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Carbon Emissions Prediction of China Civil Aviation Based on Improved STIRPAT Model

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Abstract. After COVID-19, the development of civil aviation in the country has been revived, in order to achieve 'Peak Carbon', scientific forecasting of carbon emissions from civil aviation is essential. The study used grey correlation analysis to screen the factors affecting civil aviation carbon emissions, and finally obtained five key variables at the industry level: total transport turnover, passenger traffic, take-off and landing sorties, GDP, disposable income of urban residents and five key variables at the airline company level: total transport turnover, passenger traffic, flight hours flight, occupancy rate and operating revenue. Based on the relevant data from 2000 to 2024, the STIRPAT model was developed and improved using partial least squares regression to obtain carbon emission equations at both the industry and airline levels, and validated against the industry data using airline data. The results show that the improved STIRPAT model can accurately predict the civil aviation carbon emissions, and then predict the emissions in 2025-2030, and the prediction results show that the civil aviation carbon emissions in China will reach 228.42 million tons in 2030.

Keywords: Civil aviation; Carbon emissions; Grey Correlation Analysis; STIRPAT Model; Partial Least Squares Regression

1 Introduction

As a strategic industry in China, the civil aviation industry has been showing stable development over the past decades, with the total transport turnover, passenger traffic and the number of aircraft on the roster increasing year after year[1]. However, because of the rapid growth rate of the industry, its total carbon emissions have always been on the rise, and China has now become the second largest civil aviation transport carbon emitter in the world. Scientific and reasonable civil aviation carbon peak prediction is of great practical significance to the formulation of relevant emission reduction policies[2].

At present, the carbon emission prediction models that have been established are mainly based on the prediction of carbon peaking based on the data before the popu-

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larity of COVID-19, and the prediction methods adopted mainly include linear regression prediction model[3], ARIMA prediction model[4] and BP neural network[5].

This paper uses the industry data after COVID-19 to populate the data in COVID-19. The study used the STIRPAT model to forecast carbon emissions from civil aviation at both the industry and airline levels. At the industry level, a prediction of peak carbon in the civil aviation industry was made, and at the airline level, the industry prediction was verified by fitting the data of the airline companies. Finally, Taking into account the ‘14th Five-Year Plan for Green Aviation’ and ‘China's Population Policy’ the variables are adjusted to complete the projection of carbon emissions from civil aviation in 2025-2030..

2 Research Methods

The study uses data from the civil aviation industry as well as airline companies for the period 2000-2024, selects key variables through grey correlation analysis methods and performs covariance tests, and finally improves the STIRPAT model through partial least squares regression to obtain the final model.

2.1 Grey Relational Analysis (GRA)

The grey system analysis method is based on the idea of grey curve correlation analysis, and the concept of grey system correlation mainly involves the use of the development and change of grey system curves[6]. By using the geometric shape of the relationship between the data for correlation analysis, it is determined whether there is a relatively close internal connectivity, thus reflecting the dynamic *correlation* process between the grey curve systems.

The specific steps are as follows:

Step 1: Determine the analysis series.

Step 2: Performs dimensionless data processing. The dimensionless data processing equation is:

$$X_i(k) = \frac{X_i'(k)}{\frac{1}{m}\sum_{k=1}^{m} X_i'(k)} \; (i = 0,1,\cdots,n; k = 1,2,\cdots,m) \tag{1}$$

Step 3: Calculate the correlation coefficient. Each correlation coefficient is calculated separately from equation :

$$\xi_i(k) = \frac{min_s min_t |x_0'(t) - x_s'(t)| + \rho max_s max_t |x_0'(t) - x_s'(t)|}{x_0'(k) - x_s'(k)| + \rho max_s max_t |x_0'(t) - x_s'(t)|} \tag{2}$$

Step 4: Calculation of correlation. The average of the relative correlation coefficients between each of the analysis and comparison indicators is taken as the number of correlation indices between the comparison and reference data.

$$r_i = \frac{1}{m}\sum_{k=1}^{m} \xi_i(k) \tag{3}$$

2.2 Variance Inflation Factor (VIF) and Partial Least Squares Regression (PLSR)

Multicollinearity refers to the presence of strong correlations between independent variables, which can lead to instability in the estimation of model parameters, affecting the explanatory and predictive power of the model. Therefore before performing the regression analysis we need to exclude certain variables with multicollinearity by using VIF test.

In order to obtain the VIF for each variable, the study performed a linear regression analysis of all the remaining variables with each variable as the dependent variable, obtained the respective R2 for each variable, and substituted it into the following equation to obtain the VIF for each variable.

$$VIF = \frac{1}{1-R^2} \tag{4}$$

Partial Least Squares Regression (PLSR) is a multivariate data analysis method in statistics and machine learning that is particularly suitable for dealing with situations where there is a multicollinearity problem between the dependent and independent variables.

Step 1: Extraction of principal components. The covariance matrices of the independent and dependent variables are calculated, and the first set of principal components, which reflect the trends of both the independent and dependent variables, are extracted by an iterative algorithm[7].

Step 2: Regression modelling. The extracted principal components were used as new independent variables and the dependent variable was modelled by linear regression.

Step 3: Repeat the iteration. Continue to extract new principal components for the remaining independent variable residuals and regress until the predefined stopping criterion is met.

2.3 STIRPAT Model

The STIRPAT model is based on an extended deformation of the IPAT equation[8], whose fundamental equation is:

$$\mathrm{I} = aP^b A^c T^d e \tag{5}$$

In practice, in order to eliminate the effect of possible heteroskedasticity in the model, the equation is deformed as:

$$\ln I = \ln a + b\ln P + c\ln A + d\ln T + \ln e \tag{6}$$

where In I is the dependent variable and ln P, ln A, ln T are the independent variables, ln a is the constant term and ln e is the error term[9][10]. This paper is a researcher on the issue of carbon emissions from civil aviation in China, and based on the indicators that have been selected, the equation (7) is expanded as:

$$\ln C = \ln a + b\ln P + c\ln T + d\ln A + e\ln G + f\ln R + \ln g \tag{7}$$

3 Empirical Analysis

This paper selects the data of civil aviation transport indicators and macroeconomic indicators from 2000 - 2024, and builds the STIRPAT model to forecast its future development from both the industry and airline company levels. Civil aviation transport indicators include: total civil aviation transport turnover, passenger transport volume, cargo and mail turnover, flight hours, take-offs and landings, fleet size, transport revenues, airline operating revenues and so on[11][12]. Macroeconomic indicators include GDP, population, disposable income of urban residents, proportion of tertiary industry, value added of tertiary industry, and number of airports. Data for the above indicators can be obtained from the 2000-2024 Statistical Yearbook, Civil Aviation Production Statistics, Airline Division Social Responsibility Report, and Airline Division Sustainable Development Report.

3.1 Results of Grey Relation Analysis

At the airline level, total transport turnover, passenger traffic, take-off and landing sorties, flight occupancy rate, fleet size, flight hour, international flight turnover, cargo and mail traffic, passenger turnover, and airline operating revenue were selected as transport indicators to arrive at the grey correlation coefficient as shown in Table 1.

Table 1. The grey correlative degree of Transport indicators

Transport indicators	Degree of correlative
Total Transport Turnover	0.968
Passenger Traffic	0.959
Take-off And Landing Sorties	0.972
Flight Occupancy Rate	0.936
Fleet Size	0.844
Flight Hour	0.905
International Flight Turnover	0.887
Cargo And Mail Traffic	0.865
Passenger Turnover	0.852
Airline Operating Revenue	0.905

In terms of macroeconomics, GDP, population, disposable income of urban residents, share of tertiary industry, value added of tertiary industry, and number of airports were selected as macroeconomic indicators. The grey correlation coefficient as shown in Table 2.

Table 2. The grey correlative degree of Macroeconomic indicators

Macroeconomic indicators	**Degree of correlative**
Population	0.606
GDP	0.893
Disposable Income Of Urban Residents	0.917
Share Of Tertiary Industry	0.642
Value Added Of Tertiary Industry	0.837
Number Of Airports	0.714

3.2 Multi-Collinearity Analysis Results

At the industry level, the study selected total turnover, passenger traffic, flight hours, GDP and disposable income per capita of urban residents as key variables and their covariance results are shown in Table 3.

Table 3. Results of covariance analysis of key variables at the industry level

Variant	***VIF***
Total Transport Turnover	319.533
Passenger Traffic	462.963
Take-off And Landing Sorties	211.067
GDP	937.935
Disposable Income Of Urban Residents	748.107

At the airline level, the study selects total airline turnover, passenger traffic, flight hours, flight occupancy rate and operating revenue as key variables and their multi-collinearity results are shown in Table 4.

Table 4. Results of covariance analysis of key variables at the airline level

Variant	***VIF***
Total Transport Turnover	17.079
Passenger Traffic	67.629
Flight Hours	1.717
Flight Occupancy Rate	4.711
Operating Revenue	70.194

The covariance results show a large variance inflation factor (VIF) between the variables and significant multicollinearity. If the multiple linear regression model is used directly, the problem of multicollinearity arises. Therefore, this study adopts partial least squares regression (PLSR) to establish a prediction model for carbon emissions from civil aviation in China.

3.3 Predictive Model

3.3.1 Industry Forecast Results.

To overcome the detrimental effects of multicollinearity of variables in the modelling process, all five variables were decomposed using Partial Least Squares Regression (PLSR). The R^2 values indicate the explanatory power of the independent variables with respect to the dependent variable. Table 5 shows the R^2 values for the different principal components.

Table 5. the R^2 values for the different principal components.

Dependent Variable	*One Principal Component*	*Two Principal Component*	*Three Principal Component*	*Four Principal Component*
Carbon Emission	0.959	0.9722	0.9748	0.9747

In this study, three principal components are taken and their cumulative variance contribution has reached 97.48%, which can fully explain the variable information. Finally, the regression equation is established under the current principal components, and the regression equation between the dependent variable and the independent variable group is obtained through standardization.

The industry forecast equation is shown:

$$\ln C_1 = 1.857 + 0.411 * \mathrm{In} \cdot P_1 + 0.366 * \mathrm{In} T_1 - 0.226 * \mathrm{In} A_1 - 0.009 * \mathrm{In} G_1 - 0.0075 * \mathrm{In} R_1 \quad (8)$$

Calculate the results of the fit and test set data comparison results, as shown in Fig 1.

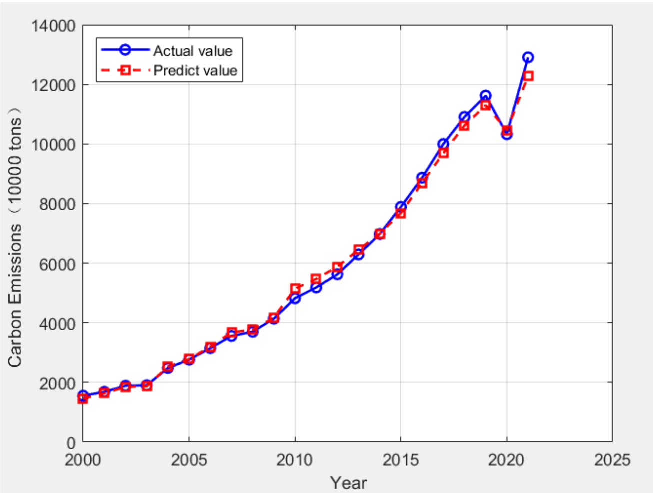

Fig. 1. Comparison of actual and projected carbon emissions from civil aviation

3.3.2 Airline Forecast Results.

This regression equation was obtained by fitting the airlines data.

$$\ln C_2 = 3.934 + 0.355 * \ln P_2 + 0.239 * \ln T_2 - 0.052 * \ln A_2 + 0.049 * \ln G_2 + 0.215 * \ln R_2 \quad (9)$$

Calculate the operation data of airlines A, B, C and other carriers for 2015-2024 (excluding 2020-2022) substituting into Equation 2, and compare the results with the industry prediction results to achieve the purpose of verifying the reliability of the model, and the comparison results are shown in Figure 2.

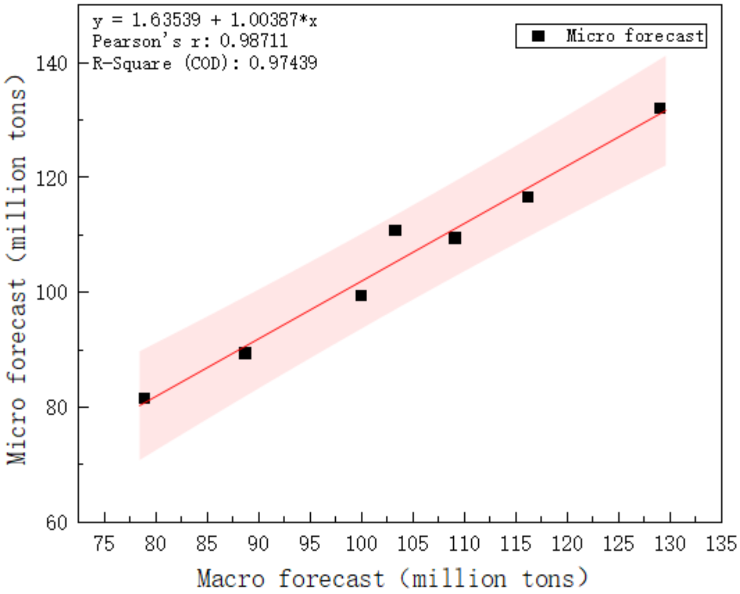

Fig. 2. Macro forecast versus micro forecast results

3.3.3 Carbon Peak Projections.

Based on the '14th Five-Year Plan for Civil Aviation Development' and the average growth rates of the indicators for 2017, 2018, 2019, 2023 and 2024, as shown in Table 6, which are substituted into the STIRPAT prediction model to obtain the predict curves (Figure 3).

Table 6. Growth rates of indicators in 2025-2030

	Total Transport Turnover	*Passenger Traffic*	*Take-off And Landing Sorties*	*Disposable Income Of Urban Residents*	*GDP*
2025	17%	17.8%	12.9%	5.3%	5.8%
2026-2030	10.26%	10.6%	8.9%	5.3%	5.8%

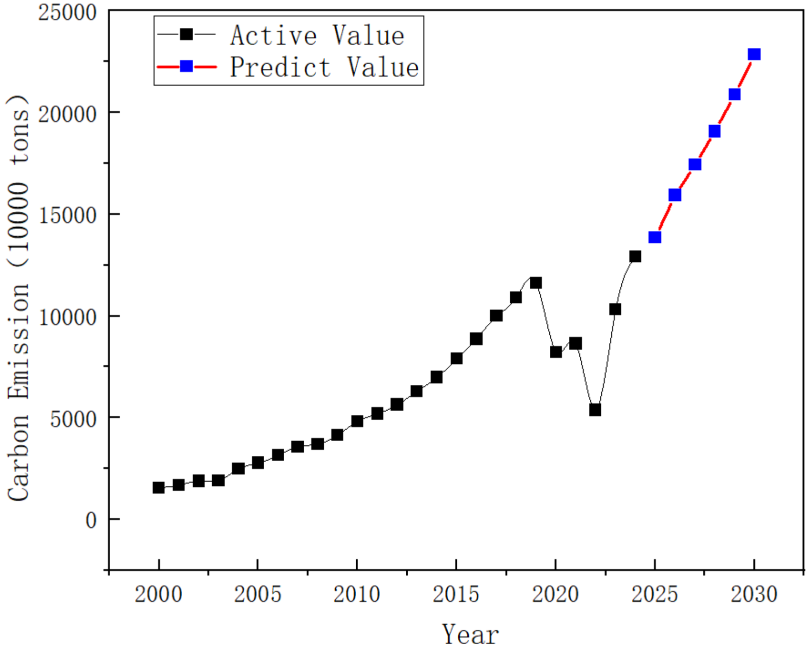

Fig 3 Projected results for 2025-2030

4 Conclusion

The innovation of this study is mainly in the data selection and prediction methods:

(1) In terms of data selection, the study used post COVID-19 data to populate the 2020-2022 epidemic period, rather than using pre-2019 data for projections.

(2) In terms of method selection, considering the availability of civil aviation development data, the STIRPAT model was used to make a industry prediction of the industry's carbon emissions in the short term, and the industry prediction was verified by using the data of the airline company to verify the accuracy of the industry prediction.

In conclusion, the Institute proposes an improved STIRPAT model whose accuracy is applicable to short- and medium-term projections of future trends in carbon emissions or peak carbon for small samples.

Of course, the study of civil aviation carbon emissions in this paper has shortcomings:

(1) The models designed in this study can be used for short- and medium-term forecasting, and for long-term forecasting the STIRPAT model can be combined with system dynamics models or machine learning to capture non-linear trends.

(2) Follow-up studies could introduce policy drivers such as R&D subsidies, use of sustainable aviation fuel (SAF), etc. into the STIRPAT model. Table 7 shows the civil

aviation carbon reduction strategies and modelling improvement methods in other countries.

Table 7. Carbon reduction strategies and modelling improvement methods for civil aviation in selected countries or regions.

Country/Region	Strategy	Effectiveness	Lessons for STIRPAT
EU	ETS, ReFuel EU, flight bans (e.g., short-haul)	High (emissions down 5% post-ETS)	Policy stringency can be quantified.
USA	SAF tax credits, FAA efficiency programs	Moderate (SAF adoption lagging)	Incentives may need stronger enforcement.
China	Fleet modernization (e.g., COMAC C919)	Rapid efficiency gains	Technology diffusion rates matter.

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