Journal of Cleaner Production 275 (2020) 122734

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

Short-term carbon emissions forecast for aviation industry in Shanghai

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ARTICLE INFO

Article history:
Received 23 April 2019
Received in revised form
16 May 2020
Accepted 8 June 2020
Available online 17 July 2020

Handling Editor: Dr Sandra Caeiro

Keywords:
Aircraft emissions
Sustainable aviation
Time series
ARIMA
Shanghai
Aircraft fuel consumption

ABSTRACT

Given the China's fast-evolving aviation market, a reliable carbon dioxide (CO_2) emissions forecast is essential to identify and mitigate the environmental impact of aviation market. Due to slot limits and airport capacity constraints in Shanghai, the rate of traffic growth has slowed down in recent years. However, the increasing number of regional and international flights tends to drive the fuel consumption and carbon emissions to an unexpectedly high level. This study uses a two-tiered bottom-up emissions prediction method for empirically estimating and forecasting air transport CO_2 emissions on all the passenger flights to/from Shanghai. The Autoregressive Integrated Moving Average (ARIMA) linear model was applied for a 5-year prediction of air transport fuel consumption and en route CO_2 emissions. The research established that 36.49 million tonnes of CO_2 will be emitted into the atmosphere by the end of June 2021, representing a 6.41% increase compared to the same period a year earlier. Market-based recommendations are proposed including a nationwide carbon market and a carbon offset scheme, accordingly.

1. Introduction

The aviation industry is identified as one of the most energy-consuming and pollution-intensive sectors. It contributes approximately 2% of global CO_2 emissions (Brasseur and Gupta, 2010). These emissions disrupt the global carbon cycle and lead to a range of planetary warming impacts, including the potential ecological, physical and health problems (Ritchie and Roser, 2019). Moreover, this results in a large amount of external costs for the air transport industry. For example, the external climate change costs for CO_2 emissions produced by passenger flights accounted for €19.1 billion in selected 33 European airports in 2016, making up 0.2% of the EU28 GDP (European Commission, 2019).

Such pollutants from China are growing with alarming concern as its CO_2 emissions from 1990 to 2014 increased by 468% (IEA, 2016). In 2015, over 390 million sectors were flown by passengers on Chinese domestic routes, filling most of the 436 million seats offered by 48 airlines (CAAC, 2016a, 2016b). It is undisputable that China will produce more carbon emissions, as it begins to overtake the United States as the world's largest passenger market by 2030 (IATA, 2014).

Although measurements, such as biomass-derived jet fuel and the replacement of aircraft with better fuel-efficiency alternatives, could be utilized to reduce CO_2 emissions in the air transport industry, those measures appear either time-consuming or high-priced (Zhou et al., 2016) or in some cases not enough. There is constant pressure to control the environmental impact of air transport (Efthymiou and Papatheodorou, 2019). The Chinese government has taken a number of actions to mitigate carbon emissions. China has been actively participating in the global carbon market since 2005 (Swartz, 2016). A national Emissions Trading System (ETS) was put into action in 2017 to reduce carbon emissions in electricity, building materials, nonferrous metals, as well as aviation industry (KPMG, 2017). It was estimated that the China's ETS will become the world's largest scheme with twice the size of the EU ETS after its fully implementation in 2019 (Zhang, 2015). By the end of May 2017, more than 160 million tonnes of CO_2 ($MtCO_2$), worth over 3.7 billion RMB, have been traded in 7 pilot regions. Shanghai was the second region in China that piloted ETS in 2013, and the first city whose emissions reduction plan covered 57% of the city's emissions, including emissions from non-industrial sectors like aviation (ICAP, 2017).

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https://doi.org/10.1016/j.jclepro.2020.122734
0959-6526/

Serving over 100 million passengers annually, Shanghai has become the largest aviation market in China. While there are measures in place to mitigate aviation externalities and fight climate change, their success depends in proper target setting. Targets and environmental indicators need proper measurement of the externality in order to have a positive impact. Despite the size of the market and the growth rate of air transport in Shanghai, studies seldom measured the emissions.

To bridge this gap, this study attempts to empirically estimate and forecast carbon emissions caused by air transport in routes to/from Shanghai with a two-tiered bottom-up prediction method. This approach combines two existing techniques (the ICAO Fuel Consumption Formula and the seasonal Autoregressive Integrated Moving Average model) in order to contribute to the ongoing work on the development of the sustainable aviation framework planning.

This paper is structured as follows. Section 2 reviews previous literature regarding carbon emission forecast approaches, while Section 3 explains the data and methodology adopted. Section 4 examines the air transport development and the amount of carbon emitted in Shanghai. Section 5 discusses the findings and results, while Section 6 concludes this paper with emphasizing on the new insights.

2. Review of carbon emission prediction methodologies

An extensive body of empirical literature has explored carbon emission and its determinants (Yi et al., 2016; Lin and Nelson, 2019). Determinants, such as economic factors, are widely selected as explained and explanatory variables for decomposition-based multivariate forecast methods (Lei et al., 2016; Huang et al., 2018; Acheampong and Boateng, 2019). For example, the Department for Transport (2013) generated a complicated CO_2 forecast from 2010 to 2050 for the UK based aviation industry leveraged on the National Air Passenger Allocation Model together with the Fleet Mix Model that compassed domestic flights and international flights. It also claimed that there were significant uncertainties about the future path of the factors driving changes in CO_2 emissions in the UK market such as unforeseen recessions or other external shocks. Likewise, Chen et al. (2016) considered the relationship between environmental problems and economic growth. They estimated and predicted the carbon emissions from urban transportation in Beijing with a combination of the environmental Kuznets curve and the ARIMA model. Like other multivariant methods, they can hardly avoid the uncertainty brought by the response of carbon reduction schemes, such as the predicted GDP.

Multivariate models demonstrate superiority in identifying such influencing factors. Major improvements emanating from environmental policies and modern technologies cannot be accurately forecast. Consequently, the advantage of the multivariate approach does not necessarily translate into better forecasts (Hosseini et al., 2019). By contrast, the univariate forecasts are based on a model fitted only to present and past observations over a given time series (Chatfield, 2003). While multivariate methods emphasize hypothesis and explanation, most univariate analysis emphasizes description, which minimises the above-mentioned uncertainty in the prediction. Ardakani and Ardehali (2014) claim that the accuracy of multivariate methods can be improved when the energy consumption is predicted with socio-economic indicators and demand side management (DSM) data. But those indicators are constantly changing in fast-evolving markets such as China and difficult to predict (Yuan et al., 2016). Therefore, the univariate models are primarily relied upon in this paper.

Statistical techniques, including exponential smoothing models, Holt-Winters and ARIMA are commonly used to undertake predictions in the air transport passenger demand (Grubb and Mason, 2001; Chen et al., 2009; Sammagio and Wolters, 2010). While ordinary regression models provide an initial description of the data and form the basis of several simple forecasting methods, ARIMA models, detail the present value of a series of past values and past prediction errors. Rather than put more weights to the last observations, ARIMA model relies more on data points which are significant in the autocorrelation, providing a parsimonious and cost-effective model structure for quick decision-making. Therefore, the ARIMA model becomes one of the most popular standalone statistical methods that are used to forecast energy consumption and greenhouse gas emissions (Samer et al., 2001). Particularly, CO_2 emissions forecast by ARIMA has been tested on several countries including Malaysia, United States, Iran and Zimbabwe (Ang et al., 2013; Silva, 2013; Lotfalipour et al., 2013; Chigora et al., 2019). For instance, Chigora et al. (2019) investigated the effects of carbon dioxide on the attractiveness of Zimbabwe as a tourism destination with a basic non-seasonal ARIMA technique. Since they used annual data from the World Bank, the effects of seasonality was unattended. Likewise, other similar research rarely predicted of carbon emissions caused by aviation activity at a regional level during a short/mid-term. This paper tends to fill the gap and provide guidance for the control of carbon emissions. Although hybrid methods based on ARIMA model and machine learning have gained more attentions recently, those empirical studies were based on either annual data or monthly data without seasonality (Yuan et al., 2016; Wang et al, 2018a, 2018b; Li and Wang, 2019). Research showed that the classic ARIMA model is more effective at capturing cycles among other time series models (Reikard, 2019). The monthly data in this study captured the trend and seasonality in the demand of air travel, which fits the specialty of ARIMA model. Moreover, the prediction accuracy of ARIMA model decreased as the forecasting step increased, which made it suitable for short/mid-term forecast (Liu et al., 2014). Consequently, these specifications of data sequence and research scope justify the applicability of ARIMA model in this study. Despite its simplicity, the ARIMA model was chosen as the primary methodology to forecast the fuel consumption and carbon emission in the aviation industry.

3. Emissions prediction method

The Emissions Prediction Method is a 2-tiered methodology for estimating and forecasting emissions. The first tier is based on the ICAO Fuel Consumption Formula, which provides a primary approach to estimating fuel consumption for each flight (ICAO, 2017). The second tier will estimate the historical fuel consumption and present a 5-year prediction with seasonal ARIMA linear models. Thereafter, the projected en route fuel consumption will be converted to the amount of carbon emission with a constant emission factor as shown in Fig. 1.

3.1. Data and carbon emissions estimation

Geographically, CO_2 emissions emitted from aviation sector are usually investigated at a worldwide or national wide level, because those emissions are produced along the routes. Theoretically, an airport-level or city-level emission estimation should be more focused on the terminal area or during the Landing and Take-Off (LTO) cycle. However, the reporting standard for aviation greenhouse gas in Shanghai considers carbon emissions from engine start up to engine shutdown (SDRC, 2012). Therefore, this study evaluates how carbon emission increases with the growing number of passenger flights connecting Shanghai to the rest of the world.

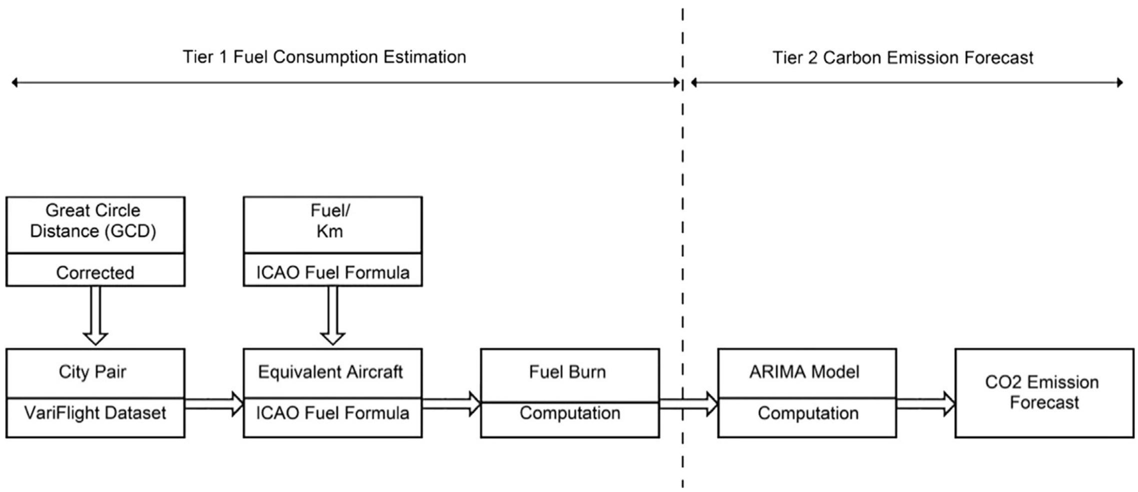

Fig. 1. Methodology flow chart.

Due to the unavailability of historical fuel data, this study conducts a bottom-up method for fuel consumption assessment, as it is recommended by the Intergovernmental Panel on Climate Change (IPCC) for its accuracy (Zhou et al., 2016). The ICAO Fuel Consumption Formula serves as the analytical tool for the fuel consumption evaluation based on aircraft type and route length (ICAO, 2017). The historical airline schedule data comes from VariFlight, which is a Chinese information technology company specialising in aviation data services. The dataset includes date, time, origin, destination, carrier and aircraft type from July 2009 to June 2017.

The Great Circle Distance (GCD) for each route was obtained from VariFlight's Location Indicators database, which represents the distance between the origin and destination measured by latitude and longitude coordinates. While the GCD illustrates the shortest distance between two points on the surface of a sphere, the actual flight path tends to be prolonged due to circuitous routings, stacking, traffic and weather-driven corrections (Efthymiou and Papatheodorou, 2018). Consequently, a GCD Correction Factor measured by additional GCD length is employed to adjust the actual distance flown in reality and include the emissions generated during the distance (ICAO, 2017). For routes that are less than 550 km, a correction factor of 50 km was applied; routes that are more than 5500 km, 125 km was applied; otherwise, 100 km was applied.

Next, the estimated fuel consumption for each flight was calculated based on the corrected GCD and aircraft type extrapolated from the ICAO Fuel Consumption Formula. While aircraft fuel consumption is nonlinear, the formula demonstrates as a look-up table that provides fuel consumption by segment distances. Hence, the fuel consumption can be estimated when the corrected GCD and aircraft type are pivoted to each of the segments.

Attention is required to the uncertainty of this method. First, the actual flown distance may vary considerably for the same city pair. Precisely, circuitous routings and stacking has become commonplace at airports operating at or close to their capacity. A constant correction factor based on route length cannot capture for all of the inconsistencies. Furthermore, there are considerable differences in fuel consumption among the same aircraft type, due to factors such as age, weight, configuration and engines. Pagoni and Psaraki-Kalouptsidi (2017) proposed an aircraft-distance-direction method to map CO_2 emissions with flight tracking data in the United States, however, no similar research been conducted in China. Although ICAO Fuel Consumption Formula may produce relatively lower results, it becomes the only option to estimate aircraft fuel consumption with minimum inputs.

3.2. Autoregressive Integrated Moving Average model

The general form of the ARIMA model consists of three parts: the auto-regression (AR); the integration (I); and the moving average (MA). The auto-regression part in a time series model for the variable x_t refers to a lagged value of x_t. For example: a lag 1 autoregressive term is x_{t-1} (multiplied by a coefficient). When the autocorrelation of any particular lag is the same regardless of where it is in the time series, the series can be defined as stationary. Then, the sample autocorrelation function (ACF) will be implemented to identify a structure of time series data. Otherwise, the time series needs to be differenced to be made stationary until it becomes an "integrated" version of a stationary series. Therefore, “I” denotes the time of difference. Likewise, the moving average part represents a past error (multiplied by a coefficient). A typical ARIMA model can be specified by three order parameters (p,d,q), where p represents the order of the auto-regressive field, d represents the order of the differencing, while q represents the order of the moving average process. A typical ARIMA (p,d,q) model can be expressed as follows:

$$
\begin{aligned}
&\varnothing_p(B)(1-B)^d x_t = \delta + \theta_q(B) w_t \\
&\varnothing_p(B) = 1 - \varnothing_1 B - \varnothing_2 B^2 - \ldots - \varnothing_p B^p \\
&\theta_q(B) = 1 - \theta_1 B - \theta_2 B^2 - \ldots - \theta_q B^q
\end{aligned}
\tag{1}
$$

where x_t denotes a linear function of the values of x; B is the backshift operator; $\varnothing_p(B)$ and $\theta_q(B)$ are polynomials in B of order p and q, respectively; while d is the order of regular differences; whilst δ and w_t denotes independent random shocks, and the function w_t is portrayed as white noise (Sen et al., 2016).

When time series data illustrates a regular pattern of change which repeats over S time periods, it can be defined as seasonality. A seasonal ARIMA model can be built with seasonal AR and MA terms, predicting x_t using data values and errors at times with lags during the span of the seasonality. One general notation for the model is denoted as ARIMA (p,d,q) (P,D,Q)[S], where p, d and q refer to the orders of the non-seasonal AR, I and MA, while P, D and Q refer to the orders of the seasonal AR, I and MA parts of the model, respectively. S denotes the number of time periods until the pattern repeats again. Without differencing, the ARIMA (p,d,q) (P,D,Q)[S] model could be written more formally as follows:

$$\Phi\left(B^S\right) \varnothing(B)(1-B)^d\left(1-B^S\right)^D x_t=\theta\left(B^S\right)\theta(B)w_t \tag{2}$$

The non-seasonal components are:

$$AR: \quad \varnothing_p(B)=1-\varnothing_1 B-\varnothing_2 B^2-\ldots-\varnothing_p B^p \tag{3}$$

$$MA: \theta_q(B)=1-\theta_1 B-\theta_2 B^2-\ldots-\theta_q B^q \tag{4}$$

The seasonal components are:

$$\text{Seasonal AR:} \quad \Phi\left(B^S\right)=1-\Phi_1 B^S-\Phi_2 B^{2S}-\ldots-\Phi_P B^{PS} \tag{5}$$

$$\text{Seasonal MA:} \quad \theta\left(B^S\right)=1-\theta_1 B^S-\theta_2 B^{2S}-\ldots-\theta_Q B^{QS} \tag{6}$$

Despite its advantages and popularity in forecasting, ARIMA also places limitations on observations and forecast periods. Firstly, the ARIMA model requires a certain number of observations (at least 50) to maintain its accuracy, which demands a data range covering a relatively long period of time. Secondly, the ARIMA model is more suitable for short-term projecting periods rather than long-term ones. In this sense, the ARIMA model demonstrates its potential in the short-term forecast with a long time series dataset.

Due to the trend and seasonality of aviation industry, a series of seasonal ARIMA will be measured and tested to define the most appropriate one. Once an adequate ARIMA (p,d,q) (P,D,Q)[S] model is identified, a forecast using recursive process with minimum mean squared error linear predictions can be produced. Furthermore, the en route CO_2 emission can be estimated by fuel consumption multiplied with the emission factor (3.15), which is a constant representing the number of tonnes of CO_2 produced by burning a tonne of jet fuel in Shanghai (SDRC, 2012). The function is listed below, where i refers to flight i.

$$CO_2 \; emission=\sum(fuel\ consumption_i \times emission\ factor_i) \tag{7}$$

3.3. Model validation and comparison

Air transport demand is sensitive to unexpected events, such as the 2008 global recession, terrorist attacks and propagation of disease (Franke and John, 2011). The grounded capacity usually lead to less fuel consumption and carbon emission in the short-term. Those major historical events can be identified as structural breaks econometrically with Chow test (Stock and Watson, 2017). However, it chooses a null hypothesis for a structural change in an exogenous manner. In this regard, the endogenous technique proposed and extended by Bai and Perron (1998, 2003) is adopted to detect multiple structural breaks in longitudinal data. Meanwhile, the breakpoints assume that each segment is independent. In this sense, data prior to the break is uninformative for the data after the break. Only post-break data will be used for training.

Several metrics are used to evaluate the predictability power of the ARIMA models. The mean error (ME) and mean percentage error (MPE) are signed measures of error, indicating if the forecasts are biased. Mean squared error (MSE) is introduced to measure the average of the squares of errors (or deviations), which is expressed by the variance of errors plus the square of the ME. The RMSE is the square root of the MSE and known as the estimated white noise standard deviation in the ARIMA analysis when adjusted for the degrees of freedom for error. During the parameter estimation process, the RMSE will be minimized and it determines the width of the confidence intervals for predictions. Where bias exists, the variance of errors and MSE will also be minimized. The mean absolute scaled error (MASE) is used to compare forecasts across data sets with different scales, where the method with the lowest MASE is the most preferred one. The mean absolute error (MAE), mean absolute percentage error (MAPE) and Theil's U statistics are expressed as equations below, where P_t and x_t denote the forecasting and actual values at period t, while n represents the total number of predictions. Lewis (1982) interprets the MAPE results as a way to judge the accuracy of the forecast stating that: less than 10% is a highly accurate forecast; 10%–20% is a good forecast; 20%–50% is a reasonable forecast; while more than 50% is a weak and inaccurate forecast. Due to the defects in Theil's U_1 framework, this study adopts U_2 as a measure of forecast quality (Bliemel, 1973). When U_2 is less than 1, it indicates the forecast result is better than the naïve forecast, which uses the last period's actuals as this period's forecast. Otherwise, it indicates the opposite.

$$MAE=\sum_{t=1}^{n}|P_t-x_t| \Big/ n \tag{8}$$

$$MAPE=\sum\nolimits_{t=1}^{n}|(P_t-x_t)/x_t| \Big/ n * 100 \tag{9}$$

$$U_2=\frac{\sqrt{\frac{1}{n}\sum_{t=1}^{n-1}\left(\frac{P_{t+1}-x_{t+1}}{x_t}\right)^2}}{\sqrt{\frac{1}{n}\sum_{t=1}^{n-1}\left(\frac{x_{t+1}-x_t}{x_t}\right)^2}} \tag{10}$$

Last, the most preferable prediction from ARIMA model will be compared with forecasts conducted by popular time-series predictors (Holt-Winters and TBATS) to see if ARIMA model outperforms the others. The Holt-Winters forecasting procedure is one of the most popular forecasting techniques for time series. It monitors three aspects of a dataset: the typical value (average), the slope (trend) over time, and the cyclical repeating pattern (seasonality). Then, the three aspects are expressed as three types of exponential smoothing to predict for the present and future (Holt, 1957; Winters, 1960). The TBATS model was introduced by Livera et al. (2010). This innovation state space framework was originally designed for forecasting complex seasonal time series. The framework incorporates Box-Cox transformation, ARMA errors, trend and seasonal components to exponential smoothing models.

4. Empirical analyses: CO_2 emissions projection in Shanghai

A total number of 96 data points of traffic and fuel consumption by month were aggregated from each flight and plotted as a time series data from July 2009 to June 2017. During this 8-year spread, there was a sizable 73.7% increase in the total traffic, whereas the fuel consumption increased exponentially by 195.3%, tripling in magnitude since mid 2009. Approximately 26% of the total traffic to/from Shanghai are regional and international flights, which consume more than 55% of fuel among all the flights.

In the initial two years, the correction factor uplifted the GCD by approximate 8%, which is consistent with the study conducted by the Department for Transport (2013). Meanwhile, the adjusted flight distance produced at least a 5% increase in monthly fuel consumption, which revealed that the fuel consumption and fuel efficiency at cruise are significantly lower than take-off and landing. As the average GCD increased from 1223 km in 2009 to

1860 km in 2017, the adjusted rate for route length decreased to around 5%. This reveals the mechanism behind the ICAO corrected factor. The longer the flight length, the lower the adjusted rate.

4.1. ARIMA model results

Fig. 2 illustrates the perpetual increase in fuel consumption and decomposition in Shanghai from the mid 2009 to 2017, as noted by the trend and data component. The seasonality component in Fig. 2 is displayed through a regularly repeating pattern of highs and lows relating to each month. In terms of the estimated seasonal factors, the largest one emerges in August (approximately 40), whereas the lowest is evident in February (approximately −50), indicating a peak in fuel consumption in August and a trough in February each year. It also implies that suitable differencing will be necessary to remove trend and seasonality to obtain stationary. The trend component presents evidence that the fuel consumption almost doubled during 8 years. A relatively steady growth in the last year has witnessed the effects of market maturity and airport capacity constraints, which slowed down the growth of air traffic movements.

However, the highly irregular behaviour and the sudden increase in trend from 2011 to 2012 imply that the historical fuel consumption may be affected by unexpected events. Table 1 shows the optimal number of breakpoints, estimated break dates and their confidence intervals for the fuel consumption dataset. Although as many as 5 optimal breakpoints have been identified, all the estimated break dates fall into their confidence intervals only when the optimal number is 1 and 4. Therefore, the original dataset (Group 1) and two sub-group datasets from pose-breaks will be used for training. Group 2 denotes pose-break dataset from July 2011 to June 2017, when optimal number is 1. Group 3 denotes pose-break dataset from July 2015 to June 2017.

To measure the accuracy of each forecast model, the historical fuel consumption data is split into two parts for training and testing. Similarly, the forecast results can be divided into the ex post and the ex ante periods. The best possible forecast model can be identified by comparing testing dataset against forecasted ex post result. For instance, the first 7-year data (from July 2009 to June 2016) in Group 1 is analysed as the in-sample training data for initial parameter estimation and model selection. Then, the out-sample test will be processed with the last year of data (from July 2016 to June 2017) to evaluate the forecast accuracy. Consequently, Group 3 is dropped from the test, because it is less than two periods (24 months).

Table 2 demonstrates the ARIMA model outputs with a series of evaluation statistics. The statistics for training set measures the fitness of the "best model" in properly monitoring the trend in the past. Meanwhile, the second row in each group tests the model with the out-sample data to reveal the uncertainty in the measurement. In this sense, a small gap between in-sample and out-sample data not only represents the accuracy of the prediction, but also the consistency in the dataset. Overall, the gaps in Group 2 are smaller, by which the last year test data can be better measured through ARIMA (0,1,1)(0,1,1)[12]. As discussed in Section 3, RMSE, MAE, MAPE and MASE assess the errors from different perspectives. Those indicators that have negatively-oriented scores establishes the criteria that the lower, the better. Group 1 gets the higher results of RMSE, MAE and MAPE, which makes it less competitive. Theil's U also confirms that 2 groups are better than the naïve models with less than 1, among which Group 2 is better than Group 1 due to smaller results.

The sum-of-squared-errors are usually applied to measure the in-sample forecast errors of the predictive model. Fig. 3 shows a correlogram of the in-sample forecast errors for lags 1−20. The blue dotted lines indicate the 95% confidence bounds. Although the autocorrelations for the forecast errors in Group 1 touches the significant bounds, it does not exceed. Deeper analysis through Ljung-Box test statistics indicate that the p-values are greater than 0.05, signalling that there is little evidence of non-zero autocorrelations in the forecast errors at lags 1−20. To summarise, the residuals obtained have the property of white noise, and the models are well-fitted and desirable.

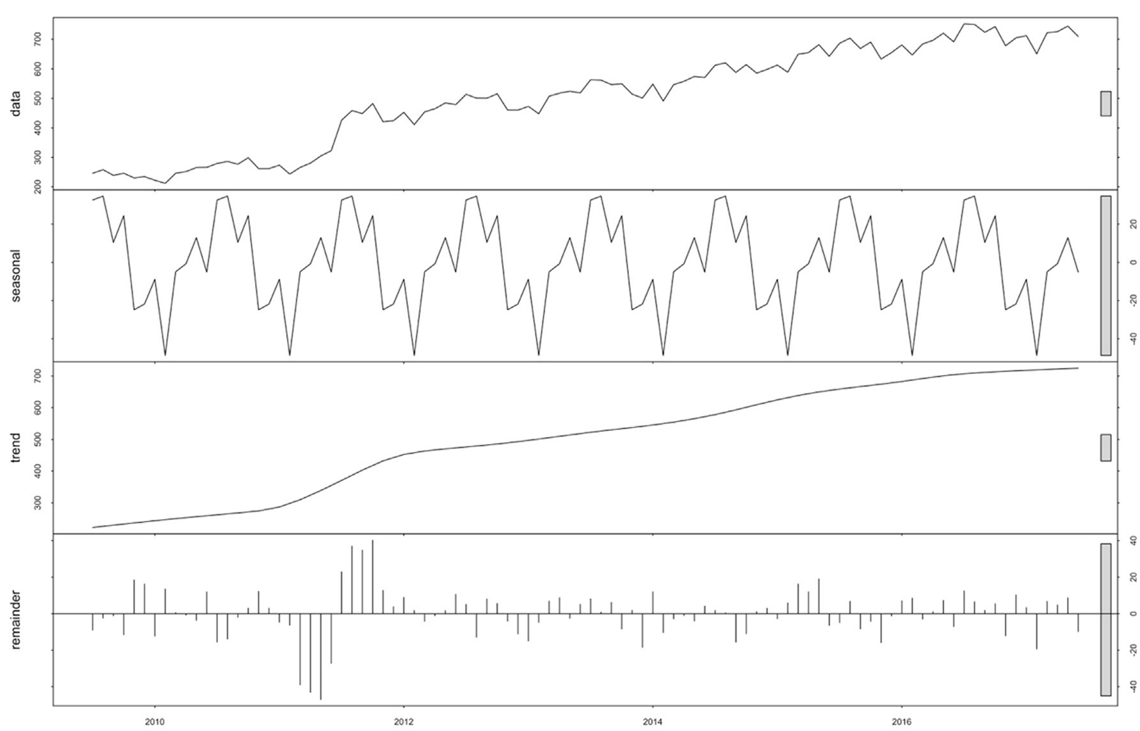

Fig. 2. Fuel consumption and decomposition in Shanghai (in million kilograms).

Table 1
Break dates and their confidence intervals.

Optimal number of breakpoints	Estimated Break dates	95% Confidence interval for break dates
1	2011 (6)	2011(5) - 2011(7)
2	2011 (6) 2014 (6)	2011(5) - 2011(7)
3	2011 (6) 2013 (3) 2015 (2)	2011(5) - 2011(7)
4	2011 (6) 2013 (2) 2014 (4) 2015 (6)	2011(5) - 2011(7) 2012(12) - 2013(5) 2014(2) - 2014(5) 2015(4)- 2015(8)
5	2011 (6) 2012 (8) 2013 (12) 2011 (5) 2015 (2) 2016 (4)	2011(5) - 2011(7)

Table 2
ARIMA model output comparison.

			Results	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1	Theil's U
Group 1	Training period	July 2009–June 2016	Training set	−0.1320831	15.9646	11.36931	−0.09552988	2.444152	0.1562054	−0.01952432	NA
	Best model	ARIMA (1,0,0) (2,1,0)[12] with drift	Test set	−26.3272803	36.29738	28.74718	−3.74581586	4.067613	0.3949639	0.61540169	0.9509738
Group 2	Training period	July 2011–June 2016	Training set	−0.8506824	11.86625	8.568141	−0.1788947	1.497259	0.1494746	0.02358116	NA
	Best model	ARIMA (0,1,1) (0,1,1)[12]	Test set	−14.5987457	23.61249	18.616089	−2.0972633	2.634703	0.3247651	0.49614531	0.608241

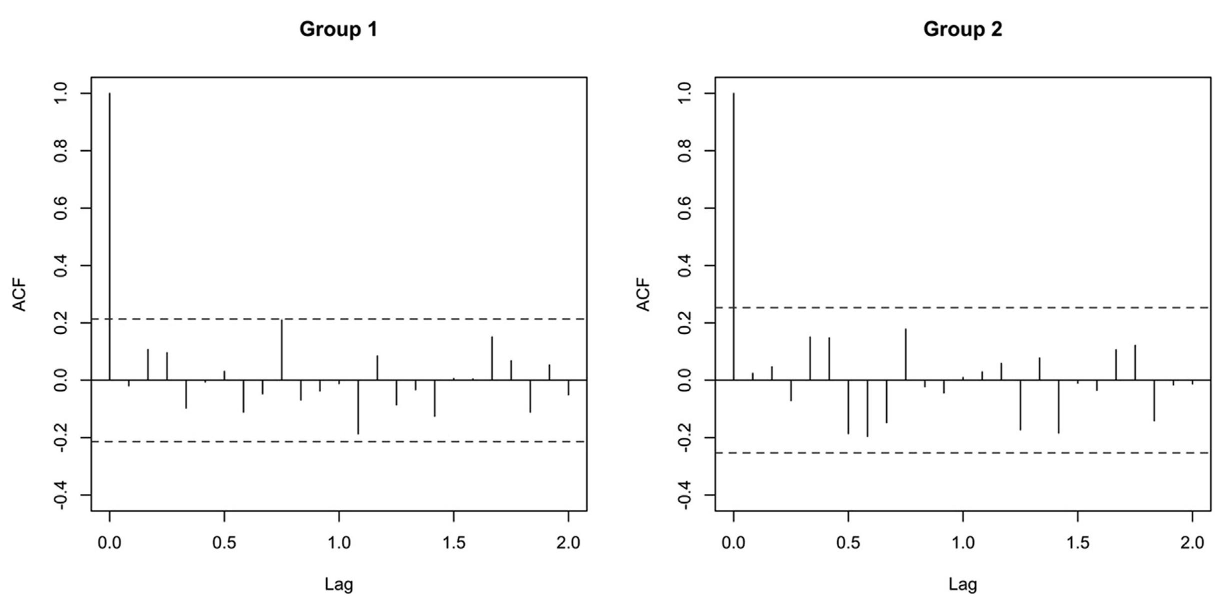

Fig. 3. Autocorrelation function (ACF) from forecasting fuel consumptions using ARIMA methods.
Note: the blue dotted lines indicate the 95% confidence bounds.

Plots of the forecast errors were extrapolated to check if the forecast errors are normally distributed with mean zero and constant variance as illustrated in Fig. 4. The plots show that the forecast errors seem to have a constant variance over time. However, the forecast errors for Group 1 fluctuate dramatically between −30 and 70 while forecast errors for Group 2 fluctuates between −30 and 30, which indicates that the rapid growth during structural break (June 2011) affects the model most.

From July 2009 to June 2011, the aircraft movements and fuel consumptions in domestic and international market remain stable, which resulted from a gradual post global economy recession recovery. Initially, the relatively lower fuel consumption came from weakened demand for air travel during the cyclical downturns. Meanwhile, service entry for the 787 and A380 were severely delayed, as Chinese based airlines were encouraged to cancel or delay their aircraft orders by the CAAC (Bailey and Clark, 2008; Brothers, 2008;

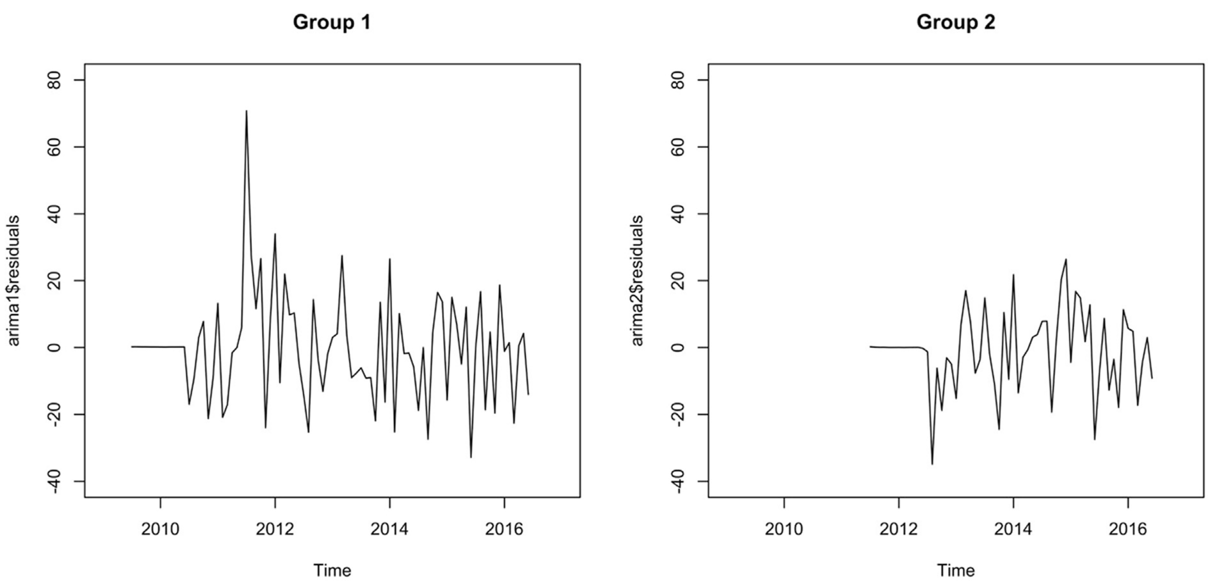

Fig. 4. Residuals plots from forecasting fuel consumptions using ARIMA methods.

Karp, 2009). Therefore, the lack of extra capacity also contributed to a lower level of fuel consumption and the comprehensive recovery. International air transport recovered to pre-recession levels in early 2009 (Pagoni and Psaraki-Kalouptsidi, 2017). However, the rather volatile increase of fuel consumption in the mid-2011 indicated that the aviation industry in Shanghai fit the Extended “U-Shape” crisis proposed by Franke and John (2011) with a considerable time lag between Economic cycle and aviation downturns.

Fig. 5 checks the ex post forecast (blue line) against historical data (black dotted line). It is noticeable that 2 groups provide ex post forecasts slightly above the historical data, due to the rapid growth at the early stage and the mechanism of the ARIMA model that depend more on data points that are significant in the auto-correlation. Since data between 2016 and 2017 was excluded for out-sample test, the ARIMA models fail to capture the slowdown during that period. As a consequence, the fast-paced increase from 2011 to 2016 leads to a higher out-sample ex post forecast.

Fig. 6 illustrates 5-year en route fuel consumption forecasts from July 2016 to June 2021, where: the black line represents the observed in-sample data from July 2011 to June 2016; the blue line represents the out-sample evaluation and prediction from July 2016 to June 2021; dark and light grey areas denote 80% and 95% confidence intervals, respectively. Overall, the forecast result for Group 1 is the higher, because it catches the rapid increase in the initial two years. Group 2 captures the overall upward trend and the cyclical fluctuation with wider confidence intervals.

To sum up, the model validation among 2 groups suggests that dataset Group 2 provides an adequate predictive model for en route fuel consumption from July 2011 to June 2016, which is difficult to improve upon. The ARIMA model (0,1,1) (0,1,1)[12] indicates that en route fuel consumption data shows a clear cyclical pattern every 12 months. To capture both non-seasonal and seasonal factors, the first order of the differencing and the first order of the moving average process are necessary for both non-seasonal and seasonal parts of the model.

Table 3 presents a comparative analysis of the forecast accuracy of three proposed methods (ARIMA, Holt-Winters and TBATS). The results indicate that the three models are better than the naïve model in terms of forecast accuracy. The ARIMA model is slightly more stable and reliable than the other two methods with smaller Theil's U. Therefore, the ARIMA model is applied to predict the en route fuel consumption and carbon emission in the next 5 years.

4.2. Fuel consumption forecast and carbon emission estimation

The ARIMA model (0,1,1) (0,1,1)[12] predicted that the en route fuel consumption will continue to increase, albeit at a slower rate over the next five years. It is very likely that the en route fuel consumption would not sustain its rate of growth as it did from 2011 to 2016, due to slot limits and airport capacity constraints. However, it could be further stimulated by the increasing number of regional and international flights. The primary task enforced by the civil aviation development, which is endorsed in the “Thirteenth Five-year Plan”, is to build a nationally integrated airport system and enhance the competitiveness of Shanghai as an international hub (CAAC, 2016a, 2016b). The Shanghai Master Plan also claims that Pudong and Hongqiao International Airports will serve for 160–180 million passengers annually by 2040, 40% of which will represent international travellers (Shanghai Government, 2016). To achieve this, some short-haul domestic flights may be shifted to nearby cities, such as Nantong, Wuxi, Changzhou and Suzhou. Furthermore, the new international slot allocation policy forced Chinese carriers to end their monopolistic positioning on major international routes by now competing with other Chinese and international carriers and to also operate on secondary routes and new routes (CAAC, 2018a, 2018b). In this sense, a larger proportion of regional and international flights will consume more fuel over the coming years.

Table 4 outlines the CO_2 emissions forecast from July 2016 to June 2021. The monthly en route emission forecast characterises the cyclical behaviour and uncertainty of the carbon emission. It forecasts that 36.49 $MtCO_2$ will be emitted into the atmosphere by the end of June 2021, which represents a 6.41% increase when compared to the same time frame one year earlier.

The Chinese ETS sets historical emissions based on data pertaining to 2013–2015 as the benchmark for the free volume allocation. Any excess emissions above this baseline warrant financial penalties. These fines can amount to 100,000 RMB, together with further sanctions regarding credit record and access to special funds for energy conservation and emissions reduction measures

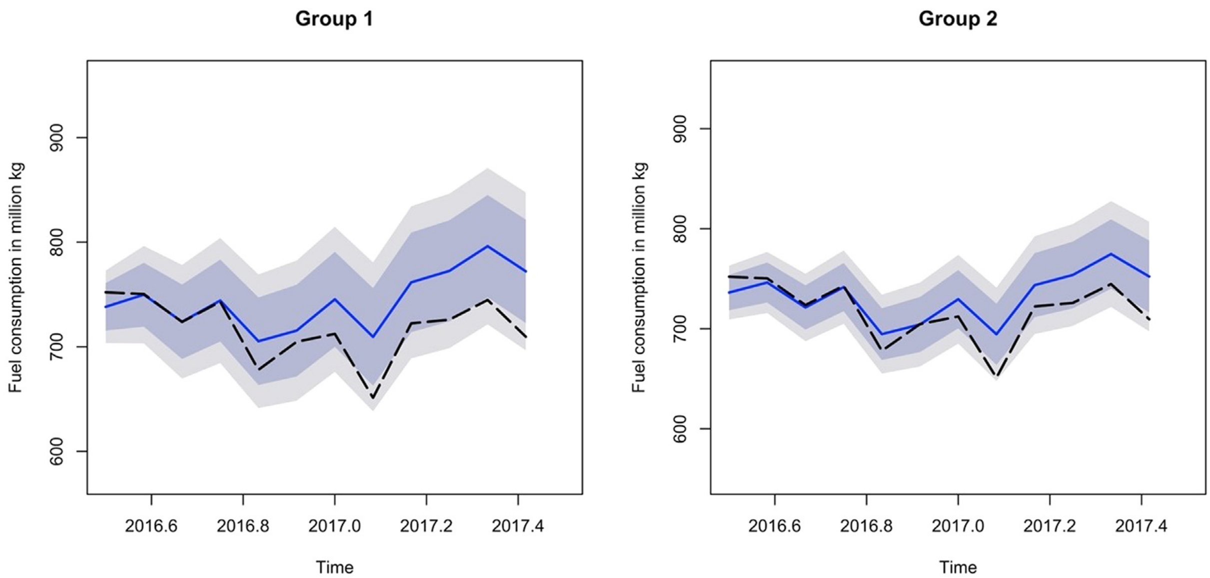

Fig. 5. Comparison between ex post predicts and historical data
Note: the black dotted lines indicate the monthly fuel consumptions estimation; the blue lines show the ex post forecast results from ARIMA models; the dark and light grey areas denote 80% and 95% confidence intervals of the forecast. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

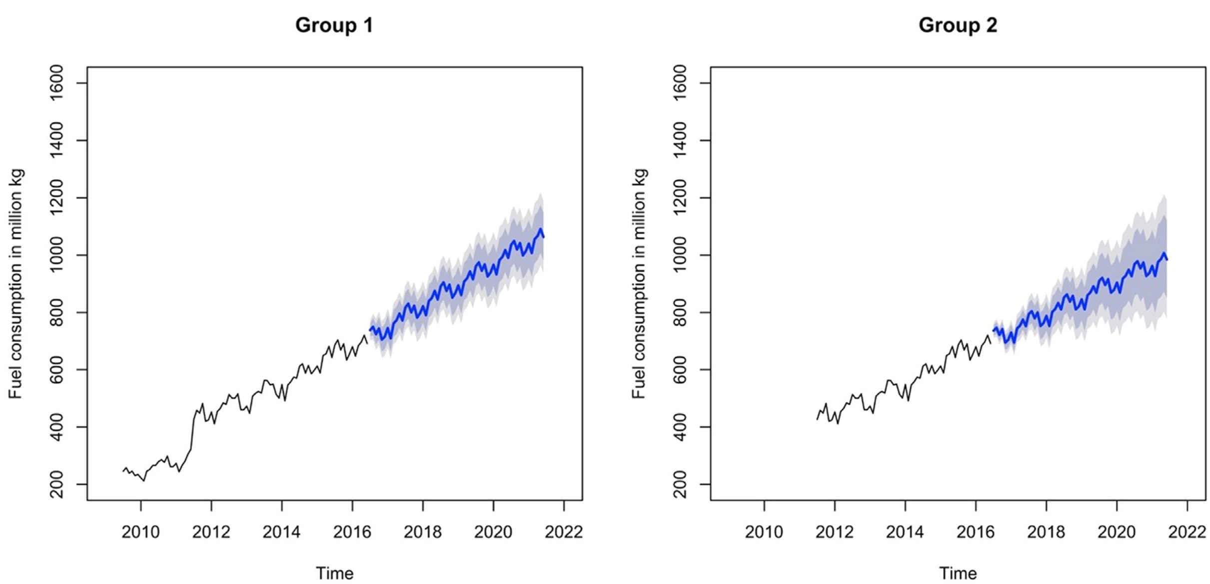

Fig. 6. 5-year en route fuel consumption forecasts from July 2016 to June 2021.
Note: the blue lines show the forecast results from ARIMA models; the dark and light grey areas denote 80% and 95% confidence intervals of the forecast. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Table 3
Comparison of the fuel consumption prediction results among models.

		ME	RMSE	MAE	MPE	MAPE	MASE	ACF1	Theil's U
ARIMA	Training set	−0.8506824	11.86625	8.568141	−0.1788947	1.497259	0.1494746	0.02358116	NA
	Test set	−14.5987457	23.61249	18.616089	−2.0972633	2.634703	0.3247651	0.49614531	0.608241
Holt-Winters	Training set	2.041994	12.77157	10.51301	0.3613733	1.81204	0.1834036	0.006052892	NA
	Test set	−17.219147	23.44075	18.51265	−2.4614565	2.63345	0.3229606	0.411951628	0.612555
TBATS (1,{0,0},1,{⟨12,5>})	Training set	−1.458286	11.20447	8.977057	−0.3341414	1.674006	0.1566083	−0.02820245	NA
	Test set	−15.392383	25.69253	20.105092	−2.2115278	2.841437	0.3507413	0.39960026	0.6518658

Table 4
Forecast results for fuel consumption and CO_2 emissions.

	Fuel Consumption (in million tonnes)						Emissions ($MtCO_2$)	
	Actual	Forecast	Lo 80	Hi 80	Lo 95	Hi 95	Actual	Forecast
Jul-16	0.75	0.74	0.72	0.75	0.71	0.76	2.37	2.32
Aug-16	0.75	0.75	0.73	0.77	0.72	0.78	2.36	2.35
Sep-16	0.72	0.72	0.70	0.74	0.69	0.76	2.28	2.27
Oct-16	0.74	0.74	0.72	0.77	0.70	0.78	2.34	2.34
Nov-16	0.68	0.69	0.67	0.72	0.66	0.73	2.14	2.19
Dec-16	0.70	0.70	0.68	0.73	0.66	0.75	2.22	2.22
Jan-17	0.71	0.73	0.70	0.76	0.69	0.77	2.24	2.30
Feb-17	0.65	0.69	0.66	0.73	0.65	0.74	2.05	2.19
Mar-17	0.72	0.74	0.71	0.78	0.69	0.79	2.28	2.34
Apr-17	0.73	0.75	0.72	0.79	0.70	0.80	2.29	2.37
May-17	0.74	0.77	0.74	0.81	0.72	0.83	2.35	2.44
Jun-17	0.71	0.75	0.72	0.79	0.70	0.81	2.24	2.37
Jul-17		0.79	0.75	0.83	0.73	0.85		2.50
Aug-17		0.80	0.76	0.85	0.74	0.87		2.53
Sep-17		0.78	0.74	0.82	0.71	0.85		2.46
Oct-17		0.80	0.75	0.85	0.73	0.87		2.52
Nov-17		0.75	0.71	0.80	0.68	0.83		2.37
Dec-17		0.76	0.71	0.81	0.69	0.84		2.40
Jan-18		0.79	0.74	0.84	0.71	0.87		2.48
Feb-18		0.75	0.70	0.81	0.67	0.83		2.37
Mar-18		0.80	0.75	0.86	0.72	0.88		2.53
Apr-18		0.81	0.76	0.87	0.73	0.90		2.56
May-18		0.83	0.78	0.89	0.75	0.92		2.62
Jun-18		0.81	0.75	0.87	0.72	0.90		2.55
Jul-18		0.85	0.79	0.91	0.76	0.95		2.69
Aug-18		0.86	0.80	0.93	0.76	0.96		2.72
Sep-18		0.84	0.77	0.90	0.74	0.94		2.64
Oct-18		0.86	0.79	0.93	0.75	0.96		2.70
Nov-18		0.81	0.74	0.88	0.70	0.92		2.55
Dec-18		0.82	0.75	0.89	0.71	0.93		2.58
Jan-19		0.85	0.77	0.92	0.73	0.96		2.66
Feb-19		0.81	0.74	0.89	0.70	0.93		2.55
Mar-19		0.86	0.78	0.94	0.74	0.98		2.71
Apr-19		0.87	0.79	0.95	0.75	0.99		2.74
May-19		0.89	0.81	0.97	0.77	1.01		2.81
Jun-19		0.87	0.79	0.95	0.74	0.99		2.74
Jul-19		0.91	0.82	1.00	0.78	1.04		2.87
Aug-19		0.92	0.83	1.01	0.79	1.06		2.90
Sep-19		0.90	0.81	0.99	0.76	1.03		2.82
Oct-19		0.92	0.82	1.01	0.77	1.06		2.89
Nov-19		0.87	0.77	0.96	0.72	1.01		2.74
Dec-19		0.88	0.78	0.98	0.73	1.03		2.77
Jan-20		0.90	0.81	1.00	0.75	1.06		2.85
Feb-20		0.87	0.77	0.97	0.71	1.02		2.74
Mar-20		0.92	0.82	1.02	0.76	1.08		2.89
Apr-20		0.93	0.82	1.03	0.77	1.09		2.92
May-20		0.95	0.84	1.06	0.79	1.11		2.99
Jun-20		0.93	0.82	1.04	0.76	1.09		2.92
Jul-20		0.97	0.86	1.08	0.80	1.14		3.05
Aug-20		0.98	0.86	1.09	0.80	1.15		3.08
Sep-20		0.95	0.84	1.07	0.78	1.13		3.00
Oct-20		0.97	0.86	1.09	0.79	1.16		3.07
Nov-20		0.93	0.81	1.05	0.74	1.11		2.92
Dec-20		0.94	0.81	1.06	0.75	1.13		2.95
Jan-21		0.96	0.84	1.09	0.77	1.15		3.03
Feb-21		0.93	0.80	1.06	0.73	1.12		2.92
Mar-21		0.98	0.85	1.11	0.78	1.18		3.07
Apr-21		0.99	0.85	1.12	0.78	1.19		3.11
May-21		1.01	0.87	1.14	0.80	1.21		3.17
Jun-21		0.98	0.85	1.12	0.78	1.19		3.10

(ICAP, 2017). Therefore, airlines and airports are liable for reducing direct and indirect emissions by over 10,000 tonnes CO_2/year. However, with over 10% year-over-year increase in annual fuel consumption, the prediction result envisions an increase of approximately 35.45%–69.19% of carbon emissions over the 5-year period from the mid 2016 to mid 2021 compared with the baseline. The carbon emission allowance could not only become one of the natural barriers for new entrants but also slow down the growth of incumbent carriers.

The current costs for such for allowances are 8.5 RMB per ton in Shanghai, while the IMF estimates that a carbon price of 15 RMB per ton could be in place by 2017. It also predicts that the price could rise to 227.5 RMB by 2030 (IMF, 2016; Swartz, 2016). Subsequently, the fluctuating carbon cost also reveals that the short-term prediction of aviation emissions may benefit airlines in carbon emission trading and exchanging, but they need to take proper initiatives to control the demand in advance.

5. Findings and discussion, contribution, limitations and future work of the study

5.1. Findings and discussion

The research aims to assess the carbon footprint of the air transport industry with a two-tiered bottom-up Emissions Prediction Method. Shanghai was chose as a case study due to the size of its market and its expected growth rate.

The estimation suggests that the fuel consumption in Shanghai tripled in magnitude since mid 2009. By the end of June 2017, the regional and international flights composed approximately 26% of total traffic and consumed more than half of the fuel. The structural breaks identified during model validation pointed out that the economic recession and strict policy during June 2011 contributed to the recession in the air transport industry. The study established that 36.49 $MtCO_2$ will be emitted into the atmosphere by the end of June 2021, representing a 6.41% year-over-year growth. Compared with baseline, the carbon emissions will increase by between 35.45% and 69.19%. Despite the slot constrains, the continuing increase of fuel consumption may come from the changing landscape as there is a continuous increase in flights to more regional and international destinations rather than domestic points.

There has been very limited research targeting the aviation emissions market in Shanghai. Liu et al. (2019) established a bottom-up fuel-based method to develop CO_2 emission inventory in airports in Shanghai (see Table 5). Since their study only considered emissions during the LTO cycle, it is reasonable to conclude that the LTO phase contributed 6.33% of emissions in 2015, which is slightly lower than the 7% global average (Kim et al., 2007). This can be explained by a larger proportion of long-haul international flights, which consumed more than half of the total fuel consumption in the Shanghai market. Liu et al. (2018) adopted a scenario-based top-down approach and argued that the emissions will reach 21.74 and 28.61 $MtCO_2$, by 2020 and 2030 respectively. Their lower predictions may result from the top-down method, second-hand data sources, as well as idealised growth rates. Nevertheless, both studies claimed that the carbon intensity of aviation sector in Shanghai will increase, which is consistent with findings identified in this research.

The accuracy of the fuel consumption estimation largely depends on the ICAO corrected factor. While the adjusted rate of route length drops with the growth of flight distance, chances are that the actual carbon emission would be higher than the estimation. Moreover, the Chinese aviation market continues to surge as there was an increase of 10.9% of passenger aircraft movements in 2017, which outweighs any gains in attempting to reduce aviation emissions (CAAC, 2018a, 2018b). Without proper correcting measurements, the emissions will continue to increase year-over-year. The command and control (CAC) approach and self-regulation are commonly promoted in the environmental sector, such as the Ecodesign Directive (EUR-Lex, 2009). But the CAC relies on imposing obligations and standards to ensure the improvements in the quality of the environment through non-monetary incentives (Görlach, 2013). To achieve environmental goals at the least cost, market-based recommendations are proposed based on the

Table 5
Comparative analysis among aviation CO_2 emission research in Shanghai.

Year	$MtCO_2$	Scenario	Citation
2015	1.57		Liu et al. (2019)
	24.79		This study
2020	21.74	BaU (without carbon emissions cap and carbon emissions trade)	Liu et al. (2018)
2030	28.61	CAPsec (only with emissions constraints policies)	

analysis presented above to mitigate the environmental impact of the fast-evolving aviation industry.

The market rationale has lived on mainly through emissions trading systems and voluntary carbon offsetting schemes. Firstly, it is necessary to accelerate the construction of a nationwide carbon market and allow emission trading outside of the pilot regions. Existing carbon pilots needs to be further expanded in terms of geographical coverage and sectoral scope (Zhang, 2015). Meanwhile, the possibilities of carbon market jeopardizing the development of the aviation industry need special attention in taking proper initiatives of demand control. On the other hand, the carbon-offsetting scheme requires a company or individual to finance reductions in different activities or locations to compensate and neutralize for the emissions from aviation sector (Efthymiou and Papatheodorou, 2019). In this sense, the offsetting scheme offers a more solid basis for carbon emission trading, which allows organizations outside an ETS to offset their carbon emissions by purchasing credits from emission reduction projects (Gaast et al., 2018). Therefore, the combination of ETS and offsetting scheme provide incentives for the aviation sector to drive efficiency improvements.

Scholars may argue that carbon offsetting has lost acceptance to the unfolding climate crisis (Blum and Lövbrand, 2019). However, measures can be taken to avoid not meeting the program targets of emission offsetting. For example, the CORSIA mechanism promoted by ICAO only applies to international civil aviation flights with voluntary participations from both origin and destination countries with minimal climate ambition (ICAO, 2019). The externalities of domestic aviation can be monitored and controlled by additional remarks, such as a nationwide offsetting scheme. Having witnessed the weak ambition of CORSIA, ICSA urges governments and the aviation industry to enhance action now with aspirations of achieving “zero climate impact” by 2050 (ICSA, 2019).

Lastly, selecting an emission target is never easy. Specific details need to be worked out by sectoral, regional, and countrywide studies on carbon abatement. An aggressive basis would collapse with potentially devastating consequences, especially in developing countries with an immature aviation industry. Therefore, certain exemptions should be given, such as the three-year exemption or the 0.1% of the total reference value to new entrants proposed by CORSIA.

5.2. Contribution

Geographically, CO_2 emissions emitted from aviation sector are usually investigated at a worldwide or national wide level. However, this research set about to forecast carbon emissions from aviation at a regional level during a short/mid-term. Hence, an investigation into the emissions of Shanghai is definitely worthy of deeper investigative analysis as it is China’s financial capital whose airline growth is expanding exponentially. More importantly, the rarely discussed regional industry-specific issues was explored based on the environmental regulations in the commercial world.

The aviation industry is one of the most energy-consuming and pollution-intensive sectors. However, there is very limited literature that has investigated the trend of the emissions emitted by aircraft through a bottom-up method. This paper contributes to the existing literature by presenting a two-tiered bottom-up Emissions Prediction Method for estimating and forecasting air transport CO_2 emissions. This study combined two existing models and presented an applicable approach to map and predict carbon emissions with limited inputs, which has not been investigated in previous research.

This method is applicable to any airline that operate different types of aircraft to any city pair that have readily available records of their historical flight schedules. While most of the other studies examines the emissions from a viewpoint of the Landing and Take-Off (LTO) cycle, this study uniquely examined it from engine start up to engine shutdown. Consequently, the historical emissions throughout the network were mapped and assessed, while the fuel consumption and carbon emissions can be predicted. The results can be used for policy making and can also be applied as a guidance for sustainable framework planning. It could also be used as a template for measuring the emissions at other large Chinese and foreign international cities that have such a large volume of aircraft traffic.

The ICAO fuel consumption formula has become the official tool for all United Nations entities, but it is mostly UN-system-wide used (ICAO, 2016). This paper examined the applicability of this method in estimating aircraft fuel consumption regionally with a case study. Although the formula improves the estimation accuracy by considering the circuitous routings with the correction factor based on the governance underwritten by the ICAO, no previous investigations has captured the mechanism and uncertainty underpinning the correction factor. This paper detected and highlighted the points of attention when using the correction factor. More precisely, the adjusted rate of the flight distances was slightly higher than that of fuel consumption. With the increase of the flight length, the adjusted rate dropped, which may lead to a relative low carbon emission estimation and prediction.

Previous top-down approaches are incapable of adequately capturing cyclical seasonality (Summer vs Winter), whereas the bottom-up process applied in this study is able to measure not only the uncertainty but also the cyclical nature of the aviation market. The application of seasonal ARIMA model uniquely captures the trend and seasonality, which significantly impact atmospheric emissions due to the low relative demand in the winter and the corresponding high demand during the summer months.

Furthermore, the possible impacts of the structural breaks were tested and discussed during model validation, which has rarely been investigated before. The earlier financial crisis coupled with the strict aviation policy contributed to the recession in the air transport industry, which subsequently became reversed, thus leading to the rapid growth during the first structural break in June 2011.

While market-based recommendations were commonly mentioned in mapping carbon emissions, the importance of proper target setting was rarely discussed. This study shed light on this gap and claimed that certain exemptions should be given to the airlines when the goal is too difficult to achieve. Although studies seldom targeted the aviation emissions market in Shanghai, a comparative analysis was conducted among the published results from the limited available research. This overall ensemble of unique inputs that were applied in this study separates it from other studies.

5.3. Limitations and future work of the study

As discussed in Section 3, the mechanism behind the ICAO corrected factor may bring a lower fuel consumption and carbon emission estimation. The accuracy of fuel consumption estimation can be further enhanced by using the actual flight length data recorded by Automatic Dependent Surveillance – Broadcast, if the historical fuel data is not available. Additionally, this study presents an unconstrained univariate forecast of the carbon emission in the absence of airport capacity constraints. Although slot limits and constraints in Shanghai may slow the growth rate of CO_2 emissions, the prediction is developed independent of the ability of the airport capacity and air traffic control system. Further research is necessary to fill these gaps.

6. Conclusion

The rapid expansion of China's aviation industry has raised concerns about the CO_2 emissions emitted each year. Targets and environmental indicators need proper measurement of the externality in order to have a positive impact. This paper presented a two-tiered bottom-up Emissions Prediction Method for the estimation and prediction of CO_2 emissions emitted from aviation activities.

This study assessed flight-based fuel consumptions using the ICAO Fuel Consumption Formula. The mechanism underpinning the ICAO correction factor indicate the discreet possibility of a relatively lower result in the estimation and forecast. The uncertainty and the cyclical nature of aviation market were analysed using the monthly en route carbon emissions. The way that the structural breaks which affected the model were investigated. The ARIMA (0,1,1) (0,1,1)[12] model was evaluated and identified as the best forecast framework, which was applied to a 5-year prediction and established that a 6.41% year-over-year increase followed. The accruing carbon emission may be slowed down due to the slot limitation in Shanghai. But it is more likely to see a continuing growth under government plans and as a result of the new international slot allocation policy. Lastly, market-based recommendations were established based on the growing trend of aviation-related emissions. The implementation of a domestic version of CORSIA was highly recommended. This study also argued that the target amount of carbon emissions was too ambitious and suggested that certain exemptions should be given to the airlines.

CRediT authorship contribution statement

Huijuan Yang: Writing - original draft, Writing - review & editing. **John F. O'Connell:** Writing - review & editing.

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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