Changi Airport Passenger Volume Forecasting Based on an Artificial Neural Network

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Abstract

Neural networks are remarkable tools for extracting data changing patterns with the existence of noise distraction. Thus neural networks are widely used for forecasting problems, for instance weather forecasts and airport passenger volume forecasts. Airport passenger volume forecasting is extremely useful to predict the passenger demand in the future. Based on the passenger movement forecast, the airport managing group can adjust the airport service, resources and facilities to meet the passenger demand while improving the airport efficiency and resource usage. Airport passenger forecasting can be classified into short-term forecasts, medium-term forecasts and long-term forecasts. Here we focus on the long term passenger movement forecasting which plays an important role for airport expansion plans, including new airport terminal construction. If the forecasting model is accurate and has a high confidence level, the airport group can make development plans based on the forecasting results in order to cater the future passenger demand. In this case, we use the passenger data of Changi Airport for the past 20 years and data from the Singapore Statistics to train our neural network model and make a prediction for the future passenger demand.

Keywords- Neural Network, Passenger Volume Forecasting, MATLAB Simulation, Statistical Analysis, Changi Airport

I. INTRODUCTION

Airport passenger volume forecasts could be assorted into three groups: short-term forecasts, medium-term forecasts and long-term forecasts. Short-term forecasts which mean forecasts for less than 3 years demonstrate strong seasonal and cyclic characteristics. While long-term forecast has a forecasting range of 10 to 20 years. Long-term forecasts are useful for airport strategic plans such as expansion of new terminal and new runway. Here, we focus on the medium-term forecasts with a 3 years to 10 years forecasting range which are useful for aviation annual plans [6].

Fabbiani [4] evaluated fog forecasts at Canberra International Airport based on artificial neural networks (ANNs). Even though there are many methods available for fog forecasting, ANNs can provide better accuracy. It is because ANNs are suitable for complex nonlinear forecasting. 44-year historical meteorological data is used to train and validate the ANNs. Finally fog occurrence prediction was made based on the designed neural networks.

Grosche [5] made airline passenger volume forecasting based on gravity models. All the models treated geo-economic variables as independent factors to forecast. The models can be deployed to forecast the passenger volume between city pairs when service data is not accessible or no air service is established. In the end, the author used Europe city pair data to validate this model.

Proffilidis [10] used econometric models and fuzzy linear regression model to forecast the demand of Rhodes Airport with satisfactory prediction results. The author analyzed the relations between air traffic growth and the Gross Domestic Product (GDP). The fuzzy model can use probability distribution to deal with uncertainties and unknown knowledge. The ambiguity between the estimated value and the historical data transfers to the fuzzy coefficients which can be used to give an accurate forecast [7].
In the real world, systems or environment are always complex and nonlinear. For instance, aircraft en route path planning under adverse weather conditions [13]. Algorithms can deal with uncertainties and complexity can be applied to real situations [14].

We use a neural network to forecast the passenger volume at Changi Airport because neural networks can deal with nonlinear and complex systems. Modern airport passenger volumes are related to multiple factors including GDP, population, airfare, passenger preference, airport location, and other transportation alternatives. Moreover, we could also consider the seasonal factors because weather and holiday time also may influence the traveler volume. Airport passengers can be divided into transit passengers, arriving passengers, and departing passengers. The relation between the passenger volume and factors is nonlinear. Also, forecast accuracy of neural networks is promising. As a result, a neural network is suitable for this forecasting situation.

II. Methodology

We first choose and evaluate the factors which have effects on the passenger volume. These factors are GDP, population, sudden incidents. We will investigate these factors in detail in the following sections. Then, we input data to train the neural network in order to get the accuracy and adaptability needed for the passenger volume forecasting. The training method is the Levenberg-Marquardt training method. We use the mean squared error to assess the performance. Finally, we use the trained neural network to produce the forecasting for the passenger volume.

a. Gross Domestic Product

The GDP is a main factor for the passenger volume forecast. Citizens can have more spare money with the increase of GDP. Citizens will spend their spare money on vacations or visiting friends or relatives by airplane. A higher GDP has a positive effect on the overall passenger volume at Changi Airport.

Fig. 1 demonstrates Singapore GDP historical data at market prices from 1960 to 2014 [2].

![GDP at market prices](image1)

![GDP per capita](image2)

b. Population

Population serves as the base for economic development. As the increase of population, the number of passengers who want to go travelling will also have ascending trend. The Singapore population slowly increase from 1.65 million in 1960 to 5.47 million in 2014 [3].

Most importantly, population together with GDP also decide the GDP per capita. As we can see in Eq. 1, the GDP per capital is equal to nominal GDP divided by Population [12]. We can check historical GDP per capita in Fig. 2. At first, the GDP per capita goes up slowly until 1986. After that, it grows rapidly till 1996 when GDP per capita is 26263.02 USD. Then it fluctuates till the year 2004. Finally, the curve increases again and reaches 56284.33 USD in 2014. Overall population is an inevitable factor of passenger volume forecasting.
\[
 GDP_{\text{opt}} = \frac{GDP}{Population}.
\]  

### c. Passenger Volume

As shown in Fig. 3, the passenger volume includes three parts: arrival passengers, departure passengers and transit passengers. The numbers of arrival passengers and departure passengers are nearly the same for Changi airport [1]. The two curves both go up gradually from 1975 to 2015. We can clearly see that there is a sudden drop in 1997, 2004 and 2009. In 1997 and 2009, the passenger volume clearly goes down because Asia had a financial crisis at that time. Unemployment and less salary can lead people to stay home rather than travel abroad. The passenger volume drop in 2004 is probably because SARS broke out worldwide at that time including Singapore. People avoid to go travelling or go to public places which led to the significant passenger volume decrease.

![Figure 3. Changi airport passenger numbers](image1)

![Figure 4. Changi airport total passengers](image2)

The number of transit passengers in Singapore increases at a slow pace from 1975 to 2005. After that, the number drops slowly until 2015. The curve is flat when comparing to arrival or departure passenger numbers. The total number of passengers can be found in Fig. 4. We can conclude that arrival and departure passengers are the main elements of total passengers. The total passenger curve has the same changing trend as the arrival and departure passengers.

### d. Dummy Variables

In the contemporary society, we must take into consideration of sudden incidents which can cause the passenger volume to drop or go up. These variables can be treated as dummy variables. For instance, terrorist threat, financial crisis and diseases are the most common incidents happening around the world.

As a result, the incident that infectious virus SARS broke out in 2014 has a negative influence on the passenger volume. We treat it as a dummy variable. For the 1997 and 2009 Asian financial crisis, we also treat them as dummy variables which caused the number of passengers to fall significantly. Last but not least, terrorist threat can also cause people to avoid travelling by public transport. Thus can lead to sudden drop of passenger volume, for example September 11 attacks in 2001.

### e. Neural Network

We deploy an artificial neural network with 2 hidden layers. The first hidden and second hidden layers contains 20 neurons and 1 neuron respectively. The input data can be time, GDP and population. We train the neural network by Levenberg - Marquardt backpropagation algorithm. After that, we use original data to test and validate the neural network in order to get the least Mean Square Errors and a high R value. The equation to predict the output is as follows [8]:

\[
 W_2 \cdot \tanh \left( \sum_{i=1}^{n} \sum_{j=1}^{m} (I_i W_{ij} + B_{in}) \right) + B_2 = O.
\]
\( n \) stands for the number of neurons in the first hidden layer. \( w_1 \) is weight of the first hidden layer. \( w_2 \) is weight of the second hidden layer. \( b_1 \) is bias for the first hidden layer. \( b_2 \) is bias for the second hidden layer. \( I_n \) is input. \( O \) is output.

III. RESULTS ANALYSIS AND DISCUSSION

\textit{a. Curve fitting based on neural networks}

The three factors we take into consideration are year, GDP and population. These three factors are inputs for the neural network. The target is the passenger volume. We use the historical data from 1976 to 2015 for the three factor to forecast the passenger volume from 2016 to 2020. At first, we use neural network fitting tools to fit the passenger volume curve in order to train the neural network and validate the biases and weights for the two hidden layers. As we can see in Fig. 5, the neural network fitting curve fit the data well except the three incident points. That is to say, the 1997, 2009 financial crisis and the 2014 SARS. The three points have the largest errors. Training, validation and testing all have a high R value. The predicted data and the real data are approximately distributed along Y=X. A high R means that the neural network fitting and prediction are accurate and keep a high fidelity rate. The average R value for this neural network is 99.604% which is promising.

\begin{figure}[h]
\centering
\includegraphics[width=0.45\textwidth]{figure5.png}
\caption{Neural network fitting}
\end{figure}

\begin{figure}[h]
\centering
\includegraphics[width=0.45\textwidth]{figure6.png}
\caption{Passenger volume forecasting}
\end{figure}

\textit{b. Forecasting based on trained neural networks}

After that, based on the fitting neural network, we can get all the hidden layer biases and weights from the trained neural network. The biases and weights can be used to forecast the future passenger demand.

\begin{figure}[h]
\centering
\includegraphics[width=0.45\textwidth]{figure7.png}
\caption{Forecasting block diagram}
\end{figure}

Fig. 7 shows the forecasting block diagram for passenger volume forecasting. We input the Singapore GDP forecasting data, population forecasting data and year into the trained neural networks. The GDP forecasting data can be found in [11]. The population forecasting can be found in [9]. The population of Singapore in 2020 is expected to reach 6 million. So each input will multiply by weights and plus biases, then process through first hidden and second hidden layer. Finally, the output is the passenger volume forecasting. The results are shown in Fig. 6. We used the historical data to forecast the passenger volume.
from 2016 to 2020. From 2015 to 2020, the growth rate of passenger volume drops to a low increase speed. In 2020, the passenger volume for Changi Airport is expected to hit 60 million.

IV. CONCLUSION

We deploy an artificial neural network for the forecasting of passenger volume in Changi Airport from 2016 to 2020. The input factors are GDP, population and time. We use the historical data of the three factors to train and validate the neural network in order to get the biases and weights of the two hidden layers. Finally, based on GDP and population forecast, we use the validated weights and biases to forecast the passenger volume. The results show that neural network can have a good fit for the total passenger volume and the forecasting seems promising for the future development for the airport. Both the fitting and the forecasting have high R value. The neural network method is suitable for dynamic and nonlinear situation which is close to the real situation. We can develop further forecasting based on neural networks. In this paper, we only consider three inputs. In real situation, passenger volume is related to much more factors. Future works will be including more inputs for the neural networks and better passenger volume forecasting.

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REFERENCES