RESEARCH

Modeling and forecasting of CO_2 emissions resulting from air transport with genetic algorithms: the United Kingdom case

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Abstract

The increase in the air transportation density affects global warming negatively by increasing the CO_2 emitted to the environment. The issue becomes even more important when the agricultural lands and drinking water resources on the flight routes are considered. This situation leads to the development of certain environmental concerns in the society and makes it necessary for the countries to forecast in the correct direction to develop some preventive strategies. To make a contribution to this issue, emission modeling and forecasts regarding emissions originating from air transportation were made in this study through genetic algorithms, a popular artificial intelligence technique. Using the flight information of 32 European countries, the degree of relationship between the number of flights and passengers and CO_2 emission from air transportation was calculated. Based on the highly correlating results obtained, time series models were developed for the UK's domestic and international airline transportation in which the highest number of flights takes place and passengers are carried. Using these models, the forecasts based on the UK's flight numbers until 2029, the number of passengers to be transported, and air transportation–related emissions were made. Results with high correlation values ranging from 0.99 to 0.87 were obtained in the implementations.

1 Introduction

The share of airline transportation in the total passenger transportation across Europe is increasing day by day. People's preferences in passenger transportation are shifting from road to maritime, rail, and air transportation (Fig. 1a). Considering the increase in annual passenger numbers in the European Union member countries between 2013 and 2017, the airline transportation has the highest percentage increase ranging between 4 and 12% compared to other types of transportation (Fig. 1b). This increasing rate has caused several problems to emerge brought about by air transportation. Although air transport has advantages in many aspects such as duration and comfort of travel, emissions released to the atmosphere during the travel affect the environment negatively. It directly and indirectly harms the health of people and other living creatures through inhalation of

polluted air and drinking waters being polluted by this air because of precipitation.

Emissions from air transport constitute 2.5% of the total emissions in the world (Ritche 2020). The climate effect is thought to be greater in total anthropogenic warming (Lee et al. 2021). While this may seem like a relatively small amount, consider that if global commercial aviation were a country in the national CO_2 emissions standings, the industry would rank number six in the world between Japan and Germany (Overton 2022). The organization of the European Civil Aviation Conference (ECAC), in which the European Union member and candidate countries and the UK as the founding member are included, shares the view that environmental concerns represent a potential obstacle in the future for the international aviation industry (ECAC 2019). ECAC countries carry out studies on competitive and sustainable transportation systems that are linked to combating climate change and emphasize the efficient use of resources. Working closely with the European Commission, it carries out activities in terms of the environmental impacts of the aviation industry. In this context, it encourages the member states to regularly report on aviation-related CO_2 emissions. Accurate evaluation of the CO_2 emission data collected and making

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Fig. 1 a Air, maritime, rail, and road percentage ratios in passenger transportation in European Countries between 2013 and 2017 (Eurostat 2019). **b** Increase rates of passengers transported in European Countries between 2014 and 2017 by type of transportation (Eurostat 2019)

(a)   (b)
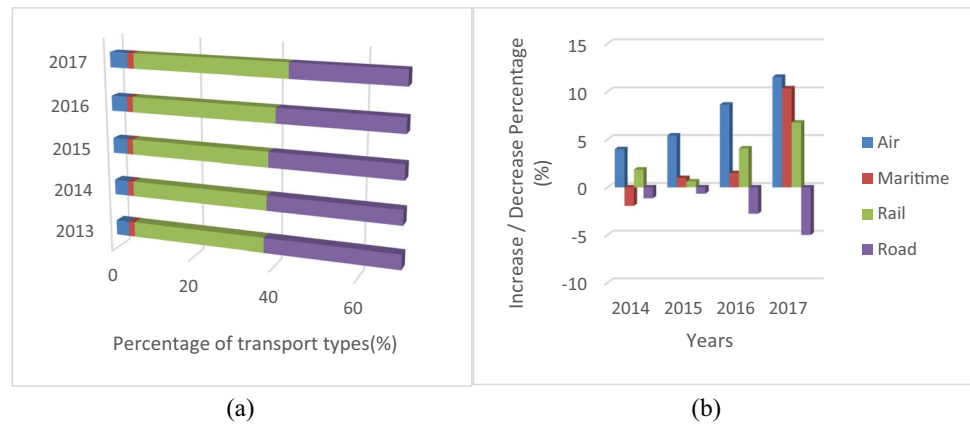
correct predictions for the future will increase the effectiveness of the activities of countries and organizations such as ECAC that take environmental concerns into consideration. The UK, one of the ECAC member countries, has the largest air connection level (based on IATA connection level index value) in Europe (IATA 2019). It constitutes an important destination point in aircraft movements originating from international passenger transportation. Until reaching this destination, aircraft pass over many countries (agricultural lands, lakes, seas, etc.), especially many European countries (Fig. 2). Emissions that

occur during air passenger transportation affect the living areas, agricultural lands, lakes, and seas with drinking water sources. This situation also significantly affects the climate of the countries on the transit route together with global warming.

With this study, it is thought that it will contribute to the prediction of the future emissions of domestic and international airline passenger transportation from other countries, especially the UK, and their harmful effects on the climate, and to determine the timing and size of the measures to be taken by the countries.

Fig. 2 UK origin flights and affected countries (Update: 30.05.2022) (Radarbox 2022)
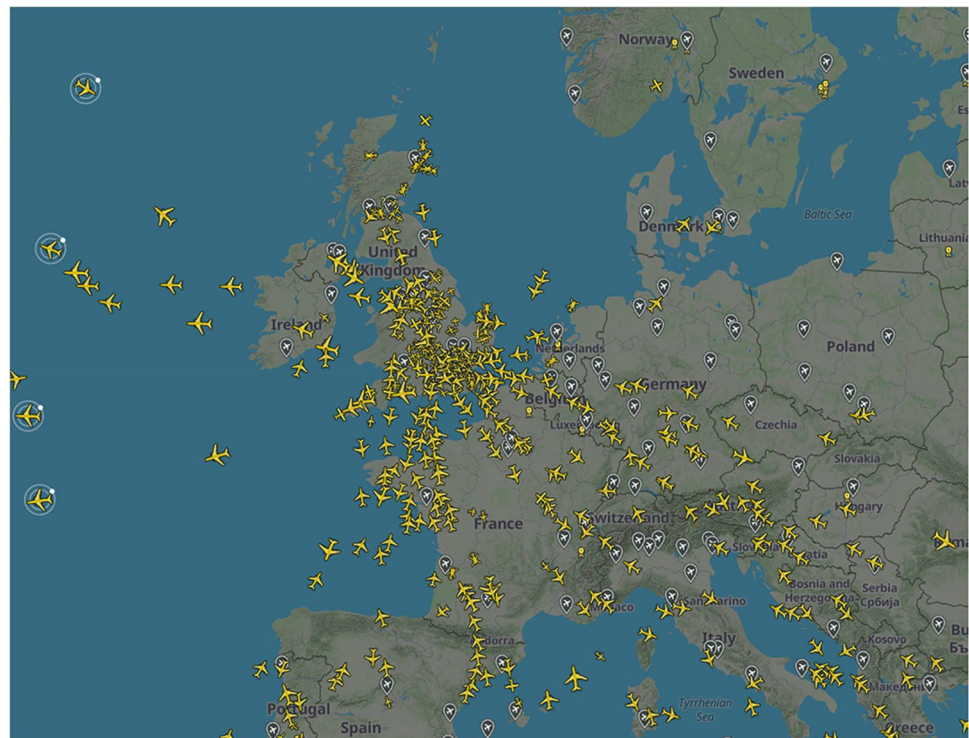
2 Literature

In the literature, there are forecasting studies on various emission sources. Most of these studies comprise CO_2 modeling and forecasting studies carried out on certain geographic sizes such as provinces and countries.

Wu et al. (2015) made modeling and forecasting of CO_2 emissions for BRICS countries. In the study, by applying different multi-variable gray forecasting models, mean absolute percent error (MAPE) results were compared and it was emphasized that the highest CO_2 emission increase rate was in China.

Sen et al. (2016) applied autoregressive integrated moving average (ARIMA) for forecasting. In the study carried out at a company operating in the steel industry in India, they forecast energy consumption and greenhouse gas (GHG) emissions with high accuracy.

In another study where CO_2 emission was forecast along with wind energy and energy demand, evolutionary neural networks technique was compared with different techniques such as Particle Swarm and Differential evolution. In the study, 1-month data of Ireland taken every 15 min for 2017 were used. More accurate predictions were obtained with the evolutionary neural network (Mason et al. 2018).

When other studies carried out in this context are examined, it is seen that classical and artificial intelligence techniques are frequently used in modeling and forecasting of emission types such as CO_2 and NO_x (Chitnis et al. 2012; Wang and Ye 2017; Huang et al. 2019; Segnon et al. 2017).

Studies on the emissions forecast originating from transportation are more limited compared to the forecasting studies on CO_2 and its derivatives based on geographical size. In another study conducted on the Belgian sea territory, maritime emissions forecasting and inventory were calculated through an activity-based emission model. While an increase in CO_2 and NO_x was predicted, a decrease in SO_2 emissions was calculated (Schrooten et al. 2008).

In the study in which vehicle miles traveled, energy consumption, and GHG emissions for passenger transportation were forecast, simultaneous equation models were developed with a random coefficient panel data model (Rentziou et al. 2012).

Using curves of retirement models and econometric analysis, Hernández-Moreno and Mugica-Álvarez (2013) forecast an increase by 31% in vehicle-related greenhouse gas emissions. The forecast results were obtained with a confidence level of over 95% in the medium term.

There are also studies that emphasize the advantages of genetic algorithm in solving problems with large solution space in the field of aviation. Singh (2018) aimed to minimize fuel consumption in order to contribute to emission reduction in transport aircraft design. He emphasized that the probability of finding the global optimum is higher in the study in which the genetic algorithm is used.

In another study, it was emphasized that the human brain would be limited in the evaluation of comprehensive data in the field of aviation, and that genetic algorithms would be a good element of the decision support system in solving problems. In addition, the use of genetic algorithms has been recommended for the solution of transportation-related (combinatorial) problems in which many alternatives are evaluated (Fernández et al. 2014).

In this study, unlike other studies in the literature, using the genetic algorithm (GA) technique, modeling and forecasting of air transportation–related emissions based on the data of 32 European countries were discussed. At this point, unlike other studies, instead of using two or more functions, a model comprised of 4692 linear and nonlinear functions was tested. With the models developed using GA, the number of flights, the number of passengers, and CO_2 forecasts regarding the UK until 2029 were made.

3 Genetic algorithm

Genetic algorithm is an artificial intelligence technique developed by Holland in 1975 (Holland 1992). Since that date, it has been applied in many fields from manufacturing to health. The basis of the technique
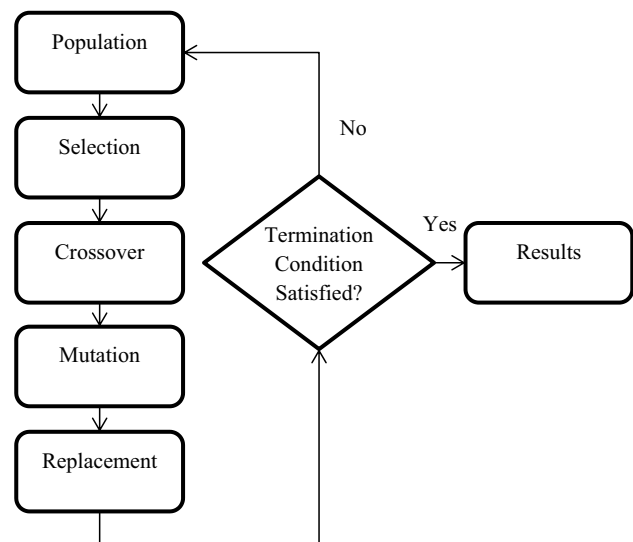

**Fig. 3** Genetic algorithm process

is based on Darwin's theory of evolution. Genetic algorithm technique, which uses the approach that strong parents have strong children, concentrates on looking for a good solution in a good solution. In this process, it benefits from the genetic transmission mechanism in the theory of evolution. In this context, new solutions are produced after selection, crossover, and mutation stages from an initial population of solutions referred to as chromosomes. In the replacement part, which is the last stage of the genetic algorithm, the quality of the new solutions produced is compared with the solution quality of the starting population, and the process is repeated by eliminating the low-quality solutions (Fig. 3).

4 Implementation

4.1 Preparation of the data and the model

During the first phase of the implementation, the data on the flight type, year, number of flights, number of passengers carried by airline, and aviation-related CO_2 in 32 European countries between 2001 and 2015 were obtained from European Civil Aviation Conference and the Statistical Office of the European Union sources (Eurostat 2019; EEA 2019). Out of the data, two separate databases were created to use in the study. The first database consists of the number of flights,

Fig. 4 Flow chart of implementation steps
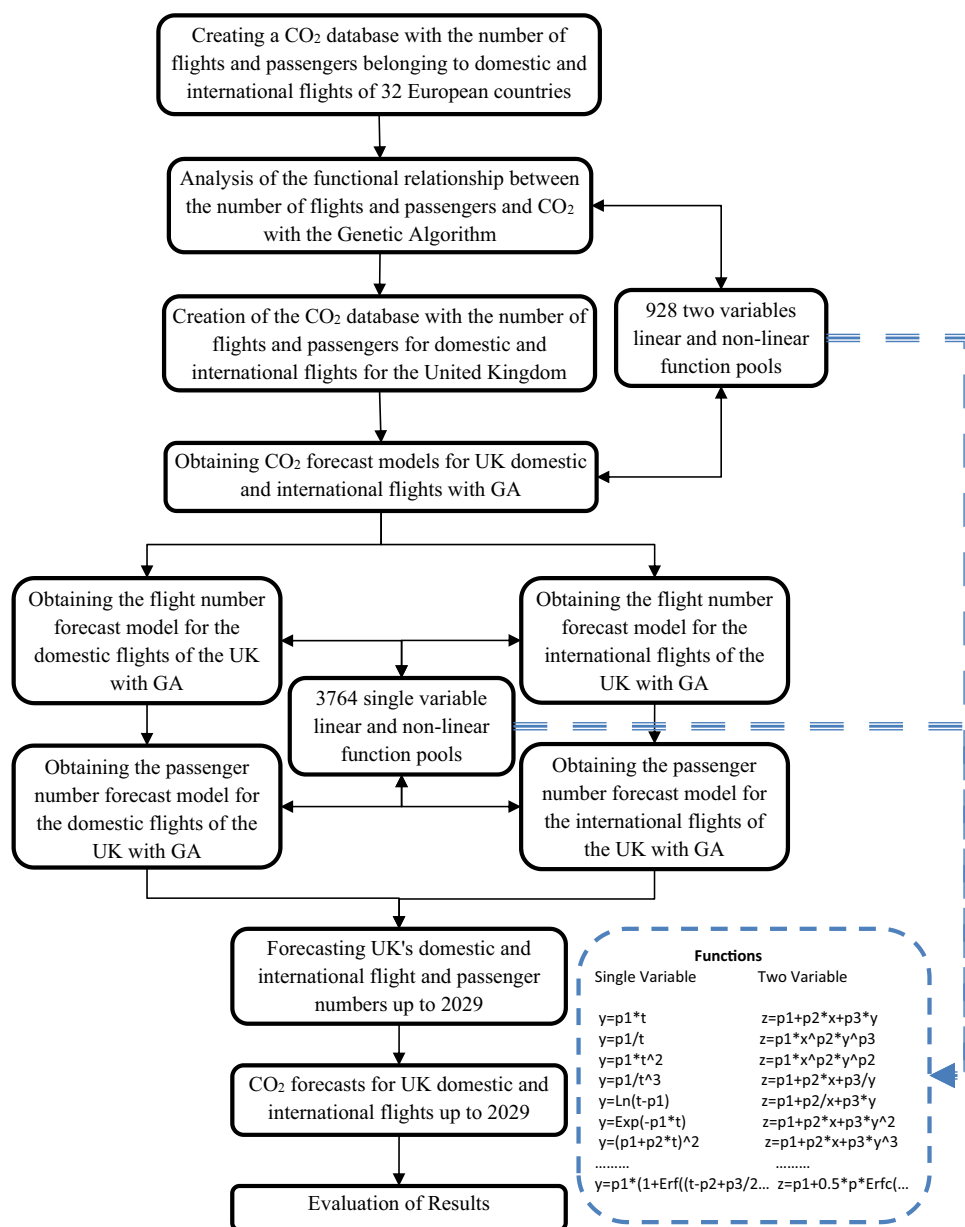
the number of passengers, and CO_2 emission values of the countries. This database will be used to find the mathematical relationship between the number of flights and the number of passengers and the amount of air transportation–related CO_2. The second database consists of information on the number of passengers and number of domestic and international flights of the UK between 2004 and 2015. These databases will also be used to predict the UK's domestic and international flights and passenger numbers in the coming years and to determine mathematical models (Fig. 4).

Since the implementation required high computation time, it was carried out in an advanced computer environment. A computer which had 64-bit Windows 10 operating system with i7-7700 K CPU 4.2 GHz processor, 32 GB RAM, and SSD hard disk was used for computations. Despite the high features of the computer, each application period took as much as half a day. The model was prepared in Auto2fit 3.0 software (Auto2fit 2020).

4.2 Determining the degree of relationship between flight and passenger numbers and CO_2

At this stage of the application, information on the domestic and international flights of 32 European countries, which constituted the first database prepared in the previous step, was used to find the degree of relationship between the number of flights and passengers and CO_2. In order to determine this relationship, 928 two-variable (the number of flights x and the number of passengers y) linear and nonlinear functions were utilized. These functions were tested individually with the genetic algorithm and aviation-related CO_2 forecasts for European countries were made (z) and the most suitable function parameters that minimize Root Mean Square Error (RMSE) were determined by comparing them with real CO_2 values. The highest correlation coefficient (R) 0.9786 was obtained from the results (Fig. 5). The genetic algorithm parameters used in the applications were determined as population number 100, crossing and mutation rate as 0.1, and one-point crossover was used as cross type. The maximum number of iterations was taken as 5000 to determine the most suitable parameters of each function. Convergence tolerance was taken as $1.00E-10$.

4.3 Determination of the CO_2 forecasting models for the UK

The high correlation rate of 0.9796 between the number of flights and passengers and CO_2 determined in the previous step provided the motivation to develop the CO_2 forecasting

Fig. 5 CO_2 forecasting results with flight and passenger numbers (blue: real values, red: forecast values)
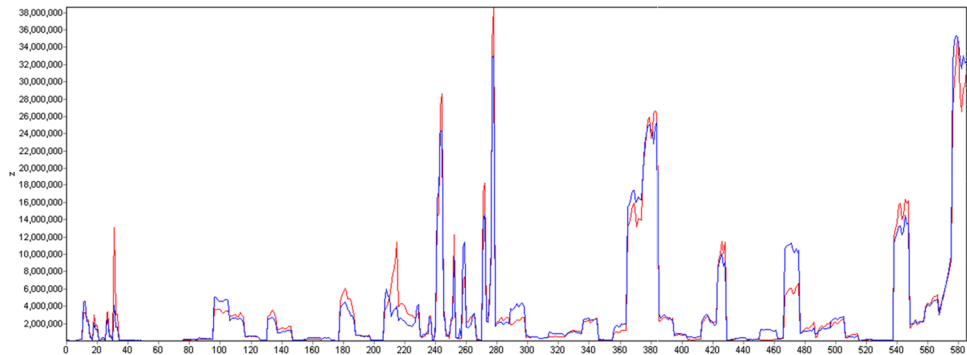
Table 1 The best parameter and correlation coefficient (R) values for genetic algorithm for Eqs. 1 and 2

Parameters	Domestic flight sourced CO_2 forecast model parameter results	International flight sourced CO_2 forecast model parameter results
p1	100,138.384536924	31,860,546.1257734
p2	478,853.436994852	670,674.804775637
p3	−113,677,212.030793	1,469,623.80970488
p4	−8072.11769544973	53,458.7865149365
p5	1,063,465,102,555.61	−6,522,956,882.92109
p6	9,449,386,032.32814	24,248,061.3607427
p7	−13,015.9093624317	−14,843,625.9921016
p8	−178,995,401.943751	54,747,074,297.0994
p9	4.04071898852382	-
R	**0.9960**	**0.9722**

Table 2 Forecasting model, R, and parameter values found with GA for domestic flights for the UK

Forecast variable	Forecast model	Correlation coefficient (R)	Function parameters calculated with GA
Number of flights	$x_d = p_{1+} p_2 * Cos(p_3 * t + p_4)$	0.979877	p1 = 426,988.47892 p2 = 57,710.300447 p3 = 333,053.24855 p4 = 55,232,874.076
Number of passengers	$y_d = p_{1+} p_2 * Cos(p_3 * t + p_4)$	0.988280	p1 = 23,866,581.41 p2 = − 3,238,055.859 p3 = − 44,593,004.4 p4 = − 16,551.41845

Table 3 Forecasting model, R, and parameter values found with GA for international flights for the UK

Forecast variable	Forecast model	Correlation coefficient (R)	Function parameters calculated with GA
Number of flights	$x_i = p_1 * Sin(p_2 * t + p_3) + p_4$	0.902479	p1 = − 77,772.61574 p2 = 341,800,499.9 p3 = − 1.19937E + 11 p4 = 1,350,965.105
Number of passengers	$y_i = p_1 * Cos(p_4 * t)$ $+ p_2 * Cos(2 * p_4 * t)$ $+ p_3 * Cos(3 * p_4 * t)$	0.874200	p1 = 321,260,800.8 p2 = − 187,766,415.5 p3 = 79,404,807.74 p4 = 3562.703181

models for the UK, which is the European country where the airline traffic was experienced the most intensely. To increase the sensitivity of CO_2 forecasts, domestic and international flights were handled separately. Using the data of the UK, the most appropriate functions and parameters were determined from 928 two-variable functions (Eqs. 1 and 2 and Table 1).
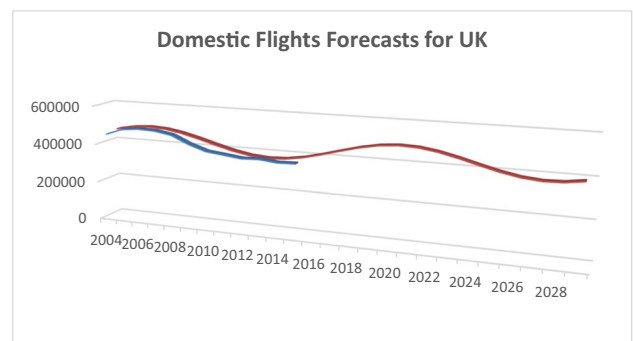
$$z_{Domestic} = \frac{p_1 + p_2 * x + p_3 * x^2 + p_4 * x^3 + p_5 * y}{1 + p_6 * x + p_7 * x^2 + p_8 * y + p_9 * y^2} \quad (1)$$

$$z_{International} = p_1 + 4 * p_2 * \frac{e^{\left(-\left(\left(\frac{x-p_3}{p_4}\right)\right)\right)}}{\left(1 + e^{\left(-\left(\left(\frac{x-p_3}{p_4}\right)\right)\right)}\right)^2}$$
$$+ 4 * p_5 * \frac{e^{\left(-\left(\left(\frac{y-p_6}{p_7}\right)\right)\right)}}{\left(1 + e^{\left(-\left(\left(\frac{y-p_6}{p_7}\right)\right)\right)}\right)^2}$$
$$+ 16 * p_8 * \frac{e^{\left(-\left(\left(\frac{x-p_3}{p_4}\right)\right)-\left(\frac{y-p_6}{p_7}\right)\right)}}{\left(1 + e^{\left(-\left(\left(\frac{x-p_3}{p_4}\right)\right)\right)}\right)^2 * \left(1 + e^{\left(-\left(\left(\frac{y-p_6}{p_7}\right)\right)\right)}\right)^2} \quad (2)$$
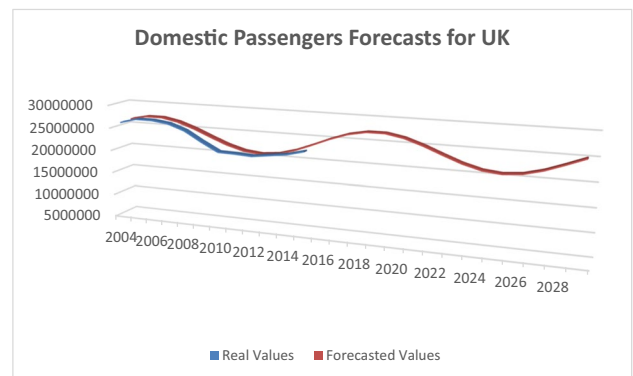
z   *CO2 amount*

x   *number of flights*

y   *number of passengers*

(a)

(b)

Fig. 6 **a** Domestic flight and **b** domestic passenger forecasts for the UK by 2029
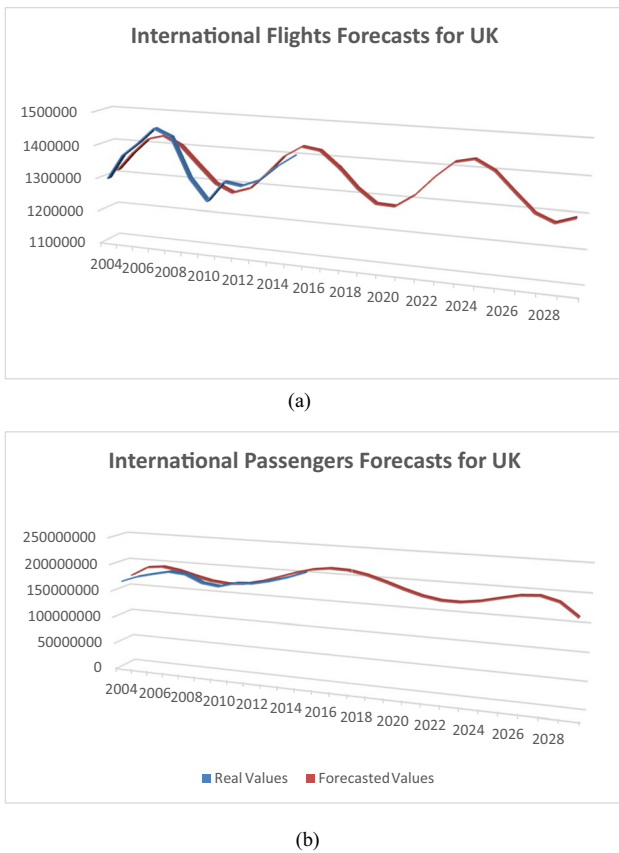
(a)

(b)

Fig. 7 **a** International flight and **b** international passenger forecasts for the UK by 2029

4.4 Creating time series models for the UK

In this section, time series models that best forecast the number of flights and passengers for the UK were created. A total of 3764 linear and nonlinear univariate (year: t) functions were optimized separately by genetic algorithms. In the optimization process, the genetic algorithm parameters mentioned in Sect. 4.2 of the study were used. The model with the highest correlation coefficient in 3764 functions and whose prediction pattern resembled the pattern of real values
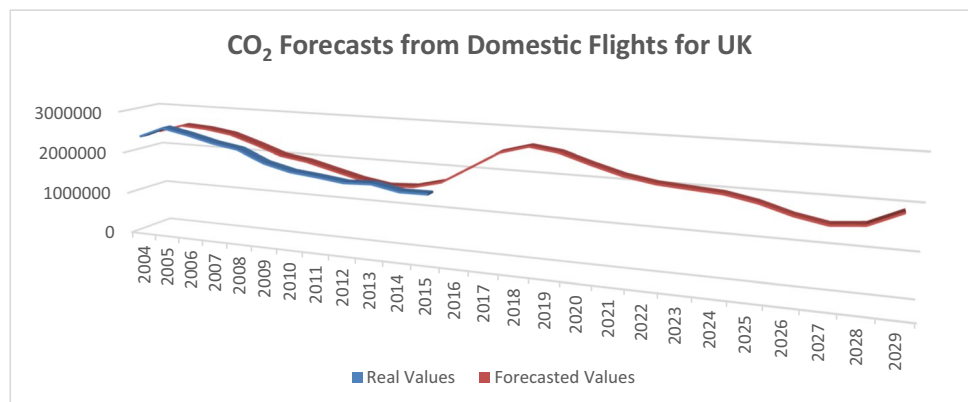
the most was chosen to be used in the forecasting stage. This part of the application was repeated separately for domestic and international passenger transportation (Tables 2 and 3).

5 Results and discussion

In the domestic and international time series flight equations with high correlation coefficients found with GA, time values were determined until 2029 and the number of flights and passengers was forecasted for the UK (Figs. 6 and 7). According to the results obtained, it is seen that the number of domestic and international flights and passengers decreased towards 2008 compared to 2004–2006. This can be explained by the economic stagnation experienced before the recession, especially in the UK in 2008 (BBC 2008). Although there was a recovery from this economic recession towards 2015, this situation did not reflect much on the number of domestic flights and passengers (Fig. 6a and b). There is a faster increase especially in international flights towards 2015 in comparison to domestic flights (Fig. 7a and b). This situation can be explained by the effect of foreign tourist mobility. It is seen that this situation will continue in a fluctuating course in the following years. Such situations, called cycles in time series, are usually repeated between 2 and 10 years (or more). Although economic, political, etc. developments have an impact, they cannot be easily forecast (Stevenson 2015; Gor 2009). The model results forecast that this situation will be repeated every 12 years in domestic passenger transportation and approximately every 10 years in international passenger transportation (Figs. 6b and 7b). As for the number of flights, it is repeated approximately every 8 years in international flight numbers and every 10 years in domestic flight numbers (Figs. 6a and 7a). This implies that the impact of the general deterioration in the world economy on air transportation for the UK is more dominant and more sensitive than its effect on domestic air transportation.

The forecasts obtained were placed in the domestic and international air transportation–related emission model in Eqs. 1 and 2, and forecasts regarding air transport–related

Fig. 8 Domestic passenger transportation–related CO₂ forecasts for the UK by 2029

Fig. 9 International airline transportation–related CO_2 forecasts for the UK by 2029
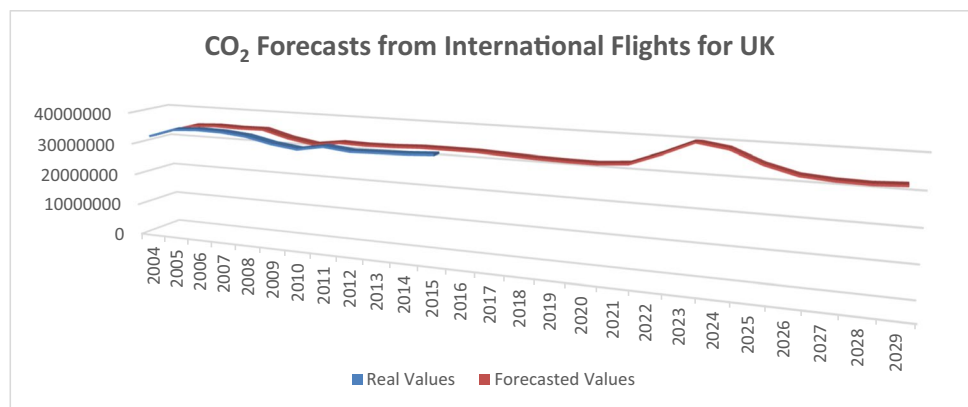
emission for the UK until 2029 were obtained (Figs. 8 and 9). When the results are examined, although the amount of emission in international flights is higher than that in domestic flights, it follows a more stable course. It is seen that the amounts of emission from domestic flights fluctuate in a cycle of approximately 14 years. In international flights, this period is close to 20 years. This period is sufficient for the UK to take the necessary measures to reduce air transportation–related CO_2 emission. The improvement in the economy and the liveliness in tourism seem to increase CO_2 emissions resulting from air transport. The effect of advances in technology is also reflected in the results. Especially, the increase in the number of aircraft that use fuel efficiently in recent years also causes CO_2 emissions to be reduced. The inclusion of fuel-efficient aircraft in the fleets by the date when CO_2 amount reaches the peak both on the domestic and international flights will have a positive effect on the reduction of CO_2 emission. At least these issues should be considered while preparing investment plans. In addition, the increase in aircraft capacity and occupancy rates will also contribute to CO_2 emission reduction. At this point, well-planned flight planning and directing customers through effective campaigns to increase the occupancy rates will lead to reduction of unnecessary flight traffic and resulting CO_2 emission.

6 Conclusions

Air transport (planes, drones) will form an important part of personnel transport in the future. Unfortunately, it seems unlikely that fossil fuels will be abandoned in a short time as the main energy source of these vehicles due to the trade wars, the pandemic, the Ukraine-Russia war, etc. Until the world reaches global peace in terms of economy and politics, a fossil fuel–based airline passenger transportation period waits for a while in this transition period. This means that emissions from air passenger transportation will continue to increase.

In recent years, we have entered a period in which awareness about the reduction of emission types has increased in both academic and industrial circles. Raising awareness is of great importance to combat global warming and other effects

of global climate change. With this study, it was tried to provide a perspective to this struggle in terms of air transportation in the service sector. In the study, modeling and forecasting of air transport–related CO_2 was aimed. In doing so, data on flight types, year, the number of flights, the number of passengers carried by airline, and aviation-related CO_2 values for 32 European countries were used. As a method, genetic algorithms, which have been successfully applied in many fields, were benefited from. Firstly, the relationship between the information on the number of flights and passengers and air transportation–related CO_2 was measured and a correlation value of 0.97 was obtained. Based on the highly significant result obtained, CO_2 forecasting models related to domestic and international air transportation were obtained for the UK, where the density of air transportation among the European countries is most experienced. The results show that CO_2 resulting from domestic and international flights can be forecasted with high correlation values and there is a positive and significant relationship between them.

In the study, time series models to be used to forecast the number of flights and passengers for the UK's domestic and international flights were developed. While developing these models, again, genetic algorithms were utilized, and highly correlated results that minimize the error were obtained.

In the last part of the study, flight and passenger numbers and CO_2 forecasts for the UK by 2029 were made. The results obtained show that these phenomena are affected by economic conditions. Rising risk and uncertainty, trade wars, protectionist policies, and epidemic diseases such as coronavirus (COVID-19), which appeared in the preparation period of the study, will further affect air transportation. Although these factors reduce the resulting CO_2 emissions and have a positive effect on global warming, it is desirable to develop strategies to reduce CO_2 emissions while increasing airway traffic. At this point, in parallel with the advances in technology, the production of hybrid engines that consume less fuel and are supported by renewable energy, use of biofuels, development of flight plans, and aircraft occupancy rates with a view to protecting the environmental sensitivity are important issues. In this context, negative effects can be limited by defining "Green Routes" and removing existing flight routes from agricultural lands and drinking water

sources. In the long term, the negative effects of a temperature increase of a few degrees on the current flight route on agricultural lands and drinking water resources may leave countries in a difficult situation, especially in these days when there are problems in food supply in the world.

It is thought that the study will create a starting point and awareness within the scope of modeling and estimating the effects of emissions from air transport on countries. Maybe, even if not in its full sense, in the future, an "Air Carbon Swap" mechanism such as a carbon offset mechanism will be created, and countries will exchange their emissions from air transport among themselves.

A few limitations were also encountered in the study. As it is known, as the forecast time horizon gets longer, the consistency in the prediction results decreases. For this reason, in this study, unlike some studies in the literature, the forecast time horizon was kept short. In future studies, the results can be improved by making use of different artificial intelligence techniques. The forecast values obtained from these techniques can be revised with qualitative forecasting techniques (such as Delphi). In addition, the increases in air cargo transportation and e-commerce can be used as inputs, and their effects on global emissions can be analyzed. It should not be forgotten that timely forecasting of emission types with high accuracy will enable countries to use their resources more effectively to develop preventive strategies.

Declarations

Ethics approval Not applicable.

Consent for publication Not applicable.

Competing interests The author declares no competing interests.

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