

Application of Artificial Neural Network to Predict the use of Runway at Juanda International Airport

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Abstract. Artificial neural network approaches are useful to solve many complicated problems. It solves a number of problems in various areas such as engineering, medicine, business, manufacturing, etc. This paper presents an application of artificial neural network to predict a runway capacity at Juanda International Airport. An artificial neural network model of backpropagation and multi-layer perceptron is adopted to this research to learning process of runway capacity at Juanda International Airport. The results indicate that the training data is successfully recognizing the certain pattern of runway use at Juanda International Airport. Whereas, testing data indicate vice versa. Finally, it can be concluded that the approach of uniformity data and network architecture is the critical part to determine the accuracy of prediction results.

1. Introduction

Indonesia is a big country that has a numbers of islands. Consequently, the easiest way to transport is by using air transportation. This leads to airport become an important part of economic growth due to its role for connecting cities and nations [1]. However, increasing of air traffic demand without improvement of airport infrastructure is the main problem that effect to severe traffic management. According to the International Airport Transportation (IATA) [2], during 2013 to 2014 there was increasing about 5.1% regarding the demand of air travel. This is equivalent to more than 3 billion passengers. In addition, Juanda International Airport in Indonesia is serving the city of Surabaya, East Java and surrounding areas. It is located in District Sedati, Sidoarjo. According to Umilia [3], the number of passengers using the service of Juanda International Airport is in the range of 30000 to 35000 people per day and it makes Juanda International Airport become the second busiest airport in Indonesia after Soekarno-Hatta International Airport due to its aircraft movement and passengers. Therefore, predicting the airport capacity in terms of its runway use can be very useful to be considered as one of strategies to avoid the congestion of air traffic management.

The numerous methods have been previously developed regarding to this problem were deal with probability, statistics, and operations research [4]–[6]. Khanmohammadi *et al.*, [4] introduced a new type of multilevel input layer ANN that can handle nominal variables and is interpretable in a sense that one can easily see the relationship between different input variables and output variables. Marinelli *et al.*, [5] proposed a method based on the Bee Colony Optimization (BCO) to find an optimal flight gate assignment for a given schedule. This approach is expected to solve the problem in the gate scheduling as a key of airport operation. Additionally, Gianazza [6] had combined tree search



methods with neural network to forecast air traffic workload. However, the consideration of using ANN in those problems can be beneficial in solving nonlinear problems [4].

Based on the study above, it had motivated the author to conduct a research about predicting the use of runway at airport by using artificial neural network.

2. Artificial Neural Networks

Artificial neural networks (ANN) are the processing system that imitates the concept of biological nerve system. According to Ata [7], ANN is consisted of a group of units called “neurons” that are analogous to nerve neurons and its connected with each other by weights. In order to determine the weights, the ANN use inductive learning process. This process is deal with the numbers of data that will be trained. Once it done, a new pattern may be come out to them for prediction or classification [8]. Subsequently, the main issue of using ANN is how to handle the nominal variables due to converting nominal variable to numerical variable introduce order to the variable which is not desired [4]. Additionally, the process of data conversion from initial data to normalization data need some of adjustments prior to be inputted to hidden layer as shown in figure 1.

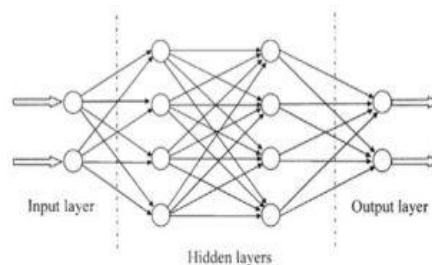


Figure 1. Schematic diagram of a multilayer feed-forward neural network [9].

Based on figure 1, it described that artificial neural network is consisted of three steps which are input layer, some hidden layers, and an output layer. Each single neuron is connected to other neurons by using adaptable synaptic weights [9]. Generally, knowledge is assigned as a set of connection weights. Besides, training is a process of modifying some connection weight properly using a suitable learning method. A learning mode is used in network and it need to prepare the input data in order to generate the desired output. Subsequently, figure 2 shows how information is processed using single node.

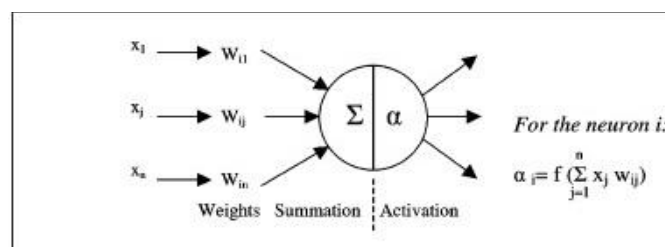


Figure 2. Information processing in neural network [9].

According to Kalogirou et al., [9] the node receives weighted activation of other nodes through its incoming connections. For the first step is the summation of entire neurons. Then the result is come off by activation function. Finally, to activate value for each of outgoing connections is achieved by multiplying it with the specific weight and transferred to the next node [9].

3. Methodology

The use of the runway at Juanda International Airport during January to March 2016 are considered as our research. It retrieved from the AirNav Indonesia-Surabaya. Subsequently, the following preparations are made up prior to analysis the data:

3.1. Input Data

Prior to train the data, it needs to prepare the initial data. The following step is to divide the initial data into two categories which are training data and testing data. A number of training data will be used for network training, whereas testing data will be used once the network training done. This is aimed to evaluate whether the output data can recognize certain patterns which is not previously learned.

The data of the use of runway at Juanda International Airport are used as training data and testing data regarding to this research. Prior to use that data as input, it needs to conduct normalization process or pre-processing regarding the data. The normalization process is needed to convert the data within the range of 0 to 1. In addition, this method is commonly known as an approach to activate the function of binary sigmoid. Although the normalization of data is expected in the range of 0 to 1, yet practically it will be normalized in the range of 0.1 to 0.9. The following equation is used to normalize the data:

$$X' = \frac{0.8(X - b)}{(a - b)} + 0.1 \quad (1)$$

Where;

X' : Normalized data

X : Initial data

a : Maximum value of initial data

b : Minimum value of initial data

However, the initial data for January to March 2016 have a different dimension in which the initial data for January and March have 31 data. While, the initial data for February only has 29 data. Therefore, the initial data for January and March are adjusted to 29 data. In addition, the approach of how to input the data in ANN is described as in table 1.

Table 1. Input Data Pattern.

Pattern	Input Data	Target
1	Data at the date of 1 to date of 29	Data at the date of 30
2	Data at the date of 2 to the date of 30	Data at the date of 31
3	Data at the date of 3 to the date of 31	Data at the date of 32
•	•	•
•	•	•
•	•	•
29	Data at the date of 29 to the date of 57	Data at the date of 58

3.2. Determination of Network Architecture

The selection of the number of layers and pattern of each layer is the principal of network architecture. Based on feedback neural network architecture, this research uses only one artificial

neural networks multilayer which is 29 – 10 – 1 pattern. This means that 29 data for input data, 10 data as hidden layer, and only 1 data used as a target.

3.3. Learning and Training Process

A learning process in artificial neural network aims to adjust the weighting factor in order to obtain the desired weight. In this research, back propagation approaches as a learning process is adopted. Furthermore, there are several steps of algorithms preparation for backpropagation learning, namely:

1. The initial weight initialization
2. Forward propagation steps in order to find an error by using activation function such as:
 - Input layer to hidden layer 1 and it continued to hidden layer 2

$$\text{Sigmoid function, } y: f(x) = \frac{1}{1 + \sigma x} \quad (2)$$

- Hidden layer 2 to output layer
Identity function: $f(x) = x$ (3)

3. Backward propagation is a training process of weighting value of artificial neural network. This is carried out by decreasing total error system to entire data through weighting correction using either gradient descent method or adaptive learning rate.

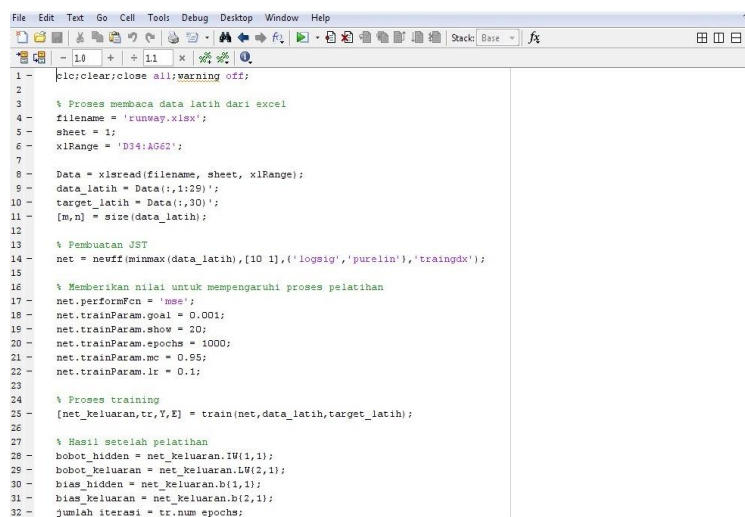
3.4. Testing Process

Testing of artificial neural network is carried out to identify whether the trained network is capable to recognize the certain patterns. To evaluate the trained network, there are several approaches used regarding to this research, namely

1. Mean Square Error (MSE): MSE is an estimator that measures the average of the squares of the errors or deviations. It is a risk functions, corresponding to the expected value of the squared error loss or quadratic loss. The difference occurs because of randomness or because the estimator doesn't account for information that could produce a more accurate estimate [10]. Subsequently, it values always non-negative and closer to zero are better.
2. Regression: regression is a statistical process for estimating the relationship among variables. It includes many techniques for modelling and analyzing several variables

3.5. Codes preparation for training data and testing data

This step is carried out in order to train the normalization data and test the output data. It is aimed to assess whether the data capable to recognise certain patterns. The codes for training data and testing data are shown in figure 3 and figure 4 respectively.



```

1 clear; close all; warning off;
2
3 % Proses membaca data latih dari excel
4 filename = 'runway.xlsx';
5 sheet = 1;
6 x1Range = 'D14:AG62';
7
8 Data = xlsread(filename, sheet, x1Range);
9 data_latih = Data(:,1:29);
10 target_latih = Data(:,30);
11 [m,n] = size(data_latih);
12
13 % Pembuatan JST
14 net = newff(minmax(data_latih),[10 1],{'logsig','purelin'},'trainingdx');
15
16 % Memberikan nilai untuk mempengaruhi proses pelatihan
17 net.performFcn = 'mse';
18 net.trainParam.goal = 0.001;
19 net.trainParam.show = 20;
20 net.trainParam.epochs = 1000;
21 net.trainParam.mc = 0.95;
22 net.trainParam.lr = 0.1;
23
24 % Proses training
25 [net_keluaran,tr,Y,E] = train(net,data_latih,target_latih);
26
27 % Hasil setelah pelatihan
28 bobot_hidden = net_keluaran.IW(1,1);
29 bobot_keluaran = net_keluaran.LW(2,1);
30 bias_hidden = net_keluaran.b(1,1);
31 bias_keluaran = net_keluaran.b(2,1);
32 jumlah_iterasi = tr.num_epochs;
  
```

Figure 3. Developed code for training normalization data.

Figure 3 shows the code for training normalization data where the number of initial input data is 29 and the initial target data is the data of number 30. Besides, the code involves 1000 iterations of epochs.

```

1  %clear;close all;
2
3  % load jaringan yang sudah dibuat pada proses pelatihan
4  load net.mat
5
6  % Proses membaca data uji dari excel
7  filename = 'runway.xlsx';
8  sheet = 1;
9  xlRange = 'D103:AG131';
10
11 Data = xlsread(filename, sheet, xlRange);
12 data_uji = Data(:,1:29);
13 target_uji = Data(:,30);
14 [m,n] = size(data_uji);
15
16 % Hasil prediksi
17 hasil_uji = sim(net_keluaran,data_uji);
18 nilai_error = hasil_uji-target_uji;
19
20 max_data = 1213;
21 min_data = 0;
22 hasil_uji = ((hasil_uji-0.1)*(max_data-min_data)/0.8)+min_data;
23
24 % Performansi hasil prediksi
25 error_MSE = (1/n)*sum(nilai_error.^2);
26
27 filename = 'runway.xlsx';
28 sheet = 1;
29 xlRange = 'D13:AF13';
30
31 target_uji_asli = xlsread(filename, sheet, xlRange);
32

```

Figure 4. Developed code for testing output data.

Figure. 4 shows the number of testing output data is 29 data with the target of data is the data of number 30. This means the dimension of testing output data is [29 x 29] with the maximum output data is 1213.

4. Results

The results are presented to show both training network outcome and testing network outcome in following subsection:

4.1. Training network outcome

Once the code for training network has made up, then the process of training network is shown as in figure 5.

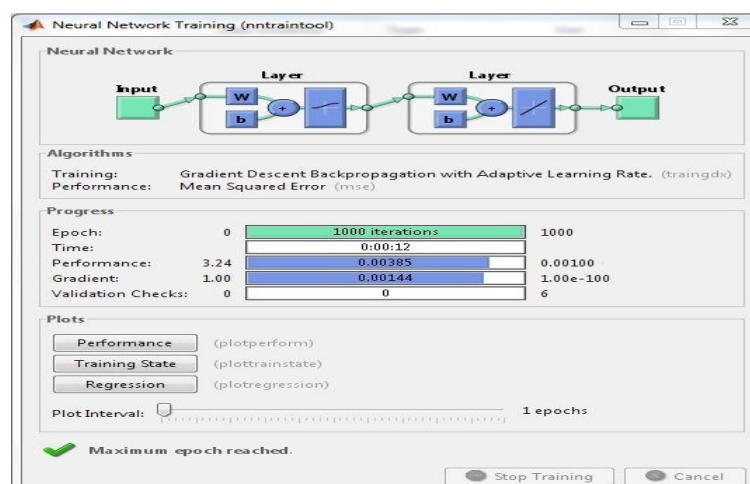


Figure 5. Neural Network Training Tool for Trained Networking.

Based on figure 5, it shows that neural network for training tool complete 1000 iterations within 12 sec. Consequently, the following approach needs to estimate the average of the squares of the deviation. It shows in figure 6.

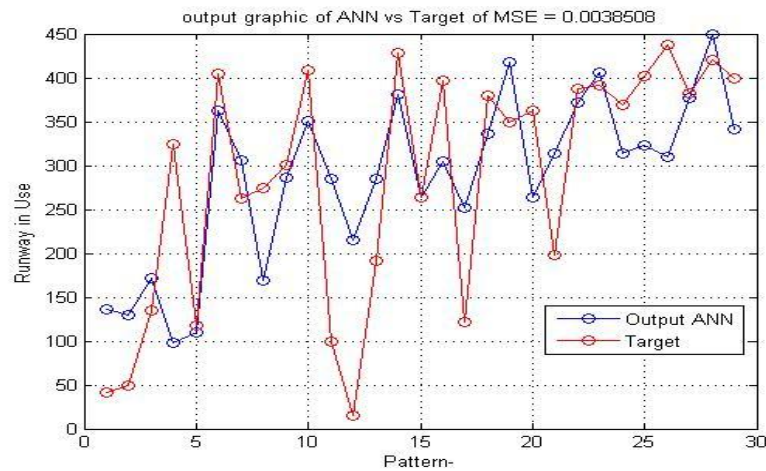


Figure 6. MSE of Trained Networking.

Based on figure 6, the value of MSE is 0.003858. This value shows that the estimation is quite good. Additionally, it also supported by the behaviour of target that is capable to imitate the pattern of target. Subsequently, the following step is to estimate the relationship between input data and target whether these two variables are really connected. It used regression approach as shown in figure 7 to complete it.

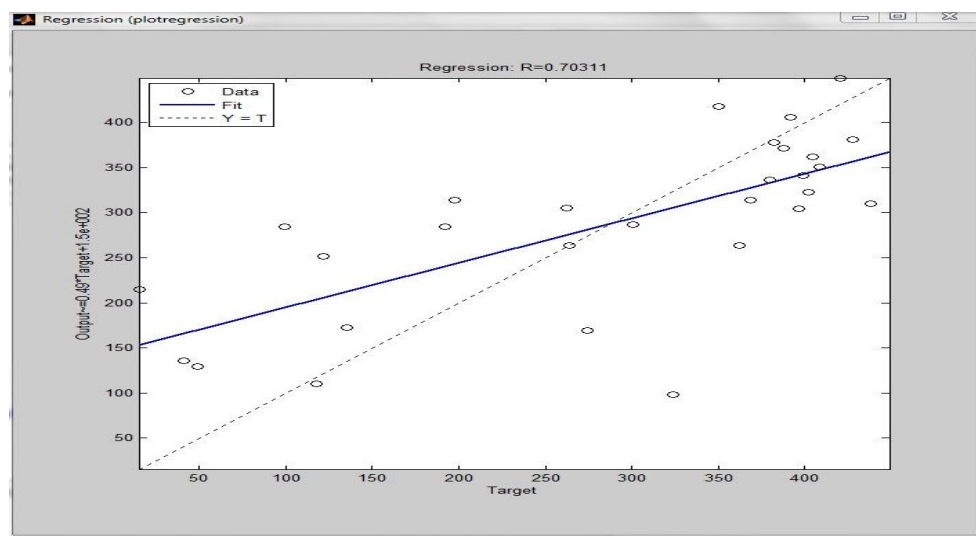


Figure 7. Regression of Trained networking.

The regression results as depicted in figure 7 shows that the relationship between input data and target are quite good as the result shows the value of 0.70311. It means that these two variables between input data and target are having positive relation, if one of them is decreasing, then the other one will follow it and vice versa.

4.2. Testing network outcome

This step is needed to test the network in order to identify the capability of trained network to recognize certain patterns properly. Once the code for testing network done, then the value of MSE can be calculated and the result is shown as in figure 8.

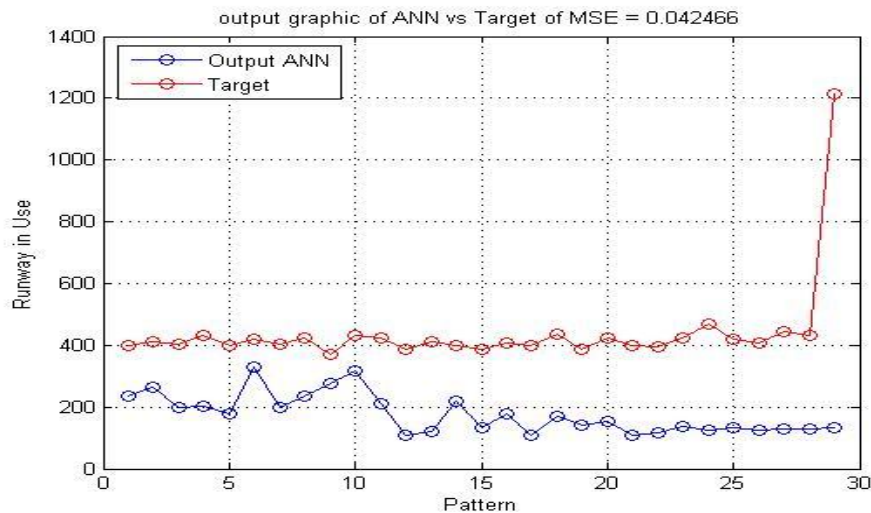


Figure 8. Regression of tested networking.

Figure 8 shows that the pattern between target data and input data is not precise with the value obtained of 0.042466. Consequently, this pattern will affect to the regression results as depicted in figure 8.

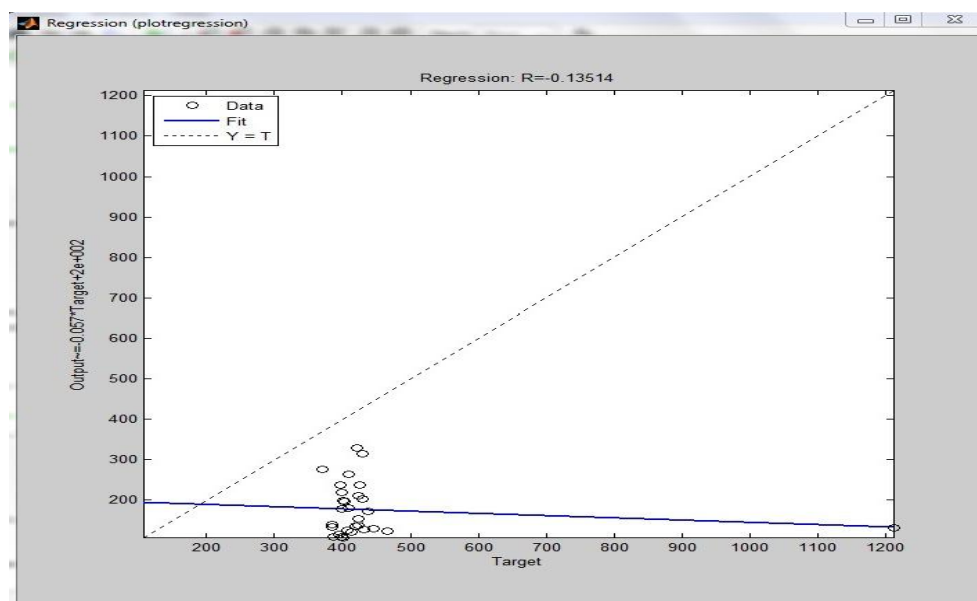


Figure 9. Regression of Tested Networking.

The figure 9 shows the pattern that is resulted between trained network and tested network. From these two variables are obtained the result value of 0.13514. This means that the relationship between trained network and tested network are in weak condition. Consequently, each of these variables having a weak correlation.

This result is also affected by the process of adjusting the data dimension which is changed from the dimension of [31 x 31] to the dimension of [29 x 29]. Besides, according to Khanmohammadi et al., [4] one of factors that contribute to error in predicting using artificial neural networks is process of converting nominal variables into numerical variables. Therefore, it will increase the complexity of datasets that leads to more difficulty for interpreting the result of neural network model due to being a black box model.

5. Conclusions

Based on the results of this research, several findings can be drawn as follows:

To uniformity the data, it needs a certain approach. Unless, the trained network will not be capable to recognize the pattern of data.

It needs to model a number of network architectures to obtain an optimum model which is indicated by its regression value.

Generally, the model that developed using artificial neural network has capability to imitate the fluctuation of runway capacity of Juanda International Airport during January 2016 to March 2016.

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