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Application of an ANFIS to Estimate Kansai International Airport's International Air Passenger Demand

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Abstract

This study presents an Adaptive Network Based Inference System (ANFIS) model to forecast international passenger demand at Osaka's Kansai International Airport. The study covered the period 1994 to 2018. The study used nine determinants of air travel demand and three dummy variables as input variables. The results reveal that the model successfully forecasts Kansai International Airport's international passenger demand. The coefficient of determination (R^2) was high, being around 0.9776%. The overall MAPE of Kansai International Airport's international air passenger demand model was 7.40%.

1. Introduction

Air passenger transport demand forecasting is one of the most important determinants of airport planning, design, and operations (Karlaftis et al., 1996). Passenger demand forecasts are regarded as an important parameter for aviation planners and airport authorities (Sohag & Rokonuzzaman, 2016; Wadud, 2014) as future passenger demand forecasting could be the most critical factor in the development of airports as well as airline networks (Karlaftis, 2010). Indeed, forecasting air passenger demand is regarded as a critical aspect of formulating appropriate operation plans for airport operations (Kim & Shin, 2016). The forecasting of passenger demand is a key requirement for the daily management of an airport (Zheng, Lei & Wang, 2018). Errors in forecasting can be very costly for an airport. This is because the underestimation in passenger demand may result in increased congestion, delay, and inadequate airport facilities. Conversely, the overestimation of passenger demand may also present serious economic problems for airport authorities. Accordingly, it is essential for airport planners to develop reliable forecasting models (Karlaftis et al., 1996). as highly accurate and reliable airport passenger demand forecasts are regarded as imperative for policymaking and planning by airport managers (Tsui, & Balli, 2015). Passenger demand forecasts form for the basis of airport planning (Cook & Billig, 2017). Forecasting air travel demand helps and airport to reduce its risk profile (Adeniran, Kanyio & Owoeye, 2018). Furthermore, the forecasting of future air transport demand is particularly critical in airport master plans (Andreoni & Postorino, 2006).

The aim of this paper is to develop and empirically evaluate for the first time an adaptive neuro-fuzzy inference system (ANFIS) model for estimating Osaka's Kansai International Airport international passenger demand. Kansai International Airport commenced operations in September 1994 (Dempsey & O'Connor, 1997; Morikawa, Tabata & Emura, 2007; Ohta, 1999). Kansai International Airport is a major air transport hub and is Japan's third busiest airport. A secondary reason for focusing on Kansai International Airport in the study was the ready availability of the enplaned passenger datasets that covers the period from the commencement of operations in 1994 to 2018.

2. Materials and Methods

2.1 Variables selection and data normalization for the adaptive neuro fuzzy inference system (ANFIS) modelling

Nine determinants of passenger air travel demand were included as input parameters in the adaptive neuro fuzzy inference system ANFIS) modelling. These included world GDP, world real air fares, world oil prices, world population size, outbound flights from Kansai International Airport, Japan's unemployment, Japan's tourism expenditure, the annual exchange rate between the Japanese yen and United States dollar and Japan's real interest rates, which are among the most important drivers of air passenger travel demand.

There were three dummy variables included in the ANFIS modelling. The first dummy variable accounted for the downturn in passenger demand following the impact of the 9/11 terrorist attacks on air travel demand (Chi & Baek, 2013; Dileep & Kurien, 2022). The second dummy variable, the impact of SARS in Japan in 2003, which had an impact on Japanese travel patterns (Cooper, 2005). The third dummy variable modeled the impact of the 2008 global financial crisis (GFC) on Kansai International Airport international air travel demand, as air travel demand was negatively impacted by the GFC (Pearce, 2012; Piccioni, Stolfa & Musso, 2022; Wong et al., 2019).

Before training the data in the adaptive neuro fuzzy inference system (ANFIS), it is important to normalize the raw data into patterns. The normalization of the data ensures that the adaptive neuro fuzzy inference system (ANFIS) will be trained effectively and this will also prevent any variable skewing the results (Papageorgiou,et al., 2020; Srisaeng, Baxter & Wild, 2015). In this study, each variable was normalized to [0, 1] prior to the forecasting model being applied (Narang, Kumar & Verma, 2017; Papageorgiou,et al., 2020; Srisaeng &, Baxter, 2021). The data collected for the study were normalized using the following equation:

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \qquad (1)$$

2.2. Adaptive neuro fuzzy inference system (ANFIS)

The ANFIS is comprised of a fuzzy inference system (FIS) and an artificial neural network (ANN) (Papageorgiou,et al., 2020; Pigatto, & Balbinot, 2018; Ravi et al., 2008). Three types of data are used in ANFIS modelling. These are the training, checking, and testing data sets. The training set is used to build the model. In the following steps, test and control sets are used to generalize and validate ANFIS models (Mardani et al., 2018).

The training set is used to build the model. In the following steps, test and control sets are used to generalize and validate ANFIS models.

The Takagi-Sugeno fuzzy model inference system was used in this study (Adewuyi, 2013; Chaudhari & Patil, 2014; Khosravanian et al., 2016). The Takagi-Sugeno Model was originally developed in 1985, and it consists of four principal elements of membership functions, internal functions, rules, and the subsequent outputs (Zounemat-Kermani & Scholz, 2013). To present the study's adaptive neuro-fuzzy inference system (ANFIS) structure, the two fuzzy if-then rules based on the first order Takagi-Sugeno Model are considered (Bagheri, Peyhani & Akbari, 2014; Srisaeng &, Baxter, 2021; Übeyli et al., 2010).

Rule1: If a_1 is MF_{A1} and a_2 is MF_{A2} then b is MF_B
Rule2: If a_1 is MF_{A1} and a_2 is MF_{A2} then $b = f(a_1, a_2)$

Where MF_{A1} and MF_{A2} denote two input membership functions, respectively; MF_B denotes the membership function of the output; and $f(a_1, a_2)$ is a function of the two inputs (Alhumade & Rezk, 2022, p. 4).

Alhumade and Rezk (2022) have noted that "the Sugeno-type fuzzy inference system is recommended in modelling applications". Once each rule has produced its output, they are subsequently combined to generate one final fuzzy equation. Following this, it is defuzzified to generate its corresponding crisp value. The defuzzification method is chosen according to type of rules. The Wavg, weighted average, is suggested in the modelling using Takagi- Sugeno inference system (Srisaeng & Baxter, 2021). For a given input example x the output y of the whole system can be summed up by the weighted average Wtaver method as shown in equation 2 below:

$$y(x) = \frac{\sum_{i=1}^{n} w_i . y_i(x)}{\sum_{i=1}^{n} w_i} \qquad (2)$$

Where w_i and y_i are the rule i 's weight and output, respectively; and n is the amount of rules (Alhumade & Rezk, 2022, p. 4)..

The ANFIS system is comprised of five different adaptive layers. The study's adaptive neuro fuzzy inference system (ANFIS) architecture is presented in Figure 1. As previously noted, the fuzzy rules were configured based upon the Takagi-Sugeno fuzzy model and the adaptive neuro fuzzy inference system (ANFIS) with a back-propagation algorithm that was used for error correction (Cho et al., 20120; Srisaeng, Baxter & Wild, 2015; Takagi & Sugeno, 1985).

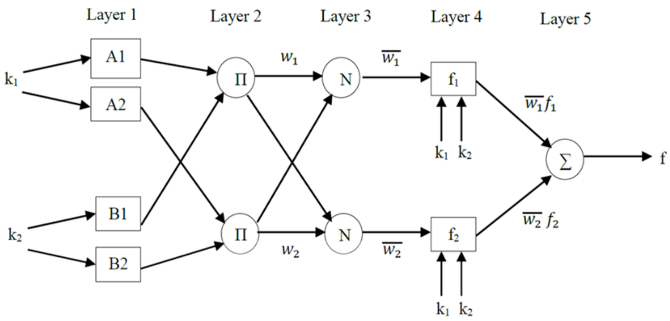

Figure 1. The adaptive neuro-fuzzy inference system architecture

In this study, the total number of data used to produce the ANFIS model was 25. The data was split as follows: 80% of the overall data was used to successfully train the ANFIS model. Five data were then used for verifying and testing the robustness of the proposed ANFIS model (Srisaeng & Baxter, 2021; Yetilmezsoy, Fingas & Fieldhouse, 2011). Hence, in this study, 20 training, 3 validating, and 2 test data points were used in the ANFIS modelling.

In this study, the Linear membership functions and the Gaussian membership were selected. From the crisp input, the artificial neural network passes data utilizing the membership functions. The algorithm of the hybrid learning was employed during the training stage (Srisaeng & Baxter, 2021; Srisaeng, Baxter & Wild, 2015). The training was conducted using 400 epochs. Following the guidance of Savkovic et al. (2019), "during the model training, new rules and forms of membership functions were constantly generated to produce the output with the smallest error". Once the ANFIS model's error rate was deemed acceptable, the model was subsequently tested. The final model was accepted once the relative errors of training and testing fell below 10% (Srisaeng & Baxter, 2021; Srisaeng, Baxter & Wild, 2015). Each combination of the model parameter with a varying number of epochs was tested to avoid possible overfitting of the ANFIS model. (Efendigil, Önüt & Kahraman, 2009; Srisaeng & Baxter, 2021; Srisaeng, Baxter & Wild, 2015).

The process of Takagi-Sugeno ANFIS network setup was developed with 18 Gaussian membership type functions. The adaptive neuro fuzzy inference system (ANFIS) model developed in this study used the hybrid learning algorithm (Srisaeng & Baxter, 2021; Srisaeng, Baxter & Wild, 2015). Figure 2 depicts the study's ANFIS architecture.

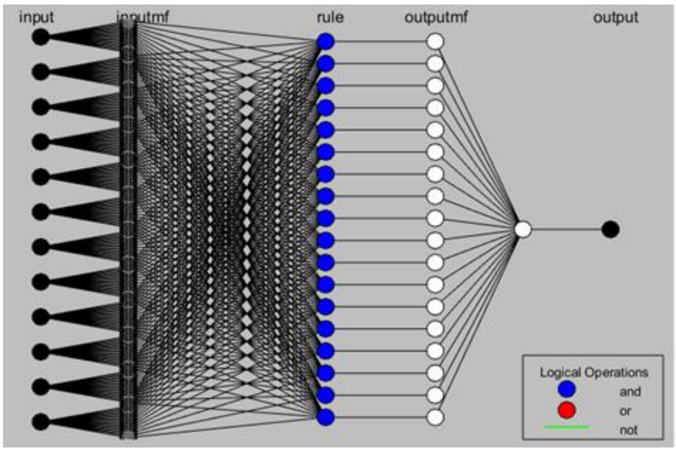

Figure 2. Optimal ANFIS model architecture for forecasting Kansai International Airport international passenger demand.

3. Results

The final structure of Kansai International Airport international airline passenger ANFIS forecasting system is presented in Figure 3.

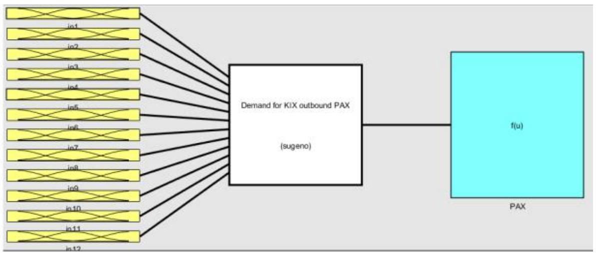

Figure 3. The structure of Kansai International Airport international airline passenger ANFIS forecasting system

The ANFIS model was trained by the Matlab R2020a software that used various possible combinations of the subtractive clustering parameters. These parameters included range of influence (ROI), squash factor (SF), accept ratio (AR), and reject ratio (RR). The developed ANFIS model was operated until the best scenerios were achieved depended on the lowest value of RMSE. The training process was concluded whenever the maximum epoch number was found, or the training error target was accomplished (Srisaeng & Baxter, 2021; Srisaeng, Baxter & Wild, 2015). In this study, the RMSE became assured after running two epochs of training data. The ultimate convergence values were 0.0000002127.

Upon the conclusion of the training phase, the ANFIS model for predicting Kansai International Airport's international air passenger was tested and validated by choosing five points of data, which are different from the other 20 points utilized for the training stage (Srisaeng & Baxter, 2021; Srisaeng, Baxter & Wild, 2015). Each validation data point was fed into the adaptive neuro fuzzy inference system (ANFIS) system and then Kansai International Airport's forecasted international passenger values were calculated and matched to the actual values.

A comparison between the actual and predicted of the ANFIS Kansai International Airport's international passengers' model for the ANFIS training are presented in Figure 4. Figure 4 shows that the ANFIS system is well-trained to forecast Kansai International Airport international enplaned air passengers.

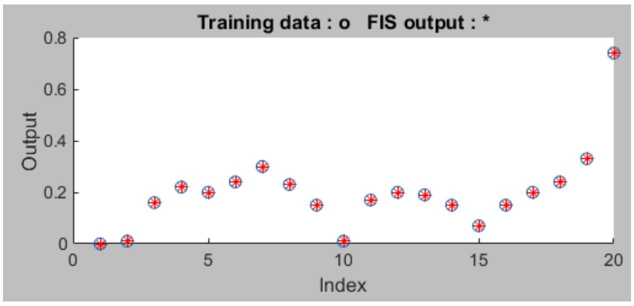

Figure 4. Kansai International Airport's actual and predicted international air passenger values

Figure 5 presents the surface graphs obtained from ANFIS. These graphs show the variation of the output according to two different parameters (X and Y axes). (Hamed, Sadkhan & and Hameed, 2018; Patil et al., 2011; Raihana et al., 2017).

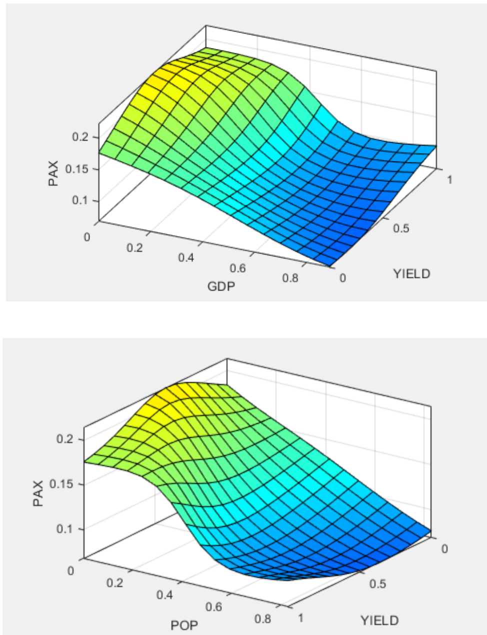

Figure 5. Obtained surfaces in the ANFIS model: Kansai International Airport's international passengers versus world GDP, world international passenger yields, and world population.

The performance index of training, testing, validation and general data of the international air passenger ANFIS model of Kansai International Airport was calculated as shown in Table 1. Table 1 shows that the ANFIS model has a very satisfactory predictive capability. The ANFIS model shows that the mean absolute error (MAE), mean absolute percent error (MAPE), mean square error (MSE), and root mean square error (RMSE) are very low for training, testing, validation, and general datasets.

Table 1. The training, validating, testing, and overall data set performance indexes of the ANFIS model

Performance Index	Training Data	Validating Data	Testing Data	Overall Data
MAE	2.06×10^{-3}	4.32×10^{-2}	1.52×10^{-1}	1.89×10^{-2}
MAPE	2.96%	31.43%	15.78%	7.40%
MSE	5.77×10^{-6}	3.19×10^{-3}	2.40×10^{-2}	2.31×10^{-3}
RMSE	2.40×10^{-3}	5.65×10^{-2}	1.55×10^{-1}	4.81×10^{-2}

The regression between the overall predicted and actual value of Kansai International Airport's international passengers are shown in Figure 6. The coefficient of determination (R^2) is high, being around 0.9776.

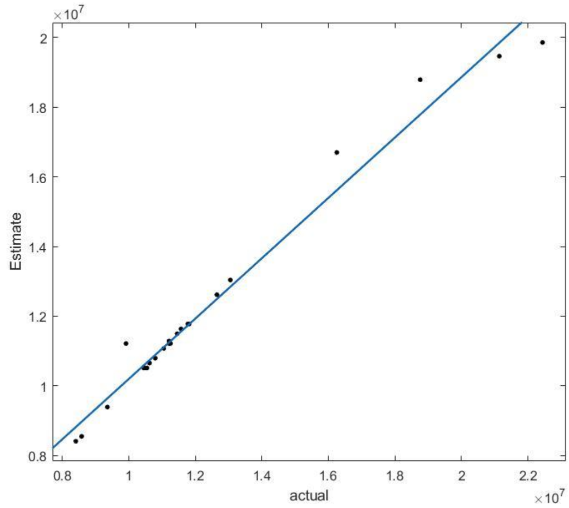

Figure 6. The regression of predicted and actual values of the ANFIS model for estimating Kansai International Airport international passenger demand

The actual and forecasted values of Kansai International Airport's international air passenger demand model are plotted in Figure 7. Figure 7 clearly illustrates the very good fit of the ANFIS to the actual data, exhibiting the high estimation precision of the Kansai International Airport international passenger demand ANFIS model.

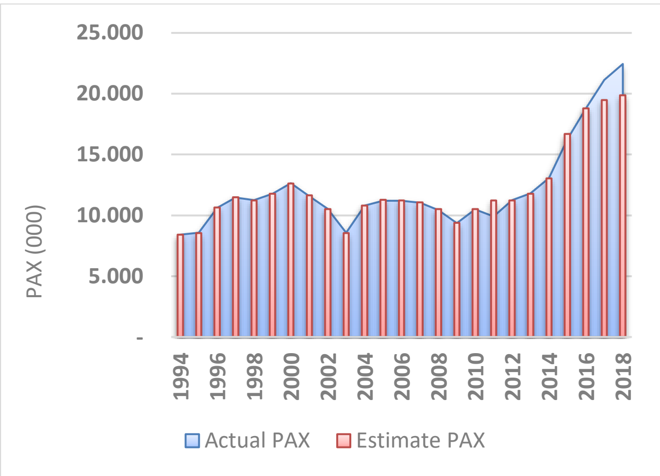

Figure 7. A comparison of Kansai International Airport actual and forecasted international passengers: 1994-2018. Legend: PAX = Passengers

4. Conclusion

This study has presented an adaptive neuro-fuzzy inference system (ANFIS) that has successfully predicted Kansai International Airport's international air passenger demand. The study used nine determinants of air travel demand and three dummy variables as input variables. The results reveal that the model successfully forecasts Kansai International Airport's international passenger demand. The coefficient of determination (R2) was high, being around 0.9776%. The results show that the average absolute percent error (MAPE) for the overall data set of the international air passenger demand model of Kansai International Airport is 7.40%. The proposed adaptive neuro-fuzzy inference system (ANFIS) structure provided very encouraging results for the successful forecasting of an airport's international air passenger demand. Airports as require highly accurate passenger forecasts, as these underpin key decisions on the very capital-intensive infrastructure and facilities that will be required to handle the predicted growth in passenger demand.

A key component of an airport's passenger throughput are passengers connecting through the airport. Thus, should connecting passenger become available, then possible future research could consider the application of an adaptive neuro-fuzzy inference system (ANFIS) for forecasting future connecting passenger traffic at an airport.

Ethical approval

Not applicable.

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