

DEMAND FORECASTING FOR A DOMESTIC AIRPORT-A CASE STUDY

Md. Salahuddin Sohag*¹ and Md. Rokonzaman²

¹ Student, Khulna University of Engineering & Technology, Bangladesh, e-mail: sohagkuet@gmail.com

² Professor, Khulna University of Engineering & Technology, Bangladesh, e-mail: rokoncekuet@yahoo.com

ABSTRACT

Passenger demand forecasting of an airport is regarded as a critical and important activity for an economic airport planning and development process. Different demand models are usually used to forecast the demand of an airport. In this paper, a back propagation neural network model is developed to forecast the demand of a new domestic airport in a divisional capital in Bangladesh. Several factors such as GDP, Population and Travel time ratio etc. have been used for the forecasting process. From the results of this study, it is observed that ANN serves as a reliable and simple predictive tool for air travel demand forecast. A comparative study is also done between the predictions of neural network and gravity type demand model.

Keywords: Airport, passenger demand, ANN model, gravity model

1. INTRODUCTION

Air transportation system is regarded as a special mode of transportation due to its operational and level of service characteristics. The infrastructure needed for air transportation is very large and involves huge investment (Rangaraju, 1992). The effectiveness of an air transport system mostly depends on the number of users using it. Forecasting passenger transport demand is therefore of critical importance for existing airport authorities. Air traffic forecasts are one of the key inputs into an airline's fleet planning, route network development, and are also used in the preparation of the airline's annual operating plan (BaFail et al., 2000; Doganis, 2009). Furthermore, analyzing and forecasting air travel demand may also assist an airline in reducing its risk through an objective evaluation of the demand side of the airline business (Abed et al., 2001; Ba-Fail et al., 2000). Consequently, the forecasting of passenger demand plays an important role in decision making and planning (srisaeng et al., 2015).

In this paper, passenger demand of a new airport of Bangladesh named Khan Jahan Ali airport has been forecasted. Here, a back propagation neural network model has been developed for the forecasting process. Several factors such as GDP growth rate, population growth rate and travel time ratio have been considered for the prediction. The performance of ANN model is compared with gravity type model.

2. AIR TRANSPORT STATISTICS IN BANGLADESH

Bangladesh is a small developing country containing flat ground. There are overall 15 airports in Bangladesh. According to the Civil Aviation Authority of Bangladesh (CAAB), they are classified as follows: three international airports (Hazrat Shahjalal International Airport, Shah Amnanat International Airport, and Osmani International Airport) and twelve domestic airports of which 5 are operational, 3 needs prior approval for operation, service not available for 3 airports and 1 is under construction (Khan Jahan Ali Airport) (Source: www.caab.gov.bd/adinfo/airports.html). Among 15 airports eight are considered as commercial airports in Bangladesh (Table 1). Dhaka is the capital of Bangladesh and center of all economic activities of the country, and accordingly Dhaka airport is by far the largest and the busiest. Five of the airports cater only to domestic flights. Apart from Dhaka, airports in Chittagong and Sylhet also cater to international flights, but only a few. All domestic flights within the country either start from or end at Dhaka. Despite small travel distances, Bangladesh can afford eight active airports because of a lack of bridges over its major rivers during the earlier years, which made road and rail travel a time-consuming and unpleasant experience. However, over the years there has been significant investment in surface transport, including new road and rail bridges over some major rivers. This change made surface travel more attractive than patronage for those air routes (Wadud, 2011). Figure 1 shows the annual air passenger patronage for the year 1972-2010.

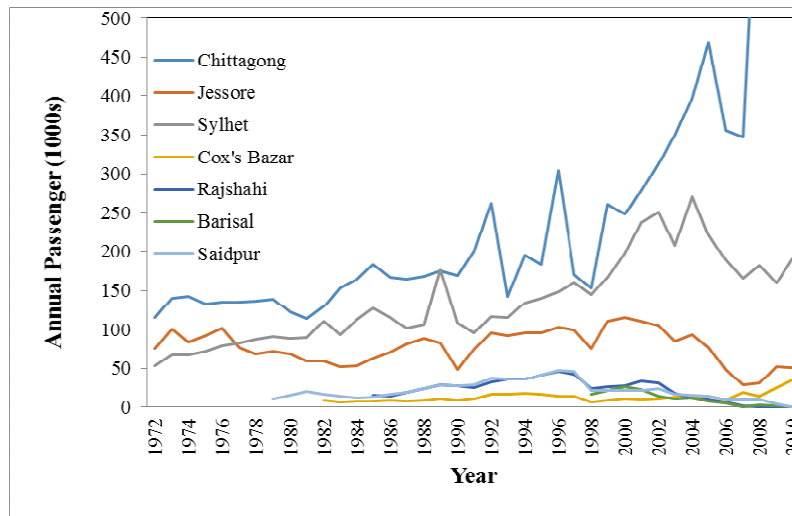


Figure 1 : Passenger patronage of different airports in Bangladesh (Source: BBS and CAAB)

Table 1: Brief description of airports in Bangladesh (Source: BBS and CAAB).

City	Airport name	IATA code	Latitude	Longitude	Runway length(ft)	Passenger in 2007(thousands)
Barisal	Barisal	BZL	22.801(N)	90.301(E)	5995	4
Chittagong	Shah Amanat Int'l	CGP	22.250(N)	91.813(E)	9646	348
Cox's Bazar	Cox's Bazar	CXB	21.452(N)	91.964(E)	6790	9
Dhaka	Hazrat Shahjalal Int'l	DAC	23.843(N)	90.398(E)	10500	3140
Jessore	Jessore	JSR	23.184(N)	89.161(E)	8000	29
Rajshahi	Shah mokhdum	RJH	24.437(N)	88.617(E)	6000	2
Saidpur	Saidpur	SPD	25.759(N)	88.909(E)	6000	10
Sylhet	Osmani Int'l	ZYL	24.963(N)	91.867(E)	9478	166

Note: IATA: International Air Transportation Association

3. AIR TRAVEL DEMAND FORECASTING METHODS

The Transportation Research Board (TRB), in its synthesis of aviation activity forecasting methods for U.S. airports, found four general approaches to model and forecast airport-specific demand: Market share forecasting, Time-series modeling, Econometric modeling, and Simulation modeling. Market share forecasting is a top-down approach in which demand at an airport is a proportion of national/regional demand for which a demand prediction already exists. Time-series modeling extrapolates existing historical data at an airport by using time-series econometric techniques or, more recently, by using neural network or fuzzy regression. The third approach, econometric modeling, involves establishing a causal relationship between passenger demand and a set of independent explanatory variables. This is the most commonly used model to predict passenger demand in airports. Simulation models actually use the output of the previous three types of models to simulate the activity patterns of passengers or movement patterns of aircraft within an airport (Wadud, 2011). This paper concentrates on ANN and gravity type econometric model.

3.1 Gravity Demand Model

Gravity-type demand models originate from the laws of gravity in physics, which state that the force between two terrestrial bodies is proportional to their mass and inversely proportional to their distance. In gravity-type demand models, the travel demand between two cities or regions is proportional to the mutual attraction factors and inversely proportional to their distance. Therefore, it is assumed that there exists no competition between origins or destinations or different transport modes and that demand is solely a function of the characteristics of

the city pairs. The mutual attraction factors in gravity models are generally expressed by employment opportunities or GDP of the cities, or both. The cost of travel enters the gravity model as the deterrence factor. Ideally it includes the cost associated with travel time (which also takes care of the distance aspect) and out-of-pocket costs, such as air fare, taxi fare to the airport, and so forth. (Wadud, 2011)

3.2 Artificial Neural Network (ANN) model

Neural Network is an intelligent computer system that mimics the processing capabilities of the human brain. The most basic element of the human brain is a specific type of cell, which provides us with the abilities to remember, think and apply previous experience to our every action. These cells are known as neurons as shown in Figure 1, each of these neurons can connect with up to 200,000 other neurons. All natural neurons have four basic components, which are dendrites, soma, axon, and synapses. Basically a biological neuron receives inputs from other sources, combines them in some way, performs a generally nonlinear operation on the result, and then output the final result. A typical structure of ANNs consists of a number of processing elements (PEs), or nodes, that are usually arranged in layers: an input layer, an output layer and one or more hidden layers (Figure .It is a forecasting method that specifies output by minimizing an error term indicated by the deviation between input and output through the use of a specific training algorithm and random learning rate (Black, 1995; Zhang et al, 1998). (Yaldi et al., 2015). The ANN 'learns' through training using cases where inputs and outputs are known. It can then be used to predict outputs for a new set of inputs. Emulating the human brain, ANN is capable of mapping between defined input conditions. Kolmogorov's 'Mapping Neural Network Existence Theorem' has demonstrated that ANN is capable of implementing a function to a desired degree of accuracy (Hechi-Nielson, 1989). (Yang and Rosenbaum, 2002)

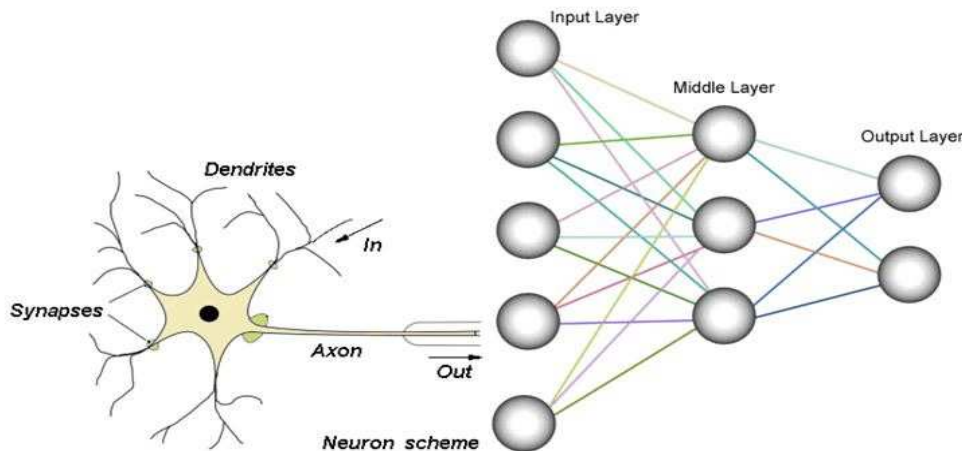


Figure 2: A biological neuron and a neural network

4. METHODOLOGY

The total prediction work consists of following steps: collection and preparation of database, creation of the network, training, testing and validation of network, prediction of demand using the network. Finally the performance of the ANN model will be compared with the gravity demand model.

4.1 Collection and Preparation of Database

It is generally difficult to incorporate prior knowledge into a neural network; therefore the network can only be as accurate as the data that are used to train the network. It is important that the data cover the range of inputs for which the network will be used.

Passenger data for different airports are available as a time series for all airports in Bangladesh, but per capita GDP or population around the airport's zone of influence is not. The definition of district and city boundaries has changed over the years, making the available city-specific GDP and population data unsuitable in the time-series context. Therefore, national GDP and national population are used as proxies, the primary objective is to forecast passenger demand in a new airport, and the national data only serve as an indicator to understand the relationship of air travel demand with per capita GDP and population. Passenger travel data in the chosen airports and national GDP and population were collected from the Bangladesh Bureau of Statistics (BBS) for

1972 to 2010. The time ratio was calculated on the basis of road distance and average speed (considering obstacles like ferry crossings over the rivers) using information from the Bangladesh Roads and Highways Division. Although air travel times change by only very small amount over the years, the road travel time, and thus time ratio, changes over time because of the construction of new bridges over the rivers, widening and straightening of existing roadways, and increased congestion on some highways. By replacing the cost ratio with the time ratio, the impact of air fare is ignored (KUET CRTS). Table1 shows the sample database. Here, GDP and population data has been converted to growth rate.

The whole database contains the data i.e. the GDP growth rate, population growth rate, travel time ratio and passenger demand of four airports- Chittagong, Sylhet, Cox’s Bazar and Jessore airport. Data series for Sylhet, Chittagong and Cox’s Bazar airports are used because these cities continue to show an increasing trend despite significant improvements in road conditions, a trend expected for KJA as well. The data of Jessore is most significant as it is very near to KJA and in the same region. Figure3 represents the database of Chittagong Airport.

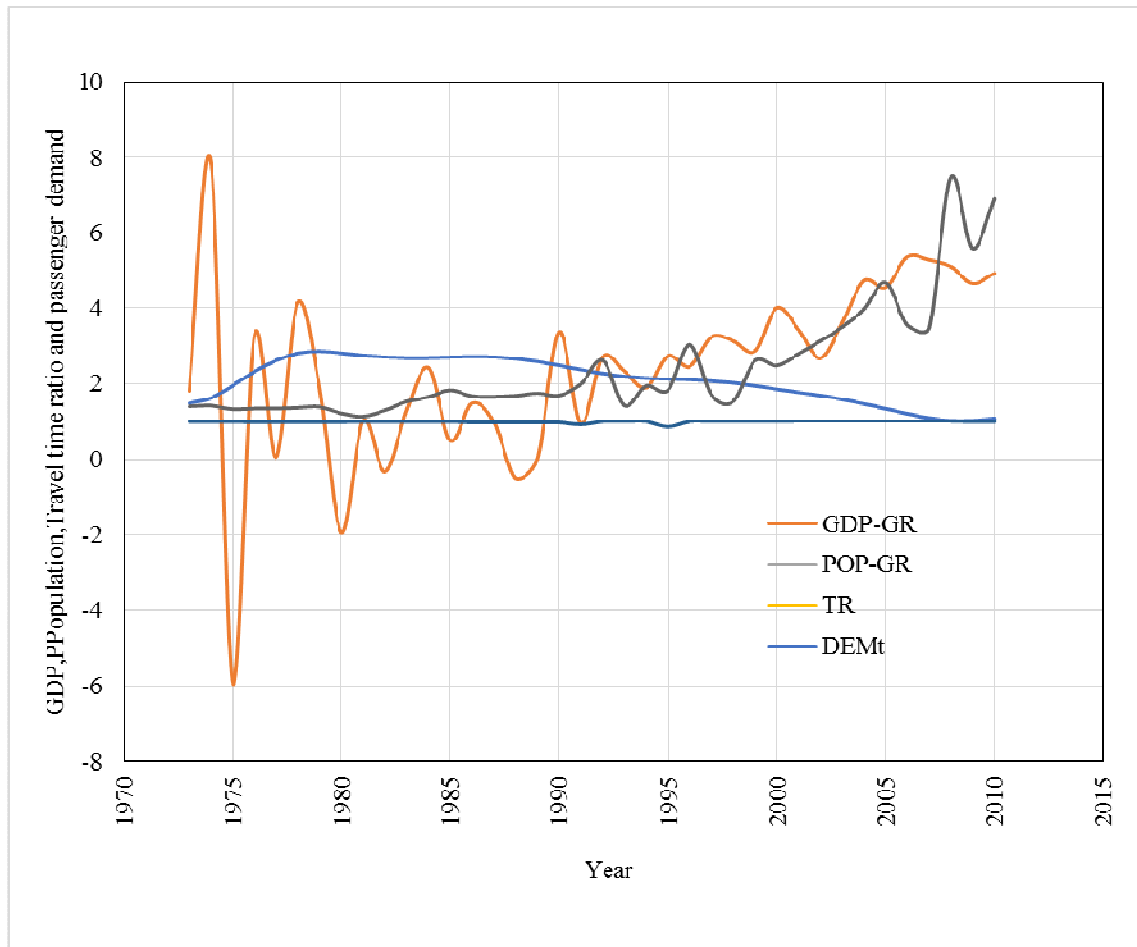


Figure 3 : Database, Chittagong Airport(source BBS)

4.2 Creation of Network

By using the time series data provided by BBS as mentioned earlier, a neural network is created. From the above discussions it is now known that a neural network consists of three layers: input, output and hidden layer. In this paper, GDP growth rate, population growth rate, travel time ratio and passenger demand of the previous year have been used as input data and passenger demand of the existing year has been used as target data (Figure 3). ANN toolbox of Matlab 2012a version has been used to create the network and for overall prediction.

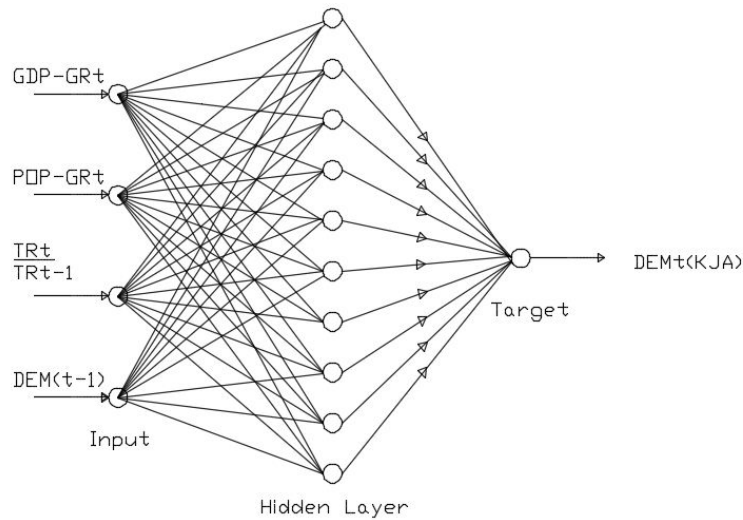


Figure 4 : ANN structure

4.3 Training, Testing and Validation of Network

Training is the algorithmic process in the hidden neuron where parameter weights can be adjusted appropriately to forecast accurately. Among various training algorithms, the back-propagation is the most popular algorithm used (Claveria and Torra, 2014); Tso and Mather, 2009). The basic idea being to propagate a gradient of the transfer function back and compare actual output from output units with a target output, then re-adjust weights backward in the network. Weights are adjusted and repeated until the mean squared error (MSE) between network prediction and actual data is close to the target (Tiryaki and Aydın, 2014). For the purpose of the training process, data for the neural networks are separated into three datasets: training is used for model fitting and selection, testing is used for evaluating the model’s forecasting ability and validation datasets to determine the end point for the training process to avoid model over fitting (Alekseev and Seixas, 2009; Garrido et al., 2014; Tiryaki and Aydın, 2014).

In this study, the data was randomly divided into a 70:15:15 ratios i.e. 70% data for training, 15% for testing and 15% for validation. Stopping criteria are those used to decide when to stop the training process. They determine whether the model has been optimally or sub optimally trained. In this study, the training process stopped when it reached 1,000 epochs or 0.01 error tolerance once the training phase of the model has been successfully accomplished, the performance of the trained model is validated using the validation data, which have not been used as part of the model building process. The purpose of the model validation phase is to ensure that the model has the ability to generalize within the limits set by the training data, rather than simply having memorized the input–output relationships that are contained in the training data. (Srisaeng et al., 2015). The training, testing, validation regression value, the MSE value and the Errors of Target and output are shown in figure 5,6,7 &8.

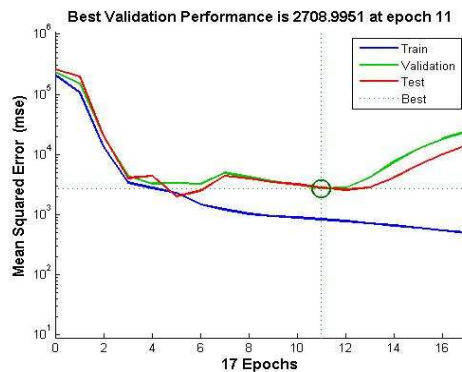


Figure 5: Validation performance graph

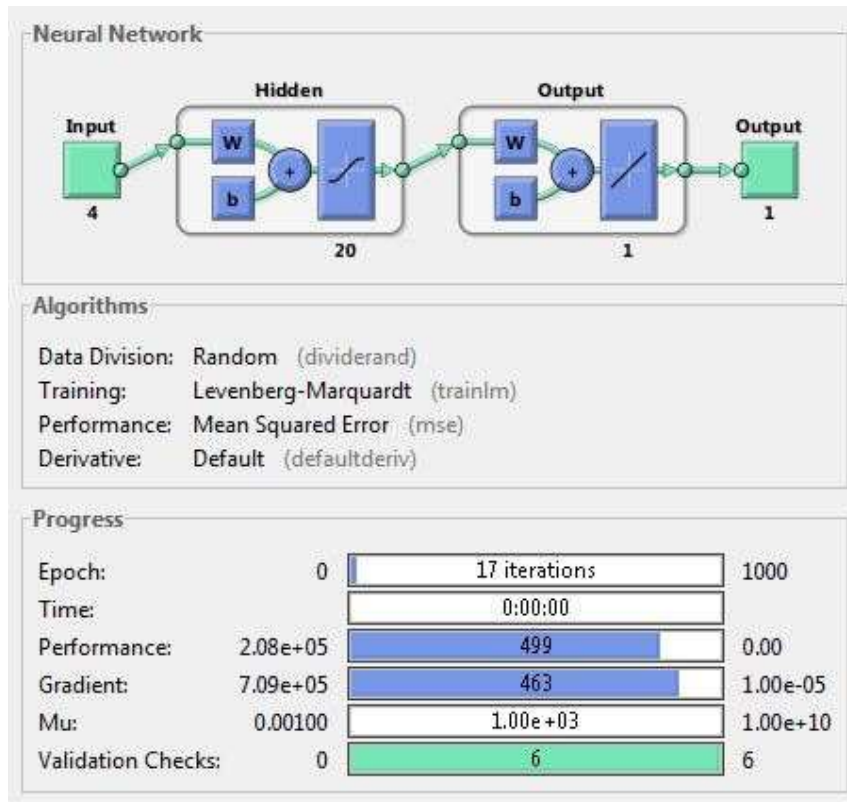


Figure 6: training operation of network

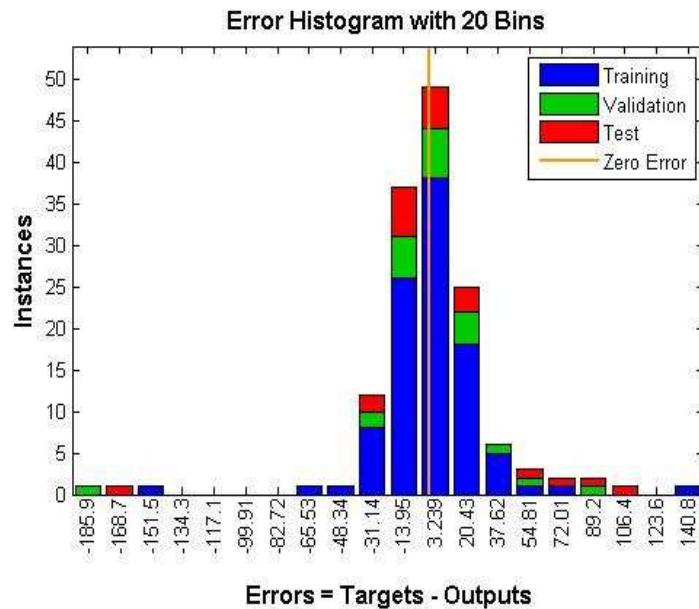


Figure 7: Error histogram

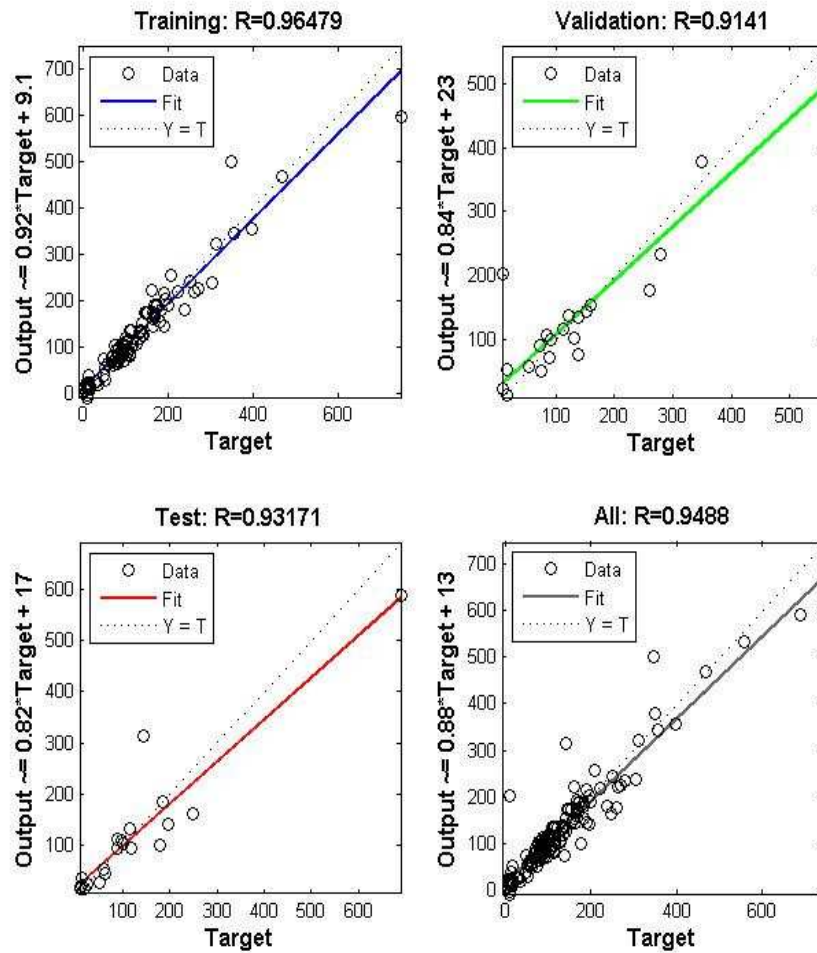


Figure 8: Regression graph

4.4 Prediction of Demand Using the Network

The passengers from the year 2015-2037 have been forecasted by using the trained network. A Matlab program has been developed for the simulation process. Input values of the future years were collected from KUET CRTS. As the previous year passenger demand value, initial passenger demand value calculated by KUET CRTS team has been used. In this paper, only one scenario i.e. high initial passenger demand combined with most likely economic growth and low modal shift due to the Padma Bridge has been considered. Figure 8 represents a demo for regression and performance of prediction.

4.4.1 Other scenario that would be considered

Another scenario that might be considered is low initial passenger demand followed by low economic growth and high modal shift to the surface mode after the Padma Bridge opens. In this case, the average of the two scenarios would be the predicted value. Due to the significant uncertainties in the forecasting, it is better to consider as more scenarios as possible for prediction.

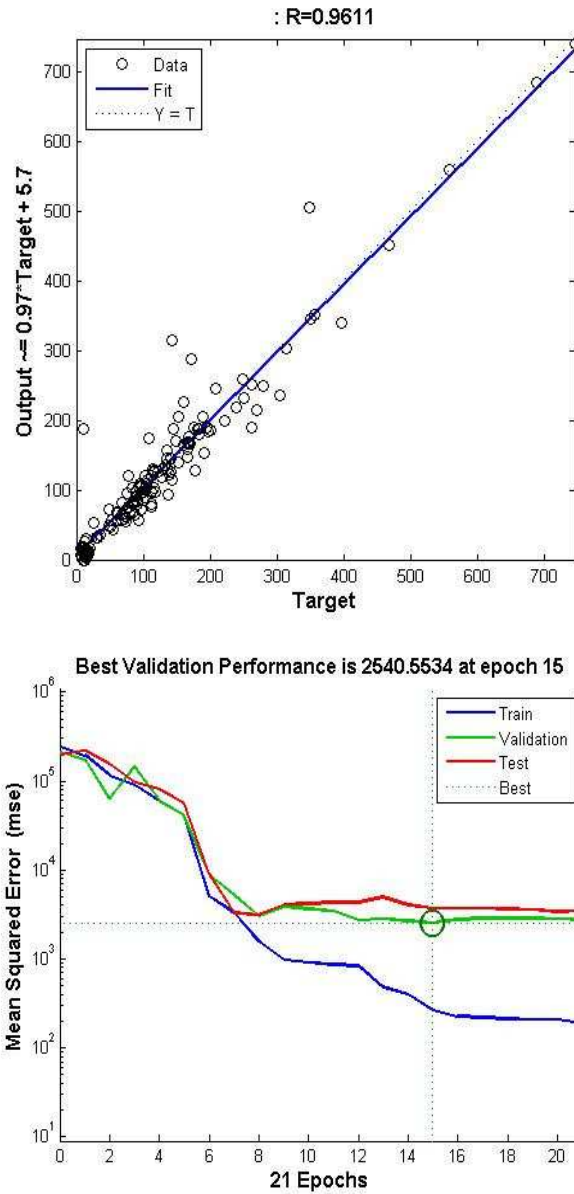


Figure9 : Regression and performance graph for 2015

Table 3: Scenerio used in this study for forecasting(source : KUET CRTS)

Scenario	Initial Demand	GDP growth	Population growth	Travel time ratio	Remarks
High	61000	3.5% until 2016, 4.3% for 2017, 6.1% afterward	1.8% until 2016, 2.0% in 2017, 2.3% after that	No change until 2017, 50% change after that, econometric Model describes modal shift	National real GDP per capita grew by 4.3%. Currently Khulna growth rate is smaller. Padma bridge study by AECOM expects the region to grow by 1.8% point higher, which is close to KCCI estimates having gas, bridge and port development

4.4.2 Impact of Padma Bridge

The Government of Bangladesh has already started to construct a bridge over the river Padma which would reduce the surface travel time between Dhaka and the southwest region significantly. The Padma Bridge would have two opposite impacts on the patronage of the airport. First, it would significantly increase the commercial and business activities in Khulna and the nearby region, thereby increasing the GDP of the region. The growth in GDP and population would possibly enable more people to afford air travel, thereby increasing potential patronage. Second, it would reduce the travel time from Dhaka to Khulna and nearby regions significantly, making road and rail more attractive as compared with aviation. Existing trends do not offer a consensus on which effect will govern. Chittagong airport continued to grow despite two major road bridges constructed in the 1990s. The long-term impact of the bridge on the Meghna River on the Dhaka–Sylhet highway is still unclear. However, Rajshahi and Saidpur airports suffered a drastic and sustained reduction in passenger patronage after the opening of the Jamuna Bridge in 1998. These two airports now serve only 10% and 20% of their peak patronage in 1997. The passenger survey in this study also shows that more than 65% of the current air transport users are willing to switch to road or rail transport from aviation once the Padma Bridge is built. (Wadud, 2011). It is therefore not unreasonable to assume that current Khulna bound air passengers are less sensitive to air fare and the opening of Padma Bridge in future. The impact of the Padma Bridge was incorporated for passenger forecasts in different ways in the demand model. Our study already incorporates the elasticity of air travel demand with respect to the travel time ratio, and the passenger for the new airport after Padma Bridge is also based on the remaining passengers, not on the basis of all potential passengers as from this demand model.

5. RESULTS AND DISCUSSIONS

The forecasted values of passenger are shown in the following figure (figure10)

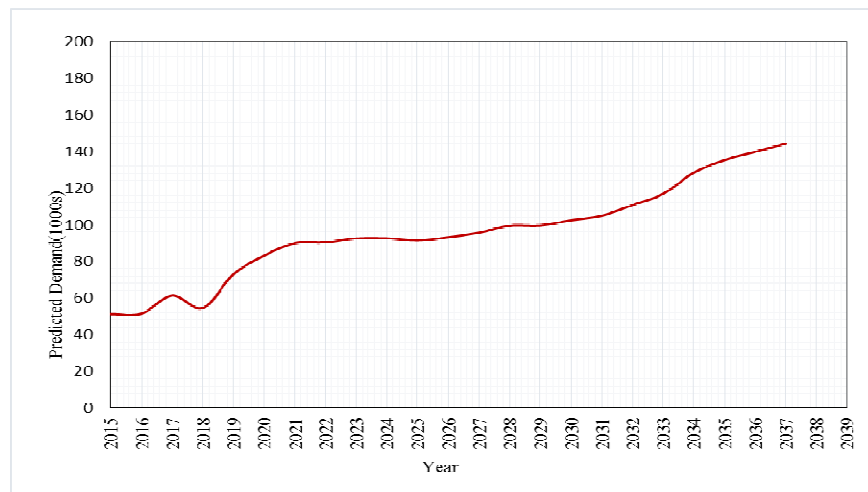


Figure 10: Future passenger demand at KJA

The predicted passenger for the year 2015 and 2037 are 51.285 and 144.28 respectively. From the figure it is seen that the no of passengers are increasing gradually except year 2018. It's because of the opening of Padma Multipurpose Bridge on that year. In 2017, the value is 61.441 while in 2018 it reduces to 54.629. The most important fact is that just after the opening year of Padma Bridge, the demand begins to increase as before.

5.1 Comparison with the predictions of Gravity Demand Model

The same forecast was done by KUET CRTS team but they used gravity type demand model for the forecasting. Figure 11 shows both the predictions at a time. It is seen that both the curves show same trend. For both the prediction the passenger demand is increasing gradually. Again, the Passenger demand for both the model during the opening year of Padma Bridge decrease and then increase again. For gravity demand model both scenarios have been considered for forecasting. This might be a cause of some dissimilarity between the two curves.

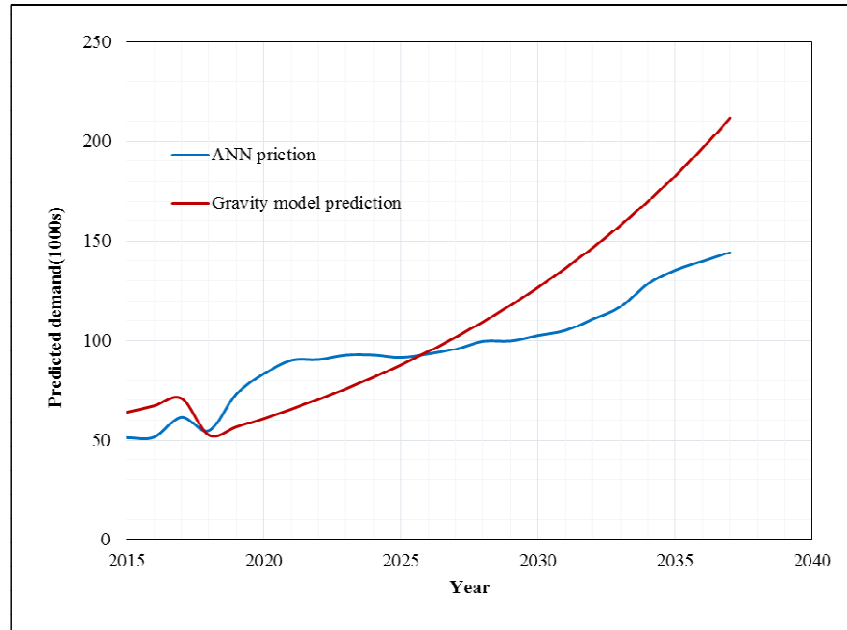


Figure11 : Predicted passenger demand by ANN and Gravity model

6. CONCLUSIONS

As the number of passengers using an airport is used as an indicator of its performance and also influences on future planning, accuracy must be provided while forecasting it. In this paper, an Artificial Neural Network has been created for forecasting purpose. ANNs are used a lot in all engineering fields for prediction purpose. The accuracy of ANN predictions greatly depends the creation of the network and data division for training, testing and validation. The network that shows the best performance needs to be used for accurate forecasting. From the results of our study and from the comparison of gravity type demand model, it is seen that ANN serves as a reliable tool for air travel demand forecasting.

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