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MODELLING AUSTRALIA'S EXPORT AIR CARGO DEMAND USING AN ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM APPROACH

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ABSTRACT

This paper proposes an adaptive neuro-fuzzy inference system (ANFIS) model for predicting Australia's annual export cargo demand, as measured by enplaned tonnage. The study used annual data for the period 1993 to 2016. The data was divided into two discrete data sets. The first was used to train the ANFIS, whilst the second was used for model estimation. The data was normalized to increase the ANFIS model's training performance. Sugeno fuzzy rules were used in the ANFIS structure. Gaussian membership function and linear membership functions were developed to optimize the model's performance. The hybrid learning algorithm and the subtractive clustering partition method were used to generate the optimum ANFIS model. In the computational analysis, the predictive capability of the ANFIS was examined for the following ranges of clustering parameters: range of influence (ROI), squash factor (SF), accept ratio (AR), and reject ratio (RR). The results indicated that the ROI, SF, AR and RR were obtained to be 0.50, 1.25, 0.50 and 0.15, respectively, for the optimum fuzzy inference system (FIS) structure. The mean absolute percentage error (MAPE) for the out of sample testing dataset was 3.42%. The actual R^2 value of the final ANFIS model was 0.9857%, demonstrating that the model has a high predictive capability.

KEYWORDS: air cargo; adaptive neuro-fuzzy inference system; ANFIS; Australia; export air cargo; forecasting.

INTRODUCTION

Due to Australia's relatively remote geographical location, the international air cargo mode underpins the country's international trade. Air and ocean transport are the only two modes available for any trade being shipped to or from Australia. Timely and efficient air cargo services enable Australian firms to compete with rivals in export markets. The types of commodities exported from Australia by the air cargo mode are typically low bulk and high value, and/or time-sensitive (including perishable cargoes. [1] According to Baxter and Bardell[2], in Australia's air cargo market, air cargo capacity is provided by combination passenger airlines, that is, airlines that carry passengers on the main deck and air cargo in their passenger aircraft lower lobe belly-holds and by dedicated all-cargo carriers.[2] In 2016, sixty-one international scheduled airlines, including 5 dedicated all-cargo airlines, operated services to/from Australia.[3]

The long-term forecasting of air cargo demand is regarded as essential for the industry's key stakeholders – government, airports and air freight operators. The forecasting of future air cargo demand is critical for planning and investment decision making purposes.[4]. Air cargo demand forecasting is also vital for the analysis of existing cargo flight schedules as well as identifying air cargo-related firm's future facility requirements.[5]

Despite the importance of forecasting air cargo demand, there have been a relatively small number of studies that have focused on the on the estimation of future air cargo demand. Several studies have used the traditional multiple linear regression (MLR) approach to forecast a country's national export and import air cargo demand. In an early study, Jiang et al. [6] analyzed China's future air cargo demand and developed a forecast of the country's air cargo demand through to 2020. The authors also discussed the implications of China's predicted air cargo demand on infrastructure, and particularly major hubs and emerging airports [6]. Atapattu[7] developed and empirically tested multiple linear regression models (MLR) to forecast Sri Lanka's import and export air cargo demand. Basak et al. [8] has also proposed and tested a multiple linear regression (MLR) model for forecasting India's air cargo demand. Kupfer et al. [9] proposed an error correction model (ECM) for modeling the underlying drivers of world air cargo demand and the authors developed forecasts to 2023. Quang[10] proposed and tested linear and non-linear regression models to forecast Vietnam's export and import air cargo and the turnover in Vietnam's export and import air cargo. The International Civil Aviation Organization uses an econometric model (log-log model) for its long-term forecast of world air cargo demand [11]. In other modeling approaches, Hamal [4] developed single equation models to predict Australia's import and export air cargo demand from 2009/2010 to 2029/2030. These equations were specified using a double logarithmic linear functional form [4]. Chen et al. [12] developed and empirically tested back-propagation neural networks (BPN) to enhance the forecasting accuracy of air cargo (and air passenger) demand from Japan to Taiwan. Chou et al. [13] have applied a Fuzzy Regression Forecasting Model (FRFM) to forecast an international air cargo market demand. Hathurusingha and Mudunkotuwa[14] used Box- Jenkins ARIMA modeling to forecast Sri Lanka's import and export air freight demand. More recently, Baxter and Srisaeng[15] developed and empirically tested an artificial neural network (ANN) for modeling Australia's annual export air cargo demand.

Notwithstanding the importance of the international air cargo mode to Australia's economy and to many firms supply chains as well as the reported benefits of an adaptive neuro-fuzzy inference system (ANFIS), the objective of this study is to propose and empirically test for the first time an ANFIS for predicting Australia's annual export air cargo demand. A secondary aim of the study is to examine the significance of world merchandise trade as a determinant of Australia's annual export air cargo demand.

ADAPTIVE NEURO-FUZZY INFERENCE SYSTEMS (ANFIS): A BRIEF OVERVIEW

The adaptive neuro-fuzzy inference system (ANFIS) was first introduced by Jang in 1993[16]. An ANFIS is composed of an artificial neural network (ANN) and fuzzy inference system (FIS) [17]. The FIS brings prior knowledge into a set of constraints to obtain the optimal solution, while the ANN is highly efficient at capturing various patterns [18-21]. The principal objective of an ANFIS is to determine the optimum values of the equivalent fuzzy inference system (FIS) parameters [21, 22].

The literature suggests that there are many advantages associated with the use of an ANFIS. Firstly, the advantages associated with the ANN and fuzzy-based systems are combined in an ANFIS. Consequently, the ANFIS proves to be adaptive and robust when dealing with finite variations [23]. Other advantages of an ANFIS are that it uses the ANN's ability to classify data and identify patterns; a fuzzy expert system is more transparent to the user(s); it is less probable that an ANFIS will produce memorization errors than an ANN [24]; and an ANFIS can be trained without the requirement for the expert knowledge that is normally required for the standard fuzzy logic design [25]. A further advantage when using an ANFIS is that both numerical and linguistic knowledge can be combined into a fuzzy rule base using fuzzy methods. Giovanis[26] further notes that other important advantages of an ANFIS include their nonlinear ability, the capacity for rapid learning, and an ANFIS adaptation capability [27].

An ANFIS is fundamentally a rule-based fuzzy logic model where the rules are created during the model's training process. The training process of an ANFIS is data-based [28]. Şahin and Erol [28] (p. 32) have observed that an "ANFIS constructs a fuzzy inference system (FIS) whose membership parameters are derived from training example". Mamdani-type and Sugeno-type are the two principal types of fuzzy inference system used in an ANFIS [29]. The principal difference is that in the Sugeno-system, the output membership functions are either constant or linear [30, 31]. This study used the Sugeno-type FIS system.

An ANFIS uses hybrid learning method and back propagation (BP) learning methods [20]. The output variables are obtained by applying fuzzy rules to the fuzzy sets of input variables [16, 29, 32]. To present the ANFIS architecture, two fuzzy "if-then" rules, based on a first order Sugeno model, are considered [30, 33]. These rules are:

1. $\boldsymbol{if\ x\ is\ A_1\ and\ y\ is\ B_1\ then\ f_1 = p_1x + q_1y + r_1}$
2. $if\ x\ is\ A_2\ and\ y\ is\ B_2\ then\ f_2 = p_2x + q_2y + r_2$

where x and y are the inputs, A_i and B_i are the fuzzy sets, fi are the outputs within a fuzzy rule [24], and p_i, q_i, and r_i are the design parameters. The design parameters are determined during the training process [33]. Figure 1 shows the fuzzy reasoning mechanism.

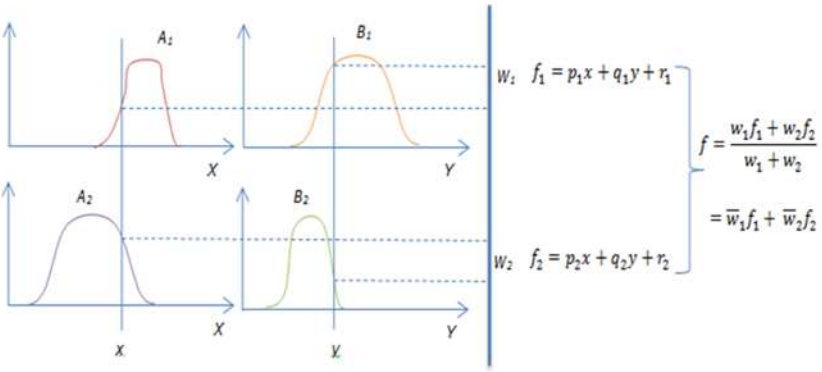

Figure 1. Fuzzy reasoning mechanism.

Source: based on Srisaeng et al. [30].

The ANFIS architecture to implement the two fuzzy if-then rules is depicted in Figure 2 [21]. An ANFIS is comprised of 5 layers [28, 30]. As can be seen in Figure 2, each node in the ANFIS is characterized by a node function which has either fixed or adjustable parameters. The circles in Figure 2 indicate a fixed node, while a square indicates an adaptive node [34]. The ANFIS model parameter values are determined through the learning or training phase of its artificial neural network (ANN). The model performance is evaluated by the training and test data. Furthermore, the model evaluates error values, for example, root mean square error (RMSE), which are in turn minimized through back-propagation as well as by the hybrid learning algorithms allowed by the ANFIS [30].

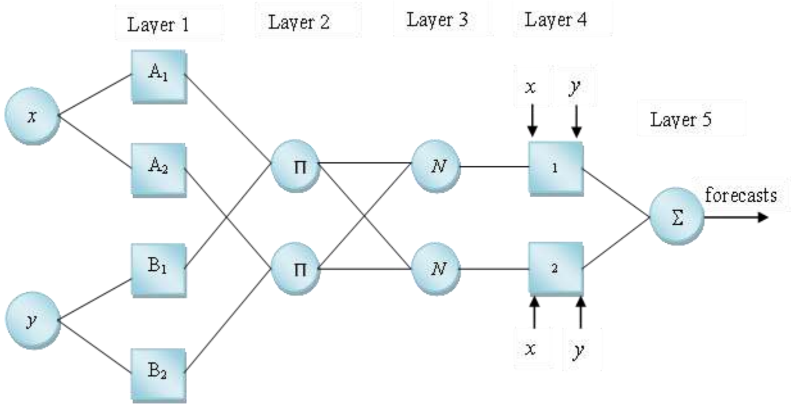

Figure 2. ANFIS model architecture with two inputs and two rules.

Source: adapted from [21].

Layer 1 is the "fuzzification" layer that directly passes crisp external signals to Layer 2 [18]. In the fuzzy layer, x and y are the input of nodes A_1, A_2, B_1, and B_2, respectively. A_1, A_2, B_1, and B_2 are the linguistic labels used in fuzzy theory for dividing membership functions [26]. Every node i in layer 1 is an adaptive node [20, 35]. The nodes in Layer 1 implement the fuzzy membership functions and maps the input variables to the corresponding fuzzy membership values [20]. The parameters in this layer are referred to as the premise parameters. According to Laouafi et al. [36] (p. 103), "the outputs of Layer 1 are the fuzzy membership grade of the inputs". The given inputs are determined by the fuzzy membership function [19]. The output of layer 1 is:

$$O_i^1 = \mu A_i(x), i = 1,2 \ or \ O_i^1 = \mu B_{i-2}(y), i = 3,4 \qquad (1)$$

where x and y are the input to the *ith* node and A_i and B_{i-2} are linguistic labels associated with this node [30, 35]. Thus, O_i^1 is the membership grade of a fuzzy set A (=A_1, A_2, B_1, or B_2) and it specifies the degree to which the given input x/y satisfies the quantifier A, where $\mu A_i(x)$ and $\mu B_{i-2}(y)$ can adopt any fuzzy membership function [37]. The bell-shaped membership can be calculated by using Equation 2.

$$\mu A_i(x) = \frac{1}{1+\left[\left(\frac{x-c_i}{a_i}\right)^2\right]^{b_i}} \quad (2)$$

where $\{a_i, b_i, c_i\}$ are the function parameters [19]. During the ANFIS learning stage the back-propagation algorithm adapts their values [38]. As the values of these parameters change, the bell-shape function varies, thus exhibiting various forms of the membership functions on the linguistic label *Ai* [39].

In Layer 2, the incoming signals are multiplied in each node [40]. Their output is the product of all the incoming signals. In this layer, each node represents the firing strength of the reasoning rule [41]. In Layer 2, the membership functions are multiplied through a T-norm operator to determine the level of fulfillment of $w_i$the rule [30, 42]. The nodes are fixed nodes and are labeled "$\prod$". Their output is the product of all the incoming signals. In this layer, each node represents the firing strength of the reasoning rule [41]. The outputs of this layer can be represented as:

$$O_i^2 = w_i = \mu A_i(x) \times \mu B_i(y), i = 1,2 \quad (3)$$

Layer 3 is the normalization layer, whose nodes are labeled "N". Srisaeng et al. [30] note that "this layer normalizes each rule's output with respect to the rest of the rule set". Also, normalization scales the fuzzy rule's output to a value between zero and one. This is obtained by dividing its output by the number of inputs [43].

$$O_i^3 = \overline{w}_i = \frac{w_i}{w_1+w_2}, i = 1,2 \quad (4)$$

where w_i is the firing strength of the *ith* rule that is computed in Layer 2 of the ANFIS. Node *i* computes the ratio of the *ith* rule's firing strength to the sum of all fuzzy rules' firing strengths [44].

Layer 4 is the "defuzzification" layer. This layer is comprised of adaptive nodes [20, 35]. Every node in Layer 4 computes a linear function. The function coefficients are adapted in this layer using the error function of the multilayer feed-forward artificial neural network (ANN) [16]. The parameters in Layer 4 are referred to as the consequent parameters. These consequent parameters are required to be adjusted. This is because they tune the output of the consequent part of the ANFIS system [45].

$$O_i^4 = \overline{w}_i f_i = \overline{w}_i(p_1 x + q_1 y + r_1), i = 1,2 \quad (5)$$

where (p_1, q_1, r_1) are the parameter set. The fifth ANFIS layer, whose node is labeled "$\sum$", is called the output layer. In this layer the model's overall output is computed as a summation of all incoming signals [19, 46]. The overall output of the ANFIS model can be written as:

$$O_i^5 = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad (6)$$

where $\overline{w}_i f_i$ denotes the consequent part of rule *i*. The overall output of the neuro-fuzzy system is the summation of all the rule consequences [19].

MODELING THE DEVELOPMENT OF AUSTRALIA'S ANNUAL EXPORT AIR CARGO DEMAND

The ANFIS Process

The determinates of air cargo demand were identified from the literature and were analyzed in detail [28, 30]. The data for the candidate input and output variables was subsequently sourced. The collected data was then normalized [47, 48]. The following step involved the data input, which included both the input data and output data in the form of data array [49]. The next step involved defining and partitioning the input variables universe of discourse using the subtractive clustering method [43, 46].

The next step in the study involved the generation of the fuzzy inference system (FIS). The fuzzy system was initialized using the "*genfis 2*" command [30]. This function specifies the structure and initial parameters of the FIS with the training data matrix, the number of membership functions (MFs), and the membership types associated with each input [50]. Normally, the coefficients for the MFs are initially selected by trial and error. The MFs are subsequently fine-tuned using the ANFIS hybrid learning algorithm [30].

The FIS parameters from the training datasets were then optimized. This was achieved using the least square method and the back-propagation gradient descent method for training the ANFIS models [30, 35]. The data allocated for training was trained automatically in the ANFIS system. During this process an array of training errors was obtained [49]. Following the data training, an ANFIS model was obtained for output forecasting. The ANFIS model computed the overall output as a summation of all the incoming signals [30, 51]. Finally, a performance index, which was based on R, MAPE, MSE and RMSE, was established to evaluate the performance of the ANFIS model.

Variable Selection and Data Sources

To develop the ANFIS model for predicting Australia's annual export air cargo demand, the data for the variables shown in Table 1 was collected for the period 1993 to 2016.

Table 1. The study's variables, data duration period and data sources

Variable	Duration	Data Source
World Merchandise Exports	1993-2016	World Trade Organization
World Population	1993-2016	United States Census Bureau
World Air Cargo Yields	1993-2016	Boeing Commercial Airplanes
World Jet Fuel Prices	1993-2016	U.S. Energy Information Agency
Australian/United States Exchange Rate	1993-2016	Reserve Bank of Australia
Outbound Flights from Australia	1993-2016	Bureau of Infrastructure, Transport and Regional Economics
Australia's Annual Export Air Cargo Tonnage	1993-2016	Bureau of Infrastructure, Transport and Regional Economics

The types of products and goods transported by the air cargo mode have grown in recent times and now include fashion items, perishable products, for example, fresh fruit and chilled meat, machinery, and electronic products. Shippers have increasingly regarded the speed of the air cargo mode as being ideally suited to their requirements for more expeditious and reliable delivery given the growing supply chain complexity [52]. However, changing market dynamics have added to the volatility in air cargo demand in recent times. Fluctuations in demand of +/- 15 to 20% within one year are not uncommon in the air cargo industry. The major driver of these fluctuations in air cargo demand is the global economy, which is the primary driver of world trade, and hence, the demand for air cargo services [53]. An example of the fluctuation in air cargo demand occurred in Australia during 2003, when both enplaned air cargo (and passengers) traffic recorded a marked decline. Australia's export air cargo volumes in 2003 declined by 12.7 per cent [54]. Thus, the first dummy variable (DUMMY 1) accounted for the quite strong downturn in Australia's export air cargo demand in 2003. This dummy variable had a value of 1 in 2003 and 0 for all other years.

A second dummy variable (Dummy 2) was included in the study to control for the influence of the 2000 Olympic Games which were held in Sydney during 2000. The Olympic Games were subsequently followed by the Para-Olympic Games [55]. During the Sydney Olympic Games, extra international services were operated to carry both passengers and air cargo for the Olympic Games. This dummy variable had a value of 1 in 2000 and 0 otherwise. During the ANFIS modeling process, this variable was found not to be significant and was therefore discarded.

In 2015, Australia's export air cargo demand fluctuated quite strongly growing by 23.2% on 2014 export air cargo volumes [56]. The strong expansion in Australian exports, particularly for perishable goods, to Asia had resulted in strong demand for air cargo capacity, and, in some cases, demand exceeded the available air cargo capacity [57]. Thus, to control for this significant fluctuation in demand export air cargo demand from Australia in 2015, a third dummy variable (DUMMY 3) was included in the modeling and had a value of 1 in 2015 and 0 for all other years.

To convert collected data from current prices to real or constant prices, consumer price index at 2011 constant prices was used [30, 51]. In this study, each input/output pair contains 9 inputs (that is, world population, world merchandise exports, world air cargo yields, outbound flights from Australia, Australia/United States foreign exchange rates, world jet fuel prices, and the 3 dummy variables and one data output, that is, Australia's export air cargo traffic (enplaned tonnage).

Data Normalization Process

Prior to commencing the data training phase in the ANFIS, it is important that the data be processed into patterns. Training and testing pattern vectors are formed. Each data pattern is formed with an input condition vector and the corresponding target vector. The scale of the input of the input and output data is an important matter for consideration. This is especially so when the operating ranges of process parameters are different. Data normalization ensures that the ANFIS will be trained effectively. This step also avoids the possibility of a variable significantly skewing the results [30]. Accordingly, all input parameters are of equal importance when training the ANN [58].

As previously noted, all data were normalized prior to their inclusion in the ANFIS training stage. The data were normalized using Equation 7, which transformed the data into a symmetric distribution. This step improved the model's performance because the data more closely satisfies the assumption of a statistical inference procedure following the transformations of variables [47]. Data was therefore normalized using the following equation:

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \qquad (7)$$

where x_{norm} is the normalized value, x is the actual value, x_{max} is the maximum value, and x_{min} is the minimum value [21, 59].

The normalization of data prior to processing it in the ANFIS has several important advantages. Firstly, it avoids attributes in greater numeric ranges dominating those of smaller data ranges. Data normalization also avoids numerical difficulties experienced during the calculation [30]. When normalizing data, the data are scaled so they fall within a pre-specified range, such as [0, 1] [21, 60]. In this study, all data values were scaled in the range between 0 and 1 using Equation 7. A further advantage of normalizing the data is that normalization also removes any arbitrary effects of similarity between objects whilst also increasing the answer rate data to the input signal [48].

ANFIS Model Setup

In this study, the Sugeno-type fuzzy inference system has 8 membership functions [25]. The membership function type is Gaussian [21]. The ANFIS models used the hybrid learning algorithm. The study's neuro-fuzzy model was run for each combination of model parameter with varying epoch numbers. This was to avoid the over-fitting of the model [30, 35]. The Gaussian-curve membership function together with the 9 rules provided the optimum ANFIS architecture for predicting Australia's annual export air cargo demand (Figure 3).

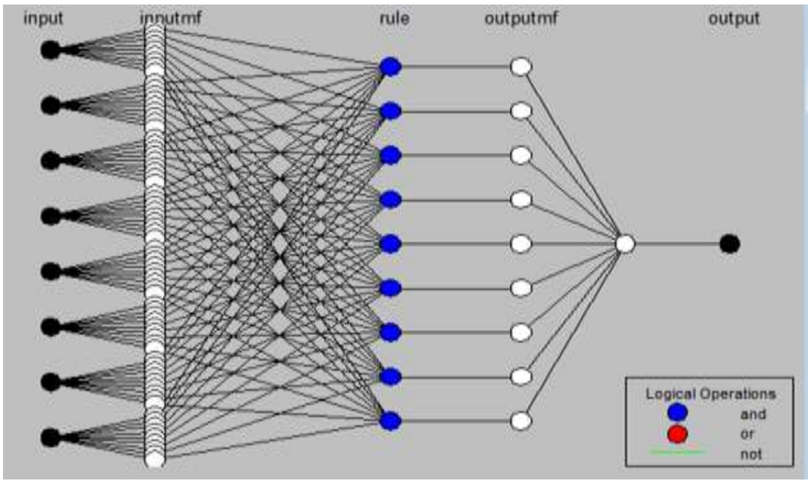

Figure 3. The optimum ANFIS model architecture for predicting Australia's annual export air cargo demand

The generated membership functions can display the interactions and relationships between the various ANFIS levels [30]. Figure 4 shows the fine curves of the trained model with smooth curve interaction for each parameter suggesting the best fit of the developed ANFIS model [30, 51].

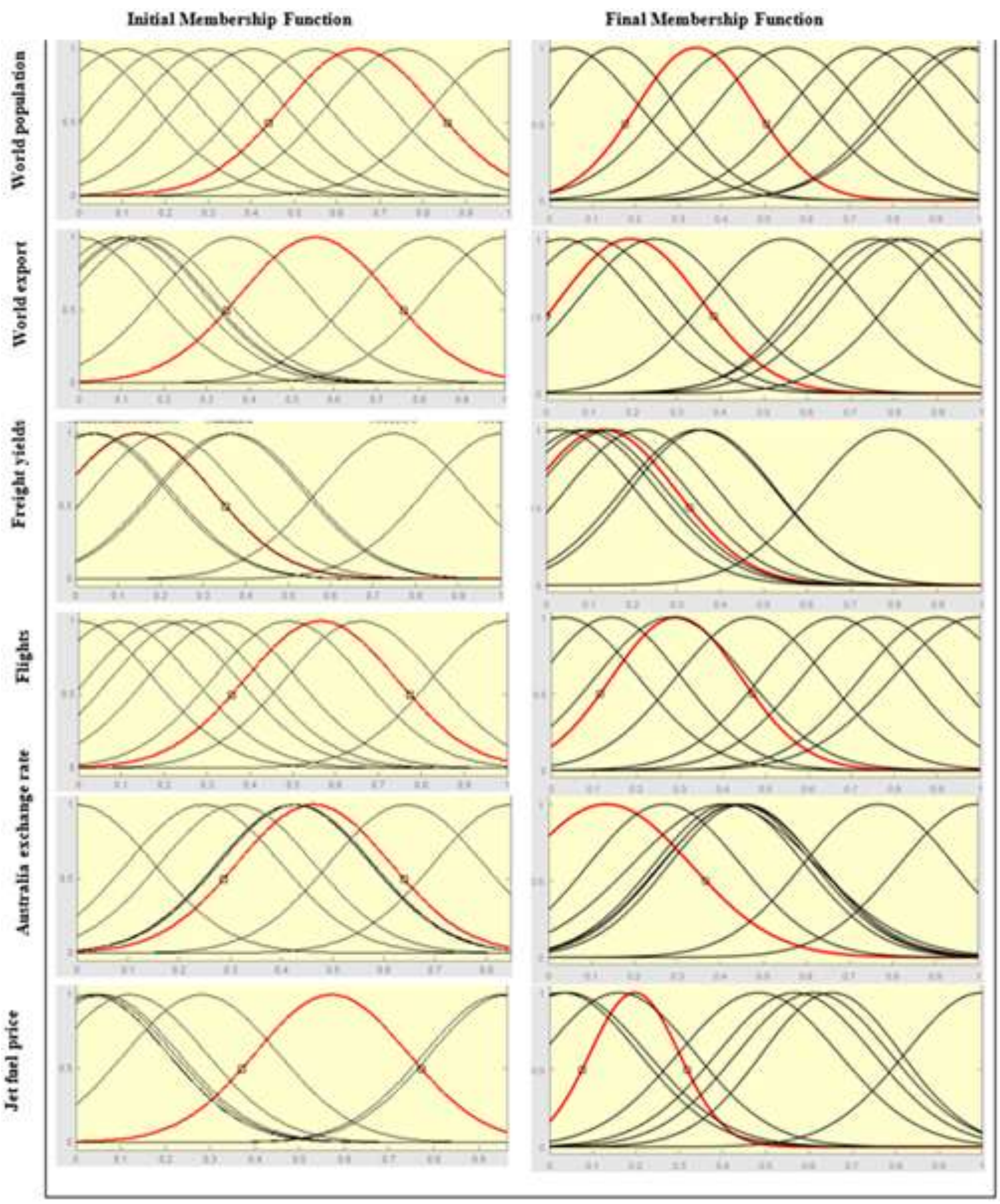

Figure 4. Initial and final Gaussian membership functions for the ANFIS Model

In this study, the ANFIS model was structured for predicting Australia's export air cargo demand using the Sugeno approach with 8 inputs and one output. The ''*product*" function is used for linking the rules together, whilst the ''*weighted average*" is used for rule "defuzzification" and the subtractive clustering algorithm partition method is applied to generate optimum 9 fuzzy rule base sets [37]. The membership functions shape in the input layer (Layer 1) is set as a Gaussian membership function and the shape of linear membership function is used in output layer [30, 51].

ANFIS Model Training

In the present study, the testing data subset was independent from the training data set. These data were used to train the ANFIS model. The testing data set was subsequently used to verify the accuracy and effectiveness of the ANFIS model [30, 51]. The data was therefore separated into two groups [20]. The first group of 21 data was used as the training set (about 85% of the overall data), and the remaining 3 data was used for verifying and testing the robustness of the ANFIS-based prediction model [30, 51].

According to Morales-Flores et al. [61] (p. 219), "the task of the learning algorithm for the study's ANFIS architecture is to tune all modifiable parameters defining the fuzzy partitions and making the ANFIS output match the training data". That is, (a_1, b_1, c_1) and (p_1, q_1, r_1); when the premise parameters a_1, b_1, c_1 of the membership function are fixed, the output of the ANFIS can be expressed as [35]:

$$f = \frac{w_1}{w_1+w_2} f_1 + \frac{w_2}{w_1+w_2} f_2 \qquad (8)$$

Substituting Eq. 4 into 9 yields:

$$f = \overline{w}_1 f_1 + \overline{w}_2 f_2 \qquad (9)$$

Further substituting the fuzzy if-then rules into Eq. 10, it becomes:

$$f = \overline{w}_1(p_1x + q_1y + r_1) + \overline{w}_2(p_2x + q_2y + r_2) \qquad (10)$$

Following, rearrangement, the output can be expressed as [24]:

$$f = (\overline{w}_1x)p_1 + (\overline{w}_1y)q_1 + (\overline{w}_1)r_1 + (\overline{w}_2x)p_2 + (\overline{w}_2y)q_2 + (\overline{w}_2)r_2 \qquad (11)$$

which according to Übeyli[35] (p. 682), "is a linear combination of the modifiable consequent parameters p_1, q_1, p_2, q_2, r_1 and r_2".

According to Srisaeng et al. [30], "the optimal values of these parameters can be obtained from the least squares estimation (LSE) method". This study used Jang's standard hybrid learning algorithm [16]. Each epoch of this hybrid learning procedure comprises a forward pass and back propagation. In the forward pass, functional signals proceed forward to till Layer 4. The resulting parameters are subsequently identified by the least square estimate (LSE) [62,63]. Once the optimum consequent parameters are identified, the backward pass immediately commences [21]. In the backward pass, the error rates propagate backward. Also, at the same time, the premise parameters are updated through gradient descent [64, 65]. The ANFIS output is calculated by using the consequent parameters. These parameters are found in the forward pass [66, 67]. Previous studies have demonstrated that this hybrid algorithm is highly efficient in ANFIS training phase [21, 30].

As previously noted, the ANFIS model used 21 training data in 1-400 training epochs [30]. The training curve of ANFIS model is presented in Figure 5. The model has a root mean square error (RMSE) of 0.000004. Figure 5 shows the level of modeling accuracy in terms of error (RMSE) achieved [30, 51].

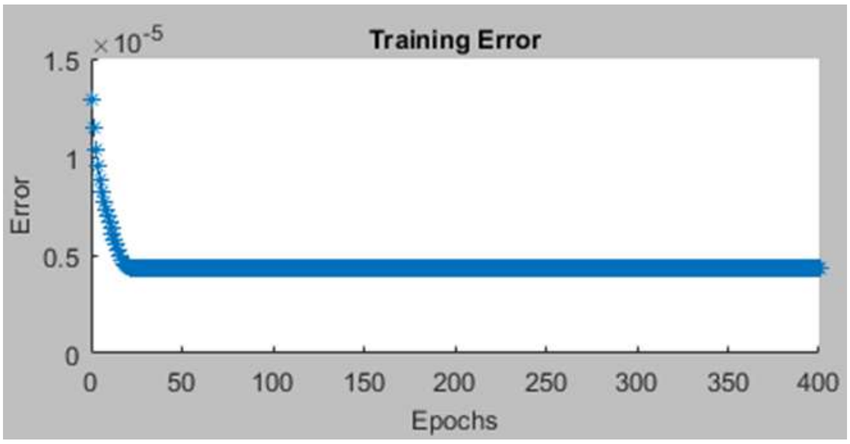

Figure 5. Error change during training the ANFIS export air cargo prediction model

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Figure 6 shows the comparison between the actual and the Australian export air cargo demand ANFIS prediction model values following the end of the training phase. As can be observed in Figure 6 the ANFIS system is well-trained to model Australia's annual export air cargo demand, as measured by enplaned tonnage [30].

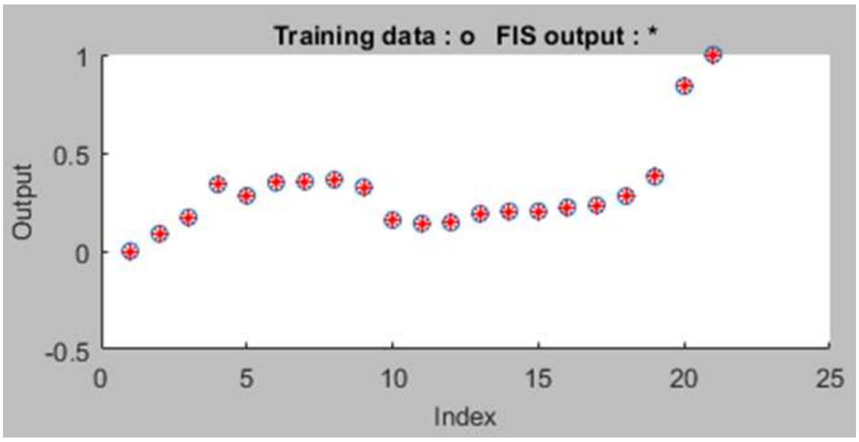

Figure 6. The ANFIS actual and predicted values of Australia's export air cargo demand model

Model Goodness-of-Fit Measures

This study used the Root Mean Squared Error (RMSE), mean absolute error (MAE), the mean absolute percentage error (MAPE), mean square error (MSE), and coefficient of determination (R^2) as the goodness of fit measures which were calculated using Eq. (12)–Eq. (16):

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(t_i - td_i)^2} \qquad (12)$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left[\left|\frac{t_i - td_i}{t_i}\right|\right] \qquad (13)$$

$$MAPE = \frac{1}{N}\left(\sum_{i=1}^{N}\left[\left|\frac{t_i - td_i}{t_i}\right|\right]\right) \times 100 \qquad (14)$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(t_i - td_i)^2 \qquad (15)$$

$$R^2 = 1 - \left[\frac{\sum_{i=1}^{n}(t_i - td_i)^2}{\sum_{i=1}^{n}(t_i - \overline{(t_i)})^2}\right] \qquad (16)$$

where t_i is the actual values td_i is the predicted values, N is the total number of data [68] (p.104).

ANFIS MODELING RESULTS

The modeling included the various possible combinations of the subtractive clustering parameters (range of influence (ROI) = 0.45-0.60, squash factor (SF) = 1.20-1.35, accept ratio (AR) = 0.40-0.55 and reject ratio (RR) = 0.10-0.20) for the range of epoch number from 1- 400 epochs [30]. The ANFIS model was manipulated by systematically changing the clustering parameters around their default values until the optimal settings were obtained. The optimal setting was based on the model's lowest RMSE value [30, 51].

The root mean square errors (RMSE) became steady after running 20 epochs of training data [24]. The final convergence values were 0.000004. Following the approach of Yetilmezsoy[20], "the subtractive clustering fuzzy inference system parameters included the range of influence (ROI), squash factor (SF), accept ratio (AR) and reject ratio (RR)". In this study the optimum ANFIS structure had ROI = 0.50, SF = 1.25, AR = 0.50 and RR = 0.15 returned the lowest value of RMSE at 0.000004 [21, 24]. The optimum ANFIS model architecture, based on the Sugeno fuzzy model approach, for predicting Australia's export air cargo demand is shown in Figure 7.

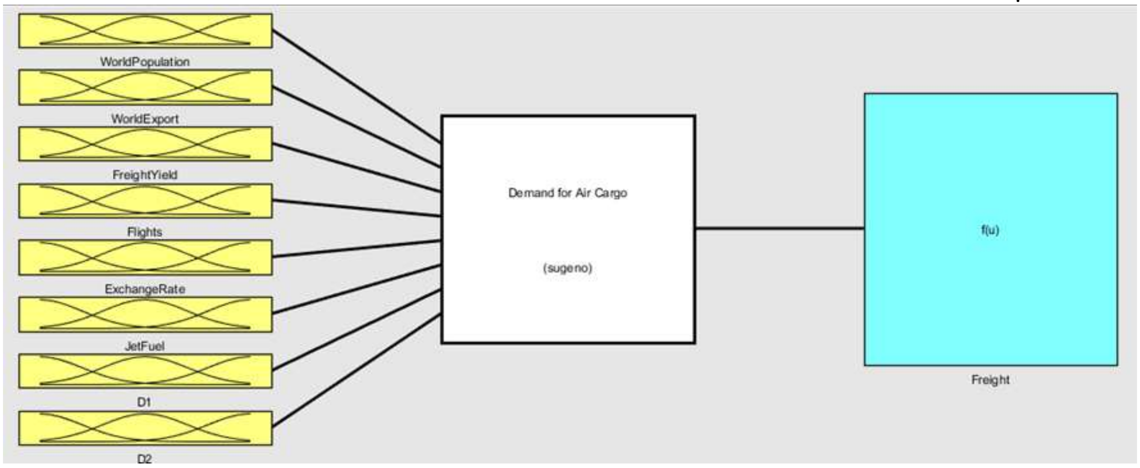

Figure 7. Australia's export air cargo ANFIS forecasting system structure

Upon the completion of the training phase, the ANFIS model for predicting Australia's annual export air cargo demand was validated through the selection of 3 data points [21, 51]. These data were different from the other 21 points that were used for training the ANFIS [24]. Following Srisaeng et al. [30] "each validation data point was fed into the ANFIS system and then Australia's predicted export air cargo values were computed and compared to the actual values". Surface graphs were subsequently obtained from the ANFIS to show the variation of output with respect to two various parameters (X and Y-axis) [52]. Figure 8 shows the non-linearity and complexity associated in mapping Australia's export air cargo demand ANFIS model input and output parameters.

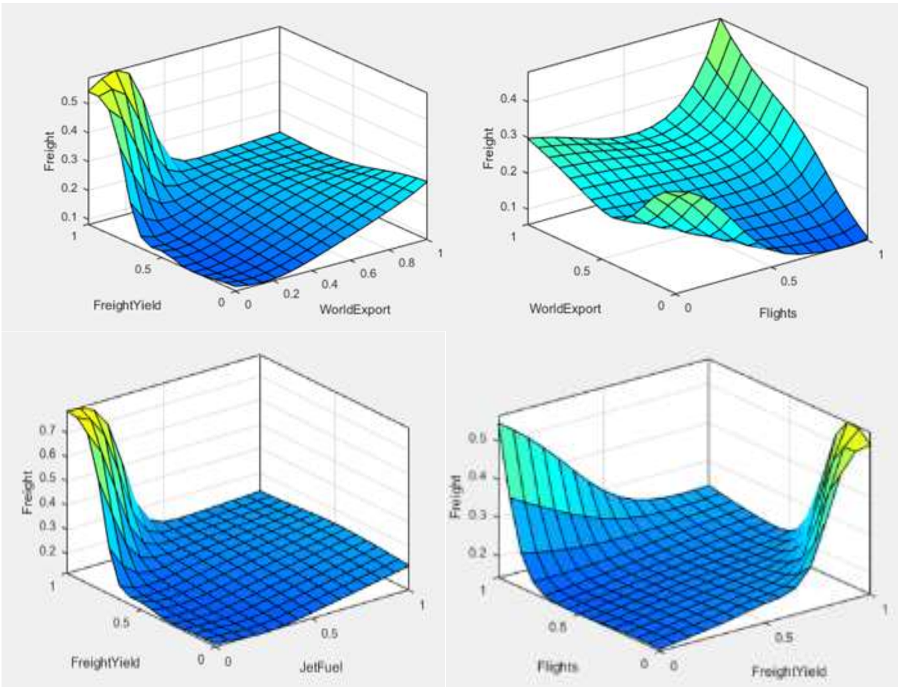

Figure 8. Obtained Surfaces in the ANFIS Model: Australia's export air cargo versus world merchandise exports, world jet fuel prices, outbound flights from Australia and world air cargo yields.

The performance index for training, testing and overall data of Australia's export air cargo demand model were calculated as shown in Table 2 [30, 51], which shows that Australia's export air cargo demand ANFIS model has achieved a very satisfactory predictive accuracy. In this study, the goodness-of fit measures – MAE, MAPE, MSE, and RMSE – in the model are very low for the training, testing, and overall data sets (Table 2) [30].

Table 2. Performance index of the ANFIS model for the training, testing and overall data set

Performance index	Training Data	Test Data	Overall Data
MAE	0.0002	0.06	0.074
MAPE	0.10%	26.59%	3.42%
MSE	0.0000001	0.01	0.001
RMSE	0.0003	0.074	0.026

The overall estimated and actual value of Australia's export air cargo demand were regressed and as Figure 9 shows the R^2 was very high, being around 0.9857.

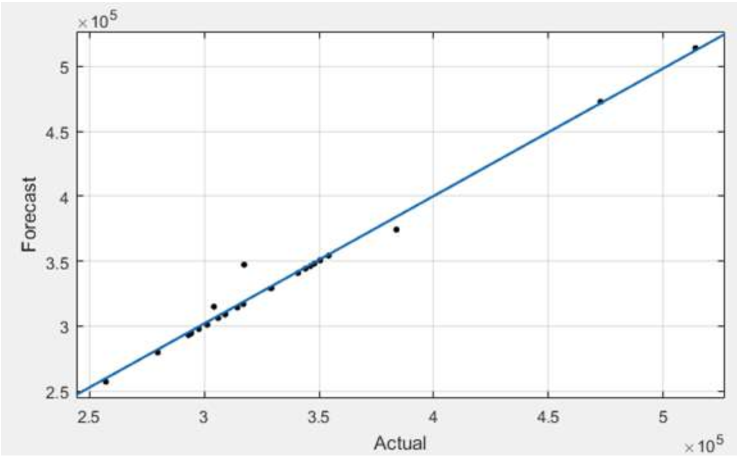

Figure 9. Comparison of the forecast and actual values of the ANFIS model for predicting Australia's export air cargo demand

The actual and predicted values of Australia's export air cargo ANFIS demand model are plotted in Figure 10. This figures clearly illustrates the robust fit of the ANFIS to the actual data. This also demonstrates the high estimation accuracy of the study's ANFIS model.

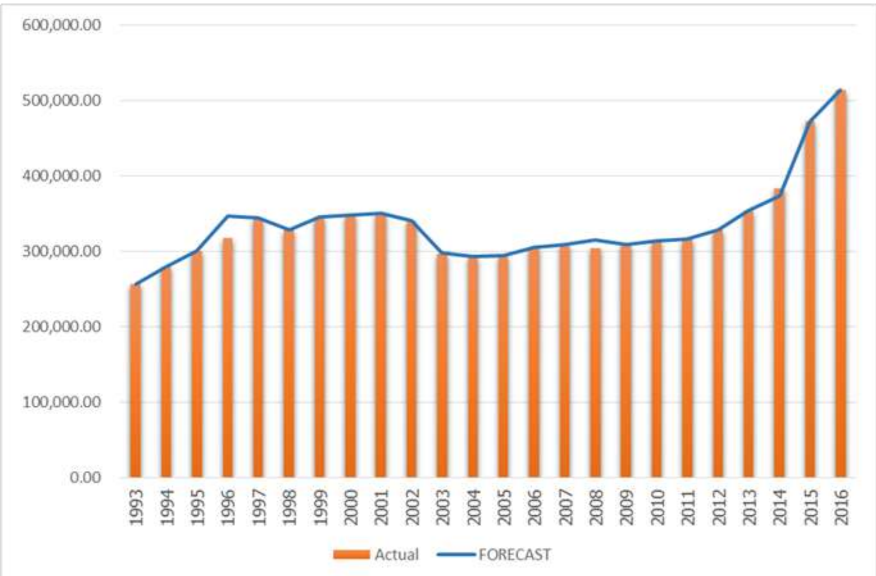

Figure 10. A comparison of Australia's annual actual and predicted export air cargo demand

CONCLUSION

Due to Australia's relatively remote geographical location, the international air cargo mode plays a vital role in the country's international trade. Export air cargo capacity is provided from Australia by full service network (FSNC), for example, Cathay Pacific Airways, Qantas and Thai International and low-cost carriers (LCCs), such as AirAsia-X and Jetstar Airways. Five dedicated all-cargo airlines also provide services from Australia to key markets. Irrespective of the airline business model, forecasting future demand is viewed as being a critical management function. Air cargo demand forecasts are used by the industry's ley stakeholders for analyzing existing cargo flight schedules and to identify future facility requirements Furthermore, the long-term forecasting of air cargo demand is also regarded as essential for government and airports for planning and investment decision making purposes.

This study has been proposed and tested an ANFIS for predicting Australia's annual export air cargo demand. The ANFIS structure used Sugano fuzzy rules and the Gaussian and linear membership functions. The hybrid learning algorithm and the subtractive clustering partition method were used to generate the optimum ANFIS model. Data were normalized to the scale [0,1] to increase the ANFIS model's training performance. Six independent variables – world merchandise trade, world population, world air cargo yields, world jet fuel prices, outbound flights from Australia, the Australian/United States dollar exchange rate and two dummy variables were used as input variables and the overall value of ANFIS model was very high with an R^2 of 0.9857. The results found that the mean absolute percentage error (MAPE) for the overall data set of Australia's export air cargo demand model was 3.42%.

The study concludes that an ANFIS is a modeling approach that can be used effectively to model and forecast Australia's annual export air cargo demand. The ANFIS model produced robust results and displayed high forecasting accuracy. Thus, the application of the ANFIS approach for the prediction of other countries or regions air cargo demand may be worthy of future research

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