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Underestimated impact of the COVID-19 on carbon emission reduction in developing countries – A novel assessment based on scenario analysis

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ABSTRACT

Existing studies on the impact of the COVID-19 pandemic on carbon emissions are mainly based on inter-annual change rate of carbon emissions. This study provided a new way to investigate the impact of the pandemic on carbon emissions by calculating the difference between the pandemic-free carbon emissions and the actual carbon emissions in 2020 based on scenario analysis. In this work, derived from Autoregressive Integrated Moving Average (ARIMA) method and Back Propagation Neural Network (BPNN) method, two combined ARIMA-BPNN and BPNN-ARIMA simulation approaches were developed to simulate the carbon emissions of China, India, U.S. and EU under the pandemic-free scenario. The average relative error of the simulation was about 1%, which could provide reliable simulation results. The scenario simulation of carbon emission reduction in the US and EU were almost the same as the inter-annual change rate of carbon emissions reported by the existing statistics. However, the scenario simulation of carbon emission reduction in China and India is 5% larger than the inter-annual change rate of carbon emissions reported by the existing statistics. In some sense, the impact of the pandemic on carbon emission reduction in developing countries might be underestimated. This work would provide new sight to more comprehensive understanding of the impact of the pandemic on carbon emissions.

1. Introduction

The Coronavirus disease 2019 (COVID-19) pandemic on a global scale has caused serious loss of life. The widespread nature of the virus forced economic activities and industrial production in many countries to stagnate in 2020, which has led to a severe decline in carbon emissions (Wang and Wang, 2020). According to a report from the Global Carbon Project (GCP) (Global Carbon Project, 2021), global carbon emissions have dropped by 2.4 GT (close to 7%) compared to 2019. This is the highest rate of decline in the past decade (International Energy Agency, 2020), which also sparked discussions about the true impact of pandemics on carbon emissions.

The extent to which COVID-19 curbs carbon emissions varies from country to country (Syed and Ullah, 2021). The measurement around the decline of carbon emissions has become the forefront of environmental governance research. By summarizing the carbon dioxide emissions of different countries around the world, the global carbon dioxide emissions in the first half of 2020 dropped by 8.8% compared with the same period in 2019 (Liu et al., 2020). During the peak period, the average rate of decline in emissions of a single country even reached 26% (Le Quéré et al., 2020). Most of the current studies were based on the inter-annual change rate of carbon emissions, that was, the change in 2020 compared to 2019, which was impossible to simulate the pure effect of the epidemic. To fully measure the reduction in carbon emissions due to the pandemic, this study proposed a new analysis angle in scenario simulation. Relying on historical carbon emissions data, we intend to build an accurate forecasting model to simulate the carbon emissions under pandemic-free scenario. Comparing this result with the actual 2020 carbon emissions, the difference between the two was regarded as the carbon emissions reduction caused by the pandemic. This kind of measurement could better reflect the influence of COVID-19 than the rate of annual decline in carbon emissions.

China, the United States, the European Union, and India are the four economies with the largest carbon emissions in the world, and the impact of COVID-19 pandemic on them has always been the focus of scholars. The current carbon emission situation and epidemic control policies of these four economies are different, broadly representative of global economies. As typical representatives of developing economies, China and India are still in the growth stage of carbon emissions. The U.S. and EU, typical representatives of developed economies, have entered a stage of declining carbon emissions. In terms of epidemic prevention...
Europe showed a picked up. Among them, China emissions experienced a slight decline of 3.7% and 205.2 (15.4%) million tons respectively, compared with the same period in 2019. China (3.7%) and 205.2 (15.4%) million tons respectively, compared with the same period in 2019. China emissions in 2020 was around 8% lower than the same period in 2019 (Sharma et al., 2020). The near real-time monitoring results of carbon emissions pointed out that China and India were the most affected by the epidemic among all developing countries. Their emissions in the first half of 2020 had dropped by 187.2 (3.7%) and 205.2 (15.4%) million tons respectively, compared with the same period in 2019. China’s carbon emissions fell on a large scale only in the early stage of COVID-19, and began to rebound rapidly in March 2020, which was closely related to the strictness of its epidemic supervision measures. Other countries such as India only officially adopted blockade measures in March, and carbon emissions began to decline (Liu et al., 2021).

Although the carbon emissions of the European Union and the United States had entered a decline stage, they were still the developed economies with the largest emissions. The impact of the epidemic on them also affected the global carbon reduction cause. Carbon emissions in Europe showed a –12.1% emissions change between January and June 2020, compared to the same period of the previous year (Andreoni et al., 2021). Compared to the start of the lockdown, the average decline was 11% across Europe, with France (42%), Germany (21%), the United Kingdom (13%), Spain (11%) and Italy (8%) among them (Evangelou et al., 2021). According to different benchmark standards, the results obtained were not the same (Rugani and Caro, 2020). For example, Filimonau et al. pointed out that the carbon footprint of the United Kingdom during the blockade fell by 30% during the April to June 2020 period, by comparing it with the response time period of previous years (Filimonau et al., 2021). Research based on near-real-time activity data pointed out that among the 11 major regions of the world, the carbon emissions of the U.S. and EU were most affected by the epidemic. The U. S. emissions in the first half of 2020 fell by 338.3 million tons (13.3%) compared to the same period in 2019, while Spain, Germany, France and Italy fell by 18.8%, 15.1%, 14.2% and 13.7%, respectively.

Abbreviations
COVID-19 Corona Virus Disease 2019
ARIMA Auto-Regression Integrated Moving Average
BPNN Back Propagation Neural Network
AR Auto-Regression Model
MA Moving Average Model
BP Back propagation
MAPE Mean Absolute Percentage Error
RMSE Root Mean Square Error
U.S. The United States
EU The European Union

and control, China was the first country to control the spread of the epidemic. India, U.S. and EU had relatively weak risk awareness and were at different stages of epidemic control. Once the impact of the epidemic on the carbon emissions of these large economies was incorrectly estimated, it might have an adverse impact on the planning of global carbon emission reduction pathways. Therefore, this study would carry out case studies for China, India, U.S. and EU, and apply the proposed forecasting methods to the carbon emission forecasts of these four economies under the pandemic-free scenario.

The rest of this paper is as follows. The second section conceived the existing literature and put forward the innovative points of this study. The third section introduced the modeling process of the forecast method. The fourth section gave the predicted process parameters and the accuracy of results. The fifth section focused on the comparison and discussion of the two analysis scenarios. Finally, section 6 summarized the main findings and gives policy recommendations.

2. Literature review

2.1. Literature review on epidemic’s impact on carbon emissions

China and India are the developing economies with the largest carbon emissions. The acceleration of industrialization and urbanization has led to a rapid increase in carbon dioxide emissions. The impact of the epidemic on carbon emissions in China and India has caused concern. Tollefson et al. pointed out that global carbon emissions declined in the early stage of the epidemic, but the decline was not large, and it quickly picked up. Among them, China emissions experienced a slight decline of 1.4% throughout the year (Tollefson, 2021). Han et al. estimated the real-time change of carbon dioxide based on the change of GDP and found that China’s carbon emissions had a reduction of 11.0% over Q1 2019 during the worst period of the pandemic (the first quarter of 2020) (Han et al., 2021). For India, carbon emissions in 2020 was around 8% lower than the same period in 2019 (Sharma et al., 2020). The near real-time monitoring results of carbon emissions pointed out that China and India were the most affected by the epidemic among all developing countries. Their emissions in the first half of 2020 had dropped by 187.2 (3.7%) and 205.2 (15.4%) million tons respectively, compared with the same period in 2019. China’s carbon emissions fell on a large scale only in the early stage of COVID-19, and began to rebound rapidly in March 2020, which was closely related to the strictness of its epidemic supervision measures. Other countries such as India only officially adopted blockade measures in March, and carbon emissions began to decline (Liu et al., 2020).

In this research idea, how to build a scientific and accurate forecasting model becomes a supporting part. Following the development rules of existing forecasting technologies, innovating high-precision forecasting methods and applying them to predictions under no-pandemic scenarios is the key to answering the true impact of the pandemic on carbon emissions (Wang et al., 2021). Existing forecasting technologies can be divided into two categories: statistical analysis and artificial intelligence (Deb et al., 2017; Yin et al., 2017). The former was dedicated to finding the law of data changes (Jia et al., 2015; Jiang et al., 2017), while the latter took learning and correction into consideration (Raza and Khosravi, 2015). In applied research, autoregressive integrated moving average (ARIMA) model and back propagation neural network (BPNN) model had been broadly implemented in energy fields (Kaytez et al., 2015; Ye et al., 2018). Among them, the ARIMA model reflected the changing characteristics of the sequence itself by constructing a linear equation (Ding et al., 2018). It only needs endogenous variables and does not resort to other exogenous variables. But it only capture linear relationships, not nonlinear fluctuations. Therefore, unless the error was compensated, some type of error propagation must occur. The ARIMA model had excellent linear prediction capabilities. It expanded predictions based on the relationship between past and future values, so it relied heavily on historical data. The predictive effect of the ARIMA model was limited in the presence of outliers that cause data instability. The BPNN model was a multi-layer feedforward network trained by the error back propagation algorithm (Yu and Xu, 2014). The BP neural network model had strong learning ability and data fitting ability, and could handle the instability and fluctuation of the residual sequence well. It approximated nonlinear functions with arbitrary precision. Therefore, the time series forecasting model based on BP neural network could well reflect the nonlinear development trend. Most of the energy predictions made by the previous generations had focused on improving (Arora and Taylor, 2018) and upgrading the original model with some practical principles (Wong et al., 2009). For example, Farag Sen et al. (2016) used the ARIMA (0,1,4) model to predict greenhouse gas emissions for Indian iron and steel manufacturing enterprises. Barak et al. (Barak and Sadegh, 2015) proposed a model that combined ARIMA and ANFIS to predict Iran’s energy consumption. With regard to BPNN model, a simulated-based neural network was adopted to predict Iranian monthly electrical consumption (Azadeh et al., 2008). Stamenkovic et al. (Stamenkovic et al., 2017) proposed an optimized neural network and got better results with input selection based on correlation between...
input variables. In the process of reviewing the literature (Yang et al., 2017), the performance of the hybrid model could be more advantageous (Qiu et al., 2016). In order to make better use of the advantages of models and make up for their shortcomings, the hybrid model that combined the ARIMA and the BPNN was a way out (Wang and Li, 2021; Wang and Petropoulos, 2016).

In short, the innovations of this research include the following three aspects. First, this study measured the impact of the pandemic on carbon emissions from a more systematic perspective, that was, comparing the carbon emissions when there was no pandemic with the actual carbon emissions in 2020. Second, this research integrated advanced ARIMA and BPNN to develop two new combined high-precision prediction techniques, with the principle of “error correction + secondary modeling”. Third, this study applied the constructed new method to the prediction of pandemic-free carbon emissions in typical developing countries (China, India) and developed regions (U.S., EU). By comparing the rate of decline in carbon emissions caused by the pandemic with the rate of inter-annual decline, this study would assess whether there was an underestimation of the decline in carbon emissions in some places.

3. Methods

The principles of ARIMA-BPNN and BPNN-ARIMA hybrid models were closely related to the single ARIMA and BP. The formulas for calculating a single model were shown below. Its combination of the two was shown in the flow chart.

3.1. Autoregressive integrated moving average model

ARIMA (p, d, q) called differential autoregressive moving average model was the combination of Integration and ARMA model (Sowell, 1992). ARMA model was made of autoregressive model (AR) and moving average model (MA).

Assuming that raw sequence is $X_t = \{x_0, x_1, \ldots, x_T\}$, and prediction sequence is $\hat{X}_t = \{\hat{x}_1, \hat{x}_2, \ldots, \hat{x}_p\}$.

On the one hand, AR model was established by the correlation (autocorrelation) between the data in the front part of itself and the data in the latter part (shown in Eqn 1):

$$x_t = \delta + \varphi_1 \mu_{t-1} + \varphi_2 \mu_{t-2} + \cdots + \varphi_p \mu_{t-p} + \epsilon_t$$  

(1)

On the other hand, MA model described the relationship between current value and historical error term to smooth random fluctuations (shown in Eqn 2):

$$\hat{x}_t = \mu + \mu_{t-1} + \theta_1 \mu_{t-1} + \theta_2 \mu_{t-2} + \cdots + \theta_q \mu_{t-q}$$  

(2)

ARMA model was established as Eqn 3 follows.

$$\hat{x}_t = \delta + \varphi_1 \mu_{t-1} + \varphi_2 \mu_{t-2} + \cdots + \varphi_p \mu_{t-p} + \mu_{t-1} + \theta_1 \mu_{t-1} + \theta_2 \mu_{t-2} + \cdots + \theta_q \mu_{t-q}$$  

(3)

The final predicted value was calculated by the following Eqn 4 formula:

$$\hat{x}_t = (1 - B)^d x_t$$  

(4)

Where, $B = [\vdots : \vdots : \vdots ; \vdots : \vdots ]$.

$$\frac{(x_1^2 + x_1^1)}{2}$$  

$$\frac{(x_m^2 + x_m^1)}{2}$$  

3.2. Back propagation neural network model

The basic idea of the BP algorithm was to first give the network initial weights and thresholds, calculated the output value through forward information transfer between layers, and modified the weights and thresholds of the network according to the error between the actual output and the expected output. Through continuous repeated training and comparison, the error between the actual output and the expected output was minimized (Xiao et al., 2009).

The common BP neural network was topology (Fig. 1). BP network was a neural network with three or more layers of neurons, including an input layer, an intermediate layer (hidden layer), and an output layer (Ren et al., 2014). The upper and lower layers were completely connected through the weight network, and there was no connection between the same layer.

When a pair of learning samples provide input neurons (Fig. 2), the activation value of the neurons (the output values of the neurons in the layer) was transmitted from the input layer through the hidden layer to the output layer, and then went back through the layers to the input layer, thereby correcting each connection weight (Guo et al., 2011). The algorithm was called “error reverse propagation algorithm”, or BP algorithm.

The learning process of the algorithm was composed of two processes: the forward propagation of the signal and the backward propagation of the error. In the forward propagation, the input samples were passed in from the input layer, and after being processed by the hidden layers, they were passed to the output layer. If the actual output was inconsistent with the expected output, it would enter the error back propagation stage. In back propagation, the output was transmitted back to the input layer through the hidden layer, and the error was apportioned to all units of each layer, so as to obtain the error signal of each layer unit. This error signal was used as the basis for correcting the weight of each unit (Abdi et al., 1996).

3.3. ARIMA-BPNN and BPNN-ARIMA

ARIMA-BPNN and BPNN-ARIMA were formed by using error correction principle, which combined linear model-ARIMA and nonlinear model-BPNN. It was also an example of traditional statistical method and new artificial intelligence method. The hybrid models combined the advantages of ARIMA model and BPNN model and made up the deficiency.

As for the ARIMA-BPNN model construction, the main idea was to use the ARIMA model for initial prediction, and then performed BPNN prediction on the residual sequence. While avoiding the shortcomings of the single model, the construction process of the ARIMA-BPNN model makes it possible to predict the future and obtain more accurate predictions.

The specific operation could be divided into three steps:
Step 1: Input the raw data into the ARIMA model to obtain the predicted value and subtract the original data to calculate the residual value.

Step 2: Input the residual value of ARIMA model into the BPNN model and correct the residual value multiple times to obtain a new excellent residual value.

Step 3: On the one hand, for the data of known years, the sum of the new residual value and the original data is used as the new predicted value. On the other hand, for the data part of the unknown year, that is, the part of the forecast data, the ARIMA prediction value minus the new residual value is used as the new forecast value.

At this point, the combination is complete. In terms of the construction principle, both the first prediction and the second revision require the chosen model to be suitable for each step. We use ARIMA to predict and use BPNN to correct, establish the BPNN model of ARIMA residual sequence, rely on the superiority of ARIMA model itself and BPNN self-learning ability to obtain the predicted value of hybrid model.

The first step in applying ARIMA model was to smooth the non-stationary sequence and to perform differential operations on it. The ARIMA model had good applicability in dealing with fluctuation residual sequences. In contrast, if BPNN and ARIMA were combined according to the above combination steps, using the unique advantages of the ARIMA model in dealing with fluctuations to process the residual sequence of BPNN may yield unexpected results. And then reverse the experiment. At the same time, it can verify the fitting ability of linear ARIMA model and the modified learning ability of nonlinear BPNN. According to the fitting principle, the BPNN-ARIMA hybrid model was established in this sector. The specific steps of modeling were similar to the above operations and would not be repeated here. The specific modeling process and modeling steps of the hybrid model were as shown in Fig. 3.

3.4. Prediction of carbon emissions under the pandemic-free scenario

Forecasting the carbon emissions written in the 2020 pandemic-free scenario in China, India, the United States and European Union was carried out in this section. ARIMA-BPNN and BPNN-ARIMA were applied to short term forecasts. In this chapter, the data of the four economies in 1995–2019 was used to build a prediction model, aiming to obtain the carbon emissions free of pandemic in 2020 based on the historical law. The historical data sequence was from the British BP

![Fig. 3. The flowchart of the ARIMA-BPNN and BPNN-ARIMA models.](image-url)
3.5. ARIMA-BPNN model parameters

The first was to determine the three parameters of the ARIMA (p, d, q) model with the help of the Eviews software. "P" represented the number of lags (lags) of the time series data itself. "d" represented the order that the time series data needed to be stable. "q" represented the number of lags (lags) of the prediction error. Therefore, the first step of the ARIMA model was to determine the difference order through unit root test. ARMA required data to be normally distributed, stable and zero mean. Stationarity generally referred to: the mean was constant, the variance was constant, and the autocovariance was constant. If only the mean was non-zero, then the difference was used to make the series stationary. Here the difference order was ‘d’. If the autocorrelation coefficient was tailed (decayed regularly in exponential or sinusoidal form), and the partial autocorrelation coefficient was p-order truncated (cut off to 0 after a certain value), then the p-order AR model was used. If the autocorrelation coefficient was q-order truncated and the partial autocorrelation coefficient was tailed, the q-order MA model was used.

As mentioned before, these two historical sequences were not stable enough. When using the ARIMA model to predict carbon emissions in China, India, the U.S. and EU, the unit root tests in Table 1 indicated that the historical data sequence needed to be differentially processed. Here, Eviews software was used to calculate the correlation coefficient of the sample.

After that, the model was fixed. Autocorrelation and partial autocorrelation were the basic methods for judging the trailing truncation and choosing the ARIMA model. The ARMA model required that both the autocorrelation function (ACF) and the partial autocorrelation function (PACF) were tailing (Ervural et al., 2016). Due to the randomness of the sample, the sample correlation coefficient did not exhibit a perfect case of theoretical truncation.

From Fig. 5, it could be seen that the China historical data series, whose autocorrelation coefficient was censored after the third order, and the partial autocorrelation coefficient was censored after the fifth order. The obtained model was ARIMA (3, 2, 5). In the same way, the historical data of India was input into the software to identify its ARIMA (2, 1, 5). The US and EU data series meet the parameter conditions of ARIMA (3, 1, 3) and ARIMA (5, 1, 5).

After modeling, ARIMA (3,2,5), ARIMA (2,1,5), ARIMA (3,1,3) and ARIMA (5,1,5) were input to the SPSS software to obtain initial fitted values and predicted values. At this time, the initial prediction part of the ARIMA model was completed. The forecast data of 1995–2018 was used as fitting value to measure the accuracy of the model. The residual error sequence obtained by subtracting the fitting sequence from the original sequence was shown in Fig. 6. It can be seen that the overall fluctuation was large, which showed that the initial prediction accuracy
of the ARIMA model still had room for improvement, and its error could be further reduced. Therefore, this study used the BPNN model to correct its residuals.

Part I: Selection of network structure design and excitation function.

The number of hidden layer neurons in the network was directly related to the complexity of the actual problem, the number of neurons in the input and output layers, and the setting of the expected error (Li et al., 2018). In order to control the over-fitting phenomenon, this paper gave priority to the 3-layer network (that is, there is only one hidden layer). Although the network structure shown in Fig. 7 had 4 layers, in reality, the second hidden layer had only one node. The transfer function between it and the output layer was \(y = x\), so only the first hidden layer was valid. However, the simplified model structure should be based on ensuring the accuracy of the model. In order to reduce the error of the neural network, we appropriately increased the number of hidden layer nodes, which was easier to implement than increasing the number of hidden layers. The maximum number of iterations was set to 1000, and the prediction accuracy of the training set on the network was \(10^{-8}\). After 40 tests, the number of hidden layer nodes was finally determined to be 10. ‘TrainRatio’, ‘ValRatio’ and ‘TestRatio’ was used to divide the sample data, of which 70% was used for training, 15% for verification and 15% for testing. In order to improve the prediction accuracy, the BPNN model added a loop statement in the network design: each predicted value was calculated based on the first four residual data.

Part II: Model Implementation.

The prediction used the neural network toolbox in MATLAB to train the network. The specific implementation and correlation coefficient of the prediction model were shown in Fig. 7.

Table 1

| Sequence | ADF Statistic | Critical Value 1% | Critical Value 5% | Critical Value 10% |
|----------|---------------|------------------|------------------|------------------|
| China    |               |                  |                  |                  |
| Q        | -2.705767     | -4.416345        | -3.622033        | -3.248592        | 0.2433           |
| Q*       | -2.777403     | -4.467895        | -3.644963        | -3.261452        | 0.2193           |
| Q**      | -4.811472     | -4.440739        | -3.632896        | -3.254671        | 0.0046           |

| India    |               |                  |                  |                  |
| Q*       | -4.537457     | -4.416345        | -3.622033        | -3.248592        | 0.0077           |
| Q**      | -9.698250     | -4.440739        | -3.632896        | -3.254671        | 0.0000           |

| U.S.     |               |                  |                  |                  |
| Q        | -2.444077     | -4.394309        | -3.612199        | -3.243079        | 0.3499           |
| Q*       | -4.931456     | -4.440739        | -3.632896        | -3.254671        | 0.0036           |
| Q**      | -8.639159     | -4.467895        | -3.644963        | -3.261452        | 0.0000           |

| EU       |               |                  |                  |                  |
| Q        | -1.731972     | -4.394309        | -3.612199        | -3.243079        | 0.7052           |
| Q*       | -5.414444     | -4.416345        | -3.622033        | -3.248592        | 0.0012           |
| Q**      | -9.351718     | -4.440739        | -3.632896        | -3.254671        | 0.0000           |

Note: Q means zero order difference; Q* means first order difference; Q** means second order difference.

Fig. 5. Correlation diagram of AC and PAC about China, India, the U.S. and EU.
that, the initial residual sequence of the ARIMA model was input to predict the new residual sequence. Fig. 8 showed the calculation results. The black curve represented the original residual value produced by the ARIMA model, while the BPNN model was used to correct the residual sequence, and the resulting new residual sequence was shown as an orange curve. Comparing the original value of ARIMA with the BPNN corrected new residual, it could be seen intuitively that BPNN model could correct the original residual and alleviate the fluctuation.

Take China as an example. In terms of the average of absolute error, the average absolute error of China’s CO$_2$ emissions predicted by ARIMA model was 116.1 million tons, but the average absolute error after the correction of BPNN model was only 77.4 million tons. In terms of the peak of absolute error, the peak error of China’s CO$_2$ emissions predicted by the ARIMA model appeared in 2003, which was 331.5 million tons, but the peak error after the correction of BPNN model was only 293.9 million tons (2012). For the other three economies, after the correction of the BPNN model, the forecast errors had all been converged to varying degrees.

The last task was to use existing data to calculate the final predicted value of the hybrid model. Specifically, the actual residual carbon emissions were subtracted from the new residuals to obtain the fitted value of the hybrid model from 1995 to 2019, and the initial predicted value of the ARIMA model plus the residual sequence of the BPNN correction was used to obtain predictive value of 2020–2025. The difference between the final predicted value and the true value of the two models ARIMA, ARIMA-BPNN was shown in Fig. 9. Based on the principle that the curve was closer; the model predicted better. We could see that the fitting effect of ARIMA and ARIMA-BPNN was good, but in comparison, the ARIMA-BPNN model combining the advantages of the two models had a better fitting effect.

For the four economies, it could be seen from Fig. 9 that due to the impact of emergencies, the carbon emissions of U.S. and EU had been
constantly fluctuating, and the carbon emissions of China and India had been rising all the way with very little fluctuation. Therefore, compared with U.S. and Europe, the overall trend of China and India was easier to identify and the fitting effect was better. Although the smaller scale made the fitting errors of U.S. and EU appear larger, the error analysis in Section 3.3 proved that the forecasting model had good performance in the carbon emission forecasts of the above four economies.

3.6. BPNN-ARIMA model parameters

Similarly, the two models were used to process the data, but this time the initial model became BPNN and the residual correction model became the ARIMA model. The first step was to use the BPNN model to train and predict the raw data in China, India, the U.S. and EU. It was found that the above neural network model was still applicable to this data and was not repeated here. After the BPNN training was completed, the raw data was taken into the prediction sequence, and the original residual value obtained by subtracting the BPNN prediction sequence from the raw sequence.

After that, ARIMA model was applied to correct the errors of the original residual sequence. In the ARIMA model, ARIMA (3,1,1), ARIMA (1,0,0), ARIMA (1,1,1) and ARIMA (4,1,2) were validated by unit root test, autocorrelation coefficients and partial autocorrelation coefficients. The new residual sequence was obtained in the corresponding model. Compared to the initial error sequence of the BPNN model, the ARIMA model corrected residual sequence was significantly flatter, and the corrective effect is also exerted.

Using the initial predictions of BPNN model and the corrected residuals of ARIMA model, the final predictions of the BPNN-ARIMA model could be calculated. Take the original data from 1995 to 2019 minus the corrected residual sequence as the fitted value to determine the accuracy of the mixed model, and use the BPNN data plus the new
residual sequence from 2020 to 2025 to obtain the final prediction sequence.

To present the advantages of the hybrid model more intuitively, Fig. 10 showed the prediction results of a single model BPNN and a hybrid model BPNN-ARIMA. The correction was based on a single model, and the general trend of the hybrid model was consistent with the single model. The closer the curve was, the better the model predicted. BPNN-ARIMA combined linear and nonlinear models, and used ARIMA to modify BPNN. Among the four economies, Fig. 10 showed that the EU had the worst fitting effect, which was mainly caused by the smaller scale. In terms of the mean value and peak value of the error, the combined model had better prediction performance than the single model.

3.7. Error analysis, goodness evaluation

This section would respond to the above prediction process. Combined with the objectives of this paper, the error and goodness of the model was evaluated to predict the accuracy of the model. The prediction results of these four models were fitted to the actual data of carbon emissions in China, India, the U.S. and EU. The data in 1995–2019 were used as fitting samples to evaluate the proposed hybrid model.

To scientifically evaluate and describe the accuracy of multiple models, we introduced the mean absolute percentage error (MAPE) to measure prediction error. As one of the tools widely used to calculate prediction errors, MAPE’s measurement principle was that the smaller the value, the higher the accuracy of the model. Fig. 11 showed the prediction results for ARIMA, BPNN and two hybrid ARIMA-BPNN and BPNN-ARIMA in two economies. It could be seen intuitively that the accuracy of the four models was basically above 90%. The MAPE value below 5% proved that the prediction results of this study were convincing. In addition, the hybrid model had a clearer advantage over a single model.

Tables A1, A2, A3 and A4 in the appendix gave the results and deviations of the US (Table A1), China (Table A2), India (Table A3) and EU (Table A4) carbon emissions predicted using these four models in detail. It can be seen from the MAPE results that the prediction performance of the ARIMA model and the BPNN model itself was not bad, but after the residual correction, the prediction accuracy of the hybrid models ARIMA-BPNN and BPNN-ARIMA was better.

From the error value, the mean absolute percentage error (MAPE) of BP-ARIMA model was about 1%, which was 0.962%, 0.715%, 0.451% and 1.359% respectively. The MAPE values of ARIMA-BP model were 1.515%, 0.829%, 0.702% and 1.075% respectively. This error result proved that the two combination models established in this study had perfect accuracy. Therefore, the predicted results were also convincing. BPNN-ARIMA had the best data processing accuracy for China, India and U.S.. The ARIMA-BPNN model showed superiority when dealing with EU data. BPNN-ARIMA based on a nonlinear BP neural network model showed better performance when dealing with fluctuation data like China. ARIMA-BPNN was better when dealing with flat data in the European Union.

Root mean square error (RMSE) was often used as a measure of the prediction of machine learning model predictions. MAPE and RMSE were given in Table 2. The measurement results shown by RMSE were consistent with the conclusions of the above MAPE.

4. Measurement of carbon emissions affected by the pandemic

After the previous chapter, the carbon emissions of the four economies under the pandemic-free state were predicted. This chapter gave the amount of carbon emissions affected in two measurement scenarios. The analysis results were discussed.

4.1. Scenario I: measurement of inter-year comparison

Scenario I was to measure the amount of change in carbon emissions in the 2020 pandemic year from the perspective of inter-annual comparison. Combined with the latest statistics from authoritative databases, Fig. 12 showed the total carbon emissions of the four major economies in 2019 and 2020. The arrow showed the relative percentage change between years. According to the calculation results, compared with the carbon emissions in 2019, the reduction rate of carbon emissions in various economies in 2020 was different. Among them, China’s decline was the smallest among the four economies, at 3.45%. The European Union saw the largest decline at 21.6%. The rates of decline in India and the United States were 14.8% and 16.4%, respectively.

This measurement method gave a statistically intuitive judgment and was often referred to as the rate of decrease in carbon emissions during the pandemic year. If we want to measure the impact of the pandemic on carbon emissions, we need to use the following scenario assumptions.

![Fig. 10. The gap between forecast value and actual value for the three models in China, India, the U.S. and EU.](image-url)
4.2. Scenario II: measurement of hypothetical scenarios

The core setting of the scenario method was to simulate the value of carbon emissions in a pandemic-free state. Specifically, mathematical modeling needed to be used to predict the trend of carbon emissions in 2020. Then compare the carbon emissions in this ideal state with the actual carbon emissions. The difference between the two was regarded as a quantification of the impact of the pandemic on carbon emissions. Fig. 13 showed the carbon emissions of the four economies under the pandemic-free state and the actual state. Among them, green represented the 2020 carbon emissions in an ideal state, and orange represents the actual carbon emissions in 2020. Subtracting the two, the percentage difference was regarded as the reduction in carbon emissions caused by the pandemic. It could be found that there was a significant difference between the extent of carbon emissions affected by the pandemic and the decline in carbon emissions in 2020. Numerically speaking, the pandemic had reduced China’s carbon emissions by 8.8%. India, the United States and the European Union were 19.2%, 16.6% and 19.8% respectively.

In summary, the first measure gave the degree of reduction in carbon emissions in 2020. The second measurement method gave the extent of changes in carbon emissions caused by the 2020 pandemic. There were obvious differences between the two measurement methods and different economies. This became the focus of our next analysis.

Table 2
Measurement results of three error measurement coefficients.

|                | MAPE  | RMSE  |
|----------------|-------|-------|
|                | BP-ARIMA | ARIMA-BP |   | BP-ARIMA | ARIMA-BP |
| China          | 0.962% | 1.515% | 72 | 105      |
| India          | 0.715% | 0.829% | 17 | 18       |
| U.S.           | 0.451% | 0.702% | 28 | 57       |
| EU             | 1.359% | 1.075% | 71 | 59       |

Fig. 11. The goodness of four models (ARIMA, ARIMA-BPNN, BPNN and BPNN-ARIMA).

Fig. 12. Comparison of carbon emission between 2020 and 2019.

Annual emissions total: 2020 vs 2019
4.3. Discussion and summary

The above gave the changes in carbon emissions from two perspectives. From a numerical point of view, there was a difference in the magnitude of change between the two. Further subdivided, this difference had different manifestations in developed and developing economies. This section focused on this difference and aimed to draw interesting conclusions. In the process of result analysis, we divided the four economies into developing and developed two groups for analysis.

The first analysis was for China and India. From the data in Fig. 14A, the relative changes in carbon emissions calculated by the two scenarios were significantly different. The reduction in China’s carbon emissions affected by the pandemic was 8.8%, far exceeding the 3.4% decline in 2020. There was a 5.35% gap between the two. Similar to China, India’s carbon emissions decline in Scenario II was 19.2%, while the interannual decline was 14.8%. The difference between the two scenarios was 4.4%. In other words, the extent of changes in carbon emissions

![Fig. 13. Comparison of carbon emission between 2020 and expected 2020.](image)

![Fig. 14. A. The relative changes in carbon emissions calculated by the two scenarios (China and India). Fig. 14B. The relative changes in carbon emissions calculated by the two scenarios (U.S. and EU).](image)
affected by the pandemic in the two economies had been greatly underestimated.

Comparing the results of these two economies, it was easy to find that the impact of the epidemic on India’s carbon emissions was far greater than that of China. The reason was closely related to the epidemic control measures of the two countries. China adopted strict measures at the beginning of the epidemic and became the first country to control the spread of the epidemic. China’s infrastructure was also more complete, and the living conditions of residents were better. Therefore, the ability to withstand the risks of emergencies such as the epidemic was also stronger. China had restored its normal economic order earlier, so its impact on carbon emissions was therefore relatively small (Wang and Zhang, 2021). India announced its victory over the epidemic too early, and the whole people relaxed their vigilance. The huge population size increased the risk of transmission, and the low vaccination rate made it difficult for people to resist virus infection. Moreover, the living conditions of the bottom people in India were extremely poor, making it difficult to withstand the harm caused by the epidemic. The epidemic had a serious impact on the Indian economy, and as a result, carbon emissions had fallen sharply.

Following the two regions of the United States and the European Union (as shown in Fig. 14B). As developed economies that had been more severely affected by the pandemic, the carbon emissions of the United States and the European Union had fallen sharply in 2020 by 16.4% and 21.6%, respectively, lower than in 2019. Among the calculation methods used in this study, the reduction in carbon emissions due to the sudden event of the pandemic was 16.6% and 19.8%, respectively. It could be seen that the results obtained by these two calculation methods did not show obvious differences. Therefore, in measuring the reduction in carbon emissions, the statistical results of the two typical methods did not show obvious differences. Therefore, in measuring the reduction in carbon emissions, the statistical results of the two typical developed economies, the United States and the European Union, were not much different from the actual impact. This confirmed that the extent of changes in carbon emissions affected by the pandemic in developed economies had basically been accurately measured.

Comparing the results of these two economies, the impact of the epidemic on the carbon emissions of U.S. and EU was similar. This was related to the relatively similar epidemic control strategies of these two economies. Early risk awareness in EU and U.S. was relatively weak. The U.S. was the country with the largest number of deaths. At present, some regions were still hesitant to vaccinate, and the epidemic had not yet been effectively controlled. Therefore, the economic development caused by the epidemic had been stagnant for a long time, and its impact on carbon emissions was also great, and the decline was much greater than that of China.

5. Conclusion

Statistical information from different scholars confirmed the unified conclusion that the pandemic had curbed carbon emissions in many regions of the world (Carbon Brief, 2020). However, the existing methods for measuring the reduction in carbon emissions based on inter-annual comparisons cannot accurately measure the impact of the pandemic on carbon emissions. To fully calculate the decline of carbon emissions caused by the pandemic, this study presented a measurement method based on scenario simulation. Specifically, we predicted the carbon emissions in 2020 without pandemic situation and compared this value with the actual carbon emissions in 2020. The resulting reduction rate was considered as the effect induced by the pandemic. We innovatively developed ARIMA-BP and BP-ARIMA hybrid prediction technology. By comparing with historical data, we found that the MAPE of the two prediction techniques was less than 1%. The high accuracy of the method confirmed the reliability of the carbon emission prediction under the scenario of no pandemic.

After comparison, results showed that the specific impact of the pandemic on carbon emissions was greatly underestimated in developing economies. In developed economies, this misappraisal phenomenon was not obvious. In terms of the magnitude of the decline, the decrease in carbon emissions in developing economies during the pandemic was underestimated by about 5%. In other words, the reduction in carbon emissions based on inter-year comparisons cannot accurately reflect the specific impact of the pandemic on developing economies. The actual impact was far more serious than reported. Therefore, this study puts forward the following recommendations. (1) This study provides a new perspective to study the impact of the COVID-19 pandemic on carbon emissions. We hope that the public and policymakers will have a more systematic understanding of the impact of emergencies on carbon emissions, rather than being limited to inter-year comparisons. (2) Judging from the results of this study, the epidemic has caused a greater decline in carbon emissions from developing economies such as China and India. Compared with developed economies, developing economies have greater pressure to reduce carbon emissions, so in the post-epidemic period, the changes in carbon emissions in developing economies should be given greater attention. (3) Developed economies are more resilient and the epidemic has less impact on them. Therefore, they should provide more assistance to developing economies, especially in the field of carbon emission reduction.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

Table A1
U.S. actual carbon emissions and ARIMA, ARIMA-BPNN, BPNN and BPNN-ARIMA predictions

| Year | Actual data | ARIMA (3,1,3) | ARIMA-BPNN | BPNN | BPNN-ARIMA |
|------|-------------|--------------|-------------|------|------------|
|      | Forecasts   | APE (%)      | Forecasts   | APE (%) | Forecasts   | APE (%) | Forecasts   | APE (%) | Forecasts   | APE (%) |
| 1995 | 5228.00     | 5228.00      | 0.00        | 5228.00 | 0.00       | 5228.00 | 0.00       | 5228.00 | 0.00       | 5228.00 |
| 1996 | 5407.87     | 5304.26      | 1.92        | 5407.87 | 0.00       | 5407.87 | 0.00       | 5407.87 | 0.00       | 5397.74 |
| 1997 | 5483.18     | 5456.29      | 0.49        | 5483.18 | 0.00       | 5483.18 | 0.00       | 5483.18 | 0.00       | 5468.79 |
| 1998 | 5524.20     | 5503.45      | 0.38        | 5524.20 | 0.00       | 5524.20 | 0.00       | 5524.20 | 0.00       | 5506.06 |
| 1999 | 5574.14     | 5620.89      | 0.84        | 5568.69 | 0.10       | 5496.73 | 1.35       | 5552.72 | 0.38       |
| 2000 | 5740.77     | 5642.47      | 1.71        | 5764.23 | 0.41       | 5689.98 | 0.88       | 5700.54 | 0.70       |
| 2001 | 5650.72     | 5751.70      | 1.79        | 5643.66 | 0.13       | 5640.02 | 0.19       | 5602.78 | 0.85       |
| 2002 | 5672.40     | 5648.46      | 0.42        | 5660.58 | 0.21       | 5649.15 | 0.41       | 5624.75 | 0.84       |

(continued on next page)
Table A3
India actual carbon emissions and ARIMA, ARIMA-BPN, BPNN and BPNN-ARIMA predictions

| Year   | Actual data | ARIMA (2,1,5) | ARIMA-BPN | BPNN | BPNN-ARIMA |
|--------|-------------|---------------|-----------|------|------------|
|        |             | Forecasts     | APE (%)   | Forecasts | APE (%)   | Forecasts     | APE (%)   |
| 1995   | 773.08      | 773.08       | 0.00      | 773.08 | 0.00        | 773.08       | 0.00      |
| 1996   | 811.90      | 808.17       | 0.46      | 811.90 | 0.00        | 811.90       | 0.00      |
| 1997   | 854.11      | 849.46       | 0.54      | 854.11 | 0.00        | 854.11       | 0.00      |
| 1998   | 894.41      | 896.37       | 0.22      | 894.41 | 0.00        | 894.41       | 0.00      |
| 1999   | 911.26      | 940.57       | 3.22      | 895.61 | 1.72        | 923.30       | 1.32      |
| 2000   | 950.03      | 961.09       | 0.21      | 952.31 | 0.70        | 971.13       | 1.26      |
| 2001   | 967.57      | 997.85       | 3.13      | 966.38 | 0.12        | 979.45       | 1.23      |
| 2002   | 1019.03     | 1026.05      | 0.69      | 1013.86 | 0.51      | 1029.53       | 1.03      |
| 2003   | 1062.19     | 1057.24      | 0.47      | 1052.12 | 0.95      | 1071.71       | 0.90      |

Continued on next page
### Table A4

**EU actual carbon emissions and ARIMA, ARIMA-BPNN, BPNN and BPNN-ARIMA predictions**

| Year     | Actual data | ARIMA (5,1,5) | ARIMA-BPNN | BPNN | BPNN-ARIMA |
|----------|-------------|---------------|------------|------|------------|
|          |             | Forecasts     | APE (%)    |      | APE (%)    | Forecasts | APE (%) |
| 1995     | 4068.84     | 4068.84       | 0.00       | 4068.84 | 0.00   | 4068.84   |         |
| 1996     | 4187.33     | 4093.22       | 2.25       | 4187.33 | 0.00   | 4187.33   | 0.00    |
| 1997     | 4131.00     | 4179.19       | 1.61       | 4131.00 | 0.00   | 4131.00   | 0.00    |
| 1998     | 4131.69     | 4162.53       | 0.75       | 4131.69 | 0.00   | 4131.69   | 0.00    |
| 1999     | 4072.67     | 4127.85       | 1.36       | 4138.94 | 1.63   | 4013.80   | 1.45    |
| 2000     | 4081.01     | 4077.01       | 1.00       | 4041.50 | 0.97   | 3961.59   | 2.93    |
| 2001     | 4154.02     | 4116.41       | 0.91       | 4126.61 | 0.66   | 3979.78   | 4.19    |
| 2002     | 4136.62     | 4111.11       | 0.62       | 4109.19 | 0.66   | 4155.60   | 0.46    |
| 2003     | 4240.35     | 4173.91       | 1.57       | 4162.61 | 1.83   | 4187.46   | 1.25    |
| 2004     | 4262.18     | 4169.68       | 2.17       | 4216.80 | 1.06   | 4176.38   | 2.01    |
| 2005     | 4256.20     | 4261.74       | 0.13       | 4271.91 | 0.37   | 4326.53   | 1.65    |
| 2006     | 4293.56     | 4232.94       | 1.41       | 4290.44 | 0.07   | 4149.94   | 3.35    |
| 2007     | 4225.88     | 4205.20       | 0.49       | 4223.95 | 0.05   | 3984.35   | 5.72    |
| 2008     | 4146.62     | 4226.32       | 1.92       | 4197.88 | 1.24   | 4058.96   | 2.11    |
| 2009     | 3830.27     | 4058.62       | 5.96       | 3931.78 | 2.65   | 3811.06   | 0.50    |
| 2010     | 3922.93     | 3820.67       | 2.61       | 3911.07 | 0.30   | 3850.07   | 1.86    |
| 2011     | 3800.36     | 3835.36       | 0.92       | 3851.43 | 1.34   | 3807.97   | 0.20    |
| 2012     | 3737.70     | 3793.16       | 1.48       | 3776.40 | 1.04   | 3535.80   | 5.40    |
| 2013     | 3653.47     | 3727.33       | 2.02       | 3641.12 | 5.26   | 3584.55   | 1.89    |
| 2014     | 3446.59     | 3505.26       | 1.73       | 3415.80 | 0.86   | 3508.57   | 1.83    |
| 2015     | 3496.94     | 3464.47       | 0.64       | 3463.48 | 0.67   | 3496.29   | 0.27    |
| 2016     | 3498.50     | 3389.05       | 3.13       | 3409.84 | 2.53   | 3505.11   | 0.19    |
| 2017     | 3527.15     | 3493.92       | 0.94       | 3530.52 | 0.10   | 3490.30   | 1.04    |
| 2018     | 3466.48     | 3424.19       | 1.22       | 3402.15 | 1.86   | 3456.42   | 0.29    |
| 2019     | 3330.44     | 3328.82       | 0.06       | 3273.55 | 1.72   | 3464.38   | 4.02    |

MAPE  
/      /      /          1.44  /      /          1.07  /      /          1.70  /      /          1.36

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