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Forecasting System for Passenger, Airplane, Luggage and Cargo, Using Artificial Intelligence Method-Backpropagation Neural Network at Juanda International Airport

Sistem Peramalan Untuk Penumpang, Pesawat, Bagasi, dan Kargo dengan Menggunakan *Artificial Intelligence Method-Backpropagation Neural Network* di Bandara Internasional Juanda

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***ABSTRACT* / ABSTRAK**

Juanda International Airport is the third busiest airport, after Soekarno Hatta International Airport and Ngurah Rai International Airport. Because the number of Airplane, passengers, luggage and cargo at Juanda International Airport is increasing every year, it is important to improve infrastructure facilities and services, and all facilities at Juanda Airport.

In this research, it was designed and built a forecasting system for Airplane, passenger, luggage and cargo. This research is expected to be a consideration in increasing the readiness of infrastructure and services, and all facilities at Juanda Airport. In addition, this system is also expected to be one of the decision supporting system for the management.

This system uses one of the Artificial Intelligent methods, Backpropagation Artificial Neural Network. It is known in previous research that Backpropagation is a method of artificial neural networks with the best performance in pattern recognition, or forecasting. The forecasting system has two main processes, the training process and the forecasting process.

Bandara Internasional Juanda merupakan bandara tersibuk ketiga, setelah Bandara Internasional Soekarno Hatta dan Bandara Internasional Ngurah Rai. Karena jumlah Pesawat, Penumpang, Bagasi dan Kargo di Bandara Internasional Juanda semakin meningkat setiap tahunnya, maka penting untuk meningkatkan sarana dan prasarana pelayanan, dan segala fasilitas di Bandara Juanda.

Pada penelitian ini dirancang dan dibangun sebuah sistem peramalan untuk pesawat, penumpang, bagasi dan kargo. Penelitian ini diharapkan dapat menjadi bahan pertimbangan dalam meningkatkan kesiapan infrastruktur dan pelayanan, serta seluruh fasilitas yang ada di Bandara Juanda. Selain itu, sistem ini juga diharapkan dapat menjadi salah satu sistem pendukung keputusan bagi manajemen.

Sistem ini menggunakan salah satu metode *artificial intelligent* yaitu *jaringan syaraf tiruan backpropagation*. Telah diketahui pada penelitian sebelumnya bahwa *backpropagation* merupakan metode jaringan syaraf tiruan dengan performa terbaik dalam pengenalan pola, atau peramalan. Sistem peramalan memiliki dua proses utama, proses pelatihan dan proses peramalan.

INTRODUCTION

Airport is a facility where planes take off and land. In addition to the runway, there are air side facilities and land side facilities inside the Airport. In accordance with the Regulation of the Minister of Transportation of the Republic of Indonesia Number PM 178 Year 2015 Regarding Standards for User Service and Airport Services, service standards include facilities used in the process of departure, and arrival of passengers, facilities that provide comfort to passengers, and facilities that provide added value, and terminal capacity to accommodate passengers during peak hours. Facilities used in the departure process include passenger and Luggage checks, check-in services, departure immigration, arrival immigration, customs services, departure lounge, and Luggage services. Facilities that provide comfort to passengers include temperature conditioning, light conditioning, ease of transporting luggage, cleaning, information services, toilets, parking lots, and facilities for users with special needs. Facilities that provide added value include prayer rooms, nurseries, shopping facilities, restaurants, smoking rooms, children's play rooms, ATM / Money Changer, Internet / Wifi, ticket purchase facilities, charging stations, drinking water facilities, and executive lounges. And airport facilities to accommodate passengers during peak hours include the area per passenger during peak hours, an early indication of construction and operation. (Perhubungan, 2015)

Juanda International Airport is an airport located in Sedati District, Sidoarjo, south of Surabaya. Juanda International Airport is the third busiest airport in Indonesia after Soekarno-Hatta International Airport and Ngurah Rai International Airport, based on Airplane and passenger movements (Liputan6.com, 2019). The increasing number of flights at Juanda Airport, makes the increasing number of planes, passengers, luggage and cargo at Juanda Airport.

In this research, it was designed and built forecasting system for an Airplane, passenger, luggage and cargo. This research is expected to be a consideration in increasing the readiness of infrastructure and services, and all facilities at Juanda Airport. In addition, this system is also expected to be one of the decision supporting system for the management.

This system uses one of the Artificial Intelligent methods, Backpropagation Artificial Neural Network. It is known in previous research that Backpropagation is an artificial neural network method with the best performance in pattern recognition, or forecasting (Zhang, Patuwo, & Hu, 1998). The forecasting process, there are two main processes, the training process and the forecasting process.

METHODS

Backpropagation Algorithm

This algorithm is generally used in artificial neural networks of multi-layer feed-forward type, which are composed of several layers and signals are transmitted the input to the output in the direction. The backpropagation training algorithm basically consists of three stages:

a. Input training data values so the output values are obtained
b. Backpropagation of the error value obtained
c. Adjusting correction weights to minimize error values

The three stages are repeated continuously until they get the desired error value. Error information is propagated sequentially starting from the output layer and ending at the input layer, so this algorithm is called backpropagation.

The training of artificial neural network using backpropagation algorithm, as follows (Fausett, 1994):

- Initialization of weights
  Determine the learning rate (α).
  Also specify the error tolerance value or threshold value (when using the threshold value as a stop condition) or set the maximum epoch (when using the number of epoch as a stop condition).
- Perform the following steps as long as the stop condition is FALSE:

1. For each pair of elements that will be studied, do:

Feed Forward Stage

a. Each input unit (X_i, i = 1,2,3, ..., n) receives the x_i signal and transmits the signal to all units in the layer above it (hidden layer).
b. Each hidden unit (Z_i, j = 1,2,3, ..., p) sums the weighted input signals:

$$z\_in_j = v_{0j} + \sum_{i=1}^{n} x_i v_{ij}$$

Use the activation function to calculate the output signal:

$$z_j = f(z\_in_j)$$

And send the signal to all the units above it (output units).

c. Each unit in the output layer (Y_k, k = 1,2,3, ..., m) sums the weighted input signals:

$$y\_in_k = w_{0k} + \sum_{i=1}^{p} z_i w_{jk}$$

Use the activation function to calculate the output signal:

$$y_j = f(y\_in_k)$$

And send the signal to all the units above it (output units).

Backpropagation Stage

a. Each unit of output (Y_k, k = 1,2,3, ..., m) receives a target pattern related to the learning input pattern, calculating the error information:

$$\delta_k = (t_k - y_k) f'(y\_in_k)$$

Then calculate the weight correction (which will be used to correct the time value):

$$\Delta w_{jk} = \alpha \delta_k z_j$$

Also calculate the correction bias (which will later be used to correct the value of w0k):

$$\Delta w_{0k} = \alpha \delta_k$$

b. For each unit in the hidden layer (Z_j, j = 1,2,3, ..., p) add up the input delta (of the units in the layer above it):

$$\delta\_in_j = \sum_{k=1}^{m} \delta_k w_{jk}$$

Multiply this value by the derivative of the activation function to calculate the error information:

$$\delta_j = \delta\_in_j f'(z\_in_j)$$

Then calculate the weight correction (which will be used to correct the value of vij):

$$\Delta v_{jk} = \alpha \delta_j x_i$$

Also calculate the correction bias (which will later be used to correct the value of v0j):

$$\Delta v_{0j} = \alpha \delta_j$$

Update Weight and Bias

At each unit of output yk (from the 1st to the mth unit) the bias and weight are updated (j = 0, ..., pk = 1, ..., m) so that the bias and weight which just became:

W_{jk} (new) = W_{jk} (old) + ΔW_{jk}

From the *1st* unit to the *P* unit in the hidden layer, also update the bias and weight (i = 0, ..., n j = 1, ..., p):

V_{ij} (new) = V_{ij} (old) + Δ V_{ij}

2. Stop condition test

One of the earliest methods proposed to overcome the problem of the length of training time is to add term momentum (Fausett, 1994) :

$$\Delta w_{ij} = -\varepsilon \frac{\partial E}{\partial w_{ij}}(t) + \mu \Delta w_{ij}(t-1)$$

where the momentum parameter $0 < \mu < 1$ will determine the effect of changes in weight on the previous iteration.

Linier Data Normalization (Min-Max)

Normalize the data by dividing the value of the data by the range of data (maximum data value - minimum data value). Input data normalization aims to match the value of the data range with the activation function in the Backpropagation system. This means that input values must be in the range of 0 to 1. So that the input range is the value of input data from 0 to 1 or from –1 to 1. Therefore, the output result will be in the range of 0 to 1. Then, needs to do the denormalization process to get the true output value. For Normalizing data, using the formula:

$$f(x) = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}}$$

In the testing process, the output produced by the network ranges from 0 to 1, so needs to do the denormalization process which is useful for converting back the results of network output to normal prices. After that, compare a actual data and a predicted data, for calculating an error or percentage of error. For denornormalize data using the formula:

$$x_i = y(x_{\max} - x_{\min}) + x_{\min}$$

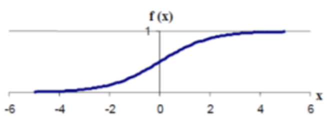
Sigmoid Activation Function

The activation function is a function that determines the level of activation, the internal state of a neuron in a network (Fausett, 1994). This activation output is usually sent as a signal to several other neurons. Keep in mind that a neuron can only send signals once at a time, even though these signals can be sent at once to several other neurons. Most units in the Neural Network transform the input value using the activation function to produce an output value.

Functions called sigmoid functions include functions in the form of an S curve. For example, logistic functions. The Sigmoid function has the advantage of training Neural Networks using backpropagation algorithms, because of the simple relationship between the value of a function at a point and its derivative values, thereby reducing the computational burden during learning. The sigmoid function equation is as follows:

$$f(x) = \frac{1}{1 + e^{-x}}$$

This function is specifically used as an activation function for Neural Networks where the output value is located at intervals between 0 and 1.



Measuring Accuracy Forecasting Results

A measure of the accuracy of forecasting results is a measure of forecasting error. It is a measure of the degree of difference between forecasting results and actual demand.

Root Mean Squared Error = RMSE (Root Square Mean Error). RMSE is formulated as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum (F_t - A_t)^2}$$

Where:
A_t = Actual demand for period -t
F_t = Forecasting the demand for the t-period
n = Number of forecasting periods involved.

RESULT AND DISCUSSION

System Plan

The following flowchart system consists of the Training Process and Forecasting Process. The training process is a calculation process that uses the Backpropagation method to improve the new weights that will be used in the forecasting process. Input data from the training process, are Data History, Backpropagation variables, and Random Weights. The results of the training process are new weights and RMSE.

The forecasting process is the process of calculating the output value using new weights obtained from the previous training process using the feedforward algorithm. Data input from the forecasting process, is a new weight obtained from the previous training process. The results of the forecasting process, then denormalized to become the predictive data.

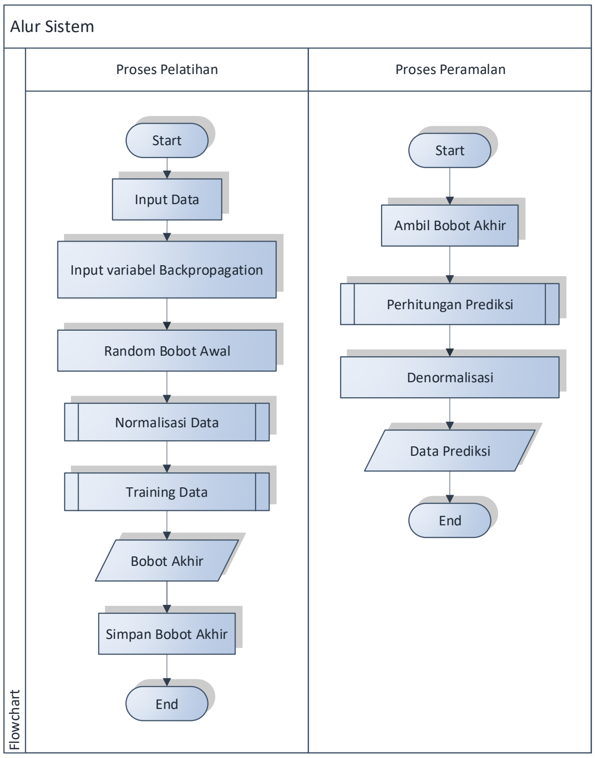


Figure 1. Flowchart System

Network Architecture

The following Backpropagation Network Architecture. The number of input layers, hidden layers, and output layers can be adjusted

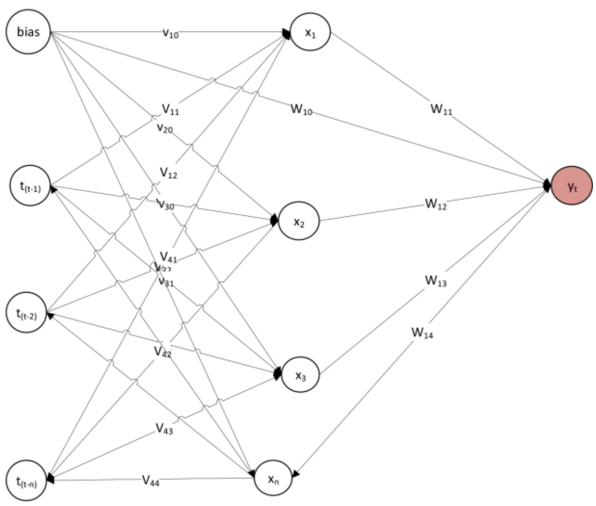


Figure 1. Backpropagation Network Architecture

Forward Process

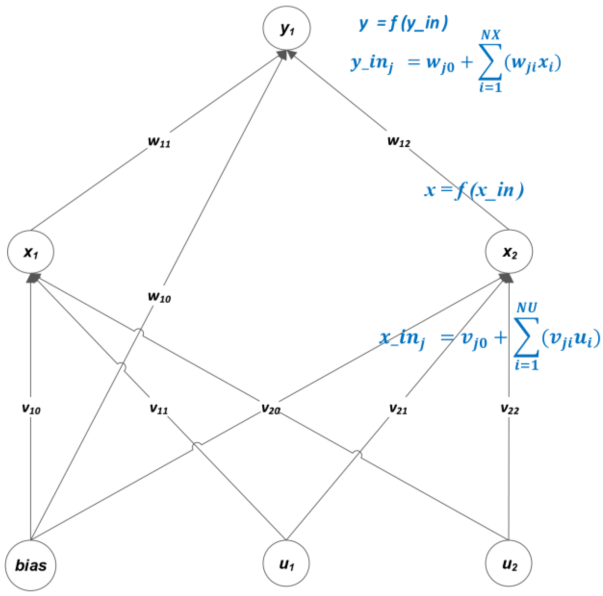


Figure 3. Backpropagation Network Architecture

Backward Process

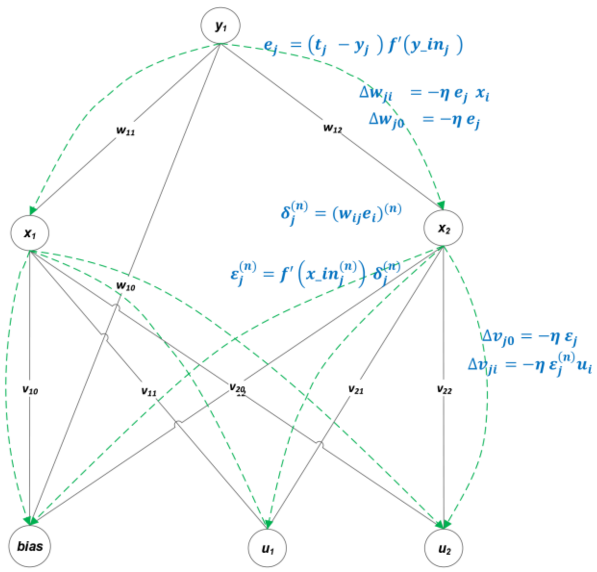


Figure 4. Backpropagation Network Architecture

Input Data

Input data that used in this research are the number of airplane, the amount of luggage, the number of passengers, and the amount of cargo, from May 2014 to May 2019. The data obtained from the Surabaya Region III Airport Authority Office and PT Angkasa Pura I Juanda International Airport Surabaya. Airplane Data is the total number of planes coming and leaving from and to Juanda

Airport. Both domestic and international flights. Luggage Data is the total amount of luggage that arrives and departs from and to Juanda Airport. Both domestic and international luggage, in kilograms. Passenger Data is the total number of passengers arriving and departing from and to Juanda Airport. Both domestic, international and transit passengers. Cargo Data is the total amount of cargo coming and leaving from and to Juanda Airport. Both domestic and international cargo, in kilograms.

Table 1. Movement of Air Transport Traffic at Juanda Airport

No	Bulan	Pesawat	Penumpang	Bagasi (Kg)	Kargo (Kg)
1	Jan 2014	11.823	1.501.535	11.455.447	8.681.867
2	Feb 2014	9.178	1.187.158	8.676.511	7.544.920
3	Mar 2014	10.904	1.342.918	8.950.002	8.967.050
4	Apr 2014	10.205	1.272.927	8.859.299	8.176.215
5	Mei 2014	11.235	1.412.087	10.025.823	8.317.533
...	.....	.....	.....	.....	.....
65	Mei 2019	9.864	1.153.071	7.565.609	8.197.423

Normalization Data

From the initial data in the table above each will be normalized as follows:

Table 2. Normalized Data of Luggage

No	Month	Luggage
1	Jan-14	0.45424725323054554
2	Feb-14	0.16010378560458988
...	...	...
65	May-19	0.04251757042273274

Table 5. Normalization Data of Airplane

No	Month	Airplane
1	Jan-14	0.5646883005977796
2	Feb-14	0.0
...	...	...
65	May-19	0.14645602049530315

Table 6. Normalized Data of Luggage

No	Month	Passengers
	Jan-14	0.400901517600647
2	Feb-14	0.03921647582089758
...	...	...
65	May-19	0.0

Table 7. Data Normalized Data of Cargo

No	Month	Cargo
1	Jan-14	0.5052715247189048
2	Feb-14	0.309707710492892
...	...	...
6	May-19	0.42194335162120844

Training Data

Training Data is the data that is ready to be used as input data in the training process. The result table of the normalization data then compiled into a Training Set for the Training Process. The following training set for each data.

Table 3. Training Set of Luggage

No	(t-12)	(t-11)	(t-10)	(t-9)	(t-8)	(t-7)	(t-6)	(t-5)	(t-4)	(t-3)	(t-2)	(t-1)	(t)
1	0,1601	0,1890	0,1794	0,3029	0,4643	0,3221	0,5861	0,3625	0,3957	0,2895	0,4542	0,3647	0,1499
2	0,1890	0,1794	0,3029	0,4643	0,3221	0,5861	0,3625	0,3957	0,2895	0,4542	0,3647	0,1499	0,1730
...	...	...	...	...	...	...	...	...	...	...	...	...	...
52	0,1794	0,3029	0,4643	0,3221	0,5861	0,3625	0,3957	0,2895	0,4542	0,3647	0,1499	0,1730	0,2220

Table 4. Training Set of Cargo

No	(t-12)	(t-11)	(t-10)	(t-9)	(t-8)	(t-7)	(t-6)	(t-5)	(t-4)	(t-3)	(t-2)	(t-1)	(t)
1	0,3097	0,5543	0,4182	0,4426	0,4979	0,3475	0,404	0,3163	0,3731	0,4490	0,4709	0,3857	0,2570
2	0,5543	0,4182	0,4426	0,4979	0,3475	0,4040	0,3163	0,3731	0,4490	0,4709	0,3857	0,2570	0,2771
...	...	...	...	...	...	...	...	...	...	...	...	...	...
52	0,5995	0,4434	0,5929	0,7857	0,8705	0,9232	0,9272	1,0	0,6187	0,2272	0,3866	0,1827	0,4219

Table 8. Training Set of Airplane

No	(t-12)	(t-11)	(t-10)	(t-9)	(t-8)	(t-7)	(t-6)	(t-5)	(t-4)	(t-3)	(t-2)	(t-1)	(t)
1	0,0	0,3684	0,2192	0,4391	0,4423	0,3584	0,6263	0,6880	0,5909	0,5228	0,7427	0,4607	0,1056
2	0,3684	0,2192	0,4391	0,4423	0,3584	0,6263	0,688	0,5909	0,5228	0,7427	0,4607	0,1056	0,3149
...	...	...	...	...	...	...	...	...	...	...	...	...	...
52	0,6825	0,9269	1,0	0,9829	0,8704	0,9141	0,6814	0,6974	0,3906	0,0491	0,2245	0,1240	0,1464

Table 9. Training Set of Passengers

No	(t-12)	(t-11)	(t-10)	(t-9)	(t-8)	(t-7)	(t-6)	(t-5)	(t-4)	(t-3)	(t-2)	(t-1)	(t)
1	0,0392	0,2184	0,1378	0,2979	0,4305	0,1478	0,5866	0,3645	0,4576	0,3497	0,5358	0,2253	0,0028
2	0,2184	0,1378	0,2979	0,4305	0,1478	0,5866	0,3645	0,4576	0,3497	0,5358	0,2253	0,0028	0,1090
...	...	...	...	...	...	...	...	...	...	...	...	...	...
52	0,5559	0,8158	1,0	0,8387	0,7039	0,6621	0,5401	0,6211	0,3280	0,0878	0,1678	0,0699	0,0

System Testing, Analysis and RMSE Calculation of Training Process

For testing the system, variables or parameters used are input layer, hidden layer, learning rate, error goal, and output layer. The variable can be changed as needed. At this stage of the Trial, the training data used are Luggage, Cargo, Airplane and Passenger Data. And the same variable is used:
Input layer = 12, Hidden Layer = 7, Output layer = 1, Total Connection = 99, Learning rate = 0.01
Goal Error = 0.001, Forecasting = 12 months ahead
Following are RMSE values, the Training Results with different iterations.

Table 10 Comparison of the RMSE Value of the Training Process

Amount of Iteration	Passenger	Luggage	Cargo	Airplane
10000	0.06036	0.071603	0.091425	0.07972
25000	0.04665	0.035795	0.07291	0.05972
50000	0.05672	0.02434	0.04958	0.04708
75000	0.01816	0.02753	0.05823	0.02422
100000	0.01885	0.01164	0.03419	0.02720
150000	0.01644	0.014420	0.04182	0.01737
200000	0.00353	0.009671	0.00919	0.01240
The Best Iteration	**200000**	**200000**	**200000**	**200000**
Lowest RMSE Value	0.00353	0.009671	0.00919	0.01240

Following is the RMSE Graph on each Training Process Data with 200,000 iterations.

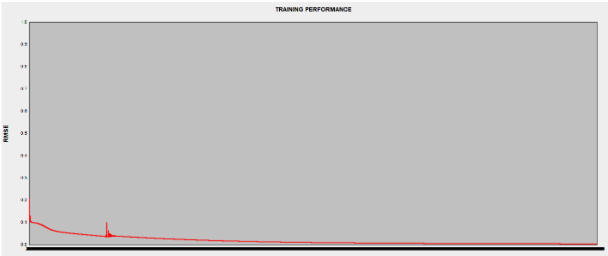


Figure 5. RMSE Chart of Training Data of Passenger Amount

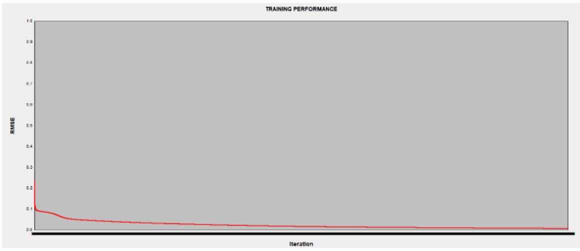


Figure 6. RMSE Chart of Training Data of Luggage Amount

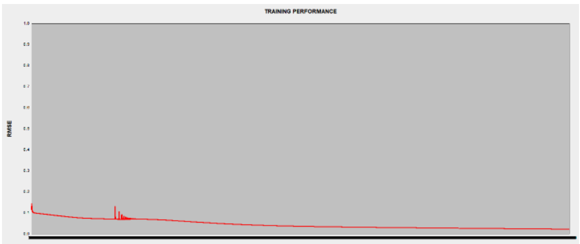


Figure 7. RMSE Chart of Training Data of Cargo Amount

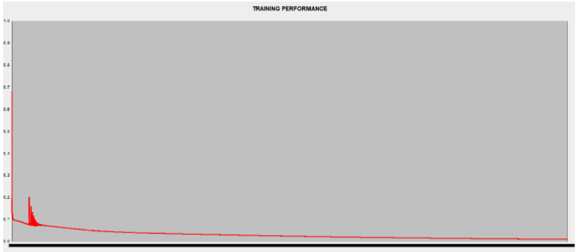


Figure 8. RMSE Chart of Training Data of Airplane Amount

The following is a Comparison Graph of Output Value and Target Number of Passengers, Luggage, Airplane and Cargo, with 200,000 iterations, and training data from May 2014 to May 2019.

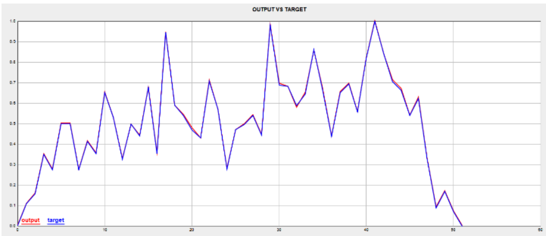


Figure 9. Comparison Chart of Output Value and Target Number of Passenger

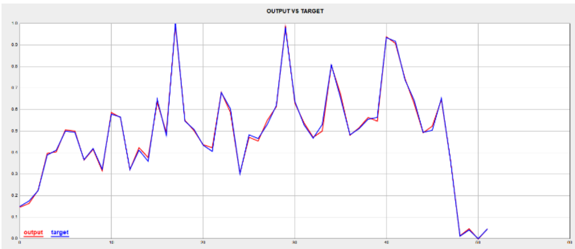


Figure 10. Comparison Chart of Output Value and Target Number of Luggage

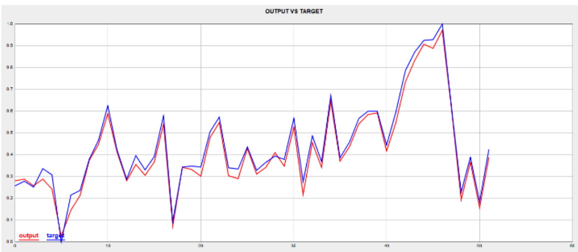


Figure 11. Comparison Chart of Output Value and Target Number of Cargo

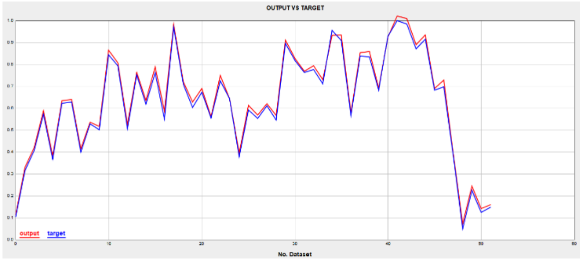


Figure 12. Comparison Chart of Output Value and Target Number of Airplane

The following is a Comparison Graph of Output Value, Target, and forecast for the next 12 months with 200,000 iterations. The training data used are data from May 2014 to May 2018. Forecast data is prediction data from June 2018 to May 2019. Then the forecast data will be calculated by RMSE Data Forecast.

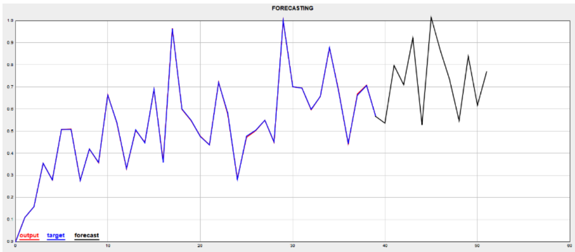


Figure 13. Comparison Chart of Passenger Output and Target Data, and Forecast for the next 12 months

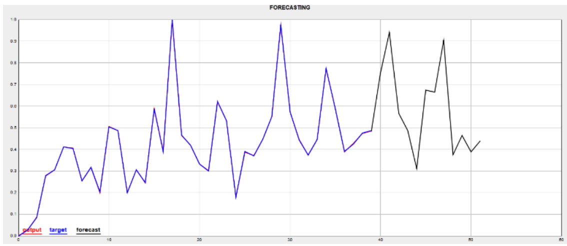


Figure 14. Comparison Chart of Luggage Output and Target Data, and Forecast for the next 12 months

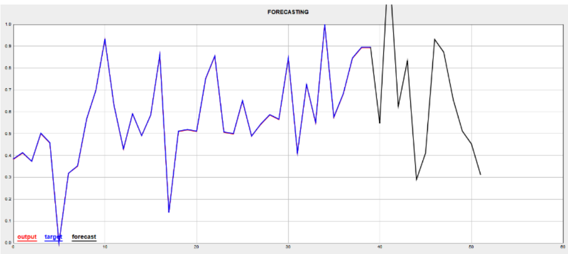


Figure 15. Comparison Chart of Cargo Output and Target Data, and Forecast for the next 12 months

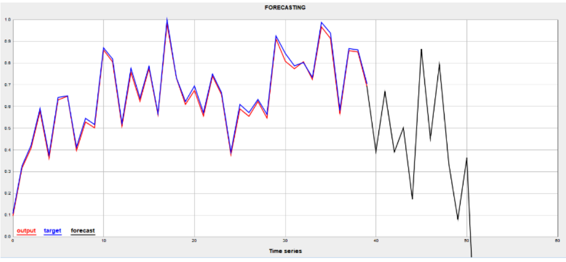


Figure 16. Comparison Chart of Airplane Output and Target Data, and Forecast for the next 12 months

RMSE Calculation Forecasting Process

The forecasting process can be done, after the training process. In the RMSE Forecasting Process calculation, the data used as training data are Total Passenger, Cargo, Luggage, and Airplane Data from May 2014 to May 2018, to predict June 2018 to May 2019 data. Then the forecasting results is compared with actual data from June 2018 to May 2019. The following table calculates RMSE 12-month forecasting data, with 200,000 iterations of the previous training process. Following is the RMSE Data Forecasting Process.

Table 12. RMSE Value of Airplane Data Forecasting Process

Bulan Kedepan	Target (t)	Forecasting Value (n)	$\sqrt{(t-n)^2}$	RMSE
1	13.520	11.441,4559	2.078,5441	2.078,5441
2	13.862	13.579,5199	282,4801	1.483,2634
3	13.782	12.319,5447	1.462,4553	1.476,3599
4	13.255	11.861,8784	1.393,1216	1.455,9966
5	13.460	11.603,0674	1.856,9326	1.544,5325
6	12.370	12.150,1800	**219,8200**	1.412,8118
7	12.445	13.401,7548	956,7548	**1.357,0769**
8	11.008	12.880,4528	1.872,4528	1.431,6809
9	9.408	10.834,7079	1.426,7079	1.431,1292
10	10.230	11.762,6788	1.532,6788	1.441,6061
11	9.759	12.536,4001	2.777,4001	1.609,5237
12	9.864	13.212,0507	3.348,0507	1.819,0125

Table 13. RMSE Value of Passenger Data Forecasting Process

Bulan Kedepan	Target (t)	Forecasting Value (n)	$\sqrt{(t-n)^2}$	RMSE
1	1.862.235	1.397.888,4069	464.346,5931	464.346,5931
2	2.022.272	1.743.818,6782	278.453,3218	382.853,7651
3	1.882.096	1.653.303,6444	228.792,3556	339.362,1237
4	1.764.941	1.712.968,2447	**51.972,7553**	**295.042,8444**
5	1.728.584	1.305.713,3851	422.870,6149	324.660,0305
6	1.622.570	1.972.212,6729	349.642,6729	328.955,5887
7	1.693.012	1.605.016,4605	87.995,5395	306.364,3701
8	1.438.232	1.879.112,2333	440.880,2333	326.226,3920
9	1.229.411	1.384.003,5049	154.592,5049	311.856,1124
10	1.299.006	2.059.111,9316	760.105,9316	381.188,8168
11	1.213.908	1.715.580,9166	501.672,9166	393.668,6258
12	1.153.071	1.865.656,3842	712.585,3842	429.389,3713

Table 11. RMSE Value of Luggage Data Forecasting Process

Bulan Kedepan	Target (t)	Forecasting Value (n)	$\sqrt{(t-n)^2}$	RMSE
1	15.986.851	14.988.814,7219	998.036,2781	998.036,2781
2	15.815.476	15.183.577,7419	**631.898,2581**	**835.275,9487**
3	14.134.023	12.776.869,2408	1.357.153,7592	1.038.787,4577
4	13.236.767	11.710.341,3299	1.526.425,6701	1.179.747,1629
5	11.830.927	11.312.978,7625	517.948,2375	1.080.322,5306
6	11.906.050	13.321.411,6224	1.415.361,6224	1.143.002,7976
7	13.311.297	14.504.447,3834	1.193.150,3834	1.150.300,5949
8	10.591.168	14.211.805,4674	3.620.637,4674	1.672.249,8273
9	7.258.483	12.300.468,3431	5.041.985,3431	2.304.415,3773
10	7.542.179	11.553.342,0750	4.011.163,0750	2.527.496,8110
11	7.163.922	12.002.504,8124	4.838.582,8124	2.817.063,0245
12	7.565.609	11.909.309,7141	4.343.700,7141	2.974.362,9685

Table 14. RMSE Value of Cargo Data Forecasting Process

The Next Month	Target (t)	Forecasting Value (n)	√(t-n)²	RMSE
1	8.322.336	7.875.231,3526	**447.104,6474**	**447.104,6474**
2	9.191.635	10.777.629,2726	1.585.994,2726	1.165.178,1835
3	10.312.273	8.178.612,1219	2.133.660,8781	1.556.469,2032
4	10.805.309	8.985.220,9209	1.820.088,0791	1.626.384,7759
5	11.111.769	6.875.548,3958	4.236.220,6042	2.388.559,1793
6	11.134.892	7.348.664,3361	3.786.227,6639	2.672.751,2257
7	11.558.064	9.368.742,9416	2.189.321,0584	2.609.179,4382
8	9.341.332	9.145.227,6984	196.104,3016	2.441.648,4770
9	7.065.650	8.294.646,4751	1.228.996,4751	2.338.176,1795
10	7.992.327	7.735.544,2823	256.782,7177	2.219.674,4802
11	6.806.673	7.505.098,3157	698.425,3157	2.126.827,4688
12	8.197.423	6.959.422,1264	1.238.000,8736	2.067.405,6219

Table 15. The Conclusion Table

FORECAST	The Lowest Target and Output Difference		Lowest RMSE	
	Value	Month	Value	Month
Passenger	51,972.7553	4	295,042,8444	4
Airplane	219.8200	6	1,357.07769	6
Luggage	631,898.2581	2	835,275,9487	2
Cargo	256.782,7177	10	447.104,6474	1

CONCLUSION

In the data training process of passenger, luggage, airplane and cargo, it is found that the smallest RMSE value is in 200,000 iterations. So it can be concluded that the more iterations, produce the better training process, and has a smaller RMSE value.

The lowest RMSE value in the passenger data training process is 0.00353. The lowest RMSE value in the luggage data training process is 0.009671. The lowest RMSE value in the cargo data training process is 0.00919. And the lowest RMSE value in the Airplane data training process is 0.01240.

The forecasting process can be done after the training process. In this research, the forecasting process is carried out in the next 12 months. In the forecasting process, the data used as training data is data from May 2014 to May 2018. And forecasting data result will be compared with data from June 2018 to May 2019.

In the Passenger Data forecasting process, the lowest target and output difference is 51,972.7553 in the 4th month and the lowest RMSE value is 295,042,8444 in the 4 month forecasting. In the Airplane Data forecasting process, the lowest target and output difference is 219.8200 in the 6th month and the lowest RMSE value is 1,357.07769 for the 7 month forecasting. In the Luggage Data forecasting process, the lowest target and output difference is 631,898.2581 in the second month and the lowest RMSE value is 835,275,9487 in the second forecasting months. In the Cargo Data forecasting process, the lowest target and output difference is 256.782,7177 in the tenth month and the lowest RMSE value is 447.104,6474 in the first month.

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