

ESTIMATING A REGIONAL AIRPORT AIR PASSENGER DEMAND USING AN ARTIFICIAL NEURAL NETWORK APPROACH: THE CASE OF HUAHIN AIRPORT, THAILAND

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Abstract: Artificial neural networks (ANNs) are a promising modelling approach for predicting an airport's air passenger demand. The study proposed and empirically tested an artificial neural network model to predict the annual passenger demand for Huahin Airport, a regional and tourist focused airport located in Thailand. The ANN input variables included Thailand's population size, Thailand's real GDP, world jet fuel prices, Thailand total passengers carried, Thailand's tourist numbers and Thailand's unemployment rates. The data were trained using the Levenberg-Marquandt back-propagation algorithm. The ANN comprises eight neurons in the hidden layer and one neuron in the output layer. 80 per cent of the data was used in the training phase with the remaining data divided into validation (10 per cent) and testing (10 per cent) phases. The proposed ANN provided very accurate prediction values. The coefficient of determination R value of model was around 0.995, and the mean absolute percentage error (MAPE) of the final ANN model was 13.27%. The study found that the four key determinants of Huahin Airport annual air passenger demand were Thailand population size, the commencement of AirAsia services at Huahin Airport, Thailand's tourist numbers, and Thailand's real GDP.

Keywords: air transport, artificial neural networks (ANN), airport, forecasting, Huahin Airport.

1. Introduction

In today's competitive business environment, forecasting is an integral element in a firm's planning and control system, and firms require a forecasting procedure that enables them to predict the future effectively and in a timely manner (Hoshmand, 2010). Forecasting is a vital part of airport management. This is because airports require accurate passenger traffic forecasts for operational,

tactical, and strategic objectives (Kroes, 2010). According to Bradley (2010, p. 1), "all major airport developments require the provision of detailed and accurate forecasts". Furthermore, the forecasting of future air transport demand has a great influence on the development of airport master plans, including both the airside (runways, taxiways, aprons, technological devices) and the landside (for example, boarding/landing area, waiting rooms) (Andreoni and Postorino, 2006).

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In the global air transport industry, there are various categories of airports, and these include rural airstrips, private airstrips, military airports, regional community airports, regional airports, major city airports, and hub airports (Meincke and Tkotz, 2010). In recent times, regional Airports have become increasingly developed into very important elements of airline's air route network systems, acting as both as feeder's passenger traffic of hub-and-spoke services and as origins or destination of point-to-point services (Postorino, 2011). The focus of this study is on Huahin Airport, a key regional airport in Thailand that primarily serves the Huahin region's tourism traffic. The objective of this study is to develop and empirically evaluate artificial neural networks (ANNs) for predicting Huahin Airport (HHQ) passenger demand. A secondary objective is to identify the key determinants of the airport's passenger demand.

The paper is structured as follows: Section 2 begins with an overview of the study's site description, and this is followed by the artificial neural modelling (ANN) approach. The empirical results of the ANN modelling are presented in Section 3. The key findings of the study follow in Section 4.

2. Modelling Air Passenger Demand at Huahin Airport, Thailand

2.1. Site Description

Hua Hin Airport (IATA Airport Code: HHQ) serves the city of Hua Hin, which is located in Prachuap Khiri Khan, Thailand. Hua Hin acts as a tourist destination and

provides port access to the Gulf of Thailand (Centre for Aviation, 2021). At the time of the present study Hua Hin airport was in the middle of a 250-million-baht renovation program, that commenced in 2020. As part of this airport upgrade program, the airport's runway is being widened from 35 to 45 metres to enable narrow-body jets, such as the Airbus A320 and Boeing 737, to operate out of the airport. Upon conclusion of the upgrade program, the airport will have the capability to handle up to five of these aircraft types at the same time. The airlines serving the airport typically deploy their aircraft for regional hops with flight times of up to 4–5 hours." A new taxiway and passenger terminal was being constructed, which will enable the airport to handle a maximum of 900 passengers an hour, or equivalent to 2.6 million passengers annually. Prior to the upgrade program, the airport could handle around 300 passengers an hour, or the equivalent of 860,000 annually (Satyaem, 2021).

Figure 1 presents the annual enplaned passengers and aircraft movements at Huahin Airport for the period 2001 to 2019. On 19 May 2018, AirAsia began four weekly services from Kuala Lumpur to Huahin Airport (The Star, 2018). In August 2020, AirAsia commenced services from Hua Hin to Chiang Mai in northern Thailand and to Udon Thani in the northeast of Thailand (AirAsia, 2020). As can be observed in Figure 1, both the annual enplaned passengers and aircraft movements have fluctuated quite widely over the study period reflecting the market entry of the low-cost carriers, such as, AirAsia-X and the cancellation of domestic services by Kan Air in 2017.

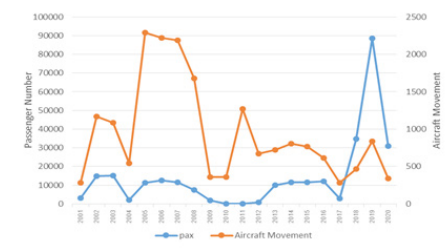


Fig. 1.
The Annual Growth in Passenger Traffic and Aircraft Movements at Huahin Airport: 2001-2019

2.2. Data Processing

Data normalization plays a vital role in the training and testing of artificial neural networks (ANNs). The data normalization process normalizes the input and the output in the same order of magnitude (Chaturvedi, 2008). The normalization of data in an ANN provides better responses and reduces the time for training the ANN (Zhang and Sun, 2009). The normalization of the data is frequently done through the rescaling of the features or outputs from one range of values to form a new range of values (Priddy and Keller, 2005). Priddy and Keller (2005, p. 16) have observed that most often the features are rescaled to lie within a range of 0 to 1 or from -1 to 1.

The data collected for the present study were normalized using the following equation:

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

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 (Kalkhaheh *et al.*, 2012). In this study’s modelling process, all data values were scaled in the range between 0 and 1 using equation 1 (Alfassi *et al.*, 2005; Bisi and Goyal, 2017).

3. Artificial Neural Network Modelling

3.1. Artificial Neural Network Input Variable Selection

In the present study, a comprehensive review of the literature was undertaken to identify the various exogenous and endogenous factors that influence air travel demand. Based on this analysis, six variables were considered as input variables in the passenger demand artificial neural network (ANN) mode: Thailand’s population size, Thailand’s real GDP, world jet fuel prices, Thailand total passengers carried, Thailand’s tourist numbers and Thailand’s unemployment rates.

Two dummy variables were considered in the modelling to control for major factors that influenced Huahin Airport passenger demand over the study period. The first dummy variable (DUMMY 1) accounted for the commencement of AirAsia services in 2019, which resulted in a spike in passenger movement at Huahin Airport. The second dummy variable controlled for the airlines that ceased operations at Huahin airport, Bangkok Airways stopped Bangkok – Huahin – Samui Island Flights in 2004, Kan Air, stopped regional route Huahin –

Chiang Mai in 2017, which had an adverse impact on passenger traffic.

The availability of a consistent data set allows the use of annual data from 2001 to 2019. The longest possible data set was collected for the study. Teodorović and Vukadinović (1998) have noted that when using an ANN, the greater length of the data, the better the solution to the problem being investigated. In this study, the collected data was converted from current to real or constant prices with the 2011 consumer price index (CPI) constant prices being used for this function (BaFail *et al.*, 2000; Baxter and Srisaeng, 2018).

3.2. Division of the Study Data

To avoid the potential over-fitting of the study's ANN model, the gathered data was divided into three discrete data sets: a training, a validation, and test dataset (Bali *et al.*, 2020; Baxter and Srisaeng, 2018; Joshi *et al.*, 2021). The overtraining of an ANN can be avoided using a cross-validation technique (Khadir, 2020). The cross-validation data process consisted of randomly selected data which were separate to the model's training data (Chew *et al.*, 2011). In this study, the data was randomly divided into an 80:10:10 ratio (Rojek and Studzinski, 2019; Sharma *et al.*, 2019). To conclude the training phase, a validation data set was used in the ANN modelling. The stoppage criterion in the training phase was the mean square error (MSE) of the estimated demand with respect to the samples belonging to the validation set. The validation dataset was not used in adapting the weight vectors of the neural estimator (Alekseev and Seixas, 2009). As previously noted, for estimating the generalization capacity of the ANN forecasting model, a testing data set was also

used in this study (Abedelbary, 2020; Mittal, 2019). Thus, once the training process was completed, a testing process was applied to ensure the model accuracy was sufficiently reliable. Once the values of the training data set were determined, a data testing set was fed into the model and the output compared to the target value. The model was accepted if the difference was low enough (Garrido *et al.*, 2014). In ANN modelling the testing set simulates the forecasting of the samples (Alekseev and Seixas, 2009).

3.3. Artificial Neural Network Model

In the present study, the feed-forward back propagation artificial neural network was applied to predict Huahin Airport annual air passengers. The architecture of the ANN consisted of three layers in a multilayer neural layer. These layers are the input layer, hidden layer, and the output layer (Na-udom and Rungrattanaubol, 2020; Wang *et al.*, 2020). The first layer is the input layer, and this layer corresponds to the problem input variables with one node for each input variable. The second layer is the hidden layer. This hidden layer is used to capture non-linear relationships among variables. The third layer is the output layer which is used to provide predicted values. The input layer receives the initial values of the variables included in the ANN model. The output layer presents the results of the ANN for the input, whilst the hidden layer performs the operations designed to achieve the output (Nunes da Silva *et al.*, 2017; Tiryaki and Aydın, 2014).

The transfer function plays a crucial role in producing the output of an artificial neural network (ANN) (Srisaeng *et al.*, 2015; Terzic *et al.*, 2012). There are three transfer function categories: linear (or ramp), threshold, and sigmoid (Deka, 2020; Dua and Du, 2011).

3.4. ANN Model Development

In this study, the input variables in the ANN models were for each determinant of airport passenger demand and also included two dummy variables, while the required model output from the network was Huahin Airport annual passenger's volumes. The number of experimental data used for the modelling was nineteen, which were divided into three discrete data sets. Fifteen data were used for training the ANN, two data were used for the model validation, and the remaining two data were used for

testing the model. The normalization of the data was the range 0-1 and this was necessary to quicken the back propagation learning process (Ibrahim et al., 2020). The MATLAB R2020a computational system was used in the present study to code and optimize the structure of the ANN models.

The Huahin Airport passenger ANN model was comprised of one input layer, one output layer, and one hidden layer, with eight neurons in each layer. The proposed architecture of the Huahin Airport passenger ANN model is presented in Figure 2.

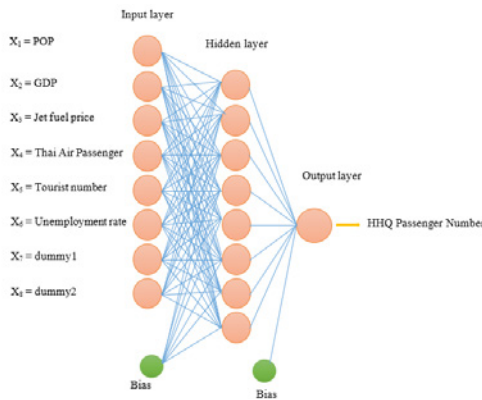


Fig. 2.

The Huahin Airport Passenger Artificial Neural Network (ANN) Architecture

The objective of ANN training is to minimize the global error, for example, the root mean square error (RMSE), mean average error (MAE), mean square error (MSE), and mean absolute percent error (MAPE) (Srisaeng et al., 2015). ANNs are normally started with randomized weights for all their neurons. This means that ANNs are not aware of everything, and consequently, they require training to solve the problem under study. When a satisfactory level of performance is attained, the training process is concluded, and the ANN uses

these weights in the subsequent testing phase (Akgüngör and Doğan, 2009). The training data set was used to adapt the ANN's synaptic weights in the multilayer network. This process used the back propagation of estimation errors (Yadav et al., 2011). All the inputs were entered into the model and the ANN networks were trained. During the supervised learning process, an error function is defined (Srisaeng et al., 2015). In this process, the synaptic weight values are iteratively updated until the provided output is as anticipated. In the present study

the training process was concluded when it reached 1,000 epochs or 0.01 error tolerance (Efendigil *et al.*, 2009).

To conclude the training phase of the study, a validation data set was used in the modelling. The stopping criterion in this phase was the mean square error (MSE) of the estimated demand of the samples in the validation set. The study's validation data set was not used in adapting the weight vectors of the neural estimator. As a result, it was possible to detect over-fitting in the ANN's training phase (Alekseev and Seixas, 2009). Once the training process was finished, a testing process was applied to ensure the model accuracy was sufficiently reliable. During this process, the values of the training data set were determined, and a data testing set was fed into the ANN model and the output compared against the target value. The model was accepted if the difference was sufficiently low enough (Garrido *et al.*, 2014). The back-propagation algorithm was applied to determine errors and was used to modify the weight of neurons in the ANN's hidden layer (Akgüngör and Doğan, 2009).

3.5. ANN Model Performance Evaluation Measures

Validation is a vital part of ANN modelling. The validation process indicates that the model(s) are a realistic representation of the actual system (Yugendar and Ravishankar, 2018). As a result, the selection and proper understanding of the evaluation metrics that are used for measuring and determining the model performance on both the testing and training datasets are a vital element of the validation process (Misra *et al.*, 2020). The accuracy of an ANN model is normally assessed by the predicted and actual results through the application and calculation of

various indicators (Ibrahim *et al.*, 2020). A review of the literature reveals that there are several model performance evaluation measures that can be used in ANN Modelling. These measures are the root mean square error (RMSE), the mean absolute error (MAE), mean absolute percentage error (MAPE), and correlation coefficient (R) (Kunt *et al.*, 2011; Ruiz-Aguilar *et al.*, 2014; Srisaeng and Baxter, 2017). In this study, the five goodness-of-fit measures were used in the modelling, and they were defined by the following formulas:

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

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (t_i - td_i)^2} \quad (3)$$

$$MAE = \frac{1}{N} \sum_{i=1}^N \left[\left| \frac{t_i - td_i}{t_i} \right| \right] \quad (4)$$

$$MAPE = \frac{1}{N} \left(\sum_{i=1}^N \left[\left| \frac{t_i - td_i}{t_i} \right| \right] \right) \times 100 \quad (5)$$

$$R = \frac{\sum_{i=1}^N (t_i - \bar{t})(td_i - \overline{td})}{\sqrt{\sum_{i=1}^N (t_i - \bar{t})^2 \sum_{i=1}^N (td_i - \overline{td})^2}} \quad (6)$$

Where t_i is the actual values, td_i is the predicted values, N is the total number of data, and \overline{td} is the average of the predicted values (Tiryaki and Aydın, 2014, p. 104).

4. Results of the Artificial Neural Network Modelling

The final Huahin Airport passenger ANN model comprised 8 inputs, 8 neurons in the hidden layers, and 1 neuron in the output layer. The forecasting Huahin Airport passenger ANN model is presented in the following equations:

$$PAX = 0.23 + 0.45H_1 - 0.31H_2 + 0.06H_3 - 0.45H_4 + 0.04H_5 - 0.49H_6 + 0.55H_7 - 1.05H_8 \quad (7)$$

Where: H_n = network hyperbolic tangent activation function:

$$H_n = \text{TANH}(Z_n) = \frac{(e^{Z_n} - e^{-Z_n})}{(e^{Z_n} + e^{-Z_n})} \quad (8)$$

Where Z_n is calculated by multiplying the value of each input by the corresponding weight (w_i) (Gonzalez, 2000):

$$Z_n = \text{Bias}H_n + w1 X_1 + w2 X_2 + w3 X_3 + w4 X_4 + w5 X_5 + w6 X_6 + w7 X_7 + w8 X_8 \quad (9)$$

Where: X_1 = Thailand Population size, X_2 = Thailand's real GDP, X_3 = Jet fuel prices, X_4 = Thailand Air passenger Carried, X_5 = Thailand's tourist Number, X_6 = Thailand's unemployment rates, X_7 = Dummy variable for the commence of AirAsia at Huahin Airport, X_8 = Dummy variable for the airlines ceased operation at Huahin Airport.

The results of Huahin Airport passenger demand ANN model are presented in Table 1 in the form of a prediction table, which shows the prediction level of Huahin Airport passenger demand during the training, testing, and validation phases of the study.

Table 1
Prediction of Huahin Airport Passenger ANN Model

Phase of the Study	R
Training	0.999
Validation	1
Testing	1
All	0.995

Figure 3 shows the regression plots of the Huahin airport passenger's model output with respect to training, validation, and testing data. The value of the correlation coefficient (R) for each phase was also calculated (Kunt *et al.*, 2011; Srisaeng and Baxter, 2017). The R value was around 0.995 for the total response in the ANN model. The solid lines in Figure 3 show the perfect linear fit between actual values and estimated values of Huahin Airport passengers. The correlation coefficient (R) between actual values and estimated values is another important indicator to check the validity of the model. Importantly, when the R value is close to 1, forecasting accuracy increases (Tiryaki and Aydın, 2014).

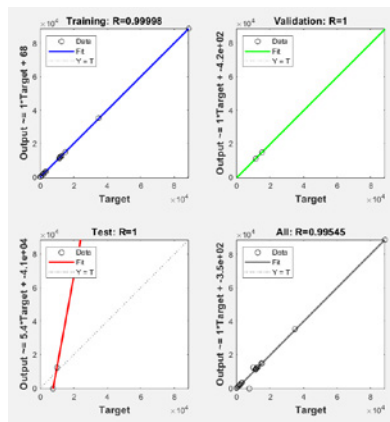


Fig. 3.
The Regression Plots for Training, Testing, and Validation Phases and the Total Response in the Huahin Airport Passengers ANN Model

In this study, the training errors, validation errors and testing errors were plotted to determine validation errors in the training phase for the Huahin Airport passengers ANN model (Figure 4). The best validation performance in the model occurred at epoch 4 with MSE at 1.56×10^5 (Figure 4). The plot in Figure 4 shows the mean squared error (MSE) beginning with a large value and decreasing to a smaller value. This indicates that the artificial neural network (ANN) learning is improving. The plot in Figure 4 has three lines, this is because 19 input and target vectors were randomly divided into

three sets (Garrido *et al.*, 2014; Kunt *et al.*, 2011). As noted earlier, 80 per cent of the vectors were used for training the network. 10 per cent of the vectors were used for validating how well the network model was generalized. Training vectors continues for as long as it takes for training to reduce the network error on validation vectors. After the network has memorized the training set, the training was concluded (Sathe-Pathak *et al.*, 2016; Šibalija and Majstorović, 2016). Also, as previously noted, the training process stopped when it reached 1,000 epochs or 0.01 error tolerance (Efendigil *et al.*, 2009).

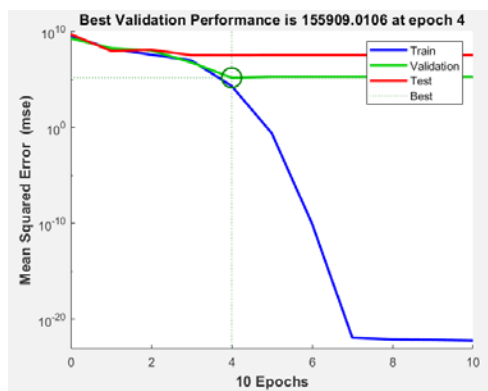


Fig. 4.
The Validation Error in Huahin Airport Passengers ANN Model

Huahin Airport’s actual and estimated passengers from 2001 to 2019 are plotted and presented in Figure 5.

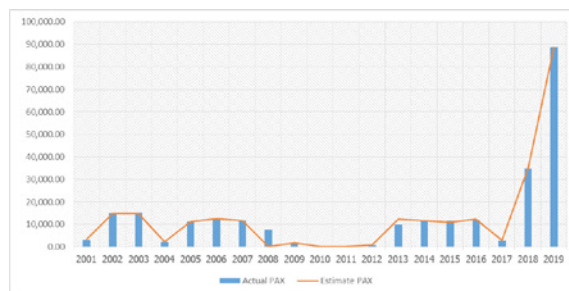


Fig. 5.
A Comparison of Huahin Airport Actual and Estimated Passengers

Table 2 presents mean absolute error (MAE), mean squared error, mean absolute percentage error (MAPE) and the root mean square error (RMSE) of the estimated

ANN models. These results suggest that the constructed ANN is very promising for modelling Huahin Airport passenger demand.

Table 2

The Performance Measurement of Huahin Airport Passenger Demand ANN Model

Performance Measurement	ANN Model
MSE	3.13 x 10 ⁷
RMSE	2.5 x10 ¹
MAE	6.47 x 10 ²
MAPE	13.27 %

To analyse the major contributing factors that influence Huahin Airport passenger demand, this study used a contribution table (Gately, 1996; Srisaeng et al., 2015). The contribution of factor (C_i) in the input layer is the sum of absolute values of the weight of connection between the input neuron and the hidden neuron.

$$C_i = \sum_{j=1}^k |W_{ij}| \tag{11}$$

Where: C_i is the contribution value of factor *i* and W_{ij} is the weight of connection between the *i*th input neuron and _jth hidden neuron.

The scale of contributing factor was used to evaluate the influences of input variables (Gately, 1996). Based on this scale, any input variable with a contribution value lower

than 2 is viewed as a weak contributing factor while in contrast any input variable with a contribution value greater than 5 is considered a high contributing factor (Chen et al., 2012).

Table 3 shows the contribution value of input variables in the Huahin Airport passengers demand model and shows that all the input variables in the model have a contribution value higher than 2 which means that no input variables are considered a weak contributing factor. Also, the four most important input variables for forecasting Huahin Airport passengers' demand are: X₁ = Thailand Population size, X₇ = Dummy variable for the commencement of AirAsia services at Huahin Airport, X₅ = Thailand's tourist numbers, and X₂ = Thailand's real GDP.

Table 3

The Contributions of the Study's Input Variables for predicting Huahin Airport Passenger Demand

Input Variables	ANN Passenger Model	Rank
X ₁ = Thailand population size	5.63	1
X ₂ = Thailand's real GDP	4.78	4
X ₃ = World jet fuel prices	3.05	8
X ₄ = Thailand air passengers carried	3.81	7
X ₅ = Thailand's tourist numbers	5.09	3
X ₆ = Thailand's unemployment rates	4.44	5
X ₇ = Dummy variable for the commencement of AirAsia services at HHQ	5.40	2
X ₈ = Dummy variable for the airlines that ceased operation at HHQ	4.14	6

In this section, three scenarios were set to forecast the number of passengers at Hua Hin Airport where assumption used in each scenario based on data from the Civil Aviation Authority of Thailand, Bank of Thailand, International Monetary Fund, Airport of Thailand, and insights from airport experts' interview (Civil Aviation Authority of Thailand, 2020). Table 4 shows details of the three assumptions which are as following

1. The best-case scenario based on assumptions that the economy will recover in 2022, three new airlines will start operating in 2023, and the existing airline will increase flight frequency in 2023;
2. The moderate-case scenario based on assumptions that the economy will recover in 2023, two new airlines will start operating in 2024, and the existing airline will increase flight frequency in 2024;
3. The worst-case scenario based on assumptions that the economy will recover in 2024, one new airline will start operating in 2025, and the existing airline will increase flight frequency in 2025.

Table 4
The Three Scenarios' Assumptions for Hua Hin Airport Passenger Demand Forecasting

Scenario	Year that the economy is expected to recover	Year that new airlines is expected to start operating	Number of new airlines expected to start operating	Year that existing airlines increased flight number
Best Case Scenario	2022	2023	3	2023
Moderate Case Scenario	2023	2024	2	2024
Worst Case Scenario	2024	2025	1	2025

The results of Huahin Airport passenger demand during 2021 – 2040 using Artificial Neural Network (ANN) model are shown in Table 5 and Figure 6.

Table 5

The Three Forecasting Scenarios Results of Huahin Airport Passenger Demand during 2021 – 2040

Year	Best	Moderate	Worst
2021	52,159	14,166	14,166
2022	70,203	53,760	10,374
2023	127,612	70,888	51,719
2024	132,071	127,798	71,661
2025	290,907	131,639	125,983
2026	294,757	289,861	126,240
2027	373,792	292,988	280,695
2028	386,545	370,833	281,926
2029	544,622	381,449	364,523
2030	576,552	537,004	387,839
2031	635,277	546,876	528,988
2032	655,173	598,338	537,065
2033	718,058	609,853	586,507
2034	742,572	663,089	595,755
2035	810,583	676,520	646,450
2036	840,788	731,826	657,037
2037	874,314	747,492	709,166
2038	911,529	764,411	721,287
2039	952,837	782,684	734,258
2040	998,689	802,419	748,136

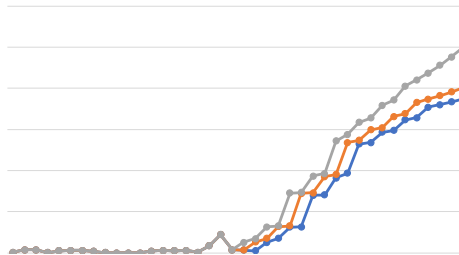


Fig.6.

The Three Forecasting Scenarios Results of Huahin Airport Passenger Demand for the Period 2021 – 2040

The modelling results found that the Huahin Airport passenger demand in 2040 for the best-case, moderate-case and worst-case are 998,689 passengers, 802,419 passengers, and 748,136 passengers, respectively.

5. Conclusion

The application artificial neural networks (Anns) appear to offer a promising approach for predicting an airport’s annual air

passenger demand. This is supported by the results of the present study, in which an ANN was proposed and empirically tested to predict Huahin Airport, Thailand annual air passenger demand. The final ANN model was based on multi-layer perceptron (MLP) with a single hidden layer comprising eight neurons and one neuron in the outer layer provided the optimum architecture for predicting the airport's annual air passenger demand. The best ANN architecture was the MLP ANN in which the hyperbolic tangent function acted as an activation function in the hidden layer, whilst the linear function was utilized as the activation function in the output layer neuron.

The ANN modelling process was undertaken in three discrete stages: training, testing, and validation. In this study, 80 per cent of the data was used in the training phase with the remaining data divided into validation (10 per cent) and testing (10 per cent). The R-value of Model was around 0.995 and the mean absolute percentage error (MAPE) was 13.27%. The ANN modelling results revealed that the four key determinants of Huahin Airport passenger demand were Thailand's population size, the commencement of AirAsia services at Huahin Airport, Thailand's tourist numbers, and Thailand's real GDP.

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