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ORIGINAL CONTRIBUTION

Utilizing Regression Algorithms for ATS Route Forecasts

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***Abstract*— The air traffic forecast methodology by FAA assumes that the route network for flights will not change. The route forecasts are, therefore, derived from the origin-destination demand by assigning the origin-destination passengers to routes based on the percentage distribution of passengers. Assuming the static nature of routes, our study employed traffic feedback results from European airspace design evaluation tool combined with econometric modeling to forecast air traffic on selected ATS routes in the ASEAN region. A case study involving evolution scenarios of the economy from 2004 to 2019 was used to show the importance of regression modeling and form an ATS route forecast procedure in order to illustrate current capabilities. The results of the study provide valuable insights on the ASEAN ATS route network and the future direction for efforts to prevent structure imbalances by increasing capacity or reducing demand.**

***Index Terms*— Air Traffic, ATS Route, Forecasting**

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I. INTRODUCTION

Forecasts for air travel demand form an important input for government decision-making and policy formation. For the purpose of long-term planning, the civil aviation authorities are often interested in determining the future demand, shortfalls in the operational requirements and the benefits of future investments. The current approach to forecast air traffic on a specific route involves an extensive procedure. Once the origin-destination passengers are forecasted, the traffic is assigned to routes to obtain segment or route level forecasts. This process, however, is tedious and increases the forecast error every time an origin-destination traffic is forecasted. Overall, in order to enhance the air transportation services' forecast precision, a better understanding of ATS route network and its air traffic is required. The remainder of this paper is as follows. After an introduction to the methodologies, econometric modelling and variables used in previous efforts to analyze route forecasts, Section 3 describes the data source and assumptions for the analysis. A detailed explanation of forecast algorithm for selected ATS routes will follow in Section 4. Lastly, Section 5 summarizes the results from the forecast model.

A. Background

The liberalization and rapid growth of air traffic in the ASEAN region have gained considerable attention in the past 10 years [1, 2]. The improved connectivity in ASEAN has helped in developing the growth of aviation, tourism sector, and further greater integration [3]. The increasing traffic volumes make the demand analysis play an important role in deciding the runway adequacy, route demand, and capacity of a terminal. A number of papers have attempted to develop a method for forecasting traffic on the routes. Dennis developed a methodology, which involves an analysis of the future origin-destination demand and converting this demand into route traffic in order to assess the future route network [4]. Kotegawa et al. implemented network restructuring algorithm to forecast service route in order to improve the forecasting performance [5]. Busquets et al. used machine learning and data mining techniques to forecast air traffic. They employed a 2-stage log-log model and further introduced a 2-stage model using logistic regression and discrete choice modeling in their study [6]. In order to predict a number of passengers on existing and new connections, Terekhov et al. simulated demand connections between cities using a neural network and forecasted the demand network. They presented a concept to forecast origin-destination traffic taking into consideration the probability of changes in demand connections within the ATS over time [7]. DeLaurentis et al. investigated forecast algorithms such as logistic regression, fitness function and artificial neural network with a goal of improving overall air transportation system forecasts. They showed that the logistic regression model captures more new city-pairs, but in an inefficient manner as compared to fitness function models [8]. Similarly, Bhadra and Hogan determined the choice of routes by users employing instrument flight rules using binary logistic regression. They showed some important variables such as distance, flight altitude and commercial flights behind route decisions [9]. Researchers have found that factors like gross domestic product, population, airfares, etc. have a significant role to play in air travel demand forecasting [10, 11]. In their research, Grosche et al. found some variables such as buying power index, GDP, and population that can affect air travel demand [12]. The motivation for the current work arose from an increasing complication in the ASEAN

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airspace and limited studies done for the forecasting of ATS routes. This paper attempts to forecast air traffic on selected ATS routes using regression analysis. The methodology presented in the paper is an alternative approach that can be followed to provide projections for a specific ATS route using the flight path information and query results obtained from an airspace design evaluation tool.

II. DATA

The data used in this study were obtained from Flightglobal INNOVATA, which provides worldwide airline schedules data. Both passenger and cargo direct flights from the period of 2004 to 2016 were taken into account. The data for real gross domestic product at country level were obtained from World Bank database. Route network and way point information was obtained from SkyVector and modeled using System for Traffic Assignment and Analysis at Macroscopic Level (SAAM). The air traffic was measured in terms of a number of flights passing through chosen segments of an ATS route.

III. METHODOLOGY

The current assignment process by FAA in routing passengers in a metropolitan pair involves selection of routes by origin and destination. The percentage distribution of passengers by route is then applied to origin-destination forecasts. It is further enhanced by determining the type of aircraft flown on each route to determine the number of departures per route.

Our methodology offers a different perspective by utilizing an airspace design tool to find flights on a specific ATS route. Once the way points and route network were updated according to the most recent data extracted from historical weekly sample data of the previous year, the query function in SAAM was utilized in order to get segment based flights. The results were then converted in the form of origin, destination, and airline following the route.

Due to data limitations beyond ASEAN flight information regions (FIRs), our study restricts the segment query to within the region thus, offering an understanding of air traffic on ATS routes within a specific FIR. For example, to find the origin, destination and airline data for flights flying on ATS route A1, only those waypoints that lie in ASEAN region were considered. With the availability of complete data set from relevant sources, this assignment process can be completed beyond a certain region as well.

Once the query results were obtained, the yearly data concerning the origin, destination, and airline were extracted from Flight global INNOVATA database, giving us the yearly traffic on a specific route.

A variety of techniques exists for air traffic forecasting. Since no single technique guarantees accuracy in prediction, researchers often use and compare forecasts from different models to find the best suitable alternative. Within the set of models used, the most widely used is the regression model. In recent years, regression algorithms have produced meaningful results concerning how real world network evolves. Cheze et al. proposed an econometric analysis for aviation demand using variables such as GDP, jet fuel prices and dummy variables [13]. Similarly De Vany and Garges studied determinants of air travel demand and used the regression model to estimate forecasts for passenger demand and airline flights [14].

A prototype forecast algorithm, which involves estimating statistical significance of independent variables in relation to the historical dependent variable data was created. The model estimated is as follows:

$$lnQ_t = B_1 lnG_t + u_t$$

The dependent variable lnQ_t is the natural log of number of flights passing through the segments of the selected ATS route in our study. The economic variable lnG_t is the sum of gross domestic product of the origin country weighted according to the proportion of total flights passing through the ATS route, in a given year. The last term u_t is an error term; assumed to be normally distributed with mean zero and variance σ^2.

The air traffic on ATS routes was forecasted using the econometric model shown above. 3-period ahead forecasts for origin country gross domestic product were obtained from World Bank database. The forecasts were utilized as explanatory variables and weighted according to the most recent distribution of flights.

IV. RESULTS AND DISCUSSION

The ASEAN countries have experienced a high volume of inbound and outbound traffic over the past 5 years. The accumulation of flights over the airspace is likely to affect airway capacity and workload in the coming years. Thus, ATS route forecasts become necessary in order to meet such heavy traffic conditions and plan new ATS routes.

For the purpose of this study, we have narrowed down our forecasts to only top priority routes that fall in Southeast Asia flight information region. Fig. 1 shows the traffic density of ATS routes in Southeast Asia flight information region.

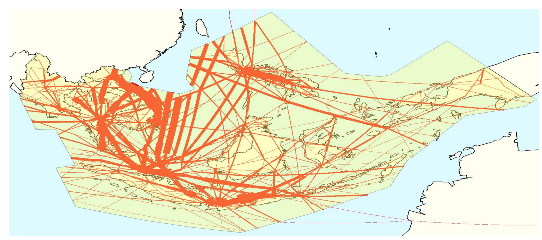

Fig. 1. Traffic density of ATS routes in ASEAN region, 2016 scenario

In recent years, much attention has been paid to ATS route M771, L642, A1, and A202 [15]. As an outcome of an airspace design workshop, ICAO identified 3 areas of priority, namely A1/A202 as the first priority, L642/M771 as the second priority, and A461/A583/N892/L625 as the third priority [16]. Our study provides forecast for the top two priority groups mentioned above. Fig. 2 shows the weekly traffic on these routes.

For flights on bi-directional ATS routes such as A1 and A202, flights from both directions were added together and weights to GDP were given based on total flights on the route.

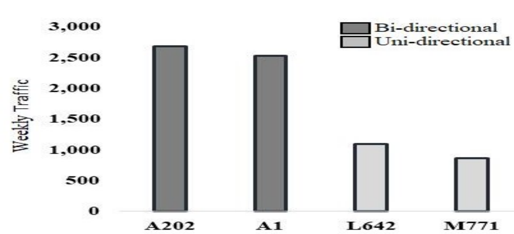

Fig. 2. Weekly traffic on ATS routes, June 2016 scenario
Note: Segments only in ASEAN FIR are considered

The air traffic forecasts on these routes are derived from the regression model shown above. In order to build confidence in the forecast process, prediction accuracy is necessary to get a deeper understanding of the model. Table I exhibits the estimation results for log-log regression analysis we used to assess the impact of economic variable on ATS route traffic along with Mean Absolute Percentage Error (MAPE) to measure the prediction accuracy.

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TABLE I
SUMMARY OF REGRESSION FOR ATS ROUTES

ATS Route	β_1 Coefficient	Adj.R^2	MAPE
A202	0.71	0.99	2.884
A1	0.68	0.99	2.737
M771	1.57	0.98	3.098
L642	0.86	0.96	4.138

The coefficient β_1 was found to be significant and positive in all the cases. However, the effect of explanatory variable on route traffic was less than 1% for ATS routes A202, A1, and L642. Once all the segments are defined for A202 and A1 routes beyond ASEAN FIR, the β_1 coefficient is expected to be more than 1. Table II summarizes the forecasted growth rate obtained from regression analysis.

TABLE II
SUMMARY OF ATS ROUTE TRAFFIC GROWTH FORECASTS

ATS Route	2017	2018	2019
A202	4.4%	3.5%	3.5%
A1	2.8%	2.5%	2.4%
M771	5.1%	6.6%	6.7%
L642	3.3%	5.2%	5.2%

Our study employs GDP as an explanatory variable. However, there is scope of adding more variables given that they contribute significantly to the ATS route traffic. In addition, our forecasts are short-term projections based on forecasts for GDP available from open source such as World Bank database. Long-term forecasting for the ATS route can be performed if long-term forecasts for gross domestic product are available. In our study, the regression estimation helped to forecast flights on a specific ATS route. The forecasts can also be obtained by taking Q_t as passengers and converting the data into aircraft movements using assumptions of load factors and aircraft size. It will help in improving the reliability and accuracy of short and long-term forecasts. Further aircraft movements distribution can be mapped onto aircraft types to understand the traffic patterns better. Although the overall forecasting procedure described in this paper is in many respects quite simple, some of the assumptions can be added and redefined based on methodologies provided by other forecasters in the aviation field.

V. CONCLUSION

This paper presents an approach to forecast ATS route traffic using regression algorithms as well as tools for traffic assignment and analysis. The principle aim was to consider ways in which ATS route traffic can be forecasted without increasing the forecast errors at every stage of origin-destination traffic forecasts preceding route forecasts. It is important to provide projections for ATS route traffic in order to support the long term succession planning. The rapid growth in route traffic will spur the authorities to plan for improvements in route structure and enhancements in airspace capacity, such as creating new routes or using better technology to manage the traffic on existing routes more efficiently. This study can be considered as a pilot study in order to evaluate the traffic on ATS routes and to help in determining the improvements needed to meet the future demand.

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