicators to ensure that the final path is the optimal one that can take into account economic development. Here, we select the forecasted GDP for the years 2025, 2030 and 2035 for calculation. What's more, this paper has defined the different decision-maker preferences: no preference means that decision-makers consider the indicators of total energy consumption, energy intensity, carbon emission and carbon emission target completion degree to be of equal importance and no focus, i.e., these indicators are given equal weights; preference for intensity control means that decision makers focus more on energy intensity and carbon intensity control than total energy consumption and total carbon emission control, and the weights corresponding to carbon intensity target completion degree in 2025 and 2030 are set to 1/4, i.e., the path selection prefers lower carbon intensity scenarios; preference for total control means that decision makers focus more on total energy consumption and total carbon emission control than total energy consumption and total carbon emission control, i.e., the path selection prefers lower carbon intensity scenarios. The weight corresponding to the degree of accomplishment of the carbon intensity target in 2025 and 2030 is set to 1/4, i.e., the path selection prefers the scenario with lower carbon intensity; the preference for total control refers to the decision makers' preference for total energy consumption and total carbon emission control compared with total energy intensity and carbon intensity, and the weight corresponding to the degree of accomplishment of CO_2 emission in 2025 and 2030 is set to 1/4, i.e., the path selection prefers the scenario with lower carbon emission. This means that the path selection is more biased towards the scenario with lower total carbon emissions.

5.3.2. Model Construction

The weighting coefficients of each indicator are assigned according to different decision preferences, and then the indicators are weighted to obtain the composite index under different preference scenarios.

$$Q = W \cdot X = \sum_{k=1}^{12} W_k \cdot X_k \tag{24}$$

where X_1, X_2, $\cdots$, X_{12} represent total energy consumption in 2025, 2030 and 2035, total carbon dioxide emission in 2025, 2030 and 2035, energy intensity in 2025, 2030 and 2035 and GDP in China in 2025, 2030 and 2035, respectively. W_k denotes the weight of the k indicator, and the sum of the weight coefficients of the indicators is one. Q is the composite index of each scenario in different decision preference periods; the larger the value of Q, the better the scenario is, then the scenario with the largest value of Q is the optimal path in that decision preference period. According to the different emphasis on carbon emission reduction goals in different periods, the weights of each indicator are set in this paper (Table 11).

Table 11. Weighting table of each indicator.

Indicator	Code	No Preference	Preference for Carbon Intensity Control	Preference for Total Energy Control	Preference for Total Carbon Emission Control
X_1	W_1	1/12	1/18	1/6	1/18
X_2	W_2	1/12	1/18	1/6	1/18
X_3	W_3	1/12	1/18	1/6	1/18
X_4	W_4	1/12	1/18	1/18	1/6
X_5	W_5	1/12	1/18	1/18	1/6
X_6	W_6	1/12	1/18	1/18	1/6
X_7	W_7	1/12	1/6	1/18	1/18
X_8	W_8	1/12	1/6	1/18	1/18
X_9	W_9	1/12	1/6	1/18	1/18
X_{10}	W_{10}	1/12	1/18	1/18	1/18
X_{11}	W_{11}	1/12	1/18	1/18	1/18
X_{13}	W_{13}	1/12	1/18	1/18	1/18

No preference indicates that intensity control, total energy control, total carbon intensity control, and GDP control are equally important and have no focus, for which the weight of all indicators is set to 1/12. Preference for total energy control means that assuming that China focuses on total energy consumption control during 2024–2035, the weight of total energy-related indicators is set to 1/6 in this model, i.e., the path selection is biased towards the less total energy scenario, and the weight of total energy indicators, energy intensity indicators, and carbon intensity indicators is set to 1/18, compared to total energy control gross regional product, although important, is more focused on total energy targets under the premise of ensuring that the economy grows by at least 5% (low economic development scenario), so the weight of gross regional product indicators is also set to 1/18. Similarly, under other decision preferences, the weights of energy intensity and total carbon emission indicators are set to 1/6, and the rest are set to 1/18, respectively, and the scenario to which the maximum value belongs in the model solution results is the optimal path under a decision preference. In the construction of the model, the positive and negative indicators should be considered.

According to research by Zhang et al. (2022) [55] and relevant government plans, the smaller the energy consumption, energy intensity and carbon emissions, the easier it is to achieve the carbon emission peak and carbon intensity targets, so these three types of indicators are negative indicators. Conversely, a higher gross national product indicates a higher and more developed economy and is a positive indicator. The Min-Max standardization method was used to preprocess the required data, where the formula for standardization of positive indicators is $a'_{ij} = \frac{\left[a_{ij} - \min\left(a_{ij}\right)\right]}{\left[\max\left(a_{ij}\right) - \min\left(a_{ij}\right)\right]}$, and the negative indicator normalization formula is $a'_{ij} = \frac{\left[\max\left(a_{ij}\right) - a_{ij}\right]}{\left[\max\left(a_{ij}\right) - \min\left(a_{ij}\right)\right]}$.

5.3.3. Model Solving and Optimal Path Analysis

The indicators are standardized and brought into the constructed multi-attribute decision model to find the composite index of each scenario that can achieve the carbon peak and carbon intensity targets under different decision preferences, as shown in Table 12. In the above analysis, all scenarios can exceed China's 2030 carbon intensity target by more than 20%, but only six scenarios with policy constraints and cost constraints under high, medium, and low economic speed can reach peak carbon emissions, so three scenarios under natural evolution are excluded, and the composite index of different decision preferences under the remaining six scenarios is calculated.

Table 12. Composite index for each scenario under different decision preferences.

Scenario	High Economic Growth			Medium Economic Growth			Low Economic Growth		
	N.E	P.C	C.C	N.E	P.C	C.C	N.E	P.C	C.C
No preference	0.000	0.436	0.498	0.000	0.405	0.464	0.000	0.397	0.456
Preference for intensity	0.000	0.525	0.567	0.000	0.435	0.475	0.000	0.368	0.407
Prefer total energy control	0.000	0.380	0.422	0.000	0.385	0.425	0.000	0.407	0.446
Prefer total carbon emission control	0.000	0.346	0.471	0.000	0.401	0.520	0.000	0.470	0.587

Under the no-preference control, the highest composite index is the "high economic development-cost constraint" scenario with a composite index of 0.498, followed by the "medium economic development-cost constraint" scenario with a value of 0.464. The lowest value is 0.397 for the "low growth-policy constraint" scenario. According to the aforementioned analysis, China's carbon peak target is around 2030, and the government proposed to reach the carbon peak around 2030 in February 2020. Therefore, under the no-preference control, although the "high economic development-cost constraint" scenario has the highest composite index, it does not reach the carbon peak time requirement, so this scenario is excluded. Under the "medium-speed economic development-cost constraint" scenario, the economic growth rate is 6.5% between 2024 and 2028 and 5.5% between 2028 and 2035, except for the lower economic development level compared with the high-speed economic development scenario, all other energy indicators reach the ideal level. The percentages of coal, oil, natural gas and non-fossil energy in 2035 are 47.5%, 14.7%, 15.75% and 22.05%, respectively, which are most consistent with the development requirements of low-carbon China under the no-preference control scenario.

Under the preferred intensity control, the highest composite index is the "high economic development-cost constraint" scenario, with a composite index of 0.567. The energy intensity indicator is given a relatively high weight under the preferred intensity control, and the energy intensity depends on the regional GDP and total energy consumption. The growth rate of GDP is much higher than the growth rate of total energy consumption in the period 2024–2035; therefore, under the preferred energy intensity control, the high economic development can greatly contribute to the achievement of the intensity target, but this scenario is also excluded because the carbon peak target cannot be achieved under this scenario. The scenario with the second highest composite index is the "moderate economic development-cost constraint" scenario, with a composite index of 0.475. This scenario can maximize the carbon intensity target and ensure stable economic development, and at the same time, ensure the carbon peak target in 2024–2027. Therefore, the "medium economic development-cost constraint" scenario is considered the optimal path under the preference of intensity control.

Under the preferred total energy control, the total energy consumption indicator is given a higher weight. According to the previous analysis, regional GDP and total energy consumption show a positive correlation in general, while total energy consumption is a negative indicator, so the composite index is lower under the high economic development scenario and higher under the low economic development scenario. Compared to the other scenarios, the "low growth-cost constraint" scenario has the lowest energy consumption, the highest energy restructuring, and the smallest share of coal. Compared with the other scenarios, the "low economic development-cost constraint" scenario has the lowest energy consumption, the highest energy structure adjustment, and the smallest proportion of coal, while the carbon emission factor of coal is the largest among the major energy sources, so its carbon emissions in different years are also the smallest among the scenarios. Therefore, the "low economic development-cost constraint" scenario is identified as the optimal path for preferring total energy control.

The largest composite index is still the "low economic development-cost constraint" scenario, with 0.587 under the preferred total carbon emission control, which is similar to the total energy control scenario. The "low economic development-cost constraint" scenario is taken as the optimal path under the preferred total carbon emission control.

6. Discussion

Compared with previous research, some differences can be found in this paper. These differences are complementary to relevant follow-up research, and discussions about the differences are following.

The potential negative effects of COVID-19 may not be as serious as reported by previous research [37]. At the end of 2019, the impacts of COVID-19 on the "Dual Carbon" target become a hot topic. Almost all previous research insists that COVID-19 has abilities to promote carbon reduction in the short term; however, the positive effect in the short term would turn negative in the long term [16,37]. The reasonable view to explain the phenomenon is that the sudden shock of COVID-19 brought international economic activity to a standstill, and the reduction in transnational activity significantly reduced carbon emissions, and only negative growth of carbon emissions in 2020 proves this [16]. For negative effects in the long-term, the view supports that negative economic growth with ongoing COVID-19 prevention reduces people's quality of life and even creates more serious survival problems than COVID-19, and under survival press, the public will become rebellious and thus put pressure on the government [23,53]. In order to seek a balance between epidemic control and economic development, the government may tilt economic activities toward traditional polluting industries, thus hurting the advancement of carbon reduction [17,60,69]. Unexpectedly, analyzing forecasting results considering existing policies for the "Dual Carbon" target, the long-term negative effect from COVID-19 has not shown significant inhibiting shocks on carbon emissions. Further, with China's attitude and policy liberalization towards COVID-19, the long-term inhibiting effect initially explored is no longer convincing.

Analyzing research results, only scenarios with low-speed economic growth and effective policy guiding could achieve China's target of peaking carbon with a better carbon intensity. What's more, middle-speed economic growth with strict cost control could contribute to optimizing carbon intensity but fails to reach carbon peaking. Specifically, comparing all scenarios of energy structure optimization, this paper finds that the carbon intensity decreases the most under the scenario with policy constraints. In 2030, the average values of carbon intensity under the scenario with no-constrains or minimum energy production cost are 1.15 t/million dollars and 1.14 t/million dollars, respectively, which are 61.41% and 62.11% lower than in 2005. The average carbon intensity under the scenario with policy constraints is 1.07 t/million dollars, with the largest decrease of 67.20% compared to 2005. Therefore, for the carbon intensity target, the optimization of the energy structure under the scenario with policy constraints is the best. The reason for this is that, compared with other scenarios, the share of coal consumption in this scenario is the smallest in the same year. Coal is an inferior energy source with low calorific value and high carbon emissions per unit. The lower the coal consumption, the lower the carbon emissions, and the greater the reduction of carbon intensity. From the perspective of reality, China is still in a developing stage, and the low pace of economic development is not conducive to securing social progress and improving its international status. In addition, a significant restructuring of the energy structure implies a significant increase in natural gas and non-fossil energy sources, but the high cost of natural gas and clean energy makes it difficult to balance basic domestic demand and energy restructuring under low economic development, making it more difficult to implement. Therefore, although the scenario with policy constraints and low-speed economic development has the highest composite index theoretically, it is not the most suitable one considering the reality of achieving the "Dual Carbon" target. At the same time, the scenario with middle-speed economic development and strict cost control has an average annual GDP growth rate of nearly 5% from 2017 to 2030, which is suitable for the "new normal" of China's economic development, so as to be considered as the optimal path in the no-preference state.

More efforts are needed for the achievement of the "Dual Carbon" target. Research results indicate that existing policies announced for the "Dual Carbon" target even have no ability to realize carbon peaking before 2030, which means failure of the "Dual Carbon" target. On the one hand, although difficulty in reaching an equilibrium between high-speed economic growth and lowest carbon emissions can be expected [42,60], low carbon emissions with low-speed economic growth seem impossible because a low-speed economy can cause public panic, social unrest, and government instability, which can lead to severe economic stagnation, such as the Great Depression and financial crisis [18,20,21,32]. On the other hand, the energy consumption structure needs further optimization, but the research results of this paper provide an optimizing orientation. First of all, measures should establish policy guidance; then improving energy efficiency, developing policies to adjust the structure of energy consumption and vigorously developing and using clean energy is essential to optimize energy consumption structure (clean energies involve nuclear power, hydropower, biogas energy and solar energy, etc.).

What is more, developing technological innovations for green or low-carbon fields can significantly help China to increase the proportion of non-fossil energy consumption in the energy structure. Research designs of this paper focus on the most critical structural transformation of energy consumption, eliminating the predictive noise of previous research on "ongoing carbon reduction technology innovations" or "carbon reduction technology innovations that have reached the end of the technology development phase but cannot be translated into applications in the near future". Then the findings show that the primary stage of the "Dual Carbon" target cannot be achieved by relying on existing carbon abatement technologies and policy initiatives, and thus infers that carbon peaking may realize on time or even sooner with unknown carbon abatement technologies that can be translated for immediate application. The extrapolation of carbon peak times after noise removal is consistent with previous research, suggesting the futility of predicting and evaluating the application of existing carbon abatement technology innovations.

China's new energy technology presents the following characteristics: (1) China's new energy development status is not the same overall high degree of external dependence. China's new energy industry started late compared to the developed countries in the West, and the technology is relatively backward. The current development status of new energy varies: the photovoltaic industry has a high degree of maturity, but the overcapacity is obvious, the wind power industry is growing steadily, the biomass industry is still in its initial stage, and the geothermal industry is characterized by the initial formation of the development and utilization pattern. On the whole, China's new energy industry in general and foreign dependence is high, and key equipment and core technology still need to be imported from Europe and the United States. (2) The government actively guides and supports new energy technology innovation. The government's active fiscal policy guides financial leverage to support the configuration of new energy industry policy. First, improve the policy measures of new energy technology innovation. The government frequently issued a "green new policy" to guide and support new energy technology innovation: new energy as one of the strategic emerging industries, and vigorously develop new energy technology. Second, the establishment of national new energy research institutions to speed up the promotion and application of new energy technologies in China. (3) Technological innovation has obvious regionality. Geographically, Shanghai has more R&D achievements in solar energy technology, while Liaoning Province has more R&D achievements in wind energy technology. From the national provinces and cities of technology research and development, Beijing, Shanghai, Zhejiang Province and Guangdong Province and other developed areas are the main new energy technology output areas, while some less developed areas in the central and western new energy technology progress is relatively lagging behind. (4) Private enterprises to lead the PV industry technology innovation. At present, more than 90% of photovoltaic enterprises are private enterprises; in the field of solar photovoltaic equipment manufacturing and solar cell manufacturing, the top 10 manufacturers are also private enterprises, making great contributions to the technological innovation of

China's photovoltaic industry. (5) Stability-related technology has become a key bottleneck that restricts development and utilization. Most new energy output power has a strong randomness and intermittency, which means that stability-related technology will become a key bottleneck to restrict the development and utilization of new energy on a large scale.

So, how does the state support new energy projects? Firstly, policy support. Policy support is an important means for the state to support new energy projects. The government can introduce various tax incentives, subsidy policies, loan policies, etc., to encourage enterprises to invest in new energy projects. For example, China has issued Several Opinions on Encouraging the Development of the New Energy Industry, which clearly proposes to give tax preferences, subsidies and other support policies to new energy projects. Secondly, technical support. Technical support is also an important means for the state to support new energy projects. The government can fund scientific research and provide technical consulting services to reduce the technical difficulties and risks of new energy projects for enterprises. For example, China's 863 Program is an important technical support project, providing a lot of technical support and financial support for new energy projects. Thirdly, market support. Market support is an important means for the state to support new energy projects. The government can expand the scale of the new energy market through policy guidance, public procurement and other means to provide a broader development space for enterprises. For example, China's Photovoltaic Poverty Alleviation Project is an important market support project, through policy guidance and public procurement, to provide a broader market space for photovoltaic enterprises.

There are still some shortcomings in this paper. Due to the limitation of relevant data and information, this paper sets nine scenarios for predicting carbon peaking, only compares and analyzes the scenarios from the perspective of volume and time for carbon peaking, and does not discuss the parameter growth rate up and down in depth in this paper. The author believes that multiple scenarios should be set up in the future to make the scenarios more diversified, and a richer combination of factors can be predicted to reduce the prediction error as much as possible and ensure the reasonableness and accuracy of the parameter changes before making the scenario prediction, which will be further explored in future research. Perhaps, when the experimental data are more complete and the development of emission reduction policies and technologies reaches a new stage, more accurate predictions of carbon neutrality are expected to be achieved based on the study of carbon peaking in this paper.

7. Conclusions and Policy Recommendations

Based on the reality of China's economic and social development and the current situation of carbon emissions, this paper sets three economic development scenarios: high, middle and low speed, and three energy structure scenarios: natural evolution, policy constraint and cost constraint, and uses a combination of prediction models and Markov chain prediction models to predict the energy demand and energy consumption structure of China in each scenario from 2024 to 2035, and then combines the scenarios to obtain the carbon emissions and carbon intensity values of China from 2024 to 2035 under nine scenarios. Based on this analysis of the optimal path to achieve China's "Dual Carbon" target, the main findings of this paper are as follows: (1) potential negative effects caused by COVID-19 are not as serious as reported; (2) only the scenario with low-speed economic growth and effective policies guiding, which doesn't follow laws of social development, can contribute to reaching carbon peaking by 2030 while maintaining a high-quality carbon intensity; (3) the optimal path that scenario with middle-speed economic growth and strict cost control is a sub-optimal choice subject to realities; (4) technologies innovations in green or low-carbon fields are needed to accelerate energy consumption structure optimization.

Based on the findings above, the following policy insights emerge from this paper.

(1) Strengthen the investment in R&D of new energy technologies and financial subsidies. First of all, we should increase the proportion of non-fossil energy consumption in the energy structure by increasing the investment in new energy technology research and development.

In view of the current situation of China's energy consumption, the main way to optimize the energy structure is to replace fossil energy with non-fossil energy, so we should further improve the level of technological research and development in the field of new energy so as to achieve sustainable energy development. Second, strengthen financial subsidies for the new energy technology industry; new technologies often face technical difficulties, high costs, low yield rates and other characteristics, thus facing the traditional energy industry and unprofitable, photo-electricity and wind power have environmental protection and sustainable characteristics, but its existence of high costs, unstable power generation and other characteristics, in the face of traditional thermal power competition has no advantage, so in this case, China should provide policy support for these new In this case, China should support these new technology industries with policies such as taxation and political participation subsidies. In this case, China should provide policy support to these new technology industries, such as taxation and political subsidies, and then remove the incentives when the technology is mature. Finally, the use of market mechanisms to guide the development of relevant technology industries, only the use of relevant market mechanisms to force the withdrawal of certain old production capacity to guide the development of new kinetic energy, the use of market mechanisms to promote the use of new technologies and new products. For example, the high pollution, high emissions, and old production capacity to impose taxes to force its transformation and technological upgrading so as to achieve the withdrawal of the old kinetic energy and use the relevant financial subsidies to guide the application of new technologies, tax incentives, etc., so as to guide the generation of new kinetic energy, thus driving the upgrading of relevant industry technology, and thus achieve the role of energy saving and emission reduction;

(2) Upgrading and adjustment of industrial structure. Industrial structure has a suppressive effect on carbon emissions and can achieve the goal of carbon emission reduction. Although the impact of industrial structure adjustment on carbon emission reduction is not as great as that of energy structure adjustment, it is the relatively least costly way in China, and it is necessary to adjust the industrial structure as the economy is transformed. The current share of secondary and primary industries is still relatively high, so the government should play a guiding role and should gradually reduce low-quality and low-technology industries and introduce and develop high-tech and high-value-added industries. With the policy of Made in China 2025, China should speed up the adjustment of industrial structure, suppress the industries with high energy consumption and high emission, and prompt them to upgrade the relevant technology. Moreover, China should expand domestic demand to promote a domestic demand-driven economy to change the traditional investment-driven economy. For the traditional real estate industry, the fuel car industry and other overproduction can be corresponding transformation and upgrading, vigorously developing new energy vehicles and high-tech industry. The future of the new round of global technology revolution is related to the Internet of Things, artificial intelligence, big data and cloud computing and other technologies that widely penetrate all areas of the economy. Therefore, China should grasp the major opportunities of the new round of global technological revolution, cultivate new momentum for development, promote supply-side reform, enhance innovation capabilities, and vigorously develop a new generation of information technology industries, high-end equipment, new materials, new energy vehicles and other strategic industries;

(3) Controlling the total energy consumption and strengthening the control of carbon emissions while maintaining the decreasing trend of coal consumption. To achieve the goal of carbon emission reduction, controlling the total energy consumption from the root and reducing the consumption of fossil energy is the key initiative research results show that the proportion of coal consumption will gradually decrease in the future, and further efforts must be made to maintain the decreasing trend of the proportion of coal consumption, gradually eliminate the excess capacity of coal and improve the level of clean coal utilization. At the same time, China should also be in strict control of carbon dioxide emissions in the industrial sector, actively promote new low-carbon technologies and techniques, strengthen

the construction of enterprise energy and carbon emission management system, enhance the management of enterprise carbon emissions and vigorously develop carbon sink technology, speed up the pace of afforestation and greening, promote the national greening action, continue to implement forest protection, return farmland to forest and grass, strengthen wetland protection and restoration and stabilize and enhance the carbon sequestration capacity of wetlands;

(4) Strengthen policy guidance while improving the role of market mechanisms in the low-carbon transition. The comparison of carbon emissions and carbon intensity projections under natural evolution and policy constraints shows that the Chinese government's energy policy plays a crucial role in guiding the direction of the primary energy consumption structure. Therefore, it is necessary to continuously improve energy policies and regulations so that policies can play an important role in energy guidance, security and use, and thus make continuous adjustments and optimize the energy consumption structure.

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References

1. Cansino, J.M.; Román, R.; Rueda-Cantuche, J.M. Will China comply with its 2020 carbon intensity commitment? *Environ. Sci. Policy* **2015**, *47*, 108–117. [CrossRef]
2. Chai, Q.M.; Xu, H.Q. Modeling an Emissions Peak in China around 2030: Synergies or Trade-Offs between Economy, Energy and Climate Security. *Adv. Clim. Change Res.* **2014**, *5*, 169–180. [CrossRef]
3. Dai, Y.; Zhu, Y.; Quan, B. *China 2050: Scenarios of Energy Consumption and Carbon Emissions*; Springer International Publishing: Berlin/Heidelberg, Germany, 2013.
4. Liu, Q.; Chen, Y.; Teng, F. Pathway and Policy Analysis to China's Deep Decarbonization. *Chin. J. Popul. Resour. Environ.* **2017**, *27*, 162–170. [CrossRef]
5. Liu, W.; Li, H. Improving Energy Consumption Structure: A Comprehensive Assessment of Fossil Energy Subsidies Reform in China. *Energy Policy* **2011**, *39*, 4134–4143. [CrossRef]
6. Su, M.; Chen, C.; Yang, Z. Urban Energy Structure Optimization at the Sector Scale: Considering Environmental Impact Based on Life Cycle Assessment. *J. Clean. Prod.* **2016**, *112*, 1464–1474. [CrossRef]
7. Wang, S.; Chen, S.; Zhang, H. Effect of income and energy efficiency on natural capital demand. *Environ. Sci. Pollut. Res.* **2021**, *28*, 45402–45413. [CrossRef]
8. Fan, Q.; Liu, J.; Zhang, T.; Liu, H. An Evaluation of the Efficiency of China's green investment in the "Belt and Road" countries. *Struct. Change Econ. Dyn.* **2022**, *60*, 496–511. [CrossRef]
9. Cheng, Y.; Sinha, A.; Ghosh, V.; Sengupta, T.; Luo, H. Carbon tax and energy innovation at crossroads of carbon neutrality: Designing a sustainable decarbonization policy. *J. Environ. Manag.* **2021**, *294*, 112957. [CrossRef]
10. Chi, Z.; Heller, T.C.; May, M.M. Carbon Intensity of Electricity Generation and CDM Baseline: Case Research of Three Chinese Provinces—ScienceDirect. *Energy Policy* **2005**, *33*, 451–465.
11. Du, K.; Xie, C.; Ouyang, X. A Comparison of Carbon Dioxide (CO_2) Emission Trends among Provinces in China. *Renew. Sustain. Energy Rev.* **2017**, *73*, 19–25. [CrossRef]
12. Jiang, K. An ambitious CO_2 mitigation target will bring much benefit to China's social economy development. *Clim. Change Res.* **2019**, *15*, 103–106. [CrossRef]
13. Jie, F.; Pingxing, L. Analysis on the Future Energy Consumption and Preliminary Discussion on Carbon Emission of China from the Perspective Urbanization. *Adv. Earth Sci.* **2011**, *26*, 57.

14. Liu, Q.; Chen, Y.; Tian, C.; Zheng, X.-Q.; Li, J.-F. Strategic deliberation on development of low-carbon energy system in China. *Adv. Clim. Change Res.* **2016**, *7*, 26–34. [CrossRef]
15. Lyu, C.; Ou, X.; Zhang, X. China automotive energy consumption and greenhouse gas emissions outlook to 2050. *Mitig. Adapt. Strat. Glob. Change* **2014**, *20*, 627–650. [CrossRef]
16. Zhang, T.; Zhang, S.; Qu, J. The impact of China's carbon neutrality target on its energy consumption structure by 2050. *Energy Sources Part B Econ. Plan. Policy* **2022**, *17*, 2088896. [CrossRef]
17. Xu, L.; Chen, N.; Chen, Z. Will China make a difference in its carbon intensity reduction targets by 2020 and 2030? *Appl. Energy* **2017**, *203*, 874–882. [CrossRef]
18. Zhongying, W.; Sandholt, K. Thoughts on China's energy transition outlook. *Energy Transit.* **2019**, *3*, 59–72. [CrossRef]
19. Xue, F.; Feng, X.; Liu, J. Influencing Factors of New Energy Development in China: Based on ARDL Cointegration and Granger Causality Analysis. *Front. Energy Res.* **2021**, *9*, 718565. [CrossRef]
20. Li, A.; Zhang, A.; Zhou, Y.; Yao, X. Decomposition Analysis of Factors Affecting Carbon Dioxide Emissions across Provinces in China. *J. Clean. Prod.* **2017**, *141*, 1428–1444. [CrossRef]
21. Liang, Q.M.; Fan, Y.; Wei, Y.M.; Okada, N. A Scenario Analysis of China's Energy Requirement and Energy Intensity: Model and Its Applications. *Chin. J. Manag.* **2004**, *35*, 62–66.
22. Shen, L.; Lou, L.; Wang, L.; Chen, F.; Zhang, C.; Shen, M.; Zhong, S. 2050 Energy Consumption Projection for China. *J. Nat. Resour.* **2015**, *30*, 361–373.
23. Wu, C.B.; Huang, G.H.; Liu, Z.P.; Zhen, J.L.; Yin, J.G. Scenario Analysis of Carbon Emissions' Anti-Driving Effect on Qingdao's Energy Structure Adjustment with an Optimization Model, Part II: Energy System Planning and Management. *J. Environ. Manag.* **2017**, *188*, 120–136. [CrossRef]
24. Wen, S.; Zhou, K.; Lu, Q. A discussion on CBM development strategies in China: A case study of PetroChina Coalbed Methane Co., Ltd. *Nat. Gas Ind. B* **2019**, *6*, 610–618. [CrossRef]
25. Hu, K.; Raghutla, C.; Chittedi, K.R.; Zhang, R.; Koondhar, M.A. The effect of energy resources on economic growth and carbon emissions: A way forward to carbon neutrality in an emerging economy. *J. Environ. Manag.* **2021**, *298*, 113448. [CrossRef] [PubMed]
26. Feng, T.; Sun, L.; Zhang, Y. The relationship between energy consumption structure, economic structure and energy intensity in China. *Energy Policy* **2009**, *37*, 5475–5483. [CrossRef]
27. Fang, Y.; Yan, J.J.; Fan, L. *Energy Plan-Based Planning and Modeling for Energy System Structure Optimization in Beijing-Tianjin-Hebei*; DEStech Publications: Lancaster, PA, USA, 2017.
28. Hao, Y.; Zhang, M.; Zhang, Y.; Fu, C.; Lu, Z. Multi-Scale Analysis of the Energy Metabolic Processes in the Beijing–Tianjin–Hebei (Jing-Jin-Ji) Urban Agglomeration. *Ecol. Model.* **2018**, *369*, 66–76. [CrossRef]
29. He, J.K. The Strategic Choice of Chinese Energy Revolution and Low Carbon Development. *Wuhan Univ. J.* **2015**, *68*, 5–12.
30. Sarwar, S. Role of urban income, industrial carbon treatment plants and forests to control the carbon emission in China. *Environ. Sci. Pollut. Res.* **2019**, *26*, 16652–16661. [CrossRef]
31. Qi, Z. *A Bottom-Up Energy Efficiency Improvement Roadmap for China's Iron and Steel Industry Up to 2050*; Lawrence Berkeley National Laboratory: Berkley, CA, USA, 2016.
32. Yuan, J.; Xu, Y.; Zhang, X.; Hu, Z.; Xu, M. China's 2020 clean energy target: Consistency, pathways and policy implications. *Energy Policy* **2014**, *65*, 692–700. [CrossRef]
33. Yi, W.-J.; Zou, L.-L.; Guo, J.; Wang, K.; Wei, Y.-M. How can China reach its CO_2 intensity reduction targets by 2020? A regional allocation based on equity and development. *Energy Policy* **2011**, *39*, 2407–2415. [CrossRef]
34. Xie, Y.L.; Huang, G.H.; Li, W.; Ji, L. Carbon and Air Pollutants Constrained Energy Planning for Clean Power Generation with a Robust Optimization Model—A Case Study of Jining City, China. *Appl. Energy* **2014**, *136*, 150–167. [CrossRef]
35. Aydin, C.; Esen, Ö. Does the level of energy intensity matter in the effect of energy consumption on the growth of transition economies? Evidence from dynamic panel threshold analysis. *Energy Econ.* **2018**, *69*, 185–195. [CrossRef]
36. Kahouli, B. The short and long run causality relationship among economic growth, energy consumption and financial development: Evidence from South Mediterranean Countries (SMCs). *Energy Econ.* **2017**, *68*, 19–30. [CrossRef]
37. Klemeš, J.J.; Van Fan, Y.; Jiang, P. COVID-19 pandemic facilitating energy transition opportunities. *Int. J. Energy Res.* **2020**, *45*, 3457–3463. [CrossRef]
38. Bakirtas, T.; Akpolat, A.G. The relationship between energy consumption, urbanization, and economic growth in new emerging-market countries. *Energy* **2018**, *147*, 110–121. [CrossRef]
39. Li, J.; Guo, B.; Liu, K.; Zhou, J. Low Power Scheduling Approach for Heterogeneous System Based on Heuristic and Greedy Method. *Comput. Intell. Neurosci.* **2022**, *2022*, 9598933. [CrossRef]
40. Ma, X.; Wang, C.; Dong, B.; Gu, G.; Chen, R.; Li, Y.; Zou, H.; Zhang, W.; Li, Q. Carbon emissions from energy consumption in China: Its measurement and driving factors. *Sci. Total Environ.* **2018**, *648*, 1411–1420. [CrossRef]
41. Broto, V.C.; Bulkeley, H. A survey of urban climate change experiments in 100 cities. *Glob. Environ. Change* **2012**, *23*, 92–102. [CrossRef]
42. Dai, Y.D.; Tian, Z.Y.; Zhu, Y. A Roadmap for China's Energy Consumption and Production Revolution by 2050. *Rev. Econ. Res.* **2016**, *75*, 3–14.

43. Salvia, M.; Reckien, D.; Pietrapertosa, F.; Eckersley, P.; Spyridaki, N.-A.; Krook-Riekkola, A.; Olazabal, M.; De Gregorio Hurtado, S.; Simoes, S.G.; Geneletti, D.; et al. Will climate mitigation ambitions lead to carbon neutrality? An analysis of the local-level plans of 327 cities in the EU. *Renew. Sustain. Energy Rev.* **2021**, *135*, 110253. [CrossRef]
44. Rosenzweig, C.; Solecki, W.; Hammer, S.A.; Mehrotra, S. Cities Lead the Way in Climate–Change Action. *Nature* **2010**, *467*, 909–911. [CrossRef] [PubMed]
45. Mahalingam, B.; Orman, W.H. GDP and energy consumption: A panel analysis of the US. *Appl. Energy* **2018**, *213*, 208–218. [CrossRef]
46. Cao, B.; Du, G.; Wu, H. World Energy Trend to 2030—Analysis of Major Global Energy Outlook Reports. *Int. Pet. Econ.* **2016**, *24*, 8–15.
47. Chen, J.; Gao, M.; Mangla, S.K.; Song, M.; Wen, J. Effects of technological changes on China's carbon emissions. *Technol. Forecast. Soc. Change* **2020**, *153*, 119938. [CrossRef]
48. Wang, C.; Wang, F.; Zhang, X.; Deng, H. Analysis of influence mechanism of energy-related carbon emissions in Guangdong: Evidence from regional China based on the input-output and structural decomposition analysis. *Environ. Sci. Pollut. Res.* **2017**, *24*, 25190–25203. [CrossRef] [PubMed]
49. Lin, J.; Shen, Y.; Li, X.; Hasnaoui, A. BRICS carbon neutrality target: Measuring the impact of electricity production from renewable energy sources and globalization. *J. Environ. Manag.* **2021**, *298*, 113460. [CrossRef]
50. Hoefnagels, R.; Resch, G.; Junginger, M.; Faaij, A. International and Domestic Uses of Solid Biofuels under Different Renewable Energy Support Scenarios in the European Union. *Appl. Energy* **2014**, *131*, 139–157. [CrossRef]
51. Yu, X.; Zhou, Y.; Liu, X. Impact of financial development on energy consumption in China: A spatial spillover analysis. *Energy Strat. Rev.* **2022**, *44*, 100975. [CrossRef]
52. Ze, H.E.; Zhou, Y.N.; Liu, Y. System Dynamics Simulation on China's Energy Consumption in 2050: Based on the Policy Scenarios of Key Industries. *J. Nat. Resour.* **2020**, *35*, 2696.
53. Zhang, X.; Zhao, X.; Jiang, Z.; Shao, S. How to achieve the 2030 CO_2 emission-reduction targets for China's industrial sector: Retrospective decomposition and prospective trajectories. *Glob. Environ. Change* **2017**, *44*, 83–97. [CrossRef]
54. Li, J.; Liu, K.; Li, M.; Li, D. Combined Prediction Energy Model at Software Architecture Level. *IEEE Access* **2020**, *8*, 214565–214576. [CrossRef]
55. Duan, H.; Tang, X.; Ren, K.; Ding, Y. Medium- and long-term development path of natural gas consumption in China: Based on a multi-model comparison framework. *Nat. Gas Ind. B* **2021**, *8*, 344–352. [CrossRef]
56. Energy Research Institute National Development and Reform Commission Research Group. *China's Low Carbon Development Pathways by 2050: Scenario Analysis of Energy Demand and Carbon Emissions*; Science Press: Beijing, China, 2009.
57. Fallahi, F. Causal relationship between energy consumption (EC) and GDP: A Markov-switching (MS) causality. *Energy* **2011**, *36*, 4165–4170. [CrossRef]
58. Koondhar, M.A.; Tan, Z.; Alam, G.M.; Khan, Z.A.; Wang, L.; Kong, R. Bioenergy consumption, carbon emissions, and agricultural bioeconomic growth: A systematic approach to carbon neutrality in China. *J. Environ. Manag.* **2021**, *296*, 113242. [CrossRef]
59. Jian-Kun, H.E. An Analysis of China's CO_2 Emission Peaking Target and Pathways. *Adv. Clim. Change Res.* **2014**, *5*, 7.
60. Agovino, M.; Bartoletto, S.; Garofalo, A. Modelling the relationship between energy intensity and GDP for European countries: An historical perspective (1800–2000). *Energy Econ.* **2019**, *82*, 114–134. [CrossRef]
61. Zhang, X.; Gu, M.; Wang, M.; Zhang, Z.; Pan, W.; Jiang, Z.; Zheng, H.; Lucero, M.; Wang, H.; Sterbinsky, G.E.; et al. Molecular engineering of dispersed nickel phthalocyanines on carbon nanotubes for selective CO_2 reduction. *Nat. Energy* **2020**, *5*, 684–692. [CrossRef]
62. Zhu, B.; Wang, K.; Chevallier, J.; Wang, P.; Wei, Y.-M. Can China achieve its carbon intensity target by 2020 while sustaining economic growth? *Ecol. Econ.* **2015**, *119*, 209–216. [CrossRef]
63. Román-Collado, R.; Cansino, J.M.; Botia, C. How far is Colombia from decoupling? Two-level decomposition analysis of energy consumption changes. *Energy* **2018**, *148*, 687–700. [CrossRef]
64. Jia, Z.; Lin, B. How to achieve the first step of the carbon-neutrality 2060 target in China: The coal substitution perspective. *Energy* **2021**, *233*, 121179. [CrossRef]
65. Luukkanen, J.; Panula-Ontto, J.; Vehmas, J.; Liyong, L.; Kaivo-oja, J.; Häyhä, L.; Auffermann, A. Structural Change in Chinese Economy: Impacts on Energy Use and CO_2 Emissions in the Period 2013–2030. *Technol. Forecast. Soc. Change* **2015**, *94*, 303–317. [CrossRef]
66. Gabriel, S.A.; Kydes, A.S.; Whitman, P. The National Energy Modeling System. *Oper. Res.* **2001**, *49*, 14–25. [CrossRef]
67. Green, F.; Stern, N. China's changing economy: Implications for its carbon dioxide emissions. *Clim. Policy* **2016**, *17*, 423–442. [CrossRef]
68. Elzen, M.D.; Fekete, H.; Höhne, N.; Admiraal, A.; Forsell, N.; Hof, A.F.; Olivier, J.G.; Roelfsema, M.; van Soest, H. Greenhouse gas emissions from current and enhanced policies of China until 2030: Can emissions peak before 2030? *Energy Policy* **2016**, *89*, 224–236. [CrossRef]
69. Li, Y.; Lan, S.; Ryberg, M.; Pérez-Ramírez, J.; Wang, X. A quantitative roadmap for China towards carbon neutrality in 2060 using methanol and ammonia as energy carriers. *iScience* **2021**, *24*, 102513. [CrossRef]