

Research Article

Forecast of China's Carbon Emissions Based on ARIMA Method

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Global warming caused by carbon emissions has become increasingly prominent. As the world's second-largest economy, China is under enormous pressure to cut down its carbon dioxide emissions. It is urgent to seek effective methods to forecast carbon emissions and put forward the pointed and effective measures to reduce emissions. In this paper, we first use the software Eviews to make an analysis of randomness on data of carbon emissions in the four representative provinces and city, Beijing, Henan, Guangdong, and Zhejiang, in terms of their carbon emissions data from 1997 to 2017. Then, according to their distinct characteristics, the methods of stationary processing of the difference, moving average, and substituting strong impact points, respectively, are adopted to perform the data preprocessing. Then, model identification, parameter estimation, and model test are carried out to establish the model of $ARIMA(p, d, q)$ for the prediction of the carbon emissions of the four regions, respectively. Finally, the model is used to forecast the data and analyze their tendency for their carbon emissions in the next three years. The results can provide guidance for decision-makers to set reasonable carbon emission reduction targets and take appropriate energy conservation and emission reduction measures.

1. Introduction

Global warming has become a pressing issue in modern society, and this has led to concerns about greenhouse gas emissions. Many greenhouse gases, such as CO_2 , are highly permeable to visible light from the sun and highly absorbent to long-wave radiation reflected from the Earth, which is often referred to as the "greenhouse effect." Excessive carbon emissions are not only the cause of global warming but also a threat to human survival by causing natural and social problems such as climate change, glacial melting, sea level rise, and biodiversity destruction [1].

In the process of rapid economic growth, China's carbon emissions are also increasing dramatically. As the world's largest emission of carbon dioxide, China is the world's largest emission of carbon dioxide per capita, with over 6 billion tons of carbon dioxide per year [2]. China is now at the beginning of the Fourteenth Five-Year Plan, and the Chinese government's work report in 2021 proposes to do a good job in achieving carbon peaks and carbon neutrality, aiming to reduce energy consumption and CO_2 emissions per unit of GDP by 13.5% and 18%, respectively [3].

Therefore, it is important to establish a suitable model to predict the future trend of carbon emissions in China through a scientific and rigorous method, in order to better formulate policies and take measures to reduce carbon emissions.

There have been many studies on carbon emission forecasting at home and abroad. Wu et al. [4] used the STIRPAT model to predict CO_2 emissions in Qingdao in the future. Li et al. [5] used the SVM-ELM model to predict the carbon emissions in some regions. Liu et al. [6] identified the key factors affecting carbon emissions and constructed a BP neural network model to predict the carbon emissions of Beijing in the next five years under different development scenarios. Sun et al. [7] used a hybrid prediction model combining principal component analysis (PCA) and regularized extreme learning machine (RELM) to reduce the dimension of the influencing factors and adopted the RELM method to forecast China's CO_2 emissions. Ahmadi et al. [8] used an artificial neural network (ANN) approach to predict CO_2 emissions for five countries in the Middle East. Zou [9] explored the interactive relationships among American oil prices, carbon emissions, and GDP through the data analysis

from 1983 to 2013. Cheng et al. [10] established a cooperation decision model for a mixed carbon policy of carbon trading-carbon tax in a two-stage supply chain. Zhang et al. [11] found the key sectors and factors which induce the changes in carbon emissions in China's industrial sectors. Zhu [12] investigated the effect of government regulation and market trading on carbon emission. Yuan et al. [13] used discrete-time optimal control theory and the optimal emission reduction strategies for each period to explore maximizing the sum of net profit under cap and trade.

The Autoregressive Integrated Moving Average (ARIMA) model is one of the most widely used and generalized time series forecasting methods, with the advantage of being simple and requiring only endogenous variables without the need for other exogenous variables. Some scholars have employed it to forecast the spatial distribution of precipitation and the birth rate of population. The spatial characteristics of precipitation were analyzed using monthly rainfall data from 16 major meteorological stations in Jiangxi Province and the cumulative monthly rainfall data were predicted based on the ARIMA model [14]. A total of 254 samples of closing prices of Vanke A stock were selected to predict its short-term closing prices accurately by constructing an ARIMA model [15]. The closing prices of Bitcoin from October 2013 to April 2019 were used to predict its short-term closing prices by building a reasonable ARIMA model [16]. The data of social electricity consumption in Beijing from 1978 to 2018 were used to construct the model ARIMA(1, 1, 0) to make its short-term forecasts [17]. An ARIMA(1, 2, 2) model was developed to predict the birth rate of China in the next five years [18]. An ARIMA model is used to fit and forecast the time series of customer electricity consumption [19]. The forecasting of multidimensional ARMA(p, q) series was investigated and the forecasting formula was derived using only a limited number of observations [20]. The Bayesian estimation of the model parameters was obtained from the sample distribution of the AR(p) series, and the forecasts were obtained [21]. A combination of BP neural network and ARIMA was used to develop short-term traffic flow prediction algorithm [22]. A seasonal ARIMA model was developed and applied to the monthly runoff forecasting of reservoirs [23]. The ARIMA and ANN models are used to forecast the performance of published stock data obtained from the New York Stock Exchange [24]. Three different methods are used to forecast SO₂ pollution episodes, Elman neural networks, ARIMA models, and a hybrid method combining both [25]. Unnikrishnan et al. [26] determined the impact of government policies of import of gold in India on the domestic price of gold during 2013 using the ARIMA model. Wang et al. [27] presented a hybrid short-term traffic speed prediction framework through empirical mode decomposition (EMD) and ARIMA. Saboia [28] developed ARIMA models for birth time series.

In this paper, four representative provinces and city, namely, Beijing, Henan, Guangdong, and Zhejiang, are selected to analyze their carbon emissions from 1997 to 2017 and build suitable ARIMA models to predict the carbon emissions and trends in the following three years. Beijing, as

the capital, has been attracting national attention in terms of energy-saving and emission reduction, while its economy is growing rapidly. Henan Province, as a major energy-consuming province in central China, is facing the challenge of a low-carbon economy due to the increase in carbon emissions caused by its energy structure in the past. Guangdong and Zhejiang, two major industrial provinces, have been carrying out carbon reduction actions in parallel with their economic development. As carbon emissions are affected by various factors such as industrial structure, economic development, and policy management, many problems may arise in the modeling process, such as failing the smoothness test, white noise test, or model fit. The aim of this paper is to solve these problems so that the residuals should become white noise series; it needs to build reasonable models to forecast the carbon emissions of each region in the next three years. In the analysis of the carbon emission data of Beijing and Henan, the second-ordered difference is obtained to achieve a smooth series. Then, the models can be determined as ARIMA(2, 2, 0) by using the AIC and SC criteria. The prediction results indicate that their carbon emissions will slowly decrease in the next three years. In the analysis of Guangdong's carbon emissions data, the 2011 data form a strong influence point, and the model coefficients cannot be determined after differencing. We perform a moving average on the raw data and find that the obtained time series is smooth. The model coefficients are determined and it predicts that carbon emissions will continue to grow in the short term, but with a decreasing rate. Similarly, in the analysis of which for Zhejiang, the strong impact points of the data in 2011 are replaced since the difference and moving average processing do not satisfy the requirement of smoothness. It is replaced by the average of which in 2009, 2010, 2012, and 2013, and the model ARIMA(3, 2, 4) is obtained and predicts a slow increase in carbon emissions in the next three years.

The paper is structured as follows. In Section 2, the ARIMA model and the associated notations used in this paper are introduced. In Section 3, Section 4, Section 5, and Section 6, the suitable models for four representative provinces and city are obtained, namely, Beijing, Henan, Guangdong, and Zhejiang. The predictions and analysis of carbon emissions data for four representative regions are presented in Section 7. The conclusions of this paper are presented in Section 8.

2. ARIMA Model and Associated Notations

The ARIMA model, known as a differentially integrated moving average autoregressive model, treats time-varying data as a random series [17]. It is assumed that the variation in variables is only related to the effect of time, excluding the effect of accidental factors. The ARIMA(p, d, q) model has three parameters: p which is the autoregressive term, denoted as AR(p); the order of differences to make the nonstationary time series stationary, denoted as d ; and the number of moving average terms, denoted as MA(q). The general expression for the autoregressive process of order p , AR(p), is

$$X_t = \varphi_0 + \varphi_1 X_{t-1} + \varphi_2 X_{t-2} + \cdots + \varphi_p X_{t-p} + \varepsilon_t. \quad (1)$$

The moving average process of order q , $MA(q)$, can be expressed as

$$X_t = \mu + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q}. \quad (2)$$

The general expression for the ARMA(p, q) model is

$$X_t = \varphi_0 + \varphi_1 X_{t-1} + \varphi_2 X_{t-2} + \cdots + \varphi_p X_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q}. \quad (3)$$

The general expression for the ARIMA(p, d, q) model is

$$\Phi(B)\nabla^d x_t = \Theta(B)\varepsilon_t, \quad (4)$$

where $\nabla_d = (1 - B)^d$, $\Phi(B) = 1 - \varphi_1 B - \cdots - \varphi_p B^p$ is an autoregressive coefficient polynomial of the smooth reversible ARMA(p, q) model, and $\Theta(B) = 1 - \theta_1 B - \cdots - \theta_q B^q$ is the moving smoothing coefficient polynomial of the smooth reversible ARMA(p, q) model.

For the AR(p) model, the autocorrelation coefficient decays geometrically or oscillatingly with the increasing lag order, while the partial autocorrelation coefficient cuts off at order p .

For the MA(q) model, the autocorrelation coefficient is truncated at order q . The partial autocorrelation coefficient decays geometrically or oscillatingly with the increasing lag order.

For the ARMA(p, q) model, the autocorrelation coefficient decays geometrically or oscillatingly with increasing lag order and tends to be zero after order q . The partial autocorrelation coefficient decays geometrically or oscillatingly with increasing lag order and tends to be zero after order p .

3. Forecast Model for Carbon Emissions in Beijing

3.1. Data Sources and Characterization. The carbon emissions data for Beijing from 1997 to 2017 are obtained from the China Carbon Emissions Database (<https://www.ceads.net.cn/>) as raw data, which is all the available data we can obtain; no data are available after 2017. The most appropriate forecast method is chosen to predict Beijing's carbon emissions from 2018 to 2020. A line graph of Beijing's carbon emissions from 1997 to 2017 is shown in Figure 1.

It follows from Figure 1 that Beijing's carbon emissions presented a continuous upward trend until 2007 and began to fall slowly in 2007 and beyond, with the peak occurring in 2007. Analysis of the data shows that this is closely related to the development situation in Beijing and the requirements of national policies.

Beijing, as the capital and the political, economic, cultural, and educational center of China, has certain special characteristics in terms of carbon emissions and has attracted much attention in terms of energy-saving and emission reduction. The rapid economic growth has been accompanied by a rapid increase in carbon emissions, which were on the rise until 2007. With the promotion of air

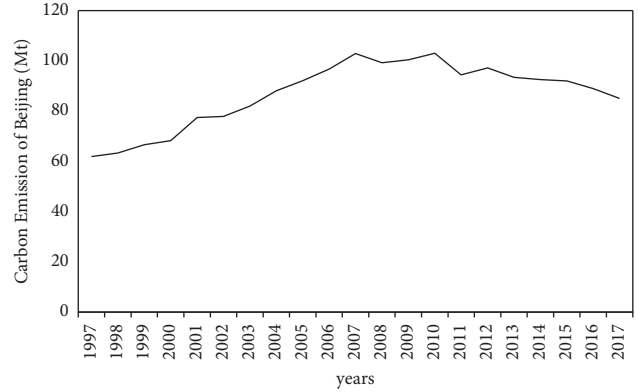


FIGURE 1: Time series diagram of Beijing's carbon emissions.

pollution control, Beijing has continued to promote the optimization of industrial structure and clean energy transformation, and the amount of coal burning has dropped significantly. At the same time, Beijing, as one of the first pilot provinces in China to launch carbon emissions trading, has officially launched its carbon market since 2013. While achieving continuous improvement in air quality, Beijing has also effectively controlled its total CO₂ emissions.

3.2. Construction of the ARIMA Model

3.2.1. Data Stability Tests. The ARIMA(p, d, q) prediction model is only applicable to smooth time series. If the series is nonsmooth, the original series will be differenced into smooth series. Then, the corresponding carbon emission prediction model can be found by analyzing the differenced carbon emission time series. A smooth carbon emission series ensures that the fitted curve continues to follow the existing pattern for a short period of time, thus allowing the prediction of future carbon emissions based on past carbon emission series.

Firstly, we perform a unit root test on the carbon emissions time series X_t , and the results are presented in Table 1. The value of the t -statistic is -3.040068 , p -value is more than 0.05, and time series X_t is not smooth.

Figure 2 indicates the autocorrelation and skew-correlation plots for the time series X_t . The autocorrelation plot of the series X_t is neither trailing nor truncated, and it shows an obvious inverted triangle feature, which is typical of a monotonic trend, so the series is non stationary.

The original data series X_t is not smooth, so the series X_t needs to be differenced to achieve a smooth trend. Firstly, the series X_t is differenced to the first order, and the new series is called as Z_t . The unit root test is then performed on the series Z_t , and the output results are shown in Table 2.

The value of the t -statistic is -0.292940 , which is still greater than the 5% threshold of the test level, with a p -value more than 0.05, and the sequence Z_t is not stationary.

Then, the second-ordered difference is performed and the new series is denoted as Y_t . A unit root test is performed on the series Y_t and the output results are shown in Table 3. The value of the t -statistic is -7.071084 , which is less than the

TABLE 1: Results of unit root test for carbon emission series X_t in Beijing.

Variables	ADF values	5% threshold	p -value	Stability
X_t	-3.040068	-3.052169	0.0511	Nonstationary

Sample: 1997 2017
Included observations: 21

Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob
1		0.852	0.852	17.547	0.000
2		0.698	-0.103	29.949	0.000
3		0.524	-0.167	37.309	0.000
4		0.305	-0.280	39.954	0.000
5		0.148	0.079	40.614	0.000
6		-0.029	-0.202	40.640	0.000
7		-0.203	-0.174	42.058	0.000
8		-0.307	0.025	45.562	0.000
9		-0.383	0.013	51.468	0.000
10		-0.425	-0.080	59.390	0.000
11		-0.378	0.153	66.307	0.000
12		-0.358	-0.156	73.176	0.000

FIGURE 2: Correlation diagram of carbon emission series X_t in Beijing.

TABLE 2: Unit root test results for the first-ordered difference series Z_t of the Beijing carbon emission series X_t .

Variables	ADF values	5% threshold	p -value	Stability
Z_t	-0.292940	-3.052169	0.9072	Nonstationary

TABLE 3: Unit root test results for the second-ordered difference series Y_t of the Beijing carbon emission series X_t .

Variables	ADF values	5% threshold	p -value	Stability
Y_t	-7.071084	-3.052169	≤ 0.01	Stable

5% threshold of the test level, and the p -value is less than 0.05. The series Y_t is stationary after the second-ordered difference. So $d = 2$.

It follows from Figure 3 that the values of the second-ordered difference series fluctuate around the value of zero, which is consistent with the characteristics of a smooth series, indicating that the second-ordered difference carbon emission series are suitable for prediction by the ARIMA model.

3.2.2. *Determination of Model Parameters.* Based on the above smoothed second-ordered difference series, the autocorrelation coefficient (ACF) and partial autocorrelation coefficient (PACF) are obtained to plot the correlation plot of the series Y_t in Figure 4. Observe the ACF and PACF figures, determine the optimal order p and q , and build an ARIMA model from the resulting p , d , and q .

The ACF and PACF of smoothed carbon emissions data in a model are usually in two states: trailing or truncated. A truncated tail means that the ACF or PACF function is said to be truncated after p or q if it is zero after lag p or q . A trailing

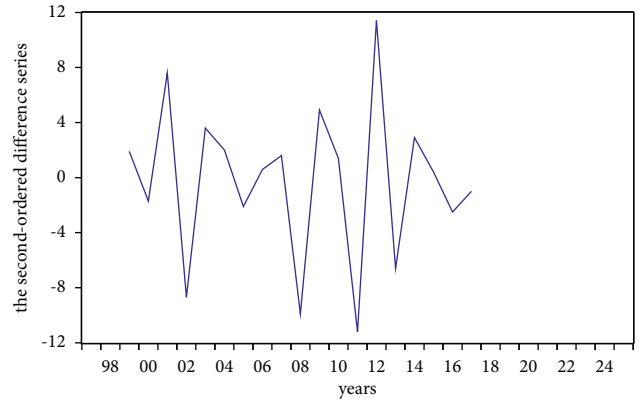


FIGURE 3: Smoothed series of the second-ordered difference series Y_t of the Beijing carbon emission series X_t .

Sample: 1997 2017
Included observations: 19

Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob
1		-0.674	-0.674	10.067	0.002
2		0.124	-0.605	10.427	0.005
3		0.303	0.085	12.716	0.005
4		-0.379	0.155	16.546	0.002
5		0.127	-0.187	17.009	0.004
6		0.183	-0.018	18.032	0.006
7		-0.297	0.089	20.965	0.004
8		0.103	-0.229	21.349	0.006
9		0.175	-0.082	22.572	0.007
10		-0.328	-0.018	27.341	0.002
11		0.302	0.175	31.894	0.001
12		-0.196	-0.267	34.091	0.001

FIGURE 4: Correlation diagram of the second-ordered difference series Y_t of the carbon emission series X_t in Beijing.

tail means that the ACF or PACF function decays geometrically or oscillatingly to zero as the lag order k increases.

It follows from Figure 4 that the ACF of the second-ordered difference series Y_t have a trailing state and the PACF are truncated after lag 2, so $q = 0$. To determine the value of p , AR(1) and AR(2) models were established, respectively, and then EvIEWS is used for ARIMA(1, 2, 0) combined with ARIMA(2, 2, 0). The comparison results are shown in Figure 5.

Compared with the fit tests of the ARIMA models in Figures 5 and 6, the results are as follows.

Combining Figures 5 and 6 and Table 4, it follows that, comparing the established models ARIMA(1, 2, 0) to ARIMA(2, 2, 0), R^2 of ARIMA(2, 2, 0) is 0.667719, which is relatively larger, and its AIC value is 5.643812 and its SC value is 5.790850, which are relatively smaller. The fit accuracy is high. Therefore, the optimal model is ARIMA(2, 2, 0), and its specific equation is

$$Y_t = -0.295995 - 1.103541Y_{t-1} - 0.628199Y_{t-2} + \varepsilon_t. \tag{5}$$

3.3. Testing of the Model

3.3.1. *White Noise Test.* In order to ensure the authenticity of the time series model results, it is necessary to check

Sample (adjusted): 2000 2017
 Included observations: 18 after adjustments
 Convergence achieved after 3 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.340666	0.632721	-0.538415	0.5977
AR(1)	-0.674368	0.183328	-3.678478	0.0020
R-squared	0.458200	Mean dependent var	-0.405556	
Adjusted R-squared	0.424338	S.D. dependent var	5.923182	
S.E. of regression	4.494061	Akaike info criterion	5.947830	
Sum squared resid	323.1454	Schwarz criterion	6.046760	
Log likelihood	-51.53047	Hannan-Quinn criter.	5.961471	
F-statistic	13.53120	Durbin-Watson stat	2.821361	
Prob(F-statistic)	0.002033			
Inverted AR Roots	-.67			

FIGURE 5: Statistical analysis of ARIMA(1, 2, 0) fitting results for the second-ordered difference series Y_t of the carbon emission series X_t in Beijing.

Sample (adjusted): 2001 2017
 Included observations: 17 after adjustments
 Convergence achieved after 3 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.295995	0.333732	-0.886924	0.3901
AR(1)	-1.103541	0.210552	-5.241180	0.0001
AR(2)	-0.628199	0.210644	-2.982287	0.0099
R-squared	0.667719	Mean dependent var	-0.329412	
Adjusted R-squared	0.620250	S.D. dependent var	6.096389	
S.E. of regression	3.756828	Akaike info criterion	5.643812	
Sum squared resid	197.5926	Schwarz criterion	5.790850	
Log likelihood	-44.97240	Hannan-Quinn criter.	5.658428	
F-statistic	14.06652	Durbin-Watson stat	1.675232	
Prob(F-statistic)	0.000447			
Inverted AR Roots	-.55-.57i	-.55+.57i		

FIGURE 6: Statistical analysis of ARIMA(2, 2, 0) fitting results for the second-ordered difference series Y_t of the carbon emission series X_t in Beijing.

TABLE 4: Fit tests of the second-ordered difference series Y_t for the carbon emission series X_t in Beijing.

	ARIMA(1, 2, 0)	ARIMA(2, 2, 0)
R^2	0.458200	0.667719
AIC	5.947830	5.643812
SC	6.046760	5.790850

whether the residuals are white noise. Software Eviews is used to test the ARIMA(2, 2, 0) model for Q-statistics and the results are shown in Figure 7.

It follows from Figure 7 that the residual ACF values and PACF values of the sequential model are distributed within a range centered on 0, with p -values greater than 0.05. So the residuals of the model are independent of each other, which means that the residuals are white noise. In summary, the predicted ARIMA(2, 2, 0) contains all valid information, which means that the ARIMA prediction is good.

3.3.2. *Fitting of the Model.* After the model is constructed, the fitted model is tested for suitability. It follows from

Sample: 1997 2017
 Included observations: 17

	Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob
1			-0.007	-0.007	0.0010	0.975
2			0.060	0.060	0.0783	0.962
3			-0.021	-0.021	0.0889	0.993
4			-0.040	-0.044	0.1293	0.998
5			-0.079	-0.077	0.2957	0.998
6			-0.036	-0.033	0.3332	0.999
7			-0.298	-0.295	3.2076	0.865
8			-0.110	-0.133	3.6385	0.888
9			0.226	0.268	5.7055	0.769
10			-0.222	-0.263	7.9784	0.631
11			0.028	-0.055	8.0200	0.712
12			-0.060	-0.064	8.2541	0.765

FIGURE 7: ARIMA(2, 2, 0) residual statistics for the second-ordered difference series Y_t of the Beijing carbon emission series X_t .

Figure 8 that, after the ARIMA test, the actual and fitted values of the data fit well overall, and the relative residuals are small. It indicates that the fit is good and the model is valid overall.

4. Forecast Model for Carbon Emissions in Henan Province

4.1. *Characterization of the Data.* We also obtained carbon emissions data for Henan Province from 1997 to 2017 from the China Carbon Emissions Database (CEADs) as the original data. The data are plotted as a time series diagram for carbon emissions in Henan Province in 1997–2017, as shown in Figure 9.

It follows from Figure 9 that carbon emissions in Henan Province show an upward trend until 2011, followed by a few years of decline but with fluctuations. The overall trend after 2014 is slowly declining.

Henan Province, a province with a large population and energy consumption, is located in the central region of China, with a well-developed transportation network, dense production factors, and a wide range of industries, and is an important base for grain production, energy and raw materials, modern equipment manufacturing, and high technology industries. The past coal-based energy consumption structure has led to a rising trend of carbon emissions. To cope with the challenge of a low-carbon economy, they firstly proposed “vigorously develop a circular, green and low-carbon economy and accelerate the construction of a resource-saving and environment-friendly society” in the Government Work Report in 2010. Carbon emissions have been declining since 2009. In 2011, the 12th National Five-Year Plan formally incorporated the Central Plains Economic Zone into the national development strategy, and Henan’s carbon emissions have continued to decline.

4.2. Construction of the ARIMA Model

4.2.1. *Data Stability Tests.* Through the unit root test, we find that the carbon emission time series of Henan Province and the first-ordered difference series are still unsteady, while the second-ordered difference series Y_t is steady, and the output results are displayed in Table 5. The value of the t -statistic is

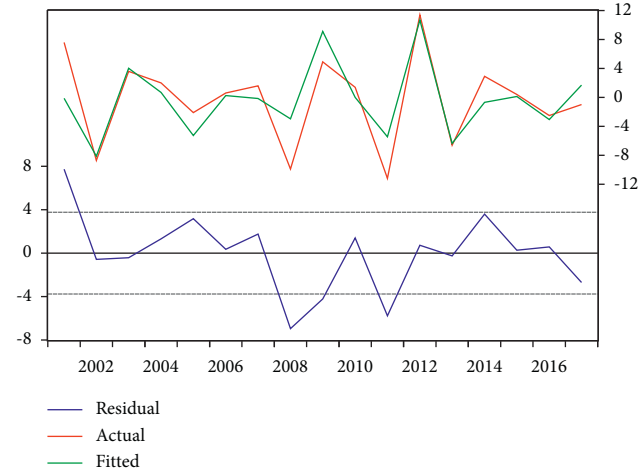


FIGURE 8: ARIMA(2, 2, 0) model test curve for the second-ordered difference series Y_t of the Beijing carbon emission series X_t .

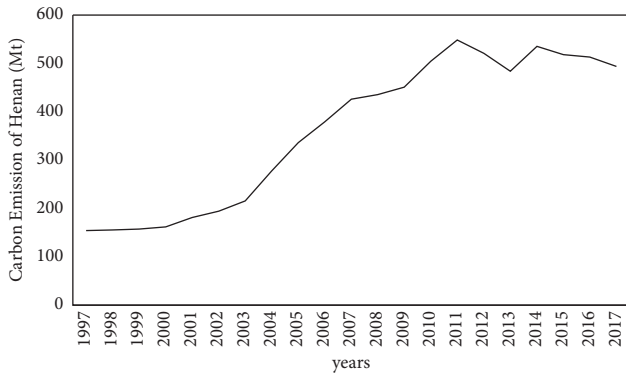


FIGURE 9: Time series diagram of Henan's carbon emissions.

TABLE 5: Unit root test results for the second-ordered difference series Y_t of carbon emissions in Henan Province.

Variables	ADF values	5% threshold	p -value	Stability
Y_t	-5.087783	-3.052169	0.0009	Stationary

-5.087783, which is less than the 5% threshold of the test level. And the p -value is less than 0.05. The series Y_t is smooth after the second-ordered difference, so $d=2$.

It follows from Figure 10 that the second-ordered difference series Y_t fluctuates around the value of zero, which is suitable for the ARIMA model.

4.2.2. Determination of Model Parameters. The correlation plot of the Y_t series in Figure 11 shows that the ACF are trailing and the PACF are truncated, so $q=0$. Similarly, to determine the value of p , the AR(1) and AR(2) models are developed, respectively. And then the ARIMA(1, 2, 0) and ARIMA(2, 2, 0) models are fitted for comparison.

The fit tests results of the two models are displayed in Table 6.

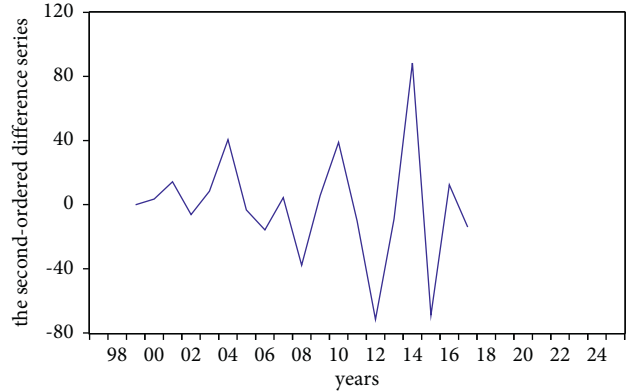


FIGURE 10: Smoothed series of the second-ordered difference series Y_t of the carbon emission series of Henan Province.

Sample: 1997 2017
Included observations: 19

Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob	
█	█	1	-0.299	-0.299	1.9822	0.159
█	█	2	-0.346	-0.479	4.7971	0.091
█	█	3	0.138	-0.226	5.2704	0.153
█	█	4	0.171	-0.032	6.0443	0.196
█	█	5	-0.071	0.019	6.1873	0.288
█	█	6	-0.006	0.129	6.1884	0.402
█	█	7	0.096	0.225	6.4927	0.484
█	█	8	-0.236	-0.147	8.5210	0.384
█	█	9	0.043	-0.128	8.5949	0.475
█	█	10	0.168	-0.091	9.8470	0.454
█	█	11	-0.122	-0.168	10.591	0.478
█	█	12	-0.041	-0.019	10.688	0.556

FIGURE 11: Correlation diagram of the second-ordered difference series Y_t of the carbon emission series of Henan Province.

TABLE 6: Fit tests of the second-ordered difference series Y_t for the carbon emission series X_t in Henan Province.

	ARIMA(1, 2, 0)	ARIMA(2, 2, 0)
R^2	0.090087	0.300009
AIC	10.13593	10.06055
SC	10.23486	10.20759

ARIMA(2, 2, 0) has a relatively larger R^2 of 0.300009, a smaller AIC value of 10.06055, and a smaller SC value of 10.20759 and has a good fit. Therefore, the optimal model is selected as ARIMA(2, 2, 0), and the specific equation of the ARIMA model is obtained as

$$Y_t = -1.095290 - 0.443151Y_{t-1} - 0.482723Y_{t-2} + \varepsilon_t. \tag{6}$$

Using Software Eviews, the ARIMA(2, 2, 0) model is tested for Q-statistics, and the results are displayed in Figure 12.

It implies that the residual series of the model is white noise and that the predicted ARIMA(2, 2, 0) contains all valid information and can predict it well.

4.2.3. Fitting of the Model. It follows from Figure 13 that the forecast values of the data fit well and the model is good overall.

Sample: 1997 2017
Included observations: 17

Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob	
		1	-0.112	-0.112	0.2528	0.615
		2	-0.070	-0.084	0.3584	0.836
		3	-0.132	-0.153	0.7596	0.859
		4	0.139	0.102	1.2422	0.871
		5	0.184	0.200	2.1512	0.828
		6	-0.051	-0.001	2.2276	0.898
		7	-0.073	-0.023	2.3985	0.935
		8	-0.225	-0.231	4.2164	0.837
		9	0.020	-0.121	4.2325	0.895
		10	0.070	-0.011	4.4557	0.924
		11	-0.086	-0.114	4.8542	0.938
		12	-0.044	0.014	4.9784	0.959

FIGURE 12: ARIMA(2, 2, 0) residual statistics of the second-ordered difference series Y_t of the carbon emission series X_t in Henan Province.

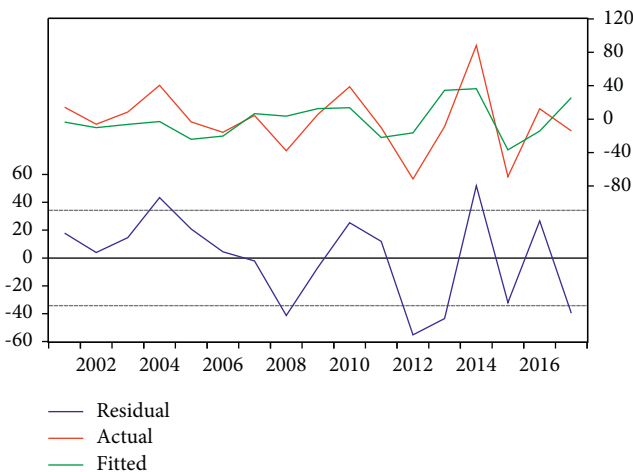


FIGURE 13: ARIMA(2, 2, 0) test curve for second-ordered difference series Y_t of carbon emission series X_t of Henan Province.

5. Forecast Models for Carbon Emissions in Guangdong Province

5.1. *Smoothing of Data.* The raw data of carbon emissions for Guangdong Province from 1997 to 2017 are shown in Figure 14. Figure 14 indicates that there is a significant salient point in the 2011 data, which affects the smoothness of the whole series. Following the previous treatment, we guess that perhaps the second-ordered difference series will satisfy the smoothness after the ADF unit root test. However, the ACF and PACF of the correlation diagram of the second-ordered difference series are insignificant and cannot be well ordered.

To make better use of the ARIMA model for prediction, we replace the current year’s data with a three-year central moving average for the original data. The time series of Guangdong’s carbon emissions after smoothing is shown in Figure 15.

Figure 15 implies that carbon emissions in Guangdong Province are decreasing in magnitude in recent years. As a major energy-consuming province, Guangdong’s carbon emissions have been increasing year by year in parallel with

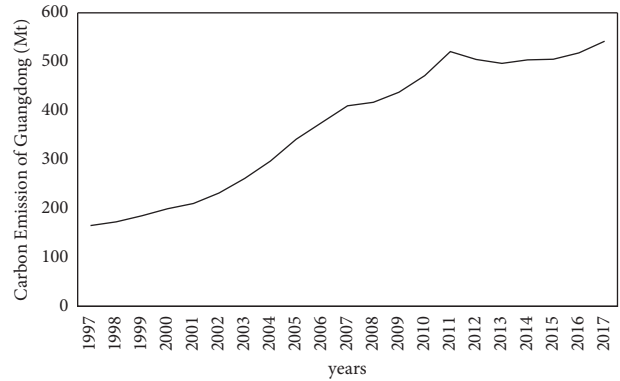


FIGURE 14: Time series diagram of Guangdong’s carbon emissions.

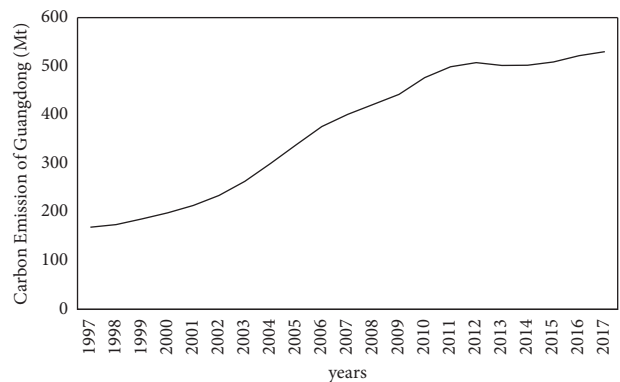


FIGURE 15: Time series diagram of the modified Guangdong’s carbon emissions.

its rapid economic development. During the “Eleventh Five-Year Plan,” Guangdong Province set the target of reducing the total amount of major pollutants, accelerating the construction of pollutant reduction projects and facilities, and resolutely eliminating backward production capacity. In 2011, Guangdong Province was one of the pilot provinces to launch a carbon market. Since then, the rate of increase in carbon emissions has been decreasing year by year and has leveled off basically.

5.2. Construction of the ARIMA Model

5.2.1. *Data Stability Tests.* The results of the unit root test on the moving average time series Y_t of carbon emissions in Guangdong Province are shown in Table 7, where the p -value is smaller than 0.05 and the data are already stable.

5.2.2. *Determination of Model Parameters.* The correlation diagram of the time series Y_t is shown in Figure 16. Obviously, the PACF of the time series Y_t have obvious first-ordered truncated tails and the ACF have trailing tails, so the AR(1) model is built for fitting.

The results of the fit are shown in Table 8.

TABLE 7: Unit root test results for the moving average series Y_t of carbon emission in Guangdong Province.

Variables	ADF values	5% threshold	p -value	Stability
Y_t	-4.120051	-3.065585	0.0068	Stationary

Sample: 1997 2020
Included observations: 23

Autocorrelation		Partial Correlation		AC	PAC	Q-Stat	Prob	
	█		█	1	0.891	0.891	20.755	0.000
	█		█	2	0.773	-0.104	37.105	0.000
	█		█	3	0.651	-0.084	49.272	0.000
	█		█	4	0.521	-0.108	57.493	0.000
	█		█	5	0.389	-0.095	62.335	0.000
	█		█	6	0.257	-0.098	64.561	0.000
	█		█	7	0.125	-0.097	65.125	0.000
	█		█	8	-0.001	-0.094	65.125	0.000
	█		█	9	-0.115	-0.062	65.671	0.000
	█		█	10	-0.209	-0.027	67.599	0.000
	█		█	11	-0.281	-0.022	71.395	0.000
	█		█	12	-0.341	-0.059	77.491	0.000

FIGURE 16: Correlation diagram of carbon emission series Y_t for Guangdong Province.

TABLE 8: Fitting results of the moving average series Y_t of the carbon emission for Guangdong Province.

	R^2	AIC	SC
AR(1)	0.985529	8.376870	8.426656

Therefore, the combined determination of the selection is model AR(1), and the specific equation of the model is

$$Y_t = 1309.535 + 0.980186Y_{t-1} + \varepsilon_t. \quad (7)$$

5.3. *Testing of the Model.* It follows from Figure 17 that the moving average series Y_t represents the trend of the original data very well, while the AR(1) model fits well to the original data.

6. Forecast Model for Carbon Emissions in Zhejiang Province

6.1. *Alternative Methods of Processing Data.* The raw data of carbon emissions in Zhejiang Province in 1997–2017 are shown in Figure 18. When we perform smoothing and difference, we find that they cannot fix the order well on the basis of satisfying the smoothness condition, and the moving average processing also cannot satisfy the smoothness requirement. In order to make better use of the ARIMA model, we replace this strong influence point with the average of the carbon emissions in 2009, 2010, 2012, and 2013 as that in 2011, and the curve of the processed data is shown in Figure 19.

6.2. Construction of the ARIMA Model

6.2.1. *Data Stability Tests.* We find that the carbon emission time series and the first-ordered difference series are still

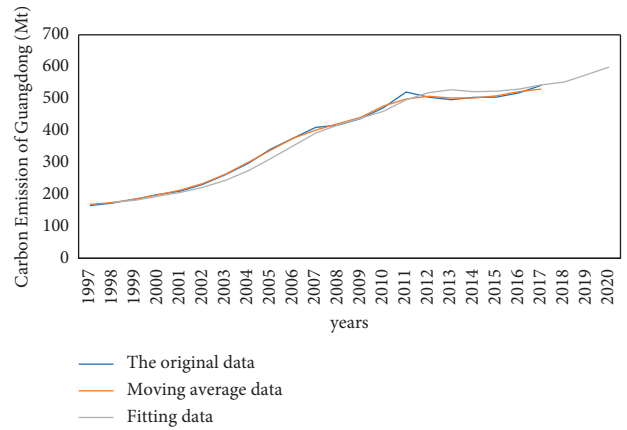


FIGURE 17: Fitting of carbon emission series for Guangdong Province.

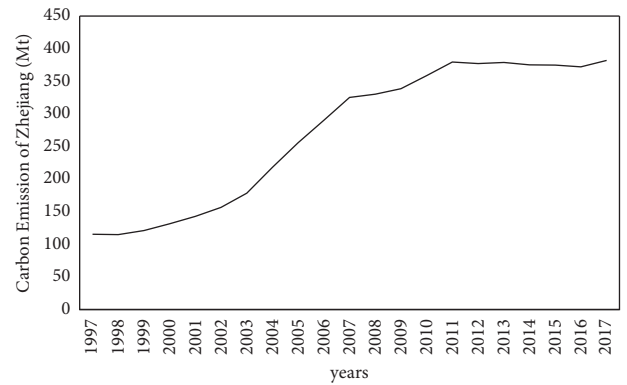


FIGURE 18: Time series diagram of Zhejiang's carbon emissions.

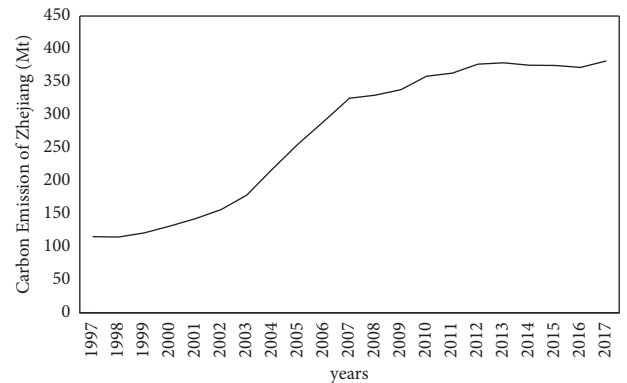


FIGURE 19: Time series diagram of Zhejiang's carbon emissions after replacing strong impact points.

unsteady by testing the unit root of the carbon emission time series after replacing the strong impact point. The second-ordered difference series Y_t is tested to be smooth, and the output is shown in Table 9. The value of the t -statistic is -4.580024 , which is less than 5% threshold of the test level and has a p -value which is less than 0.05. The second-ordered difference series Y_t is smooth, so $d = 2$.

TABLE 9: Unit root test results for carbon emission series Y_t in Zhejiang Province.

Variables	ADF values	5% threshold	p -value	Stability
Y_t	-4.580024	-3.040391	0.0023	Stationary

6.2.2. *Determination of Model Parameters.* The correlation figure of the second-ordered difference series Y_t of the carbon emission series of Zhejiang Province is shown in Figure 20.

In order to determine the values of p and q , we build AR(1), AR(2), AR(3), AR(4), MA(1), MA(2), MA(3), and MA(4) models, respectively, and then fit them for comparison. The comparison results are shown in Table 10.

From Table 10, R^2 of ARIMA(3, 2, 4) is 0.948259, which is the maximum. The AIC value is 5.773116, which is the smallest. The SC value is 6.159410, which is also the smallest. It has a good fit. Therefore, the optimal model is selected as ARIMA(3, 2, 4). The equation is as follows:

$$\begin{aligned}
 Y_t = & 4.033468 + 0.410785Y_{t-1} - 0.431936Y_{t-2} \\
 & + 0.168636Y_{t-3} + \varepsilon_t + 0.692157\varepsilon_{t-1} - 2.107537\varepsilon_{t-2} \\
 & + 1.224011\varepsilon_{t-3} - 4.409364\varepsilon_{t-4}.
 \end{aligned}
 \tag{8}$$

6.3. *Testing of the Model.* After the model is constructed, the fitted model is tested for suitability and is shown in Figure 21. The overall fit between the actual and fitted values is good and the relative residuals are small, indicating that the fit and the model are good overall.

7. Forecast

7.1. *Forecast Results.* Using the models of the four regions, by making static forecasts in-sample (1997–2017) to forecast 2018–2020 carbon emissions in Beijing, Henan, Guangdong, and Zhejiang, the results are presented in Table 11.

7.2. Analysis

7.2.1. *Analysis of Beijing’s Carbon Emissions.* The predictions show that Beijing’s carbon emissions will continue to decline in the coming years, with a slow downward trend.

Prior to 2007, as energy consumption in Beijing’s industrial sectors increased at a faster rate, infrastructure construction in the city accelerated, and residents’ living and consumption levels increased, energy consumption in the transportation, construction, and residential sectors also increased at a faster rate, resulting in a year-on-year increase in carbon emissions. Since 2008, Beijing has been implementing the “2008 Action Plan for Accelerating the Development of Circular Economy and Building a Resource-Saving and Environment-Friendly City,” which has led to a significant decrease in carbon emissions. Since then, Beijing has continued to innovate and introduce contractual energy management policies, achieving new leaps in market-based energy conservation and emission reduction. Continuous

Sample: 1997 2017
Included observations: 19

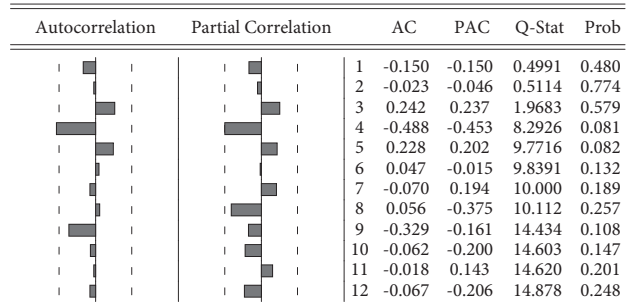


FIGURE 20: Correlation figure of the second-ordered difference series Y_t for the carbon emission series of Zhejiang Province.

TABLE 10: Fitting comparison results.

ARIMA coefficient	R^2	AIC	SC
(1, 2, 1)	0.215267	7.715942	7.864337
(1, 2, 2)	0.697359	6.874256	7.072116
(1, 2, 3)	0.23581	7.911636	8.158962
(1, 2, 4)	0.608297	7.354436	7.651226
(2, 2, 1)	0.238677	7.872626	8.068676
(2, 2, 2)	0.74294	6.904526	7.149588
(2, 2, 3)	0.80484	6.746679	7.040755
(2, 2, 4)	0.652201	7.442134	7.785222
(3, 2, 1)	0.828792	6.59475	6.836184
(3, 2, 2)	0.81598	6.791914	7.081635
(3, 2, 3)	0.614244	7.657075	7.995082
(3, 2, 4)	0.948259	5.773116	6.15941
(4, 2, 1)	0.57945	7.73057	8.01379
(4, 2, 2)	0.894893	6.477322	6.807746
(4, 2, 3)	0.900642	6.554407	6.932033
(4, 2, 4)	0.927169	6.377155	6.801986

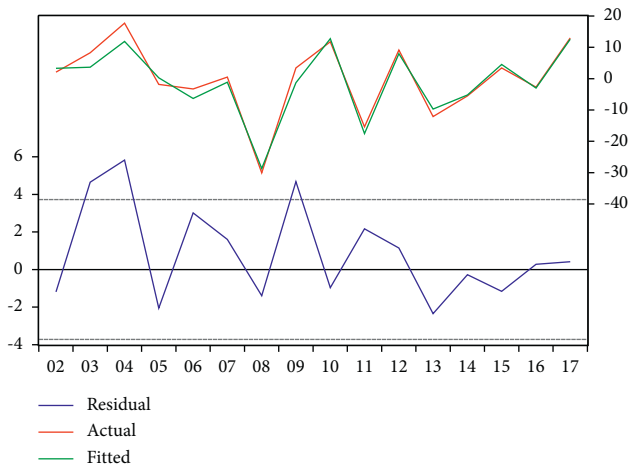


FIGURE 21: ARIMA(3, 2, 4) model test curve for the second-ordered difference series Y_t for the carbon emission series of Zhejiang Province.

reforestation of the plains has been carried out, and the city has basically completed the reforestation of one million areas of plains. Carbon emissions are on a steady decline. It can be

TABLE 11: Numerical predictions of carbon emissions in four regions in 2018–2020.

Year	Predictions in Beijing (Mt)	Predictions in Henan (Mt)	Predictions in Guangdong (Mt)	Predictions in Zhejiang (Mt)
2018	82.8	474.9	552	388.5
2019	78.4	460.8	575	400
2020	74.5	442.7	599	412.5

inferred from the forecast data that carbon emissions in Beijing will also continue to decline in the future and will show a steady downward trend.

7.2.2. Analysis of Henan’s Carbon Emissions. The results show that carbon emissions in Henan Province will continue to decline in the coming years, and the rate of decline will accelerate slightly.

As a province with a large population, large grain and agricultural production, and a large new industrial province, Henan Province has always had a high energy consumption intensity, and its economic development has come at the cost of large energy consumption and material capital investment [29]. According to the data, the consumption of coal in Henan Province has decreased between 1997 and 2010, but the proportion of coal consumption has always been above 80%. Coal has the highest carbon emission factor and therefore produces more carbon dioxide under this energy mix. In 2010, in response to the challenges of a low-carbon economy, Henan Province proposed “vigorously develop a circular economy, a green economy, and a low-carbon economy and accelerate the construction of a resource-saving and environment-friendly society” for the first time in the Government Work Report. In 2011, the outline of Henan’s 12th Five-Year Plan set the target of “reducing carbon dioxide emissions per unit of GDP by 17%.” Since then, Henan has insisted on correctly handling the relationship between energy conservation and economic growth and insisted on economical, clean, and safe development, and carbon emissions are on a decreasing trend. The forecast data show that the rate of reduction will increase slightly.

7.2.3. Analysis of Guangdong’s Carbon Emissions. It follows from the forecast results that carbon emissions in Guangdong Province will still be on an upward trend in the coming years, but the rate of increase will be stable.

Guangdong Province is a pioneering region in China’s socioeconomic development. In the process of rapid industrialization and urbanization, resource consumption and environmental pollution are serious problems, and the growth of carbon emissions cannot be ignored. Guangdong Province is not only a major energy-consuming province but also a major carbon-emitting province. As can be seen from the data, before 2011, carbon emissions were increasing at an accelerated rate. In 2011, the carbon market pilot project was launched. Guangdong, as one of the carbon emission trading pilot provinces [30], played an active role in promoting low-carbon development and effective control of carbon emissions in participating enterprises and pilot regions. Since then, Guangdong’s carbon emissions have been decreasing, but without a timely change in development; the potential

for further reduction is limited, so carbon emissions are still increasing slightly. In the future, Guangdong should actively explore and practice in the areas of energy-saving and carbon reduction from large emission sources, low-carbon lifestyle, carbon trading market, and low-carbon demonstration zones, in order to promote low-carbon development in the country at an early stage and on a pilot basis.

7.2.4. Analysis of Zhejiang’s Carbon Emissions. From the forecast results, it can be seen that carbon emissions in Zhejiang Province will continue to rise in the coming years, but the rate of increase will fluctuate.

As a developed coastal region in the China East, Zhejiang Province has one of the highest GDP values in China. Since 1993, the secondary sector has accounted for more than 50% of the province’s GDP. And as its direct consequence, energy consumption in Zhejiang has grown considerably in parallel with economic growth. For a long time, primary energy consumption in Zhejiang Province has been dominated by fossil energy. As a result, carbon emissions in Zhejiang Province have been on the rise. Since 2006, Zhejiang Province has been improving its energy-saving and emission reduction planning system, introducing policies and measures to promote energy-saving and emission reduction, stepping up energy-saving supervision and industrial pollution control, and increasing financial investment in energy-saving and emission reduction. So the positive results and effects of energy-saving and emission reduction are gradually manifested. However, we have reason to believe that, through continuous improvement of measures and awareness raising, the contribution of economic output to carbon emissions in Zhejiang Province will continue to decrease in the future and will enter the sustainable development path of low energy consumption and low-carbon emissions as soon as possible.

8. Conclusion

In this paper, we use the actual carbon emission data from Beijing city, Henan Province, Guangdong Province, and Zhejiang Province, four representative provinces and city in China, from 1997 to 2017 as the base data and establish four ARIMA prediction models for carbon emissions by plotting the original time series and stationary test. Different smoothing methods were applied according to the different characteristics of the data. In the analysis of Beijing City and Henan Province data, we perform difference to transform the original unsteady data series into a steady time series after the second-ordered difference. In the analysis of Guangdong Province data, the time series could not be well ordered after the second-ordered difference, so we adopt the

moving average method, use a three-year central moving average as the carbon emission data of the current year, and obtain the time series with good smoothness. In the analysis of Zhejiang Province data, neither the 2nd ordered difference nor the moving average treatment could satisfy the smoothness, so we adopt the alternative strong influence point method, replacing the strong influence point data in 2011 with the average of the carbon emission data in 2009, 2010, 2012, and 2013, and the time series satisfy the smoothness after the 2nd ordered difference treatment. The model then passes a white noise test and error analysis to predict carbon emissions for the next three years, and the corresponding predicted values are obtained.

Possible causes of error in the predictions are that the model is set up to apply temporal inertia and does not take into account the influence of other factors [31]. The factors that influence carbon emissions include population size, energy consumption, and economic patterns, as well as energy mix and industry type [32]. Our model is limited in its ability to deal with the factors influencing carbon emissions and does not include special circumstances such as national population policies, carbon emission policies, major breakthroughs in new energy development, changes in economic development patterns, and changes in industrial structure. Therefore, the time series model developed in this paper is suitable for predicting carbon emissions under conventional circumstances. In case of special circumstances such as changes in national policies or major breakthroughs in new energy sources, the carbon emission data in these circumstances should be included. This is the basis for the construction of the special carbon emission forecast model.

Carbon emissions are the key to achieving coordinated economic, environmental development and sustainable development: on the one hand, considering the goal that integrates the construction of ecological civilization into economic construction and achieves the goal of developing a low-carbon economy and reaching sustainable development; on the other hand, based on the results of the above-mentioned studies, taking into account the current national conditions of China's efforts to promote the construction of ecological civilization. This paper proposes the following recommendations in light of socioeconomic conditions:

- (1) Accelerate the adjustment of industrial structure and improve the efficiency of energy use
- (2) Optimize the energy structure
- (3) Accelerate the development and promotion of energy-efficient products

Data Availability

The carbon emissions data for four regions in China from 1997 to 2017 were obtained from the China Carbon Emissions Database (<https://www.ceads.net.cn/>) as raw data, which were all the available data; no data after 2017 were available.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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