



# Predictability of Fog Visibility with Artificial Neural Network for Esenboga Airport

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## Abstract

Fog event affects air, land and sea transportation adversely by reducing visibility, thus causes economic loss. Besides, it has an important role in construction planning. For this reason, it is very important to predict visibility before and during fog events. In this study, fog visibility prediction was made with artificial neural networks and validations were made for Esenboğa Airport. Temperature, dew point temperature, pressure, wind speed and relative humidity, which are considered to be the most important parameters for fog occurrence, were used for 2013-2015 years to train an artificial neural network. We selected only January, February, November and December months, as those are the foggiest months for Esenboğa airport. Correlation of test part was evaluated after training. Then, whole data for 2016-2017 years (regardless of fog existence) were used for validation of the output again. As a result, we found a correlation value (R) of 0.80 for the test part of 2013-2015 years; R=0.41 and root mean square error (RMSE) of 2652m for all data of the 2016 year; and R = 0.53 and RMSE = 2464m for all data of the 2017 year. The error rate (R = 0.80) for the test part (2013-2015) was found acceptable. However, consistencies for the years 2016 and 2017, when all data were tested regardless of fog existence were found below expectations.

**Keywords:** Artificial neural network, Levenberg-Marquardt method, Fog estimation, Esenboğa Airport.

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## **1. Introduction**

Fog is a phenomenon in which water droplets and/or ice crystals near the surface are completely suspended in the air, reducing the visibility below 1 km. The appearance of the fog can basically be considered as a function of the humidity and temperature of the air. For saturated air, the liquid water content increases with the moisture as a result of evaporation from the wet surface or with the horizontal and vertical mixture. However, when a fog occurs, it is expected that the wind conditions at the lowest levels of the atmosphere will be calm. The fog phenomenon is under the influence of many meteorological factors. For this reason, the fog phenomenon is a complex meteorological phenomenon, and predictability of this is very difficult with simple methods. As a matter of fact, despite the use of various atmospheric models for the prediction of the visibility reduction due to fog around the world, an effective method has not been developed at present. The first reason for this is the lack of sufficient knowledge of the fog physics in current operational models. In most of the operational models, cloud schemes for rainfall are designed instead of fog clouds. Numerous important processes such as gravitational settlement on the surface of the system, surface layer turbulence are not considered in the cloud schemes. The second reason is that the operational models do not have enough resolution for fog representation. The third reason is that the operational fog forecasting is usually not carried out directly with a numerical weather forecasting model, but with a post-processor model. However, such models are rarely operated properly due to very high operating and maintenance costs [1].

The use of artificial neural networks (ANN) in modeling studies is increasing day by day because of low cost and reliable results. ANN is a powerful data modeling tool that can basically capture and represent complex input and output relationships. The motivation for the development of neural network technology systems comes from the desire to implement an artificial system that can perform intelligent tasks similar to those performed by the human brain. A neural network model is a structure that can be adjusted to produce a match to the properties of the data or a relationship between them with a particular set of data. The model is set or trained using a set of data taken as input from a particular source and often referred to as a training set. After this training, the neural network can classify, predict or simulate according to the new data coming from the same or similar sources [2].

Modeling studies have been carried out with ANN for many years all over the world. Fabbian et al. [3] applied the ANN method using 44-year observational data for the Canberra international airport, which is one of Australia's foggy regions. As input in the model, they have trained the parameters of temperature, dew temperature, wind intensity and direction, average sea level pressure, total cloud cover, visibility and rainfall. As a result, they concluded that the model had good predictive power. Again, Colabone et al. [4] used the ANN method to estimate the fog using 1989-2008 data obtained from Academia da Forca Aérea, the place where flight activities were performed. In the model, temperature, relative humidity, pressure and wind speed parameters were trained. As a result, they concluded that the method's performance they studied on is  $R = 0.95$  for the region. In the study conducted by He et al. [5], the relationship between the temperature, relative humidity, air pressure and wind speed parameters and the visibility was investigated by using the ANN method. As a result, the difference between the predicted and actual visibility was found as 7.56%. In spite of all these studies, no study has been conducted with ANN for the estimation of visibility in Turkey. In this study, Esenboğa airport was trained by Levenberg-Marquardt method which is one of the ANN methods with 2013-2016 year's visibility, temperature, dew point temperature, pressure, wind speed and relative humidity observation data. Validation and testing of the results obtained afterwards were carried out.

## **2. Material and Methodology**

### **2.1. Study Area**

Esenboğa Airport is located 28 km north of Ankara on the border of Çubuk District and the airport is located on topographical level of 1200-1400 m in the north, west and southwest of 800-1200 m altitude [6, 7]. The image of the location and surroundings of Esenboğa airport, which serves approximately 16 million passengers per year, is presented in Figure 1. In the meteorology office of Esenboğa, which is located in the airport, there is a METAR every half hour and SPECI are made if needed. Meteorology office of Esenboğa airport publishes short and long term forecasts (TAF) and SIGMET messages.



Figure 1. Location of Esenboğa airport

In order to evaluate the fog condition of Esenboğa Airport, annual and seasonal fog condition was investigated. Figure 2 shows annual and seasonal foggy day (fog observations) numbers.

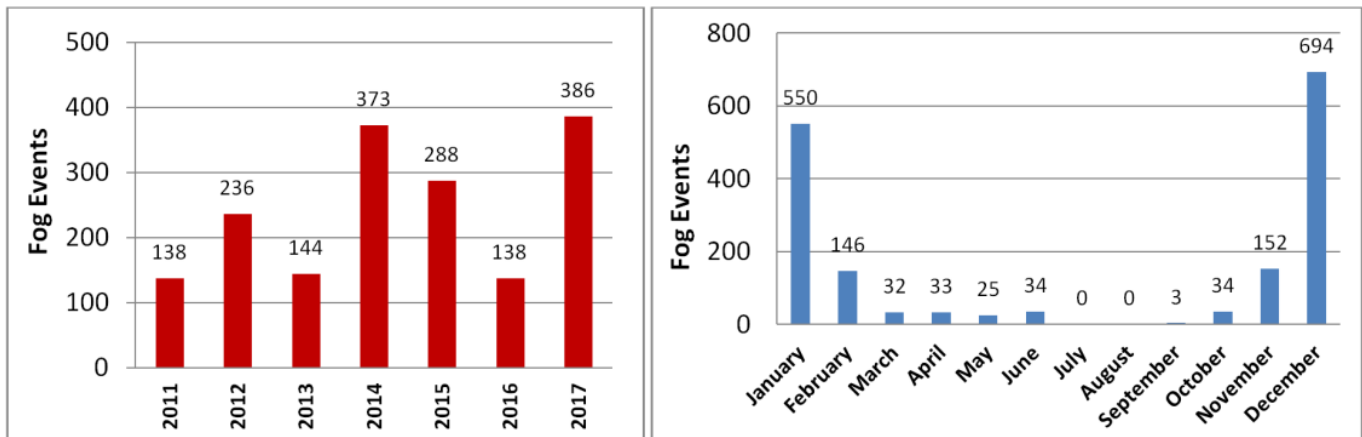


Figure 2. Annual (left figure), seasonal (right figure) fog observation numbers of Esenboğa Airport

It is observed that the number of fog observations, which was 138 and 236 in 2011 and 2012, increased up to 373 in 2014. The number of fog observations that shows declining trend afterwards dropped up to 138 in 2016, but increased significantly up to 386 in 2017. Seasonally, it is seen that December and January months are the foggiest periods. While 694 fog observations were seen in December, 550 fog observations were seen in January. No fog event was observed in July and August, and 3 fog observations in September.

## 2.2. Data Set

We used MATLAB program to evaluate ANN. The dataset used as an input into the ANN model is obtained from the METAR and SPECI codes of the General Directorate of Meteorology for the years 2013-2017 belonging to Esenboğa Airport. METAR is a meteorological report showing meteorological conditions that are published at regular intervals (30-minute or 1-hour periods) determined by regional agreements and that are subject to an aerodrome. SPECI is a special meteorological report, which is identical to METAR coding, published to inform operators of improvements as supplementary or supplemental information to METAR if there are significant changes (fog etc.) affecting aviation activities between two METAR periods [8].

## 2.3. Artificial Neural Networks and Levenberg-Marquardt Training Method

Artificial Neural Network (ANN) is a mathematical model that operates by taking into account the structure and functionality of biological neural networks. The basic structure of each artificial neural network is an artificial neural cell, a simple mathematical function. Such a model has three sets of simple rules: multiplication, addition, and activation. At the entrance of ANN, the weight of the entries means that each input value is multiplied by the individual weight. In the middle part of the artificial neuron, there is a collecting function that collects all the weighted inputs and tendencies. At the exit of the artificial nerve cell, the sum of the pre-weighted entries and trends passes to the activation function, also called the transfer function [9].

ANN has a multilayered structure because it consists of a combination of many simple nerve cells. The layers in the ANN, the cells in each layer, bring links to information from one layer to another, as if it were an information network. In such a network there are parallel strata and communication paths that provide sequential connections between cells and their interiors [10]. Figure 3 shows the YSA model scheme considered in this study.

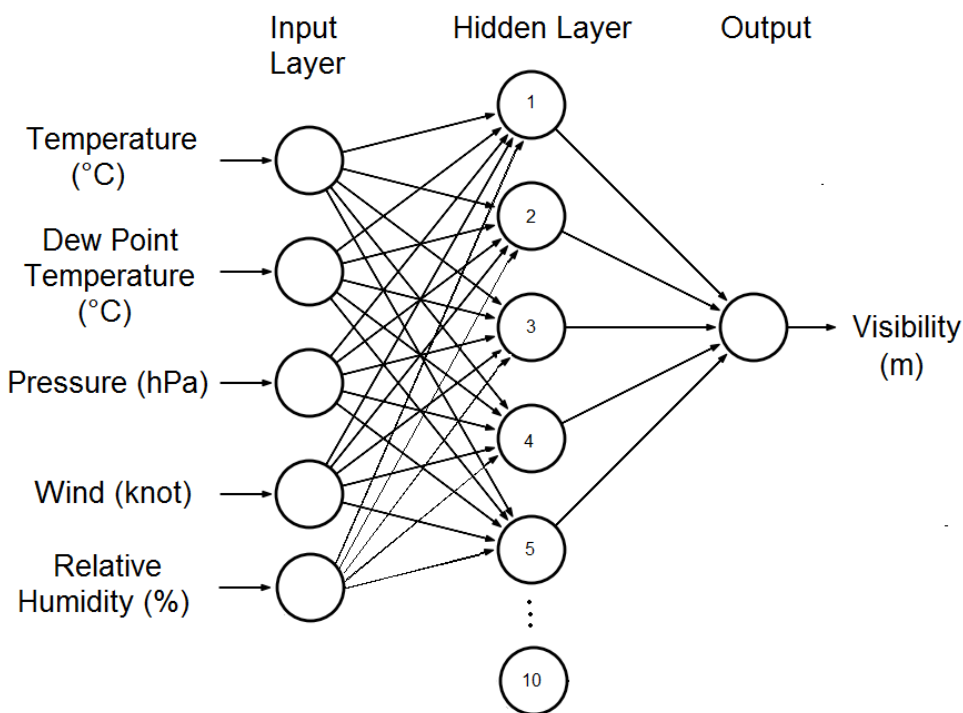


Figure 3. Artificial Neural Network Scheme (Input, Hidden and Output Layers)

There are many different types of ANN, and many of them are used quite frequently. Since the first neural model developed by McCulloch and Pitts [11], he has developed hundreds of different models. The main differences between them are functions, accepted values, topology and learning algorithms. There are also many hybrid models in which each neuron has more features. However, one of the most common models used in ANN is backpropagation [12] algorithms.

In the study, tangent hyperbolic activation function (Tanh) in training phase (hidden layer) and pureline (linear) function in output layer were used. The tanh activation function provides the curvilinear relationship between the input and output units. Correct selection of the activation function significantly affects the performance of the network. Tanh is widely used in ANN nowadays. Tanh is a function similar to the sigmoid function. For this activation function, the output value is usually between [-1,1] or [0,1]. This is usually a non-linear function. The use of nonlinear activation functions enabled the application of artificial neural networks to complex and very diverse problems [13]. The tangent hyperbolic function  $f(x)$  with bipolar property is shown in as follows:

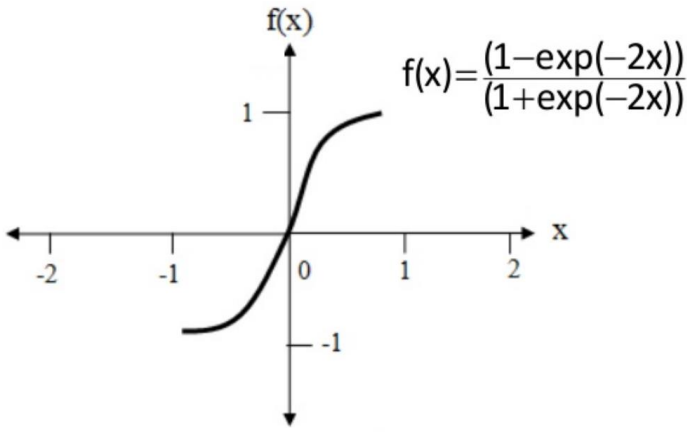


Figure 4. Tangent hyperbolic activation function used in the hidden layer

Neuron output varies linearly according to the change of neuron input in the pureline activation function used in the output layer. The range of change in the output value is in the range [-1 1]. The graph of the pureline activation function [14] is shown in Figure 5.

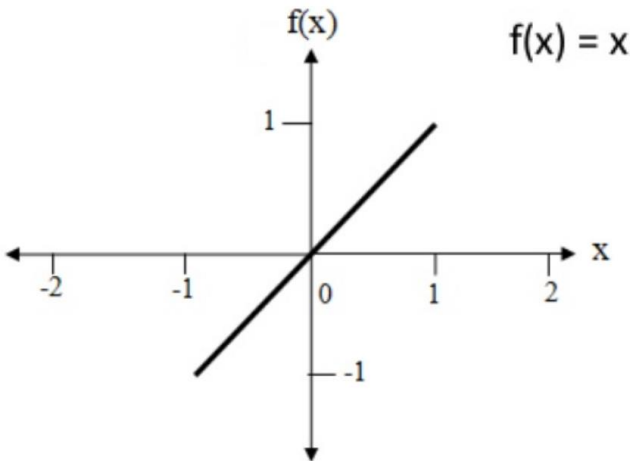


Figure 5. Pureline activation function used in the output layer

The Levenberg-Marquardt training method (algorithm), which is applied to the ANN model in the study, is a forward-feed and postback method. The Levenberg-Marquardt algorithm, which is derived from steepest descent and Newton's algorithm, is given below (Equation 1).

$$\Delta w = (J^T J + \mu I)^{-1} J^T e \tag{1}$$

here;  $w$  weight vector,  $I$  unit matrix,  $\mu$  combination coefficient.  $J$  ( $P \times M$ ) is the Jacobian matrix of dimension  $xN$ , and  $e$  ( $P \times M$ ) is the error vector of dimension  $x1$ .  $P$  represents the number of training samples,  $M$  is the number of outputs, and  $N$  is the number of weights.  $\mu$  is an adjustable parameter. If this parameter is too large, the method behaves like the Newton method if the method is very small, such as the steep descent method. An adaptive structure for this parameter is shown in Equation 2:

$$\mu(n) = \begin{pmatrix} \mu(n-1)k & E(n) > E(n-1) \\ \mu(n-1)/k & E(n) \leq E(n-1) \end{pmatrix} \tag{2}$$

Where  $k$  is a fixed number.  $E$  eligibility [15].

Correlation of the results was done using Correlation Coefficient ( $R$ ) and Mean Error Squares Root (RMSE). The correlation coefficient indicates the relation and the degree between the two variables. Values are between -1 and +1. If the  $R$ -value is greater than 0.70, the existence of a high correlation can be mentioned. The correlation coefficient is calculated from the formula shown in Equation 3:

$$R = \frac{\Sigma(xy) - (\Sigma x)(\Sigma y)/n}{\sqrt{(\Sigma x^2 - (\Sigma x)^2/n)(\Sigma y^2 - (\Sigma y)^2/n)}} \tag{3}$$

where x and y represent the variables of interest.

The mean error squares are the root of the mean of the root, the difference between the estimated and the actual. The result of the obtained result means that the created model is very good. It is calculated by the formula shown in Equation 4:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (\hat{y}_i - y_i)^2} \quad (4)$$

Where  $\hat{y}_i$  is the calculated data and  $y_i$  is the estimated data.

### 3. Results

In this study, it is aimed to estimate the visibility for Esenboğa airport by using ANN model. Ground observation data from the months of January, February, November and December in 2013-2015 (Fig. 3) were used as the model input data set at Esenboğa airport. These months are known to be the foggiest months. However, total number of no-fog observations (15152) are 7 times more than total number of fog phenomena (2359). Therefore, we removed most of the non-fog observations. In this way, it is aimed to focus on the change in the periods of the fog effect of the artificial neural network.

A total of 2623 ground observation data were available in the input data set. 90% (2361) of them were used for training, 5% (131) for validation and 5% (131) for testing purposes. Whole dataset of 2016 and 2017 years were only used for the test regardless of fog (35572). The results obtained for training, validation and testing are presented in Fig. 6.

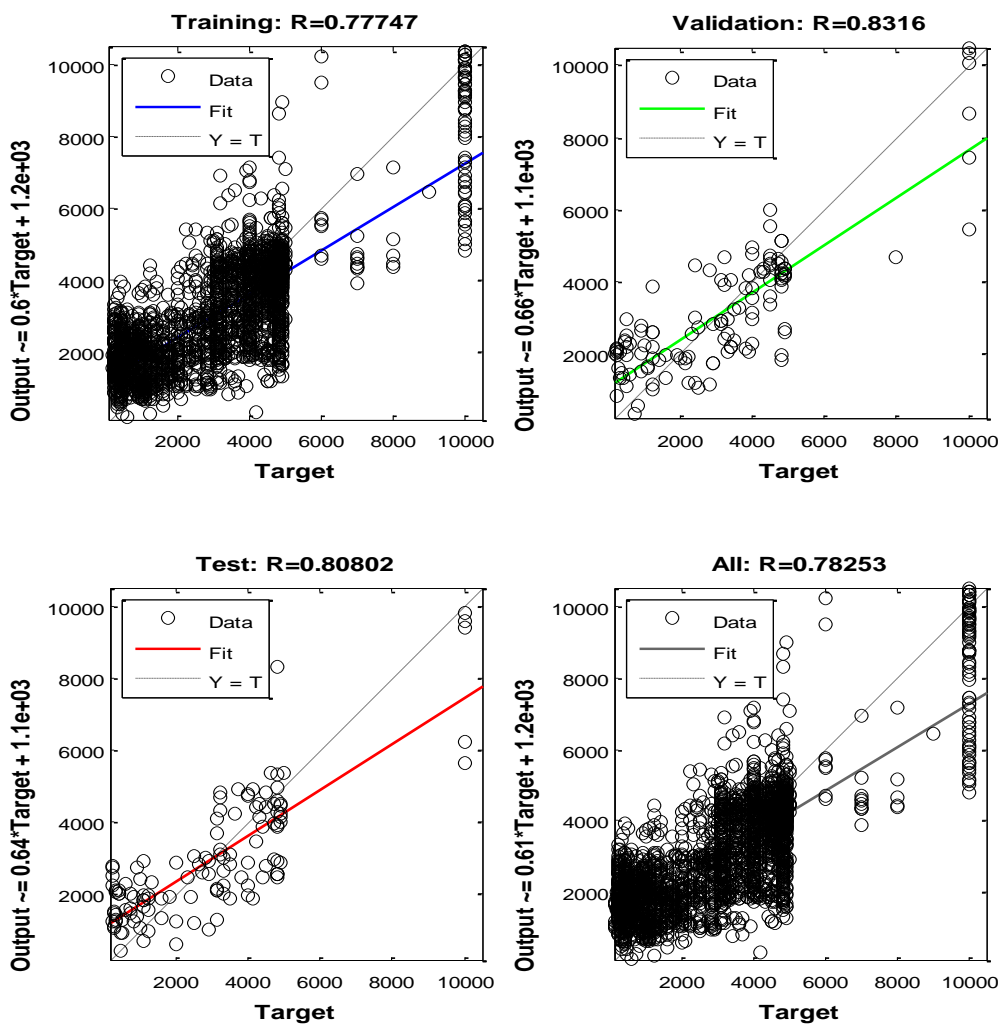


Figure 6. Education Results (2013-2015) of ANN Model

According to the obtained results, the correlation coefficient is calculated as  $R = 0.77$  for the trained part,  $R = 0.83$  for the validation part,  $R = 0.80$  for the test part and  $R = 0.78$  for the whole part. Mean error squares were found as  $RMSE = 1300$  m. These correlation coefficients show that there is a high correlation between what is estimated by the ANN model and what happens. These results are considered as acceptable.

The test results for the years of 2016 and 2017 are shown in Figure 7 and Figure 8. The correlation coefficient of the ANN model for 2016 is calculated as  $R = 0.41$ . According to the error histogram, the majority of the tested data seems to have accumulated at around 181 m. The mean error squares were found as  $RMSE = 2652$  m.

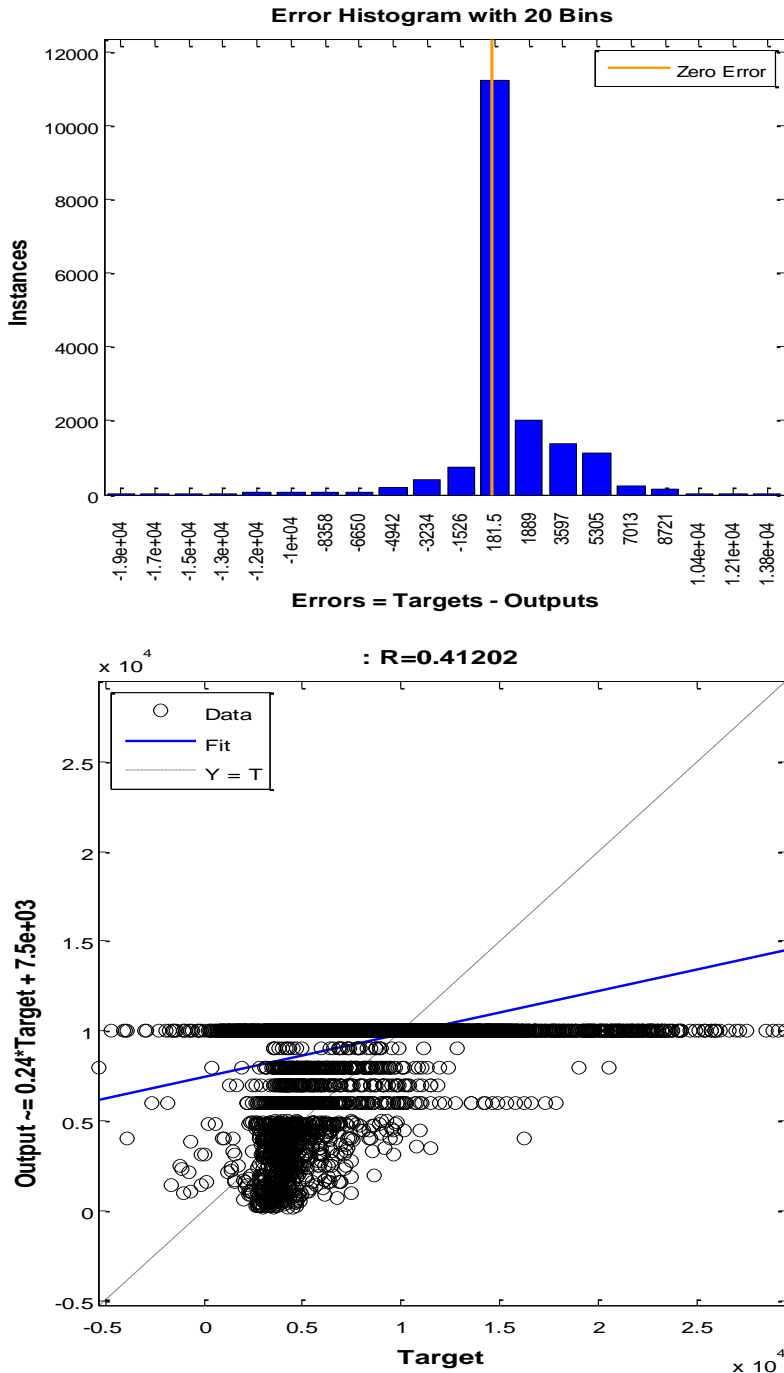


Figure 7. Error Histogram and Distribution Graph of ANN Model for 2016 year

For the year of 2017 of the YSA model, the correlation coefficient is calculated as  $R = 0.53$ . According to the error histogram, the majority of the tested data seems to have accumulated at around 1238 m.  $RMSE = 2464$  m was found for the mean squared error squares.

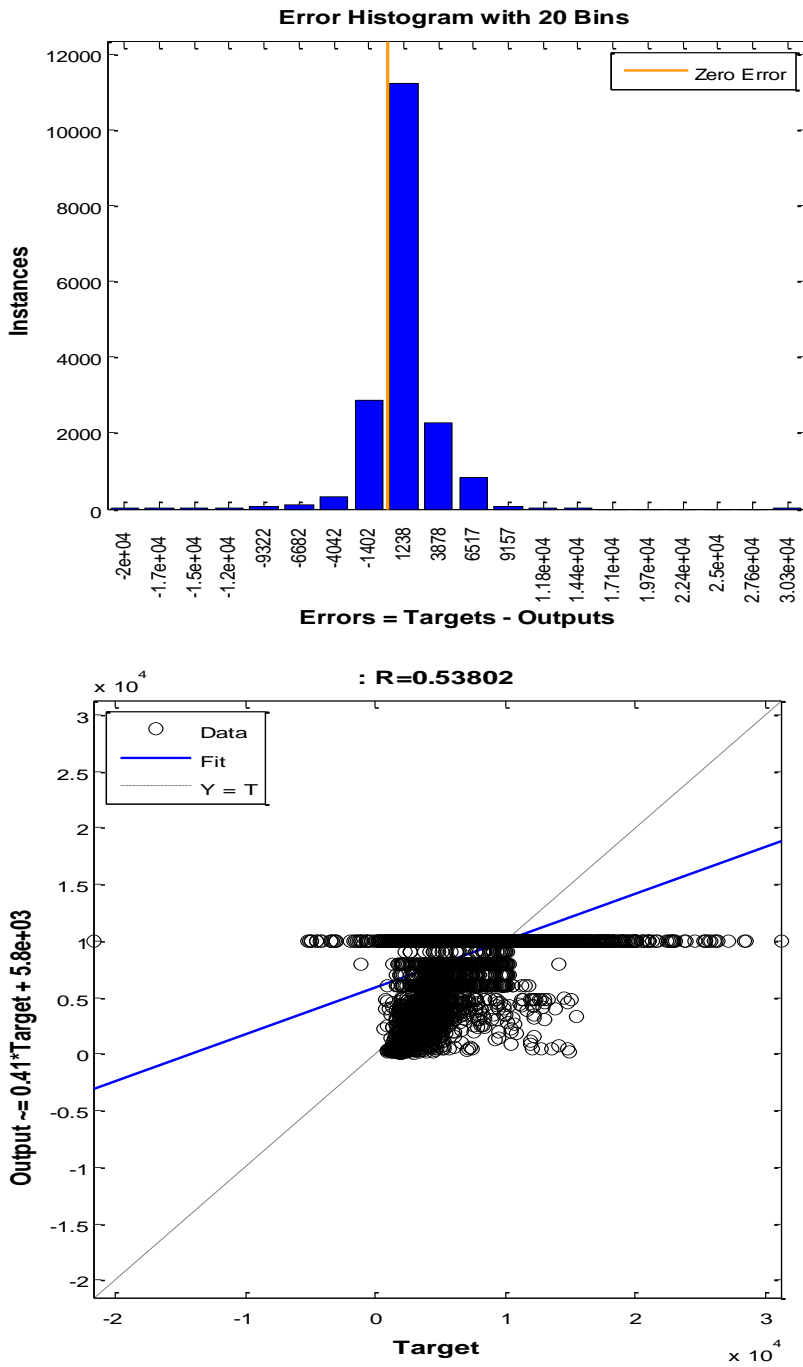


Figure 8. Error Histogram and Distribution Graph of ANN Model for 2017 year

The weight and bias values of the training results obtained from artificial neural network are shown in the Table 1 and Table 2.

Table 1. Weights for hidden layer

WEIGHT (Hidden Layer)						
Hidden nodes	T	Td	RH	P	W	BIAS
<i>n1</i>	-0,0037	1,7406	-0,7698	-1,3410	0,2043	2,0644
<i>n2</i>	-1,6155	-0,0303	0,2051	0,0547	0,2206	-0,3015
<i>n3</i>	-0,4288	0,4945	-2,1879	-2,4152	0,5994	2,5449
<i>n4</i>	-2,6486	0,5733	1,8795	-0,4241	2,4723	-1,5213
<i>n5</i>	4,1268	-1,6879	-0,4010	-0,2098	1,4139	0,0821



<i>n6</i>	2,2593	0,6538	3,2892	-2,0494	1,7393	0,1150
<i>n7</i>	0,9290	1,8943	-1,0765	-0,7986	-0,3245	1,2667
<i>n8</i>	-2,0197	-1,8456	-1,6192	0,7565	-0,8895	-2,3826
<i>n9</i>	-4,5245	3,5005	-0,5650	-0,5699	6,8459	-8,2413
<i>n10</i>	2,5578	1,0693	-1,5221	-0,9442	-2,2122	3,8593

Table 2. Weights for output layer

WEIGHT (Output)	
Nodes	Weights
<i>n1</i>	0,7116
<i>n2</i>	2,2081
<i>n3</i>	0,6023
<i>n4</i>	-0,8445
<i>n5</i>	3,3541
<i>n6</i>	0,9113
<i>n7</i>	-2,7107
<i>n8</i>	1,9928
<i>n9</i>	-0,6317
<i>n10</i>	1,7913
<i>BIAS</i>	-1,0127

#### 4. Discussion

The forward-feed backpropagation ANN model undergoes a recursive training process to minimize the error by comparing the observed output and the target output repeatedly. Each error obtained is used repeatedly to readjust the weight and difference values to obtain a more consistent output. Therefore, this method is focused on minimizing the error. For this reason, this training method seems to be more suitable ANN method especially for complex events.

Temperature, dew point temperature, pressure, wind and relative humidity parameters have a significant effect in the formation of fog. In this study, a forward feed back backpropagation artificial neural network model has been tested for the estimation of the visibility, which significantly decreases in the event of fog. The majority of the data for 2013-2015 given as inputs to train the model includes the fog (low visibility) conditions.

As a result, the error rate ( $R = 0.80$ ) for the part (5%) that was separated from the test input was found acceptable. However, consistencies for the years 2016 and 2017, when all data were tested regardless of fog, were found below expectations. This shows that the model designed with ANN has good representation of the visibility for fog, but predictive ability decreases for the increasing actual visibility.

#### References

- [1] Zhou, B., Introduction to a New Fog Diagnostic Scheme. U.S. Department of Commerce, National Oceanic and Atmospheric Administration, National Weather Service, National Centers for Environmental Prediction, 2011.
- [2] Baboo, Dr. S. S. and Shereff, I. K., An Efficient Weather Forecasting System using Artificial Neural Network, International Journal of Environmental Science and Development, Vol. 1, No. 4, October 2010.
- [3] Fabbian D., De-Dear R., Lellyett S., Application of artificial neural network forecasts to predict fog at Canberra international airport, Weather Forecast 22:372–381, 2007.
- [4] Colabone R.O., Ferrari A., da Silva-Vecchia F., Bruno-Tech A., Application of artificial neural networks for fog forecast, Journal of Aerospace Technology and Management 7(2):240-246, 2015.
- [5] He Y.D., He H.Y., Guo Y.Y., Shen J.T., Fog Visibility Based on Neural Network Algorithm Research, 14th COTA International Conference of Transportation Professionals, Changsha, China, July 4-7, 2014.
- [6] Turan, L., Dengiz, Ş., Yüksel, E. ve Ertaş, C., Ankara Esenboğa Havalimanı Vahşi Hayat ve Kuşla Mücadele Çalışması. Ankara: İnforama, 2009.
- [7] Oto, N., Çevresel Sürdürülebilirlik ve Havaalanları: Esenboğa Havalimanı Örneği, Doktora Tezi, Sosyal Çevre Bilimleri ABD, Sosyal Bilimler Enstitüsü, Ankara Üniversitesi, 2011.
- [8] Ertaş, S.K., Meteoroloji Ders Kitabı, Devlet Hava Meydanları İşletmesi Genel Müdürlüğü, 2004.

- [9] Krenker, A., Bester, J., Kos, A., Introduction to the artificial neural networks. In: Suzuki, K. (ed.) Artificial Neural Networks, Methodological Advances and Biomedical Applications, pp. 3–18. Croatia: InTech, 2011.
- [10] Keskin M.E. ve Taylan E.D., Orta Akdeniz Havzasındaki Akımların Stokastik Modellemesi, İMO Teknik Dergi, 4271 -4291, Yazı 282, 2007.
- [11] McCulloch, W. and Pitts, W., A Logical Calculus of the Ideas Immanent in Nervous Activity, Bulletin of Mathematical Biophysics, Vol. 5, pp. 115-133, 1943.
- [12] Rumelhart, D. and McClelland J., Parallel Distributed Processing, MIT Press, Cambridge, Mass, 1986.
- [13] Yavuz, S. ve Deveci M., İstatiksel Normalizasyon Tekniklerinin Yapay Sinir Ağın Performansına Etkisi, Erciyes Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi, Sayı: 40, ss. 167-187, 2012.
- [14] Uslu M., Yapay Sinir Ağları ile Sınıflandırma, İleri İstatistik Projeleri, Fen Fakültesi, İstatistik Bölümü, Hacettepe Üniversitesi, 2013.
- [15] Çavuşlu M.A., Becerikli Y. ve Karakuzu C., Levenberg-Marquardt Algoritması ile YSA Eğitiminin Donanımsal Gerçeklenmesi. Türkiye Bilişim Vakfı Bilgisayar Bilimleri ve Mühendisliği Dergisi 5, 2012.