Article

Analysis of Influencing Factors and Trend Forecast of CO₂ Emission in Chengdu-Chongqing Urban Agglomeration

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Abstract: Urban agglomeration is a primary source of global energy consumption and CO₂ emissions. It is employed as a major means of modern economic and social activities. Analysis of the temporal and spatial characteristics of CO₂ emissions in urban agglomerations and prediction of the future trends of CO₂ emissions in urban agglomerations will help in the implementation of CO₂ reduction policies within region-wide areas. So, based on that, this study contains four aspects. Firstly, it calculates the energy CO₂ emissions of China's Chengdu-Chongqing urban agglomeration. Secondly, it analyzes the time and space changes in the area by using ArcGIS. Then, the STIRPAT model is used to investigate the factors influencing CO₂ emissions, and the elasticity coefficient of the influencing factors is estimated using the ridge regression method, and the important influencing factors are screened on the basis of the estimated results, which are then used as input features for prediction. Finally, a combined prediction model based on the improved GM (1, N) and SVR models is constructed, and then the optimal solution is found through the particle swarm optimization algorithm. It sets up different CO₂ emission scenarios to predict the energy CO₂ emission of the region and its cities. The results show that, first, the CO₂ emissions of the Chengdu-Chongqing urban agglomeration have accumulated year by year, but by 2030, as predicted, it will not reach its peak. The spatial layout of CO₂ emissions in this region is not expected to undergo major changes by 2030. Second, population, GDP, gas and electricity consumption, and industrial structure have served as important factors affecting energy CO₂ emissions in the region. Third, on the basis of the prediction results for different scenarios, the CO₂ emissions in the baseline scenario are low in the short term, but the CO₂ emissions in the low-carbon scenario are low in the long run. This study also puts forward some policy recommendations on how to reduce CO₂ emissions.

Keywords: CO₂ emissions; Chengdu-Chongqing urban agglomeration; scenario prediction; influencing factor analysis; temporal and spatial characteristics

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1. Introduction

Currently, CO₂ emissions are considered to be the main cause of global warming [1]. Global warming tends to cause a variety of natural disasters, such as a sharp decline in biodiversity, extreme weather, food production loss, and an increase in infectious diseases and other disasters. The environmental problems caused by global warming are receiving a lot of attention from different countries around the world. China is the world's largest emitter of CO₂, and its emissions have been growing rapidly over the last few decades [2]. To cope with the challenges of climate change and relieve the pressure on CO₂ emissions at home and abroad, China has formulated and adopted a series of CO₂ reduction measures in a responsible manner to turn the challenges of climate change into opportunities for low-carbon transition. In 2014, the corresponding leaders of China and the United States issued

the Sino-US Joint Statement on Climate Change, which clarifies the respective action goals of the two countries to deal with climate change after 2020. The Paris Agreement (2016), a climate change agreement signed by 178 parties from around the world, explicitly limits the increase in global average temperature to 2 °C compared with the pre-industrial periods and strives to limit temperature increases to 1.5 °C [3]. At the 75th United Nations General Assembly in September 2020, the Chinese government made a commitment to the world that “China strives to peak its CO₂ emissions before 2030 and works towards achieving CO₂ neutrality by 2060” [4]. However, as far as the current situation of China’s CO₂ emission is concerned, it still faces considerable challenges. Many scholars believe that the pressure on China’s environment and CO₂ emissions stems mainly from the rapidly increasing energy consumption [5,6]. According to the fifth assessment report of the Intergovernmental Panel on Climate Change (IPCC), the energy-related CO₂ emissions produced by global cities account for 71–76% of the total global emissions. The CO₂ emissions of cities have become the main force. In conclusion, China must carry out energy conservation and emission reduction work in cities if it wants to achieve its carbon reduction goals.

With the growth of population and economy, cities have become home to more than half of the world’s population, and countries and cities are inseparable. The study on CO₂ emissions of cities is currently a top trending topic, such as the impact of urban landscapes [7], transport [8,9], building [10–12] and energy consumption [13,14] on CO₂ emissions. In the course of China’s urban development, single city development has gradually been replaced by urban clusters development. The urban agglomeration is composed of multiple large, medium and small cities. It is the highest form of spatial organization for a city to develop into a mature stage with the characteristics of compact spatial organization and close economic connections. Therefore, the environmental threats and causes of urban agglomerations are very complex and unevenly distributed. With a large economic volume and human resources, urban agglomerations are important carriers of modern economic and social activities on the one hand, and a major source of energy consumption and CO₂ emissions on the other. Based on this, it is necessary to conduct related research on CO₂ emissions from the urban agglomeration dimension to help the government formulate carbon reduction measures and economic development policies. China has four world-class urban agglomerations: Beijing-Tianjin-Hebei, Yangtze River Delta, Guangdong-Hong Kong-Macao, and Chengdu-Chongqing, among which the Chengdu-Chongqing urban agglomeration is the only urban agglomeration located in the western inland. In recent years, the Chengdu-Chongqing urban agglomeration has received significant support from the Chinese government, which has transformed it from a backward western region to a new level of economic growth in China. Therefore, the temporal and spatial changes of CO₂ emissions in the Chengdu-Chongqing urban agglomeration have come under the spotlight, including its future changes in CO₂ emissions. Based on the 14-year energy CO₂ emission data of 16 cities, this article uses ArcGIS to analyze the temporal and spatial characteristics of the region and then constructs the STIRPAT model to screen the important influencing factors of CO₂ emissions. Taking important influencing factors as the input features of the prediction model, a combined prediction model of improved GM (1, N) and SVR is constructed to predict the trend of CO₂ emissions under different scenarios.

Compared with previous studies, this research makes the following three main contributions: ① What is different from the previous studies is that the STIRPAT model is used to explore the ten influencing factors of CO₂ emissions in urban agglomerations from the following three dimensions: population, economy, and technology. To eliminate the multicollinearity between factors, the ridge regression method is used to estimate the impact of these factors on CO₂; this model may provide a basis for formulating CO₂ emission policies. ② It analyzes the temporal and spatial changes in CO₂ emissions based on ArcGIS. In this way, it is possible to reveal the time and space change laws of urban agglomerations. The spatial layout of CO₂ emissions can further demonstrate the economic and environmental interactions among cities and provide a new reference for the coordinated development of CO₂ emissions in urban agglomerations. ③ A combined model based on improved GM

(1, N) and SVR predicts future CO₂ emissions of urban agglomerations, and the combined model can effectively solve small samples, nonlinear and multi-factor data. Firstly, we set up different scenarios based on the actual conditions of city clusters and government policies, and then make CO₂ emission predictions under different scenarios. Secondly, we use important factors as input features of the model to improve the accuracy of the prediction. Finally, based on the prediction results, some suggestions for low carbon policies are made.

The rest of the article is organized as follows: The second part describes the relevant research literature on CO₂ emissions. The third part describes the research method. The fourth part explains the research data. The fifth part analyzes the temporal and spatial characteristics, influencing factors, and prediction results of energy CO₂ emissions. The sixth part summarizes the research conclusions of this article and proposes some policy implications.

2. Literature Review

At the level of the influencing factors of carbon dioxide, current research studies related to the influencing factors of carbon emissions can be divided into micro and macro influencing factors. Micro-level influencing factors refer to the influencing factors on a specific research subject. Lei Wen et al. [15] used the STIRPAT model to investigate the power structure of economic growth, urbanization level, industrialization level, power consumption efficiency, power generation efficiency, and CO₂ emissions from the power industry. The results show that power generation efficiency is a more decisive factor in reducing CO₂ emissions, while urbanization and industrialization levels are less important influencing factors. Yanan Wang et al. [16] aimed to conduct research on carbon emission factors. They used the STIRPAT model to investigate the impact of population, economic level, technology level, urbanization level, industrialization level, and foreign trade level on energy-related CO₂ emissions. The results of the study showed that energy intensity has the greatest impact on economically developed regions, while urbanization, industrial structure, and foreign trade have a large impact on underdeveloped regions, and population and per capita GDP have a large impact on developing regions. Macro-level influences are mainly the basic influences on carbon emissions in a particular country, region, or city, and they can be divided into three categories: demographic change, economic wealth, and industrial structure. The increase in population will lead to an increase in social and productive activities in cities, with a corresponding increase in carbon emissions. Changes in population structures will also influence changes in carbon emissions [17]. Population mobility reduces the growth of carbon emissions; meanwhile, regional population aging and improved knowledge structures caused by population mobility contribute to a reduction in carbon emissions, while improved regional urbanization and increased household miniaturization caused by population mobility are not significantly correlated with carbon emissions [18]. The wealth of a society reflects the level of development of a region. Economic indicators of a society include GDP, GDP per capita, urbanization rate, etc. Many regions are currently aiming at economic development, but neglecting environmental protection. Economic growth comes with an increase in carbon emissions [19]. There is no significant correlation between carbon emissions and urbanization in less urbanized areas; in moderately urbanized areas, urbanization has a negative effect on carbon emissions [20]. The industrial structure, which includes the primary, secondary, and tertiary industries, can reflect the technology, energy structure, and economic development of a region. Carbon emission reduction will promote industrial structure upgrading, which has a positive impact on economic growth [21]. In conclusion, industrial structure upgrading and economic growth will facilitate emission reduction. In short, carbon emissions are correlated with factors such as population size, GDP, energy intensity, industrial structure, and urbanization [22].

When it comes to the temporal and spatial evolution of CO₂, many researchers have analyzed and discussed the spatial layout of CO₂ emissions in a region based on existing data. Jinzhao Song et al. [23] applied social network analysis to conduct empirical research

on the spatial structure and correlation effects of CO₂ in the region, and put forward relevant policy recommendations. Kangyin Dong et al. [24] discussed the relationship between CO₂ emissions, economic growth, and natural gas consumption in 30 provinces in China. Zuo Zhang et al. [25] constructed a CO₂ emission network for the urban agglomeration in the middle reaches of the Yangtze River in China, and visually discussed the complexity and spatiality of the region's CO₂ emission network based on the characteristics and structure of the social network. Licheng Sun et al. [26] estimated the CO₂ transfer and analyzed the characteristics of the CO₂ emission transfer network.

In terms of CO₂ prediction, many scholars have used econometric methods and statistical methods to estimate it. Aiming at the CO₂ emissions of the power industry, Herui Cui et al. [27] came up with a CO₂ emission prediction model based on a hybrid PLS (partial least square)–Grey–Markov model, which has a high prediction accuracy. Kailing Li et al. [28] proposed the new information priority generalized accumulative gray model, which is used in the prediction of greenhouse gas emissions in the member states of the Shanghai Cooperation Organization. Aysha Malik et al. [29] applied a univariate autoregressive integrated moving average model (ARIMA) to forecast Pakistan's CO₂ emissions. Yan Li et al. [30] used the ARIMA model, the traditional gray model, the discrete gray model, and the rolling gray model to predict China's CO₂ emissions, and they also discussed whether China can reach its carbon peak in 2030 under the guidance of the current policy environment. The results of their study show that there is still a gap between the targets set by the Chinese government.

Combining the research literature, it is found that the existing literature has the following limitations: ① In the relevant research on the influencing factors of CO₂, the energy consumption of the city is not considered as an influencing factor. Moreover, many studies still focus on the investigation of the factors affecting urban CO₂ emissions, without applying the important factors obtained from the investigation as variables for predicting future CO₂ emissions. ② In the relevant research on the spatio-temporal evolution of CO₂, the existing research studies only orbit around the discussion of the existing data, without taking into consideration the prediction of possible spatio-temporal changes in the future. ③ The prediction of CO₂ lacks a combined prediction model that combines machine learning and intelligent optimization algorithms. Therefore, relevant research on the temporal and spatial characteristics and trend prediction of CO₂ emissions in urban agglomerations has a strong practical significance in helping the government to formulate relevant implementation paths in order to further improve the existing CO₂ emission policies. The relevant conclusions of the study can provide some references for the coordinated development of the environment and economy of similar urban agglomerations.

3. Methods

The research processes and associated research methods are as follows: firstly, the STIRPAT model of CO₂ emissions is constructed and then the elasticity coefficients of the influencing factors are estimated, and those with high elasticity coefficients are screened as input features. Then, for prediction, the factors are inputted into the improved GM (1, N) and SVR models. Finally, a particle swarm optimization algorithm is used to find the optimal weights for the combined prediction models; thereby the optimal combined prediction value can be obtained.

3.1. STIRPAT Model

Ehrlich and Holden first proposed the “IPAT” model in the 1870s [31]. The IPAT model decomposes all environmental impact factors into three dimensions: population, economy, and technology. The formula is shown in Equation (1):

$$I = P \times A \times T \quad (1)$$

I represents the degree of impact of environmental pollutants on the environment; P represents the impact factors in the population dimension; A represents the impact

factors in the economic dimension; and T represents the impact factors in the technology dimension. Although the IPAT model can explain the impact of multiple dimensions on the environment, there are still some limitations. It is difficult for the IPAT model to explain the non-proportional relationship of the impact of different influencing factors on the environment. On this basis, the STIRPAT model [32] can better solve this problem. The formula is shown in Equation (2):

$$I = aP^b A^c T^d e \quad (2)$$

As before, I represents the degree of environmental impact; P represents the impact factor in the population dimension; A represents the impact factor in the economic dimension; T represents the impact factor in the technical dimension, a represents a constant term, and e represents an error term; and b, c, d represent the regression coefficients of influencing factors, which are also called elastic coefficients. When the coefficient of elasticity of a certain influencing factor is positive, it indicates that the influencing factor has a positive effect on the environment; otherwise, it indicates that the influencing factor has a negative effect on the environment. Since Equation (2) is a nonlinear multivariate equation, it is difficult to calculate and estimate, and to avoid the influence of heteroscedasticity, Equation (2) is logarithmized as shown in Equation (3):

$$\ln I = \ln a + b \ln P + c \ln A + d \ln T + \ln e \quad (3)$$

a is a constant and e is an error; b, c, d are elastic coefficients; the higher the value as quoted achieves, the greater the impact it has. The STIRPAT model can reasonably estimate the degree of impact of multiple influencing factors on the environment and point out the relationship among the influencing factors and the relationship between the influencing factors and the environment.

3.2. Improved GM (1, N)

When the amount of data is low and the information law is poorer, the multidimensional gray models can make more accurate predictions and reasonably explain the relationship among multiple variables in the system as well. As a result, the prediction effect is satisfying. Among them, the most classic multidimensional gray model is GM (1, N), which can reasonably describe the relationship between the dependent variable and multiple independent variables. The model is constructed as follows:

Assume that the system has a characteristic data sequence as Formula (4):

$$X_1^{(0)} = (x_1^{(0)}(1), x_1^{(0)}(2), \dots, x_1^{(0)}(n)) \quad (4)$$

Assume that the system has a sequence of related factors as Formula (5):

$$\begin{aligned} X_2^{(0)} &= (x_2^{(0)}(1), x_2^{(0)}(2), \dots, x_2^{(0)}(n)) \\ X_3^{(0)} &= (x_3^{(0)}(1), x_3^{(0)}(2), \dots, x_3^{(0)}(n)) \\ &\vdots \\ X_n^{(0)} &= (x_n^{(0)}(1), x_n^{(0)}(2), \dots, x_n^{(0)}(n)) \end{aligned} \quad (5)$$

Let the one-time accumulation sequence (1-AGO) of $X_i^{(0)} = (i = 1, 2, \dots, n)$ be $X_i^{(1)}$, where:

$$X_i^{(1)} = \sum_{k=1}^n x_i^{(0)}(k) (i = 1, 2, \dots, n) \quad (6)$$

$Z_1^{(1)}$ is the sequence for generating the mean value immediately adjacent to $X_1^{(1)}$, where:

$$z_1^{(1)}(k) = \frac{1}{2} [x_1^{(1)}(k) + x_1^{(1)}(k-1)], k = 2, 3, \dots, n \quad (7)$$

Then, let $x_1^{(0)}(k) + az_1^{(1)}(k) = \sum_{i=1}^n b_i x_i^{(1)}(k)$ be the GM (1, N) model. In the GM (1, N) model, a is the development coefficient, b is the driving coefficient, and $b_i x_i^{(1)}(k)$ is the driving term. Let $\beta = (a, b_1, b_2, \dots, b_n)^T$; then we can get $\beta = (B^T B)^{-1} B^T Y$ from the least-square parameter estimation, where:

$$B = \begin{bmatrix} -z_1^{(1)}(2) & x_2^{(1)}(2) & \cdots & x_n^{(1)}(2) \\ -z_1^{(1)}(3) & x_2^{(1)}(3) & \cdots & x_n^{(1)}(3) \\ \vdots & \vdots & \cdots & \vdots \\ -z_1^{(1)}(n) & x_2^{(1)}(n) & \cdots & x_n^{(1)}(n) \end{bmatrix}, Y = \begin{bmatrix} x_1^{(1)}(2) \\ x_1^{(1)}(3) \\ \vdots \\ x_1^{(1)}(n) \end{bmatrix} \quad (8)$$

where $\frac{dx^{(1)}}{dt} + ax_1^{(1)} = \sum_{i=2}^n b_i x_i^{(1)}$ is the whitening equation of the GM (1, N) model. Solve the whitening equation to get the corresponding time response function:

$$\hat{x}_i(k+1) = \left[x_1^{(0)}(1) - \frac{1}{a} \sum_{i=2}^n b_i x_i^{(1)}(k+1) \right] e^{-ak} + \frac{1}{a} \sum_{i=2}^n b_i x_i^{(1)}(k+1) \quad (9)$$

Cumulative reduction is:

$$\hat{x}_1^{(0)}(k+1) = \hat{x}_1^{(1)}(k+1) - \hat{x}_1^{(1)}(k) \quad (10)$$

The above-mentioned prediction accuracy based on GM (1, N) depends extremely on the smoothness of the data sequence, which has a lot to do with the selection of the initial value of the model. Choosing $x_1^{(0)}(1)$ be the initial value will cause the model to overuse old information and ignore new information in the prediction process. Therefore, this paper draws on the research results of the predecessors [33] and takes $x_1^{(1)}(k)$ to be the initial value of the improved GM (1, N) model, which considers not only the role of the old information, but also the impact of the new information.

According to the discrete solutions of the whitening equation, the time-corresponding function of the whitening equation of the improved GM (1, N) model is:

$$\hat{x}_i^{(1)'}(k+1) = \left[x_1^{(1)}(k) - \frac{1}{a} \sum_{i=2}^n b_i x_i^{(1)}(k+1) \right] e^{-a} + \frac{1}{a} \sum_{i=2}^n b_i x_i^{(1)}(k+1) \quad (11)$$

The fitting value of $x_1^{(0)}(k+1)$ can be obtained after one accumulation and subtraction:

$$\hat{x}_1^{(0)}(k+1) = \hat{x}_1^{(1)'}(k+1) - \hat{x}_1^{(1)'}(k) \quad (12)$$

3.3. Support Vector Regression

Support vector regression (SVR) is a machine learning algorithm based on statistical learning theory proposed by Vapnik et al. [34]. SVR has shown a good ability to capture nonlinear data and can effectively solve the problem of small sample, multi-factor, high-dimensional, and nonlinear regression predictions. The principle of SVR is as follows [35]:

For a given sample dataset $V = (x_i, y_i)$, $i = 1, 2, \dots, n$, $x_i \in R^d$, $y_i \in R^d$, where x_i is the input sample value, y_i is the corresponding output value, n is the number of training

samples, and the regression model of the high-dimensional feature space is established as shown in Equation (13):

$$y = \omega \cdot \phi(x) + b \quad (13)$$

$x_i \in R^d$ is the sample set, d is the dimension of the input variables, $\phi(x)$ is the input–output mapping relationship, ω is the regression weight, b is the bias value, and y is the value of the prediction function to be fitted, which is obtained by the penalty risk function $R(C)$:

$$\begin{cases} R(C) = C \frac{1}{n} \sum_{i=1}^n L_\varepsilon(y) + \frac{1}{2} \|\omega\|^2 \\ L_\varepsilon(y) = \begin{cases} |f(x) - y| - \varepsilon, (|f(x) - y| > \varepsilon) \\ 0, (|f(x) - y| \leq \varepsilon) \end{cases} \end{cases} \quad (14)$$

$\|\omega\|^2$ is the penalty function, C is the penalty coefficient, ε is the insensitive function parameter, $L_\varepsilon(y)$ is the insensitive loss function, and if the slack variable δ ($\delta^* > 0$) is introduced, then Equation (14) is equivalent to:

$$\begin{aligned} & \min \frac{1}{2} \|\omega\|^2 + \sum_{i=1}^n (\delta_i + \delta_i^*) \\ & s.t. \begin{cases} y_i - [\omega \cdot \phi(x)] - b \leq \varepsilon + \delta_i, (\delta_i \geq 0) \\ [\omega \cdot \phi(x)] + b - y_i \leq \varepsilon + \delta_i^*, (\delta_i^* \geq 0) \end{cases} \end{aligned} \quad (15)$$

Introducing Lagrange multipliers a_i and a_i^* to construct the pLagrange function, the dual problem of Formula (15) optimization is:

$$\begin{aligned} & \max \sum_{i=1}^n y_i (a_i - a_i^*) - \varepsilon \sum_{i=1}^n (a_i + a_i^*) - \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n (a_i - a_i^*) (a_j - a_j^*) K(x_i, x_j) \\ & s.t. \begin{cases} \sum_{i=1}^n (a_i - a_i^*) = 0 \\ 0 \leq a_i, a_i^* \leq C \end{cases} \end{aligned} \quad (16)$$

$K(x_i, x)$ is a kernel function, and a Gaussian radial basis kernel function with a width of σ is selected. Equation (16) needs to meet the KKT condition, namely:

$$\begin{cases} a_i^* (\omega \cdot \phi(x) - y_i - \varepsilon - \delta_i^*) = 0; \\ a_i (y_i - \omega \cdot \phi(x) - \varepsilon - \delta_i) = 0; \\ a_i^* a_i = 0, \delta_i^* \delta_i = 0; \\ (C - a_i^*) \delta_i^* = 0, (C - a_i) \delta_i = 0. \end{cases} \quad (17)$$

The function Formula (18) of the final SVR is obtained, where λ is the parameter of the kernel function, and both it and the penalty coefficient C directly affect the prediction performance of SVR:

$$\begin{cases} f(x) = \sum_{i=1}^n (a_i - a_i^*) K(x_i, x) + b \\ K(x_i, x) = \exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right) = \exp(-\lambda \|x_i - x_j\|^2) \end{cases} \quad (18)$$

3.4. Construction of the CO₂ Emission Prediction Model

This paper uses the improved GM (1, N) and SVR models to construct a combined model. The construction process is as follows: assume that CE_i is the actual CO₂ emissions in the i -th year, and CE_{im} the CO₂ emissions in the i -th year predicted by the m -th method, ω_m the combined weight coefficient corresponding to the m -th method, and $\hat{CE}_i$ the com-

combined predicted value of CO₂ emissions in the corresponding year. The combined model is shown in Formula (19):

$$\hat{CE}_i = \sum_i^m \omega_m CE_{im} \quad (19)$$

i is the year in which CO₂ emissions are calculated, and m is the number of models. The improved GM (1, N) model and SVR model are adopted here, so $m = 2$. The prediction accuracy of the combined model is related to the weight coefficient ω_m , and the weight value is usually determined by the principle of the smallest sum of squares of errors:

$$\begin{aligned} \min_{\omega_m} E_{ST} &= \sum_{i=1}^n (CE_i - \sum_i^m \omega_m CE_{im})^2 \\ s.t. \sum_m^M \omega_m &= 1, (\omega_m \geq 0, m = 1, 2, \dots, M) \end{aligned} \quad (20)$$

To find the optimal weight, this paper adopts the particle swarm optimization algorithm to find the optimal weight. The principle of the particle swarm optimization algorithm is to randomly initialize a group of particles $X = (X_1, X_2, \dots, X_n)$ in a multidimensional space, and it finds the optimal position of the particles through iteration. In each iteration, the objective function of each particle is evaluated, and the optimal solution P_{best} passed by the particle and the optimal solution G_{best} of the current population are recorded. According to these two optimal solutions, it updates the velocity and position of the particles according to Equation (21):

$$\begin{aligned} v_{ij}(k+1) &= v_{ij}(k) + c_1 r_1 [p_{ij} - x_{ij}(k)] + c_2 r_2 [p_{gj} - x_{ij}(k)] \\ x_{ij}(k+1) &= x_{ij}(k) + v_{ij}(k+1) \end{aligned} \quad (21)$$

c_1, c_2 are non-negative acceleration factors; r_1, r_2 are random numbers belonging to $[0, 1]$; p_{ij} is the local optimal solution, and p_{gj} is the global optimal solution. The weight ω_m in Equation (20) is optimized by the particle swarm optimization algorithm, and then the optimized ω_m is substituted into Equation (19) to obtain the combined prediction value with the smallest sum of square error, that is, the best prediction result.

In summary, the energy CO₂ emission prediction model of this article is divided into two parts. The first part is to estimate the elasticity coefficient of the STIRPAT model and screen the influencing factors. The second part is to use the selected influencing factors as input features and input them into the combined model. The combined model is composed of an improved GM (1, N) model and supports vector regression. The optimal weight of the combined model is optimized by PSO. Finally, the best prediction result is achieved. The model frame is shown in Figure 1.

Figure 1. Model framework.

4. Data Source and Description

4.1. Study Area

The Chengdu-Chongqing urban agglomeration is one of the four world-class urban agglomerations in China, and it ranks alongside the Beijing-Tianjin-Hebei urban agglomeration, the Yangtze River Delta urban agglomeration, and the Guangdong-Hong Kong-Macao urban agglomeration. It is the only urban agglomeration in the western inland of these four regions. According to the Chengyu Urban Agglomeration Development Plan of March 2016, by 2030, the Chengdu-Chongqing urban agglomeration will make a historic leap from a national-level urban agglomeration to a world-class urban agglomeration. According to the Outline for the Construction of the Chengdu-Chongqing Double-City Economic Circle (October 2021), until 2035, the Chengdu-Chongqing urban agglomeration will be built into an active growth pole and a strong driving force for economic development with an international influence. The establishment and development of the Chengdu-Chongqing urban agglomeration reflect China's concept of deepening inland opening up and the determination to deepen reform and opening up. A part of the specific scope of the Chengdu-Chongqing urban agglomeration is the municipality directly under the Central Government of Chongqing. The other part consists of Chengdu, Mianyang, Deyang, Zigong, Luzhou, Suining, Neijiang, Leshan, Nanchong, Meishan, Yibin, Guang'an, Dazhou, Ya'an, and Ziyang in Sichuan Province. The total area of these 16 cities is about 185,000 square kilometers, accounting for 1.9% of the country. The Chengdu-Chongqing urban agglomeration is mainly located in the Sichuan basin, the interior of which is divided from west to east into the Chengdu Plain, the central Sichuan hills, and the eastern Sichuan parallel ridge and valley, with mountainous areas surrounding the basin's edge.

The Chengdu-Chongqing urban agglomeration was chosen as the study area of this paper based on the following considerations. ① In terms of its own conditions, the Chengdu-Chongqing city clusters are important ecological barriers in the upper branches of the Yangtze River and the Yellow River, and the area has a good foundation of energy, industry, and human resources. The Chengdu-Chongqing area is rich in natural gas, shale gas, hydropower, coal, and other energy resources. In particular, the natural gas reserves in this region account for 60% of the country's total, and there still remains huge development potential. On the other hand, there are a complete range of industries, a good industrial foundation, and a dense distribution of cities and towns. In 2019, the permanent population was 96 million, and the regional GDP was nearly 6.3 trillion yuan, accounting for 6.9% and 6.3% of the country's total, respectively. ② In terms of the development positioning of the Chengdu-Chongqing urban agglomeration, the Chengdu-Chongqing urban agglomeration is a strategic urban agglomeration built by the Chinese government. Its rapid development and rapid rise must be accompanied by resources consumption and environmental changes, which have not yet received enough attention from scholars. ③ In terms of the "carbon neutrality" development path of the Chengdu-Chongqing urban agglomeration, the changes in CO₂ emissions of the Chengdu-Chongqing urban agglomeration are inseparable from energy consumption and economic development. Unlike the Beijing-Tianjin-Hebei, Yangtze River Delta, and Guangdong-Hong Kong-Macao urban agglomerations, the Chengdu-Chongqing urban agglomeration has no inherent advantages in industrial and economic development. It has gradually developed in recent years with the support of national policies. Therefore, the Chengdu-Chongqing urban agglomeration is typical of the national level of urban development. Although its development is very different from that of developed cities along the eastern coast of China, its successful development experience can also provide references and experiences for other cities in western areas of China. At the world level of urban development, the cities of Chengdu and Chongqing are China's international gateway hub cities and node cities of the Belt and Road. According to the World City Rankings 2020 published by the Group on Globalization and World Cities (GaWC), Chengdu is at Beta+ level, in the same league as cities such as Washington, Miami, Rome, and Berlin. Chongqing is at Beta level, in the same league as cities such as Athens, Seattle, Cape Town, and Rio de Janeiro. This reflects that the position

of the two cities—Chengdu and Chongqing share similarities with other cities of the same class in the world.

4.2. Data Sources

To calculate and predict the CO₂ emissions of the Chengdu-Chongqing urban agglomeration, this paper collects energy consumption data of each city in the region, as well as industrial data, economic data, and population data related to CO₂ emissions. The data come from the Statistical Yearbook of Sichuan Province, Statistical Yearbook of Chongqing, statistical yearbooks of cities and districts, Statistical Yearbook of China Cities, Statistical Yearbook of China Energy, etc.

The data range involved in this article is from 2006 to 2019, with 2020 as the base year, and the approved calibers are all municipal district data. Since the 2021 statistical yearbooks of the urban areas have not yet been released, the data for 2020 are reasonably extrapolated from the statistical yearbooks of the past five years. The method of extrapolation is the trend extrapolation method, which is a method of extrapolating future trends based on past and current circumstances. The extrapolation of trends is based on the continuity and regularity of the development of the forecast object over time. When the development of the forecast object over time is mainly progressive, the forecast object will show a certain trend. If the forecaster can find a function curve that reflects this trend, a trend extrapolation model can be established with time t as the independent variable and the time series value y as the dependent variable.

$$y = f(t) \quad (22)$$

This article deals with the data of 2006 because the Chinese government issued the Eleventh Five-Year Plan for the development of the western region in 2006 and clearly proposed the construction of the Chengdu-Chongqing Economic Zone. As a result, the Chengdu-Chongqing urban agglomeration developed rapidly and on a considerable scale. In addition, due to the lack of data of some years from 2006 to mid-2019, this article uses Jing Q's urban CO₂ emission allocation method [36] to fill in the missing data.

4.3. CO₂ Emission Estimation Method

The CO₂ emissions of cities are mainly energy CO₂ emissions, including natural gas and liquefied petroleum gas, as well as CO₂ emissions from the consumption of electricity and heat [37]. The CO₂ emissions from direct energy resources such as natural gas and liquefied petroleum gas are calculated using the IPCC2006 emission factors. Since electricity is not created from a single energy resource, the CO₂ emissions caused by electricity consumption are more complicated. Here we draw on the calculation method of electric energy CO₂ emission by Edward L. Glaeser and Matthew E. Kahn [38], that is, the grid in each region uses the emission factors of the corresponding regions. China's power grid is divided into six regions: North China, Northeast China, East China, Central China, Northwest China, and South China [39]. Both Chongqing City and Sichuan Province belong to the Central China regional power grid. The Ministry of Ecology and Environment of the People's Republic of China publishes baseline emission factors for the power grids in various regions of China every year. The CO₂ emissions from the electricity consumption of the Chengdu-Chongqing urban agglomeration can be calculated from the grid baseline emission factors in the region over the years and the electricity consumption of each city. In China, the raw materials required for urban thermal energy production mainly come from raw coal. The amount of raw coal for heating can be calculated according to the heat supply, thermal efficiency, and heat generation coefficient of raw coal. Then, the amount of raw coal required for urban central heating can be calculated according to the standard coal coefficient converted from raw coal. Finally, the CO₂ emissions from central heating are calculated based on the CO₂ emission coefficient of raw coal and the amount of raw coal consumed. However, since the Chengdu-Chongqing urban agglomerations are all located in the south of China, and central heating is not implemented, the calculation of

heating is not discussed here. In summary, the CO₂ emission calculation formula is shown in Equation (23):

$$CO_2 = \sum_{i=1}^n CE_i = \sum_{i=1}^n E_i * EF_i \quad (23)$$

CO₂ represents the sum of CO₂ emissions generated by multiple energy resources; CE_i represents the CO₂ emissions of the i -th energy resources, and n represents the type of energy, such as natural gas, liquefied petroleum gas, electric energy, and other energy resources. E_i represents the consumption of energy i , and EF_i represents the emission factor of energy i . This paper mainly calculates the CO₂ emissions of natural gas, liquefied petroleum gas, and electric energy in each city in the Chengdu-Chongqing urban agglomeration. The emission factor of natural gas is 2.1622 kg-CO₂/m³, and the emission factor of liquefied petroleum gas is 3.1013 kg-CO₂/kg. The electricity emission factor refers to the baseline emission factor of the grid in China over the years.

5. Results and Analysis

5.1. Spatial-Temporal Characteristics of Energy CO₂ Emissions Based on ArcGIS

5.1.1. Time Series Characteristics

According to the calculated energy CO₂ emissions data, the total CO₂ emissions of the Chengdu-Chongqing urban agglomeration and the annual growth rate changes are plotted, as shown in Figure 2. Analyzing the total CO₂ emissions of the Chengdu-Chongqing urban agglomeration, it can be found that there was an increase trend from 2006 to 2013, a decrease trend in 2014 and 2015, and a continued increase trend from 2015 to 2019. In 14 years, the total energy CO₂ emissions of the Chengdu-Chongqing urban agglomeration increased from 7,374,300 tons in 2006 to 15,552,320,200 tons in 2019, an order of magnitude increase of twice. The average growth rate of CO₂ emissions was 6%, with negative growth rates in 2014 and 2015, the two years with the lowest growth rates.

Figure 2. 2006–2019 Chengdu-Chongqing urban agglomeration total CO₂ emissions and changes in growth rate.

In terms of CO₂ emissions of various cities over the years, the changes in CO₂ emissions of different cities are different. Figures 3 and 4 show the changes in the CO₂ emissions of each city in the Chengdu-Chongqing urban agglomeration and the proportion of each city in the Chengdu-Chongqing urban agglomeration. Through analysis, it can be found that Chongqing and Chengdu have the largest energy CO₂ emissions and the largest increase. Chengdu increased by about 2.8 times from 13,945,210,000 tonnes in 2006 to 39,057,360,000 tonnes in 2019, and Chongqing increased by about 2.2 times from 33,441,270,000 tonnes in 2006 to 72,760,280 tonnes in 2019. The CO₂ emissions of each city

generally maintained a growth trend, but there were also certain fluctuations. Among them, the increase in Chengdu was negative in 2014, and the increase in Chongqing was negative in 2015, which contributes to the Notice of the Chengdu Municipal People's Government on Issuing Low-Carbon Reduction Targets in Districts (Cities) and Counties in the 12th Five-Year Plan issued by the General Office of Chengdu Municipal Government in 2013. China regarded Chongqing as a pilot city for carbon trading from 2013 to 2014. Under the influence of the policy, CO₂ emissions in Chongqing and Chengdu have fluctuated and slowed down. On the other hand, in the above analysis, 2014 and 2015 were the two years with the lowest CO₂ emission growth rate in Chengdu-Chongqing urban agglomeration. It can be seen that the increase in Chengdu and Chongqing has a more obvious impact on the total CO₂ emissions of Chengdu-Chongqing urban agglomeration. Apart from Chongqing and Chengdu, the top three cities with the largest increase in 2019 over 2006 were Mianyang (3,578,340 t), Luzhou (3,159,130 t) and Leshan (2,924,850 t). The top three cities with the fastest average growth rates were Ya'an (16.7%), Guang'an (13.0%) and Dazhou (11.7%). In terms of the proportion of CO₂ emissions in each city, Chongqing has an average share of 46%, Chengdu 22%, and other cities 32%. It can be seen that the proportions of Chongqing and Chengdu have not changed much over the years, which can further illustrate that Chongqing and Chengdu are the central cities in the Chengdu-Chongqing urban agglomeration.

Figure 3. Changes in CO₂ emissions of cities in the Chengdu-Chongqing urban agglomeration from 2006 to 2019.

Figure 4. Proportion of CO₂ emissions of each city in the Chengdu-Chongqing urban agglomeration from 2006 to 2019.

CO₂ emission intensity (CO₂ emission intensity is equal to the ratio of CO₂ emission to regional GDP) is a measure of the CO₂ emission of a city from the perspective of efficiency. Draw a graph of changes in the CO₂ emission intensity of each city, as shown in Figure 5. The changes in the CO₂ emission intensity of each city have shown a fluctuating downward trend. In some years, the CO₂ emission intensity of some cities increased compared with the previous year, but the overall trend of the CO₂ emission intensity of each city has declined. This is inversely related to changes in the total CO₂ emissions of each city. We believe that in the context of the Western Development, the Chengdu-Chongqing urban agglomeration will develop rapidly, and various industries in the city will also develop rapidly. Urbanization and industrialization have gradually increased the demand for energy, which has led to a year-on-year increase in total CO₂ emissions. At the same time, with the green transformation and upgrading of the industry and the improvement of energy efficiency, the CO₂ emission intensity has shown a downward trend. That is, in the same unit of GDP, the CO₂ emission of each city is declining year by year. The gap between the CO₂ emission intensity of cities is gradually narrowing, especially the two large cities of Chengdu and Chongqing. Although their total CO₂ emissions account for a huge proportion, their CO₂ emission intensity is not significantly different from that of the other. It can be seen that the rapid development of the Chengdu-Chongqing urban agglomeration did not come at the expense of environment destruction, but under the guidance of relevant policies of “carbon peak” and “carbon-neutral”, green and environmentally friendly sustainable development has been practiced.

Figure 5. Changes in CO₂ emission intensity of each city in the Chengdu-Chongqing urban agglomeration.

Furthermore, we analyze the CO₂ emissions produced by major energy resources with the purpose of providing a basis for decision makers to formulate energy transition paths. The main energy resources of the city are divided into electricity and gas. The CO₂ emissions of electricity and gas are calculated, respectively, as shown in Figure 6. It is seen that the CO₂ emissions of each city mainly come from electricity consumption, and the CO₂ emissions produced by natural gas and liquefied petroleum gas are relatively small. This is because, on the one hand, electricity is everywhere in people’s production and lives, and cities have to consume a lot of electricity in order to develop. On the other hand, according to the 2018 data of the International Energy Agency (IEA) [40], from the perspective of energy structure, in global CO₂ emissions materials, the combustion and

use of coal account for approximately 44% of CO₂ emissions, oil about 34%. Natural gas accounts for about 21%, and other energy CO₂ emissions less than 1%. Natural gas is cleaner and more efficient than other fossil energy resources. Therefore, the use of gas produces less CO₂ and the use of electricity produces more CO₂. In summary, the CO₂ emissions from gas use in each city are far less than those from electricity use.

Figure 6. Changes in energy CO₂ emissions of each city in the Chengdu-Chongqing urban agglomeration.

5.1.2. Spatial Layout Characteristics

Using ArcGIS to map the spatial layout of CO₂ emissions in the Chengdu-Chongqing urban agglomeration can help us further understand the spatial distribution characteristics of CO₂ emissions and the interactions of spatial elements. Since the annual CO₂ emission changes are not too strong and natural factors (Sichuan and Chongqing suffered the Wenchuan earthquake in 2008) and policy factors (In April 2011, the State Council of China formally approved the Regional Plan for Chengyu Economic Zone. On 4 May 2016, the National Development and Reform Commission of China and the Ministry of Housing and Urban-Rural Development jointly issued the Chengyu Urban Agglomeration Development Plan, etc.) are taken into account, the four years 2008, 2012, 2016, and 2019 are selected to draw the spatial distribution maps, as shown in Figure 7. Through the spatial distribution map, we first see that the CO₂ emissions of the Chengdu-Chongqing urban agglomeration present an obvious imbalance. Chongqing and Chengdu are the two cities with the largest emissions, while those of the other cities are much lower. Secondly, in terms of CO₂ emissions from dense urban areas, the southern Sichuan (Luzhou, Leshan and Zigong), Chengdu (Chengdu, Deyang, Mianyang, Meishan), northern Sichuan (Nanchong and Dazhou), and Chongqing regions have higher CO₂ emissions, while the central Sichuan region (Suining, Ziyang and other cities) has lower CO₂ emissions. Finally, further analyses on the spatial changes of CO₂ emissions in the Chengdu-Chongqing urban agglomeration reveal that, in 2008, apart from Chengdu and Chongqing—the two CO₂ emission center cities—the top five cities for CO₂ emissions were Zigong, Meishan, Leshan, Luzhou, and Deyang; in 2012, the top five cities for CO₂ emissions were Leshan, Meishan, Luzhou,

Mianyang, and Yibin; in 2016, the top five cities for CO₂ emissions were Leshan, Mianyang, Luzhou, Deyang, and Nanchong; in 2019, the top five cities for CO₂ emissions were Mianyang, Leshan, Lu-zhou, Yibin, and Nanchong. These changes in the spatial layout reflect that the changes in CO₂ emissions from the Chengdu-Chongqing urban agglomeration follow the law of outward diffusion from node cities, that is, using Chongqing and Chengdu as the dual cores to diffuse to the periphery, and regional node cities to diffuse to non-node cities. It can be seen that taking CO₂ emission optimization measures for node cities in regional cities can lead to a reasonable carbon reduction in surrounding cities.

Figure 7. The spatial distribution of CO₂ emissions in each city in the Chengdu-Chongqing urban agglomeration.

To further observe the relationship of the CO₂ emission intensity of each city, the spatial distribution map of the CO₂ emission intensity of each city was drawn through ArcGIS, as shown in Figure 8. First, through the spatial distribution map, we can find that the CO₂ emission intensity of each city has been decreasing, and the gap between cities has been decreasing year by year. Secondly, Chongqing and Chengdu, as the two cities with the largest CO₂ emissions, their CO₂ emission intensity is not high. In 2008, the top five cities with CO₂ emission intensity were Meishan, Deyang, Dazhou, Leshan, and Luzhou; in 2012, they were Meishan, Dazhou, Leshan, Deyang, and Ya'an; in 2016, they were Leshan, Ya'an, Luzhou, Deyang, and Dazhou; and in 2019, they were Leshan, Ya'an, Luzhou, Guang'an, and Dazhou. This shows that the size of the city may affect CO₂ emissions, but it does not directly affect the intensity of CO₂ emissions. Finally, combining the development positioning of each city [41], it can be found that there is a certain relationship between the CO₂ emission intensity and the industrial composition of a city. Meishan is an important processing base for locomotive manufacturing, metallurgical building materials, and fine chemicals. Deyang is an important heavy equipment manufacturing base. Dazhou is an important processing base for natural gas, phosphorus sulfide, and metallurgical building materials. Leshan is an important industrial base for clean energy,

new materials, and metallurgical building materials. Luzhou is an important base for natural gas, coal, chemicals, energy, and equipment manufacturing. Ya'an is an agricultural product processing, clean energy industrial base and transportation node city. Guang'an is an important processing and supply base for fine chemicals, new energy, and new materials. It can be seen that the development of these cities with relatively high CO₂ emission intensity is more dependent on the primary and secondary industries. These industries have a high energy intensity and are prone to producing a lot of CO₂ and other air pollutants. However, with the transformation and upgrading of industries, the CO₂ emission intensity of these cities has been decreasing year by year.

Figure 8. Spatial distribution of CO₂ emission intensity of each city in the Chengdu-Chongqing urban agglomeration.

5.1.3. Comparison with Other Cities

By analyzing the spatial and temporal characteristics of the Chengdu-Chongqing urban agglomeration, it is found that Chengdu and Chongqing are the two core cities of the region. The next step is to further compare these two major cities—Chengdu and Chongqing—with other cities in China and abroad to provide some references for urban development in China and abroad. As shown in Table 1, Chengdu and Chongqing are compared with major cities in China. As shown in Table 2, Chengdu and Chongqing are compared with major foreign cities. The data are from the China Urban Statistics Yearbook and the Chengdu Low Carbon Development Plan.

A side-by-side comparison of eight major cities in China shows that Chengdu and Chongqing rank second to Beijing, Shanghai, Guangzhou, and Shenzhen in terms of total GDP, but are in the bottom one or two in terms of electricity consumption per capita, in the bottom two or three in terms of natural gas supply per capita, and in the bottom one or two in terms of LPG per capita. This indicates that the structure and intensity of energy consumption in Chengdu and Chongqing are better controlled. A side-by-side comparison of six foreign cities shows that Chengdu and Chongqing are not as well developed as other foreign cities, and that the gap between energy consumption and foreign cities is still wide. However, carbon emissions per capita are still at an advanced level, with Chengdu just

above London and Chongqing lower than Singapore. It can be seen that controlling energy consumption intensity and energy mix has a positive mitigating effect on urban carbon emissions, both at home and abroad.

Table 1. Comparison with major cities in China. Total GDP and resident population are for 2020. Social electricity consumption, gas supply, and LPG supply are for 2019.

City	Total GDP (Billion Yuan)	Resident Population (10 ⁴)	Social Electricity Consumption (10 ⁴ ·kWh)	Total Natural Gas Supply (10 ⁴ ·m ³)	Total LPG Gas Supply (Tonnes)
Chengdu	17,716	2093	6,938,431	387,098	119,755
Chongqing	25,002	3205	11,601,939	538,136	61,187
Beijing	36,102	2189	11,663,964	1,924,347	434,286
Shanghai	38,700	2487	15,685,775	973,605	328,008
Guangzhou	25,019	1867	10,055,838	–	758,759
Shenzhen	27,670	1756	9,839,910	365,416	335,673
Hangzhou	16,106	1193	8,167,003	133,731	122,438
Wuhan	15,616	1232	6,154,628	270,239	167,243

Table 2. Comparison with major international cities. Domestic: total GDP, resident population, and total energy consumption for Chengdu and Chongqing are 2018 data; other data are 2017 data and * are 2015 data. Foreign: London, New York, and Singapore are 2017 data. Tokyo is 2016 data.

City	Total GDP (Billion Yuan)	Resident Population (10 ⁴)	Total Energy Consumption (Million Tonnes of Standard Coal)	Energy Consumption per Unit of GDP (Tonnes of Standard Coal/Yuan)	Energy Consumption per Capita (Tonnes of Standard Coal/per Capita)	Total Carbon Dioxide Emissions (Million Tonnes)	CO ₂ Emissions per Capita (Tonnes/per Capita)
Chengdu	15,343	1633	4788	0.36	2.93	5598	3.48
Chongqing	20,363	3102	7453	0.42	2.4	24,405 *	5.49
London	42,223	879	1654	0.039	1.88	3030	3.45
New York	59,806	847	1758	0.029	2.08	6950	8.2
Singapore	22,848	561	609	0.027	1.09	5250	9.36
Tokyo	63,980	1372	2117	0.033	1.54	5855	4.27

5.2. CO₂ Emission Prediction in Different Scenarios

This article first builds the STIRPAT model, screens the important influencing factors on this basis, and then takes the key factors as input features and inputs them into the combined model of the improved GM (1, N) model and SVR for prediction. According to relevant policies and existing data, three different scenarios are constructed to discuss energy CO₂ emissions in different scenarios.

5.2.1. Analysis of the Influencing Factors of Energy CO₂ Emissions Based on the STIRPAT Model

The use of the STIRPAT model requires that more than five environmental influences be selected from three dimensions: demographic, economic, and technological. Based on this, this paper uses the resident population of the municipal area (P) as the demographic factor. Gross regional product (G), GDP per capita (R), gross primary industry (I1), gross secondary industry (I2), and gross tertiary industry (I3) are used as economic factors. CO₂ emission intensity (C), natural gas use (N), LPG supply (L), and social electricity consumption (E) are taken as technical factors [24,42–45]. The data are from the China City Statistical Yearbook, China Energy Statistical Yearbook, etc. In this paper, a total of 10 urban energy CO₂ emission influencing factors are selected, which meet the application requirements of the environmental impact assessment model (STIRPAT model); therefore, the STIRPAT model is established by combining the influencing factors as follows:

$$\ln \text{CO}_2 = a + b \ln P + c \ln G + d \ln R + e \ln I1 + f \ln I2 + g \ln I3 + h \ln C + i \ln N + j \ln L + k \ln E + l \quad (24)$$

In Formula (2), CO_2 represents the total energy CO_2 emissions of the Chengdu-Chongqing urban agglomeration; P represents the number of permanent residents in the Chengdu-Chongqing urban agglomeration; G represents the gross regional product. R represents GDP per capita; $I1$ represents the gross production value of the primary industry; $I2$ represents the gross output value of the secondary industry. $I3$ represents the gross output value of the tertiary industry; C represents CO_2 emission intensity. N represents natural gas consumption; L represents LPG supply volume. E represents social electricity consumption; a is a constant term; m is the residual; b, c, d, f, g, h, i, j , and k represent the coefficient of elasticity of each factor. The higher the value, the greater the impact of the corresponding influencing factor on CO_2 emissions.

In the linear regression model $Y = \beta_0 + \beta_1 X_1 + \dots + \beta_n X_n + \varepsilon$, the change in n explanatory variables causes a linear change in the explained variable Y . The explained variable Y is an n -dimensional vector, the independent variable X_i is an $n \times p$ -order matrix, β_0 is a constant term coefficient, β_j is a regression coefficient, and ε is a random error vector. For the explanatory variable X , if there is a set of numbers $\lambda_0, \lambda_1, \lambda_2, \dots, \lambda_n$ that is not all 0, making $\lambda_0 X_{i0} + \lambda_1 X_{i1} + \lambda_2 X_{i2} + \dots + \lambda_n X_{in} = 0$, the linear regression model is said to have complete collinearity. If there is still a random error m that satisfies $E_m = 0, E_m^2 < \infty$, making $\lambda_0 X_{i0} + \lambda_1 X_{i1} + \lambda_2 X_{i2} + \dots + \lambda_n X_{in} + m = 0$, then the linear regression model is said to have non-complete collinearity. It is necessary to diagnose the multicollinearity of the independent variables before performing model estimation. Because if the explanatory variables in the linear regression model are highly correlated, it will cause the model to be estimated to be distorted or difficult to estimate accurately.

Firstly, the independent variables were tested for multicollinearity by performing a VIF test for multicollinearity, as shown in Table 3. It is generally considered that if the tolerance (tolerance) is less than 0.2 or the VIF (variance inflation factor) is greater than 10, then multicollinearity is considered to exist between the independent variables. According to the VIF test, among the 10 variables, the tolerance of the gross regional product, CO_2 emission intensity, resident population, gross primary sector, gross secondary sector, and gross tertiary sector is less than 0.2 and the VIF is greater than 10. This indicates that there may be multicollinearity in the above STIRPAT model.

Table 3. VIF diagnosis.

Variable	Variable Interpretation	Unit	Collinearity Statistics	
			Tolerance	VIF
G	Gross regional product of municipal district	Million	0.026	392.141
C	CO_2 emission intensity	million tonnes/billion Yuan	0.046	12.835
R	GDP per capita	Yuan	0.754	1.326
P	Resident population in municipal districts	10,000 people	0.040	24.715
N	Natural gas consumption	$10^4 \cdot m^3$	0.125	8.000
L	LPG supply volume	Ton	0.890	1.124
E	Electricity consumption	$10^4 \cdot kWh$	0.159	6.278
I1	Gross primary industry	Million	0.002	476.479
I2	Gross secondary industry	Million	0.039	25.593
I3	Gross tertiary industry	Million	0.020	48.858

Then we diagnosed the collinearity of the independent variables, as shown in Table 4. If the multidimensional feature value is 0, it indicates that the variable has multicollinearity, and if the value of the condition index is greater than 10, it indicates that the variable has multicollinearity. Through the eigenvalues of the collinearity diagnosis and the value of the condition index, it can be seen that as the independent variable is added to the model, the eigenvalue gradually decreases and approaches 0, and the value of the condition index gradually increases. When the dimension is 4, that is, after adding the independent variable permanent population, the characteristic value is 0.031, the value of the condition index is

16.692, the characteristic value is close to 0, and the value of the condition index is greater than 10. The results show that there is a high degree of multicollinearity between the variables.

Table 4. Collinearity diagnosis.

Dimension	Eigenvalues	Condition Index
1	8.659	1
2	0.851	3.191
3	0.431	4.483
4	0.031	16.692
5	0.021	20.428
6	0.004	46.938
7	0.002	67.329
8	0.001	97.150
9	0.00012	139.098
10	0.00002977	539.317

Ridge regression method is a biased regression estimation method dedicated to collinearity data analysis, and it is an improved least-squares estimation method. Its estimator is $\hat{\beta}(k) = (X'X + kl)^{-1}X'Y$, where $k > 0$ and constant. When there is a high degree of collinearity, the parameters estimated by the ridge regression method are better than those estimated by the ordinary least-squares method. Therefore, this paper uses the ridge regression method to fit the model. Because there are huge numerical differences among the data, the normalized value is used for fitting to obtain the best CO₂ emission influencing factor analysis model, as shown in Equation (25):

$$\begin{aligned} \ln \text{CO}_2 = & 0.1849 + 0.1444 \ln P + 0.1349 \ln G - 0.0175 \ln R \\ & + 0.1062 \ln I1 + 0.1078 \ln I2 + 0.1057 \ln I3 - 0.1291 \ln C \\ & + 0.1294 \ln N + 0.0467 \ln L + 0.1225 \ln E \end{aligned} \quad (25)$$

The larger the coefficient of elasticity, the more significant the impact on CO₂ emissions. The absolute value of the elastic coefficient of each influencing factor is sorted from the largest to the smallest as follows: permanent resident population in municipal districts (0.1444), gross regional product (0.1349), natural gas consumption (0.1294), CO₂ emission intensity (0.1291), electricity consumption (0.1225), the gross secondary industry (0.1078), the gross primary industry (0.1062), the gross tertiary industry (0.1057), the supply of liquefied petroleum gas (0.0467), and the GDP per capita (0.0175). It can be seen that in the Chengdu-Chongqing urban agglomeration, CO₂ emission intensity and per capita GDP have a negative correlation with CO₂ emissions, and other influencing factors have a positive one. The permanent population has the most significant impact on CO₂ emissions, while the per capita GDP has the weakest impact on CO₂ emissions. The value of the coefficient of elasticity of the influencing factors indicates that when the number of permanent residents in the Chengdu-Chongqing urban agglomeration increases by 1%, CO₂ emissions increase by 0.1444%; when the regional GDP increases by 1%, CO₂ emissions increase by 0.1349%, and so on.

5.2.2. Energy CO₂ Emission Prediction Results under Different Scenarios Influencing Factors Settings

Based on the results of the analysis of the factors influencing CO₂ emissions in the Chengdu-Chongqing urban agglomeration, this paper selects the resident population, gross regional product, natural gas consumption, CO₂ emission intensity, social electricity consumption, gross primary industry, gross secondary industry, and gross tertiary industry as input features, and inputs the features into a combined model of improved GM (1, N) model and SVR.

This article sets up three scenarios: the baseline scenario, the low-carbon scenario 1, and the low-carbon scenario 2. The baseline scenario is set based on the CO₂ emissions of

the Chengdu-Chongqing urban agglomeration from 2006 to 2019 and the existing changes in various influencing factors. Low-carbon scenario 1 is based on relevant plans, adjusting the changes in influencing factors so that CO₂ emissions can be reduced. Low-carbon scenario 2 is still based on relevant policy planning, and further adjustments are made to the influencing factors on the basis of low-carbon scenario 1, so that CO₂ emissions can be further reduced. As Chengdu and Chongqing are the two major central cities in the Chengdu-Chongqing urban agglomeration, the siphon effect on the surrounding cities becomes more obvious. Therefore, the setting conditions of the influencing factors not only refer to the relevant national and provincial planning outlines, but also emphatically refer to the relevant plans of Chengdu and the relevant plans of Chongqing. In the three scenarios, the setting of social macro factors is in line with government planning and regulations, and the industrial and energy structure needs to be set based on different scenarios.

In terms of the number of permanent residents, according to the results of the seventh national census, we know that the permanent population of Chongqing in 2020 will be 3,205,200, the permanent population of Chengdu in 2020 will be 20.938 million, and the permanent population of Sichuan will be 83,674,900 in 2020. According to the Chongqing Population Development Plan (2016–2030), by 2030, the city's permanent population will reach around 36 million. According to the Chengdu National Land and Space Master Plan (2020–2035), the permanent population of Chengdu will be controlled at 24 million in 2035. From 2006 to 2019, the average growth rate of the permanent population in the Chengdu-Chongqing urban agglomeration city area was 3.27%. Based on this, the population numbers of the municipal districts in the three scenarios mentioned in this article are all set to conform to the above rules and plans, as shown in Table 5.

Table 5. The number of permanent residents in Chengdu-Chongqing urban agglomeration from 2020 to 2035.

Years	Resident Population in Municipal Districts (Ten Thousand People)
2020	5676
2021	5911
2022	6155
2023	6410
2024	6675
2025	6952
2026	7239
2027	7539
2028	7851
2029	8176
2030	8514

In terms of GDP in the municipalities, according to the 14th Five-Year Plan and the 2035 Vision and the 13th Five-Year Plan for National Economic and Social Development of Sichuan Province, the target value of Sichuan's GDP in 2020 is RMB 420 billion, with an average annual growth rate of 7%, and is expected to maintain an average annual growth rate of 6% by 2025. According to the 13th Five-Year Plan for Chongqing, the city's GDP will reach RMB 2.5 trillion in 2020. According to the China Urbanisation and Economic Growth Report, Chongqing's GDP is expected to reach RMB 5.4 trillion in 2030. According to the Chengdu Municipal Bureau of Statistics, the GDP of Chengdu in 2020 will be RMB 177.17 billion. According to the Chengdu 14th Five-Year Plan and 2035 Vision Outline, Chengdu's GDP target for 2025 is RMB 2.6–2.8 trillion, with an average annual growth rate of 6–8% between 2020 and 2025. The average growth rate of regional GDP in the Chengdu-Chongqing urban agglomeration municipalities from 2006 to 2019 was 16.58%. Based on this, the regional GDP settings for the three scenarios proposed in this paper are shown in Table 6.

Table 6. The GDP setting of the districts under the jurisdiction of the Chengdu-Chongqing urban agglomeration from 2020 to 2035.

Years	Gross Regional Product (Ten Thousand Yuan)
2020	544,608,526.3761
2021	621,296,479.3697
2022	708,783,092.0418
2023	808,588,955.9104
2024	922,448,781.5261
2025	1,052,341,549.2127
2026	1,200,524,905.4231
2027	1,369,574,402.5497
2028	1,562,428,264.2087
2029	1,782,438,454.0579
2030	2,033,428,935.7685

In terms of CO₂ emission intensity, considering that the calculation of CO₂ emission intensity is affected by the regional GDP, and based on the historical CO₂ emission intensity from 2006 to 2019, the CO₂ emission settings for the three scenarios mentioned in this paper are shown in Table 7.

Table 7. The CO₂ emission intensity setting of Chengdu-Chongqing urban agglomeration from 2020 to 2035.

Years	CO ₂ Emission Intensity (10,000 t/Ten Thousand Yuan)
2020	4.5022
2021	4.0088
2022	3.5695
2023	3.1783
2024	2.8300
2025	2.5199
2026	2.2438
2027	1.9979
2028	1.7789
2029	1.5840
2030	1.4104

The energy structure setting rules refer to the Chengdu Low-Carbon Development Path Analysis and Research Report, combined with the actual CO₂ emissions of the Chengdu-Chongqing urban agglomeration. Low-carbon scenario 1 further “changes coal to gas,” “changes coal to electricity,” and “changes gas to electricity” compared to the baseline scenario, rapidly reducing the proportion of coal used and further increasing the proportion of electricity. Low-carbon scenario 2 and lower-carbon scenario 1 vigorously promote the “electrification” of traditional coal-using companies, and only retain the use of raw material-based fossil fuels. In summary, the following rules were set for the changes in the influencing factors in the different scenarios, as shown in Table 8. The changes in energy and industry in 2020–2030 under different scenarios are shown in Figures 9 and 10.

Table 8. Rules for setting influencing factors in different situations.

Category	Influencing Factors	Baseline Situation	Low-Carbon Scenario 1	Low-Carbon Scenario 2
Energy structure	Natural gas consumption	The proportion of natural gas consumption will decrease by 0.14% annually from 2020 to 2025, and from 2025 to 2030, decrease by 0.23% annually. The proportion of electricity consumption will increase by 0.56% annually from 2020 to 2025, and from 2025 to 2030, by 0.67% annually.	The proportion of natural gas consumption will decrease by 0.04% annually from 2020 to 2025, and from 2025 to 2030, decrease by 0.25% annually. Electricity consumption accounts for an annual increase of 0.72% from 2020 to 2025, and from 2025 to 2030, an annual increase of 0.78%.	The proportion of natural gas consumption will increase by 0.04% annually from 2020 to 2025, and from 2025 to 2030, decrease by 0.39% annually. Electricity consumption accounts for an annual increase of 0.74% from 2020 to 2025, and from 2025 to 2030, an annual increase of 0.97%.
	Electricity consumption			
Industrial structure	primary industry	From 2020 to 2030, it will decrease at a rate of 0.13% per year.	From 2020 to 2030, it will decrease at a rate of 1.55% per year.	From 2020 to 2030, it will decrease at an annual rate of 2.97%.
	Secondary industry	From 2020 to 2030, it will decrease at a rate of 0.29% per year.	From 2020 to 2030, it will decrease at a rate of 0.89% per year.	From 2020 to 2030, it will decrease at a rate of 1.48% per year.
	Tertiary Industry	From 2020 to 2030, it will increase at an annual rate of 0.42%.	From 2020 to 2030, it will increase at an annual rate of 1.17%.	From 2020 to 2030, it will increase at an annual rate of 1.92%.

Figure 9. Natural gas and electricity consumption in different scenarios. (a) Natural gas; (b) Electricity.

Forecast Results

First, the improved GM (1, N) model, SVR model, and their combined model are used to predict the CO₂ emissions of the Chengdu-Chongqing urban agglomeration from 2014 to 2019. The prediction results are shown in Figure 11. The evaluation indicators are shown in Table 9. Through the prediction results and evaluation indicators, it can be seen that the prediction results of the improved GM (1, N) and SVR combined model are more likely to be true. The RMSE, MAE, and MAPE values of the combined model are the smallest. It can be seen that the improved combination model has higher prediction accuracy.

Figure 10. The GDP of the primary, secondary and tertiary industries in different scenarios. (a) Primary industry; (b) Secondary industry; (c) Tertiary Industry.

Figure 11. 2014–2019 CO₂ emission forecast results of the Chengdu-Chongqing urban agglomeration.

Table 9. Evaluation results.

Model	RMSE	MAE	MAPE (%)
Improved GM (1, N)	1241.8132	1155.6949	9.1843
SVR	1600.7115	1182.2808	8.3033
Combination model	732.2946	592.9249	4.6179

From the above prediction results and evaluation results, it can be seen that the combined model of improved GM (1, N) and SVR has the best effect. In this paper, the above set influencing factors are incorporated into the constructed combined forecasting model, combined with historical data, to predict the CO₂ emissions of the Chengdu-Chongqing urban agglomeration from 2020 to 2030 under different scenarios. The forecast results are shown in Figure 12. According to the prediction results, the following is discovered: First, the CO₂ emissions in 2020–2024 are the lowest in the baseline scenario, followed by the low-carbon scenario 1, and the low-carbon scenario 2 is the highest. However, starting from 2025, CO₂ emissions will be the lowest in the low-carbon scenario 2, followed by the low-carbon scenario 1, and the highest in the baseline scenario. Therefore, in the short term, the baseline scenario has the lowest CO₂ emissions among the three scenarios, but in the long run, the two low-carbon scenarios have the lowest CO₂ emissions. Second, the energy CO₂ emissions of the Chengdu-Chongqing urban agglomeration have been increasing year by year in three different scenarios, indicating that the energy CO₂ emissions of the Chengdu-Chongqing urban agglomeration will not reach their peak before 2030. Third,

reducing the proportion of the primary and secondary industries, increasing the proportion of the tertiary industry, and increasing the proportion of electricity can effectively affect CO₂ emissions.

Figure 12. 2020–2030 CO₂ emission forecast results of the Chengdu-Chongqing urban agglomeration.

In the long run, low-carbon scenario 2 has lower CO₂ emissions but performs better. Therefore, this article is determined to predict the energy CO₂ emissions of each city in low-carbon scenario 2 in the Chengdu-Chongqing urban agglomeration, as shown in Figure 13. Through the 2020–2030 CO₂ emission forecast trend map of each city in the Chengdu-Chongqing urban agglomeration, it can be found that: ① In the next ten years, Chongqing and Chengdu will still be the two cities with the highest CO₂ emissions, and the CO₂ emissions gap between other cities will continue to widen. It is estimated that by 2030, the energy CO₂ emissions of the two cities of Chongqing and Chengdu will not reach their peak but will be increasing instead. ② Divide the CO₂ emissions of other prefecture-level cities into two echelons. The energy CO₂ emissions of the first echelon are significantly higher than those of the second echelon. The first-tier cities include Mianyang, Dazhou, Leshan, and Luzhou, and the second-tier cities include Nanchong, Ya'an, Guang'an, Deyang, Yibin, Suining, Neijiang, Meishan, Zigong, and Ziyang. ③ In the first echelon, Mianyang has the highest CO₂ emissions and its CO₂ emissions have been increasing year by year. Dazhou's CO₂ emissions are also increasing year by year and are expected to surpass Leshan and Luzhou in 2029. Although the CO₂ emissions of Leshan and Luzhou have been increasing year by year, the growth speed has slowed down significantly and stabilized. ④ In the second echelon, Nanchong has the highest CO₂ emissions and its CO₂ emissions have been increasing year by year. However, the growth speed has been slowing. Ya'an and Guang'an have the fastest growth in CO₂ emissions. It is estimated that by 2027, the CO₂ emissions of these two cities will exceed the second-tier cities and their CO₂ emissions are after Nanchong. Yibin and Deyang's CO₂ emissions are expected to be comparable to Nanchong in 2020 and will be less than Nanchong's CO₂ emissions by 2030, but the difference is that Deyang's CO₂ emissions are reducing at an extremely slow rate, while Yibin's CO₂ emissions are increasing at an extremely slow rate. Both Suining and Neijiang's CO₂ emissions are increasing year by year, but the increase is not large. The CO₂ emissions of Meishan, Zigong, and Ziyang are decreasing year by year, and the reduction rate is relatively stable.

Figure 13. The 2020–2030 CO₂ emission forecast trend of each city in the Chengdu–Chongqing urban agglomeration. (a) Chengdu and Chongqing CO₂ emission forecast; (b) CO₂ emission forecast of other prefecture-level cities.

To further analyze the future spatial layouts of the CO₂ emissions of the Chengdu–Chongqing urban agglomeration, the temporal and spatial characteristics of the energy CO₂ emissions of the Chengdu–Chongqing urban agglomeration in 2030 are drawn as shown in Figure 14. Combined with the analyses of CO₂ emission influencing factors above, the spatial layout map shows that ① the layouts of the Chengdu–Chongqing urban agglomeration, with Chongqing and Chengdu as the core cities, remains unchanged in the next ten years, because energy CO₂ emissions are closely related to population, industry, and economy. Chongqing and Chengdu are gradually increasing their siphoning capacity for China's social resources, attracting a large number of migrants and industrial investments, which will lead to an increase in energy use, resulting in an increase in energy CO₂ emissions. ② The node cities in the regional cities are further highlighted. The CO₂ emissions of Mianyang, Dazhou, Leshan, and Luzhou are after Chongqing and Chengdu, and they are located in the four corners of the Chengdu–Chongqing urban agglomeration. Mianyang and Dazhou are located in the northern Sichuan urban agglomeration, and Leshan and Luzhou are located in the southern Sichuan urban agglomeration. On the one hand, this shows that the CO₂ emissions of the Chengdu–Chongqing urban agglomeration are more concentrated and centralized. On the other hand, this shows that the development of the

Chengdu-Chongqing urban agglomeration is no longer only concerned about Chongqing and Chengdu, but the node cities and their surrounding cities. ③ Combined with Figure 13 above, the changes in CO₂ emissions of each city over the years indicate that the regional coordinated development of the Chengdu-Chongqing urban agglomeration is still faint. Chongqing and Chengdu are still the two largest cities in the Chengdu-Chongqing urban agglomeration. Although existing policies have gradually emphasized the coordinated development of urban agglomerations, this problem has not been effectively resolved in the next ten years. ④ The CO₂ emissions of the linked cities between Chongqing and Chengdu (Ziyang, Neijiang, Suining, etc.) are still maintained at a relatively low level. It is not ruled out that these cities have effectively controlled CO₂ emissions. However, judging from the changes in the CO₂ emissions of the cities in the Chengdu-Chongqing urban agglomeration and the changes in influencing factors, it is easy to infer that because the population, economy, and industry of these cities have not been promoted. This shows that the twin cities of Chongqing and Chengdu continue to play a minor role.

Figure 14. The spatial layout of CO₂ emissions in Chengdu-Chongqing urban agglomeration in 2030.

6. Conclusions and Policy Implications

This article first estimates the energy CO₂ emission data of the Chengdu-Chongqing urban agglomeration from 2006 to 2019. Then it uses the CO₂ emission data to construct a CO₂ emission STIRPAT model from three dimensions—population, economy, and technology. Then it screens the influencing factors according to the elasticity coefficient and uses the screened influencing factors as the predicted influencing factors. Finally, different CO₂ emission scenarios are constructed based on relevant policies and existing data. The

combined model of the improved GM (1, N) model and SVR model is used to predict the CO₂ emissions of the Chengdu-Chongqing urban agglomeration in the next few years. At the same time, the temporal and spatial characteristics of CO₂ emissions in the Chengdu-Chongqing urban agglomeration are analyzed. The main research conclusions drawn are as follows:

(1) The energy CO₂ emissions of the Chengdu-Chongqing urban agglomeration are increasing year by year, and it is estimated that CO₂ emissions will not reach the peak by 2030. Chongqing and Chengdu are the two cities with the largest CO₂ emissions in the Chengdu-Chongqing urban agglomeration, and they have maintained rapid growth. The CO₂ emissions of these two cities have a profound impact on the total CO₂ emissions of the Chengdu-Chongqing urban agglomeration, and this layout is expected to remain unchanged by 2030. The CO₂ emissions of other prefecture-level cities are much lower than those of Chongqing and Chengdu. It is estimated that by 2030, Mianyang, Dazhou, Leshan, and Luzhou will become the four cities with the largest CO₂ emissions after Chongqing and Chengdu.

(2) Sort the absolute value of the elasticity coefficient of the CO₂ emission influencing factors of the Chengdu-Chongqing urban agglomeration: permanent resident population in municipal districts (0.1444), gross regional product (0.1349), natural gas consumption (0.1294), CO₂ emission intensity (0.1291), electricity consumption in society (0.1225), the gross secondary industry (0.1078), the gross primary industry (0.1062), the gross tertiary industry (0.1057), the supply of liquefied petroleum gas (0.0467), and the GDP per capita (0.0175). The larger the coefficient of elasticity, the more significant the impact on CO₂ emissions. CO₂ emission intensity and per capita GDP have a negative correlation with CO₂ emissions, and other influencing factors have a positive correlation.

(3) Under the setting of different scenarios, there are obvious differences in the prediction results of CO₂ emissions. From a short-term perspective (2020–2024), CO₂ emissions under the baseline scenario are the lowest among the three scenarios. From a long-term perspective (from 2025 to 2030), the CO₂ emissions of the two low-carbon scenarios are relatively low, and especially the low-carbon scenario 2 has the lowest CO₂ emissions. It can be seen that the industrial structure and energy structure have a significant impact on CO₂ emissions. Increasing the proportion of the tertiary industry, using clean energy such as natural gas, and electrifying traditional coal-using companies can effectively reduce CO₂ emissions.

Based on these main research conclusions, this article proposes the following policy implications.

First of all, according to the forecast results, the CO₂ emissions of the Chengdu-Chongqing urban agglomeration will not reach a turning point before 2030, which is contrary to our country's commitment to "strive to peak CO₂ emissions by 2030 and achieve carbon neutrality by 2060." Therefore, when the government formulates carbon emission policies, it must first maintain a certain awareness of the dilemma, and then the policies must be targeted. Mega cities such as Chongqing and Chengdu should aim at coordinated economic and environmental development and drive other cities in the urban agglomeration, rather than blindly pursuing their own economic expansion by ignoring CO₂ emissions. Node cities such as Mianyang, Dazhou, Leshan, and Luzhou should formulate corresponding carbon reduction measures based on the actual conditions of human resources, energy, and industries of each city to reduce carbon while maintaining rapid economic growth. Other prefecture-level cities, especially Suining, Neijiang, Ziyang, and other cities bordering Chongqing and Chengdu, can appropriately undertake related industries in Chongqing and Chengdu. However, at the same time, some high-tech and low-carbon industries should be developed to promote the rapid development of the local economy. When formulating policies, the government should consider the integrity of the Chengdu-Chongqing urban agglomeration and treat it as a system. There are close ties between core cities and other cities, node cities, and ordinary cities, and CO₂ emission policies should follow this point.

Secondly, from the perspective of energy structure, cities should vigorously implement measures, such as “coal to gas,” “coal to electricity,” and “gas to electricity,” in order to quickly reduce the proportion of coal used and further increase the proportion of electricity. On the one hand, in terms of energy production, the Chengdu-Chongqing urban agglomeration has a large amount of natural gas, shale gas, and water resources, and thermal power generation will generate a lot of pollutants and greenhouse gases. Therefore, we can combine this advantage of the Chengdu-Chongqing urban agglomeration to vigorously promote power generation technologies such as “gas power generation” and “hydropower generation.” On the other hand, in terms of energy consumption, people’s low-carbon awareness needs to be improved. Since human activities will lead to an increase in CO₂ emissions, the government should actively carry out low-carbon publicity, motivate people’s awareness of low-carbon life, and be more frugal in the use of energy. The government should also optimize the population structure and maintain the sustainable development of population growth and the environment.

Furthermore, from the perspective of industrial structure, the Chengdu-Chongqing urban agglomeration should also optimize its industrial structures and carry out industrial transformation, phase out industries with a higher energy consumption gradually, vigorously develop high-tech industries, and increase the proportion of tertiary industries. The government should increase investment in technology research and development in secondary industries such as traditional manufacturing to help realize industrial transformation, reduce energy consumption, increase energy utilization, and gradually reduce CO₂ emissions. The tertiary industry represented by the financial industry, computer industry, and service industry has the advantages of low energy consumption and high economic output. Therefore, the tertiary industry should be vigorously developed. Although the increase in the tertiary industry will still increase CO₂ emissions, the growth rate is lower than that of other types of industries. While maintaining the active development of the tertiary industry, CO₂ emission limits and energy-saving and emission reduction measures can be formulated to reduce CO₂ emissions from the tertiary industry.

Finally, from the perspective of international carbon emission policy making, first, we should accelerate the construction of a carbon-neutral policy framework and accelerate the release of a carbon-neutral, top-level design document. In the international community, countries should work together to build a human community with a shared future. All countries should unite to tackle global warming. Within countries, there should be regional coordination among cities and municipalities and reasonable allocation of resources to move towards carbon peaking and carbon neutrality. Second, emission reduction measures for key industries should be set. Each region should prioritize carbon reduction in key sectors such as energy, industry, transport, construction, and forestry and develop different carbon reduction programs for different sectors. Third, we should work together to build a carbon emissions trading system, work together to maintain the fairness and effectiveness of carbon emissions trading across countries and regions, build a carbon emissions conversion mechanism, and allow the market to effectively regulate the price of carbon. Finally, cities across countries can deepen their cooperation, so that on the one hand cities with a better carbon emission control can set an example for weaker cities, and on the other hand the experience of regional cities in reducing emissions can provide experience and lessons for other regional cities.

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