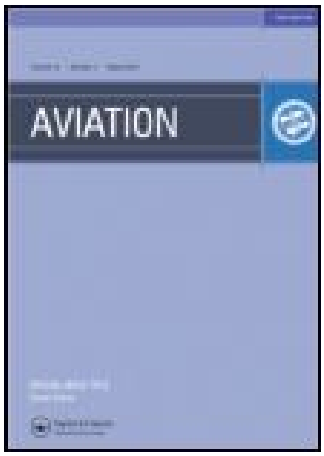

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Panarat Srisaeng[a], Glenn S. Baxter[a] & Graham Wild[a]
[a] School of Aerospace, Mechanical and Manufacturing Engineering, RMIT University, Melbourne, Australia 3001. E-mails: ;
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FORECASTING DEMAND FOR LOW COST CARRIERS IN AUSTRALIA USING AN ARTIFICIAL NEURAL NETWORK APPROACH

Panarat SRISAENG, Glenn S. BAXTER, Graham WILD

School of Aerospace, Mechanical and Manufacturing Engineering, RMIT University, Melbourne, Australia 3001
E-mails: s3125221@student.rmit.edu.au[1] (corresponding author); glenn.baxter@rmit.edu.au[2]; graham.wild@rmit.edu.au[3]

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Panarat SRISAENG, *PhD (Candidate)*
Education: Bachelor of Economics, Chulalongkorn University, Bangkok, Thailand, 1993. Master of Business Economics, Kasetsart University, Bangkok, Thailand, 1998.
Affiliations and functions: PhD (candidate) in aviation, RMIT University, School of Aerospace, Mechanical and Manufacturing Engineering and a lecturer in airline business management at Suan Dusit Rajabhat University, School of Tourism and Hospitality Management, Thailand.
Research interest: low cost airlines management; demand model for air transportation; demand forecasting for air transportation.

Glenn S. BAXTER, *PhD (Aviation)*
Education: Bachelor of Aviation Studies, University of Western Sydney, Australia, 2000. Master of Aviation Studies, University of Western Sydney, Australia, 2002. PhD, School of Aviation, Griffith University, Brisbane, Australia, 2010.
Affiliations and functions: lecturer in Aviation Management and deputy director Undergraduate Aviation Programs, RMIT University, School of Aerospace, Mechanical and Manufacturing Engineering.
Research interest: air cargo handling and operations, airport operations, sustainable aviation, supply chain management.
Publications: author of 7 scientific articles, 5 conference papers.

Graham WILD, *PhD Eng.*
Date of birth: 1981.
Education: 2001–2004 – Bachelor of Science (Physics and Mathematics), Edith Cowan University. 2004–2005 – Bachelor of Science Honours (Physics), Edith Cowan University. 2008 –Graduate Certificate (Research Commercialisation), Queensland University of Technology. 2006–2008 – Master of Science and Technology (Photonics and Optoelectronics), the University of New South Wales. 2006–2010 – PhD (Engineering), Edith Cowan University.
Affiliations and functions: 2010–2010 – Postdoctoral research associate, Photonics Research Laboratory, Edith Cowan University. 2011–2012 – lecturer of Aviation Systems, Edith Cowan University. 2012 – senior lecture in Aerospace and Aviation, RMIT University, School of Aerospace Mechanical and Manufacturing Engineering.
Research interest: aircraft systems, aerospace vehicle health monitoring, optical fibres, sensing and instrumentation, sustainable aviation, aviation technology.
Publications: author of 15 articles, 4 book chapters, 60+ conference presentations.
Present position: 2013 – Aviation Program Manager, RMIT University, School of Aerospace Mechanical and Manufacturing Engineering.

Abstract. This study focuses on predicting Australia's low cost carrier passenger demand and revenue passenger kilometres performed (RPKs) using traditional econometric and artificial neural network (ANN) modelling methods. For model development, Australia's real GDP, real GDP per capita, air fares, Australia's population and unemployment, tourism (bed spaces) and 4 dummy variables, utilizing quarterly data obtained between 2002 and 2012, were selected as model parameters. The neural network used multi-layer perceptron (MLP) architecture that compromised a multi-layer feed-forward network and the sigmoid and linear functions were used as activation functions with the feed forward-back propagation algorithm. The ANN was applied during training, testing and validation and had 11 inputs, 9 neurons in the hidden layers and 1 neuron in the output layer. When comparing the predictive accuracy of the two techniques, the ANNs provided the best prediction and showed that the performance of the ANN model was better than that of the traditional multiple linear regression (MLR) approach. The highest *R*-value for the enplaned passengers ANN was around 0.996 and for the RPKs ANN was round 0.998, respectively.

Keywords: air transport, artificial neural network (ann), Australia, forecasting methods, low-cost carrier.

1. Introduction

The emergence of low cost carriers (hereafter LCCs) has become a global phenomenon, with today virtually all travel markets containing at least some low cost carriers (Vasigh *et al.* 2008). Following the deregulation of Australia's domestic airline market in 1990, which permitted other airlines to compete with the established carriers (Forsyth 2003; Nolan 1996), a number of low cost carriers (LCCs) have entered the market. The LCCs now have around a 35 per cent market share, with the two major incumbent LCCs being Jetstar and Tiger Airways (Srisaeng *et al.* 2014).

Forecasting is considered the most critical area of airline management. Airlines forecast demand in order to plan the supply of services that are necessary to satisfy that demand (Doganis 2009). Forecasting passenger transport demand is, therefore, of critical importance for airlines as well as for investors, since investment efficiency is greatly influenced by the accuracy and adequacy of the estimation performed (Blinova 2007). Air traffic forecasts are one of the key inputs into an airline's fleet planning, route network development, and are also used in the preparation of the airline's annual operating plan (Ba-Fail *et al.* 2000; Doganis 2009). Furthermore, analysing and forecasting air travel demand may also assist an airline in reducing its risk through an objective evaluation of the demand side of the airline business (Ba-Fail *et al.* 2000). Hence, the sustainable success of any firm is closely related to the ability of its management or decision makers to foresee the future and define and implement appropriate strategies (Sivrikaya, Tunç 2013).

Consequently, the forecasting of LCC demand plays an important role in decision making and planning for both airlines and airports. In the past, regression models were generally used to predict air traffic demand (see, for example, Abed *et al.* 2001; Aderamo 2010; Ba-Fail *et al.* 2000; Bhadra 2003; Kopsch 2012; Sivrikaya, Tunç 2013). While the regression analysis method is supported by statistical theories as producing good estimates (according to certain statistical properties), for instance, being the best linear unbiased estimator, other approaches such as artificial neural network (ANN) have been found to be very useful in developing predictive models in other fields (Alekseev, Seixas 2009; Tso,Yau 2007).

In recent years, the use of artificial neural networks has grown rapidly due to its ability of mapping any linear or non-linear function and having no associated data assumption requirements (Claveria, Torra 2014; Kunt *et al.* 2011; Santos *et al.* 2014). This technique consists of training a computer to learn from substantial data based on the structure of human brain, using many simple processing elements (Haykin 1999). This approach has now been applied to a wide range of disciplines, including transportation (Jiménez *et al.* 2014), banking (Venkatesh *et al.* 2014), energy demand prediction (An *et al.* 2014; Jarimillo-Morán *et al.* 2013), tourism demand forecasting (Claveria, Torra 2014; Palmer *et al.* 2006), traffic accident prediction (Akgüngör, Doğan 2009; Kunt *et al.* 2011), and economics (Choudhary, Haider 2012).

The primary advantage of an ANN over other forecasting methods is that the network equally well predicts the processes whose regular components have any distribution law, whereas most other forecasting methods are best suited for processes that possess a regular component that belongs to a specific class (clearly, the method of polynomial smoothing is best suited for processes with a polynomial regular component, the method of smoothing by Fourier series is best suited for processes with a periodic regular component and so forth). A further advantage of ANNs is their ability to learn (Aizenberg 2011; Mrugalski 2013; Sineglazov *et al.* 2013).

This paper proposes and empirically tests for the first time classical linear regression and artificial neural network (ANN) models that can be used to forecast Australia's low cost carrier (LCC) quarterly passenger demand, as measured by enplaned passengers and revenue passenger kilometres performed (RPKs).

2. Forecasting models for estimating air transport passenger demand

While the traditional regression forecasting method has its own model assumptions and pre-defined underlying relationships between dependent and independent variables (explanatory), such as normal data, linear