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Comparison of Artificial Intelligence Techniques for The UK Air Passenger Short-Term Demand Forecasting: A Destination Insight Study

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Abstract

Web search queries become essential drivers to forecast air passenger demand for operational benefits. Scholars and marketing experts. Forecasting passenger demand is one of the most important marketing problems that experts frequently encounter, but there are very few studies in the literature using search queries. The main novelty of this study is to show that Destination Insight (DI) can be useful as an air passenger demand proxy in the UK. To prove this primary objective, this work uses several machine and deep learning multi-layer perceptron (MLP) methods based on a big-data framework. The findings indicate that DI is a crucial predictor of the UK air passenger demand. Besides, popular error metrics (RMSE, MAPE, MAD and AIC) were compared to find the best model in this study. Specifically, results indicate that MLP following feed forward neural networks works better for the UK air passenger market.

1. Introduction

Airlines play a vital role in the international trade of manufactured goods, as an important part of global supply chains, especially in cross-border trade. Although trade flows have been interrupted by the Russia-Ukraine conflict, as well as the COVID lockdowns in China, goods trade volumes of the World will increase by 3% compared to its previous levels. Notably, the value of international trade by air will be forecasted to increase from $7.5 trillion to $8.2 trillion in 2022 compared to 2021, and tourists traveling by air will spend $672 billion in 2022. According to this global outlook, air transport contributes to global economic growth by connecting countries and rises depending on the flow of people, capital, technology, and ideas (IATA, 2022). Thus, understanding market demand for air transport is an essential task to make strategic and operational decisions and this attempt leads researchers and marketing experts to examine the triggers of air demand in detail from a theoretical and practical point of view (Zhang et al., 2021). However, air transportation faces numerous uncontrollable factors, such as economic development, policy adjustments, seasonal cycles, and outbreaks that affect demand of air passengers. This complexity pushes air transport industry into forecasting passenger demand to develop strategic plans, such as capital construction, opening new routes, and network management in the long term, and daily operational plans, such as reducing costs, adjusting ticket prices, scheduling, and personal training (Jin et al., 2020; Tsui et al., 2014). Long-term forecasts are generally made for these plans. On the other hand, many airports make short-term plans to reflect short-term fluctuations in air passenger demand and to create reliable short-term forecasting models (Kim, 2016). Thus, airport operations need short-term demand forecasting for urgent issues such as airport scheduling and monthly operating and maintenance plans (Xie et al., 2014). To address these issues, this study attempts to forecast air passenger demand in the UK airline market.

Prior research on air passenger demand indicates that traditional econometric models, time series, and artificial intelligence (AI) are commonly used in the field (Dantas et al., 2017). Econometric models include relationship between air passenger demand as dependent variable and different variables as independent indicators that can be related to the number of air passengers (Jin et al., 2020). The most common indicators in economic studies for air transportation are Gross Domestic Product (GDP), GDP per capita, population, and income per capita (Carmona-Benítez et al., 2017). In econometric studies, researchers widely use regression analysis (Rolim et al., 2016), causality analysis (Zhang and Graham, 2020), gravity (Das et al., 2022), and logit models (Hsiao and Hansen, 2011). The most widely used time series models in airline sector are Autoregressive Integrated Moving Average (ARIMA) techniques (Kanavos et al., 2021), and Holt

Winters (HW) (Dantas et al., 2017). Lastly, the broader applications of AI methods are Artificial Neural Network (ANN) (Srisaeng et al., 2015), Support Vector Machine (SVM) regression (Ke-Wu, 2009), Decision Trees (DT) (Laik et al., 2014), deep neural networks (Liu and Chen, 2017), and hybrid methods (Jin et al., 2020; Wu et al., 2021). Notably, time series and AI techniques have high potential for forecasting data successfully in air transportation industry (Kanavos et al., 2021).

Passenger demand can be related some important drivers, such as Socio-economic factors (GDP, employment levels, educational level, tourism, ethnicity etc.), service-related variables (frequency, distance, price etc.) (Boonekamp et al., 2018; Wang and Gao, 2021), city and airport structure/facilities (Das et al., 2022), and behavioral drivers (human behavior, interest, reactions etc.) (Mumayiz and Pulling, 1992; Kim and Shin, 2016). Although many drivers that will impact air passenger demand are the subject of scientific works, determining the most effective ones emerges as a challenging question (Das et al., 2022).

In today's technological environment, online consumer behavior stands out as an effective variable and can be a precious predictor for forecasting techniques. Online air passenger data have also been used to develop more accurate forecasting models (Kim and Shin, 2016). Notably, access to the digital content has changed the way of purchasing products or services (Peterson and Merino, 2003). In this respect, search engines are one of essential online tools that may fulfill the need for information of consumers (Lai et al., 2017). Google also provides consumers' search data with a useful tool, namely Google Trends (GT) available for researchers and marketing experts (Dreher et al., 2018). GT gives search volumes for a specific term and region from 2004. It ranges the search frequencies on a scale of 0-100. The tool also allows users to filter search terms according to various criteria (Google, 2022).

In previous studies, GT data comes out as a driver of demand and is used for forecasting passenger arrivals in case of tourism industry employing autoregressive (Park et al., 2017) and artificial intelligence (AI) techniques (Sun et al., 2019).

In the aviation industry, forecasting demand and improving model accuracy is helpful for air transport planners to determine and escape from economic fluctuations and unnecessary infrastructure costs (Suh and Ryerson, 2019). Another problem in the aviation industry is adjusting capacity of airports, especially in Europe, that needs serious investment (Sismanidou and Tarradellas, 2017). Although the importance of web search data for demand forecasting in response to such concerns is obvious, the number of studies in the field is quite limited. In this sense, Kim and Shin (2016) have proposed an optimal forecasting model for short-term airline demand using weekly internet search data. Long et al. (2021) forecasted air passenger arrivals in Changi International Airport with 1317 Google Trends search queries using Granger Causality and deep neural networks (1D-Convolutional, Long Short-Term Memories (LSTM), and Dense layers). Liang et al. (2022) proposed a forecasting model that integrates LSTM as a deep learning algorithm to predict air passenger demand in China's airports with Internet search data. In another study, Koçak (2023) forecasted air passenger demand for New Zealand airports with DI data employing and comparing some deep learning techniques.

In most of these studies, although Google Trends is a helpful tool for forecasting demand data, researchers might face a significant problem of how to choose the right search query (Önder and Gunter, 2016). Google's new tool, DI with Google, can eliminate this problem by presenting data on consumer travel searches without a search query. This new tool can also be used for forecasting demand (Rashad, 2022).

Lastly, prior works have particularly used web search data to increase forecasting accuracy of passenger demand employing econometric models and AI techniques. However, no study, to the best knowledge of the author, forecasted the UK air passenger demand with DI so far. To fill this gap, this case study employs different artificial intelligence techniques to forecast daily air passenger arrivals in the UK air market with Google's new tool as a predictor. Also, this study uses a big-data framework which involves 4 basic steps: data extraction from DI with Google and daily air passenger arrivals in the UK, relationship exploration with Granger causality test, forecasting data with machine and MLP techniques, and model evaluation with common root mean square error (RMSE), mean absolute percentage error (MAPE), mean absolute deviation (MAD), Akaike Information Criteria (AIC) metrics.

To improve forecasting on the country level, DI is introduced as a powerful determinant into traditional machine learning (ML) techniques, such as DT, ANN, Sequential Minimal Optimization Regressor (SMOReg), and Random Forest (RF) for regression problem in air passenger demand forecasting. In deep learning techniques, the open source deeplearning4j (DL4J) library[1] that follows the model of multi-layer feedforward neural networks is employed. This study also implements three popular performance criteria: RMSE, MAPE, MAD, and AIC metrics of the testing samples using artificial intelligence techniques mentioned above to evaluate their applicability for forecasting air passenger demand in the UK market. The current work contributes to prior research on demand forecasting in the following way: This is the first study, to the best knowledge of the author, to explore whether DI with Google can improve air passenger demand forecasting.

Within the scope of this study, research framework with detailed steps is presented in section 2. Next, methodology with data representation, comparison of AI techniques, and the findings of the applied models are given. The theoretical and practical contributions built on the findings of this study are then mentioned. Lastly, suggestions will be made for future studies.

2. Methodology

In this part of the study, passenger demand for airports in the UK is forecasted using Google searches of consumers in any geographical location on Earth related to air transportation to the UK. To fulfill the forecasting task in the current research, the causal relationship between the data sets should be determined. Thus, the stationarity of the data sets was firstly examined by employing Augmented Dickey-Fuller (ADF) test, then the co-integration between variables was tested and, lastly, the Granger Causality analysis (Granger, 1969) was performed. Next, machine and MLP techniques were employed for forecasting.

This study uses consumer search data with Google to forecast air passenger demand in terms of the UK airline market. Accordingly, the research framework of the proposed methodology is illustrated in Figure 1.

[1] https://deeplearning4j.konduit.ai

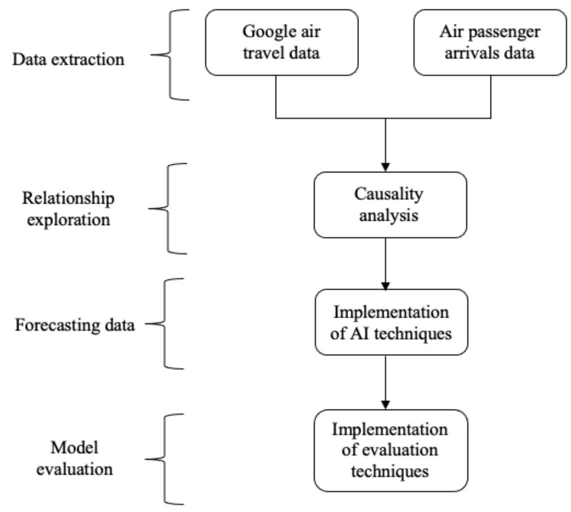

Figure 1. Research framework

The framework of the study starts from deriving Google search and air passenger data, investigating relationship between variables, forecasting air passenger data with some artificial intelligence techniques, and lastly, comparing proposed models to improve forecasting (Yu et al., 2019).

Phase 1: Data extraction

In this step, two main time series data sets are obtained from Google and air passenger arrivals. To reach consumer search data, Google provides a successful tool, namely, DI (https://destinationinsights.withgoogle.com) that monitors all consumer searches related to air travel in specific time and country indexing from 0-100.

Phase 2: Relationship exploration

To determine whether Google search data is effective trigger for the actual number of air passenger data, the co-integration and Granger causality tests are employed in this step.

Phase 3: Forecasting data

In this step, artificial intelligence algorithms can be used to forecast air passenger time series data with Google search results. The current study employs some popular techniques in ML and deep learning area to forecast air passenger demand. DT, ANN, SMOReg and RF in ML, and MLP in deep learning are conducted for this study.

DT (Quinlan, 2014) is one of the common algorithms that forecasts the value of a target class using input variables in classification problems (Treeratanaporn et al., 2021). It separates values to optimally reduce error in selected recursive classification criteria for regression. The data process starts from root node that builds new nodes and progresses until the previously specified stopping criteria is reached. The desired forecasting can be performed on the class attribute (Massaro et al., 2018). DT allows for ease of data interpretation and analysis and can also be used for numeric prediction (Nwulu, 2017).

ANNs are one of popular AI techniques that can frequently be used in solving nonlinear forecasting problems for various industries. Moreover, in this method, which produces more general and flexible functional results compared to traditional methods, the system consists of neural networks like the biological nerve structure. There are predictors in the input layer of ANNs and dependent variables to be predicted in the output layer (Zhang et al., 1998).

The following functional relationship of ANNs can be represented as:

$$y = f(x_1, x_2, x_3, \dots x_p),$$

where x_1, x_2, x_3, …, x_p are independents that are added into the input layer, y donates a dependent variable.

The following equation can be calculated for time dependent forecasting tasks:

$$y_{t+1} = f(y_t, y_{t-1}, \dots, y_{t-p}),$$

where yt donates t time observation (Zhang et al., 1998).

SMOReg is an iterative algorithm proposed by Smola and Scholkopf (1998) for solving the regression problems using Support Vector Machines. As an extension of the SMO algorithm proposed by Platt (1999), SMOReg replaces the missing values and normalizes all attributes by default. In this respect, SMOReg is a fast and easy to implement technique (Shevade et al., 2000) for forecasting studies (Hu et al., 2018).

RF proposed by Breiman (2001) is a classifier that generates many trees and chooses the most popular class. During the process, each tree is generated from a sample of data and at each split; then a random sample of predictors is examined. Lastly, forecasting is performed among the trees with the most votes. While doing this, the algorithm tries to ensure that the trees grow to maximum depth as possible by keeping the individual errors low. Thus, it is a widely used techniques in solving regression problems (Kumar and Thenmozhi, 2006).

MLP is feed-forward artificial neural network involving several neurons connected by linking weights. It maps a set of inputs into desired outputs. The process is initiated by the transfer of input data to neurons located in hidden layers. The connection between neurons is realized by weight and bias calculations, and the results are forwardly transmitted to the output layer with and activation function (Widiasari and Nugroho, 2017). Recently, many studies focus on forecasting tasks using MLP (Candel and LeDell, 2020; Tung and Yaseen, 2021). In this study, an open-source deep learning framework (DL4J) is used to train the proposed model. DL4J is a commercial grade library written in JAVA and provides GPU support for distributed framework that was developed by Adam Gibson (Parvat et al., 2017). As an optimization method in DL4J package, Adam (Kingma and Ba, 2014) is used for this study. This technique is very easy to implement and useful (Lu et al., 2021) in solving forecasting problems involving large data sets (Kingma and Ba, 2014). In this respect, the architecture of the current study is represented in Figure 2.

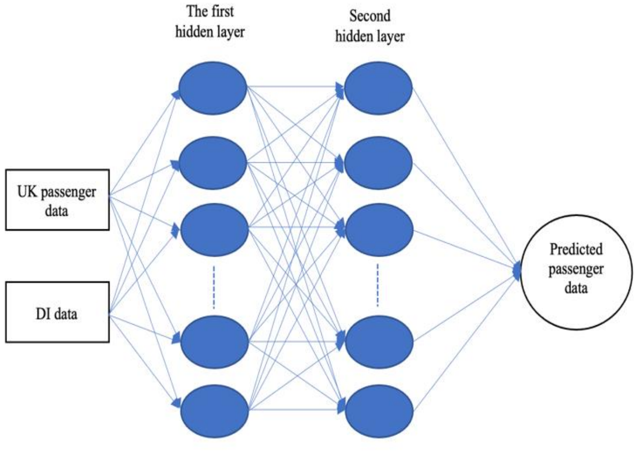

Figure 2. The MLP architecture of the study

Phase 4: Model evaluation

To evaluate the forecasting performance in this step, three popular criteria were used for determining the forecasting errors: RMSE, MAPE, and MAD. RMSE is used to measure the deviation between the actual and predicted values (Xie et al., 2014). In the case of forecast errors with significant seasonality and demand relatedness between one period and another, MAPE is an excellent means of measuring forecast error in a very accurate and straightforward way. Also, if the assumed random component is normally distributed, the MAD is used to estimate the standard deviation. As long as the cost of forecast error is proportional to the number of errors, MAD is an effective method for measuring errors (Putra and Kusumastuti, 2019). The smaller the values revealed by these three determinants the better the prediction of the model is considered (Xie et al., 2014). The following equations shows the calculations for these metrics, respectively:

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(\hat{x}_t - x_t)^2}{S}},$$

$$MAPE = \frac{\sum_{t=1}^{n}\left|\frac{x_t - \hat{x}_t}{x_t}\right|}{S} \times 100,$$

$$MAD = \frac{\sum_{t=1}^{n}|\hat{x}_t - x_t|}{S},$$

where S donates the size of observations in the test set, x_t is the number of airline passenger demand, and $\hat{x}_t$ represents the forecasted passenger demand data in the UK.

2.1. Data

This study uses daily data of Google and air passenger arrivals in the UK from January 1, 2020, to April 30, 2022. The UK was chosen for the analysis because it has the largest aviation network in Europe (CTP, 2022).

To determine consumer demand for air travel to the UK, DI with Google is used. This platform was launched in 2021 to reflect users' interest for a particular location based on searches on Google with specific queries. Google indexes these searches as travellers' demand for destinations over time. The index ranges from 0 to 100 and the data can be reached via the following website (Rashad, 2022) (https://destinationinsights.withgoogle.com//, accessed on September 14, 22).

In DI, "Worldwide" was selected for origin country and United Kingdom was chosen for destination country. International air travel demand was selected for trip type and demand category, respectively. Lastly, data range was chosen for the analysis as shown in Figure 3.

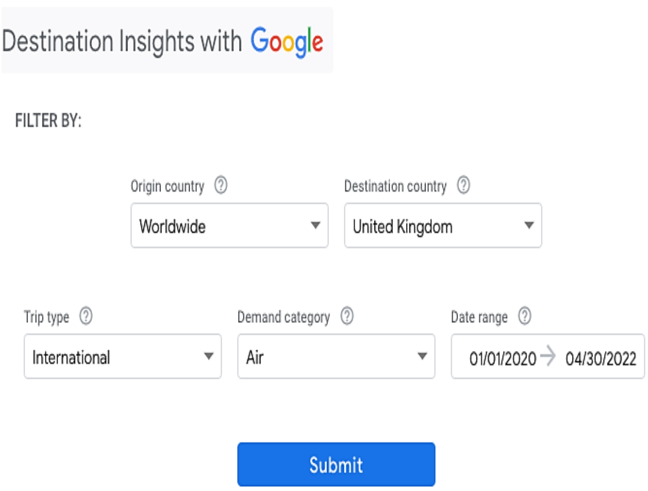

Figure 3. Data selection for air travel demand Google

These indexed data obtained from the search engine consists of online users' queries regarding flights from any destination in the world to the UK. Google lists all these destinations in a single parameter, "worldwide", and uses search volume as a proxy for travel demand. As known, online search query given that huge quantities of data associated with human behaviour, interest, and reactions are generated in real time and may sensitively represent short-term fluctuations (Kim, 2016).

In the current study, to forecast the UK air market demand, the number of daily passenger arrivals between 2020-2022 were derived from the official statistics page of the UK government database (UK, 2022) including Advance Passenger Information (API), and Border and Immigration Transaction Data (BITD). *"These data primarily relate to passengers coming to the UK via commercial aviation routes."*

Figure 4 summarizes comparison of daily air passenger arrivals in the UK and insight data with Google for a given search, respectively.

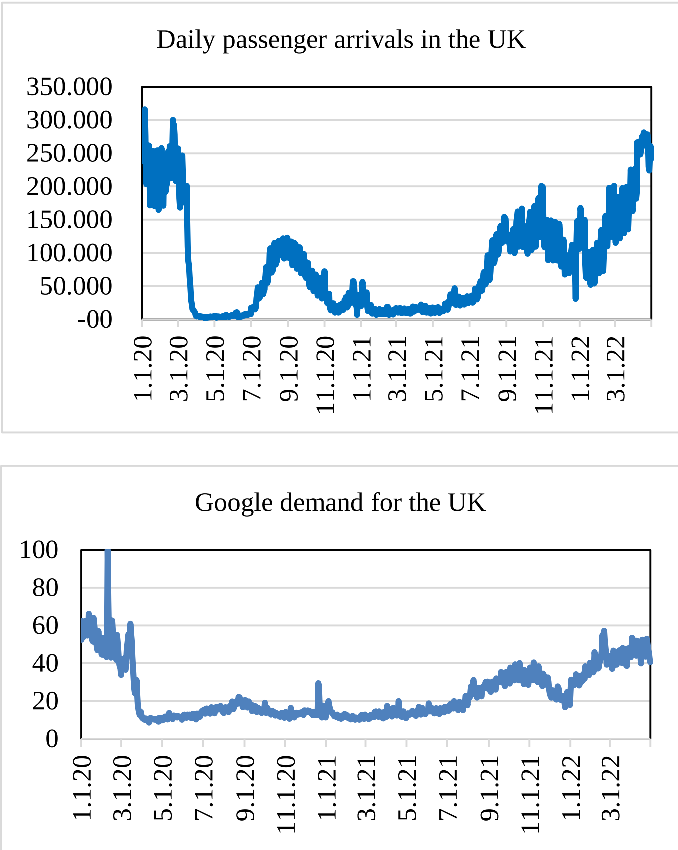

Figure 4. Daily data of passengers and Google for the UK

Looking at graphs, consumers Google searches about air travel (from the World to the UK) and the daily number of passenger arrivals at the UK airports decline dramatically at the COVID-19 pandemic period. One possible explanation for this issue is that the need and seek for information about flights may be affected by macro environmental environment. Also, it can be concluded that consumers' web search behavior has changed depending on this situation over time, which has also been mentioned in previous studies (e.g., Koçak, 2020). In this respect, the time series data for passenger arrivals in the UK and Google demand are approximately related. This indicates that online demand for air travel can reflect real passenger arrivals in the UK and implies that one can forecast air passenger demand with Google data. To test this relationship, first task is to determine the relationship between flight-related searches in the DI data and the real number of air passenger arrivals in the UK. Thus, the current study runs Granger causality analysis in the next section.

3. Result and Discussion

3.1. Cointegration and Granger Causality Tests

In the first stage of the proposed model, stationary, co-integration, Granger causality analysis are conducted to test relationship between Google and passenger arrival data. EViews12 package program are used to perform the analysis at this stage of the study. For stationary, ADF unit root tests were implemented (Dickey and Fuller, 1979). The last situation of the model parameters was determined to minimize Akaike Information Criteria (AIC) (Akaike, 1973).

According to the test results reported in Table 1, air passenger arrivals in the UK and Google air travel demand are stationary at the first-order difference, at the 1% significance level, indicates that the appropriate condition has emerged to perform the co-integration test and Granger causality analysis (see Table 1).

Table 1. Stationary test results

Datasets	Estimator	Original level		First Level	
		t-value	p-value***	t-value**	p-value***
Daily passengers (arrival) in UK	SIC*	-1.936	0.316	-6.624	0.0000
Google air demand for UK	SIC	-2.394	0.144	-8.403	0.0000

*Lag length is determined according to Schwarz info criterion, ** Null hypothesis was rejected at the 0.01 level, *** MacKinnon (1996) one-sided p-values

Second, the co-integration test is performed using Engle and Granger (1987) method to determine the long-run relationship between time series. The time series were derived from the regression analysis that use least squared method and were tested for the cointegration at the first-order difference. Table 2 shows that there is a co-integration relationship between daily passenger arrivals in the UK and Google air travel demand, at the 1% significance level.

Table2. Co-integration between datasets

Co-integration	Original level	
	ADF t-value*	p-value**
Daily passengers (arrival) in UK vs Google air demand	-6.709	0.0000

* Null hypothesis was rejected at the 0.01 level, ** MacKinnon (1996) one-sided p-values

Based on the results of this report, the Granger causality analysis can be performed to determine whether the Google data can lead to forecast the number of daily passenger arrivals in the UK in the next step.

In the third stage of the analysis, the strength, and the direction of long-term relationship between variables was determined using Granger Causality test. Accordingly, the causality of the time series was carried out by taking 14 lag-length criteria. Eq. 1 represents the proposed vector autoregressive (VAR) model for the research:

$$(passengers)_t = \sum_{i=1}^{n} a_i \, (search)_{t-i} + \sum_{j=1}^{n} b_j \, (passengers)_{t-j} + u_{1t},$$

$$(searchquery)_t = \sum_{i=1}^{n} c_i \, (passengers)_{t-i} + \sum_{j=1}^{n} d_j \, (search)_{t-j} + u_{2t}, \quad (1)$$

where a, b, c, and d are the parameters, n is the lag-length, t is the time, u_{1t} and u_{2t} are the regression residuals.

As reported in Table 3, there is a Granger causality between Google searches and the UK daily passenger demand at the 14 lag-length criteria, at the 1% significance level. This shows that DI can help to forecast air passenger arrivals in the UK.

Relationship investigation between the variables reaches one important conclusion: significant co-integration and Granger causality test results show that consumers' air travel demand on Google can help forecasting actual number of air passenger in case of the UK airline market.

Table 3. Granger Causality between DI and actual air passenger demand data.

Hypothesis	Prob	Result
H_0: Google demand for air travel in UK does not cause daily passenger arrival in UK	0.0000	Rejected

In the airline market, there are few studies providing possible explanation of why Google search indices are essential predictors of demand. For example, potential consumers can use search engines to obtain information about ticketing and reservation without the need for online agencies (Little et al., 2011). Also, prior forecasting research suggest that consumer Google searches may be related to the demand and help forecasting passenger demand (Kim and Shin, 2016; Shin et al., 2017; Park et al., 2017; Long et al., 2021).

3.2. Evaluation of Forecasting Accuracy

In this section, some useful machine learning (DT, ANN, SMOReg, and RF) and deep learning algorithms were applied via RapidMiner 9.6 package program (Mierswa et al., 2006) to forecast the UK airline market demand with Google search data. The data were divided into training and testing subsets: 80% for training and 20% for testing.

During the training and testing stages, the model parameters of ML algorithms were selected as default settings in RapidMiner for efficient operation and ease of use (Chou and Tran, 2018). These parameters and corresponding values are presented in Table 4.

Despite the default settings in the ML algorithms, some parameter specifications have been used in MLP method for consistency. The model is set as 2 hidden layers and each layers has 50 neurons. Learning cycle (Epoch) was implemented as 150, mean squared error was set for loss function, Stochastic Gradient Descent was implemented for optimization method, standard backpropagation was used, and Xavier (Glorot and Bengio, 2010) was selected for weight initialization in the model. Lastly, Adam optimizer is implemented for the forecasting model.

In MLP, Google air travel demand reflecting consumer online search data and number of air passenger arrivals in the UK were selected as input neurons. The forecasted number of air passengers constituted the output layer. During the experiment, the learning rate was gradually reduced from 0.01 to 0.001 and this parameter was set to 0.004 for the best learning outcome.

Table 4. The model parameters in RapidMiner

Algorithm	Parameters	Value
DT	Criterion	Least Square
	Maximal depth	10
	Minimal gain	0.01
	Minimal leaf size	2
	Minimal size for split	4
	Number of prepruning alternatives	3
ANN	Hidden layers	2
	Training cycles	200
	Learning rate	0.01
	Momentum	0.9
SMOReg*	The complexity constant (C)	1.0
	Normalization (N)	0.0
	Improve (I)	-L 0.001 -W 1 -P 1.0E-12 -T 0.001 -V
	Kernel (K)	-C 250007 -E 1.0
RF	Number of trees	100
	Criterion	Least square
	Maximal depth	10

* This algorithm is taken from Weka (Frank et al., 2016) libraries

Lastly, forecasting performance of the UK passenger data with DI data is evaluated using four ML and one deep learning methods and compared by RMSE, MAPE, and MAD. Accordingly, Table 5 shows the findings of the comparisons of artificial intelligence models with independent variables of time series and “time series + DI” in sample and out of sample forecasting. The experimental study shows that DI can be an effective predictor for daily air passenger arrivals in the UK when implementing SMOReg and MLP techniques in both sample and out of sample forecasting. RMSE, MAD, and AIC values of these models for “time series + DI” are smaller than the benchmarking models for “time series”.

As seen in Table 5, the results for the UK air market demand show that RMSE, MAPE, MAD, and AIC values of the MLP model are much smaller than those of DT, ANN, SMOReg, and RF models. Looking at ML results, SMOReg performs lowest forecasting errors in case of three evaluation methods. According to Yang et al. (2007), SMO has better generalization ability for time series modelling since it avoids quadratic programming numerical calculations.

Table 5. Comparisons of the forecasting models

Method		In sample				Out of sample			
	Algorithm	RMSE	MAPE	MAD	AIC	RMSE	MAPE	MAD	AIC
Time series	DT	665	0.515	236	8859	1846	0.699	1100	2563
	ANN	1516	5.375	1081	9981	1844	1.195	1572	2563
	SMOReg	483	3.505	451	8422	300	0.274	269	1945
	RF	271	0.212	86	7638	1016	0.299	507	2360
	MLP	6.064*	0.008*	4.349*	2461*	9.488*	0.006*	8.762*	771*
Time series + DI	DT	638	0.507	228	8803	1976	0.783	1204	2586
	ANN	1675	4.169	1217	10117	2154	1.734	1850	2616
	SMOReg	354	2.559	331	7999	216	0.197	193	1833
	RF	412	0.252	133	8206	1491	0.485	802	2491
	MLP	4.892*	0.030*	4.283*	2168*	5.808*	0.004*	4.677*	604*

* Indicating the lowest error rate (RMSE, MAPE, and MAD)

SMO does not need to put the whole kernel matrix into memory and to call the matrix iteration. These advantages allow the algorithm to improve its operational speed and predictive power. Also, error metrics of the ANN model are larger than other algorithms. This result supports the findings of Yu et al. (2019). According to them, a possible explanation of this result can be due to the randomness and super-sensitivity to many parameters. Moreover, previous studies also demonstrated that the MLP method could have better capability for forecasting air passenger data in case of MAPE and RMSE (Srisaeng et al., 2015; Srisaeng and Baxter, 2017) compared to other traditional techniques such as ARIMA (Xiao et al., 2014) and SARIMA (Gultekin and Kemaloğlu, 2023). In this respect, these findings not only support the previous studies mentioned, but also can present a good generalization of deep learning method.

Additionally, this study implements a paired t-test using the relative error (RE) metrics (Hadavandi et al., 2012) to test whether a statistically significant difference in forecasting precision exists between deep learning and the baseline models of ML in out of sample forecasting. The equation of RE is shown as follow (Zhang et al., 2020):

$$\left(\frac{y_t-\hat{y}_t}{y_t}\right)\times\ 100\ ,$$

where y_t and $\hat{y}_t$ are the actual and forecasted values, respectively.

Statistically, this test was conducted to verify the original hypothesis stating that the precision of MLP is equal to the ML models, so the alternative hypothesis is the opposite.

Table 6. Comparison of the forecasting performance of the MLP and baseline ML models in terms of RE

Model	Baseline models	t-stat.	p-value
MLP	DT	-0.219	0.414
	ANN	6.480*	0.000
	SMOReg	-22.930*	0.000
	RF	0.191	0.424

* Null hypothesis was rejected at the 0.01 level, ** MacKinnon (1996) one-sided p-values

In this respect, Table 6 shows the t-test results representing that the original hypothesis was rejected for ANN and SMOreg models at the 1% significance level.

On the other hand, the precision of MLP model is not equal to the DT and RF models which means that the original hypothesis was accepted for this result ($p>0.05$). This suggests that the current work found a significant difference only in forecasting precision between MLP and the baseline models of ANN and SMOreg algorithms. In other words, average prediction error of MLP is significantly lower than ANN and SMOReg models for the case of UK when using DI with air passenger arrivals.

4. Conclusion

In today's world, consumers' search data becomes an essential driver for forecasting demand. Researchers and marketing experts can now use Google Trends to investigate consumer travel demand in online environment. However, deciding what the search query should be utilized is quite a challenging task. In this sense, Google launched a new tool -namely DI-that directly provides time series search data including travel queries.

This study forecasted daily air passenger demand in the UK airline market with DI. For this purpose, firstly, daily air passenger demand and online travel demand data was retrieved in the period of 2020-2022. Second, co-integration and Granger causality tests were implemented to investigate the relationship between online and actual data. Third, several ML and MLP algorithms were conducted to forecast actual air passenger demand with DI and improve forecasting accuracy. In the last step, the forecasting performances of all models were evaluated with some common error metrics. This work has made two significant contributions to airline forecasting studies: it is the first study that implements DI to forecast air passenger demand; and uses novel forecasting models in a big-data framework.

According to the results of Granger causality tests done before the forecasting, DI with Google can statistically be an effective driver of daily air passenger arrivals. Considering the previous studies investigating the relationship between consumer online searches and demand in various industries (e.g., Önder and Gunter, 2016; Sun et al., 2019; Long et al., 2021), the experimental findings of the current research are in line with these studies. Furthermore, travel demand from Worldwide to the UK on Google is related to daily air passenger demand in the UK when looking at the direction of this relationship.

Experiments of this study indicates that MLP technique with Adam optimizer can significantly increase forecasting accuracy compared to ML algorithms (DT, ANN, SMOReg, and RF).

To conclude,

- DI with air passenger data is superior to improve forecasting performance in case of the UK air market.
- SMOReg is better than DT, ANN, and RF methods in ML area.
- Deep learning MLP technique is statistically significant and more appropriate to handle time series than ML techniques in forecasting daily air passenger arrivals.

In details, forecasting is one of the most important problems to be dealt with for the efficient use of resources or choosing more effective pricing strategies for airports in the aviation industry. Also, better forecasting approaches for airport demand provide clues for marketing managers to avoid uncertain economic conditions and undesirable costs (Suh and Ryerson, 2019). Therefore, consumers' Google search queries data stands out as an effective tool to achieve better results.

Another positive aspect of this study is that it helps marketing experts and scholars working in this field to identify trends for passenger demand. Another important implication of the research findings of this study is the ease of detecting trends in airline passenger demand with search engine queries. Thus, meaningful, and sustainable plans can be made not only for the aviation industry, but also for other transportation modes and the tourism connected to this industry. In this study, in which machine and deep learning algorithms are compared for the determination of better forecasting models, airport managers and marketers, especially in Europe, can produce better solutions to the capacity problems also defined by Madas and Zografos (2010).

In summary, with search engines, consumers reach information with more time, cost, and effort, which encourages search behavior before purchasing behavior in the airline industry (Peterson and Merino, 2003). The first limitation of this study is that it only used the Google search engine. Therefore, employing different consumer information search sources will contribute to the future studies. Second, the current study uses consumer demand for airports in the UK in practice. Next studies may use different airports. Third, the relationship between the datasets in this study was determined by Granger Causality Test. In this direction, future studies may apply different relationship investigation methods. Finally, this study only employed some machine learning and deep learning algorithms for forecasting task. The use of other AI methods will be beneficial in future studies.

Ethical approval

Not applicable.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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